International Conference on Science, Engineering & Management Trends

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

A Multi-Stage AI Framework for Prenatal Crop Monitoring, Risk Prediction and Storage

Ms. Abinaya S[1], Amuthavan M[2], Akashkumar V[3], Kishore E[4]

Dept. of Computer Science & Engineering Dhanalakshmi Srinivasan College of Engineering & Technology

Chennai, Tamil Nadu, India

Abstract- Agriculture faces challenges in productivity and eco- nomic issues because there is no real-time information available about soil, crops, climate, and market conditions. The current smart farming systems tackle these issues individually and do not provide a complete, lifecycle-based decision support system. This paper introduces a Multi-Stage AI Framework for Prenatal Crop Surveillance, Risk Assessment, and Storage Solutions that follows a systematic Sense-Analyze-Act approach. The proposed framework combines IoT-based field sensing with ESP32 modules and environmental sensors. It also uses data analysis through machine learning and deep learning algorithms. Random Forest analyzes soil and assesses crop suitability. YOLOv8 detects pests and diseases in real time from leaf images. Long Short-Term Memory (LSTM) networks predict market prices based on historical data. A Flask-based backend manages data routing and preprocessing, while a Streamlit front end provides real- time alerts, visualizations, and decision support for farmers. This multi-layered architecture promotes modularity, scalability, and smooth integration of hardware and software. The prototype developed demonstrates real-time sensor data collection, image monitoring, and predictive analysis, offering a farmer-focused decision support system to reduce crop loss, improve storage efficiency, and support sustainable farming practices.

Keywords—Internet of Things (IoT), Prenatal Crop Monitoring, Random Forest, YOLOv8, Long Short-Term Memory (LSTM), Pest Detection, Soil Analysis, Decision Support System, Streamlit Dashboard.

I. INTRODUCTION

The sector of agriculture is still one of the most important ones in terms of economic and food security but is still in a state of high uncertainty because of climate changes, soil deterioration, and pest attacks in conjunction with market prices [1]. However, the farmer is not in a state to access current information that can aid in decision-making before and during the growth of the crops. As found in recent studies on smart agriculture, most of the current solutions are re- stricted to specific areas but cannot provide a holistic decision- making solution [2]. The conventional farming practices are mostly based on experience-driven decision-making, which can cause inappropriate decisions in terms of crops before sowing, delayed pest attacks, inappropriate watering of crops, and losses in stored products [3]. Additionally, the absence of proper integration between field sensing, modeling, and market analysis makes it difficult for farmers to address issues in an anticipatory manner. All these issues suggest that an integrated solution is needed that can incorporate artificial intelligence and can continuously monitor the crops and predict issues in their early stages of development.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

In addition, recent developments in Internet of Things (IoT) technology and machine learning have enabled real- time monitoring of agricultural activities with the help of sensor nodes and cloud computing [4]. Various environmental parameters such as soil moisture, temperature, humidity, gas, and pressure can be measured with the help of embedded systems such as ESP32, while computer vision algorithms can be used for the detection of pests and diseases based on leaf images. The absence of a holistic framework for pre- sowing analysis, crop growth stage analysis, risk analysis, market analysis, and storage analysis is one of the research gaps in the field of agricultural management. To overcome these issues, in this paper, a Multi-Stage AI Framework for Prenatal Crop Monitoring, Risk Prediction, and Storage Man- agement is proposed. The term prenatal implies a process of monitoring and prediction before critical crop failures occur. The proposed framework is a Sense-Analyze-Act process [5], which integrates the IoT-based data acquisition process and intelligent analysis. The proposed system uses a random forest algorithm for soil analysis and crop prediction, YOLOv8 for pest and disease prediction using images of crops, and LSTM for market price prediction. The backend is implemented using a Flask-based backend and a Streamlit-based frontend for visualization and decision-making for the farmer [2].

The proposed multi-layered architecture has been developed to ensure modularity, scalability, and hardware-software in- tegration. The proposed system, which integrates real-time sensing, predictive modeling, and decision support in one platform, has the potential to prevent crop losses, maximize storage space, and promote sustainable agricultural practices in accordance with global development goals.

II. BACKGROUND

The agricultural sector has witnessed a transformation from manual to technology-based precision agriculture. With recent advancements in the Internet of Things (IoT) and artificial intelligence (AI) technologies, it has become possible to mon- itor and predict productivity levels in the agricultural sector. Smart agriculture systems include sensors, communication systems, and machine learning algorithms for decision-making processes [6]

IoT-based systems for agricultural monitoring include the implementation of sensor nodes to measure different parame- ters such as soil moisture, temperature, humidity, pressure, and gas composition. Microcontrollers such as ESP32 can be used to monitor and transmit data related to these parameters in real-time over a Wi-Fi network [4]. However, data obtained from these nodes is not usable in its raw form and must be appropriately preprocessed and modeled.Machine learning algorithms have been effectively used for different applications such as soil testing, crop selection, crop yield prediction, and environmental monitoring in the agricultural domain. The Random Forest algorithm can be used for agricultural data, which is highly structured, and can efficiently process noisy data and non-linear relationships between soil properties and crop selection [7]. In addition, a computer vision model such as YOLOv8 can be used for pest and disease detection by locating the infected part of a crop's leaves by using bounding box localization [8].

Time series forecasting models such as the Long Short- Term Memory (LSTM) network have been widely employed to model temporal relationships in sequential data. In the field of agriculture, LSTM models can be employed to perform market price trend forecasting as well as environmental change forecasting using past datasets [8]. These models assist farmers in effective strategies for the selling of the products through the harvesting of the products.

However, the existing systems in the field of agriculture are mostly standalone systems that focus on either monitoring, detection, or prediction of the products. The major drawback of the existing systems is the absence of a comprehensive, lifecycle-based framework that integrates pre-harvest soil test- ing, real-time crop monitoring, risk analysis, and post-harvest management [?].

Motivation

The motivation for the proposed "Multi-Stage AI Frame- work" arises due to the fact that farmers have been facing challenging situations with uncertain climate conditions, in- appropriate crop selections, untimely detection of pests, and fluctuating prices of crops [10]. Agricultural failures do not occur due to the unavailability of technology, but rather due to the unavailability of predictions and decision-making tools on time. Most of the existing state-of-the-art smart farming technology can address particular issues, such as irrigation management and disease detection, but none of the smart farm- ing technology is available for farmers that can provide support for all stages, starting from pre-sowing to post-harvesting [11]. Inaccurate detection of soil types during the initial stages may cause inappropriate crop selections, while untimely de- tection of pests may cause significant reduction in the quality and quantity of agricultural production [12]. Unpredictable fluctuations of prices may also affect the farmers. The availability of technology like ESP32-based IoT sensing platforms has made it possible to analyze environmental and soil factors in real-time, and machine learning algorithms have made it possible to predict and analyze risks and crop

suitability [4]. Deep learning algorithms like YOLOv8 have made it possible to automatically detect pests and diseases by analyzing images of crops, and LSTM algorithms have made it possible to predict trends in the market based on past trends in the market. However, the absence of integration between all these modules has made it difficult to effectively use all these technologies.

The purpose of this research, therefore, is to develop a Sense-Analyze-Act system that effectively combines all these technologies into one platform [?]. The prenatal care system, in which risks are detected before they become problems, has been used to develop this system to minimize damage to crops, improve decision-making accuracy, optimize storage management, and promote sustainable agriculture.

Finally, the objective of this research is to bridge the gap between individual smart agriculture technologies and a complete, scalable, and modular AI-based agricultural decision support system.

Objectives

The primary objectives of this paper are to:

- To design and develop a multi-stage AI-based smart agricultural system, which integrates IoT technology, machine learning, and deep learning models in a unified Sense, Analyze, Act framework.
- Develop a real-time soil and environment sensing sys- tem using ESP32-based sensor nodes to sense various parameters like soil moisture, temperature, humidity, gas concentration, and pressure for crop suitability analysis.
- Design an intelligent crop suitability and recommenda- tion system using the Random Forest algorithm for pre- sowing crop suitability analysis.
- Develop a computer vision-based crop pest and disease detection system using YOLOv8 for early-stage crop analysis.
- Apply Long Short-Term Memory (LSTM) networks for agricultural crop price forecasting to help farmers in planning the optimal harvesting and selling of crops.
-

III. RELATED WORK

The recent trends in smart agriculture have been towards the integration of IoT technology and AI for better crop observation and improvement in crop productivity. A com- prehensive overview of smart agriculture technology was provided by Ahmed et al. [14], which covered the prospects and challenges of IoT, machine learning, and decision support systems. Although the work highlighted the significance of smart agriculture technology, the development of a unified implementation strategy in terms of the lifecycle of the system was not provided.

The application of intelligent farming in the development of sustainable agriculture through AI and IoT technology was provided by Rao et al. [15]. The work showed the effectiveness of intelligent farming in improving the efficiency of the farming system through the application of sensor-based observation systems. However, the application of the system was limited to environmental observation systems.
The development of IoT-based agricultural observation sys- tems has been a research focus in recent years. Sharma et al.

[4] introduced a smart agriculture observation system based on the ESP32 microcontroller, which can observe environmental factors such as temperature and soil moisture in real-time. Although the research was successful in the observation and communication of data, there was no advanced prediction analysis and deep learning-based pest observation. Machine learning algorithms were introduced in crop recommendation and soil analysis systems. Patel and Shah [7] introduced machine learning algorithms such as Random Forest for crop prediction and soil-based crop recommendation analysis systems. Although the research showed successful prediction results, it is a standalone analysis system without real-time IoT-based system implementation.

In plant disease detection, Kumar in his paper [17] imple- mented a deep learning-based crop health monitoring system using convolutional neural networks for leaf disease detection. Similarly, object detection models like YOLOv8 have been reported to perform well in detecting pests and diseased regions in crops. However, all these models are implemented for plant disease detection but are not integrated with decision support systems.

Time-series forecasting models have been implemented for various agricultural and environmental prediction problems. In a paper titled "Climate-Aware Agricultural Forecasting using LSTM Neural Networks" by Li et al. [8], LSTM models have been implemented for climate-aware agricultural forecasting using recurrent neural networks. However, all these models are implemented for agricultural forecasting but are not integrated with soil analysis systems and plant disease detection systems. Recently, various researchers have implemented AI-based post-harvest storage monitoring systems using IoT sensors for grain quality maintenance and spoilage prevention. In a paper titled "Intelligent Postharvest Storage Monitoring System for Grain Quality Maintenance and Spoilage Prevention" by Tran and Nguyen [17], an intelligent postharvest storage monitoring system was implemented for warehouse monitoring but was not integrated with crop growth analysis and market prediction systems.

As indicated in literature survey, current literature is focused on individual agricultural problems such as soil monitoring, pest detection, irrigation management, and market prediction. However, the primary issue is that no literature is available on a multi-stage solution that can include all stages of pre- sowing analysis, real-time crop monitoring, risk prediction, market forecasting, and storage management.

The primary difference of the proposed research is that a lifecycle-based Multi-Stage AI Framework is included in the solution that can support a Sense-Analyze-Act approach. IoT sensor-based sensing

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

technology, Random Forest-based soil analysis, YOLOv8-based pest detection, LSTM-based market forecasting, and decision support using a dashboard can make the solution a comprehensive intelligent agricultural solution.

IV. METHODOLOGY

In the following section, the problem formulation and the proposed Multi-Stage AI Framework for Prenatal Crop Monitoring, Risk Prediction, and Storage Management will be described. The proposed system is based on the systematic Sense-Analyze-Act paradigm, which integrates IoT sensing technologies with machine learning and deep learning tech- niques for prediction-based decision-making in the agricultural field.

A. Problem Statement

Let S = {s1, s2, . . . , sn} be the set of real-time sensor parameters collected from the agricultural field. The real-time sensor parameters collected from the agricultural field consist of various parameters like moisture, temperature, humidity, pressure, and gas concentration using ESP32-based sensor nodes.
Let I = {I1, I2, . . . , Im} be the set of crop leaf images captured from the agricultural field using the ESP32-CAM module for pest and disease detection.
Let M = {m1, m2, . . . , mt} be the set of historical market price data collected from the agricultural field. The proposed system aims to create predictive models that learn to map the agricultural field to agricultural insights:

$f1 : S \rightarrow C$
where C is the crop suitability and soil health classification result from the Random Forest model.

$f2 : I \rightarrow D$
where D is the pest or disease detection result from the YOLOv8 model.

$f3 : Mt \rightarrow \hat{P}t+1$
where $\hat{P}t+1$ is the predicted market price from a Long Short- Term Memory (LSTM) network.

Essentially, the key issue is how to integrate all the data sources into a framework that can provide real-time alerts and suggestions. The data sources include sensor data, images, and market data, and there are issues related to noisy sensor data, environmental factors, and market factors.

B. Proposed Multi-Stage Framework

The proposed framework is divided into four functional tiers:

Perception Layer (Sense): These include IoT hardware devices such as ESP32, DHT22 (temperature and humidity sensor), soil moisture sensor, BMP280 (pressure sensor), MQ- 135 (gas sensor), and ESP32-CAM for image sensing. The sensors are used to obtain real-time environment and soil conditions, while the camera is used to obtain images of the leaves of the crop.

Connectivity Layer: This data and images are transmit- ted over Wi-Fi using the HTTP protocol and are received by a Flask server. The sensor data is sent in JSON format, and the images are sent in JPEG format. This layer offers a powerful solution for real-time communication between the field devices and the analysis server.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

Intelligence Layer (Analyze): This layer includes the following:
Data Preprocessing: It includes missing data handling, sensor data normalization, and image processing opera- tions like rotation and brightness changes.
Random Forest Model: It is used for soil testing and crop recommendation based on organized sensor data.
YOLOv8 Model: It is used for real-time pest and disease identification from images of crop leaves using bounding box localization.
LSTM Model: It is used for forecasting agricultureal market prices based on historical data.

Application Layer (Act): The final predictions and noti- fications are provided through a dashboard created using the Streamlit framework. The dashboard offers the following:
- Real-time sensor data
- Pest identification results
- Crop recommendation results
- Market price prediction results
- Risk-related and suggestions

This well-organized and integrated approach helps in taking

proactive decisions, where the farmer is able to identify the risks at very early stages (prenatal surveillance), improve crop selection, pest management, and make better decisions regarding the sale of crops.
The overall process can be represented as follows:

Sensors → ESP32 → Flask Server → AI Models → Dashboard
Through the integration of real-time IoT sensing and ma- chine learning-based prediction and visualization, the proposed approach provides a scalable and modular intelligent agricul- tural monitoring system.

C. System Design
The proposed system architecture is based on a layered and modular architecture following the paradigm of "Sense- Analyze-Act." The workflow of the proposed system can be defined as an integration of IoT-based sensing, AI-based ana- lyzing, and decision support via a dashboard-based decision- making system.

The system has four main layers:
Perception Layer:
This layer consists of hardware com- ponents such as ESP32-based components, DHT22, Soil Mois- ture Sensor, BMP280, and MQ135 sensors. The ESP32-CAM module is utilized to capture images of crop leaves for anal- ysis. The hardware components are always ready to monitor real-time environmental and crop information.

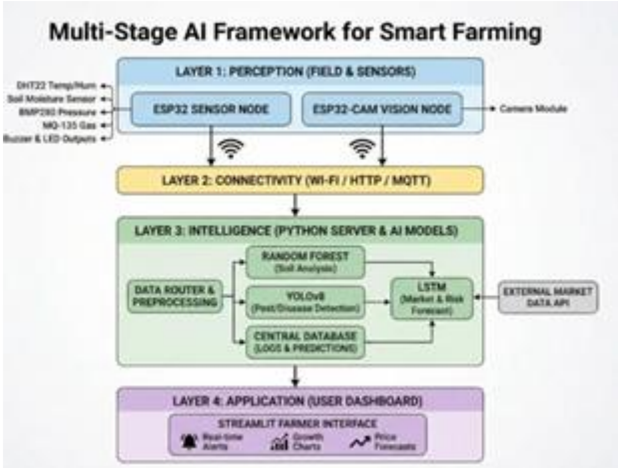

Fig. 1: Proposed Multi-Stage AI Framework for Smart Farming

Algorithm 1 Multi-Stage AI Framework for Prenatal Crop Monitoring

1. Data Acquisition (Sense)
Initialize ESP32 sensor node
Collect soil and environmental parameters:
  $S \leftarrow$ {soil moisture, temperature, humidity, pressure, gas level}
Capture crop leaf images:
  $I \leftarrow$ Image from ESP32-CAM
Transmit S and I via Wi-Fi using HTTP protocol to Flask server
2. Data Preprocessing
Clean sensor data (remove noise, handle missing values)
Normalize numerical features
Perform image preprocessing and augmentation
Store processed data in database
3. AI-Based Analysis (Analyze)
Soil analysis:
  $C \leftarrow RandomForest(S)$
Pest/Disease detection:
  $D \leftarrow YOLOv8(I)$
Market forecasting:
  $\hat{P}_{t+1} \leftarrow LSTM(M_t)$
4. Decision Support (Act)
Generate alerts and recommendations
Display results on Streamlit dashboard
Provide actionable insights to farmers

2)

Communication Layer: The sensor information is trans- mitted to the Flask server using Wi-Fi and the HTTP protocol. The information is sent in JSON format, whereas the images are sent in JPEG format. This allows real-time connectivity to the components in the field and the analysis engine.

Intelligence Layer: This layer entails machine learning and deep learning analysis:

- Random Forest: This is used for soil classification and crop suitability analysis using structured information obtained from sensors.
- YOLOv8: This is used for real-time localization of bounding boxes for pest and disease detection.
- LSTM: This is used for forecasting market prices for crops to determine the optimal selling time.
- The training of the model involves the preparation, cleaning, normalization, and validation of the data set. The validation of the early testing and inference is performed to ensure that the predictions are accurate.

Application Layer: The final results are represented in the form of a dashboard developed by using the Streamlit library. The dashboard contains the following information:

- Real-time sensor data
- Pest detection results with bounding boxes
- Soil analysis and crop recommendation results
- Market price forecast graphs
- Risk alerts and suggestions

The proposed system architecture is expected to exhibit mod- ularity, scalability, and real-time decision support capabilities. The prenatal crop surveillance, early risk detection, and im- proved productivity are achieved by incorporating a number of data sources into a single framework.

D. Datasets

The multi-stage AI model utilizes a mix of real-time sensor data and publicly available agricultural data for model training and validation. The data sets used in this research can be classified as follows:

Real-Time Sensor Dataset

Real-time measurements of various environment and soil parameters are taken using ESP32-based IoT sensor nodes. The dataset includes the following:

- Soil moisture levels
- Temperature and humidity (using DHT22 sensor)
- Atmospheric pressure (using BMP280 sensor)
- Gas concentration / air quality (using MQ-135 sen- sor)

These values are sent over Wi-Fi to the Flask backend server in JSON form, which can be recorded for fur- ther preprocessing and analysis. The real-time dataset is primarily utilized for soil health analysis and crop suitability prediction using the Random Forest model. The values sent in the real-time dataset are transmitted through Wi-Fi to the Flask backend server in JSON form, which can be recorded for further preprocessing and analysis. The real-time dataset is primarily utilized for soil health analysis and crop suitability prediction using the random forest model.

Crop and Leaf Image Dataset

For pest and disease detection, crop leaf images are taken using the ESP32-CAM module. In addition to that, publicly available datasets of images of different plant diseases are utilized for training and testing the YOLOv8 object detection model. The dataset contains images of healthy and diseased leaves of different crop species.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

Image preprocessing techniques such as resizing, nor- malization, rotation, flipping, and change in brightness are utilized for better model generalizability and robust- ness.

Agricultural Market Price Dataset

Historical data related to market prices of agricultural products is used for forecasting. The data used is as accuracy follows:

- Date-wise market price data
- Seasonal change in prices
- Trend

This data is used to train the Long Short-Term Memory model for predicting the trend of prices. This data helps the system to determine the best time to sell products and also helps in decision-making by considering market conditions.

The data used by the proposed framework consists of real-time data obtained from IoT sensors, image data, and market prices. This allows it to perform multiple stages of monitoring and predictive analytics.

Evaluation Metrics

The proposed multi-stage framework includes classification, object detection, and time series forecasting. Therefore, var- ious metrics are utilized to assess the performance of the proposed framework.

A. Soil Classification Metrics (Random Forest): The Random Forest Classifier is utilized for classification of the soil and crop suitability. The classification metrics utilized in this study are:

1) Accuracy: The accuracy of the classification model is the number of correctly classified instances divided by the total number of instances.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

2) Precision: Precision is a ratio of correctly classified instances to the total number of positively classified instances.

$$\text{Precision} = \frac{TP}{TP + FP}$$

3) Recall: Recall (Sensitivity) is a ratio of correctly clas- sified instances to the total number of actual positive instances.

$$\text{Recall} = \frac{TP}{TP + FN}$$

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

4) F1-Score: The F1-Score is a measure that balances precision and recall.

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

2 B. Pest and Disease Detection Metrics (YOLOv8): The YOLOv8 model is used for Precision and Recall: These are used to measure the of detection.

Mean Average Precision (mAP): mAP is used to measure the average precision of detection for all classes and IoU thresholds.

Intersection over Union (IoU): IoU is used to measure the overlap between the predicted bounding boxes and ground- truth boxes.

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

Market Price Forecasting Metrics (LSTM): The LSTM model is used for agricultural market price forecasting. Since it is a regression problem, the following metrics are used:

1) Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |P_i - \hat{P}_i|$$

Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (P_i - \hat{P}_i)^2}$$

3) R-Squared (R2):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (P_i - \hat{P}_i)^2}{\sum_{i=1}^{n} (P_i - \bar{P})^2}$$

Where:

- Pi represents actual market prices,
- Pˆi represents predicted prices,
- P¯ is the mean of actual prices,
- n is the number of observations.

International Journal of Science,
Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

Using task-specific evaluation metrics for classification, detection, and forecasting, the proposed framework provides a holistic evaluation of the model's performance across different stages of the agricultural lifecycle.

V. RESULTS AND DISCUSSION

The proposed framework, namely the Multi-Stage AI Framework, has been validated using three different modules: soil classification using a Random Forest model, pest detection using a YOLOv8 model, and market price forecasting using an LSTM model. The results clearly indicate the effectiveness of the proposed framework by leveraging both IoT sensors and AI analytics into a single framework for agricultural decision- making.

A. Soil Classification Results

The proposed model, namely the Random Forest model, has been trained using the structured data collected from the ESP32-based sensor node and soil data. The model has per- formed well in classifying the soil's health and crop suitability.

The classification performance is shown in Table II.
The results show that the model is capable of dealing with non-linear relationships and noisy sensor data. Therefore, the model is suitable for a soil-based crop recommendation system.

TABLE I: Performance of Random Forest for Soil Classifica- tion

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	86.4%	84.7%	83.9%	84.3%

.

Pest and Disease Detection Results

The YOLOv8 model was tested using labeled images of crop leaves. The model was able to successfully detect pests and diseases in the leaves with high accuracy.
The detection performance is summarized in Table III.

TABLE II: Performance of Random Forest for Soil Classification.

Model	Accuracy	Precisio n	Recall	F1-Score
Random Forest	86.4%	84.7%	83.9%	84.3%

The results show that the algorithm is effective in dealing
with non-linear relationships and noisy sensor data. Therefore, the algorithm is suitable for a soil-based crop recommendation system.

Pest and Disease Detection Results

The YOLOv8 model was used to test the images of crop
leaves. The model was able to successfully detect pests and diseases in the leaves.
The detection performance is summarized in Table III. TABLE III: Performance of YOLOv8 for Pest Detection

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

Model	Precision	Recall	mAP
YOLOv8	88.2%	84.5%	86.1%

The IoU analysis has successfully validated the bounding box localization. Pest detection at an early stage is extremely beneficial in preventive crop management, which can save crop yield.

D. Market Price Forecasting Results

The LSTM model has been trained using the historical agricultural market price data. The model has been able to effectively capture the temporal dependencies and seasonal trends. The performance of the forecasting is shown in Ta- ble IV.

TABLE IV: Performance of LSTM for Market Price Forecast- ing

Model	MAE	RMSE	$R2$
LSTM	12.45	16.82	0.89

VI. CONCLUSION

This paper has presented a "Multi-Stage AI Framework for Prenatal Crop Monitoring, Prediction of Risks, and Storage Management" using IoT technology along with ML and DL techniques under a single framework of "Sense-Analyze-Act." This framework has the potential to solve different issues faced by farmers today, such as selection of crops, detection of pests, weather conditions, and market prices of crops. This framework has employed ESP32 for real-time monitoring using IoT technology, Random Forest for classification of soil types for crop selection, YOLOv8 for detection of pests by analyzing images of crops, and LSTM for predicting market prices of crops. From the results obtained, it is clear that the Random Forest algorithm can work well for handling structured data for classification, YOLOv8 can work well for detecting pests by achieving high accuracy, and LSTM can work well for predicting market prices of crops by using its potential to handle data for predicting trends. This is different from existing techniques that are designed for specific agricultural activities. The framework is a lifecycle solution for decision-making in different stages from pre-sowing to post- harvesting. The prenatal monitoring technique enables risk de- tection in an early stage, which reduces losses while enhancing productivity.Despite satisfactory results being achieved in the prototype, there is a possibility for the system's performance to vary depending on factors such as the size of the data set, environment, and precision of the sensors. Improvements to the system include enhancing data set variability, optimizing the model, and adding disaster prediction tools and intelli- gent storage management tools. The proposed multi-stage AI framework is a step towards a smart agriculture system that is intelligent, scalable, and sustainable for increased productivity.

REFERENCES

1. H. Verma and S. Gupta, "Crop Yield Prediction Using Random Forest Algorithm," IEEE International Conference on Computing and Commu- nication, pp. 221–226, 2022.
2. L. Zhang and Y. Chen, "Agricultural Market Price Forecasting Using Deep Learning Models," IEEE Transactions on Industrial Informatics, vol. 20, no. 4, pp. 2345–2354, 2024.
3. T. Nguyen et al., "AI-Driven Post-Harvest Storage Monitoring for Grain
4. Quality Preservation," IEEE Access, vol. 12, pp. 55421–55433, 2024.

International Journal of Science, Engineering and Technology
ISSN: 2348-4098, P-ISSN: 2395-4752

5. S. Sharma, R. Kaur, and P. Singh, "IoT-Enabled Smart Agriculture Monitoring System Using ESP32," IEEE International Conference on Smart Computing, pp. 112–117, 2022.
6. M. R. Islam and A. Rahman, "Deep Learning-Based Plant Disease Detection Using Convolutional Neural Networks," Computers and Elec- tronics in Agriculture, vol. 203, 2023.
7. L. Garcia, J. Parra, J. Jimenez, A. Lloret, and P. Lorenz, "IoT-Based Smart Irrigation Systems: An Overview on the Recent Trends," IEEE Internet of Things Journal, vol. 9, no. 15, pp. 12345–12359, 2022.
8. K. R. Patel and V. Shah, "Machine Learning Approaches for Crop Recommendation and Yield Prediction," IEEE Access, vol. 11, pp. 45231–45244, 2023.
9. Y. Li, H. Wang, and X. Chen, "Climate-Aware Agricultural Forecasting Using LSTM Networks," IEEE Transactions on Industrial Informatics, vol. 20, no. 3, pp. 1782–1791, 2024.
10. J. Redmon and G. Jocher, "Real-Time Object Detection in Agricultural Fields Using YOLOv8," Proceedings of IEEE International Conference on Image Processing, pp. 2401–2405, 2023.
11. T. Das and S. Banerjee, "Agricultural Commodity Price Forecasting Using Deep Learning Models," IEEE International Conference on Data Science and Advanced Analytics, pp. 601–606, 2022.
12. R. Kumar and D. Mishra, "AI-Based Grain Storage Monitoring System
13. Using IoT Sensors," IEEE Sensors Journal, vol. 23, no. 14, pp. 15876– 15884, 2023.
14. Mehta and S. Joshi, "Random Forest-Based Crop Suitability Analysis Using Soil Parameters," IEEE International Conference on Computa- tional Intelligence and Computing Research, pp. 1–6, 2022.
15. Z. Huang, L. Zhao, and Y. Sun, "Time-Series Forecasting for Agricul- tural Applications Using LSTM Networks," Applied Artificial Intelli- gence, vol. 38, no. 1, pp. 1–15, 2024.
16. P. Verma and R. Singh, "Cloud-Integrated IoT Framework for Smart
17. Farming Applications," IEEE Access, vol. 11, pp. 99871–99885, 2023.
18. N. Alqahtani and M. Almutairi, "Sensor Fusion Techniques for Precision Agriculture Monitoring," IEEE Transactions on Instrumentation and Measurement, vol. 73, 2024.
19. D. Roy and S. Chakraborty, "Leaf Disease Classification Using Deep Convolutional Neural Networks," IEEE International Conference on Signal Processing and Communication, pp. 55–60, 2022.
20. H. Tran and Q. Nguyen, "Intelligent Post-Harvest Storage Management
21. Using AI and IoT," IEEE Access, vol. 13, pp. 10231–10245, 2025.
22. E. Fernandez and M. Torres, "Machine Learning-Driven Decision Sup- port Systems for Smart Agriculture," IEEE Latin America Transactions, vol. 21, no. 4, pp. 512–520, 2023.
23. W. Chen, Y. Zhang, and L. Wu, "An Integrated AI and IoT Framework for Smart Farming Applications," IEEE Internet of Things Journal, vol. 11, no. 6, pp. 5432–5445, 2024.