

F.A.R.M. (Field Analysis Revenue Management): An IoT and ML Integrated Solution

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Abstract

Decision support systems with field monitoring and predictive analysis capabilities are required for modern agriculture to increase efficiency in the field and proper management at the farm level. This research work proposes F.A.R.M. (Field Analysis and Revenue Management), an Internet of Things (IoT) and machine learning-based approach to data-centric agriculture management. The proposed solution uses an ESP32-based sensing system that includes soil moisture, temperature, humidity, rainfall, flame, and flow rate of water along with Soil Health Card (SHC) data for field analysis. Random Forest is used for crop prediction, LSTM model is used for predicting crop price, and crop yield estimation is done using the Random Forest Regressor. The outputs from the process are then displayed through a monitoring interface that is enabled by the use of ThingSpeak. Sensor decision rules have been implemented to facilitate the assessment of field conditions and monitoring operations. The experimental analysis attained a success rate of 99.32% for crop recommendation, with the LSTM model being able to capture changes in market prices.

Keywords: Smart Agriculture, Internet of Things (IoT), Random Forest, Long Short-Term Memory (LSTM), Precision Farming, ThingSpeak, Smart Farming.

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1. Introduction

Agriculture plays a crucial role to ensure food security and rural economic development, but small-scale farming continues to experience many issues such as those involving climate, efficient use of resources, water, and market prices. As a result of increased applications of IoT and machine learning, monitoring of fields and data-based agricultural management is possible on a continuous basis. However, the conversion of various pieces of data into decisions that will assist productivity and economic planning is difficult.

Recent smart agriculture solutions have proven the effectiveness of monitoring, crop suggestion, irrigation control, and predictive analytics based on IoT. However, the mentioned capabilities are usually used separately, which leads to fragmentation in decision making process and deployment difficulties. The need for a separate sensor for nutrient measurement will lead to higher implementation cost and will limit usage by small farmers. Therefore, there is a need to develop a platform that would integrate all the mentioned capabilities.

F.A.R.M. (Field Analysis & Revenue Management) – the proposed framework that resolves the issues stated above through the integration of an IoT infrastructure on ESP32 with SHC data and Machine Learning algorithms. The Random Forest algorithm is used for crop prediction, LSTM is used for market price prediction, and the Random Forest Regressor is used to predict the yield of crops for revenue management. Besides, real-time sensing will be able to help with rule-based irrigation advice, fertilizer advice, leak detection in pipelines, fire detection, while ThingSpeak will visualize the information from the system in the cloud.

2. Literature Review

The recent research innovations in the field of precision agriculture has been based on the use of Internet of Things (IoT), Artificial Intelligence (AI), and cloud computing, which allow for continuous monitoring, intelligent data management, and automation of decision-making. IoT has made it possible to achieve efficient data collection, better processing and management of agriculture operations, while effective communication systems have helped reduce latency in data transmission [1], [2], [3].

The various applications of Machine Learning (ML) algorithms have included

agricultural decision support by using crop yield prediction, soil sensing, crop advisories, and weather-based forecasts. The intelligent systems have also made improvements in water management and irrigation scheduling by using environmental and sensor information to maximize the use of resources. Moreover, deep learning systems have shown better predictive results when applied to complicated agricultural datasets [4], [5], [6], [7], [8].

Moreover, researchers have recently been working on the federated learning approach that aims at performing collaborative analysis for agriculture in a distributed farming environment while keeping the data private and secure [9], [10]. However, even with all these developments in the area, almost all existing studies consider only specific functions of agricultural solutions, such as monitoring, predictions, irrigation control, privacy-preserving mechanisms, etc. The development of an approach which will be able to combine these features with real-time sensing with the help of IoT devices, SHC data, crop recommendation, financial estimations, irrigation advice, leaks and fire detection, and visualization of collected data is still lacking.

3. Proposed Methodology

3.1 Overall Framework

The proposed Field Analysis & Revenue Management (F.A.R.M.) framework leverages IoT technology alongside machine learning to offer smart agricultural management through field surveillance, analytics, and decision support. The framework consists of six stages of operations such as data collection, data processing, machine learning analysis, prediction & revenue analysis, decision support, and finally, the visualization stage via dashboards. The environmental data gathered using field sensors together with the Soil Health Card (SHC) data is analyzed to provide crop recommendations, predict market trends, and revenues as well as provide recommendations through a single cloud-enabled platform.

Figure 1 shows the entire workflow for the suggested F.A.R.M. approach. In the beginning, the data regarding the environment and the soil will be retrieved from the sensing layer together with Soil Health Card data. These will then be preprocessed and further analyzed by applying the Machine Learning models to provide recommendation for crops and forecast prices along with revenues. Finally, the processed data will be processed by the appropriate decision-making modules, where the sensor-based rule will be utilized for irrigation, pipeline

leakage, and fire-hazard detection.

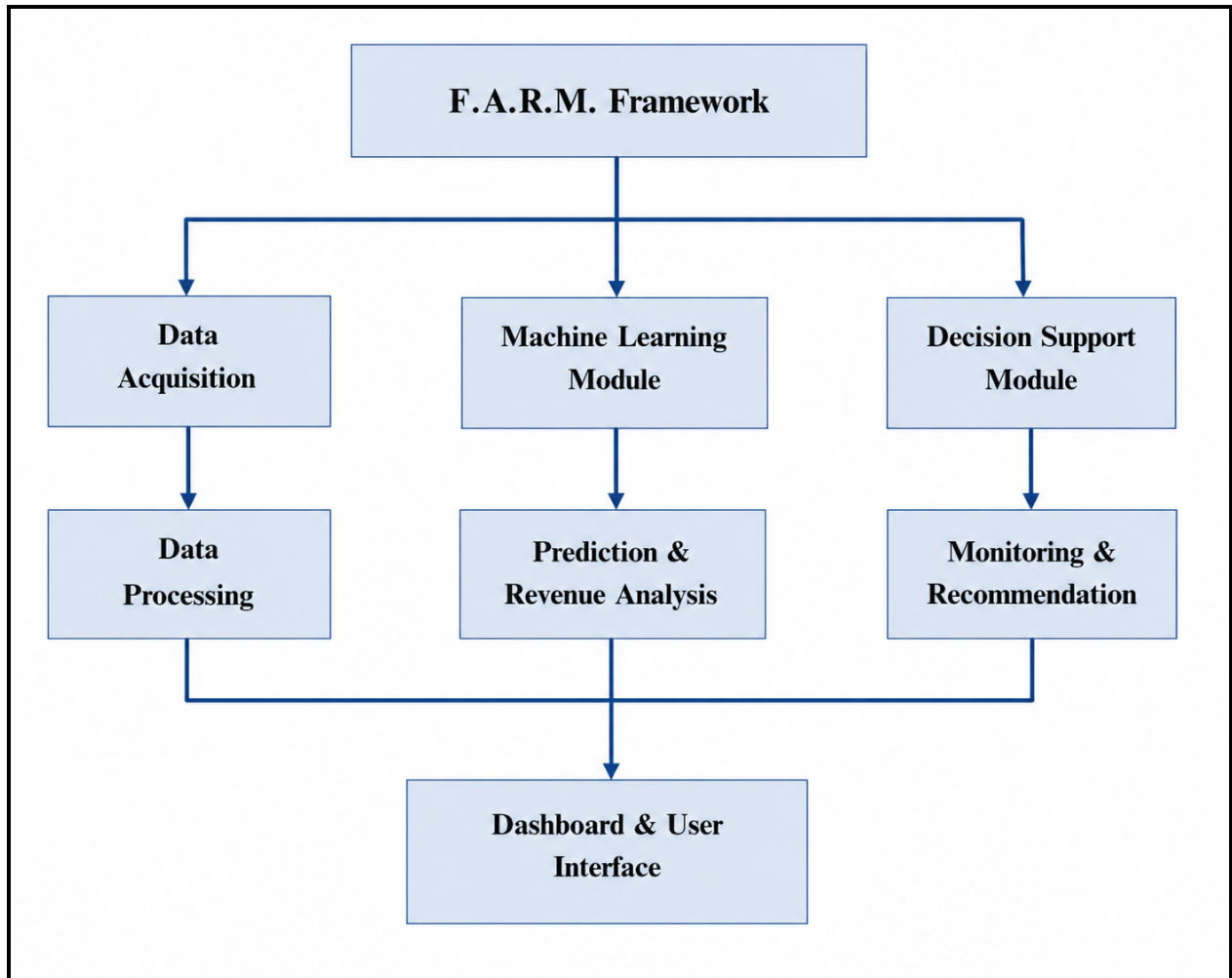


Figure 1. Overall framework of the proposed F.A.R.M. system

3.2 Hardware Architecture

In the suggested F.A.R.M framework, ESP32 microcontroller acts as the core component that processes real-time field data. This layer comprises of soil moisture sensor, DHT11 sensor for temperature and humidity detection, rain sensor, flame sensor, and double water flow sensors. Information regarding nutrients in the soil is included by integrating the Soil Health Card (SHC) in the framework and no need arises to add any hardware for sensing nutrients in the soil.

Data collected by these sensors is sent to the cloud-based service called ThingSpeak through Wi-Fi for further processing and visualization purposes. Relay module performs automatic watering operations according to the recommendations provided by the system, while LCD shows the current status of the field and information obtained from sensors. The described

hardware setup ensures efficient data acquisition process for machine learning algorithms and smart agriculture. Table 1 contains hardware devices and their functions within F.A.R.M. concept.

Table 1. Hardware specifications of the proposed F.A.R.M. framework

Component	Purpose
ESP32	Data acquisition and system control
DHT11 Sensor	Temperature and humidity monitoring
Soil Moisture Sensor	Soil moisture measurement
Rain Sensor	Rainfall detection
Flame Sensor	Fire hazard detection
Water Flow Sensors	Pipeline flow monitoring and leak detection
Relay Module	Irrigation pump control
LCD Display	Local monitoring of system status
Soil Health Card	Soil nutrient information
ThingSpeak	Cloud data storage and visualization

3.3 Data Acquisition and Communication

The proposed F.A.R.M. system will obtain real-time data from the field using integrated sensing modules, which include moisture, temperature, humidity, rain, water flow, and fire sensors. Nutritional data of the soil are added from the Soil Health Card (SHC). The ESP32 module will collect data from the sensors and do basic preprocessing on it while the nutritional data from SHC will be added to preprocessed field parameters to create one single feature vector. This entire data set will be sent via Wi-Fi communication using the ThingSpeak platform to the trained machine learning model for crop recommendations and further analysis.

The cloud platform stores the incoming data and visualizes them in real time for monitoring purposes. The analyzed data are then used for making recommendations regarding

crops, prices, profits, and decision-making, thus facilitating timely agricultural recommendations and field monitoring.

The collected sensor data is uploaded to the ThingSpeak cloud platform using the ESP32 Wi-Fi module. Each channel field is allocated for measuring various agricultural parameters. Table 2 shows the allocation of channel fields set up in the proposed monitoring system.

Table 2. ThingSpeak channel configuration for real-time agricultural monitoring

Field	Sensor / Value	Unit / Type
1	Soil moisture (GPIO 34)	ADC value 0–4095
2	Raindrop (GPIO 35)	ADC value
3	Temperature – DHT11	Degrees Celsius
4	Humidity – DHT11	Percent RH
5	Air quality – MQ135	ADC proxy
6	Inlet flow rate	L/min
7	Outlet flow rate	L/min
8	Leakage flag (computed)	Binary: 1 = leak, 0 = OK

3.4 Dataset Description

The proposed F.A.R.M. system uses two publicly available agriculture datasets to build the machine learning models. The Crop Recommendation Dataset [11], having 2,200 instances with seven soil and environmental attributes, is used to train the Random Forest classifier for crop recommendation. Further, the Crop Price Prediction Dataset [12], consisting of historical price data of crops, is used to train the LSTM model for crop price prediction. Both datasets are cleaned, missing values are treated, feature normalization is done, and then they are split into an 80:20 ratio between training and testing before developing the models. These models are then combined with real-time IoT sensor readings and SHC to make smart recommendations for crops, their market price prediction, and revenue prediction. Table 3 presents the dataset features of the proposed F.A.R.M. system.

Table 3. Characteristics of the datasets used in the proposed F.A.R.M. framework

Parameter	Crop Recommendation Dataset [11]	Crop Price Prediction Dataset [12]
Data Type	Tabular	Time-series
Total Samples / Records	2,200	Historical records (2010–2025)
Input Features	N, P, K, Temperature, Humidity, pH, Rainfall	Crop Type, Date, Minimum Price, Maximum Price, Average Price
Number of Features	7	5
Associated Model	Random Forest	LSTM
Application	Crop Recommendation	Crop Price Forecasting
Preprocessing	Data cleaning, normalization	Data cleaning, chronological ordering, normalization
Training: Testing Split	80:20	80:20

3.5 Machine Learning Framework

The proposed F.A.R.M. model makes use of three machine learning algorithms for the purpose of aiding intelligent agricultural decision making. A Random Forest algorithm acts as the classifier for crop recommendation, an LSTM model is used for predicting crop prices, while a Random Forest regressor provides predictions regarding the revenue expected. The training of the models is carried out using the Crop Recommendation Dataset [11] and the Crop Price Prediction Dataset [12], whereas the predictions are combined with IoT sensor readings and SHC data.

Crop Recommendation

Crop recommendation is carried out by the use of the Random Forest classifier with the training done on the Crop Recommendation Dataset [11]. The classifier uses seven factors related

to soil and the environment such as nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall to find out the best crop that can be grown.

$$\hat{C} = RF(X) \quad (1)$$

where $RF(\cdot)$ denotes the Random Forest classifier, $X = \{N, P, K, T, H, pH, R\}$ represents the input feature vector, and $\hat{C}$ is the recommended crop.

Price Forecasting

The historical data on crop prices taken from the Crop Price Prediction Dataset [12] is used to train the LSTM model for predicting future prices. This data is sorted chronologically and is normalized before being used in the training process. The predicted price helps the farmer choose crops that have good market value.

$$\hat{P}_{t+1} = LSTM(P_t) \quad (2)$$

where P_t denotes the historical price sequence, $LSTM(\cdot)$ represents the forecasting model, and $\hat{P}_{t+1}$ is the predicted future crop price.

Revenue Estimation

Random Forest Regressor uses a combination of the suggested crop, forecasted market value, and crop yield to predict the expected revenue. The prediction of revenue allows farmers to analyze the feasibility of crop farming.

$$\hat{R} = \hat{Y} \times \hat{P} \quad (3)$$

where $\hat{Y}$ is the estimated crop yield, $\hat{P}$ denotes the predicted market price, and $\hat{R}$ represents the estimated revenue.

The outputs from machine learning algorithms serve as crop, market price, and yield data for respective analyses whereas decision rules from sensors help with monitoring the field conditions.

Table 4 illustrates the relationship between the respective modules and the ML algorithms.

3.6 Decision Support Modules

The proposed F.A.R.M. framework incorporates various decision support tools by combining machine learning forecasts with current IoT sensors and Soil Health Cards (SHC) readings. From the output of the Random Forest classification algorithm, the framework suggests the most appropriate crop based on the current soil nutrient status and environmental conditions, which facilitates informed decision-making for crop selection and planting. With the help of the recommended crop and SHC readings, the framework also suggests fertilizer application to balance nutrients in the soil.

The irrigation advisory system continuously monitors soil moisture levels and environmental parameters to ascertain the need for irrigation. Once the soil moisture level goes below the specified threshold level, the irrigation relay automatically switches on, and the recommendation is conveyed via the monitoring interface. Further, in order to detect leakage in the irrigation pipeline, the system uses two water flow sensors to compare inlet and outlet water flow levels. The leakage detection system can be mathematically represented as

$$L = |F_{\text{in}} - F_{\text{out}}| \quad (4)$$

where F_{in} and F_{out} represent the inlet and outlet water flow rates, respectively, and L denotes the flow difference. A threshold of 1.0 L/min is configured for leak detection. If $L > 1.0 \text{ L/min}$, the system identifies a possible pipeline leak and generates an alert for immediate maintenance.

In order to improve field safety, the flame sensor always monitors the agricultural environment for possible fire incidents. Once a fire incident is detected by the sensor, an alarm is raised and sent via the cloud dashboard as well as the local display. The rule generation layer will use the data obtained from the sensors to give operational advice.

3.7 Cloud Dashboard and User Interface

The proposed F.A.R.M. architecture, the ThingSpeak cloud-based system is utilized to gather, store, and visualize live agricultural data from the IoT sensors. Data related to moisture level, temperature, humidity, water flow, and flame condition is continuously updated in the cloud dashboard, making it possible to monitor the field conditions from a distance. In addition, results generated by the machine learning algorithms, which include the suggested crop type, market price forecast, revenue estimation, and irrigation status based on rules, are presented via the web-based dashboard, as shown in Figure 2.

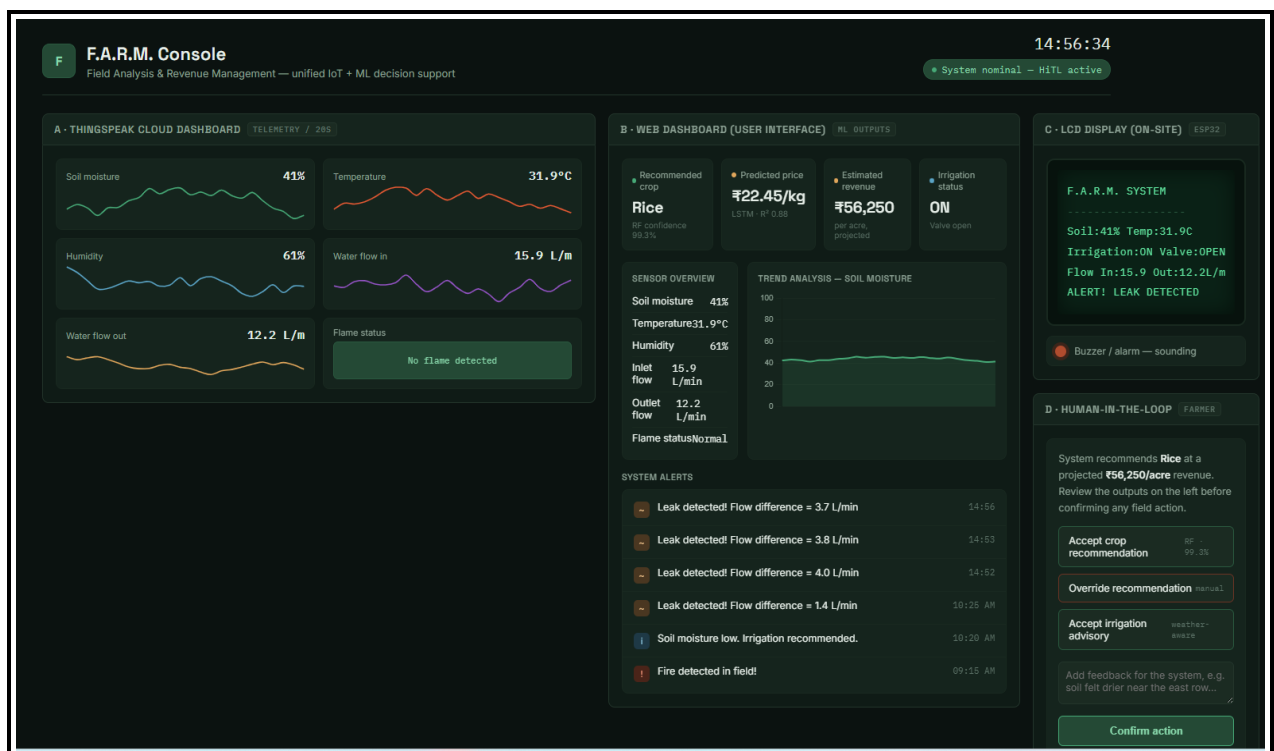


Figure 2. Cloud dashboard and user interface of the proposed F.A.R.M. framework

Moreover, the dashboard displays a summary of system alarms, such as low soil moisture alarm, water leakage, and fire detection, to enable prompt action in case of any anomaly within the field. The LCD screen connected to the ESP32 device helps to monitor all the necessary information from the sensors and irrigation systems on-site.

This model has implemented the concept of Human-in-the-Loop (HiTL), which allows farmers to check the recommended decisions before executing them. The provided information can be used by the users to verify the recommendations for crops, scheduling for irrigation, and

the alarms in accordance with their field conditions and practical experience. This model will enhance the effectiveness and utility of the proposed F.A.R.M. model.

Algorithm 1. Proposed F.A.R.M. Framework

Input: Sensor data S , SHC data H , historical price data P

Output: Crop C , predicted price P_f , yield Y_e , revenue R_e , irrigation I , leak alert L_a , fire alert F_a

1. Initialize ESP32, sensors, cloud connection, and trained ML models.
 2. Acquire real-time sensor data S and SHC data H .
 3. Preprocess and combine the required parameters.
 4. Generate crop recommendation using Random Forest.
 5. Forecast market price using LSTM.
 6. Estimate crop yield using Random Forest Regressor.
 7. Calculate revenue using $R_e = Y_e \times P_f$.
 8. Compare soil moisture with the irrigation threshold and determine I .
 9. Calculate flow difference $L = |F_{in} - F_{out}|$ and determine L_a .
 10. Check flame status and determine F_a .
 11. Transmit sensor readings, predictions, and alerts to ThingSpeak.
 12. Display results through the web dashboard and LCD for farmer decision-making.
 13. Return C, P_f, Y_e, R_e, I, L_a , and F_a .
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4. Results and Discussion

4.1 Experimental Setup

The effectiveness of the proposed F.A.R.M. model has been validated using an experimental approach by implementing it within an IoT and machine learning integrated environment. Hardware setup for the same includes an ESP32 microcontroller, soil moisture sensor, DHT11 temperature & humidity sensor, rain sensor, flame sensor, two water flow sensors, relay module, and an LCD screen. Real-time sensor data is sent to ThingSpeak via Wi-Fi communication.

The ML system was developed using Python programming language, wherein the Crop Recommendation Dataset [11] was adopted for training the Random Forest classifier, and the Crop Price Prediction Dataset [12] was used for market price prediction using LSTM. In

addition, Random Forest Regression was adopted for calculating the revenue estimate through the incorporation of crop recommendation and market price prediction. Data preprocessing was conducted via data cleaning and feature scaling prior to implementing the 80:20 split for model testing. The experimental setup for the validation of the proposed system is presented in Table 5.

Table 4. Experimental configuration of the proposed F.A.R.M. framework

Parameter	Configuration
Hardware Platform	ESP32 Microcontroller
Sensors	Soil Moisture, DHT11, Rain, Flame, Dual Water Flow
Cloud Platform	ThingSpeak
Programming Environment	Python, Arduino IDE
Crop Recommendation Model	Random Forest
Price Forecasting Model	LSTM
Revenue Estimation Model	Random Forest Regressor
Crop Recommendation Dataset	Kaggle Crop Recommendation Dataset [11]
Crop Price Dataset	Crop Price Prediction Dataset [12]
Data Preprocessing	Data Cleaning, Feature Normalization

4.2 Machine Learning Performance Analysis

The performance of the ML framework proposed for crop recommendation and forecasting of crop prices was tested using the chosen agricultural data sets. The Random Forest classifier was compared with Decision Tree, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) classifier to determine the most appropriate classifier for the task of crop recommendation. As can be seen from Figure 3, the Random Forest classifier showed the best test accuracy equal to 99.32%, surpassing Decision Tree (94.1%), SVM (88.5%) and KNN

(82.3%). The results indicate that the proposed method has high capabilities for modeling the non-linear dependencies between soil characteristics and environmental parameters.

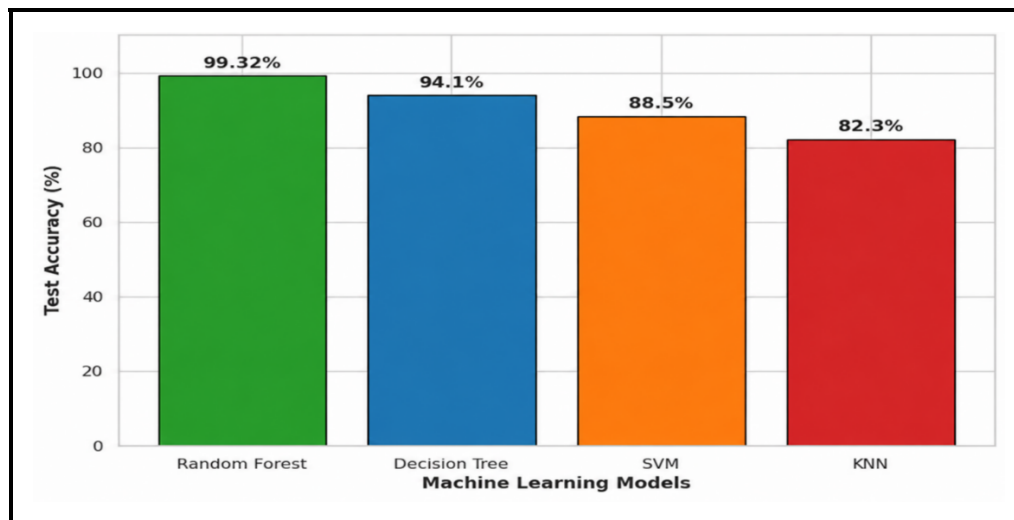


Figure 3. Test accuracy comparison of machine learning models

Evaluation of the LSTM model followed, through use of historical market prices of the crops in order to test its forecast capability. According to Figure 4, the forecasted price is highly accurate, and is quite similar to the actual price in the market for the entire period of evaluation, showing that the model is able to capture both the trends and seasonality. This high similarity of the actual and forecasted price shows how suitable the model is for market price forecasting.

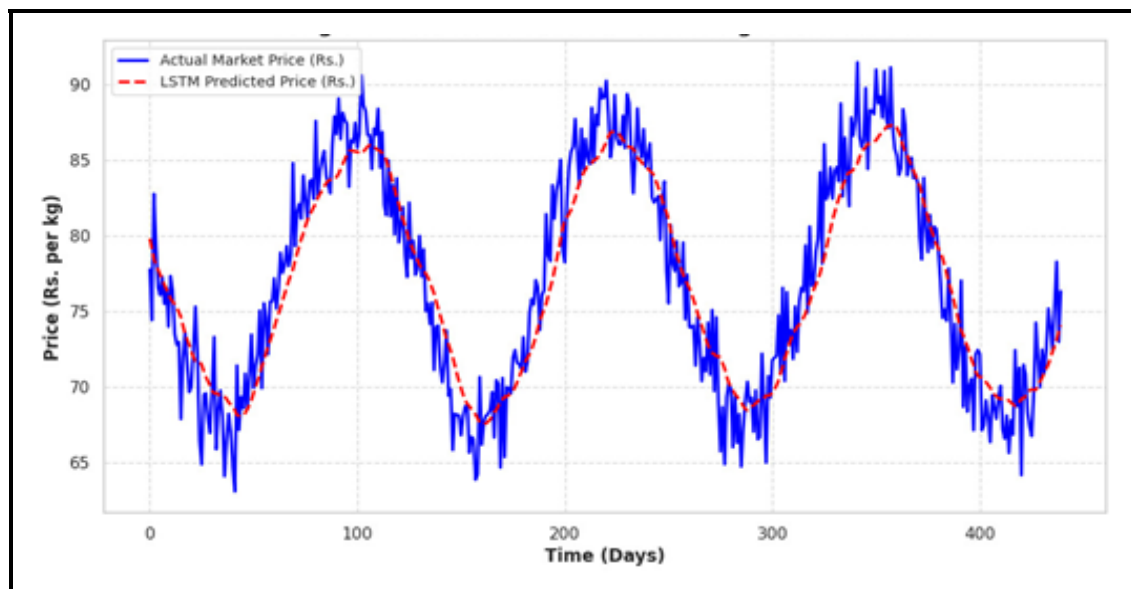


Figure 4. Actual and LSTM-predicted crop market prices.

The results from the Random Forest Classifier and LSTM-based prediction were

combined with those of the Random Forest Regressor in order to predict the expected income. These predictions were used along with the data received from IoT sensors and Soil Health Cards in order to generate recommendations for the choice of crops and irrigation.

4.3 Discussion

The results obtained from experimentation clearly show the capability of the proposed framework, F.A.R.M., for incorporating the use of IoT sensors in the decision-making process using machine learning in agriculture. In this case, the Random Forest classifier performed better in terms of accuracy and hence made it possible to make accurate crop recommendations depending on the environment, while the LSTM was used to make accurate predictions regarding fluctuations in market prices in the past for making reliable forecasts. Moreover, the use of the ThingSpeak dashboard provides convenience since continuous field monitoring and alert generation is made possible. On the other hand, the Human-in-the-Loop scheme ensures that users can evaluate and verify the system's recommendations.

5. Conclusion and Future Work

The proposed F.A.R.M. (Field Analysis and Revenue Management) architecture proves to be an efficient application of the IoT technology and machine learning algorithms for intelligent management of agricultural fields. Usage of Soil Health Card data as well as cloud monitoring increases the level of reliability of field analysis and constant accessibility of agricultural information. Also, the Human-in-the-Loop system makes the approach more efficient since it provides farmers with the opportunity to check recommendations before using them. Generally speaking, the presented model can be considered scalable and practical for improvement of agricultural productivity and sustainable farming practices. Future work will include expansion of the approach through the usage of more types of environmental and satellite data, adaptation to various crops and geographical locations, using DL techniques for better prediction and development of the edge AI-deployment to provide offline decision making in remote farms.

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