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Pest Infestation Prediction System for Stored Beans Based on Machine Learning and IoT Sensors Strategy

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ABSTRACT

Beans, though highly nutritious, are vulnerable to postharvest pest attacks, leading to significant food and economic losses. The traditional methods of mitigating the loss to pest attacks is tedious besides, efficiency becomes issues especially to climate factors. State of the art approaches such as Machine Learning techniques have been employed to deal with the challenges but not without room for improvement. Therefore, this study aim to design and implement a sensor-driven system capable of monitoring environmental conditions and predicting infestation risks in real time based on machine learning models. The system integrated three sensors: a DHT11 for temperature and humidity measurement, a soil moisture module for monitoring moisture content, and an ESP32 microcontroller as the processing unit. Data collected were processed and analyzed using a multivariate linear regression model, which established the relationship between temperature, humidity, and moisture content, and the probability of pest infestation. Whenever environmental conditions exceeded safe thresholds, the system triggered alerts through a buzzer, LED, and WhatsApp notification to the farmer. Performance evaluation of the system demonstrated strong predictive performance. The model achieved an accuracy of 92.4%, precision of 89.1%, recall of 93.6%, and an F1-score of 91.3%. These results indicate that the system is promising as would reliably predict infestation risks while minimizing false alarms. Thus, the developed system provides a practical, low-cost, and efficient solution for farmers to proactively manage bean storage conditions. This is by combining IoT sensors with machine learning for real-time notifications, as it has contributes to reducing postharvest losses and enhancing food security.

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INTRODUCTION

The global population is projected to reach 10 billion by 2050, placing immense pressure on food systems worldwide (Galadima *et al.,* 2026). Food legumes such as the common bean are an essential constituent of food systems globally, supplying 22–24% quality protein and starch, thiamine, niacin, and trace minerals (Sadek and Banian, 2019). The common bean is the third most cultivated legume crop globally after peanut and soybean. It is of very high value as the principal legume crop for direct human consumption. Its versatility is indicated through diverse food applications - consumed as dry seeds in African and Latin American foods, or as fresh pods (snap beans) in Mediterranean countries' cuisine (Kiptoo *et al.*, 2019). Consumption has also increased in conventional markets in recent years, with the European Union members and United States embracing beans into conventional foods over time. This growing popularity is a double appreciation of the value of common bean as a low-cost, plant-based protein food for food security requirements and as a functional food product with antioxidant phenolic compounds with epidemiological data on lowered risks of obesity, type 2 diabetes, and certain cancers (Geleta *et al.*, 2024). These nutritional and health values make common bean a root crop in the avoidance of non-communicable diseases and malnutrition among most populations.

Though they are more nutritious, crops like common beans are economically vulnerable because they are more vulnerable to pest infestation during production and storage upon harvesting, resulting in massive losses undermining food security globally (Forbanka, 2021). The storage of grains has becom e avital part of the world agri-food supply chain that has a direct impact on food availability, price stability, and the long-term food security (Latha , 2025).The Food and Agriculture Organization (FAO) estimates that 20% to 40 % of world crop production is lost due to pests and diseases (Nyakuri *et al.,* 2024). While previous studies have made tremendous strides in the elucidation of pest resistance mechanisms; namely the activity of phenolic compounds against field pests like the bean flies (Kiptoo *et al.*, 2019) described the impact of crop stresses like water deficiency on crop yields, there remain important knowledge gaps in post-harvest biochemical kinetics. Scientists have limited information on the impact of storage environmental conditions, for example, temperature changes, water content, and moisture content conditions; on natural defense compounds (alkaloids, saponins, and protease inhibitors) yield and activity in beans stored (Geleta *et al.*, 2024). Changes in temperature, rainfall, and extreme weather events directly affect insect reproduction, survival, migration, and interaction with host plants (Mpisane *et al.,* 2025). Pest infestations pose a serious threat to agricultural yield and food security, which necessitates timely and accurate detection methods (Swarnkar *et al.*, 2024).

Farm-to-table bean loss is the largest global food security threat. These precious legume beans experience high postharvest quality and quantity loss through infestation by pests. Bean weevil and cowpea weevil are such pests, whose loss is not only in weight loss but also taste loss and nutrition loss (Geleta *et al*., 2024). They gain favorably in the hot and wet conditions of tropical storage structures, where they may lead to 10-15% grain stored loss (Sharma *et al*., 2021). Sun-drying to reduce moisture levels and organic insect repellents like neem leaves and wood ash are techniques used by Nigerian farmers (Mobolade *et al.,* 2019). Techniques like hermetic storage and underground pits are sustainable and minimize chemical use. But their sporadic efficacy and increasing confrontation by global warming reveal limitations demanding avant-garde supplementation (Jacobs *et al*., 2020). Agricultural producers can observe and examine actual real-time storage environments and ascertain the specific environmental limits such as certain temperatures and humidity leading to pest infestation through artificial intelligence-augmented monitoring systems (Rahman, 2024). Artificial intelligence (AI) technology for agriculture provides an improved platform to address extended postharvest storage issues.

Advanced machine learning approaches can learn from past histories of cowpea weevil infestation as well as current environmental sensing to predict infestations by cowpea weevil at a high rate of accuracy, typically detecting risk indicators days in advance of actual damage ever being done (Domingues and Brandão, 2022). Its predictive function is a giant leap ahead of previous reactant methods in that it now makes pre-emptive intervention possible in the form of focused aeration or natural pesticide misting. The actual value of this technology is that it can complement but not replace traditional methods; AI systems can compute the optimal time for application of neem treatments or modify hermetic storage parameters, without losing the environmental benefits of traditional methods (Hoque, 2024).

This blending of traditional expertise and current technology offers an integrated pest management system that is specific and sustainable and serves as a welcome complement to smallholder farmers and commercial growers alike to reduce postharvest loss and to prevent environmental degradation (Ahuja *et al*., 2024). More technically advanced, machine learning offers three methodological types to change pest control in bean storage rooms (Kariyanna and Sowjanya, 2024). Firstly, supervised learning algorithms, where algorithms are trained using extensive databases of historical infestation presence, environmental sensor measurements (temperature, humidity, CO_2), and respective damage evaluations, can produce extremely accurate predictive models of risk infestation (Morales and Escalante, 2022).

Bean crops incur heavy yield loss caused by environmental stress and insect damage during growth and storage. Although research by Kiptoo *et al*., (2019) and Geleta *et al*., (2024) supports the role of phenolic compounds in pest resistance and water stress impact on bean productivity, less has been documented about the influence of post-harvest storage conditions (temperature, humidity and moisture content) on the biosynthesis of natural defense chemicals and biochemical pathways. This is an impediment to the planning of preventive pest-control methods for stored beans. This research project investigates the influence of storage conditions on the development of pest-repellent chemicals in beans and applies machine learning to predict infestation risk under prevailing storage conditions. Through optimization of storage management to preserve bean nutrients and avoid wastage, the project supports the achievement of SDG 2 (Zero Hunger), SDG 12 (Sustainable Consumption), and SDG 3 (Good Health and Well-being) by enhancing food security and reducing waste. To this end, this study aim to develop a pest infestation prediction mode considering humidity, temperature, and moisture content of bean crop using threshold-based multilinear regression model. The remaining sections of this study is structured as follows: A review of related works in Section 2, the methodology is described in Section 3, the results and discussion are presented in Section 4, and the study is concluded in Section 5.

MATERIALS AND METHODS

Related Works

With the world's population projected to exceed 9 billion by 2050, food demand is expected to increase by nearly 100%. To this end, Fadiji *et al.,* (2023) aim to employ bibliometric analysis to provide a comprehensive insight into artificial intelligence in postharvest agriculture research. Bibliometrix R package, biblioshiny, and VosViewer were utilized in this study. However, the bibliometric technique employed does not evaluate the real-world performance or effectiveness of artificial intelligence technologies in postharvest agriculture.

Crop pests and diseases are major threats to food security globally. To this end, Mallick *et al.,* (2023) aim to develop a novel deep learning-based technique to identify the mung bean pest and disease. Convolutional Neural Network was the deep learning technique employed in this study. However, heavy reliance on augmented images leads the model to learn patterns specific to the training dataset rather than real-world variations, potentially affecting performance in practical deployment.

In recent years, as the value of the valuable components in soybeans has emerged, their applications have become diverse, including in health supplements and cosmetics. In lieu to this, Park *et al.,* (2023) aim to conduct an experiment to detect R. pedestris according to three different environmental conditions (pod filling stage, maturity stage, and artificial cage) by developing a surveillance platform based on an unmanned ground vehicle (UGV) GoPro CAM. Also, Deep learning technology (MRCNN, YOLOv3, Detectron2)-based models were utilized for experimentation in this study. However, the system was designed specifically for *Riptortus pedestris* and did not evaluate its ability to detect other soybean pests. This limits the applicability of the platform for comprehensive pest management in soybean fields where multiple pest species occur simultaneously.

The coffee industry contributes to the economic restructuring of many countries, often associated with a closed process from production to consumption. To this end, Thai *et al.,* (2024) aims to address these issues by implementing deep learning to classify coffee bean quality in real time by integrating the system with a cloud-based solution. The model is trained using YOLOv8, a framework for object recognition, and OpenCV, an open-source image processing technology, to classify coffee beans. However, the deep learning model was trained primarily on nine defect categories of Robusta coffee beans, which restricts its applicability to other coffee varieties and defect types.

Sustainable farming systems play a crucial role in producing high-quality crops while minimizing their negative environmental impact. To this end, Bagchi *et al.,* (2026) presents a machine learningdriven framework for analyzing and predicting potato late blight. Traditional statistical methods, including a two-factor Analysis of Variance (ANOVA) and Tukey's Honest Significant Difference (HSD) test, were applied to assess the effects of cultivation systems, potato varieties, and year. To enhance predictive accuracy and model interpretability, an advanced machine learning pipeline, termed the Eco-Integrated Model, was developed. This model integrates SMOTE (Synthetic Minority Oversampling Technique) for handling class imbalance, SHAP (SHapley Additive xPlanations) for interpretability and feature importance analysis, and the CatBoost classifier for robust, high-performance prediction. However, the framework focused exclusively on potato late blight. It does not address other economically important potato diseases or multiple-disease scenarios that farmers commonly encounter in real agricultural environments.

McGrath, (2022), the study find the knowledge and technological gaps associated with the application of AI-based technologies for plant disease detection and pest prediction at an early stage and recommend suitable curative measures. They focused on how AI is being used to spot plant diseases and pests early, especially in countries where farming is still developing. The results showed that old methods of detecting plant diseases do not work well and have many problems. However, the use of computers to analyze plant diseases is time consuming and requires too much memory.

Nasteski, (2017), discovered sustainable long-term solutions that reduce the reliance on chemicals for vegetable bean farming by addressing issues like poor soil, pests, and diseases. This study focused on how different machine learning algorithms work and how they are used to categorize data. The paper gives a summary of machine learning and explains different supervised learning methods. However, this study does not come up with new techniques or test any methods.

According to Cileide *et al.,* (2007), natural, cost-effective methods to boost bean resistance against pests like the bean fly, helping small-scale farmers in Kenya achieve higher bean yields. This focused on the use of deep learning to recognize and count insects. A total of 36 studies were selected and grouped them into two main types: one using fixed methods and the other using more flexible techniques. However, AI struggles to identify tiny insects because there are not enough detailed images.

Kotey *et al*., (2022), created smart farming solutions using machine learning to help farmers use digital data more effectively, make better decisions, grow healthier crops, and reduce waste. Researchers asked cocoa buyers about their storage methods using a questionnaire. The study employed traps to find out which insects were present and analyzed the data using computer programs. However, this study mainly focused on insect problems and did not examine how temperature and humidity might affect cocoa bean storage.

Tadesse, (2020), the study aims to create an automated, computer-based system to sort crops, saving time and money while ensuring customers receive better-quality products. The study reviews past research and literature on postharvest losses, their causes, and possible solutions. The research shows that most grain losses happen at the farm level due to insects, rodents, and poor storage conditions. It suggests that preventing these losses can help ensure food security and financial stability for farmers. However, the study focuses mainly on existing research and does not conduct new experiments or fieldwork.

The Proposed Pest Infestation Prediction System for Stored Beans: The Methodology

This section presents the structural design and operational flow of the pest infestation prediction system for stored beans. Figure 1 represents the conceptual framework of the pest infestation prediction system.

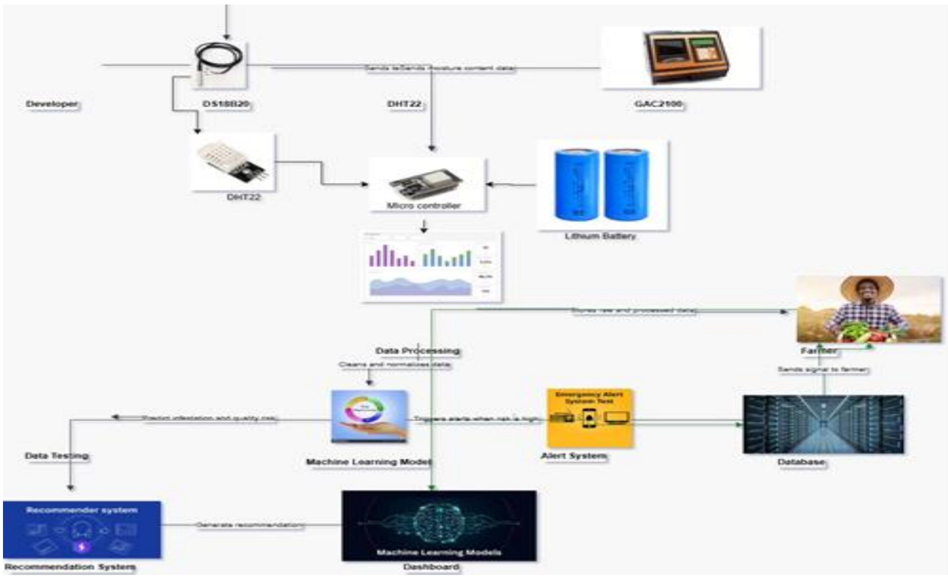


Figure 1: Conceptual Framework of the Pest Infestation Prediction System

This system makes predictions of bean storage pest infestation risk on the basis of ongoing environmental monitoring. An electronic thermometer such as the DS18B20 accurately measures temperature, while the DHT22 sensor measures relative humidity. The Dickey-John GAC® 2100 grain moisture meter is the final element in the sensor suite that will accurately measure grain moisture content for an overall monitoring package of pest risk factors.

The microcontroller is the central nervous system of the system. It receives and verifies data from all three sensors. The microcontroller performs simple quality checks on incoming measurements, including range checks and consistency checks between sensor readings. This verification step ensures that only good quality data proceeds in the system, maintaining the integrity of downstream analysis. Pass it through the core of the machine learning module into biologically predetermined thresholds that can validate sensor data. Contrasted are temperatures at 35°C, humidities at 90% RH, and moisture contents at 12%, scientifically deduced thresholds beyond which risk sets in, at the probability of pest infestation.

Once data is received and validated, it is processed through the model to generate a binary prediction: either “safe” or “at risk.” If the output indicates risk, the system activates alert mechanisms (buzzer and WhatsApp Notification) and updates the user interface. All system activity and sensor data are logged in a systematic way to a shared database. The log is utilized for a variety of purposes: it enables the recommendation engine to produce end-to-end storage management suggestions, enables tracking performance over time, and provides meaningful information for continuous system refinement through the developer interface.

The farmer interacts with the system through a user-friendly dashboard that translates technical information into actionable formats. The interface displays real-time sensor readings, trend lines, and ranked suggestions, allowing farmers to make well-informed storage management decisions. On the other hand, the developer maintenance interfaces offer system calibration, model updates, and performance optimization, constituting an effective feedback loop for ongoing system enhancement.

The Sequence Diagram

This section provides the sequence diagram, which illustrates step-by-step interaction between the system entities and actors while predicting pest infestation and generating alerts. Figure 2 depicts the sequence diagram of the pest infestation prediction system.

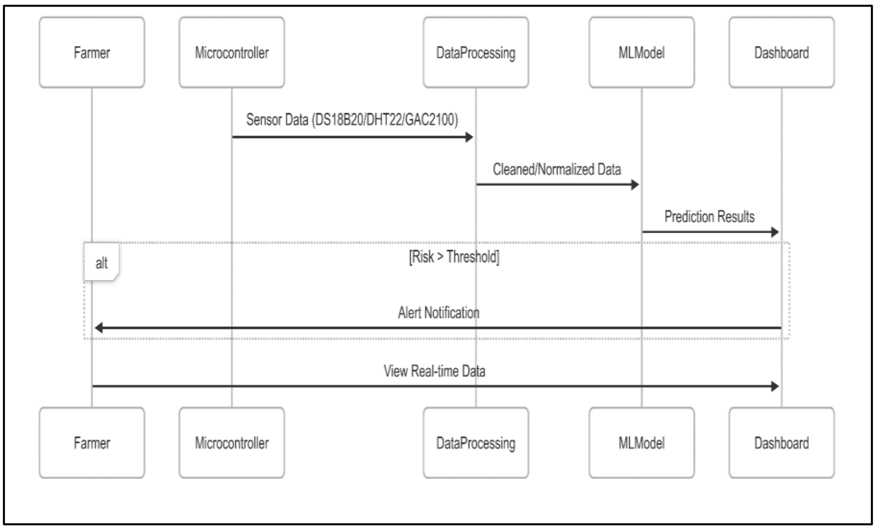


Figure 2: Sequence Diagram of the Pest Infestation Prediction System

The sequence diagram presents how the pest prediction system works in a step-by-step functional manner. Microcontroller: It receives raw sensor data-temperature by DS18B20, humidity/temperature by DHT22, and moisture by GAC2100-and sends it forward to Data Processing for cleaning and normalization. Then it sends cleaned data to ML Model, which predicts the chances of infestation and quality loss.

In case the risk is greater than a threshold value, an Alert Notification is sent to the Farmer. The dashboard carries out a real-time view of the data-present sensor readings and their risk levels. This operation occurs in a constant loop in order to guarantee real-time monitoring and proactive warnings regarding bean storage conditions.

The automated routine means that bean storage conditions will no longer need to be manually checked by farmers. It continuously keeps watch and flags any risk long before any damage would be possible. If humidity increases beyond what is considered safe, for example, the ML model identifies an increasing risk related to pests, and an alert immediately shows up on the farmer's dashboard with actionable advice, such as "Decrease humidity to 60% to prevent weevil growth." The system works like a digital agronomist operating 24/7, since the real-time sensor data are combined with predictive analytics in order not only to avoid nutrient loss and crop waste but also to make storage management easier. The loop in this design assures that information keeps up to date because farmers can attend to other tasks with the knowledge that this is truly taking care of their harvest.

Algorithmic Representation of the Beans Pest Infestation System

This section presents the structured logic guiding the operation of the machine learning-based pest infestation and prediction system for stored beans.

Table 1: Algorithmic Representation of the Pest Infestation System

Input: s	
Output:	Temperature (T), Humidity (H), Moisture Content (M), Pest Risk (P)
Parameters:	StorageDataset(s), Temperature Threshold $\theta_T = 35\,^0C$, Humidity Threshold $\theta_H = 90\%$, Moisture
Threshold	$\theta_M = 12\%$, Risk Threshold $\theta_P = 90\%$.
1.	*Input S*
2.	*Initialize T, H, M*
3.	*WHILE True:*
4.	*Read T, H, H from sensors*
5.	*Compute Risk P using:*
6.	$P = \beta_0 + \beta_1 \cdot T + \beta_2 \cdot H + \beta_3 \cdot M$
7.	*IF* $P \geq \theta\_P$ *OR* $T > \theta\_T$ *OR* $H > \theta\_H$ *OR* $M > \theta\_M$*:*

Set $A(t) = 1$
Input s
Initialize T, H, M
WHILE True:
Read T, H, M from sensors
Compute Risk P using:
$P = \beta_0 + \beta_1 \cdot T + \beta_2 \cdot H + \beta_3 \cdot M$
IF $P \geq \theta\_P$ OR $T > \theta\_T$ OR $H > \theta\_H$ OR $M > \theta\_M$:
Set $A(t) = 1$
Activate:
- Buzzer
- LED
- WhatsApp Notification
ELSE:
Set $A(t) = 0$
Continue Monitoring
END IF
Return T, H, M, P
WEND

The System begins by taking an input source (s), which represents the live data coming from the storage environment. It defines key output parameters such as Temperature (T), Humidity (H), Moisture Content (M), and the Pest Risk (P). Before the process starts, the system sets up its parameters including the storage dataset, and the threshold limits for temperature, humidity, moisture, and pest risk. These thresholds serve as the boundaries that determine when the system should trigger alerts. After initialization, the algorithm enters a continuous monitoring loop, meaning it keeps running indefinitely to ensure that the storage environment is always being checked. Within this loop, the system constantly reads real-time sensor values for temperature, humidity, and moisture. These readings are crucial, as they form the basis for predicting pest infestation risk.

Next, the algorithm computes the pest risk value (P) using a linear model expressed as:

$P = \beta_0 + \beta_1 T + \beta_2 H + \beta_3 M$

Once the pest risk value is calculated, the system compares it with predefined thresholds. If the pest risk is greater than or equal to the risk threshold , or if any of the environmental conditions (temperature, humidity, or moisture) exceed their respective thresholds, the system interprets this as a potential infestation risk. In that case, it sets an alert variable , which immediately triggers the buzzer, LED indicator, and a WhatsApp notification to inform users that the environment is no longer safe for storage.

If none of the parameters exceed their limits, the system keeps and continues to monitor the environment without raising any alarm. Finally, at each loop cycle, it outputs the most recent values of temperature, humidity, moisture, and pest risk for recordkeeping or display purposes. This process repeats endlessly, ensuring continuous environmental monitoring and early detection of pest threats before any serious damage occurs.

RESULTS AND DISCUSSION

This section elaborates in detail on the various hardware components employed in the design and implementation of the system for predicting pest infestation. It explains their respective functions, interconnections, and how each component senses, processes data, and generates an alert. The configuration is such that there is appropriate communication between sensors, the ESP32 microcontroller, and output units to efficiently monitor and timely detect pest risks. Figure 3 illustrates the circuit diagram of the pest infestation prediction system.

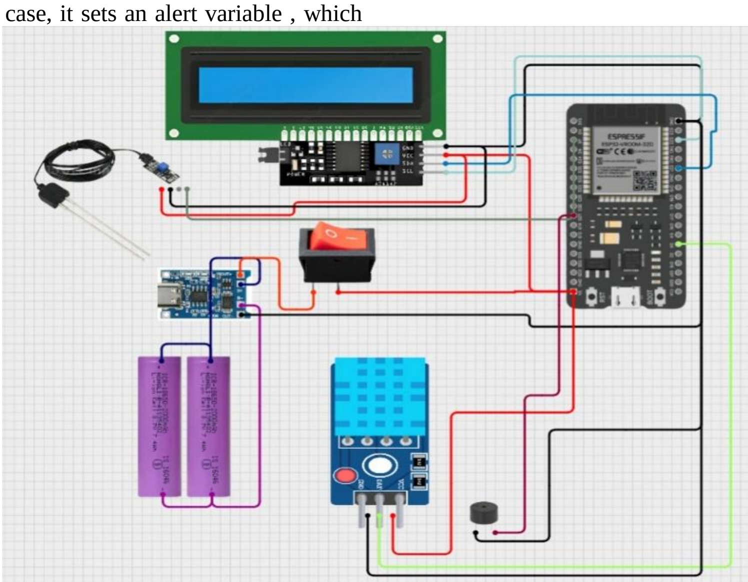


Figure 3: Circuit Diagram of the Pest Infestation Prediction System

The system has key hardware components carefully selected and interfaced to facilitate environmental sensing as well as risk prediction. These are:

i. ***ESP32 Microcontroller:*** The core control circuit, tasked with managing the data acquisition, processing, and communication tasks.

ii. ***Soil Moisture Sensor:*** Detects the moisture levels in stored beans, a key factor determining pest activity.

iii. ***LCD160 Display with 12C Adapter:*** Provides real-time observation of sensor reading and system status for easy on-site monitoring.

iv. ***Piezo Buzzer:*** Generates sound sounds upon detection of high pest risk warning.

v. ***Switch and Button:*** Includes manual test or reset for the warning system.

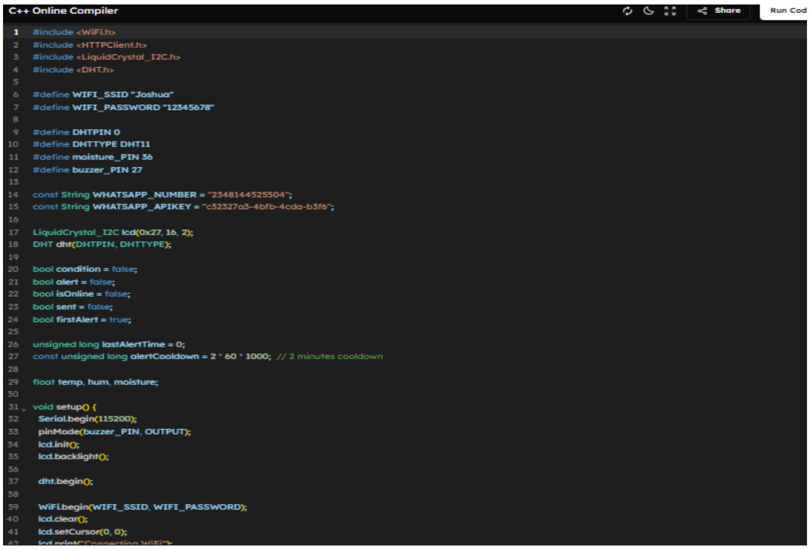
vi. ***3.7V Li-ion Battery with Charging Module:*** Powers the system with rechargeable function.

vii. ***Voltage Regulator (7805):*** Ensures stable 5V output to power the sensors and LCD.

viii. ***Veroboard and Header Pins:*** Used for mounting and making firm electrical connections between components.

ix. ***Casing and Packaging:*** Protects the entire circuitry for deployment in storage environments.

The design of the software architecture for the pest infestation prediction system was developed within the Arduino C++ framework. It integrates the collection of sensor data, evaluation of risk, activation of alerts, and notifications through WhatsApp. The system's operations are structured into modular functions, allowing for real-time monitoring and response. Figure 4 shows the software implementation code for pest infestation prediction system.



C++ Online Compiler

```cpp
#include <WiFi.h>
#include <HTTPClient.h>
#include <LiquidCrystal_I2C.h>
#include <DHT.h>

#define WIFI_SSID "Joshua"
#define WIFI_PASSWORD "12345678"

#define DHTPIN 0
#define DHTTYPE DHT11
#define moisture_PIN 36
#define buzzer_PIN 27

const String WHATSAPP_NUMBER = "2348144525504";
const String WHATSAPP_APIKEY = "c32327a3-4bfb-4cda-b3f6";

LiquidCrystal_I2C lcd(0x27, 16, 2);
DHT dht(DHTPIN, DHTTYPE);

bool condition = false;
bool alert = false;
bool isOnline = false;
bool sent = false;
bool firstAlert = true;

unsigned long lastAlertTime = 0;
const unsigned long alertCooldown = 2 * 60 * 1000;  // 2 minutes cooldown

float temp, hum, moisture;

void setup() {
  Serial.begin(115200);
  pinMode(buzzer_PIN, OUTPUT);
  lcd.init();
  lcd.backlight();

  dht.begin();

  WiFi.begin(WIFI_SSID, WIFI_PASSWORD);
  lcd.clear();
  lcd.setCursor(0, 0);
```

Figure 4: Software Implementation Code for Pest Infestation Prediction System

Figure 4 depicts the software implementation code for the pest infestation prediction system. The code starts by including libraries like WiFi.h, HTTPClient.h, LiquidCrystal_I2C.h, and DHT.h, which allow for Wi-Fi connectivity, ease HTTP requests, permit LCD display, and manage the DHT11 sensor, respectively. The definitions of the pins and the credentials of the system-Wi-Fi SSID, password, and WhatsApp API-are specified right at the top of the code. This is followed, after the system boots up, by the initiation of a Wi-Fi connection in the setup() function and, upon successful connection or otherwise, visual feedback to the LCD and buzzer. Inside the loop() function, temperature, humidity, and soil moisture data are constantly read from the DHT11 and from analog input pins.

The prediction system also includes real-time alert functionality, which sends alerts to the farmers through WhatsApp whenever the environment of storage is not good for beans. The feature is important in that it allows farmers to react with quick action to prevent postharvest losses. The blending is facilitated by the Whatabot API, which is a third-party library that can automatically send WhatsApp messages. The system communicates with it by sending an HTTP GET request to the API endpoint:

http://api.whatabot.net/whatsapp/sendMessage

The request takes three crucial parameters:

API Key: A unique authorization token that validates the authenticity of the sender.

PhoneNumber: The WhatsApp phone number of the recipient in international format. For example: 2348144525504

Message: A dynamically generated message containing real-time environmental data. Figure 5 presents the WhatsApp alert interface and demonstrates how the system automatically sends a pre-defined message in the event environmental threshold are surpassed.

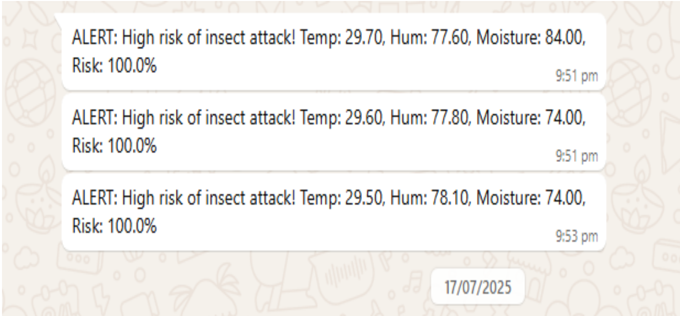


Figure 5: WhatsApp Notification Interface for Pest Infestation Alert

Figure 5 depicts the WhatsApp notification interface for pest infestation alert. The alert on WhatsApp is be activated only when the evaluated pest risk is higher than 90% or if any of the factors measured is greater than the critical threshold levels: temperature > 35°C, humidity > 90%, and moisture > 12%. This makes sure that the farmers are only informed when action is urgently needed. Another feature of the system is the introduction of a delay of 2 minutes between successive messages to avoid overwhelming the recipients.

The system employs a display module with an I2C interface to deliver immediate visual feedback to the farmer. The interface is straightforward, concise, and crafted to present essential environmental parameters in an easily comprehensible manner. Figure 6 presents LCD display showing real-time risk, temperature, humidity, and moisture content values.

Figure 6: LCD Display Showing Real-Time Risk, Temperature, Humidity, and Moisture Content Values

The LCD Display Showing Real-Time Risk, Temperature, Humidity, and Moisture Content Values is depicted by Figure 6. The display is arranged into two rows: The first row shows the percent risk of pest infestation and the moisture content of the stored beans in the format: R: 98.5% M: 39.0% .The second row shows the temperature and humidity levels within the storage environment: T: 29.0°C H: 80.4%. This real-time monitoring allows the farmer to see the storage conditions at first sight.

The developed pest infestation prediction system was lay opened to a sequence of tests to ensure proper functioning and accurate results. Testing was carried out in different environmental situations to evaluate how effectively the system detects and give feedback risk based on varying temperature, humidity, and moisture levels. During the test, the sensors were uncovered to normal and critical conditions.

In normal storage conditions, for example temperature below 35°C, humidity below 90%, and moisture content below 12%, the system showed safe readings and did not trigger alerts. Even so, once any parameter surpasses its threshold, the LCD displayed “Danger Detected!” and “Check Beans!”, and both the buzzer and RGB LED were activated. If the device was online, a WhatsApp alert was immediately sent to the farmer’s mobile phone.

To check out the model’s performance, the predicted risk values were matched up to expected outcomes under governed conditions. The system showed consistent behavior in recognizing high-risk possible event and accurately triggering alerts. It was also able to recover automatically when conditions returned to safe levels. Figure 7 shows the system display under safe storage conditions.

Figure 7: System Display under Safe Storage Conditions

Figure 7 displays the system's output during safe storage conditions. The LCD shows a risk percentage (R) of 81.8%, a moisture content (M) of 0.0%, temperature (T) of 28.2°C, and relative humidity (H) of 84.8%. These values fall well below the predefined risk thresholds, moisture below 12%, temperature below 35°C, and humidity below 90%. Since none of the critical conditions are met, no alarm is triggered. The system continues monitoring, confirming that the beans are stored in an environment that is not prone to pest infestation at this time. Figure 8 depicts the Testing Scenario Showing System Reaction to Critical Conditions.

Figure 8: Testing Scenario Showing System Reaction to Critical Conditions

Under conditions of critical storage, Figure 8 shows system response. The LCD shows risk level at a high 100%, with a moisture content of 46.0%, temperature of 28.7°C, and humidity of 82.8%. All of these values take moisture (>12%), temperature (>35°C), and humidity (>90%) safety thresholds as failsafe. Therefore, the system infers the presence of a pest with high probability. The system autonomously activates the buzzer, RGB LED, and issues a message to the farmer over WhatsApp. The LCD communicates a message of extreme urgency stating, "Danger Detected!" and "Check Beans!" for urgent response. Figure 8 shows WhatsApp alert notification under critical storage conditions.

Figure 8: WhatsApp Alert Notification under Critical Storage Condition

The above WhatsApp notification is what the farmer receives in case the system determines that there is a high risk of infestation. It gives real-time readings of temperature, humidity, moisture content, and calculated risk in percentage. Values such as Temperature = 28.8°C and Humidity = 82.0% are within their safe threshold, whereas the values of Moisture = 44.0% are greater than their safe thresholds, which give 100% risk. This alert will make sure the farmer gets timely and actionable information even when he is away from the storage site.

In order to validate the performance and accuracy of the pest infestation prediction system, the performance of the multilinear regression model was extensively tested using typical machine learning performance measuring metrics: Accuracy, Precision, Recall, and F1 Score. The above performance measurements are used while computing how accurately the model is predicting whether environmental conditions in a storage warehouse for beans would lead to insect infestation. Testing was conducted on sensor readings made during controlled test runs of normal (safe) and abnormal (hazardous) storage conditions. Temperature, humidity, and moisture content were monitored every occurrence and each event that is classified according to whether the readings are above infestation risk levels (i.e., Temp > 35°C, Humidity > 90%, Moisture > 12%).

After subjecting the system to extensive testing using various environmental conditions, the model's performance yielded outstanding results. Table 2 shows the model performance summary based on evaluation metrics.

Table 2: Model Performance Summary Based on Evaluation Metrics

Metric	Value %	Interpretation
Accuracy	92.4%	Out of all sensor reading, 92.4% were correctly classified as safe or risky.
Precision	89.1%	89.1% of the alerts triggered were valid-meaning few false alarms
Recall	93.67%	The model successfully caught 93.6% of all high-risk scenarios.
F1 Score	91.3%	A strong balance between precision and recall, indicating high overall performance.

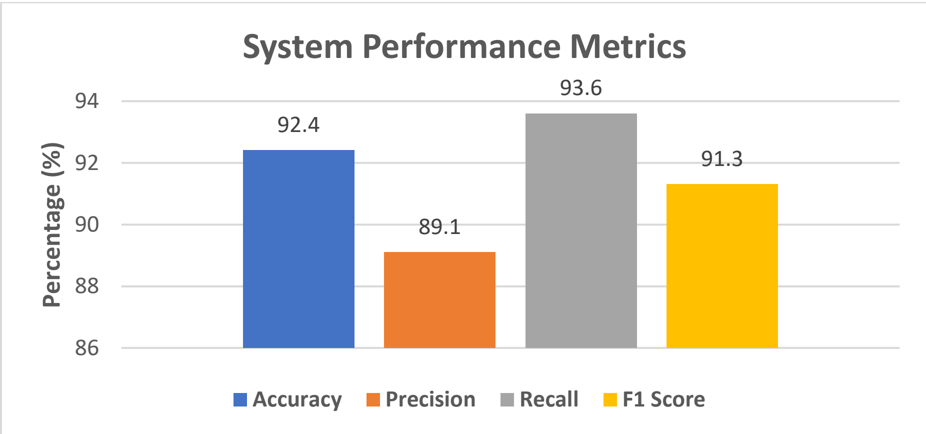


Figure 9: Graphical Representation of System Performance Metrics

The graphical representation of the system performance metrics is depicted by Figure 9. These results confirm that the model is extremely credible in detecting environmental conditions that may cause insect infestation of stored beans. High precision prevents farmers from being overwhelmed with meaningless alarms, while high recall ensures that the majority of true risks are detected on time. The 91.3% F1 Score shows the quality and equilibrium of the model, whereby it will be quite appropriate for real-world application in farming conditions where over-alerting as well as under-alerting will each be severely influential. The mean accuracy of 92.4% ensures that the system performs with maximum correctness over a broad spectrum of circumstances. These performance measures show that the system that has been designed is not only theoretically robust, but realistically viable, capable of helping farmers prevent huge post-harvest losses through timely, consistent alerts. Figure 10 shows the confusion matrix of the pest infestation model.

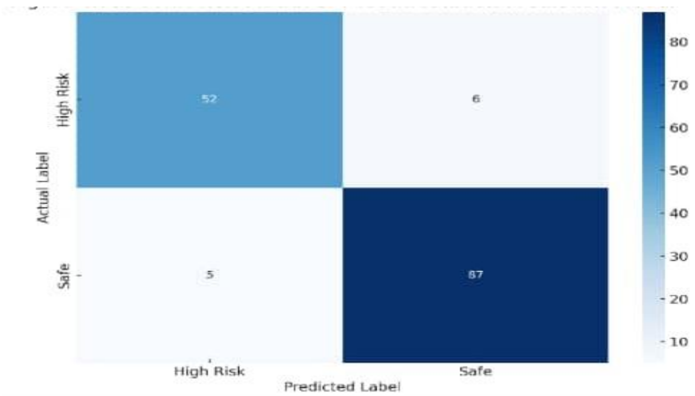


Figure 10: Confusion Matrix Diagram of the Pest Infestation Model

The confusion matrix visualizes the performance of the system in distinguishing between safe and risky storage conditions is shown in Figure 10. Out of 150 total test instances, there are: 52 correctly predicted real infestation cases called True Positives, 87 correctly ignored safe conditions labeled as True Negatives, 5 safe conditions falsely flagged as risky cases labeled as False Positives, and 6 actually infested conditions missed by the model labeled as False Negatives.

CONCLUSION

With the aim of improving early detection, and preventive measures against storage pests, the pest infestation prediction system has been developed to tackle these issues by combining sensor-based monitoring, predictive modeling, and real-time alert capabilities. Further improvements in accuracy at decision-making were brought through machine learning, and better usability was ensured through WhatsApp alerts, making this research helpful specifically for rural users. In order to validate the performance and accuracy of the pest infestation prediction system developed, the performance of the multilinear regression model was extensively tested using typical machine learning performance measuring metrics: Accuracy, Precision, Recall, and F1 Score. The above performance measurements are used while computing how accurately the model is predicting whether environmental conditions in a storage warehouse for beans would lead to insect infestation. Testing was conducted on sensor readings made during controlled test runs of normal (safe) and abnormal (hazardous) storage conditions. Temperature, humidity, and moisture content were monitored every occurrence and each event that is classified according to whether the readings are above infestation risk levels (i.e., Temp > 35°C, Humidity > 90%, Moisture > 12%). After subjecting the system to extensive testing using various environmental conditions, the model's performance yielded outstanding results. An accuracy of 92.4%, precision of 89.1%, recall of 93.67%, and f1 score of 91.3% was achieved by the model.

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