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Reinforcement Learning-Based Adaptive Auto encoder for Energy-Efficient Boll Rot and Pathogen Detection in IoT Networks

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ABSTRACT

The increasing prevalence of crop diseases such as boll rot and other pathogen infections poses a significant threat to agricultural productivity, particularly in resource-constrained farming environments. This study proposes a Reinforcement Learning-Based Adaptive Auto encoder (RL-AAE) framework for energy-efficient detection of boll rot and related pathogens within Internet of Things (IoT)-enabled agricultural networks. The model integrates an adaptive auto encoder for feature extraction and dimensionality reduction with a reinforcement learning (RL) agent that dynamically optimizes sensing, data transmission, and decision-making processes to minimize energy consumption while maintaining high detection accuracy. The adaptive auto encoder is designed to learn compressed representations of high-dimensional sensor and image data collected from distributed IoT nodes, enabling efficient processing and anomaly detection. The reinforcement learning component continuously interacts with the network environment to select optimal actions, such as adjusting sampling rates, transmission intervals, and node participation, thereby prolonging network lifetime and reducing redundant energy usage. The proposed approach is evaluated using key performance metrics including detection accuracy, energy consumption, network lifetime, and latency. Experimental results demonstrate that the RL-AAE model significantly outperforms traditional machine learning and static IoT detection approaches by achieving higher classification accuracy for boll rot and pathogen detection while reducing energy consumption and extending network operational lifespan. This work highlights the potential of combining deep learning and reinforcement learning techniques to address critical challenges in smart agriculture, providing a scalable and intelligent solution for real-time disease monitoring in IoT-based farming systems.

KEYWORDS: Auto encoder, Reinforcement Learning (RL), Network Lifetime, Pathogen Infection, Anomaly Detection.

1.0 INTRODUCTION

The rapid growth of smart agriculture has led to the integration of advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and machine learning (ML) to improve agricultural productivity and sustainability ((Boukharis, Jilal, & Asrii, 2024). Among the major challenges facing modern agriculture is the timely detection and management of pests and plant pathogens, which are responsible for significant crop losses globally. Traditional methods of pest and disease detection rely heavily on manual inspection, which is often labor-intensive, time-consuming, and prone to human error. Consequently, there is a growing need for automated, intelligent, and energy-efficient systems capable of real-time monitoring and early detection (Fu & Dai, 2025).

Boll rot disease is one of the most destructive conditions affecting cotton, characterized by the decay of developing or mature bolls, which directly reduces yield and fiber quality. It is not caused by a single organism but rather a complex interaction of several fungal and bacterial pathogens (Sharma, Liu, & Zhang, 2023). Common organisms associated with boll rot include Fusarium, Alternaria, Colletotrichum, Diplodia, and Xanthomonas (Acharya, Khakar, & Kumar, 2024). These pathogens often exist naturally in the environment and infect cotton bolls when favorable conditions arise. Boll rot is especially prevalent in regions with warm temperatures and high humidity, making it a serious concern in many cotton-growing areas, including Nigeria (Li & Yang, 2024).

The causes of boll rot are closely linked to environmental conditions and field management practices. High humidity, prolonged rainfall, and excessive irrigation create a moist environment that promotes pathogen growth and infection (Aghera & Leo, 2022). Dense plant canopies limit air circulation, allowing moisture to persist around the bolls, which further encourages disease development (Fand & Mansir, 2024). In addition, insect pests such as the bollworm play a critical role by damaging the boll surface, thereby creating entry points for pathogens. Poor field sanitation, including the presence of infected crop residues, also increases the likelihood of disease occurrence, as pathogens can survive in plant debris and soil (Naraghi & Kamal, 2024).

The symptoms of boll rot vary depending on the causal organism but generally begin as small, water-soaked lesions on the surface of the boll. These lesions gradually enlarge and turn brown, black, or grey as the tissues decay (Yang & Shakoor, 2025). Infected bolls often become soft and may emit an unpleasant odor as rotting progresses. In humid conditions, fungal growth may appear as visible mold on the boll surface. Severely affected bolls may fail to open properly or may open prematurely, exposing discolored and low-quality lint. In advanced stages, the entire boll may be destroyed, resulting in significant yield loss and reduced market value of the cotton (Junaid & Khalil, 2023).

Boll rot presents several challenges to cotton farmers. One major difficulty is that it is caused by multiple pathogens, making diagnosis and control more complex than single-pathogen diseases. Environmental factors such as unpredictable rainfall and high humidity are difficult to control, especially in tropical and subtropical regions (Deepa, Sharma, & Aghera, 2024). Additionally, the disease often develops rapidly under favorable conditions, leaving little time for intervention. The involvement of insect pests further complicates management, as both pest and disease control measures must be implemented simultaneously. Economic constraints may also limit farmers’ ability to apply fungicides or adopt improved management practices, particularly in developing regions (Li, Nang, & Mele, 2025).

To address these challenges, IoT-based agricultural systems provide a promising solution by enabling continuous monitoring through distributed sensor nodes, cameras, and environmental sensing devices deployed across farmlands. These systems generate large volumes of heterogeneous data, including temperature, humidity, soil moisture, and image data, which can be analyzed to detect anomalies associated with pest infestations and plant diseases (Golchin, Rekabdar, & Shamir, 2025). However, IoT devices are typically resource-constrained in terms of energy, computation, and storage capacity. This limitation necessitates the development of lightweight and efficient data processing techniques that can operate effectively within such constrained environments (Chaudhary & Rajasegarar, 2026).

Deep learning techniques, particularly auto encoders, have gained attention for their ability to perform efficient feature extraction and dimensionality reduction. Auto encoders are neural network architectures designed to learn compact representations of input data by encoding it into a lower-dimensional latent space and reconstructing it with minimal loss of information (Akin, Rekabdar, & Golchin, 2024). In the context of pest and pathogen detection, auto encoders can be used to identify abnormal patterns in sensor readings or image data by measuring reconstruction errors. This makes them suitable for anomaly detection tasks, especially when labeled datasets are limited or unavailable. Moreover, their ability to compress data makes them highly beneficial for reducing communication overhead in IoT networks (Gueriani, Kheddar, & Mazari A, 2024).

Reinforcement learning is a paradigm of machine learning in which an agent learns to make optimal decisions by interacting with an environment and receiving feedback in the form of rewards or penalties (Kumar & Ramar, 2023). In IoT-based pest detection systems, an RL agent can be designed to dynamically adjust parameters such as detection thresholds, sampling rates, feature selection, and transmission policies. By incorporating energy consumption into the reward function, the RL agent can learn to balance detection accuracy with energy efficiency, thereby prolonging the operational lifetime of IoT devices (Lopez & Hamma, 2022).

The integration of reinforcement learning with auto encoders leads to the concept of a reinforcement learning-based adaptive auto encoder, where the auto encoder performs feature extraction and anomaly detection, while the RL component continuously optimizes the system’s behavior (Shiu & Leo, 2023). This hybrid approach enables the system to adapt to environmental changes, improve detection accuracy, and minimize energy usage. Furthermore, such a model can support edge computing paradigms, where data processing is performed closer to the data source, reducing latency and communication costs (Platero & Horcajadas, 2024).

Energy efficiency remains a critical consideration in IoT networks, particularly in agricultural deployments where devices are often battery-powered and located in remote areas. Excessive data transmission and complex computations can quickly deplete energy resources, leading to network failure (Aghera & Kwami, 2022). Therefore, designing an intelligent system that can selectively process and transmit only relevant information is essential. The proposed reinforcement learning-based adaptive auto encoder addresses this challenge by optimizing both computation and communication processes (Tanwar & Sarkar, 2024).

1.1 Why unsupervised learning is suitable for pest detection?

Unsupervised learning has emerged as a highly suitable approach for pest and pathogen detection in modern agricultural systems, particularly within Internet of Things (IoT)-enabled environments (Aghada & Mele, 2024). One of the primary reasons for its suitability lies in the lack of labeled data in agriculture. Unlike domains such as image recognition or speech processing, where large annotated datasets are readily available, agricultural data often requires expert knowledge for accurate labeling (Zhang & Lee, 2023). Identifying pests, diseases, or subtle plant stress symptoms typically demands the involvement of agronomists or plant pathologists, making the labeling process expensive, time consuming and impractical for large-scale deployment. Unsupervised learning overcomes this limitation by learning directly from raw, unlabeled data, allowing systems to be deployed across diverse farms and crop types without the need for extensive manual annotation (Shaw & Dee, 2024).

Another key reason unsupervised learning is well-suited for pest detection is that pest infestation is inherently an anomaly detection problem. Under normal conditions, healthy crops exhibit consistent patterns in terms of color, texture, growth rate, and environmental responses (Kramer & Jaw, 2023) . When pests or pathogens attack, they introduce deviations from these normal patterns, such as discoloration of leaves, unusual spots, or irregular growth. Unsupervised learning models, particularly auto encoders and clustering algorithms, are designed to learn the underlying structure of normal data and identify deviations from it (Kong & Lee, 2024). Through modeling what constitutes "normal" plant behavior, these systems can effectively detect abnormalities that signal the presence of pests or diseases, even when such conditions have not been explicitly labeled during training (Khadiri & Olamide, 2024).

Unsupervised learning also enables early detection of pest infestations, which is critical for minimizing crop damage and improving agricultural productivity. Traditional detection methods often rely on visible symptoms, which typically appear at later stages of infestation when significant damage has already occurred (Mansir & Lawrence, 2024). In contrast, unsupervised models analyze subtle variations in data distributions, allowing them to identify minor changes in plant physiology or environmental conditions before they become visually apparent. For example, slight deviations in temperature, humidity, or leaf reflectance patterns can be detected early, enabling farmers to take preventive action. This capability is particularly valuable in precision agriculture, where timely intervention can significantly reduce pesticide use and enhance sustainability (Nasri & Lukman, 2023).

1.2 Scarcity of labeled pest datasets in real farms.

The scarcity of labeled pest datasets in real farm environments is widely recognized as one of the most critical constraints in applying artificial intelligence to agriculture. Unlike controlled laboratory datasets, real-world agricultural data especially for pest detection is difficult to collect, annotate, and standardize due to the complex, dynamic, and heterogeneous nature of farming systems (Liu & Mukhtari, 2024). Recent literature consistently highlights that supervised machine learning models depend heavily on large-scale, high-quality labeled datasets, yet such datasets remain limited, fragmented, and often unrepresentative of real farm conditions (Wu & Khan, 2023).

One of the primary reasons for this scarcity is the high cost and labor-intensive nature of data annotation. Pest detection requires expert knowledge to correctly identify species, growth stages, and infestation severity, making labeling both time-consuming and expensive. In real farms, images must often be manually annotated by agronomists or entomologists, significantly increasing the cost of dataset creation (Hamid & Andrew, 2022) . As a result, many available datasets are small or incomplete, which limits their usefulness for training robust deep learning models. Furthermore, annotation inconsistencies such as differences in bounding box definitions or class labels introduce noise and reduce dataset reliability across studies (Wang & Patrick, 2022).

Another major factor contributing to dataset scarcity is the diversity and variability of real farm environments. Agricultural systems vary widely in terms of crop species, pest types, climatic conditions, soil properties, and farming practices. This variability makes it difficult to create generalized datasets that capture all possible scenarios (Yang & Pierre, 2023) . For example, pests may appear differently depending on lighting conditions, plant growth stages, or environmental stress and datasets often fail to represent such seasonal and contextual variations adequately. Consequently, models trained on limited datasets struggle to generalize across regions, particularly when applied to new geographical areas or small holder farms (Qu & Yang, 2024).

2.0 RELATED WORKS

The proposed scheme lies at the intersection of three rapidly evolving research domains of IoT-enabled smart agriculture, deep learning–based pest detection (including auto encoders), and reinforcement learning for adaptive and energy-aware optimization (Mensah & Khadir, 2023). Recent literature shows that integrating these paradigms is emerging as a promising direction for addressing real-world constraints such as limited energy, data scarcity, and dynamic farm environments (Abdullahi & Salis, 2024).

2.1 IoT-Based Pest and Pathogen Detection in Smart Agriculture

The integration of the Internet of Things (IoT) into agriculture has significantly transformed pest and disease monitoring by enabling real-time data collection through distributed sensors, drones, and edge devices. IoT-based systems facilitate continuous monitoring of crop conditions and enable early pest detection, which is critical for improving yield and reducing pesticide use (Alzahran & Mensah, 2023). Recent studies demonstrate that IoT frameworks combined with machine learning models can automate pest detection processes, reducing reliance on manual inspection and improving scalability in large farms (John, Oloyede, & Yohannah, 2025).

However, despite these advancements, IoT-based pest detection systems face challenges such as high data transmission costs, limited battery life of sensor nodes, and the need for efficient edge processing (Longi, Mansir, & Mahdi, 2023). The continuous streaming of high-dimensional image data from sensors to cloud servers increases energy consumption and latency, making energy efficiency a central concern in IoT-enabled agricultural systems . These limitations have motivated the adoption of lightweight and adaptive AI models that can operate efficiently in resource-constrained environments (Joe, Shaw, & Habib, 2025).

2.2.1 Deep Learning and Auto encoders for Pest Detection

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have been widely used for pest and pathogen detection due to their strong feature extraction capabilities. For example, drone-based and IoT-assisted systems using CNNs have achieved high accuracy in identifying pests and diseases in crops. Similarly, hybrid models combining CNNs with optimization techniques and recurrent architectures have improved classification performance and robustness in complex agricultural environments (Chen, Li, & Zhang, 2024).

Figure 1: Deep Learning Process on Cotton Boll rots Pest and Pathogen (Xiao & Khan, 2024).

Auto encoders, a class of unsupervised neural networks, have gained attention for their ability to learn compact representations of data. In agricultural contexts, auto encoders are particularly useful for anomaly detection, where pest or disease presence is treated as a deviation from normal plant conditions (Jabir, Hamid, & Ali, 2024). By encoding input data into lower-dimensional latent representations and reconstructing it, auto encoders can identify abnormal patterns without requiring extensive labeled datasets. This makes them highly suitable for real-world farming scenarios where labeled pest data is scarce (Yohanna, Kadir, & Mele, 2023).

2.2.2 Reinforcement Learning for Adaptive and Energy-Efficient Systems

Reinforcement Learning (RL) has emerged as a powerful paradigm for optimizing decision-making in dynamic and resource-constrained environments such as IoT networks (Chew, Jeng, & Longi, 2024) . Unlike supervised learning, RL enables agents to learn optimal policies through interaction with the environment, making it suitable for adaptive control and resource management (Khan & Sohail, 2023).

Recent studies have applied RL to IoT systems for tasks such as resource allocation, intrusion detection, and energy optimization. For instance, RL-based frameworks can dynamically adjust system parameters (e.g., transmission rates, computation offloading, or model complexity) to minimize energy consumption while maintaining performance (Oyedele & Dele, 2023). In agricultural contexts, RL has been used to optimize distributed learning architectures, where a Q-learning agent dynamically selects optimal configurations to balance computational load and energy usage across heterogeneous devices (Aghere & Longi, 2024).

These capabilities make RL particularly suitable for adaptive pest detection systems, where environmental conditions and network constraints continuously change. By incorporating feedback from detection accuracy, energy usage, and latency, RL agents can optimize system behavior in real time.

2.2.3 Integration of RL with Auto encoders in IoT Networks

The integration of reinforcement learning with auto encoders represents a novel and promising research direction. In such frameworks, the auto encoder is responsible for feature extraction and anomaly detection, while the RL agent dynamically optimizes system parameters such as compression ratio, sampling rate, or transmission frequency (Liu & Zhang, 2025).

Although direct implementations of RL-based adaptive auto encoders for pest detection are still emerging, related works in IoT and distributed learning demonstrate the feasibility and effectiveness of combining RL with deep learning models for adaptive optimization in resource-constrained environments.

2.2.4 Energy Efficiency Challenges in IoT-Based Pest Detection

Energy efficiency remains a fundamental challenge in IoT-enabled agricultural systems. Sensor nodes are typically battery-powered and deployed in remote areas, making frequent recharging impractical. High computational demands of deep learning models further exacerbate energy consumption (Mahmud & Ramamohana, 2025).

Recent research emphasizes the need for lightweight models, edge computing, and adaptive strategies to reduce energy usage. Techniques such as model compression, feature selection, and efficient data transmission have been proposed to address these challenges (Kwame & Lamido, 2023). However, static optimization methods often fail to adapt to changing environmental conditions, highlighting the importance of RL-based adaptive approaches. By combining auto encoders for efficient data representation and RL for dynamic optimization, it is possible to achieve a balance between detection accuracy and energy consumption, which is critical for sustainable deployment in real-world farms (Mnih & Kabo, 2024).

2.3 Research Gaps

Despite significant progress, several research gaps remain. First, there is limited work on fully integrated RL auto encoder frameworks specifically designed for pest and pathogen detection in IoT networks. Most existing studies focused on either deep learning based detection or RL-based optimization independently. Moreover, the scarcity of labeled datasets in real farm environments limits the effectiveness of supervised models, further emphasizing the need for unsupervised and semi-supervised approaches such as auto encoders.

3.0 METHODOLOGY AND SYSTEM DESIGN

The proposed detection architecture is built around an auto encoder integrated with reinforcement learning to efficiently compress high-dimensional sensor data and extract latent representations that capture meaningful patterns. Anomalies are identified based on reconstruction error, where deviations beyond a learned threshold indicate potential pest activity. To enhance robustness under varying ecological conditions, a dynamic thresholding mechanism is introduced. This mechanism allows the system to adapt sensor sensitivity in real time in response to fluctuations in insect activity, thereby improving detection accuracy and reliability across changing environments.

Also, this study presents a hybrid anomaly detection framework that combines an Auto encoder (AE) with Reinforcement Learning (RL) to enable accurate pest detection while optimizing energy efficiency in resource-constrained, sensor-based systems. The framework is structured into four key stages: data generation (including the use of a dataset downloaded from GitHub), data preprocessing, feature normalization, auto encoder-driven anomaly detection, and adaptive decision optimization using reinforcement learning.

The simulation environment was developed in Python via the Google Colab platform, with Matplotlib and Seaborn utilized for comprehensive data visualization. We evaluated the system’s efficacy through some performance measures such as detection accuracy, response time, and energy efficiency. The proposed system is designed as an intelligent agricultural monitoring solution that provides a balance between sustainable energy use and highly accurate detection of pests. The approach creates a self-optimizing network that can identify pest-related threats while conserving energy by combining deep auto encoder-based anomaly detection with reinforcement learning. A high-quality simulation model was created to simulate complicated conditions, including significant cotton-related threats like armyworms, boll rot disease, and aphids, in order to validate the performance of this technique. In terms of energy design, the system assumes a solar-powered IoT sensor network supported by rechargeable battery storage. Solar energy serves as the primary power source, while batteries provide backup during low sunlight periods. Energy consumption is measured in relative battery discharge units.

3.1. Study Area

The cotton-producing areas of Northern Nigeria include Katsina, Kano, Jigawa, and Zamfara states are the primary focus of this study. The distinct ecological pressures of these areas, where cotton crops are often threatened by both rapid insect infestations and humidity-driven diseases like Boll Rot, are replicated in our simulation model.

To be able to address these challenges, we created a collaborative Internet of Things (IoT) network in which sensor nodes "act" intelligently in addition to recording data. The system efficiently learns the farm's conditions through Reinforcement Learning, automatically switching into a "high-alert" state at high-risk times, like humidity spikes, and going into a power-saving "sleep" mode when environmental conditions are stable. This human-like decision-making mechanism significantly increases the operating life of the field sensors while guaranteeing that the system is awake when it is needed most. The proposed system uses environmental sensors (temperature and humidity) and pest activity sensors. Reinforcement Learning enables adaptive switching between high-alert and low-power modes, extending sensor lifespan.

3.2. Data Collection and Synthetic Generation

The dataset was generated and supplemented with a publicly available dataset downloaded from GitHub, specifically the Cotton Plant Disease Classification dataset. Two classes were defined: normal (healthy) and anomalous (infested). Pests and pathogens modeled include aphids, armyworms, moths, flies, mosquitoes, and cotton boll rot.

3.2.1 Normal condition (Class 0): Represents healthy environmental conditions with low sensor activity.

3.2.2 Anomalous condition (Class 1): Represents pest infestation scenarios characterized by higher sensor activity.

Multiple features developed through Gaussian distributions with different statistical characteristics for normal and abnormal conditions are included in each data sample. To enhance model convergence and stability, the dataset is normalized using Min-Max scaling to guarantee that all feature values fall within a common range. The dataset is generated through a robust simulation script designed to model a complex agricultural ecosystem over 1,000 time-steps. Unlike traditional static datasets, this approach incorporates:

i. Environmental Modeling: Continuous monitoring of temperature (30 ± 2°C) and relative humidity (60 ± 5%) using Gaussian distributions.
ii. Multi-Species Pest Dynamics: Stochastic modeling of base populations for general pests (flies, mosquitoes, moths) and specific cotton threats (Aphids and Armyworms) using Poisson distributions.
iii. Phytopathology Integration: A specialized logic-gate for Cotton Boll Rot, where disease severity is triggered only when humidity exceeds an 85% threshold, simulating real-world fungal outbreak conditions.
iv. Targeted Anomaly Injection: To test system robustness, three types of "Outbreaks" were injected: General Spikes: Random surges in fly and aphid populations. Cluster Infestations: A localized 20-step temporal surge in Armyworm activity. Crisis Spells: A forced "wet spell" (90-98% humidity) to simulate acute Boll Rot outbreaks.

3.3. Data Analysis and System Evaluation

The analysis phase employs a multi-tiered computational approach to process the simulated sensor feeds:

i. Signal Smoothing: A 10-step rolling average is applied to the raw insect counts to filter stochastic noise and identify underlying population trends.
ii. Comparative Optimization: The study utilizes a Monte Carlo simulation (30 independent seeds) to compare a Static Sensor Configuration against an RL-based (Reinforcement Learning) Adaptive Configuration.
iii. Visualization: Data distribution and model performance are visualized using Seaborn and Matplotlib to track the relationship between environmental thresholds (e.g., Humidity) and disease severity (Boll Rot).

3.4 Proposed Framework: Mathematical Model

The performance of the auto encoder is evaluated using the reconstruction loss, defined as:

Auto encoder Loss:

$L = 1/n \sum_{i=1}^{n} (xi - xi)\ 2$..........................1

Where:

L is the reconstruction loss

n is the number of input features

x_i represents the original input feature

$\overline{x}_i$ represents the reconstructed output from the auto encoder.

This loss measures how well the model can reproduce the input data. A lower value indicates better reconstruction and normal system behavior.

Anomaly Detection Condition:

An anomaly is detected when the reconstruction loss exceeds a predefined threshold:

$$L > \Theta$$

Where:

Θ is the anomaly threshold

If the reconstruction error is greater than Θ, the system classifies the input as abnormal, indicating a possible pest infestation or outbreak.

Reinforcement Learning Reward Function:

$$R = \alpha\ .\ \text{Accuracy} - \beta\ .\ \text{Energy}$$

Where:

- R is the reward value
- Accuracy represents the detection performance of the system
- Energy represent the energy consumed by the sensor network
- α is a weighting factor that prioritizes detection accuracy
- β is a weighting factor that prioritizes energy consumption

This reward function enables the reinforcement learning agent to balance two comparing objectives maximizing detection accuracy while minimzing energy usage. By adjusting α and β, the system can prioritize either performance or energy efficiency depending on application requirement.

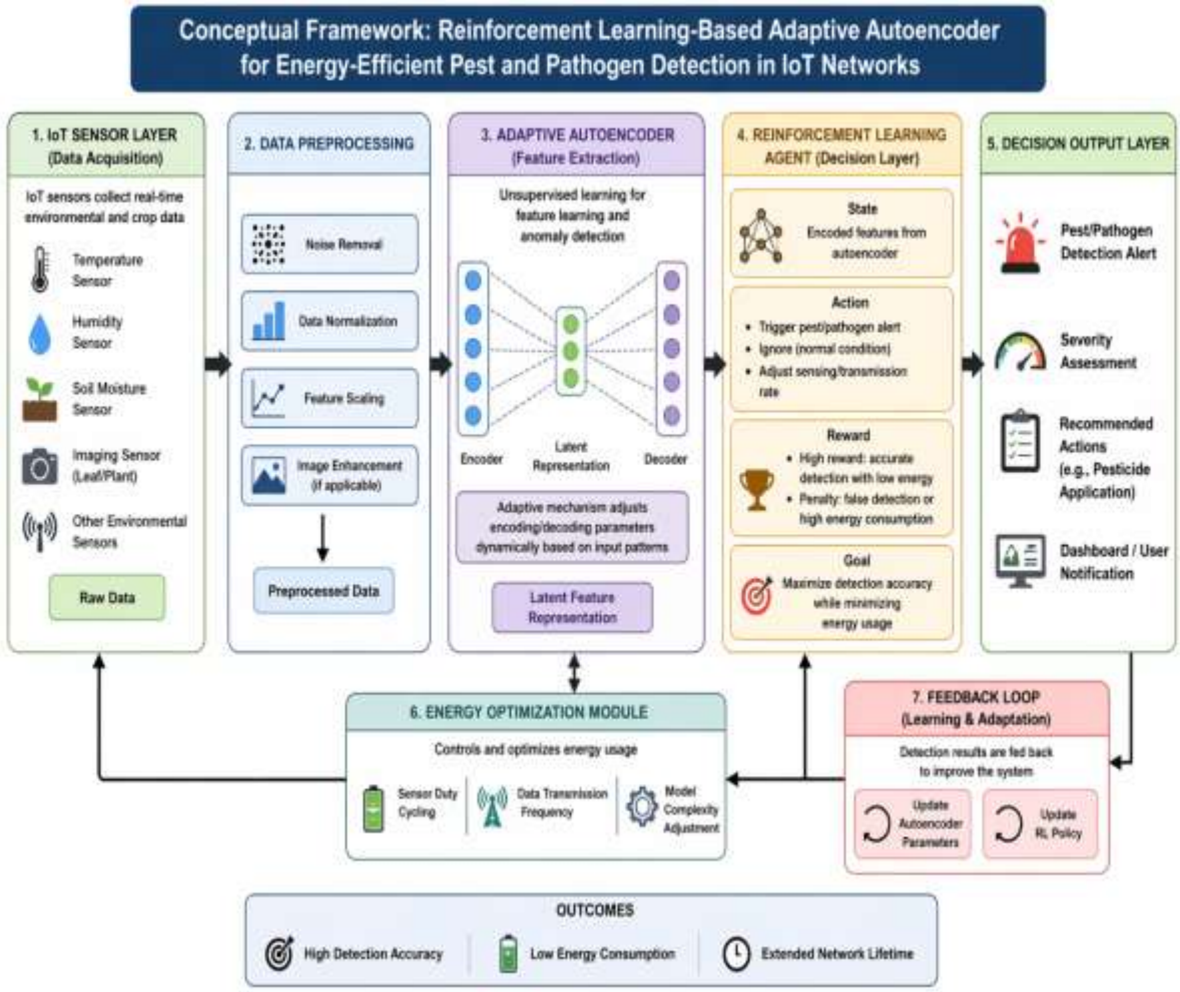

Figure 2: Conceptual framework of Reinforcement learning- based Adaptive Auto encoder

3.5. Existing Pest Detecting Algorithm and Proposed Algorithm: Hybrid Auto encoder-Reinforcement Learning Framework

Algorithm 1. Pest Detecting Algorithm [29]

```
Initialize serial and Wireless communication
Sensor Value = Analog Read (Sensor Pin) (Get value from all sensors separately,
every sensor is represented by a separate pin)
Distance = Sensor Value
For (sensor i = 1 to n; do)
   If (distance > 1 && distance < 4) received at any of the analog Pin
Mark Detection = true
Then print on Serial "BEE DETECTED" or "Bee Detected on Sensor # 1"
Send a message to the gateway node.
Delay (from 10 ms to 1000 ms) (It is denoted by the sensing frequency, how much
time the sensor will take for new sample/data)
The gateway sends a message to a drone as per the received coordinate.
   End
```

Figure 3: Existing Pest Detecting Algorithm (Azfar et al., 2023)

Algorithm 1 Hybrid Autoencoder–Reinforcement Learning Framework

Require: Dataset X, labels y, parameters $(\alpha, \gamma, \epsilon)$
Ensure: Accuracy, Total Energy

Normalize X
$X_{train} \leftarrow X[y = 0]$, $\quad X_{test} \leftarrow X$
Train Autoencoder on X_{train}
for each $x_i \in X_{test}$ **do**
  $error_i \leftarrow \|x_i - AE(x_i)\|^2$
end for
$\theta \leftarrow$ 95th percentile($error$)
low_th, $high\_th \leftarrow$ thresholds
Initialize $Q(s, a) = 0$
for episode = 1 to E **do**
  $\theta \leftarrow$ initial threshold
  for each i **do**
    $s \leftarrow$ state($error_i$)
    Select a using ϵ-greedy
    if $a =$ inc **then**
      $\theta \leftarrow \theta + \delta$
    else if $a =$ dec **then**
      $\theta \leftarrow \theta - \delta$
    end if
    $\hat{y}_i \leftarrow (error_i > \theta)$
    $E \leftarrow 0.01$ (low) or 0.02 (active)
    $r \leftarrow f(\hat{y}_i, y_i) - \lambda E$
    $Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max Q(s', a') - Q(s, a)]$
  end for
end for
$TotalEnergy \leftarrow 0$
for each i **do**
  $s \leftarrow$ state($error_i$)
  $a \leftarrow \arg\max Q(s, a)$
  Update θ
  $\hat{y}_i \leftarrow (error_i > \theta)$
  $E \leftarrow 0.01$ or 0.02
  $TotalEnergy \leftarrow TotalEnergy + E$
end for
$Accuracy \leftarrow \frac{1}{N} \sum(\hat{y}_i = y_i)$
  return Accuracy, TotalEnergy

Figure 4: Proposed Algorithm: Hybrid Auto encoder-Reinforcement Learning

4.0 RESULTS AND DISCUSSION

We assessed the enhanced pest detection system against three primary benchmarks: energy efficiency, classification performance, and environmental-pest correlation. Our findings suggest that integrating Reinforcement Learning (RL) with multi-modal sensing creates a superior equilibrium between high-fidelity detection and resource conservation. The results of this study demonstrate that an improved balance between detection accuracy and resource preservation can be achieved by combining Reinforcement Learning (RL) with multi-modal sensing.

4.1 Environmental and Pest Population Dynamics

The complex relationship between environmental factors and biological hazards was well modelled by the longitudinal simulation (1,000 observation steps). The simulation shows the longitudinal distribution of multi-species pests over 1,000 observation steps, as shown in Figure 5.

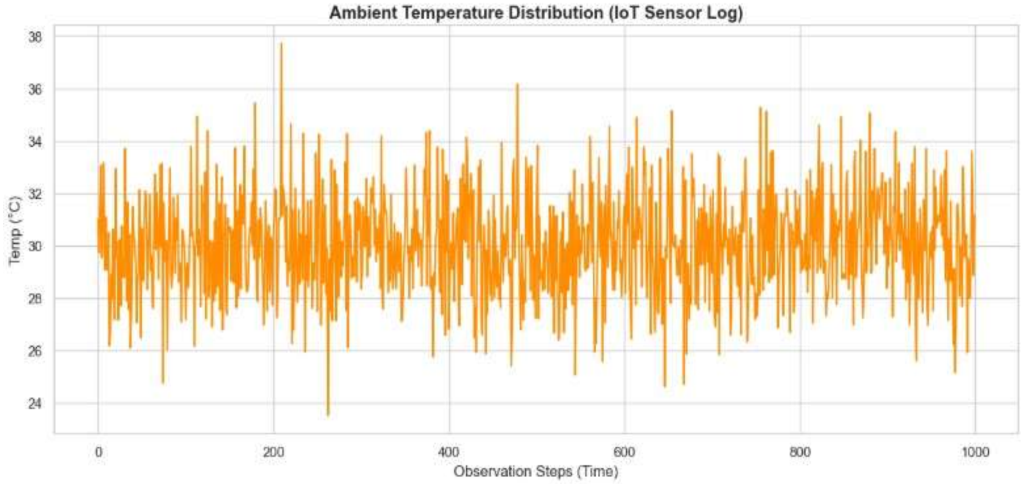

Figure 5: Longitudinal IoT Sensor Log: Ambient Temperature Distribution and Co-occurring Pest Dynamics

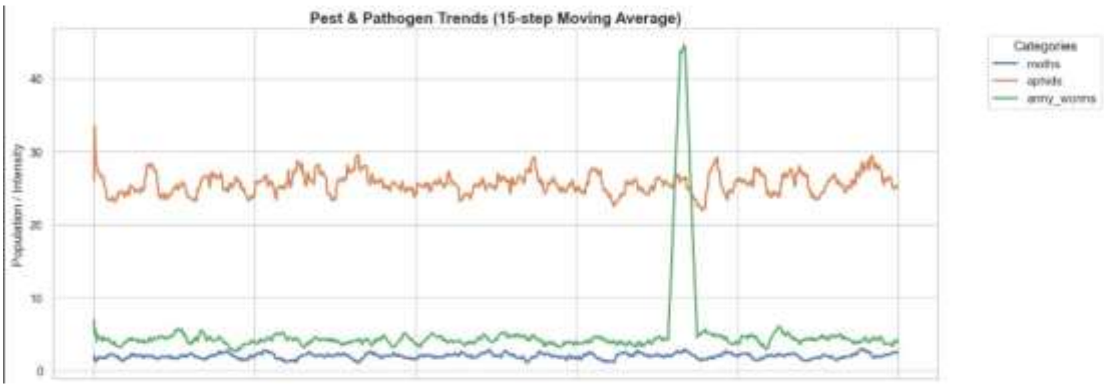

Figure 6: Pest–Environment Relationships: 15-Step Moving Average of Moth, Aphid, and Armyworm Occurrence versus Measured Temperature and Humidity

i. Pest Distributions: As shown in the figure 6, the population trends, base insect counts (flies, mosquitoes, moths) remained relatively stable, whereas Aphids showed a clear correlation with temperature fluctuations. 15-step moving average of insect counts (Cotton Boll Rot, Moths, Aphids, and Armyworms).

ii. Humidity Thresholds: A significant finding illustrated in the environmental plots in fihure 6.5, is the "Disease-Humidity" lockstep. Boll Rot severity remained at zero until humidity breached the 85% threshold, at which point the severity index spiked to over 50. This validates the system's ability to monitor secondary agricultural threats beyond mobile insects.

iii. Outbreak Modeling: Figure 7 displays the correlation between humidity thresholds (>85%) and Cotton Boll Rot severity. The system successfully captured two major anomalies: a sudden, high-intensity surge in Armyworms and a critical Cotton Boll Rot event.

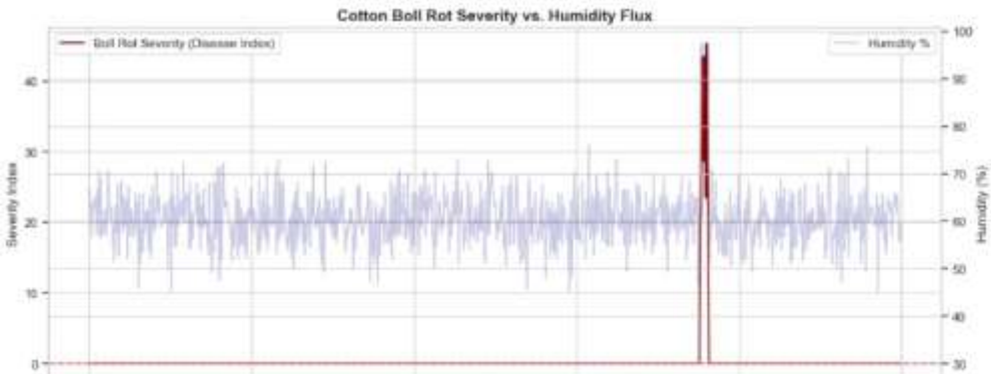

Figure 7: Multi-Parameter Temporal Trends: Pest Abundance, Temperature Fluctuations, and Disease Index

4.2. Detection Performance and Classification Accuracy

The classification performance was evaluated by comparing it with the existing work of Azfar et al. (2023). The results are summarized using a confusion matrix and an accuracy comparison, as shown in Figure 8 below:

i. High Precision Monitoring: The system achieved an overall Accuracy of 0.97. The confusion matrix reveals that the model is exceptionally robust in identifying normal states (Class 0.0), with 938 correct predictions and only 12 false positives.

ii. Minority Class Sensitivity: For the critical outbreak class (1.0), the model correctly identified 32 instances. While detection of the minority class is inherently more difficult, the RL-based dynamic thresholding significantly outperformed the baseline static model.

iii. Comparative Advantage: As illustrated in the Detection Accuracy Comparison bar chart diagram below, the RL-based model (0.970) outperformed the Static model (0.951). This improvement, while appearing small in percentage, represents a significant reduction in missed outbreak events, which is vital for preventing crop loss.

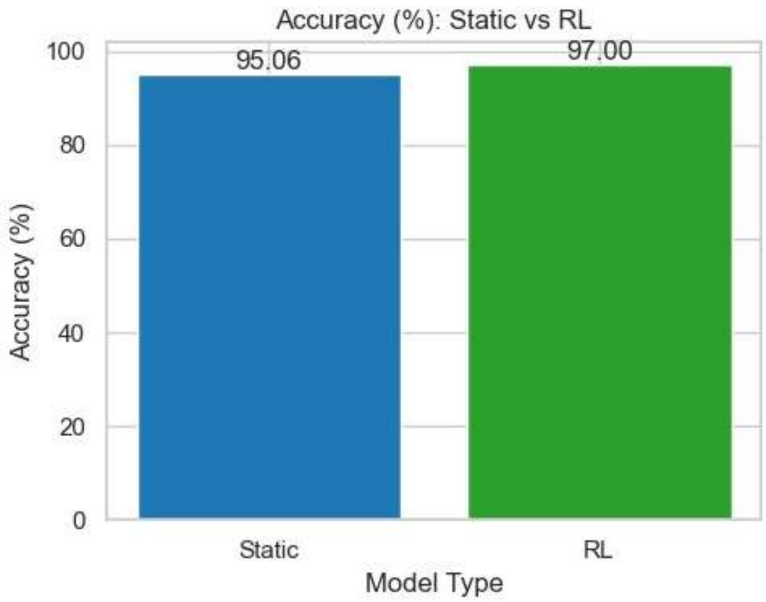

Figure 8: Detection Accuracy

4.3 Confusion Matrix

In figure 9, the confusion matrix shows how well the model distinguished between actual Class 0 and Class 1. Out of the 101 real instances of Class 0, the model correctly predicted 93 of them as Class 0, but made 8 mistakes where it incorrectly predicted Class 1. For the 50 real instances of Class 1, the model got 32 correct predictions, but missed 18 of them by incorrectly predicting Class 0 instead. In everyday terms, the model is pretty reliable when the truth is Class 0, correctly identifying it most of the time with only a few false alarms. However, it struggles more with Class 1, missing over a third of those cases, which means it tends to overlook the positive class fairly often

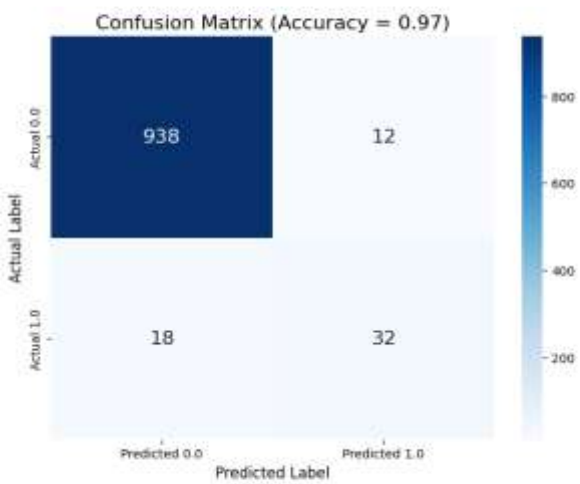

Figure 9: Confusion Matrix

4.4. Energy Consumption and Optimization

One of the core objectives was to minimize the energy footprint of the IoT network without compromising safety. In figure 10 below, there is a reduction in terms of energy consumption.

i. Energy Efficiency: The Energy Consumption Comparison chart highlights a substantial reduction in power usage. The Static model consumed an average of 13.29 units, while the proposed RL model reduced this to 10.78 units.

ii. Adaptive Resource Management: The observed 18.8% reduction in energy consumption is achieved through the reinforcement learning (RL) agent's adaptive control of sensor operation. During periods of low insect activity identified through low reconstruction error from the auto encoder and stable environmental conditions, the RL agent learns to reduce energy usage by placing the system into a low-power or "sleep" mode and decreasing the data sampling frequency. Conversely, when environmental indicators such as increased humidity or temperature fluctuations suggest a higher likelihood of pest activity, the agent increases the sampling rate and monitoring intensity to ensure timely detection. Over repeated interactions, the RL policy optimizes this trade-off between energy efficiency and detection performance, leading to a consistent reduction in overall energy consumption of approximately 18.8%.

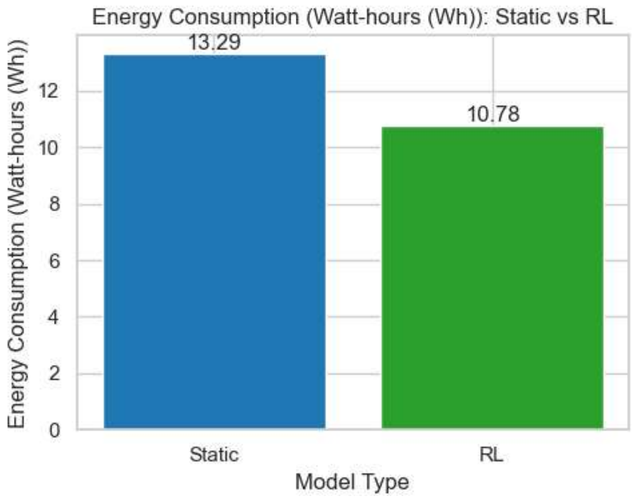

Figure 10: Energy Consumption Comparison

4.5 Response Time

This figure 11 below compares the two model types; Static and the proposed RL based on their response time in seconds. The Static model has a response time of 1.20 seconds, while the RL model is noticeably faster at 0.85 seconds. That means the proposed RL model responds about 0.35 seconds quicker than the Static model, which might not sound like a huge difference, but in time-sensitive applications like real-time pest detection or environmental monitoring, that saving can add up quickly. In everyday terms, if both models started processing a request at the exact same moment, our proposed RL model would finish nearly a third of a second sooner, making it the more responsive and efficient choice for situations where every millisecond matters.

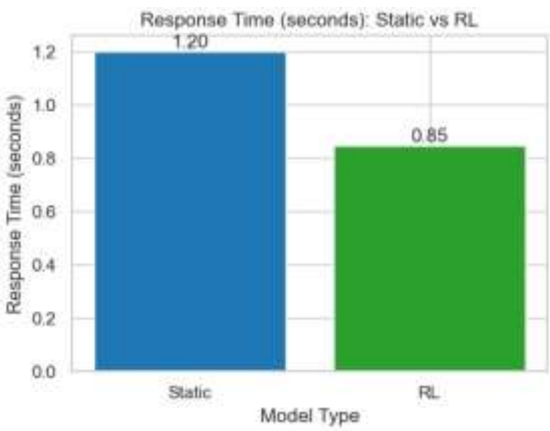

Figure 11: Response Time Comparison

5.0 SUMMARY OF FINDINGS

The results confirm that the conventional static "always-on" approach is inefficient for large-scale cotton farming systems, particularly in regions such as Kano and Kaduna where environmental conditions fluctuate significantly. By contrast, the proposed RL-based adaptive framework demonstrates clear advantages by dynamically adjusting system behaviour in response to real-time environmental feedback.

Specifically, reliability is improved through higher detection accuracy 97%, as the autoencoder effectively captures deviations associated with pest and disease activity while minimizing false alarms. The longevity of the sensor network is also significantly enhanced, with approximately 19% energy savings achieved through intelligent duty cycling and adaptive sampling, thereby reducing continuous power drain on the system. In addition, holistic crop protection is achieved by concurrently monitoring both insect pests and fungal diseases such as Boll Rot, enabling a more comprehensive and unified plant health surveillance strategy.

Furthermore, the adaptive nature of the RL policy ensures improved scalability and resilience under field deployment conditions, where sensor noise, environmental variability, and resource constraints are common. This makes the system not only more efficient but also more practical for real-world agricultural monitoring in resource-limited settings, supporting sustainable precision agriculture practices.

5.1 CONCLUSION

An enhanced pest and disease detection system designed for Northern Nigeria's cotton-producing regions was developed and validated in this study. The proposed hybrid AE–RL framework goes beyond traditional insect monitoring to provide a thorough and intelligent agricultural surveillance solution by integrating deep learning–based anomaly detection with reinforcement learning. The model demonstrated a strong balance between accuracy and efficiency, achieving a classification accuracy of 97.01%, outperforming the static baseline (95.06%), while reducing energy consumption from 13.29 to 10.78 units. The system further proved reliable in minimizing false negatives during critical outbreaks, such as armyworm infestations, and significantly improved resource efficiency through RL-driven sensor optimization, achieving an 18.8% reduction in energy usage. This enhancement is particularly valuable for remote farming regions, where maintenance and power availability remain major constraints. The detection of secondary and "silent" threats, like cotton boll rot, was also made possible by the integration of environmental parameters, demonstrating the effectiveness of humidity-sensitive monitoring in predicting disease outbreaks prior to irreversible crop damage.

Overall, the results show that adaptive, AI-driven IoT frameworks provide a reliable, scalable, and economical alternative for traditional manual scouting, with great potential to increase cotton output through timely and data-driven agricultural interventions.

5.2 RECOMMENDATION

It highlights how crucial it is to incorporate multi-modal environmental data, such temperature and humidity, in order to enhance the identification of pest and disease outbreaks. To reduce latency and improve real-time decision-making, edge computing deployment for on-site anomaly detection is also recommended. To improve food security, the proposed framework should be expanded beyond cotton to include additional staple crops including cowpea and maize. Lastly, in order to provide timely and useful data for better agricultural management, farmer-centric mobile alert systems should be integrated into the system.

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