**Towards Intelligent Pest Detection: IoT and Acoustic Sensing Powered by Reinforcement Learning in AgriTech**

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**Abstract.** Farming today is more complex , systematic, and science-based. Agriculture has made significant progress with the aid of the Internet of Things (IoT). Due to this expansion, agriculture has paved the way for various possibilities. However, pests are the number one threat to agriculture in terms of economic losses. Certainly, pests are the major factor in causing a halt to agricultural growth, yet it is not the only dimension. Heavy infestations of crops seriously interfere with their physiological processes, hindering them from growing up to their full potential. Despite this, farmers are highly concerned about these losses. A computerized pest detection method is necessary to examine the contamination and identify the type of insects that are infested. The study offers a technique for identifying pests that use network and audio analytics, deep reinforcement learning, and IoT connectivity. The Deep-Q Network (DQN) was used to train, validate, and test the models after 1700 insect audio sounds were used to compute the data and the LSF coefficients vector. The research findings highlight the potential of using AI to support field pest monitoring in terms of both immediate application and worldwide applicability. Monitoring might be done with very little assistance from humans. The proposed DQN model achieved 99.68% accuracy, 99.76% sensitivity, 99.62% specificity, 99.91% recall, 99.94% precision, and 99.89% F1 score, outperforming the conventional YOLOv5, EfficientNetB4, Faster CNN, SSD, and CNN approaches for pest identification.

# Introduction

Agriculture is affected by many factors, including pests. Pests substantially reduce the physiological function of affected crops, preventing optimal yield [1]. Thus, crop yields are low, lowering economic efficiency. As if that weren't enough, there are just so many species of agricultural plants that it becomes near impossible to identify pests by sight. Therefore, accurate and prompt identification of farming pests is of great importance to the productivity of agricultural land [2]. Crop management plant pests are efficiently and accurately evaluated for immediate and accurate decision-making, allowing for the spraying of pollutants in the affected area to optimize the application of these chemicals, which can increase the cost and affect production. There is a need for rapid and successful crop pest management practices, which product development companies can disrupt and challenge, affecting human health [3]. Pest identification is crucial for early warning of pest disasters and averting large-scale incursions. Pests are difficult to distinguish since each class of insects exhibits considerable differences, although species within the same class can have identical outbreaks [4]. Regional mobility and livelihoods depend on food supply, which is essential to national security [5]. Barn pests can cause mould and rot, which is exacerbated by repeated moisture and temperature fluctuations during storage or transport. These circumstances can also spread barn pests. This affects the stable's diet and technology, resulting in reduced barn yield. Barn pests also enhance barn losses. The solution is a key problem in barn storage [6]. Pest control, science and damage reduction will lead to effective control, which in turn will contribute to food safety. The innovative farming system utilizes computer vision to introduce more spontaneous, uniform, and precise agricultural technology. Innovative farm support systems are an essential part of the modern agriculture [7]. In this cost-effective market, various research methods are being employed, including crop monitoring, disease detection, animal monitoring, and pest monitoring, leveraging advancements in ML and DL. Pests and other insects can be efficiently detected from poor-quality images [8].

The objectives, specific goals, as well as the contributions of the study are:

* To incorporate reinforcement learning algorithms within the network, making decisions in real-time enables the system to improve its pest recognition ability through continuous observation continuously.
* To employ sound analysis technologies to differentiate acoustic pest-specific signals from surrounding noise
* To design a scalable and energy-efficient platform capable of being deployed across large farming areas without compromising performance and reliability.
* To deliver real-time alerts and advice for chemical-free insect monitoring and pest control.
* To evaluate system performance through experimentation and simulation over diverse farming scenarios, ensuring robustness and realistic applicability in real-world agricultural fields.

# Literature Review

Kalfas et al. described a successful computing crop chicory field insect with automation [9]. Two insect pests and their natural enemies were investigated in this study. Sticky-wafer image separation tests revealed the actual performance of the object identification model on all the datasets, with an average mAP of 0.76. Invasive species and natural enemies had 0.73 and 0.86 mAPs, respectively. Dewari et al. [10] proposed using the EfficientNetB4 deep convolutional neural network (CNN) architecture to detect and classify pests in real time, thereby minimizing damage. Outdoor pest control involves finding larger pests, but photo angles, bug placement, size, and background complexity can hinder this. The IP102 (102 species) dataset tests the model and conducts ablation studies on data processing, balance, and feature extraction. EfficientNetB4 classified this model with 95% accuracy. However, the proposed method appears to be a good approach for discriminating between field insect pests and plant treatment in agriculture. Lin et al. [11] demonstrated the latest pest and disease monitoring biosensing technology, including picture processing software, electronic noses, and wearable sensors. Concerns and solutions for the widespread use of these technologies are also highlighted. They believe combining technologies across fields for future study opens up unlimited possibilities for innovations and agricultural monitoring. Gupta et al. [12] recommended precision agriculture and automated pest detection to help farmers produce environmentally friendly food. The identification system requires a substantial amount of real-world data for accurate predictions. This study developed a castor pest database, but it was not sufficient to train a vision-based system. DCNN, ResNet50, VGG19, and VGG16 assess augmentation. A prediction shows the technique overcomes hurdles. Butera et al. [13] suggested smartphone bug recording to improve trap monitoring. Understudied insect recognition in nature photos is discussed. Pest insects are sometimes misinterpreted as harmless. Computer vision systems cannot detect anomalies in these insects since they are all the same. Identifying hazardous and harmless insects was stressed. The target recognition and computational capabilities of different models are compared. Inference accuracy and latency are better with Faster R-CNN than with MobileNetV3 models are feasible. This ensemble can be considered to perform better or at least on par with other authors' task-specific models (92.66% accuracy). Liu et al. [14] applied a self-monitoring features model to alleviate the influence of batch size on rice pest detection model training. The scene of the study was that most existing works focused on image pests [15-16], and very few studies have addressed sound pest analytics [17-18]. Advanced sound analytics can classify and identify pests. However, reliable analytic procedures can also prevent and control contaminates and identify pests early on. The major focus of this research includes the suppression of pest audio analysis in large-scale IoT-based farm planning.

# Materials and Methods

## Materials

### Dataset Description and Pre-processing

The archive of pest acoustics (USDA-ARS) used in the study is accessible from [19]. One thousand seven hundred sound samples from 34 pest species were analyzed following the protocol described in Table 1. Band Passes Filter to denoise pest sound audio data, Flat-Top window to minimize audio spectrum leakage, Kaiser window to convert overlapping to non-overlapping, FFT, DFT, and STFT for pest audio data characterization and analysis, and fusion with a built-in DL model and the LSF to extract pest audio sound signal features.

## System Model

### Reinforcement Learning Model

The DQN algorithm uses a neural network to estimate a Q-value function. To apply DQN for pest detection using sound pest analysis, the mapping of status and action pairings to a Q-value is accomplished through the exploitation of a Q-function, as opposed to a Q-table. Q function maps a state to the Q values for all possible actions. It self-teaches the system parameters (weights) to produce optimal Q values. DQN starts by estimating the Q-value randomly, then explores the vicinity of what it has already explored via an ε-greedy method. Moreover, it employs the same approach as the twin decisions, based on the sequential states’ Equations (1), (2) and (3). The model carried out the activation action using a reconstructed linear unit. The first tier of the convolutions consists of 8x8 by two cores, the additional layer comprises 64 4x4 by two cores, and the third layer consists of 64 3x3 cores, all of which are part of the initial stage. The output layer has one unit for every lawful activity after the fourth layer, which is fully connected and comprises 512 separate units. Figure 1 shows the process flow of the DQN Model.

**TABLE 1.** The analyzed pest collection

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **SN.** | **Pest Name** | **S.** | **SN.** | **Pest Name** | **S.** | **SN.** | **Pest Name** | **S.** |
| 1 | Rice Hispa | 50 | 13 | Rice weevils | 50 | 25 | Manduca | 50 |
| 2 | Athetis lepigone | 50 | 14 | Hadula trifolii | 50 | 26 | Spodoptera litura | 50 |
| 3 | Holotrichia parallela | 50 | 15 | Helicoverpa armigera | 50 | 27 | Spodoptera exigua | 50 |
| 4 | Mamestra brassicae | 50 | 16 | Anomala corpulenta | 50 | 28 | Plodia moth | 50 |
| 5 | Cock roach | 50 | 17 | Rodents | 50 | 29 | Agrotis ipsilon | 50 |
| 6 | Sesamia inferens | 50 | 18 | Prostephanus truncatus | 50 | 30 | Galleria mellonella | 50 |
| 7 | Noctuid moth | 50 | 19 | Planthoppers | 50 | 31 | White grubs | 50 |
| 8 | Empoasca | 50 | 20 | Colorado | 50 | 32 | Stink-bug | 50 |
| 9 | Agriotes subrittatus | 50 | 21 | Scapteriscus vicinus | 50 | 33 | Greyback grubs | 50 |
| 10 | Ostrinia furnacalis | 50 | 22 | Mole-cricket | 50 | 34 | Geotrupes egeriei | 50 |
| 11 | Lepidoptera | 50 | 23 | Grasshopper | 50 |  |  |  |
| 12 | Weevils | 50 | 24 | Mythimna separata | 50 |  |  |  |

A diagram of different layers

AI-generated content may be incorrect.

**Figure 1.**  The architecture of the DQN model

|  |  |
| --- | --- |
|  | (1) |
|  | (2) |
|  | (3) |

## Architecture of the integration of AI, IoT, and Sound Analytics

The PID sensor monitors any shifts in the amount of infrared radiation (heat) emitted by pests to determine whether they are unwelcome visitors. When the temperature of an object exceeds 0 degrees Celsius, it radiates heat for a distance of nine meters, which is the maximum that the PID sensor can detect. Figure 2 illustrates the architecture of the proposed system. After that, a pre-processed version of the insect's sound, which has already been saved in the database, is compared with these noises. The findings are compared with the previously processed and saved in the database. A hardware component that controls and operates, the microcontroller comprises memories, I/O components, and many procedures for control.

PID Sensor

Database

Large Agricultural Field

Microcontroller

Acoustic Sensor

Sound Pre-Processing Block

Pest Sound Analytics Algorithm

DQN System Model

**Figure 2.** Architecture of the integration of AI, IoT, and sound analytics

# Experimentation, Results, and Analysis

## Experimental Setup

The Intel Core i5-9300H processor operates at 2.40 gigahertz, an Nvidia GeForce GTX 970M graphics card with 2 gigabytes of memory, and a Windows 10 operating system. The GeForce GTX 1650 graphics cards were used in the experiments conducted. The implementation and construction of the network model are carried out with the assistance of Python 3.8.10 and PyTorch 1.9.0. Computer graphics processing capacity is enhanced with the utilization of CUDA version 10.2 for GPU acceleration.

## Performance Parameters

The parameters used for the performance evaluations of the proposed system are mentioned in Equations (4) to (11).

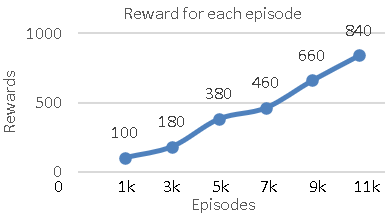
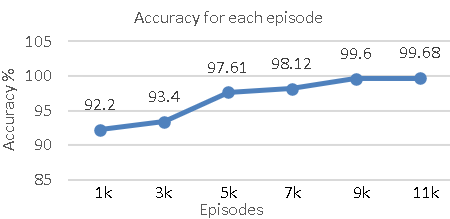
|  |  |
| --- | --- |
|  | (4) |
|  | (5) |
|  | (6) |
|  | (7) |
|  | (8) |
|  | (9) |
|  | (10) |
|  | (11) |

# Results and Analysis

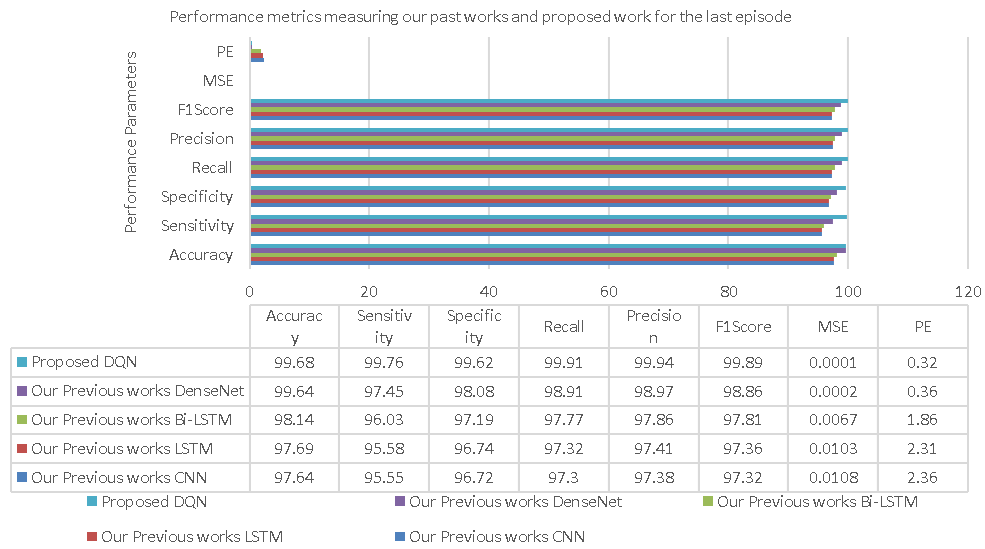
The data percentages used for testing, training, and validation are 70% (1190), 20% (340), and 10% (170), respectively. The total sample size is 1700. The reward, measurement accuracy, and performance parameters for 1000 to 11000 episodes are mentioned in Figures 3, 4, and 5, respectively. Table 2 shows the accuracy of training, validation, and testing.

**Table 2.** Accuracy of the training, validation, and testing

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Methods** | | **Accuracy (10%)** | | |
| **Training** | **Validation** | **Testing** |
| **Our Previous Works** | CNN | 97.64 | 96.98 | 97.56 |
| LSTM | 97.69 | 97.00 | 97.60 |
| Bi-LSTM | 98.14 | 97.90 | 98.08 |
| DenseNet | 99.64 | 99.51 | 99.56 |
| **Proposed** | **DQN** | **99.68** | **99.54** | **99.59** |

** **

**Figure 3.** Rewards for 1000-11000 episodes **Figure 4.** Accuracy for 1000-11000 episodes



**Figure 5.** Performance metrics measuring our past works and proposed work for the last episode

## Performance Comparisons

Findings from an examination of contrasts among the present recommended research and previous research endeavours, such as DAMI-YOLOv8l, GC-Faster RCNN, CAFPN, and M2DETR methods, are outlined in Figure 6.

**Figure 6.** Assessing the achieved work of the proposed work with previous researchers for pest detection

# Limitations AND FUTURE SCOPES

The project has developed an AI- and IoT-mediated intelligent automatic pest detection system, which utilizes less pesticide and detects pests using an embedded system and audio analysis. Nonetheless, the proposed technique has one limitation: it used only 34 types of pests and had only 99.68% detection accuracy. The proposed system is recommended to achieve 100% detection accuracy with at least 150 pests within a short period.

# Conclusion

This paper presents a novel plant pest detection system based on IoT-supported sound analytics and reinforcement learning networks, addressing large-scale challenges in farmed pest control. The proposed approach enables us to survey insect activity in real time using acoustic monitoring data and intelligence analysis, thereby minimizing crop loss through timely actions. Reinforcement learning for system agnosticism, as performance and efficiency grow over time with little human intervention in the loop. This process results in more efficient pest control and sustainable agriculture by reacting before decisions are made and eliminating chemical overuse. To enable precision agriculture, further work will extend the system to different environments, combine multi-modal data sources, and optimize the energy consumption of sparsely deployed IoT devices.

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