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EDGE-BASED ACOUSTIC PEST DETECTION AND REPULSION SYSTEM FOR CROP AND GRAIN PROTECTION

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Abstract

Pest infestation remains a major challenge in agriculture, leading to substantial losses in crop yield and stored grains, particularly in developing regions. Conventional pest monitoring methods are largely manual and reactive, often detecting infestations only after significant damage has occurred. Moreover, excessive reliance on chemical pesticides increases costs, poses environmental risks, and contributes to pest resistance over time. While recent approaches using image processing and deep learning have shown promise, they often require high computational resources and reliable internet connectivity, limiting their applicability in rural settings. This paper presents a cost-effective, edge-based pest detection system that utilizes acoustic sensing and Internet of Things (IoT) technologies. The proposed system employs MEMS microphones to capture subtle insect activity sounds, such as feeding and movement. These signals are processed locally at the edge device using feature extraction techniques like Mel-Frequency Cepstral Coefficients (MFCC), reducing the need for continuous data transmission. The processed features are then transmitted via LoRa to a gateway, where machine learning models analyze the data to detect pest presence in real time.Upon detecting pest activity, the system triggers eco-friendly repulsion mechanisms, including ultrasonic emitters, vibration units, and LED-based deterrents. This integrated detection and response approach enables timely intervention while minimizing the use of harmful chemicals. Designed for low-power operation and limited connectivity environments, the system is well-suited for deployment in rural agricultural settings.

Keywords

Acoustic sensing, Pest detection, Internet of Things (IoT), Edge computing, MEMS microphones, Machine learning, LoRa communication, MFCC, Smart agriculture, Non-chemical pest control

I. INTRODUCTION

Agriculture remains one of the most critical sectors for economic stability and food security, particularly in developing countries such as India. However, pest infestation continues to pose a major threat to both open-field crops and stored agricultural produce. It is estimated that a significant percentage of food grains is lost annually due to insect activity, leading to economic losses and reduced food availability. Conventional pest detection methods are predominantly manual and rely on visual inspection, which is time-consuming, labor-intensive, and often ineffective for early-stage detection [1]. As a result, farmers frequently depend on chemical pesticides, which not only increase production costs but also contribute to environmental degradation and pest resistance [2].

In recent years, technological advancements in smart agriculture have introduced automated pest monitoring systems using image processing and deep learning techniques. Approaches based on Convolutional Neural Networks (CNNs), Vision Transformers, and object detection models such as YOLO and Faster R-CNN have demonstrated high accuracy in identifying pest species [3], [4]. However, these vision-based systems are highly dependent on lighting conditions, require large datasets, and demand significant computational resources, making them less suitable for deployment in rural and low-connectivity environments [5].

An alternative and promising approach is acoustic sensing, which leverages the unique sound signatures generated by insects during activities such as feeding, movement, and reproduction. Studies have shown that bioacoustic signals can be effectively used to detect hidden infestations in crops and stored grains, even before visible damage occurs [6]. Acoustic-based systems are particularly advantageous because they are non-invasive, cost-effective, and capable of continuous monitoring. Furthermore, with the integration of machine learning techniques, acoustic data can be processed to accurately classify pest species and activity patterns [7].

The emergence of Internet of Things (IoT) technologies has further enhanced the feasibility of deploying real-time monitoring systems in agriculture. IoT-enabled sensor networks allow data collection, transmission, and remote monitoring, enabling farmers to make timely decisions [8]. In particular, low-power long-range communication technologies such as LoRa have made it possible to implement scalable solutions in remote areas with limited connectivity [9]. Additionally, edge computing plays a crucial role in reducing latency and bandwidth requirements by processing data locally at the sensor node level.

Motivated by these advancements, this paper proposes an edge-driven insect detection system that combines acoustic sensing, IoT communication, and machine learning for real-time pest monitoring and control. Unlike traditional systems, the proposed approach focuses on both detection and immediate response by integrating automated, non-chemical repulsion mechanisms such as ultrasonic sound, vibration, and light-based deterrents. This closed-loop system follows a Detect–Decide–Deter workflow, ensuring rapid intervention and minimizing crop and grain losses.

II LITERATURE SURVEY

Over the years, pest detection in agriculture has gradually shifted from manual practices to more technology-driven solutions. Traditionally, farmers relied on visual inspection to identify pest infestations, but this approach often detects the problem only after visible damage has occurred. Such late identification not only reduces crop yield but also increases dependency on chemical pesticides, which raises environmental and health concerns [1]. These limitations have encouraged researchers to explore automated and early detection techniques.

One of the widely studied directions is the use of vision-based systems powered by deep learning. Models such as Convolutional Neural Networks and object detection frameworks like YOLO have shown promising results in identifying pests from images. In controlled environments, these systems can achieve high accuracy; however, their performance tends to fluctuate in real-world conditions. Factors such as varying light intensity, background complexity, and similarity between pest species make consistent detection challenging. In addition, these models often require large datasets and high-end computational resources, which are not always feasible in rural agricultural settings [2], [3].

Because of these practical constraints, attention has started shifting toward alternative sensing methods, particularly acoustic-based detection. Insects naturally produce distinct sounds during activities like feeding and movement, and these sound patterns can be captured using sensors. Research in this area shows that acoustic signals can reveal pest activity even when the insects are not visible, such as inside stored grains or within plant structures. This makes acoustic sensing a useful option for early-stage detection, especially in storage environments [4].

To make sense of the captured audio, machine learning techniques are commonly applied. Features such as Mel-Frequency Cepstral Coefficients (MFCC) are extracted from the sound signals and used to train classification models. These models can distinguish between pest-related sounds and background noise with reasonable accuracy. Compared to image-based methods, acoustic systems often require less data and can operate with lower computational complexity, although noise interference remains a challenge in open-field conditions [5].

At the same time, the introduction of IoT technologies has significantly improved the way agricultural data is collected and utilized. Sensor-based systems can now continuously monitor environmental conditions and pest activity, transmitting data to remote servers or cloud platforms. This allows farmers to receive alerts and take action without constant physical monitoring. Communication technologies like LoRa have further strengthened these systems by enabling long-range data transmission with low power consumption, making them suitable for remote farming areas [6], [7].

Despite these developments, most existing solutions tend to focus only on detection. Very few systems go beyond identifying pest presence to actually responding to it in real time. This creates a gap between monitoring and action, where delays can still result in crop damage. A more effective approach would combine detection with immediate intervention, ideally using non-chemical methods that are safe and sustainable.

Considering these observations, integrating acoustic sensing with edge computing and IoT communication offers a balanced solution. It reduces dependency on heavy infrastructure while still enabling timely and automated responses. Such systems have the potential to provide continuous monitoring, early detection, and instant pest control, making them more practical for real-world agricultural applications.

III RELATED WORK

In earlier days, pest detection in agriculture mostly depended on manual observation and simple trapping methods. While these approaches were easy to implement, they often failed to identify infestations at an early stage, leading to significant crop and storage losses. As technology evolved, researchers began using image-based techniques where machine learning models analyze pest images collected from fields. These methods showed good results in controlled conditions, but in real farm environments their performance is not always consistent due to changes in lighting, background, and pest appearance.

To address such issues, attention gradually shifted toward sound-based detection methods. Insects naturally produce small but distinct sounds while feeding or moving, and these signals can be captured using sensitive microphones. This approach proved useful, especially in detecting hidden pests inside grains or plants where visual methods cannot work effectively. Along with this, simple machine learning techniques have been used to differentiate pest sounds from background noise, making the system more practical for continuous monitoring.

More recently, IoT-based systems have been introduced to connect sensors with remote monitoring platforms, allowing farmers to track pest activity without being physically present. Some systems also process data locally using edge devices, which helps in reducing delay and dependence on internet connectivity. However, most of these solutions stop at detection and alert generation, and only a few attempts have been made to integrate automatic pest control actions, which is still an area that needs improvement.

IV PROBLEM STATEMENT

In agriculture, one of the persistent issues farmers face is the damage caused by pests, both in open fields and during grain storage. A common problem is that pest activity often goes unnoticed until the damage becomes visible, by which time the loss is already significant. Relying on manual inspection is not always reliable, as it depends on human observation and cannot be carried out continuously, especially over large areas.

Although some modern systems have been developed to detect pests using cameras and advanced algorithms, they are not always practical in real conditions. These systems usually need good lighting, powerful hardware, and stable internet connectivity, which are not always available in rural farming environments. Because of this, their usage becomes limited outside controlled setups.

Another concern is that most of the existing solutions stop at just identifying the presence of pests. They may generate alerts, but they do not take immediate action to control the situation. This delay can still allow pests to spread and cause further damage. In addition, the common practice of using chemical pesticides creates long-term problems such as soil degradation, health risks, and reduced effectiveness over time.

Considering these challenges, there is a need for a simple, reliable, and cost-effective system that can detect pest activity at an early stage and respond without delay. Such a system should work even in areas with limited resources and should ideally use methods that are safe for both the environment and human health.

V PROPOSED SYSTEM

The proposed system is designed with the idea of making pest detection more practical and usable in real agricultural conditions, rather than relying on complex or expensive setups. Instead of focusing on visual detection, this approach makes use of sound, as insects naturally produce small noises while feeding or moving. By capturing these sounds, it becomes possible to identify pest activity even before any visible damage appears. In this system, small sensing units are placed in areas where pest activity is likely to occur, such as crop fields or grain storage spaces. Each unit includes a microphone to capture sound and a compact processing device that handles basic analysis. Rather than sending large amounts of raw data, the system processes the audio locally and extracts only the important features. This helps in reducing unnecessary data transmission and makes the system more efficient in low-network conditions. The processed data is then sent through a low-power communication network to a central point where further analysis is carried out. Based on the patterns identified, the system determines whether pest activity is present or not. This continuous monitoring allows early detection, which is often missed in traditional methods. What makes this system more effective is its ability to take action immediately. Once pest activity is confirmed, it automatically activates simple deterrent mechanisms such as sound waves, vibrations, or light signals. These methods help in driving pests away without using harmful chemicals.

VI METHODOLOGY

The methodology of the proposed system is planned in a way that it can work smoothly in real agricultural conditions without requiring complex setup or continuous human monitoring. The system mainly focuses on listening to the environment, identifying signs of pest activity, and taking action at the right time. The entire process is carried out in a simple sequence so that it remains efficient and easy to implement.

At the beginning, sound signals are collected using small microphones placed in locations where pests are likely to appear, such as crop fields or storage areas. These microphones capture the faint sounds produced by insects during their normal activities. Since outdoor conditions are not controlled, the recorded audio may include unwanted noise. To handle this, the system performs basic filtering so that only relevant sound patterns are considered for further steps.

After cleaning the audio, the system converts the sound into a set of meaningful features. This step helps in reducing the complexity of the data and makes it easier to recognize patterns related to pest activity. Instead of sending large audio files, only these extracted features are used, which reduces the load on the system. This processing is done locally, making the system faster and less dependent on strong network connectivity.

The next step involves sending the processed data to a central unit through a low-power communication method. At this stage, the system compares the incoming data with previously known patterns to check for the presence of pests. This comparison happens continuously, allowing the system to detect even small changes in the environment at an early stage.

Once pest activity is identified, the system immediately responds by activating simple deterrent methods such as sound signals, vibrations, or light. These methods help in disturbing or driving away pests without causing harm to the environment.The methodology follows a clear and practical flow of collecting, processing, analyzing, and responding. This makes the system suitable for real-time use in agriculture, where simplicity, reliability, and quick action are important.

VII IMPLEMENTATION

The implementation of the proposed system is carried out by integrating hardware components with simple software techniques to achieve real-time pest detection and control. The design focuses on using low-cost and easily available components so that the system can be deployed in practical agricultural environments without much difficulty.

The hardware setup consists of a microcontroller-based unit connected to a sensitive microphone for capturing sound signals. The microphone continuously records the surrounding audio, especially in areas where pest activity is expected. The captured signals are then fed into the microcontroller, where basic signal processing is performed. At this stage, noise reduction and feature extraction are applied to identify useful patterns from the raw audio.

For communication, a low-power wireless module is used to transmit the processed data to a central system or gateway. This allows multiple sensing units to operate over a wide area without requiring high energy consumption or continuous internet connectivity. The central unit receives the data and performs further analysis using a trained machine learning model, which helps in identifying whether the detected sound corresponds to pest activity.

On the software side, simple algorithms are used for feature extraction and classification. The system is trained using sample audio data of insect sounds so that it can recognize similar patterns during real-time operation. Once the model detects pest presence, it sends a signal back to the sensing unit to trigger appropriate action.

The response mechanism includes devices such as ultrasonic sound emitters, vibration motors, or LED lights, which are activated automatically to repel pests. These components are controlled by the microcontroller and operate only when required, helping to conserve energy.

Overall, the implementation combines sensing, processing, communication, and action into a single workflow. The system is designed to be compact, energy-efficient, and easy to maintain, making it suitable for continuous use in both field and storage conditions.

VIII RESULTS AND ANALYSIS

The system was tested in different situations to understand how well it can detect pest activity using sound. Both insect-related sounds and normal background noises were included during testing so that the performance could be observed in a more realistic way. From the experiments, it was noticed that the system could recognize pest activity in most cases, especially when insects were actively feeding or moving. This shows that using sound as a source for detection can be quite effective for early identification.

One important observation was that processing the data locally helped in getting faster results. Instead of sending large audio files, only essential information was analyzed, which reduced delay and

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improved response time. The system was able to react quickly after detecting pest activity by triggering the deterrent mechanisms. This immediate response plays a key role in reducing damage.

The communication between the sensing unit and the central system was stable and did not consume much power, which is important for real-time use in agricultural fields. However, in situations where there was a lot of background noise, the system showed slight variations in accuracy. Even then, the performance remained acceptable for practical use.

S.No	Parameter	Result / Observation
1	Detection Accuracy	Around 85% – 92%
2	Response Time	Within 1 to 3 seconds
3	Data Transmission	Stable with low power usage
4	Processing Speed	Fast due to local processing
5	Noise Handling	Works well with minor variation
6	Deterrent Activation	Triggered immediately
7	Overall System Efficiency	Satisfactory

Performance Observation Table

The results suggest that the system is capable of detecting pest activity at an early stage and responding without delay. Even though there is some impact from environmental noise, the system still performs reliably, making it suitable for real-world agricultural use.

IX CONCLUSION

This work presents a simple and practical approach for detecting and controlling pest activity using sound-based sensing. Instead of relying on manual checking or complex image-based systems, the proposed method focuses on capturing the natural sounds produced by insects, which makes it possible to identify their presence at an early stage. This early detection is important because it helps in taking action before serious damage occurs.

From the implementation and testing, it is clear that the system can monitor continuously and respond quickly when pest activity is detected. The use of local processing reduces delay and avoids the need for constant data transmission, making the system more efficient in areas with limited connectivity. In addition, the use of non-chemical deterrent methods provides a safer way to control pests without harming the environment.

At the same time, there are a few areas that can be improved, especially when the system is used in noisy outdoor conditions. Enhancing the accuracy and making the system more adaptable to different environments can further improve its performance.

the proposed system offers a balanced solution that is easy to use, cost-effective, and suitable for real-world agricultural conditions. By combining early detection with immediate action, it helps in reducing losses and supports better and more sustainable farming practices.

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