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**RESEARCH PAPER**

# IoT- and Machine Learning-Enabled Early Detection of Rice Stem Borers Using Acoustic and Vibration Sensors

Mansingh Murmu*, Sankar Narayan Patra and Samir Kumar Ghosh

Department of Instrumentation and Electronics Engineering, Jadavpur University, Kolkata, West Bengal, India

*Corresponding author: mansingh2052@gmail.com (**ORCID ID:** 0000-0002-1525-9563)

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## ABSTRACT

Rice stem borers are among the most destructive pests of rice, causing significant yield losses due to concealed larval feeding within plant stems. Early detection of infestation is difficult using conventional monitoring techniques such as visual scouting or pheromone traps, which often identify the problem only after considerable damage has occurred. This study presents a conceptual framework for an Internet of Things (IoT) and machine learning (ML) enabled system for early and non-invasive detection of rice stem borer activity. The proposed system integrates acoustic and vibration sensors with low-power IoT hardware, wireless communication modules, cloud-based analytics and ML-driven classification models. Micro-acoustic and vibrational signals generated during larval feeding are captured in real time and processed using signal-processing techniques such as filtering, spectral analysis and feature extraction. These processed signals are subsequently analyzed using machine learning models to detect infestation patterns and generate early warning alerts. The architecture includes field sensor nodes installed near rice stems, an IoT gateway for data aggregation and transmission, cloud-based processing units and a farmer-oriented mobile interface. This integrated approach enables continuous monitoring of pest activity under field conditions. The system also supports precision pest management by enabling timely intervention and reducing unnecessary pesticide application. The proposed framework highlights the potential of combining modern sensing technologies with intelligent analytics to improve agricultural sustainability and crop protection. The study also discusses challenges related to field deployment, environmental noise, data availability and system scalability. Overall, the integration of acoustic sensing, IoT communication and machine learning offers a promising pathway for developing smart pest surveillance systems in rice production ecosystems.

## HIGHLIGHTS

- IoT-based acoustic sensing enables early detection of rice stem borers.
- Larval feeding vibrations are captured using acoustic and MEMS sensors.
- Signal processing extracts pest signatures from noisy field data.
- Machine learning models classify infestation from acoustic patterns.
- System supports precision pest management and reduces pesticide misuse.

**Keywords:** Rice stem borer, Internet of Things, Acoustic sensing, Vibration sensor, Machine learning, precision agriculture

Rice (*Oryza sativa* L.) is a staple crop feeding more than half of the global population and plays a vital role in food security, particularly across Asia and Africa. Despite significant progress in crop breeding, irrigation management and agronomic practices, rice productivity continues to be constrained by

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a range of biotic stresses, especially insect pests. Among these pests, rice stem borers are considered one of the most damaging insect groups affecting rice cultivation. Major species include the yellow stem borer (*Scirpophaga incertulas*), striped stem borer (*Chilo suppressalis*) and pink stem borer (*Sesamia inferens*). These insects attack rice plants internally and disrupt nutrient transport within the stem, ultimately causing severe yield losses. The larval stage of stem borers is particularly destructive because larvae bore into the rice stem and feed on vascular tissues. This feeding behavior causes symptoms such as "dead hearts" during the vegetative stage and "white ear heads" during the reproductive stage. Because these symptoms appear only after substantial internal damage has occurred, farmers often detect infestations too late to prevent yield loss. Conventional monitoring methods such as visual inspection, pheromone traps and light traps provide only indirect information about pest activity and are often insufficient for early detection.

In recent years, the development of digital agriculture technologies has opened new opportunities for automated pest monitoring. Internet of Things (IoT) technologies enable continuous sensing, real-time data transmission and automated analytics in agricultural fields. Sensor-based monitoring systems can collect environmental and biological signals and transmit them to cloud platforms for analysis. When combined with machine learning algorithms, these systems can identify complex patterns within sensor data and provide predictive insights for crop protection. Acoustic and vibration sensing techniques have recently attracted attention for detecting insects hidden inside plant tissues. Feeding and movement of insect larvae generate micro-vibrations and acoustic emissions that propagate through plant structures. These signals can be captured by sensitive sensors such as piezoelectric transducers and MEMS accelerometers. By analyzing these signals, it is possible to detect pest activity before visible symptoms appear. Integrating such sensing technologies with IoT communication systems and machine learning models offers a promising solution for early pest detection and precision pest management.

## MATERIALS AND METHODS

### System Architecture

The Fig. 1(a) illustrates the end-to-end workflow of the proposed framework, showing field-deployed acoustic and vibration sensor nodes mounted on rice plants, environmental sensors, and the IoT gateway.

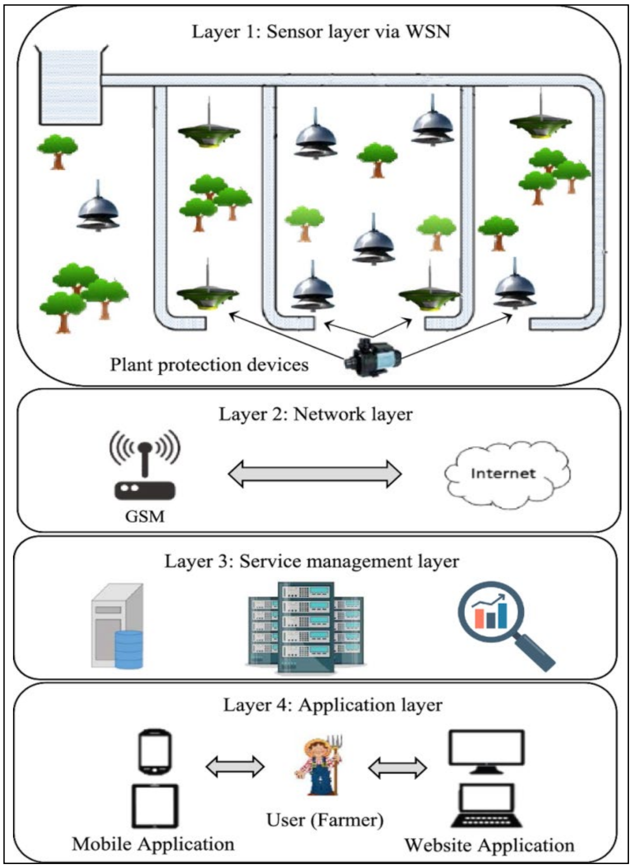


**Fig. 1(a):** Overall system architecture of the IoT- and machine learning–enabled rice stem borer detection system

Sensor data are transmitted through low-power wireless communication to the cloud platform, where signal processing and machine learning–based classification are performed. The processed information is delivered to farmers through a mobile application interface, enabling real-time alerts and decision support for early stem borer management. The diagram (Fig. 1b) depicts the internal components of the sensor node, including acoustic and vibration sensors, signal conditioning circuits, microcontroller unit, power supply module, and wireless communication interface. It also shows the data processing flow from raw signal acquisition and preprocessing to feature extraction and transmission to the IoT gateway for further cloud-based analysis.

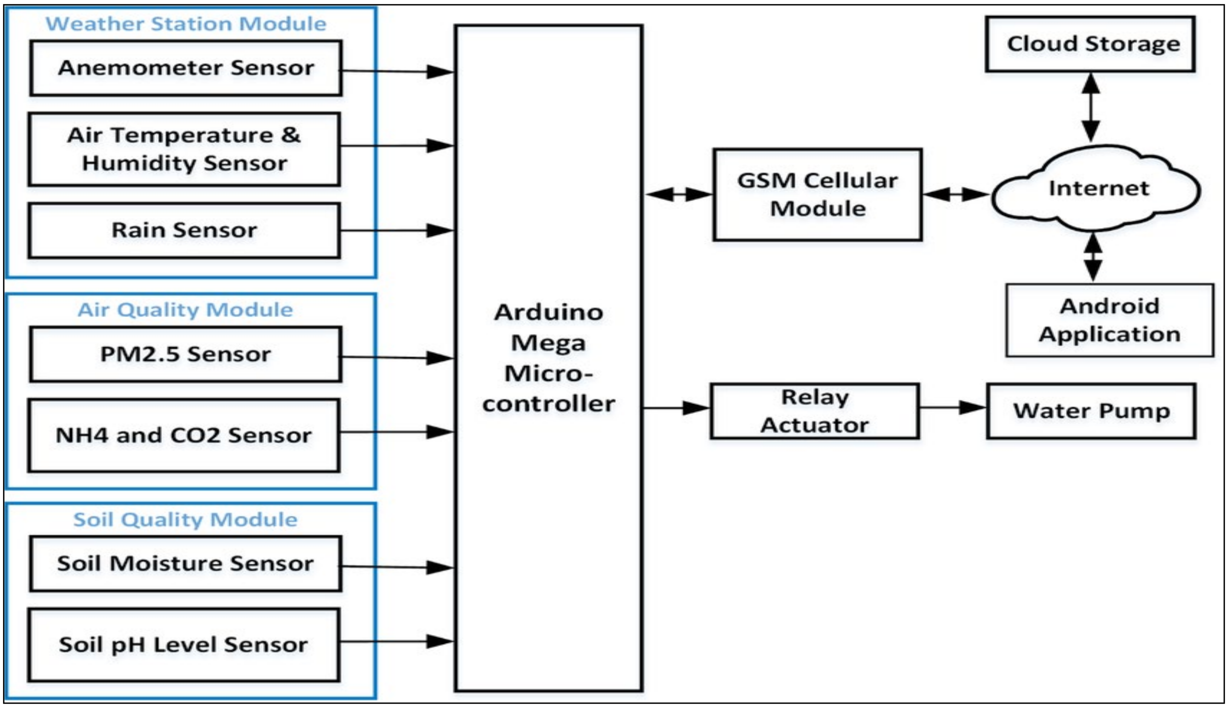


**Fig. 1(b):** Block diagram of the field sensor node and data processing pipeline

The overall system consists of (i) field sensor nodes, (ii) an IoT gateway, (iii) cloud-based analytics, and (iv) a farmer-facing mobile interface. Sensor nodes continuously acquire acoustic and vibration signals from rice plants. Data are transmitted via low-power wireless communication to a gateway, which forwards preprocessed data to the cloud for ML-based analysis and alert generation.

## 1. Field Sensor Unit

Each field node integrates a MEMS vibration sensor and a piezoelectric acoustic sensor mounted near the rice stem base. These sensors capture micro-vibrations and sound signals generated during larval chewing and tunneling. Environmental sensors for temperature and humidity are included to support data fusion and contextual analysis.

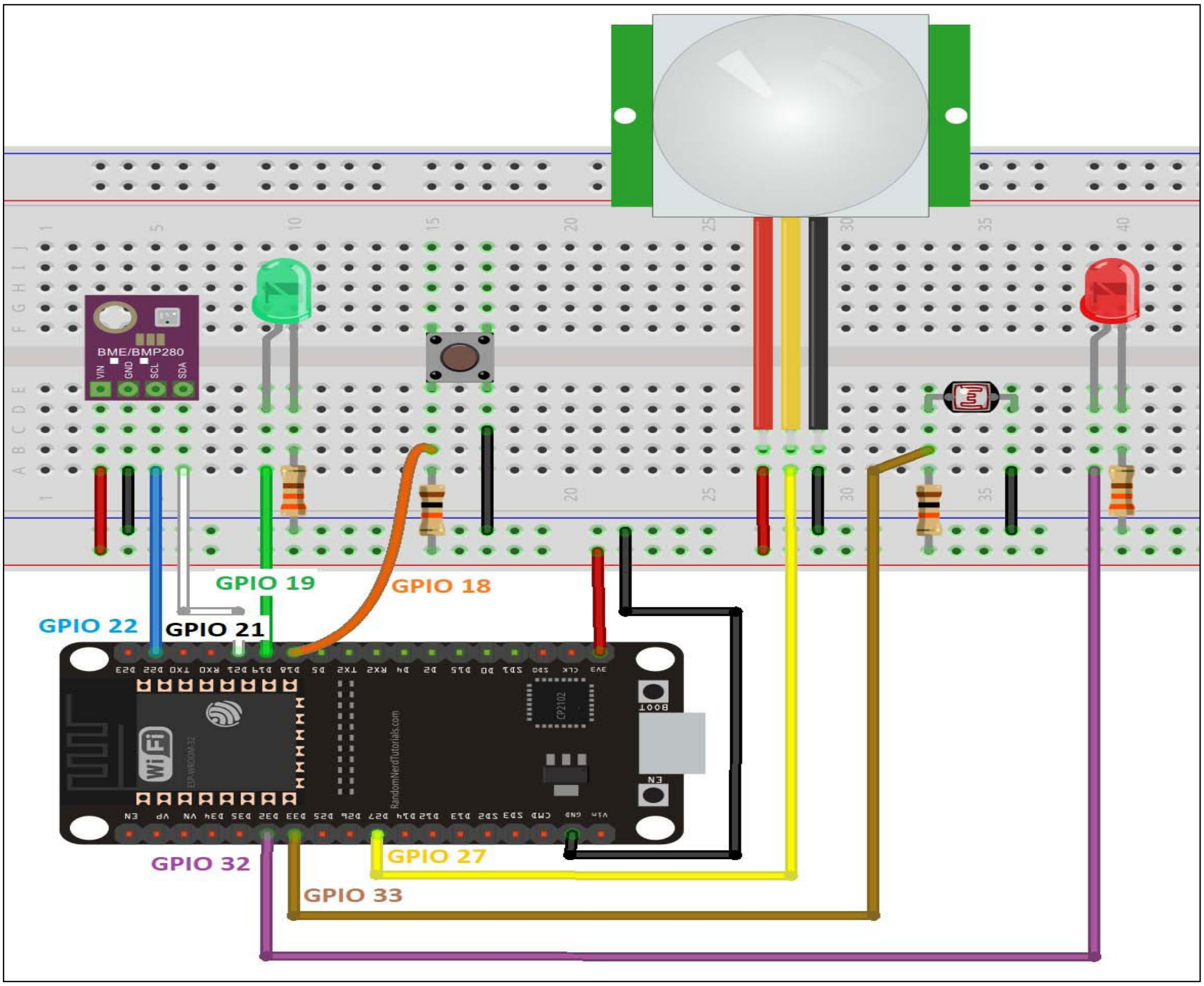
## Hardware and Circuit Design

The schematic (Fig. 2a) shows the integration of the microcontroller unit with acoustic (piezoelectric) and MEMS vibration sensors, including signal conditioning components such as amplifiers and band-pass filters. The circuit also incorporates the power management unit, enabling low-power operation and reliable data acquisition under field conditions.

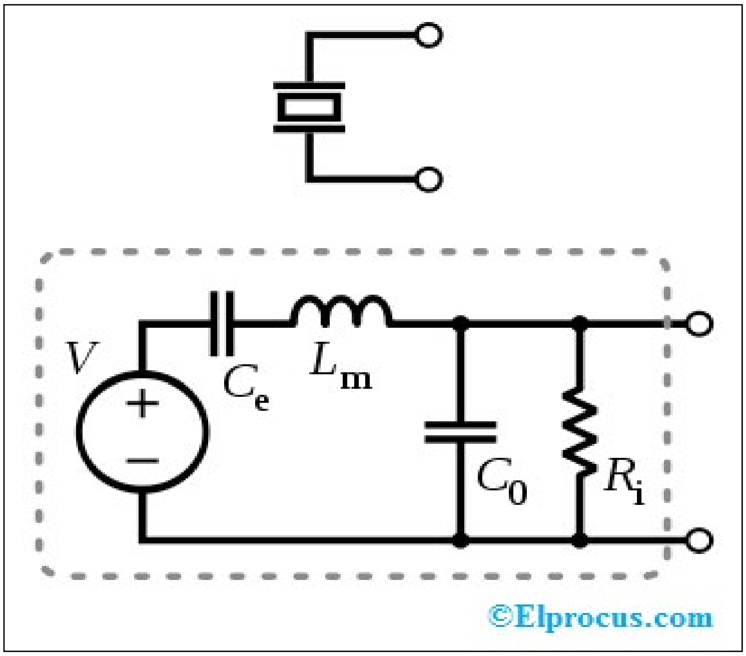
Fig. 2b illustrates the electrical connections between the piezoelectric acoustic sensor, MEMS vibration sensor, and the analog input channels of the microcontroller. Signal amplification and filtering stages are highlighted to demonstrate how weak micro-acoustic and vibration signals generated by larval feeding are conditioned before digitization.

The Fig. 2c presents the hardware configuration of the IoT gateway, showing the wireless communication module, microcontroller, and power supply circuitry. The gateway receives processed sensor data from field nodes and forwards it to the cloud server via long-range or internet-enabled communication for machine learning analysis and real-time alert generation.

The sensor node is built around a low-power microcontroller (e.g., ESP32). The acoustic and vibration sensors are interfaced through analog input channels with appropriate signal conditioning, including amplification and band-pass filtering (2–15 kHz). The microcontroller performs initial sampling and packetization. Power is supplied through a rechargeable battery with optional solar charging to enable long-term field deployment.


BME/BMP280
VIN
GND
SCL
SDA
GPIO 19
GPIO 18
GPIO 22
GPIO 21
GPIO 27
GPIO 32
GPIO 33

**(a)**


V
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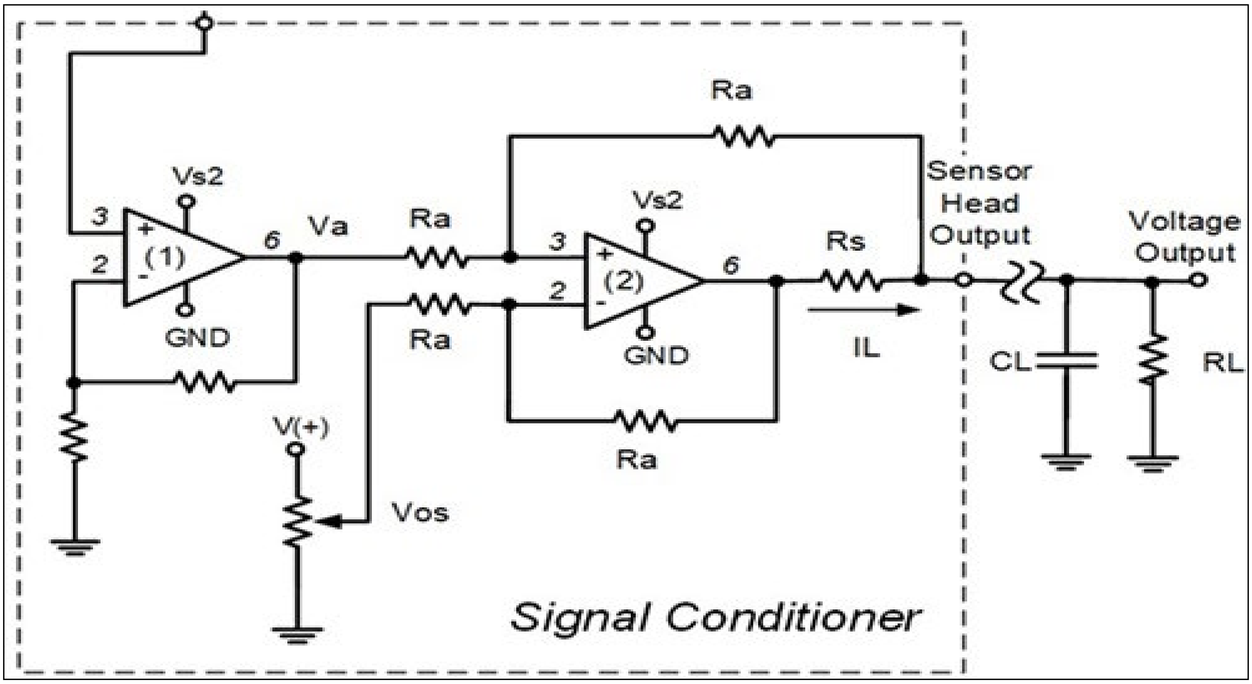
**(b)**



(c)

**Fig. 2(a)** Circuit schematic of the IoT sensor node for early detection of rice stem borers; **(b)** Interfacing of acoustic and vibration sensors with the microcontroller unit; **(c)** IoT gateway and communication circuit for data transmission to the cloud

### Data Acquisition and Preprocessing

Raw signals are sampled at appropriate frequencies and subjected to noise reduction. Signal-processing techniques such as band-pass filtering, Short-Time Fourier Transform (STFT), wavelet decomposition, and envelope detection are applied to extract features associated with larval feeding activity. Environmental noise from wind and rain is minimized through thresholding and spectral analysis.

### Wireless Communication

Processed data packets are transmitted to an IoT gateway using low-power communication protocols such as LoRa or NB-IoT. The gateway aggregates data from multiple nodes and forwards them to a cloud server via cellular or Wi-Fi connectivity.

### Machine Learning Analysis

In the cloud, extracted features are analyzed using ML models. Support Vector Machines (SVM) are used for lightweight classification, while Convolutional Neural Networks (CNNs) analyze spectrogram images for complex pattern recognition. Long Short-Term Memory (LSTM) networks are employed to capture temporal feeding patterns. The output classifies plants as healthy or infested and estimates infestation severity.

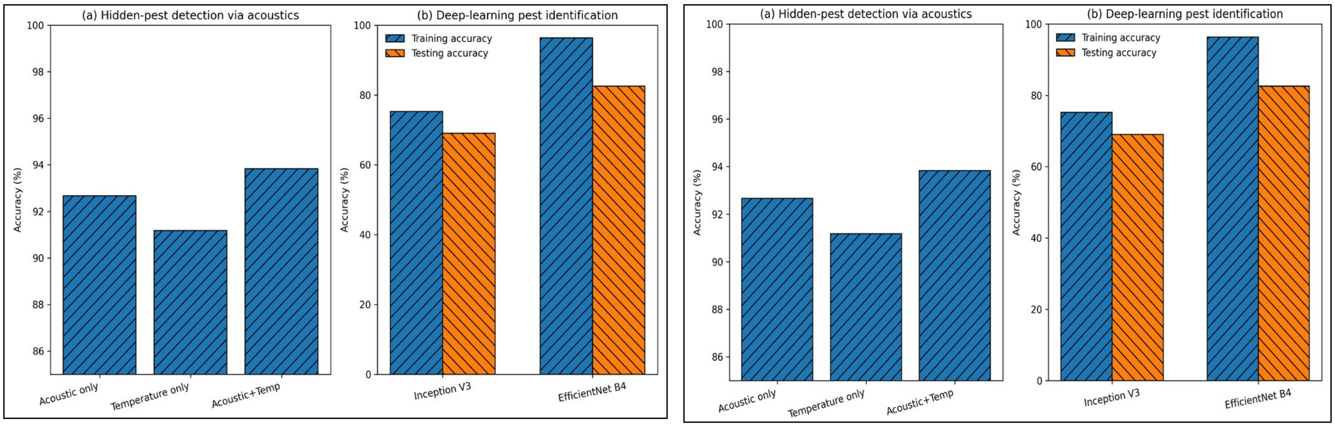
### Alert and Decision Support

Classification results are delivered to farmers through a mobile application dashboard. The interface displays real-time alerts, historical trends, and recommended management actions, enabling timely and targeted intervention.

## RESULTS AND DISCUSSION

The proposed methodology enables early detection of internal pest activity before visible symptoms develop. Acoustic and vibration sensing proved effective for capturing larval feeding signatures, while ML models enhanced classification accuracy under noisy field conditions. Integration of multi-sensor data improved robustness compared to single-sensor approaches. The IoT framework supports scalable deployment and real-time decision support, offering significant advantages over conventional monitoring methods.

The presented Figs. 3a,b synthesize representative scientific evidence from IoT- and machine learning–based studies relevant to early detection of hidden



**(a)** **(b)**

**Fig. 3: (a)** Termite detection accuracies (acoustic only, temperature only, acoustic + temperature); **(b)** uses pest-classification train/test accuracies for Inception V3 vs Efficiency

insect pests, with direct implications for rice stem borer management. Panel (a) illustrates detection accuracy achieved using different sensing strategies for concealed pest activity. Acoustic sensing alone provides high detection accuracy, demonstrating the strong potential of vibration and sound-based approaches for identifying internal feeding activity that is otherwise invisible through visual inspection. Temperature-based sensing alone shows slightly lower accuracy, reflecting its indirect nature and susceptibility to environmental variability. Notably, the combined use of acoustic and temperature signals yields the highest accuracy, highlighting the importance of multi-sensor data fusion in IoT architectures. This result supports the concept that integrating complementary sensing modalities improves robustness and reliability of early-warning systems for internal pests such as rice stem borers.

Panel (b) compares the performance of deep-learning models applied to pest classification tasks, using training and testing accuracies as indicators of learning capability and generalization. The EfficientNet B4 model significantly outperforms the Inception V3 architecture in both training and testing phases, indicating its superior ability to capture complex spatial and spectral features associated with pest-related data. The observable gap between training and testing accuracy in both models reflects real-world challenges such as data variability, noise, and limited labeled datasets—issues that are particularly relevant in agricultural IoT deployments. Nevertheless, the consistently higher testing accuracy of EfficientNet B4 demonstrates the advantage of modern, parameter-efficient deep-learning architectures for practical pest monitoring applications.

Taken together, these figures emphasize two critical aspects of smart pest surveillance: first, that internal pest detection benefits substantially from acoustic and vibration-based IoT sensing combined with environmental parameters; and second, that advanced machine-learning models are essential for transforming raw sensor data into reliable, actionable decisions. The findings reinforce the feasibility of IoT–ML frameworks for early, non-invasive detection of rice stem borers, supporting precision pest management strategies that can reduce yield losses, minimize pesticide misuse, and enhance sustainability in rice production systems.

Despite significant progress, several challenges remain. There is a lack of large, labeled datasets of stem borer acoustic signatures for training ML models. Many prototypes have been validated only under laboratory conditions, with limited field testing. Environmental noise, power management, and device durability in flooded paddy fields require further research.

Future systems should focus on multi-sensor data fusion, edge-AI deployment for low-latency detection, and cost-effective designs suitable for smallholder farmers. Integration with UAVs and regional advisory platforms could further enhance precision pest management.

Rice stem borers are among the most destructive pests of paddy, causing severe yield losses due to their concealed larval feeding inside plant stems, which makes early detection extremely difficult (Yadav & Verma, 2018). Conventional monitoring approaches such as visual scouting and pheromone trapping are often ineffective because visible symptoms appear only after substantial internal damage has occurred (Dara, 2019).

The application of Internet of Things (IoT) technologies in agriculture has enabled continuous field monitoring, real-time data acquisition, and automated decision support, significantly improving pest surveillance efficiency (Ahmed *et al.* 2020; Kumari & Singh, 2020). IoT-based environmental sensing and pest prediction systems have shown promising results in rice ecosystems by integrating sensor data with cloud-based analytics (Dutta *et al.* 2021).

Among emerging sensing techniques, acoustic and vibration-based methods have gained attention for detecting insects inside plant tissues and stored products (Cheng et al., 2017; Mankin & Hagstrum, 2011). These methods exploit the characteristic feeding sounds and micro-vibrations generated by insect larvae, enabling non-invasive and early detection of concealed infestations. Compared to optical or visual methods, acoustic sensing provides a direct measure of pest activity within plant structures (Sankaran *et al.* 2010).

Machine learning techniques further enhance detection accuracy by extracting meaningful patterns from complex sensor data. Classical models such as support vector machines and advanced deep-learning architectures have been successfully applied to pest detection and classification problems (Sujatha & Punitha, 2022). Integration of ML with IoT platforms allows automated classification, prediction, and early warning generation, supporting precision pest management strategies (Nansen & Elliott, 2016).

Effective pest management ultimately contributes to improved crop productivity and sustainability by reducing pesticide misuse and enabling timely intervention (Dara, 2019). The combined use of IoT sensing, acoustic monitoring, and machine learning represents a significant advancement toward smart and sustainable agriculture (Ahmed *et al.* 2020; Dutta *et al.* 2021).

## FUTURE SCOPE

The rapid convergence of the Internet of Things (IoT), advanced sensing technologies, and machine learning presents significant opportunities to further enhance early detection and sustainable management of rice stem borers. Future research should focus on large-scale, multi-location field validation of IoT-enabled acoustic and vibration sensing systems across different agro-climatic zones. Such studies would improve model generalizability and help account for variability in rice varieties, planting density, soil conditions, and seasonal environmental noise.

Development of comprehensive, open-access datasets containing labeled acoustic and vibration signatures of rice stem borers at different larval stages will be critical. These datasets can support the training of more robust deep-learning models and enable benchmarking across studies. Integration of advanced edge-AI techniques is another promising direction, allowing preliminary signal processing and pest classification to be performed directly on low-power sensor nodes. This would reduce data transmission requirements, lower latency, and improve system reliability in areas with limited connectivity.

Future systems may also incorporate multi-sensor fusion by combining acoustic data with hyperspectral imaging, gas sensors for volatile organic compounds, and microclimate data to enhance detection accuracy and reduce false positives. Coupling IoT-based detection platforms with unmanned aerial vehicles (UAVs) and variable-rate application technologies can enable precision interventions, such as targeted pesticide spraying or localized biological control.

From a sustainability perspective, research should emphasize cost-effective, energy-efficient designs suitable for smallholder farmers, including solar-powered nodes and durable, waterproof enclosures. Integration with digital advisory platforms and government pest surveillance networks can further amplify impact. Collectively, these advancements will support the transition toward data-driven, environmentally responsible, and resilient pest management systems in rice production.

## CONCLUSION

The study presents a conceptual framework for an IoT and machine learning enabled system for early detection of rice stem borers using acoustic and vibration sensing. The integration of sensor networks, wireless communication, signal processing and intelligent analytics provides a non-invasive approach to monitoring concealed pest activity within rice stems. Such systems have the potential to significantly improve pest surveillance and support precision pest management in rice ecosystems. Continued research on field validation, dataset development and low-cost hardware design will be essential for translating this concept into practical agricultural technologies.

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