International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** V **Month of publication:** May 2026

DOI: https://doi.org/10.22214/ijraset.2026.81328

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

A Survey on FloraVoice: TinyML and IoT Based Acoustic Stress Monitoring in Plants

Avilash Rout[1], Chandre Gowda S N[2], Prem Kumar R[3], Punith Raj H[4], Prof. Hemalatha K[1]
[1, 2, 3, 4]*Dept. of CSE Sapthagiri College of Engineering*, Bengaluru, India
[5]*Assistant Professor, Dept. of CSE Sapthagiri College of Engineering*, Bengaluru, India

Abstract: Agricultural monitoring systems are transitioning from reactive, environment-centric approaches toward proactive, plant-centric frameworks. FloraVoice exploits a less commonly studied signal source: acoustic activity produced by plants under physiological stress. When water supply is interrupted, especially during drought-induced cavitation, short ultrasonic events may be produced. This survey examines IoT plant monitoring, soil sensing, agricultural ultrasound, TinyML-based audio classification, and automated irrigation systems to understand how such acoustic evidence can be applied in a practical setting. The paper describes a FloraVoice framework using piezoelectric sensors, noise cancellation, analog filtering, ESP32-based signal processing, and edge inference, and concludes that plant acoustics can strengthen ordinary soil and climate sensing by adding a plant-response layer, although reliable deployment requires care- ful handling of noise, calibration, labelled datasets, processing overhead, and model size.

Index Terms: TinyML, IoT, smart agriculture, plant acoustics, acoustic stress detection, ESP32, precision irrigation, edge AI.

I. INTRODUCTION

Plant stress does not always announce itself through visible symptoms at the beginning; a plant undergoing drought has often lost substantial water balance before wilting, colour change, or growth reduction can be seen. Conventional mon- itoring, including manual observation and simple irrigation thresholds, therefore relies on delayed confirmation but may respond only after the stress process has already started. IoT-based agriculture has reduced this delay by making soil and climate readings available at frequent intervals. Sensors can report moisture, temperature, and humidity from the grow- ing area. These measurements describe the field environment, but they cannot always reveal how the plant itself is responding to changing internal conditions. FloraVoice adds an acoustic perspective to the monitoring problem. Studies on plant ultrasonic emissions suggest that internal changes, such as water column disruption during cavitation, can generate brief high-frequency events. If these events are captured and interpreted in real time, earlier stress alerts can be produced without waiting for visual damage. TinyML fits this requirement because the monitoring node must remain inexpensive, compact, and power-aware. A mi- crocontroller can extract a small set of signal features and run a trained classification locally, transmitting only the final status or alert. This survey reviews the technologies needed for such a system and organises them into a practical reference for the FloraVoice architecture.

II. BACKGROUND AND MOTIVATION

A. Need for Early Plant Stress Detection

A major weakness in plant care systems is that stress is often recognised only after the plant body has already shown external damage. During drought, the delay can reduce photosynthesis, increase water demand, and affect final yield. Earlier warning helps prevention decisions arrive during a corrective rather than a reactive phase.

B. Role of Acoustic Emissions

Acoustic signals should be treated as an additional evi- dence source rather than a complete alternative for soil and climate sensors. Environmental sensors explain the growing conditions, while acoustic information may indicate the plant response. Combining both can make final decisions more reliable than relying on a single parameter alone.

C. TinyML for Field Deployment

TinyML enables inference on devices with limited memory and processing power. In FloraVoice, the microcontroller can screen the signal, prepare compact spectral features, and clas- sify the output close to the sensor. This keeps communication light and makes multi-node deployment more realistic.

III. LITERATURE SURVEY

A. IoT-Based Smart Agriculture Monitoring

Author and Year: Daad et al. (2025)

Methodology: The system gathers moisture, temperature, and humidity readings through field sensors connected to a controller and mobile interface. Its main contribution is the practical use of low-cost IoT hardware to help farmers observe crop conditions and manage watering more conveniently.

Limitation: The decision process is mainly based on sur- rounding environmental values. It does not include a mech- anism for detecting stress signals produced by the plant body itself.

B. Soil Sensors in Smart Agriculture

Author and Year: Song et al. (2026)

Methodology: The review compares several sensor categories used in farming, including moisture, pH, nutrient, pollutant, pest, and plant-wearable sensing. It explains how dense and frequent measurements can improve precision agriculture and ecological management.

Limitation: The discussion is centred on soil and sensor ecosystems. It does not develop a complete microcontroller- based pipeline for recognising plant acoustic stress events.

C. TinyML Acoustic Event Detection

Author and Year: Roy et al. (2025)

Methodology: The work applies TinyML to acoustic wireless sensor networks. Instead of forwarding every captured signal, the node sends only events that are judged important, which lowers the communication load.

Limitation: The application is not specifically designed for plant ultrasound. FloraVoice would require plant-specific la- bels, agricultural noise samples, and validation under field or greenhouse conditions.

D. Ultrasound Monitoring in Agriculture

Author and Year: Sarkar and Laila (2025)

Methodology: This review surveys ultrasound use in agricul- ture, including seed evaluation, plant health assessment, pest or disease detection, and fruit inspection. It shows that ultrasound can reveal internal or structural information without damaging the crop.

Limitation: Field deployment remains difficult because acous- tic noise, equipment selection, signal interpretation, and contact-free measurement are still open challenges.

E. Sensor Technologies in Agriculture

Author and Year: Geetha et al. (2025)

Methodology: The paper organises agricultural sensor tech- nologies according to their sensing principle, energy needs, application area, and detection method. It also connects sen- sor selection with AI-assisted decisions and sustainable farm management.

Limitation: Because the scope is wide, plant-generated acous- tic emissions and embedded-model deployment are not treated in enough depth for a FloraVoice-type implementation.

F. Smart Plant Monitoring and Automated Irrigation

Author and Year: Charave et al. (2025)

Methodology: The system uses IoT sensors for soil moisture, temperature, humidity, and light intensity to support agri- cultural monitoring and automated watering. The approach improves convenience, conservation, and reduces unnecessary irrigation.

Limitation: The system remains dependent on external con- nectivity. It does not include an acoustic layer for direct plant stress detection or a local inference pipeline.

G. Plant Ultrasound Detection

Author and Year: Bonnati et al. (2024)

Methodology: The authors propose a cost-effective method for recognising and identifying plant ultrasonic emissions us- ing piezoelectric microphones, helping evaluate environmental or structural plant stress. Digital signal values are converted by the microcontroller ADC and spectral or spectrogram patterns are analysed.

Limitation: Building a labelled, multi-species dataset across varying stress levels and noise environments remains a signif- icant bottleneck for reliable model training.

IV. COMPARATIVE ANALYSIS

The seven works reviewed above span complementary parts of the design space surrounding low-cost plant monitoring, but each leaves at least one important dimension under-served. Ta- ble I summarises the contributions across four practical axes: the sensing modality employed, whether on-device (edge) inference is supported, whether the pipeline targets plant-level signals directly, and the principal limitation reported by the respective authors. The table also positions FloraVoice in the same frame for reference.

A clear pattern emerges from the comparison. IoT-centric monitoring works [1], [6] achieve low cost and field readiness but rely on indirect environmental proxies rather than plant response. Sensor and ultrasound surveys [2], [4], [5] establish that ultrasonic sensing is feasible in agriculture but stop short of providing a deployable embedded pipeline. TinyML acoustic event detection [3] confirms that microcontroller-class inference is realistic, yet is not specialised for plant ultrasonic emissions. Targeted plant-ultrasound studies [7] demonstrate the underlying signal but do not close the loop with embedded inference or actuation. FloraVoice is positioned at the conver- gence of these directions, combining low-cost piezoelectric sensing, on-device TinyML, and direct plant-level observation in a single deployable node.

V. EXISTING SYSTEM

Most low-cost IoT systems designed for plant monitoring work by placing sensors in the soil or around the plant to record environmental values such as moisture, temperature, and humidity. These readings are sent to a cloud server or local dashboard where threshold rules decide whether to trigger an alert or activate irrigation. The approach is practical and affordable, but it depends entirely on external conditions.

TABLE I

COMPARATIVE SUMMARY OF SURVEYED WORKS

Work	Modality	Edge AI	Plant- level	Key Limitation
Daad [1]	Soil + climate	No	No	Env. proxies only
Song [2]	Soil sensors review	N/A	N/A	No acoustic pipeline
Roy [3]	Acoustic WSN	Yes	No	Not plant-specific
Sarkar [4]	Ultrasound review	N/A	Yes	Field deployment open
Geetha [5]	Sensor survey	N/A	Partial	No embedded model
Charave [6]	Soil + climate	No	No	Cloud- dependent
Bonnati [7]	Plant ultrasound	Partial	Yes	Dataset bottleneck
Flora- Voice	Plant ultrasound + soil	Yes	Yes	This work

VI. PROBLEM STATEMENT

The main limitation addressed by FloraVoice is the delayed identification of plant stress in conventional monitoring sys- tems. Most low-cost IoT agricultural systems measure the environment around the plant but do not measure a direct response from the plant itself. As a result, drought stress may be detected only after a threshold is crossed or after visible symptoms appear.

The required system should detect early stress before ex- ternal conditions reach a threshold or before visible symptoms appear. The solution must be energy-efficient, non- invasive, scalable, and suitable for small farms, greenhouses, and individual mobile deployments without constant cloud dependence. The plant body itself is not observed directly. As a result, stress that has already developed internally may not produce a measurable environmental change until it has reached a visible or irreversible stage. Threshold logic also does not adapt well to differences between plant species, root systems, or growth stages, which can produce incorrect irrigation decisions in varied field conditions.

VII. PROPOSED SYSTEM

FloraVoice is structured around a dual-input piezoelectric sensing module. The primary transducer is attached directly to the plant stem, oriented to capture stress-related acoustic events originating from xylem cavitation. A secondary trans- ducer is placed on a reference surface to record ambient mechanical vibration. The difference between both channels is passed through an analog high-pass filter that removes low- frequency background interference before the signal reaches the ESP32-WROOM-32 ADC. The overall architecture is shown in Fig. 1.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

After digitisation, the signal is segmented into short frames and converted to a compact spectrogram representation. This spectrogram is forwarded to a quantised neural network clas- sifier stored in the microcontroller flash. The classifier assigns one of three labels: normal, early-warning, or active-stress. The corresponding status LED is updated immediately, and a structured data record containing the label, confidence value, current soil-moisture level, and timestamp is uploaded to the cloud dashboard. Raw waveform data is not transmitted dur- ing standard operation, which conserves energy and reduces network load.

When the active-stress label is produced in consecutive cycles while the soil-moisture reading is below the irrigation threshold, the node can activate a relay connected to the irrigation system or send a mobile notification to the farm operator. If the sensor produces no acoustic events over a prolonged window, the system raises a maintenance flag so the transducer coupling or calibration can be checked.

VIII. OBJECTIVES

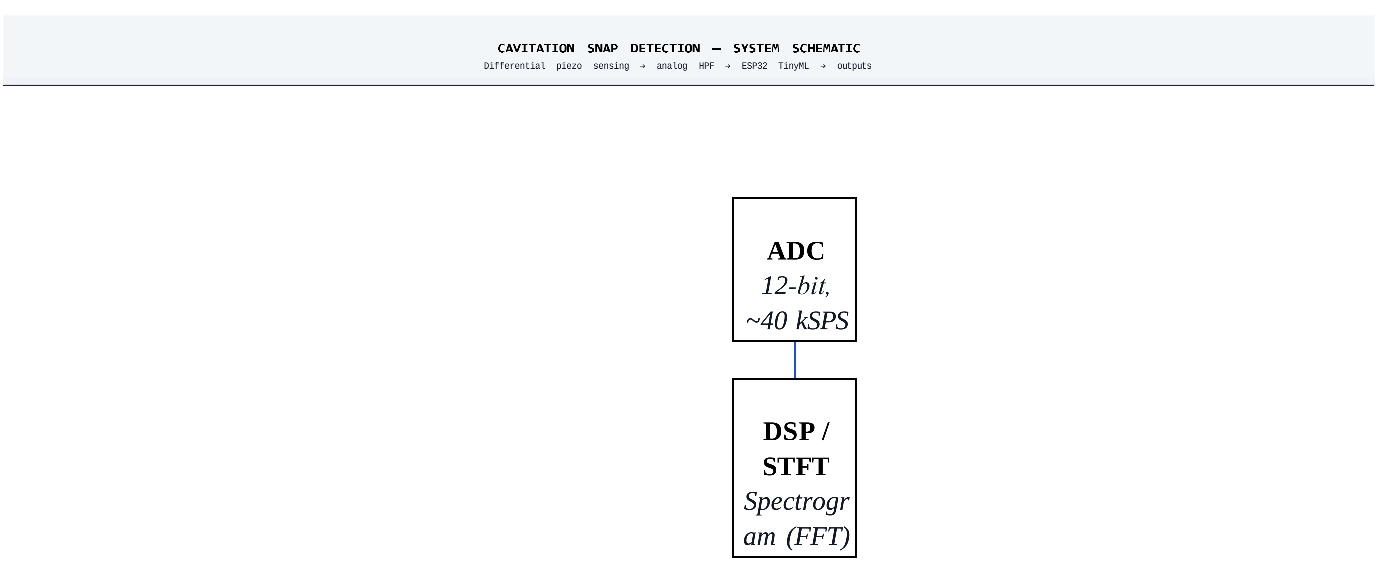
1) Acoustic stress detection: Detect possible drought or cavitation-related stress by capturing ultrasonic emissions from a plant stem using a piezoelectric sensor pair.
2) IoT-based monitoring: Combine acoustic information with environmental data such as soil moisture, temper- ature, and humidity for stronger decision support.
3) Edge AI implementation: Deploy a compact TinyML model on a resource-constrained microcontroller (ESP32- WROOM-32) that can infer stress states locally without constant cloud dependency.
4) Energy-efficient output: Transmit only alerts, labels, and summary readings at set intervals instead of continuously streaming raw acoustic data.
5) Scalable architecture: Design the sensing and inference flow so that it can be extended to multiple plants or greenhouse zones with manageable cost.

IX. DISCUSSION

The reviewed literature shows that IoT systems are mature for environmental monitoring, while ultrasound and acoustic processing are still emerging for plant-level monitoring. FloraVoice sits between these areas. It keeps the practical low- cost structure of an IoT plant monitoring setup while adding an acoustic layer to detect plant response more directly.

The most significant design challenge is noise. Agri- cultural environments contain mechanical disturbances from wind, human movement, water flow, and structural vibration. Hardware-level differential sensing and software-level filtering are both necessary. A second challenge is dataset quality: TinyML models require labelled examples of normal and stressed conditions across different plant species, stress states, and noise levels. Without diverse training data, the model may perform well in a laboratory but fail under real greenhouse or field conditions.

Energy efficiency is a notable advantage of the proposed system. A node can remain in a low-power state and wake only for scheduled sampling or when a signal amplitude trigger fires. Local classification removes the need for continuous data upload, which makes the system suitable for distributed farm



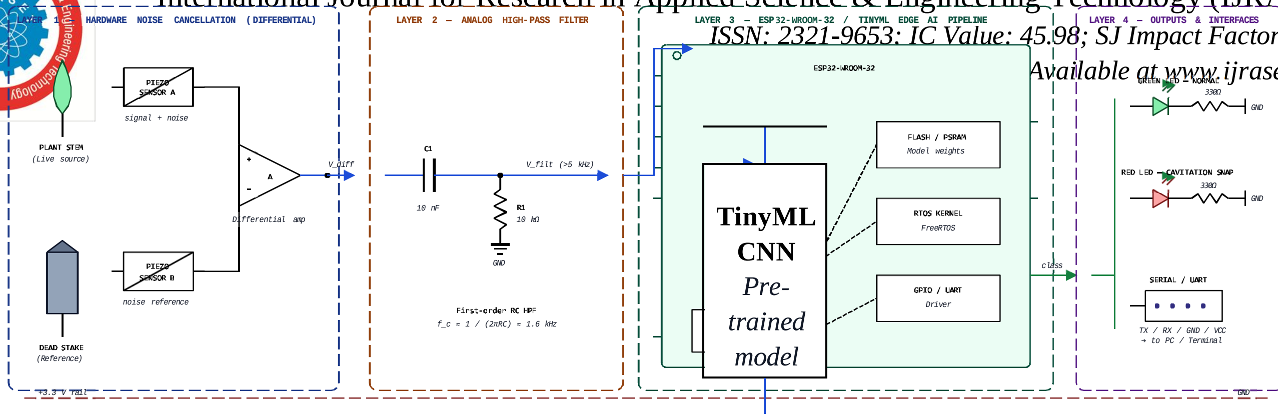


Fig. 1. Proposed FloraVoice system architecture: differential piezo sensing → analog HPF → ESP32 TinyML pipeline → outputs.

deployment. Scalability depends on sensor cost, calibration simplicity, and enclosure design.

Compared with traditional IoT irrigation systems, Flo- raVoice observes a plant-generated signal rather than a soil- linked environmental reading. Compared with laboratory ultra- sound methods, it targets a smaller and more deployable form factor. The practical success of the system depends on how accurately the classifier can separate genuine plant acoustic events from background environmental noise.

X. IMPLEMENTATION CONSIDERATIONS

Translating the FloraVoice architecture into a reliable field node depends on three practical factors: stable mechanical coupling between the piezoelectric transducer and the plant stem to keep the spectral profile consistent, a representative training dataset that includes negative samples for common confounders such as wind and irrigation noise, and a duty- cycled firmware schedule with periodic self-check routines so that the node maintains low average power draw while flagging hardware drift before it produces incorrect labels.

XI. CONCLUSION

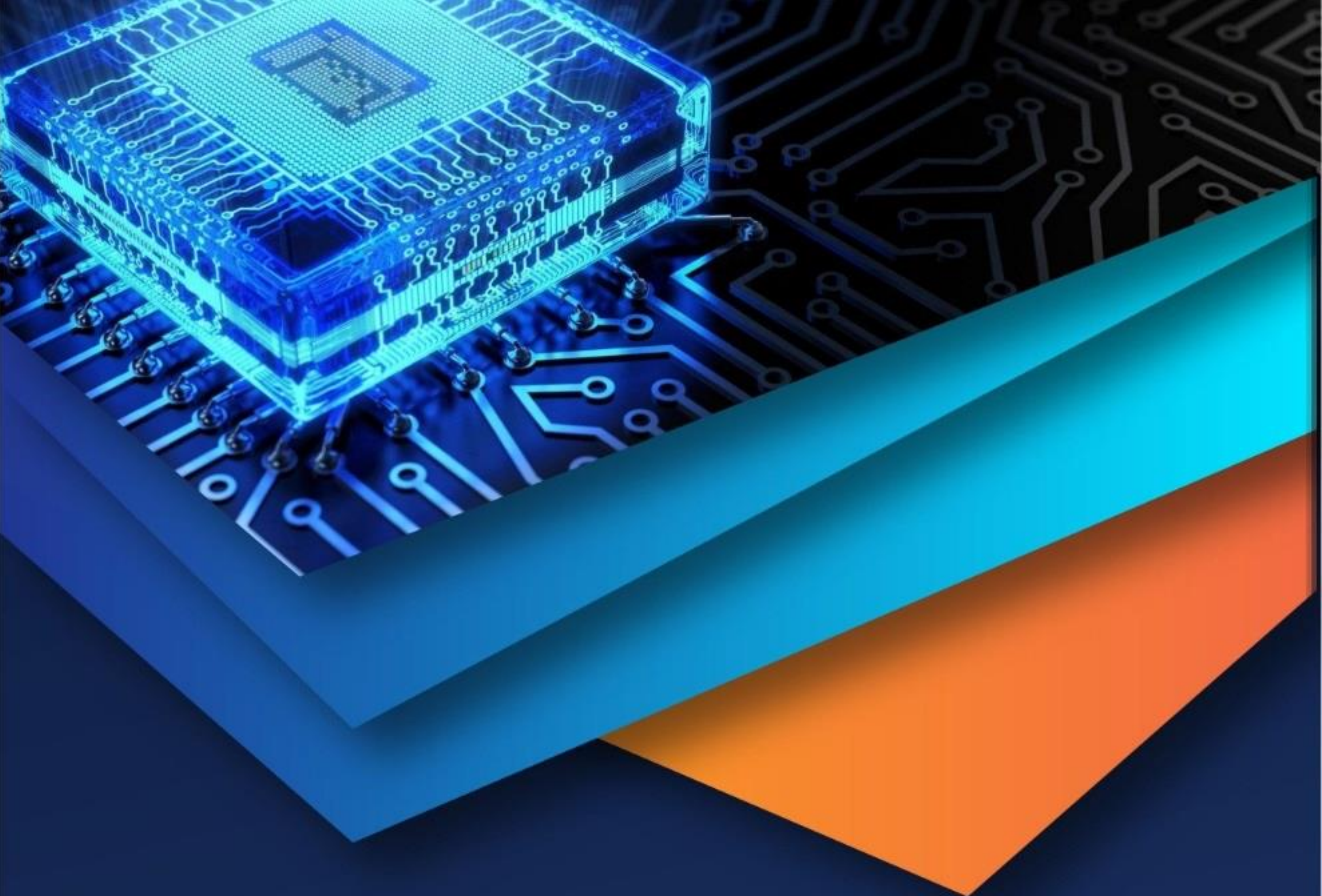
This survey reviewed IoT, sensor, ultrasound, and TinyML research relevant to FloraVoice, a plant acoustic stress moni- toring system. Existing plant monitoring systems work well for environmental observation but consistently detect stress only after external conditions or visible symptoms indicate a problem. Acoustic emissions offer a complementary signal that may reveal internal plant stress at an earlier stage and with greater specificity.

The proposed FloraVoice architecture combines piezoelec- tric sensing, analog filtering, ESP32-based digital signal pro- cessing, and TinyML classification to detect possible stress events at the edge. Future work should focus on building a labelled plant acoustic dataset that covers multiple species and noise conditions, validating the model across real field deployments, improving noise robustness through advanced filtering techniques, and integrating acoustic alerts with au- tomated irrigation control for closed-loop water management.

REFERENCES

[1] S. Daad, R. A. Rahman, and M. H. A. Zainal, “IoT-Based Smart Agriculture Monitoring System,” in Proc. Natl. Conf. Educ.—Tech. & Vocational Training, 2025.
[2] W. Song et al., “Soil Sensors in Smart Agriculture: Multi-Type Monitor- ing Technologies and Ecological Development Approaches,” Agriculture, vol. 16, no. 3, 2026, doi: 10.3390/agriculture16030159.
[3] B. B. Roy, S. Das, and U. K. Mondal, “TinyML-Driven Sensor Nodes for Energy-Efficient Acoustic Event Detection in Pervasive Acoustic WSNs,”
[4] J. Telecommun. Inf. Technol., vol. 100, no. 2, pp. 69–77, 2025, doi: 10.26636/jtit.2025.2.2086.
[5] M. A. Sarkar and D. S. Laila, “A Review of Ultrasound Monitoring Applications in Agriculture,” Front. Plant Sci., vol. 16, 2025, doi: 10.3389/fpls.2025.1620868.
[6] R. Geetha, R. Rakhi, and K. N. Anith, “Innovative Sensor Technologies in Agriculture—Applications and Challenges: A Review,” Agric. Sci. Digest, 2025, doi: 10.18805/ag.D-6344.

[7] S. M. Charave et al., "Smart Plant Monitoring and Automated Irrigation System Using IoT," Int. J. Adv. Res. Sci. Commun. Technol., vol. 5, no. 4, 2023, doi: 10.48175/IJARSCT-26481.
[8] I. Bonnati, I. Pelacha, and L. Arru, "Plant Ultrasound Detection: A Cost- Effective Method for Identifying Plant Ultrasonic Emissions," Plant Sig- nal. Behav., vol. 19, no. 1, 2024, doi: 10.1080/15592324.2024.2310874.
[9] J. Nie et al., "Real-Time Multisource Fusion of Satellite-UAV Remote Sensing Images and Acoustic Signals for Crop Monitoring," IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., 2025.



10.22214/IJRASET

INDEX COPERNICUS
45.98

IMPACT FACTOR:
7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR:
7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY