JRITM
JOURNAL OF RESEARCH AND INNOVATION IN TECHNOLOGY, COMMERCE AND MANAGEMENT

Journal of Research and Innovation in Technology, Commerce and Management
Vol. 3 Issue 9, September 2026, pp. 39089-39098
ISSN: 3049-3129 (Online)

ICAIISD–2026

IoT-Enabled Sensor Applications in Smart Healthcare, Smart Agriculture, Environmental Monitoring and Smart Energy & Safety Monitoring

Mrs.C.Nithya
Assistant Professor, Department of Computer Science and Business Systems
Knowledge Institute of Technology, Salem, Tamil Nadu, India
Email: nithya.acet@gmail.com

Mr.M.K.Sampath
Assistant Professor, Department of Computer Science and Engineering
Knowledge Institute of Technology, Salem, Tamil Nadu, India

Mrs. P.Raga Keerthana
Assistant Professor, Department of Computer Science and Business Systems
Knowledge Institute of Technology, Salem, Tamil Nadu, India

Cite as: Mrs.C.Nithya, Mr.M.K.Sampath, & Mrs. P.Raga Keerthana. (2026). IoT-Enabled Sensor Applications in Smart Healthcare, Smart Agriculture, Environmental Monitoring and Smart Energy & Safety Monitoring. Journal of Research and Innovation in Technology, Commerce and Management, Vol. 3(Issue 9), 39089–39098. https://doi.org/10.5281/zenodo.22795429

DOI: https://doi.org/10.5281/zenodo.22795429

Abstract

The Internet of Things (IoT) is becoming a fundamental technology for the development of sensorized intelligent systems in several domains of society. This paper presents a structured literature review on architectures for sensing and intelligence in the scope of four research areas: Smart Healthcare, Smart Agriculture, Environmental Monitoring, and Smart Energy and Safety Monitoring. Recent journal articles, systematic reviews, and conference papers were analysed to report sensor modalities, communication architectures, and learning algorithms, namely machine learning (ML) and deep learning (DL), that have been proposed in literature for each of the above research areas. A consolidated inventory of algorithms that have been reported in the above surveyed works, as well as a comparison of sensing technologies, learning techniques, and their

corresponding applications, are also presented. Finally, open challenges that have been found to be recurring, i.e., sensor calibration and drift, energy efficiency, security and privacy, heterogeneous data, and the gap between proof-of-concept prototypes and large-scale scalable and practical implementations, as well as future research directions, are outlined. The purpose of this work is to provide a useful, structured literature review that can serve as a background and reference for researchers interested in sensorized IoT applications using algorithmic approaches.

Keywords: Internet of Things (IoT); Smart Healthcare; Smart Agriculture; Environmental Monitoring; Smart Energy; Safety Monitoring; Sensors; Machine Learning; Deep Learning; Literature Survey.

1. Introduction

The Internet of Things (IoT) describes a network of physical sensor, actuator and embedded processor-based devices that can collect, transmit and react to real world data with little to no human interaction. In the last decade IoT evolved from single use-cases and single smart devices to bigger, more data-rich systems, where machine learning (ML) and deep learning (DL) are increasingly being used to process raw sensor data into actionable information [2, 3]. This fusion of IoT and artificial intelligence (AI) or "AIoT" is now the foundation of the many applications ranging from patient monitoring to precision farming, pollution tracking and intelligent power grids. Though previous research has surveyed a wide variety of applications, the majority of current reviews focus on a single application area, such as healthcare [2], [6] or agriculture [10], [12] and the number of studies that integrate algorithmic trends across different sensor-driven application areas of IoT is comparatively low. This paper is aimed at filling such a gap by reviewing the four major research areas: (i) Smart Healthcare, (ii) Smart Agriculture, (iii) Environmental Monitoring, and (iv) Smart Energy and Safety Monitoring. The survey is conducted for each of the domains.

This paper is divided into several sections as follows. The methodology of this survey is described in Section 2. Section 3 presents literature review of Smart Healthcare, Section 4 presents literature review of Smart Agriculture, Section 5 presents literature review of Environmental Monitoring and Section 6 presents literature review of Smart Energy & Safety Monitoring, respectively, with conclusion of each section followed by a tabular representation of the algorithms identified from the overviewed works. The cross domain comparative summary is provided in Section 7. Finally, Section 8 presents the open research challenges, future directions, and Section 9 winds up the paper.

The remainder of this paper is organised as follows. Section 2 outlines the survey methodology. Sections 3 to 6 review the literature on Smart Healthcare, Smart Agriculture, Environmental Monitoring, and Smart Energy & Safety Monitoring, respectively, each concluding with a table of algorithms identified in the surveyed works. Section 7 presents a cross-domain comparative summary. Section 8 discusses open research challenges and future directions, and Section 9 concludes the paper.

2. Survey Methodology

The survey is based on a narrative-descriptive literature review approach with a systematic review practice. Candidate literature was selected from peer reviewed journals, indexed conference proceedings, and reputable preprint servers, including key papers published between 2020 and 2026 and a few younger papers that were considered of foundational importance for the field. For every target domain the review analyzed papers that: (a) presented or tested an IoT sensor-based architecture; (b) used at least one ML/DL or optimisation algorithm on the sensor information; and (c) described the modalities of the sensors, and the technique of the ML/DL, or the optimisation algorithm, sufficiently to extract and report them. Data from each source was obtained to identify the type of sensor(s) used, the algorithm(s) employed, and the reported application or result. Finally, the information that has been extracted was combined domain by domain, to create the algorithm inventories shown in Sections 3–6.

3. IoT in Smart Healthcare

The Internet of Medical Things (IoMT) is a smart healthcare system that relies on wearable and implantable biosensors, wireless body area networks (WBANs), and analytics in the cloud/edge for continuous remote monitoring of patients [4] and [7]. The usual sensing types are electrocardiogram (ECG), electromyogram (EMG), pulse-oximetry (SpO2), blood-pressure cuffs, glucose biosensors, and (IMUs) sensors within wristbands and smartwatches [4, 8].

Machine learning plays a central role in transforming raw physiological streams into diagnostic and predictive insight. For instance, one study combined TabNet and CatBoost architectures over fused IoMT sensor data — including continuous heart-rate, ECG, and blood-pressure readings — to build a personalised coronary artery disease risk-assessment model [1]. Broader reviews of ML for big-data analytics in IoT-enabled healthcare highlight the use of both traditional classifiers (SVM, decision trees, k-nearest neighbours) and deep architectures (CNNs and RNN/LSTM networks) for tasks such as arrhythmia detection, activity recognition, and chronic-disease progression monitoring [2], [6]. More recent surveys additionally emphasise emerging techniques such as federated learning for privacy-preserving model training across distributed IoMT nodes, explainable AI (XAI) for clinician-interpretable decision support, edge learning to reduce latency, and multimodal medical-signal fusion combining wearable and clinical data sources [3]. Systematic reviews focused specifically on chronic-disease monitoring further catalogue the ML techniques applied to IoT mobile-sensing data, underlining a shift from single-signal analysis toward multimodal, continuous-monitoring pipelines [1].

Table 1 summarises representative algorithms identified across the surveyed smart-healthcare literature, together with their reported application context.

Algorithm / Technique	Reported Application in Reviewed Literature	Source(s)
Support Vector Machine (SVM)	Classification of physiological signals (ECG, EMG), disease risk stratification	[6], [8]
Random Forest / Decision Tree	Chronic disease prediction, fall and activity classification from wearable data	[2], [6]
Convolutional Neural Network (CNN)	ECG/EEG waveform analysis, medical image and signal pattern recognition	[3], [5]
Recurrent Neural Network / LSTM	Continuous vital-sign time-series forecasting and anomaly detection	[3], [7]
TabNet and CatBoost (ensemble/attention)	Coronary artery disease risk prediction from fused IoMT sensor data	[1]
k-Nearest Neighbours (kNN)	Activity recognition and symptom classification from wearable sensor streams	[6]
Federated Learning	Privacy-preserving distributed model training across hospital/IoMT nodes	[3]
Explainable AI (XAI) methods	Interpretable clinical decision support for physicians	[3]

4. IoT in Smart Agriculture

IoT-enabled precision agriculture integrates networks of soil, climate, and crop-health sensors with AI-driven analytics to optimise irrigation, fertilisation, and pest and disease management [10], [11]. Commonly deployed sensors include soil-moisture and temperature probes, pH and nutrient (NPK) sensors, optical and multispectral imaging sensors, and, increasingly, UAV-mounted remote-sensing payloads [11], [13]. A systematic review following PRISMA methodology reports a marked increase in agricultural IoT-AI research between 2020 and 2024, with soil, optical, and acoustic sensors combined with ML models such as support vector machines (SVMs), convolutional neural networks (CNNs), and random forests being used to optimise irrigation, fertilisation, and pest-management decisions [11].

Several application-specific systems illustrate this trend. IoT-based greenhouse platforms combining wireless sensor networks (WSNs) with control logic have been used for precision-irrigation scheduling [16]; cloud-based IoT data-analytics platforms have been proposed for broader farm-management decision support [15]; and fog-computing architectures have been used to perform on-the-edge data reduction of high-frequency soil and climate sensor streams before cloud transmission, easing bandwidth and latency constraints [12]. Deep-learning frameworks — including a domain-specific architecture referred to in the literature as DeepThink-IoT — have been proposed for end-to-end fusion of heterogeneous agricultural sensor data [13]. Ensemble machine-learning techniques combining multiple base learners have also been reported for joint crop-health and environmental-stress prediction within IoT farm networks [18]. In parallel, security-oriented studies have applied deep malware-detection frameworks to protect IoT agricultural gateways from cyber threats, reflecting a growing awareness that agricultural IoT deployments face the same security concerns as other IoT domains [9].

Table 2 lists the principal algorithms identified in the surveyed smart-agriculture literature.

Algorithm / Technique	Reported Application in Reviewed Literature	Source(s)
Support Vector Machine (SVM)	Soil-type classification, crop disease and pest detection from sensor/image data	[13], [16]
Convolutional Neural Network (CNN)	Leaf-disease and weed identification from field-deployed camera sensors	[13], [17]
Random Forest	Yield estimation and irrigation-scheduling decisions from multi-sensor soil data	[13], [16]
Deep Learning (DeepThink-IoT / DL frameworks)	End-to-end sensor-data fusion for precision-agriculture decision support	[12]
Ensemble Machine Learning	Combined crop-health and environmental-stress prediction in IoT farm networks	[18]
Deep Malware-Detection Models	Security/anomaly detection for IoT-based agricultural gateways	[9]
Fog-based Data-Reduction ML	Edge-level compression/aggregation of high-frequency soil and climate sensor streams	[9]

5. IoT in Environmental Monitoring

Table 3 summarises the principal algorithms identified in the surveyed environmental-monitoring literature.

Algorithm / Technique	Reported Application in Reviewed Literature	Source(s)
Random Forest	Air-quality index forecasting and pollutant classification	[14], [17]
Long Short-Term Memory (LSTM)	Time-series prediction of AQI and pollutant concentration trends	[14]
Gradient Boosting / AdaBoost	Low-cost sensor calibration against reference-grade air-quality instruments	[17]
k-Nearest Neighbours (kNN)	PM2.5 sensor-value correction and calibration	[17]
Support Vector Machine (SVM)	Water-quality classification and contamination-event detection	[19]
Linear / Multiple Linear Regression	Sensor-drift correction for temperature and humidity nodes	[17], [20]
LightGBM	Long-term calibration of low-cost urban temperature sensors	[20]
Decision Tree	Rule-based classification of water/air pollutant severity levels	[17]

6. IoT in Smart Energy and Safety Monitoring

6.1 Smart Energy Management

IoT-based smart energy systems integrate smart meters, current/voltage sensors, and environmental sensors within microgrid and smart-grid architectures to enable real-time monitoring, demand forecasting, and adaptive resource allocation [27], [30]. A systematic literature review following the PRISMA framework, covering 26 studies published between 2019 and 2024, reported that combining IoT sensor data (current sensors, motion sensors, smart meters) with ML algorithms such as SVM, decision tree, random forest, and LSTM improved energy efficiency by up to 30% and enabled real-time anomaly detection in electricity consumption [30]. Deep-reinforcement-learning-based frameworks have also been proposed for real-time adaptive resource allocation and grid optimisation, outperforming conventional

ML and rule-based approaches in simulation studies [29]. At the household level, Smart Home Energy Management Systems (SHEMS) combine IoT gateways for data acquisition with ML-based components for feature extraction,

Algorithm / Technique	Reported Application in Reviewed Literature	Source(s)
Support Vector Machine (SVM)	Load and demand classification in smart-meter data streams	[24], [21]
Decision Tree / Random Forest	Appliance-level energy-consumption classification and anomaly detection	[24]
Long Short-Term Memory (LSTM)	Short- and medium-term electricity load and demand forecasting	[24]
Deep Reinforcement Learning (DRL)	Adaptive real-time resource allocation and grid optimisation	[23]
Deep Learning (ORA-DL framework)	Renewable-integrated smart-grid resource allocation using edge/IoT sensor data	[23]
Hybrid Optimisation + ML	Microgrid energy-management scheduling combining metaheuristics with ML	[21]
Threshold-based Algorithms	Baseline smoke/gas-level triggering in fire-detection nodes	[37]
Decision Tree	Human-fall classification from accelerometer/gyroscope features	[38], [42]
Random Forest / SVM	Activity-of-daily-living vs. fall discrimination from wearable IMU sensors	[38], [42]
Recurrent Neural Network (RNN)	Sequential motion-pattern classification for fall detection	[42]
Region-based CNN (R-CNN)	Vision-based fall detection using scene analysis	[44]
Firefly Algorithm + Machine Learning	Bio-inspired optimisation of intrusion-detection accuracy in WSN-IoT security	[40]
Discrete Wavelet Transform + RNN	Denoising and classification pipeline for wearable fall-detection signals	[42]

7. Cross-Domain Comparative Summary

Table 5 consolidates the sensing modalities and algorithmic techniques reported across the four surveyed domains. While each domain has distinct sensing requirements, several algorithms — notably random forest, SVM, and LSTM — recur across all four areas, suggesting that these techniques have become a de facto baseline for sensor-data classification and time-series forecasting in IoT applications generally. Deep-learning approaches (CNNs, RNNs, and deep reinforcement learning) tend to be reserved for higher-complexity tasks such as image-based disease detection in agriculture, waveform analysis in healthcare, and adaptive grid optimisation in energy systems.

Domain	Representative Sensors	Representative Algorithms
Smart Healthcare	ECG, EMG, PPG, SpO2, wearable IMU, blood-pressure and glucose biosensors	SVM, Random Forest, CNN, LSTM/RNN, TabNet, CatBoost, kNN, Federated Learning
Smart Agriculture	Soil-moisture, temperature/humidity, NPK, pH, optical and multispectral sensors	SVM, CNN, Random Forest, Deep Learning, Ensemble ML
Environmental Monitoring	PM2.5/PM10, CO2, gas (MQ-series), turbidity, pH, dissolved-oxygen sensors	Random Forest, LSTM, Gradient Boosting, kNN, SVM, LightGBM, Regression
Smart Energy & Safety	Smart meters, current/voltage, motion, smoke, gas-leak, accelerometer sensors	SVM, Decision Tree, Random Forest, LSTM, DRL, Firefly-ML, RNN, R-CNN

ISSN: 3049-3129 (Online)

8. Open Challenges and Future Directions

- Sensor calibration and drift: Low-cost sensors used in environmental and agricultural IoT deployments are prone to drift and require ongoing ML-based recalibration against reference instruments [17], [20].
- Data heterogeneity and fusion: Healthcare and agriculture systems increasingly rely on multimodal sensor fusion, which complicates model design and increases the need for standardised data representations [3], [13].
- Energy efficiency and resource constraints: IoT nodes across all four domains operate under strict power and computation budgets, motivating continued research into lightweight and edge-deployable ML models [9], [30].
- Security and privacy: IoT devices remain vulnerable to intrusion and adversarial manipulation, particularly in smart-grid and agricultural-gateway contexts, motivating bio-inspired and ML-based intrusion-detection research [9], [32], [36].
- Standardisation and real-world validation: Several surveyed works note that many proposed systems remain at proof-of-concept scale, with limited large-scale field validation, particularly in environmental and safety-monitoring applications [19], [37].
- Explainability: As clinical and safety-critical decisions increasingly rely on DL models, explainable AI (XAI) is identified as a growing requirement, particularly in healthcare [3].

Future research is likely to focus on federated and edge learning to address privacy and latency constraints, standardised multimodal sensor-fusion frameworks, energy-aware lightweight DL architectures for constrained IoT nodes, and stronger integration of security-by-design principles across all four domains.

9. Conclusion

This survey has consolidated recent literature on IoT-enabled sensor applications across four major domains — Smart Healthcare, Smart Agriculture, Environmental Monitoring, and Smart Energy and Safety Monitoring — with particular attention to the sensor modalities and machine learning/deep learning algorithms reported in each area. Across all four domains, classical ML techniques such as SVM, decision trees, and random forests remain widely used baselines, while deep-learning and hybrid optimisation techniques are increasingly applied to higher-complexity tasks such as image-based diagnosis, adaptive grid control, and vision-based fall detection. There are common application domain problems, such as sensor calibration, data heterogeneity, energy constraints, security, and the disconnect between prototype and deployment, which suggest common research needs that may be shared between the two application domains, and that could benefit from the cross-pollination of ideas.

It is hoped that the consolidated algorithm inventory and comparative discussion presented here will serve as a useful reference point for researchers designing new sensor-driven IoT systems.

ISSN: 3049-3129 (Online)

References

[1] S. et al., "Advanced applications in chronic disease monitoring using IoT mobile sensing device data, machine learning algorithms and frame theory: a systematic review," Frontiers in Public Health, 2025.

[2] M. M. Baig et al., "A Comprehensive Survey on Machine Learning-Based Big Data Analytics for IoT-Enabled Smart Healthcare System," Mobile Networks and Applications / PMC, 2021.

[3] "A comprehensive review on key technologies toward smart healthcare systems based IoT: technical aspects, challenges and future directions," Artificial Intelligence Review, Springer, 2025.

[4] "Comprehensive Review on IoT-Based Smart Health Risk Prediction System Using AI & Biomedical Sensors," ResearchGate preprint, 2025.

[5] "IoT for Smart Cities: Machine Learning Approaches in Smart Healthcare—A Review," ResearchGate, 2021.

[6] "Machine Learning for IoT HealthCare Applications: A Review," Academia.edu, 2021.

[7] "A Survey on IoT Smart Healthcare: Emerging Technologies and Applications," arXiv:2109.02042, 2021.

[8] "Survey on Sensors and Smart Devices for IoT Enabled Intelligent Healthcare System," Wireless Personal Communications, Springer, 2023.

[9] S. K. Smmarwar, G. P. Gupta, and S. Kumar, "Deep malware detection framework for IoT-based smart agriculture," Computers and Electrical Engineering, vol. 104, p. 108410, 2022.

[10] D. S. Waghole, H. S. Joil, P. R. Morey, P. H. Hadke, and S. R. Betageri, "Smart Agriculture System Using IOT and AI/ML: A Survey," International Journal of Engineering Research & Technology (IJERT), vol. 13, no. 5, 2024.

[11] "The IoT and AI in Agriculture: The Time Is Now—A Systematic Review of Smart Sensing Technologies," PMC, 2025.

[12] "Machine Learning and IoT for Smart Agriculture: A Comprehensive Review," International Journal of Basic and Applied Sciences, 2025.

[13] "Optimizing Sensor Node Localization for Achieving Sustainable Smart Agriculture System Connectivity," arXiv preprint, citing A. Sharma, A. Jain, P. Gupta, and V. Chowdary, "Machine learning applications for precision agriculture: A comprehensive review," IEEE Access, vol. 9, pp. 4843-4873, 2020.

[14] M. Dhanaraju, P. Chenniappan, K. Ramalingam, S. Pazhanivelan, and R. Kaliaperumal, "Smart farming: Internet of Things (IoT)-based sustainable agriculture," Agriculture, vol. 12, no. 10, p. 1745, 2022.

[15] A. V. Turukmane, M. Pradeepa, K. S. S. Reddy, R. Suganthi, Y. M. Riyazuddin, and V. V. S. Tallapragada, "Smart farming using cloud-based IoT data analytics," Measurement: Sensors, vol. 27, p. 100806, 2023.

[16] H. Benyezza, M. Bouhedda, R. Kara, and S. Rebouh, "Smart platform based on IoT and WSN for monitoring and control of a greenhouse in the context of precision

agriculture," Internet of Things, vol. 23, p. 100830, 2023.

[17] "A Survey on Smart Agriculture Using IoT, AI and Modern Technologies," Journal of Information Technology and Digital World, 2026.

[18] Syed and Liyakathunisa, "Smart Agriculture Using Ensemble Machine Learning Techniques in IoT Environment," Procedia Computer Science, vol. 235, pp. 2269-2278, 2024.

[19] "Environmental Monitoring using Machine Learning and IoT: Applications, Challenges, and Cyber Security Threats," International Journal for Research in Applied Science & Engineering Technology (IJRASET), 2025.

[20] "Artificial intelligence in environmental monitoring: in-depth analysis," Discover Artificial Intelligence, Springer, 2024.

[21] "Artificial intelligence and IoT driven technologies for environmental pollution monitoring and management," Frontiers in Environmental Science, 2024.

[22] "Machine Learning–Based Calibration and Performance Evaluation of Low-Cost Internet of Things Air Quality Sensors," PMC, 2025.

[23] S. L. Ullo and G. R. Sinha, "Advances in Smart Environment Monitoring Systems Using IoT and Sensors," Sensors, vol. 20, no. 11, p. 3113, 2020.

[24] I. Essamlali, H. Nhaila, and M. El Khaili, "Advances in machine learning and IoT for water quality monitoring: A comprehensive review," Heliyon, vol. 10, no. 6, e27920, 2024.

[25] "A real-time dataset of air quality index monitoring using IoT and machine learning in the perspective of Bangladesh," PMC, 2024.

[26] "Calibration of Integrated Low-Cost Environmental Sensors for Urban Air Temperature Based on Machine Learning," PMC, 2025.

[27] "A review of machine learning and IoT-based energy management systems for AC microgrids," Computers and Electrical Engineering, 2025.

[28] "Smart energy management: real-time prediction and optimization for IoT-enabled smart homes," Cogent Engineering, 2024.

[29] "A deep learning and IoT-driven framework for real-time adaptive resource allocation and grid optimization in smart energy systems," Scientific Reports, 2025.

[30] "Utilization of Smart Technologies Based on Internet of Things and Machine Learning in Energy Management: A Systematic Literature Review," Journal of Artificial Intelligence and Engineering Applications (JAIEA), 2025.

[31] "A comprehensive review of machine learning and IoT solutions for demand side energy management, conservation, and resilient operation," Applied Energy / ScienceDirect, 2023.

[32] "A comprehensive exploration of IoT-enabled smart grid systems: power quality issues, solutions, and challenges," Science and Technology for Energy Transition (STET), 2024.

[33] Z. Zhang, M. Liu, M. Sun, R. Deng, P. Cheng, D. Niyato, M.-Y. Chow, and J. Chen, "Vulnerability of Machine Learning

Approaches Applied in IoT-based Smart Grid: A Review," arXiv:2308.15736, 2023.

[34] "A Decade of Progress in Wearable Sensors for Fall Detection (2015–2024): A Network-Based Visualization Review," PMC, 2024.

[35] "The Impact of the Accelerometer Sampling Rate on the Performance of Machine and Deep Learning Models in Wearable Fall-Detection Systems," PMC, 2025.

[36] "Firefly algorithm based WSN-IoT security enhancement with machine learning for intrusion detection," Scientific Reports / PMC, 2023.

[37] "From Inception to Innovation: A Comprehensive Review and Bibliometric Analysis of IoT-Enabled Fire Safety Systems," Fire (MDPI), vol. 11, no. 2, p. 41, 2025.

[38] "Fall Detection System using Wearable Sensor Devices and Machine Learning: A Review," ResearchGate, 2024.

[39] "A Review on Fire and Smoke Detection With Intelligent Control for Enhanced Safety Using Machine Learning (ML) and Internet of Things (IoT)," Cureus Journal of Engineering, 2024.

[40] "IoT-based Wearables: A comprehensive Survey," arXiv:2304.09861, 2023.

[41] P. Kortoçi et al., "Air pollution exposure monitoring using portable low-cost air quality sensors," Smart Health, vol. 23, p. 100241, 2022.

[42] D. N. Paithankar, A. R. Pabale, R. V. Kolhe, P. William, and P. M. Yawalkar, "Framework for implementing air quality monitoring system using LPWA-based IoT technique," Measurement: Sensors, vol. 26, p. 100709, 2023.