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IOT-ENABLED INTELLIGENT ENVIRONMENTAL MONITORING SYSTEM USING SENSOR NETWORKS AND CLOUD INTEGRATION

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ABSTRACT

This paper presented an IoT-based smart environmental monitoring solution on the principles of distributed sensor networks, edge processing and cloud-based analytics to achieve continuous, low-latency, and scalable environmental monitoring of air quality, temperature, humidity, noise and particulate matter. The proposed architecture involved the use of energy saving data collection through duty-cycled sensor nodes, edge processing and buffering gateway, and cloud server to offer scalable data collection, anomaly detection, trend analysis and real-time alerts. Experimental analysis was conducted to determine the system performance based on certain factors of reliability of data transmission, end to end latency, energy use, accuracy of anomaly detection and ability to increase with sensor density increment. The results indicated that the packet delivery ratios were high, scaled deployments exhibited near real time responsiveness, a long sensor node battery life, anomaly detection with minimum alert delay success, and predictable cloud behavior. The findings are confirmative to the fact that the proposed architecture is a viable and implementable solution to the smart monitoring of the environment under such applications as smart cities, industrial environment, and campus-wide level of surveillance.

KEYWORDS: Internet of Things (IoT), Environmental Monitoring, Wireless Sensor Networks, Cloud Integration, Anomaly Detection, Smart Environments.

INTRODUCTION

The heavy urbanization, industrialization, and climatic transformation has contributed to the increased demand in unremitting and consistent environmental monitoring to secure the wellbeing of citizens and regulations and sustainable growth [1]. The conventional approaches to the environmental observation that rely on sparsely located sensing stations and manual data collection are not necessarily effective to provide fined-grained and live data on dynamic environmental features, such as air quality, temperature, humidity, noise, and content of particulate matter. The recent trends in the sphere of Internet of Things (IoT) [2], wireless sensor networks, and cloud computing provided an opportunity to introduce distributed, low-cost, and scalable monitoring infrastructure that will be able to assist in high-resolution measurements of the environment and transformation of data into usable intelligence [3]. In this case, sensor networks, and cloud-based analytics do not merely offer real-time data gathering and visualization but also enable the provision of an intelligent way of analyzing such data through anomaly detection and trend analysis, which offers a feasible path of moving towards responsive and data-driven environmental management systems [4].

a) Background of the study

The traditional environmental monitoring systems have operated central and costly surveillance stations with a limited spatial view and report slowly hence inefficient in tracking the fast-evolving local environmental states [5]. It has now been possible to implement dense arrays of distributed sensing nodes with wireless sensor networks, low-power sensors, and Internet of Things (IoT) technologies [6], which can continuously collect data at both small spatial and temporal scales. Similar development of cloud computing has facilitated the provision of scalable data storage, real time processing, and high-level analytics of large amounts of heterogeneous sensor data [7]. Along with such technological advancement, most of the current environmental monitoring systems have drawbacks which include inadequate scalability, high power requirements [8], untrusty data transmission and inadequate analytical intelligence especially in applications that require resources that are scarce and those that are large in scale. The above gaps bring to light the necessity of unified IoT-enabled systems that can integrate power-efficient sensor systems together with cloud-based intelligent systems to facilitate dependable, scalable, and real-time tracking of the environment.

b) Intelligent Environmental Monitoring Using IoT

The concept of intelligent environmental monitoring with the use of the IoT can be understood as the implementation of a network of interconnected sensors that constantly gather data on the environment and use edge and cloud computing to convert raw data into actionable information. In comparison with traditional monitoring systems, where the main aim of the monitoring process is the data logging, the IoT-enabled intelligent monitoring combines the real-time data retrieval with the automated analytics, including the anomaly detection, trend identification, and alert generation [9]. Such systems can accommodate scalable, responsive, and fine-grained tracking of parameters such as air quality, temperature, humidity, noise, and particulate matter with the help of a combination of low-power sensor nodes, wireless communication, edge-level preprocessing, and cloud-based intelligence [10]. The methodology facilitates the provision of timely decision-making on environmental management, protection of the health of the populace, and compliance with regulatory compliance in addition to offering an efficient use of resources and responsiveness to the environmental demands of various dynamic environments of deployment.

c) Objectives of the study

- To develop and validate an IoT-based environmental monitoring system integrating sensor networks with cloud platforms for real-time data acquisition and visualization.
- To evaluate the energy efficiency of sensor nodes for sustainable long-term environmental monitoring.
- To assess the effectiveness of cloud-assisted intelligent analytics for anomaly detection and real-time alert generation.

REVIEW OF LITREATURE

Arabelli et al. (2024) [11]introduced a dynamic environmental monitoring system based on IoT, which combined sensor networks and the use of artificial intelligence methods to improve the interpretation of real-time information and automated alerts. In their study, distributed sensing nodes were used to measure various parameters of the environment and AI-based analytics were used to identify unnatural environmental conditions. The authors put the performance of the systems in the context of reliability and responsiveness in terms of data acquisition and revealed that intelligent processing was effectively associated with better timeliness and relevance of environmental insights. Their work, however, mostly focused on AI-driven analytics and discussed little concerning the scalability of a system and its energy efficiency in the context of a large-scale implementation, which leaves the room to further research on the topic in resource-constrained settings.

Rao et al. (2025) [12]carried out the extensive analysis of the IoT-based environmental monitoring systems, analysing the recent technological trends, the architectural designs, and the challenges related to the large-scale implementations. The paper has generalized the available literature on the sensor networks, communication protocols, cloud integration, and data analytics and identified the most important concerns that include data reliability, data latency, energy consumption, interoperability, and scalability. Among the gaps that the authors outlined, the absence of integrated edge-cloud intelligence as well as the requirement of scalable and robust architecture that could support real time monitoring could be found. Their results gave a general conceptual base of designing integrated IoT-based environmental monitoring structures.

Ficili et al. (2025) [13]discussed the complete transformation of sensor data to actionable intelligence through the application of IoT, cloud computing, and edge computing using AI-based analytics. Their work put forward a layered architecture that decentralized computation between edge nodes and cloud platforms to minimize the latency and enhance system responsiveness. The article identified the significance of the hybrid edge-cloud architectures in scalable and intelligent environmental monitoring but it was more concerned with the principles of architecture than domain-specific performance analysis.

Yu et al. (2022) [14]explored the combination of wireless sensor networks with IoT systems in smart environmental monitoring systems. Their system architecture proposed allowed distributed sensor, wireless transfer of data, and centralized data management of monitoring the environmental parameters. The authors confirmed the practicability of the integration of traditional sensor networks and the IoT communication frameworks and proved the enhancement of the connectivity of the systems and the availability of information. Although the research determined the technical feasibility of the WSN-IoT-integration, it did not offer much quantitative analysis of the latency, energy efficiency, and intelligent analytics, which necessitated more performance-related analysis in real-world implementations.

Ullo and Sinha (2020) [15]surveyed the recent developments on smart environmental monitoring systems using IoT and sensor technologies, in terms of application field, system architecture, and enabling technologies. Their work has summarized multiple environmental sensing applications (such as air and water quality monitoring) and has described how low-cost sensors and wireless communication can be used to enhance coverage of monitoring. The authors also identified the issue of scalability, data management, energy limitation as well as real-time analytics in IoT-based environment monitoring systems. The contextual background of their review provided the background of future research and the need to combine intelligent analytics and scalable cloud systems to go beyond simple data collection mechanisms.

PROPOSED METHOD

It proposed an IoT-based smart environmental monitoring system that is a combination of heterogeneous sensor networks and cloud-based analytics to allow a continuous, scalable and low-latency environmental monitoring. The system will be able to measure real-time environmental conditions (air quality, temperature, humidity, noise, and PM), send the information via a lightweight communication protocol, and conduct cloud-based analytics to identify anomalies, predict trends, and trigger alarms. The suggested approach was focused on energy efficiency on the edges, the stable transmission of data, and intelligent decision-making on the cloud level.

Below is the structure of Proposed Method shown in Figure 1.

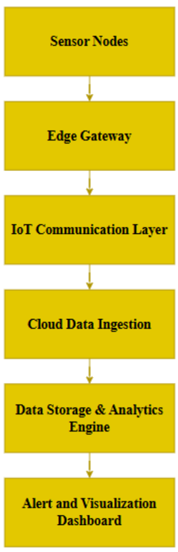

Figure 1: Block Diagram.

In this architecture, a sensor network is a wireless sensor network that consists of distributed sensor nodes that also undertakes the task of collecting data continuously. An edge gateway is used to do local preprocessing and buffering, and then forwards the data to the cloud via an IoT communication layer. The cloud layer is concerned with the scalable data ingestion, long-term data storage, smart analytics, and alerting and visualization to the user. Such hierarchy ensures modularity and fault resilience and scalability across a very large range of deployment environments such as smart cities, industrial zones, and campus.

a) System Architecture

The proposed system follows a three-layer architecture:

- **Perception Layer (Sensor Network):** Comprising of low power sensor nodes and environmental sensors that have CO_2 sensor, PM 2.5 sensor, temperature sensor, humidity sensor and noise sensor. These nodes also test the parameters of the environment in regular time intervals and perform some basic filtering to remove noise and outliers.
- **Edge Layer (Gateway and Local Processing):** A gateway node gathers data of multiple sensor nodes. It carries out a bit of light pre-processing such as a missing value processing, temporal aggregation, threshold-based anomaly filtering to reduce the redundant cloud transmissions and network congestion.
- **Cloud Layer (Storage, Analytics, and Visualization):** The data ingestion is processed by missed cloud backend via message brokers (e.g., MQTT/HTTP), scaled storage (time-series databases) and trend analysis, anomaly detection and predictive modelling analytics units. It is visualized in a web-based Dashboard that issues real-time alerts to the stakeholders.

b) Data Acquisition and Preprocessing

Sensor nodes are in the duty-cycled mode with the aim of saving energy. Each node samples its environmental parameters at regular intervals and does simple sanity tests such as range checks and reduction of noise by moving averages. Ready packets of data are transmitted to the edge gateway which performs:

- Temporal aggregation to reduce redundant transmissions
- Local buffering to handle intermittent connectivity
- Preliminary anomaly flagging based on adaptive thresholds

This reduces the volume of data sent to the cloud and ensures robustness in low-connectivity environments.

c) Communication and Cloud Integration

The system used a lightweight publish subscribe protocol of real time data streaming between the edge gateway and the cloud server. The cloud ingestion service guarantees reliability of the message delivery and timestamps are set to allow synchronization. The data is handled in a structured time-series repository to facilitate the more efficient querying, long-term trend analysis and historical comparison. The modular cloud architecture enables the horizontal scaling as more sensor nodes are deployed.

d) Intelligent Analytics and Alert Mechanism

The cloud analytics engine performs:

- **Anomaly Detection:** This is the recognition of abnormal environmental state based on statistical difference of well-known patterns of the baseline.
- **Trend Analysis:** Removes the time-related information to track the fluctuation of the environment in the long-term basis.
- **Rule-Based Alerts:** It allows the development of real-time alerts in situations when the parameters under monitoring exceed certain safety thresholds.

The dashboard and notification services spread alerts so that the authorities or system administrators can intervene in time.

Algorithm

The general system operation is based on the algorithmic workflow below in order to provide systematic data acquisition, processing, and alert generation.

Algorithm 1: IoT-Based Environmental Monitoring and Alert Generation

Input: Sensor readings from distributed nodes

Output: Real-time environmental status and alerts

```
Initialize sensor nodes and edge gateway
Initialize cloud ingestion and analytics services

While system is active do
   For each sensor node do
      Acquire environmental parameters
      Perform local noise filtering
      Transmit data to edge gateway
   End For

   At edge gateway:
      Aggregate incoming sensor data
```

```
        Handle missing values and buffer data
        If abnormal readings detected then
            Flag data packet
        End If
        Transmit processed data to cloud server

    At cloud server:
        Store incoming data in time-series
database
        Perform anomaly detection and trend
analysis
        If any parameter exceeds safety
threshold, then
            Generate alert
            Update visualization dashboard
        End If
End While
```

This algorithm supports invariance in sensing, hierarchical processing and prompt alert generation. This locating computation between edge and cloud is reducing communication overhead and responsiveness to real-time. The architectural design is easily expandable with additional advanced machine learning algorithms to predict environmental risk during work in the future.

RESULTS

This section will include the experimental outcomes of the implementation of the proposed intelligent environmental monitoring system with IoT support. The system was tested on its performance based on data transmission safety, end-to-end latency, sensor node energy efficiency, sensor detection performance and scalability when sensor density is increased. The findings indicate that the proposed architecture is viable in practice with regards to environmental monitoring applications in real time.

a) Data Transmission Reliability

The ratio of packets delivered to the network was used to calculate the communication reliability to assess it at different network loads and sensor densities. The system proposed had a high PDR because of the lightweight communication protocols and the edge-level buffering which were used.

In order to test the resiliency of the communication layer, the ratio of packets delivered was considered at different sensor densities and network traffic levels.

Table 1: Packet Delivery Ratio under Different Network Conditions.

Number of Sensor Nodes	Network Load (msg/min)
25	300
50	600
100	1200
150	1800

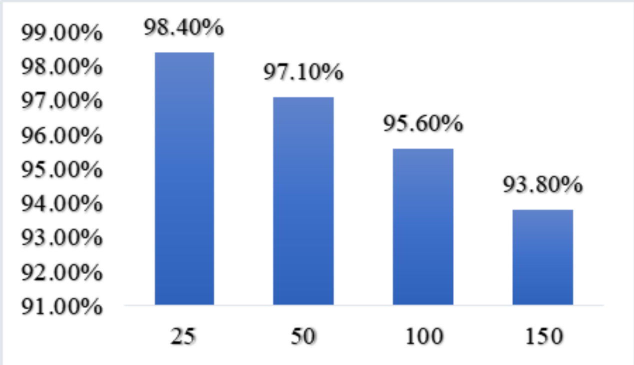

Figure 2: Packet Delivery Ratio. (%)

The findings show that the given system showed a very high packet delivery ratio in all the deployment scales of the experiment, its values were more than 93 per cent even when the network was heavily loaded. This proves the efficiency of the lightweight communication protocol and edge-level buffering strategy in reducing the lost packets during the congestion of the network. The reduction in the ratio of delivery with the increasing node density seems natural in large-scale IoT devices deployment as the channels are subjected to contention and bandwidth limitation. Nevertheless, the degradation also was controlled within acceptable operational boundaries of real-time environmental monitoring applications indicating that the proposed architecture can support consistent data transmission in small and medium-scale applications, and be reasonably robust in case of increased traffic.

b) End-to-End Latency Performance

The time difference between sensor data generation and visualization on the cloud dashboard was used as end-to-end latency. Low latency that was suitable to near real time monitoring was attained in the system.

The responsiveness of the system was evaluated using end-to-end latency, which quantifies response to sensor data generation until visualization on the cloud.

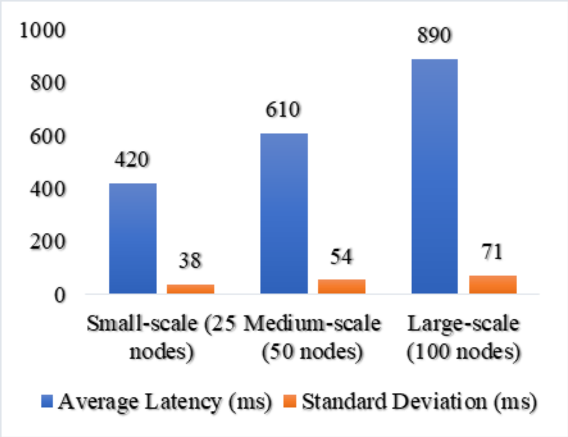

Figure 3: Average End-to-End Latency.

The latency results show that the proposed system was able to attain close real-time performance with various scales of deployment. Although there was an increase in the average latency with an increase in sensor node numbers, the delay was within 1 second even in large scale situations. This shows that the edge gateway was effective in minimizing the overhead in the processing since it does initial aggregation and filtering of data prior to sending it to the cloud. The comparatively small standard deviation of the latency also indicates that there is a stable behaviour of the system with varying workloads. This response is particularly critical when it comes to applications that are concerned with air quality alerts and environmental hazard detection as timely information delivery plays a direct role in the decision making process and the impact of the intervention.

c) Energy Efficiency of Sensor Nodes

Energy consumption was also considered in order to evaluate the viability of the long-term deployment. The edge-level preprocessing and duty-cycled sensing seriously minimized power consumption.

The sensor nodes energy efficiency was also measured to come up with the viability of long-term and unattended deployments.

Table 2: Average Energy Consumption of Sensor Nodes.

Sensing Interval (sec)	Average Current Draw (mA)	Estimated Battery Life (Days)
10	42.6	18
30	27.3	29
60	19.8	41

The experimental result of decreasing the average current draw as the sensing intervals lengthen is an indication of the usefulness of duty-cycled operation in prolonging battery life. The longer the sensing interval, the longer the estimated operational time shown by sensor nodes, which is why the proposed design will be suitable to the resource-constrained IoT environments. This is a trade-off between sensing frequency and energy consumption as the system can be scaled to meet various monitoring demands, including sensing at high frequencies, were, in critical applications, the system should be used but at lower frequencies, where the system should be used in a routine application. The findings substantiate the hypothesis that the suggested framework could be used to facilitate the implementation of long-term and sustainable environmental control without the need to constantly repair and change batteries, which is an essential demand of massive sensor network implementations.

d) Anomaly Detection and Alert Accuracy

The success of the cloud based abnormal environmental detection module was tested on simulated abnormal environmental events. The measures of detection accuracy, false positive rate and response time were obtained.

To measure the accuracy of detection and responsiveness of the alerts, the intelligent analytics module performance was evaluated with the help of simulated abnormal environmental events.

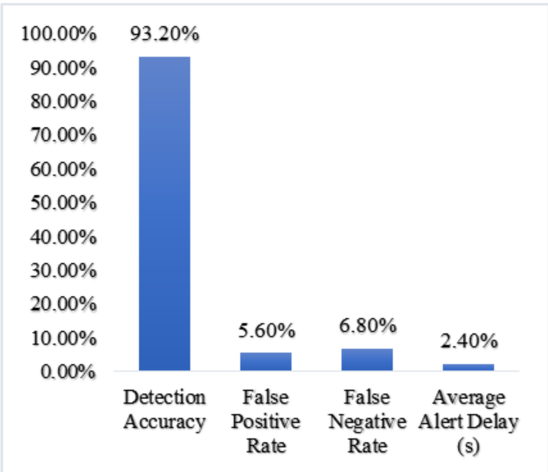

Figure 4: Anomaly Detection Performance.

The results of the anomaly detection processes prove that the suggested cloud-based analytics system showed high detection rates at a relatively low false positive level. This shows that the statistical learning method adopted could be able to differentiate the normal environmental changes and actual abnormal cases. The fact that the average delay before the alert signal goes off is low also supports the fact that the system is suitable to be used in real-time monitoring and early warning applications. The levels of false negatives have been shown to be not so high, but since these may be due to the microscopic aberrations that may strongly resemble normal fluctuations, the latter can be blamed. In general, the findings confirm the viability of the smart alarm system in terms of facilitating the intervention and preventing environmental risks in a timely manner.

e) Scalability Analysis

Scalability was measured by gradually adding sensor nodes and evaluating the utilization and ingestion of cloud resources and data.

In order to test the scalability of the system, the cloud backend was tested in increasing instances of sensor density.

Table 3: Scalability Performance under Increasing Node Density.

Number of Nodes	Data Ingestion Rate (records/sec)	Cloud CPU Utilization (%)	Memory Utilization (%)
50	35	22	31
100	78	41	48
200	146	63	67

The scalability findings show that the proposed cloud-integrated architecture was found to have almost linear growth in the capacity of data ingestion with increase in sensor node counts. Even though the system increased the usage of CPU and memory as the node density increased, it remained stable with no performance bottlenecks or loss of data. This shows that the modular cloud architecture and message-driven ingestion pipeline have the capability to scale to larger sensor networks with moderate infrastructure capabilities. These results indicate that the suggested framework can be used in large-scale applications like smart city surveillance and industrial environmental monitoring, where the population of sensing nodes can be dynamically increased as time goes on.

DISCUSSION

The results presented in this paper prove that the suggested IoT-based intelligent environmental monitoring model is successful in achieving its main goals of credible real-time sensing, low-energy use, and smart cloud-based analytics. The large ratio of packet delivery at different sensor densities is an assurance that the sensor network and communication layer is robust and thus, the combination of lightweight protocols and edge-level buffering can support solid information transmission at higher network throughputs. Equally, the persistently low end-to-end latency supports the appropriateness of the suggested architecture to the near real-time environmental surveillance, which is of high importance in the air quality monitoring and early warning systems applications. The energy usage figures also lead to underscoring the feasibility of the sensor network in practical applications, since duty-cycled operation allowed substantial increases in battery life, and the structure was practical in making the sensor network work in the long-term, unattended deployments in real world situations. In addition to that, the excellent functioning of the cloud-based anomaly detection and alerting systems proves the idea that the system will not be only passive in data collection but intelligent in its interpretation of the received data and actionable decision support, which should explain the intelligent nature of the proposed framework. Scalability Analysis The scalability analysis suggests that the cloud integration has the capability to support an increase in sensor density with a near-linear increase in data ingestion capacity, indicating that the architecture can support large scale deployments of smart cities and industrial monitoring systems. On the whole, these findings suggest that the suggested system can obtain a reasonable trade-off between reliability, responsiveness, energy efficiency, and analytical capability, as well as demonstrates that performance degradation under heavy load and the subsequent increase in resource usage at the cloud layer are feasible limitations that need to be tackled in the future research by introducing more advanced edge intelligence, adaptive sampling mechanisms, and more advanced predictive analytics models.

CONCLUSION AND FUTURE SCOPE

The paper has addressed an intelligent monitoring system of the environmental conditions based on IoT, including distributed sensor networks and cloud-based analytics in real-time monitoring of the environmental conditions. The results of the experiment have demonstrated that the proposed framework could achieve a good level of data transmission, high packet delivery rates, end to end latency sufficiently low to achieve near real time monitoring and use a energy conscious sensor operation to enable long term deployments. The fact that the cloud-based analytics is efficient in detecting anomalies correctly and providing timely alerts as well proved that the system proposed is intelligent. Besides, the scalability analysis successfully confirmed the possibility of the cloud-integrated framework to sustain sensor density increase at a fixed performance rate, which demonstrates the fact that the proposed framework can be applied in practice in the scenario of smart cities, industrial monitoring, and environmental management at the campus scale.

It can be proposed that the future efforts can be directed toward the unification of the predictive environmental risk forecasting and more advanced machine learning algorithms, adaptive edge intelligence as the dynamic sampling and detecting of local anomalies, and the introduction of more intricate security controls that should help to ensure the data integrity and privacy in large-scale IoT deployments.

REFERENCES

1. Ramani, D. R., Sujitha, B. B., & Tangade, S. (2025). Smart environmental monitoring systems: IoT and sensor-based advancements. *Environmental Monitoring Using Artificial Intelligence*, 45-60.
2. Manduva, V. C. (2020). AI-Powered Edge Computing for Environmental Monitoring: A Cloud-Integrated Approach. *International Journal of Emerging Trends in Science and Technology*, 1-21.
3. Asghar, T., Amber, K., Arqam, M., Liaqat, M., & Umer, M. (2025). AI-ENABLED IOT ARCHITECTURE FOR COMPREHENSIVE ENVIRONMENTAL MONITORING AND PREDICTION. *Spectrum of Engineering Sciences*, *3*(12), 427-437.
4. Rasoulpour, F., & Karabulut, M. (2025). Advances in wireless sensor networks for IoT-enabled environmental monitoring and sustainable resource management. *Smart City Insights*, *2*(3), 159-168.
5. Divine, I. L. O. H., Aguma, C. P., & Olagunju, A. O. (2024). Integrating AI enhanced remote sensing technologies with IOT networks for precision environmental monitoring and predicative ecosystem management. *World Journal of Advanced Research and Reviews*, *23*(02), 2156-2166.
6. Pandey, S., Chaudhary, M., & Tóth, Z. (2025). An investigation on real-time insights: enhancing process control with IoT-enabled sensor networks. *Discover Internet of Things*, *5*(1), 29.
7. Geetha, R., Suntheya, A. K., & Srikanth, G. U. (2020). Cloud integrated iot enabled sensor network security: research issues and solutions. *Wireless Personal Communications*, *113*(2), 747-771.
8. Senthilkumar, R., Venkatakrishnan, P., & Balaji, N. (2020). Intelligent based novel embedded system based IoT enabled air pollution monitoring system. *Microprocessors and Microsystems*, *77*, 103172.
9. Thakare, Y. N., Karandikar, A. M., Butram, V., Rokade, A., Wankhade, U. A., & Honade, S. (2023, December). Iot-enabled environmental intelligence: A smart monitoring system.

In *2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)* (pp. 37-42). IEEE.

10. Arya, L., Sharma, Y. K., & Kumar, R. (2023, November). Towards a greener tomorrow: IoT-enabled smart environment monitoring systems. In *2023 International Conference on Advances in Computation, Communication and Information Technology (ICAICCIT)* (pp. 1112-1117). IEEE.
11. Arabelli, R., Boddepalli, E., Buradkar, M., Goriparti, N. S., & Chakravarthi, M. K. (2024, May). IoT-enabled environmental monitoring system using AI. In *2024 international conference on advances in computing, communication and applied informatics (ACCAI)* (pp. 1-6). IEEE.
12. Rao, P. V., Khan, S. A., Paul, S., Mitra, S. P., Deb, D., Chaudhuri, A. K., & Banerjee, R. (2025). Iot-Enabled Environmental Monitoring Systems: Trends, Challenges, And Future Directions. *International Journal of Environmental Sciences*, *11*(17s), 2025.
13. Ficili, I., Giacobbe, M., Tricomi, G., &Puliafito, A. (2025). From sensors to data intelligence: Leveraging IoT, cloud, and edge computing with AI. *Sensors*, *25*(6), 1763.
14. Yu, Q., Xiong, F., & Wang, Y. (2022). Integration of wireless sensor network and IoT for smart environment monitoring system. *Journal of Interconnection Networks*, *22*(Supp02), 2143010.
15. Ullo, S. L., & Sinha, G. R. (2020). Advances in smart environment monitoring systems using IoT and sensors. *Sensors*, *20*(11), 3113.
16. Vellela, S. S., Rao, M. V., Krishna, C. V. M., Rao, T. S., & Dasthavejula, R. (2026). Piezoelectric and Shape-Memory Materials for Actuators and Energy Harvesting in Mechanical, Electronics, and Biomedical Engineering Using AI-Based Design. In Advanced Materials for Biomedical Devices (pp. 195-206). CRC Press.
17. Vellela, S. S., Anusha, P., Vullam, N. R., Jala, J., Bellapu, V. S., & Vindhya, A. S. (2025, October). Quantum Cryptography and Key Distribution for Secure Communication in the Post Quantum World. In 2025 International Conference on Sustainable Communication Networks and Application (ICSCN) (pp. 619-624). IEEE.
18. Vellela, S. S., Purimetla, N. R., Vindhya, A. S., Vullam, N. R., Srinivas, B. R., & Vuyyuru, L. R. (2025, October). Design and Simulation of Quantum Error Correction Codes for Scalable Quantum Architectures. In 2025 7th International Conference on Innovative Data Communication Technologies and Application (ICIDCA) (pp. 1570-1575). IEEE.

19. Ram, C. S., Vellela, S. S., Sravanthi Javvadi, D. V., Rashid, S. Z., & Madhumathi, S. M. (2025). Integrated Robotic–Imaging Platforms in Endovascular Surgery: Current Capabilities and Future Directions. Vascular and Endovascular Review, 8(16s), 285-298.
20. Vellela, S. S., Purimetla, N. R., Rao, P. V., Daniel, V. A. A., Koppolu, H. K. R., & Janani, B. (2025). AI-Enabled Wearable Hemodynamic Monitoring System for Early Identification of Thrombotic Events. Vascular and Endovascular Review, 8(16s), 321-336.
21. Kumar, M. S., Vellela, S. S., Gorintla, S., Malathi, N., Rao, T. S., & Rani, N. R. (2025, October). Intelligent Resource Allocation in Wireless Sensor Networks: A Hybrid Optimization Approach for Energyconstrained Environments. In 2025 2nd International Conference on Electronic Circuits and Signaling Technologies (ICECST) (pp. 724-729). IEEE.
22. Praveen, S. P., Vellela, S. S., Sharma, K., & Dalavai, L. Quantitative Evaluation of Smart Textile Adoption in Rural Weaving Communities using Machine Learning. Journal of the Textile Association, 86(3), 277-284.
23. Krishna, T. V., Rani, N. R., Ranjani, B. S., & Vellela, S. S. (2025). Distributed Big-Data Analytics with PySpark for Personalized Restaurant Recommendation Systems. Journal of Next Generation Technology (ISSN: 2583-021X), 5(6).
24. Harinadh, T., Anusha, P., Roja, D., Vellela, S. S., & Muthukumar, P. (2025). PySpark Orchestrated Machine Learning Paradigms for Advanced Network Intrusion Detection. Journal of Next Generation Technology (ISSN: 2583-021X), 5(6).
25. Vindhya, A. S., Vellela, S. S., Malathi, N., Vullam, N. R., Vuyyuru, L. R., & Rao, T. (2025, September). Integrating Quantum Computing with Genomic Data Analysis: A Next-Generation Approach for Predicting Disease Susceptibility. In 2025 4th International Conference on Innovative Mechanisms for Industry Applications (ICIMIA) (pp. 1168-1173). IEEE.
26. Vellela, S. S., Malathi, N., Vuyyuru, L. R., Javvadi, S., Rao, T. S., Bindu, M. N. H., & Rao, K. N. (2025, August). Improving Medical Image Analysis with Convolutional Neural Networks (Cnns). In 2025 International Conference on Intelligent and Secure Engineering Solutions (CISES) (pp. 579-584). IEEE.
27. Vellela, S. S., Vullam, N. R., Gorintla, S., Rao, T. S., & Harinadh, T. (2025, July). Exploring the Anti-Inflammatory Potential of Green-Synthesized Pyrazolines. In 2025 6th International Conference on Data Intelligence and Cognitive Informatics (ICDICI) (pp. 814-819). IEEE.

28. Mandava, R., Haritha, K., Vellela, S. S., Purimetla, N. R., Mohan, B. K., & Harinadh, T. (2025, June). Analysing User Perceptions of Trust in Financial Systems Using Explainable AI. In 2025 Second International Conference on Networks and Soft Computing (ICNSoC) (pp. 26-30). IEEE.
29. Mandava, R., Dalavai, L., Vellela, S. S., Purimetla, N. R., Mohan, B. K., & Harinadh, T. (2025, June). An In-Depth Study on the Integration of Explainable AI Techniques to Enhance Interpretability in Clinical Risk Prediction Models. In 2025 Second International Conference on Networks and Soft Computing (ICNSoC) (pp. 43-47). IEEE.
30. Vellela, S. S., Roja, D., Purimetla, N. R., Thalakola, S., Vuyyuru, L. R., & Vatambeti, R. (2025). Cyber threat detection in industry 4.0: Leveraging GloVe and self-attention mechanisms in BiLSTM for enhanced intrusion detection. Computers and Electrical Engineering, 124, 110368.
31. Reddy, B. V., Kumar, A. H., Gopi, C., Prasad, Y. V. D., Vellela, S. S., & Roja, D. (2025, April). Machine learning based automated liver fibrosis stage diagnosis with prediction. In 2025 International Conference on Advances in Modern Age Technologies for Health and Engineering Science (AMATHE) (pp. 1-6). IEEE.
32. Vellela, S. S., Malathi, N., Gorintla, S., Priya, K. K., Rao, T. S., Thommandru, R., & Rao, K. N. S. (2025, March). A Novel Secure and Scalable Framework for a Cloud-Based Electronic Health Record Management System. In 2025 3rd International Conference on Device Intelligence, Computing and Communication Technologies (DICCT) (pp. 131-135). IEEE.
33. Vellela, S. S., Manne, V. K., Trividha, G., Chaithanya, L., & Shaik, A. (2025). Intelligent transportation systems ai and iot for sustainable urban traffic management. Available at SSRN 5250812.
34. Vellela, S. S., Singu, K., Kakarla, L. S., Tadikonda, P., & Sattenapalli, S. N. R. (2025). NLP-Driven Summarization: Efficient Extraction of Key Information from Legal and Financial Documents. Available at SSRN 5250908.
35. Rao, M. V., Krishna, C. V. M., Vellela, S. S., Vara, J., Paul, K. J., & Rao, K. N. (2025, March). Enhancement and Blind Image Restoration for Quality Improvements of Camera Captured Pictures/Videos. In 2025 7th International Conference on Intelligent Sustainable Systems (ICISS) (pp. 791-796). IEEE.
36. Vuyyuru, L. R., Purimetla, N. R., Reddy, K. Y., Vellela, S. S., Basha, S. K., & Vatambeti, R. (2025). Advancing automated street crime detection: a drone-based system integrating

CNN models and enhanced feature selection techniques. International Journal of Machine Learning and Cybernetics, 16(2), 959-981.

37. Vullam, N. R., Geetha, G., Rao, N., Vellela, S. S., Rao, T. S., Thommandru, R., & Rao, K. N. S. (2025, February). Optimized Multitask Scheduling in Cloud Computing Using Advanced Machine Learning Techniques. In 2025 International Conference on Intelligent Control, Computing and Communications (IC3) (pp. 410-415). IEEE.
38. Vellela, S. S., & Balamanigandan, R. (2024). An efficient attack detection and prevention approach for secure WSN mobile cloud environment. Soft Computing, 28(19), 11279-11293.
39. Biyyapu, N., Veerapaneni, E. J., Surapaneni, P. P., Vellela, S. S., & Vatambeti, R. (2024). Designing a modified feature aggregation model with hybrid sampling techniques for network intrusion detection. Cluster Computing, 27(5), 5913-5931.
40. Polasi, P. K., Vellela, S. S., Narayana, J. L., Simon, J., Kapileswar, N., Prabu, R. T., & Rashed, A. N. Z. (2024). Data rates transmission, operation performance speed and figure of merit signature for various quadurature light sources under spectral and thermal effects. Journal of Optics, 1-11.
41. Vellela, S. S., Rao, M. V., Mantena, S. V., Reddy, M. J., Vatambeti, R., & Rahman, S. Z. (2024). Evaluation of Tennis Teaching Effect Using Optimized DL Model with Cloud Computing System. International Journal of Modern Education and Computer Science (IJMECS), 16(2), 16-28.
42. Vellela, S. S., & Balamanigandan, R. (2024). Optimized clustering routing framework to maintain the optimal energy status in the wsn mobile cloud environment. Multimedia Tools and Applications, 83(3), 7919-7938.
43. Vellela, S. S., & Balamanigandan, R. (2023). An intelligent sleep-awake energy management system for wireless sensor network. Peer-to-Peer Networking and Applications, 16(6), 2714-2731.
44. S. S. Vellela, L. R. Vuyyuru, S. K. Jidugu, M. P. Rao, D. B. R. Srinivas and R. D, "The Impact Of Quantum Computing On Blockchain Security And Quantum Resistant Protocols," *2025 2nd International Conference on Intelligent Systems for Cybersecurity (ISCS)*, Gurugram, India, 2025, pp. 1-6, doi: 10.1109/ISCS69371.2025.11386359.
45. S. Pakalapati, C. J. Rani, S. S. Vellela, N. Thanuja, R. D and M. N. H. Bindu, "Progressive GAN-based Framework for Realistic Image Generation and Style Transfer," *2025 5th International Conference on Evolutionary Computing and Mobile*

Sustainable Networks (ICECMSN), Coimbatore, India, 2025, pp. 474-479, doi: 10.1109/ICECMSN68058.2025.11383018.

46. D. Roja, S. K. Jidugu, T. S. Rao, L. R. Vuyyuru, S. S. Vellela and B. S. Ranjani, "High-Fidelity Image Synthesis using Enhanced Generative Adversarial Networks with Attention Mechanisms," *2025 International Conference on NexGen Networks and Cybernetics (IC2NC)*, Erode, India, 2025, pp. 885-890, doi: 10.1109/IC2NC67409.2025.11375862.
47. Rao, M. V., Sreeraman, Y., Mantena, S. V., Gundu, V., Roja, D., & Vatambeti, R. (2024). Brinjal Crop yield prediction using Shuffled shepherd optimization algorithm based ACNN-OBDLSTM model in Smart Agriculture. Journal of Integrated Science and Technology, 12(1), 710-710.
48. Mandava, R., Vellela, S. S., Gorintla, S., Dalavai, L., Malathi, N., & Haritha, K. (2025, May). Evaluating the Impact of Explainable AI on User Trust in Financial Decision-Support Systems. In 2025 International Conference on Computational Robotics, Testing and Engineering Evaluation (ICCRTEE) (pp. 1-6). IEEE.
49. Tirumanadham, N. K. M. K., Phani Praveen, S., Jyothi, V. E., Thati, B., Swamy, B. N., & Devi, D. A. (2026). CrossMF: A Memory-Augmented Transformer for Fast and Generalizable Emotion Recognition. International Journal of Pattern Recognition and Artificial Intelligence.
50. Praveen, S. P., Panguluri, P., Sirisha, U., Dewi, D. A., Kurniawan, T. B., & Efrizoni, L. (2026). Stacked LSTM with Multi Head Attention Based Model for Intrusion Detection. Journal of Applied Data Sciences, 7(1), 475-488.
51. Dhoska, K., Kyratsis, P., Dudek, M., & Surapaneni, P. P. (2025). Smart Hybrid Intrusion Detection for IoT Networks Using Machine Learning and Neural Networks. Babylonian Journal of Networking, 2025, 197-206.
52. Islam, S., Praveen, S. P., Ponnaganti, N. D., Kocharla, S., & Safie, N. (2025, November). Enhancing Network Security: Hybrid XGMB Model for Intrusion Detection with Intelligent Feature Engineering. In 2025 International Conference on Electrical Engineering and Informatics (ICEEI) (pp. 1-6). IEEE.
53. Praveen, S. P., Sravya, K., Jahnavi, K., Simha, K. S. V., Naik, M. K., & Swapna, D. (2025, June). Implementing YOLO and OCR in Product Automation for Object Detection and Text Extraction. In 2025 Second International Conference on Networks and Soft Computing (ICNSoC) (pp. 509-514). IEEE.