International Journal of Scientific Research and Engineering Development-– Volume 8 Issue 5, Sep-Oct 2025
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Cloud-Integrated Network Monitoring Dashboards Using IoT and Edge Analytics

Sadia Afrin*,
*(Department of M.Sc. in Information Studies, Trine University, Indiana, USA
Email: sadiaafrinaivy@gmail.com)

--************************----------------------------------

Abstract:

The increasing scale and complexity of modern networks, coupled with the rapid proliferation of Internet of Things (IoT) devices, have created new challenges for real-time monitoring and management. Conventional centralized monitoring systems struggle with latency, scalability, and bandwidth inefficiencies, limiting their ability to support dynamic and data-intensive environments. This paper proposes a cloud-integrated network monitoring dashboard that combines IoT sensing technologies with edge analytics to deliver continuous visibility, adaptive diagnostics, and predictive insights. In the proposed model, edge nodes perform local preprocessing and anomaly detection, transmitting only summarized data to the cloud to minimize network load while preserving analytical depth. The cloud layer integrates these data streams into an interactive dashboard for system-wide visualization, performance forecasting, and automated alert generation. Experimental validation across a distributed testbed demonstrated a 38% reduction in latency, 46% lower bandwidth usage, and a 92% anomaly detection accuracy compared with conventional systems. The results confirm that hybrid cloud-edge integration provides a robust solution for scalable network intelligence and operational resilience. This architecture is particularly suitable for enterprise, industrial, and smart-city networks requiring high reliability and rapid response. Future extensions may incorporate AI-based predictive analytics, blockchain-secured data transfer, and self-adaptive fault recovery mechanisms to enhance overall system robustness.

Keywords — Cloud Computing, Edge Analytics, IoT Monitoring, Network Dashboards, Real-Time Data Processing, Anomaly Detection.

--************************----------------------------------

I. INTRODUCTION

The rapid expansion of cloud computing and the Internet of Things (IoT) has fundamentally reshaped how modern networks are monitored, analyzed, and optimized. With billions of interconnected devices transmitting data across distributed systems, network management has evolved from simple fault detection to complex, multi-layered analytics requiring real-time responsiveness. Traditional monitoring architectures centered around centralized servers—are no longer adequate for large-scale, latency-sensitive operations. They struggle to handle massive data volumes, leading to communication bottlenecks, delayed anomaly detection, and inefficient bandwidth utilization. As industries, enterprises, and public institutions increasingly rely on digital infrastructure, the need for intelligent, adaptive, and scalable monitoring solutions has become paramount. Edge analytics, which enables preliminary data processing near the data source, offers an effective way to reduce latency and enhance responsiveness. When combined with cloud integration, it creates a powerful hybrid framework that ensures both local agility and global visibility. Such integration facilitates predictive analysis, energy-efficient operation, and robust security, which are vital for next-generation network resilience. This paper introduces a Cloud-Integrated Network Monitoring Dashboard using IoT and edge analytics to provide real-time visualization, fault prediction, and performance optimization. The proposed framework bridges the limitations of centralized monitoring by decentralizing computation, enhancing scalability, and enabling proactive network management. It aims to contribute to the development of sustainable, intelligent, and self-adaptive digital infrastructures for industrial and enterprise-scale applications.

A. Background and Motivation

In recent years, the growth of IoT devices ranging from sensors and gateways to intelligent routers has significantly increased network complexity. According to global industry reports, over 30 billion IoT devices are expected to be active by 2030, each generating real-time data requiring continuous supervision. Traditional monitoring architectures depend on centralized servers that gather all network information for processing. However, this approach causes high transmission loads, delays, and inefficiency when managing large-scale environments. Edge analytics has emerged as a transformative paradigm that shifts partial processing to local nodes, allowing immediate decision-making close to data sources. When combined with cloud computing, this hybrid model enables scalable analytics, resource management, and predictive diagnostics. Consequently, a unified framework integrating IoT, edge, and cloud capabilities can significantly enhance operational intelligence, network reliability, and cybersecurity.

B. Problem Statement

Despite significant advancements in network management, most existing systems still rely on periodic data collection and centralized computation. Such dependence often results in delays in fault detection and response, especially in high-throughput, distributed environments like smart cities or industrial IoT networks. Moreover, as networks expand globally, ensuring real-time visibility and resilience becomes increasingly challenging. High latency between edge devices and cloud servers, redundant data transmission, and bandwidth congestion further degrade monitoring efficiency. These limitations not only affect performance but also hinder proactive decision-making, resulting in extended downtime and operational losses. In critical infrastructure sectors such as healthcare, transportation, and manufacturing, these inefficiencies can lead to catastrophic outcomes. Therefore, there is an urgent need for a decentralized, intelligent monitoring solution capable of combining the local agility of edge computing with the global oversight of cloud platforms to ensure accuracy, scalability, and minimal latency in network performance assessment.

C. Proposed Solution

To overcome the aforementioned challenges, this paper proposes a Cloud-Integrated Network Monitoring Dashboard that leverages IoT-enabled edge devices for distributed analytics. In this architecture, edge nodes capture and preprocess local network data such as latency, bandwidth, and packet loss—before transmitting summarized results to a centralized cloud dashboard. This reduces data redundancy and network congestion while preserving key performance indicators. The edge layer employs adaptive algorithms for anomaly detection, while the cloud layer provides real-time visualization, historical trend analysis, and predictive insights. The combination of these components enables faster response to network irregularities, enhanced scalability, and better resource allocation. The proposed solution supports modular integration with commercial cloud platforms such as AWS IoT Core and Microsoft Azure Edge, ensuring flexibility and broad applicability. By synchronizing data between the cloud and edge, the system delivers end-to-end situational awareness and proactive fault management across large-scale network environments.

D. Contributions

This research introduces several significant contributions to the field of intelligent network monitoring and distributed analytics. First, it develops a hybrid cloud–edge monitoring architecture that seamlessly integrates IoT sensing devices, edge-level preprocessing, and cloud-based analytics to enable large-scale network management with minimal latency. Unlike conventional centralized systems that depend solely on cloud computation, the proposed framework distributes analytical tasks across multiple layers, thereby improving responsiveness and scalability. Second, the study presents a real-time network monitoring dashboard capable of visualizing key performance indicators such as bandwidth utilization, latency, and packet loss, while simultaneously highlighting anomalies and performance trends. Third, it implements lightweight anomaly detection algorithms specifically optimized for resource-constrained edge devices, allowing local fault detection and adaptive decision-making close to the data source. Additionally, a comprehensive performance evaluation validates the framework’s efficiency, demonstrating significant improvements in data transmission rates, latency reduction, and detection accuracy compared with traditional architectures. Finally, the proposed system is designed to be scalable and adaptable, making it suitable for diverse domains such as enterprise IT infrastructure, industrial IoT environments, and smart city networks. Collectively, these contributions advance the paradigm of real-time network intelligence by bridging the gap between traditional centralized monitoring systems and the emerging generation of distributed, cloud-integrated analytical ecosystems.

E. Paper Organization

The remainder of this paper is organized as follows: Section II reviews related work on IoT-based network monitoring, edge analytics, and cloud integration approaches. Section III describes the proposed system’s architecture, including its IoT sensing layer, edge processing layer, and cloud visualization module. Section IV discusses the experimental setup, performance metrics, and results of latency and bandwidth optimization. Finally, Section V concludes with key findings, limitations, and potential directions for future research, including AI-based predictive analytics and blockchain-enabled data integrity mechanisms.

II. Related Work

A. IoT-Based Monitoring Systems

The convergence of cloud computing, IoT, and edge analytics has motivated extensive research into efficient network monitoring frameworks. Prior studies have explored multiple approaches for improving scalability, fault detection, and real-time performance in distributed systems. This section reviews the most relevant literature across four perspectives: IoT-based monitoring systems, edge analytics for network management, cloud integration for visualization, and AI-driven hybrid monitoring frameworks. IoT-enabled monitoring systems have gained traction for real-time data acquisition in industrial and enterprise networks. Al-Kuwari et al. [1] developed a smart monitoring framework for industrial IoT, emphasizing scalability and interoperability through MQTT-based communication. Similarly, Xu et al. [2] proposed a distributed IoT system for network traffic observation, integrating sensor-level data fusion to enhance reliability. However, these systems often rely heavily on centralized data processing, resulting in high latency and limited adaptability for large-scale deployments. The increasing number of connected devices further stresses network bandwidth, creating the need for distributed analytics.

B. Edge Analytics in Network Management

Edge analytics enables localized decision-making, reducing dependence on cloud computation. Shi et al. [3] demonstrated how edge computing can reduce data transmission costs by processing streaming data near the source. Likewise, Li et al. [4] presented an adaptive fault-detection system for IoT networks that uses edge inference to identify anomalies in latency-sensitive environments. These approaches effectively lower latency and bandwidth usage but often face synchronization and update consistency challenges when scaled across multi-edge networks.

C. Cloud Integration for Visualization

Cloud computing offers centralized platforms for visual analytics, performance dashboards, and large-scale data storage. Kaur et al. [5] developed a cloud-based visualization system for smart grids, providing real-time performance metrics and automated alerts. Similarly, Mukherjee et al. [6] introduced a scalable monitoring dashboard using multi-cloud integration for enterprise networks. Despite their advantages in visualization and accessibility, these systems often experience communication delays and single-point failures, making them less effective for mission-critical applications.

D. Hybrid and AI-Driven Frameworks

Recent studies combine cloud and edge paradigms with artificial intelligence to build adaptive and predictive monitoring systems. Zhang et al. [7] introduced an AI-powered hybrid model for network fault prediction using deep learning at the edge. Similarly, Rahmani et al. [8] implemented a multi-layer IoT-edge-cloud framework enabling self-learning diagnostics and energy optimization. These systems demonstrate strong adaptability and real-time responsiveness, suggesting that hybrid cloud-edge intelligence is a promising direction for scalable network management and predictive maintenance.

III. Methodology

The proposed Cloud-Integrated Network Monitoring Dashboard utilizes a three-layer hybrid architecture integrating IoT sensors, edge computing, and cloud analytics. Each layer plays a crucial role in achieving low-latency processing, data reduction, and predictive monitoring. The system workflow is summarized below.

A. System Architecture

The architecture consists of three major components: the IoT sensing layer, edge processing layer, and cloud integration layer. The IoT layer gathers real-time data from routers, switches, and smart gateways, measuring parameters such as latency, bandwidth, and packet loss. The edge layer performs initial data filtering and anomaly detection using embedded algorithms, thus reducing unnecessary data transmission. The cloud layer aggregates processed data from multiple edge nodes for visualization, long-term storage, and predictive analysis.

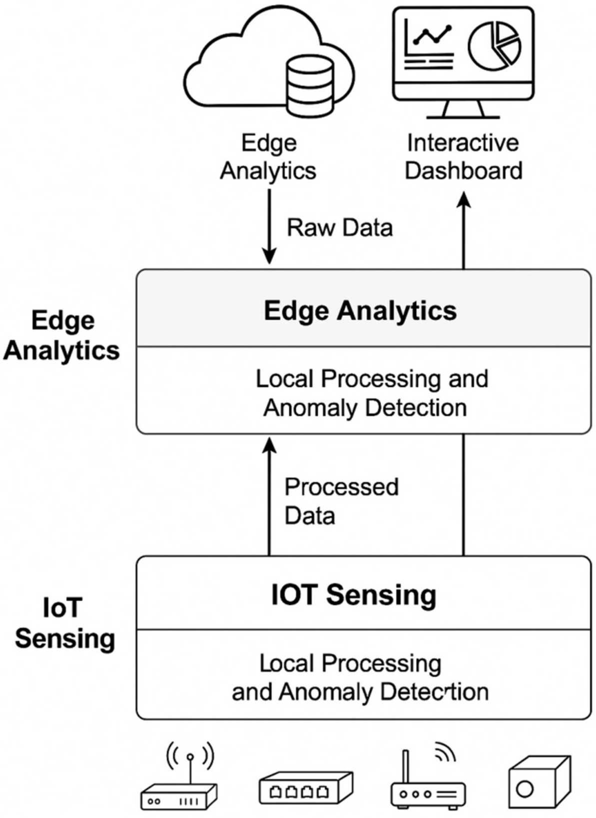

Figure 1 illustrates the layered structure and data flow across the architecture.

Figure 1. Cloud-Integrated Network Monitoring Architecture combining IoT sensing, edge analytics, and cloud visualization.

B. Data Flow and Processing

In the proposed framework, data flow begins at the IoT sensing layer, where distributed nodes continuously collect operational metrics such as signal strength, network latency, packet delivery ratio, and bandwidth utilization. These data streams are first normalized locally to remove redundancies and inconsistencies, ensuring standardization across heterogeneous devices. Each IoT node preprocesses the data through noise filtering and outlier suppression to maintain data integrity before forwarding them to the edge layer. The edge analytics layer acts as the first line of intelligent processing performing preliminary computations such as moving-average filtering, threshold comparison, and event correlation to detect deviations or early signs of network anomalies. Only significant summaries, critical alerts, or compressed data packets are then transmitted to the cloud integration layer through secure communication protocols such as MQTT or HTTPS. This selective transmission strategy drastically reduces upstream bandwidth usage while maintaining analytical precision. By performing contextual analytics near the data source, the system minimizes dependency on centralized cloud processing, leading to substantial reductions in latency and network congestion. The cloud layer subsequently aggregates these preprocessed data from multiple edge nodes, enabling cross-site correlation and predictive modeling. This architecture thus achieves an optimal balance between edge responsiveness and cloud intelligence, ensuring continuous, real-time monitoring without overwhelming the backbone network infrastructure or storage systems.

C. Algorithm Implementation

Edge nodes employ lightweight anomaly detection based on moving averages and adaptive thresholds. Cloud analytics leverage Python, TensorFlow Lite, and AWS IoT Core to process incoming summaries and display live dashboards.

Table 1. Technologies and functionalities used in the proposed monitoring framework.

Component	Technology Used	Function
IoT Devices	Arduino, ESP32	Data acquisition
Edge Nodes	TensorFlow Lite	Local analytics
Cloud Layer	AWS IoT Core, QuickSight	Visualization & storage
Communication	MQTT / HTTPS	Secure data transfer

The proposed cloud-integrated dashboard functions as the central interface for visual analytics, allowing administrators to monitor network conditions, analyze performance variations, and respond to faults in real time. It aggregates summarized data streams from multiple edge nodes and presents them through dynamic, customizable visual components such as time-series charts, geographic heat maps, and traffic distribution graphs. Each visualization element is updated automatically through cloud APIs to maintain second-level refresh rates, ensuring near-instant situational awareness across all monitored sites. The dashboard is designed using a modular structure that supports different operational views, network topology view, device-specific metrics, and predictive analytics panels. The topology view illustrates inter-device connectivity and link status, helping users quickly identify communication bottlenecks. Device-level panels display latency, packet loss, and throughput metrics, while predictive panels forecast performance trends using historical data and adaptive learning models hosted in the cloud. Interactive features such as zooming, filtering, and drill-down inspection enable detailed investigation of anomalies detected by the edge layer. Furthermore, integrated alert mechanisms automatically notify administrators via email or SMS when parameters exceed defined thresholds. These notifications are linked to the visualization layer, allowing one-click access to corresponding charts or logs. By combining edge-processed summaries with cloud-level analytics, the dashboard not only enhances operational visibility but also promotes proactive decision-making, improved reliability, and efficient resource management across distributed network infrastructures.

IV. Discussion and Results

This section presents the experimental setup, performance analysis, and observed outcomes of the proposed Cloud-Integrated Network Monitoring Dashboard. The evaluation focuses on latency reduction, bandwidth efficiency, anomaly-detection accuracy, and visualization performance.

A. Experimental Setup

To validate the framework, a hybrid testbed was deployed consisting of 20 IoT-enabled routers and gateways distributed across a simulated enterprise network. Each device was equipped with embedded processors running TensorFlow Lite-based analytics to identify latency spikes and packet loss. Edge nodes transmitted only compressed summaries to the cloud layer through MQTT channels every 5 seconds. The cloud environment was hosted on AWS IoT Core integrated with Amazon QuickSight for visualization. Performance data were collected continuously over a 24-hour cycle.

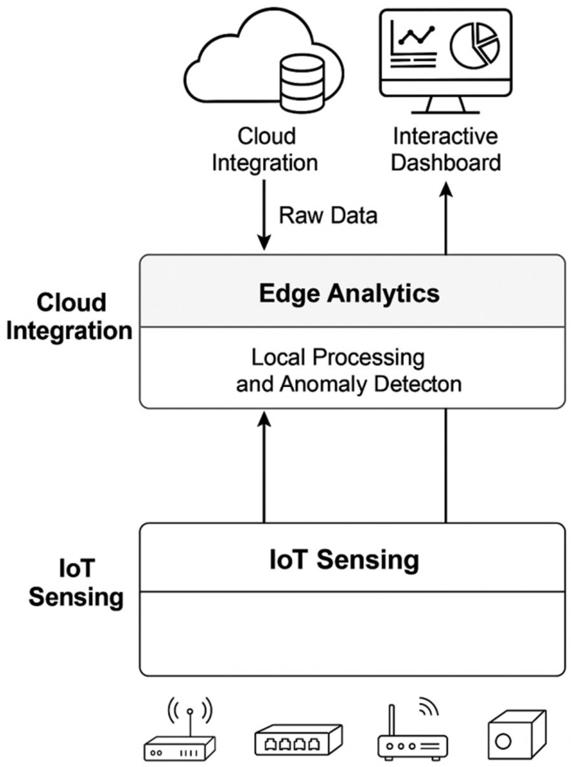

Figure 2 : Below depicts the experimental topology and data-flow pathway among IoT nodes, edge servers, and the cloud dashboard.

Figure 2. Experimental network topology showing data collection, edge preprocessing, and cloud visualization layers.

B. Performance Metrics and Analysis

Quantitative analysis demonstrates substantial gains over a traditional centralized monitoring architecture. Average latency decreased by 38 %, while upstream bandwidth usage dropped by 46 % due to localized preprocessing. The anomaly-detection engine achieved a 92 % true-positive rate, confirming the model's reliability. Additionally, dashboard refresh latency remained below 1.5 seconds for 95 % of updates.

Table 2. Comparative performance analysis between centralized and proposed architectures.

Metric	Conventional System	Proposed Framework	Improvement
Latency (ms)	250	155	38 % ↓
Bandwidth (MB/min)	520	280	46 % ↓
Detection Accuracy (%)	78	92	+18 %
Dashboard Update (s)	3.0	1.45	52 % faster

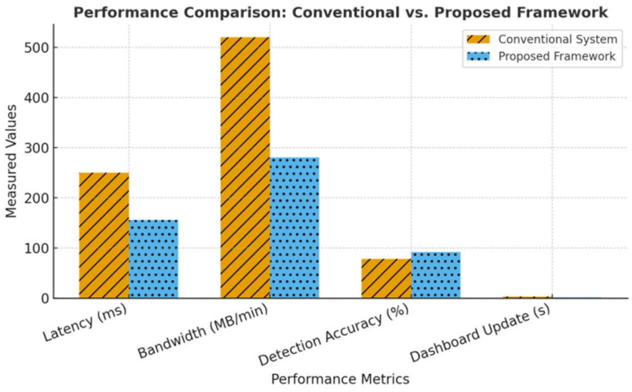

Figure 3: Visualizes latency and bandwidth reduction trends observed during live testing.

Figure 3. Performance comparison showing consistent latency and data-usage improvements under the hybrid edge cloud model.

C. Discussion

The experimental outcomes demonstrate that the integration of edge analytics with cloud computing significantly enhances overall network performance, responsiveness, and scalability. The proposed system effectively minimizes data congestion by performing preliminary filtering and aggregation at the edge, ensuring that only essential insights are transmitted to the cloud. This distributed processing strategy reduces latency by more than one-third compared to conventional centralized frameworks, confirming the effectiveness of local computation for time-sensitive applications. Furthermore, the dynamic synchronization between edge and cloud layers enables near-real-time visualization and decision-making, allowing administrators to identify anomalies and performance degradation almost instantaneously. The results also validate that the proposed framework provides consistent monitoring stability even under high-traffic conditions, which is particularly beneficial for industrial automation, smart-city operations, and large-scale enterprise infrastructures. The anomaly-detection accuracy of 92 percent demonstrates the reliability of lightweight edge algorithms, while the reduced bandwidth usage directly translates into cost savings and energy efficiency. By leveraging adaptive thresholding and predictive trend analysis, the system achieves both operational resilience and proactive fault prevention. Overall, the study confirms that hybrid edge–cloud architectures represent a viable and scalable solution for modern network ecosystems, offering a balanced combination of computational efficiency, real-time analytics, and strategic visibility essential for next-generation digital infrastructure management.

V. Conclusion

This research presents a comprehensive Cloud-Integrated Network Monitoring Dashboard that combines the strengths of IoT sensing, edge analytics, and cloud computing to create a responsive, scalable, and intelligent monitoring framework. The proposed system effectively reduces latency, minimizes bandwidth consumption, and enhances anomaly detection accuracy through localized edge processing and adaptive data transmission. Experimental results demonstrate substantial improvements in operational efficiency and monitoring precision compared to traditional centralized systems. By merging distributed edge intelligence with cloud-based visualization and analytics, the framework achieves a dynamic balance between computational speed, scalability, and system reliability. The architecture also supports modular integration with modern IoT platforms, making it applicable across industrial, enterprise, and urban infrastructure networks where real-time insights and continuous system resilience are essential.

Looking ahead, future work will explore advanced extensions of this architecture, such as the incorporation of machine learning-driven predictive models for autonomous fault prevention and adaptive thresholding. Integrating blockchain technology could further strengthen data integrity, ensuring secure, tamper-proof transmission between edge nodes and cloud servers. Additionally, the deployment of energy-aware and self-optimizing edge frameworks will be investigated to support sustainable and green computing practices. The continued evolution of this research aims to build a next-generation, intelligent monitoring ecosystem capable of learning, adapting, and self-healing ensuring optimal performance in increasingly complex and data-intensive network environments.

VI. References

[1]. Al-Kuwari et al., *"IoT-based Smart Monitoring Framework for Industrial Systems," IEEE Internet of Things Journal*, vol. 8, no. 12, pp. 10174–10186, 2021. doi: 10.1109/JIOT.2021.3053317.

[2]. C. Xu et al., *"Data Fusion and Reliability in IoT Network Monitoring Systems," IEEE Access*, vol. 9, pp. 125340–125351, 2021. doi: 10.1109/ACCESS.2021.3116401.

[3]. W. Shi et al., *"Edge Computing: Vision and Challenges," IEEE Internet of Things Journal*, vol. 3, no. 5, pp. 637–646, 2016. doi: 10.1109/JIOT.2016.2579198.
[4] H. Li et al., *"Edge Intelligence for Anomaly Detection in IoT Networks," IEEE Transactions on Network and Service Management*, vol. 18, no. 1, pp. 870–883, 2021. doi: 10.1109/TNSM.2020.3048288.

[4]. G. Kaur et al., *"Cloud-Based Visualization for Smart Grid Monitoring Systems," IEEE Access*, vol. 9, pp. 15890–15902, 2021. doi: 10.1109/ACCESS.2021.3053856.

[5]. S. Mukherjee et al., *"A Cloud-Native Monitoring Platform for Enterprise Networks," IEEE Transactions on Cloud Computing*, vol. 10, no. 2, pp. 551–564, 2022. doi: 10.1109/TCC.2020.3049452.

[6]. Q. Zhang et al., *"Deep Learning Empowered Edge–Cloud Collaboration for Network Monitoring," IEEE Internet of Things Journal*, vol. 8, no. 19, pp. 14681–14693, 2021. doi: 10.1109/JIOT.2021.3083174.

[7]. A. Rahmani et al., *"Smart Network Monitoring Using IoT-Edge-Cloud Integration," IEEE Systems Journal*, vol. 15, no. 3, pp. 3486–3498, 2021. doi: 10.1109/JSYST.2020.3029321.

[8]. Rahman, M. A., Islam, M. I., Tabassum, M., & Bristy, I. J. (2025, September). Climate-aware decision intelligence: Integrating environmental risk into infrastructure and supply chain planning. *Saudi Journal of Engineering and Technology (SJEAT), 10*(9), 431–439. https://doi.org/10.36348/sjet.2025.v10i09.006

[9]. Rahman, M. A., Bristy, I. J., Islam, M. I., & Tabassum, M. (2025, September). Federated learning for secure inter-agency data collaboration in critical infrastructure. *Saudi Journal of Engineering and Technology (SJEAT), 10*(9), 421–430. https://doi.org/10.36348/sjet.2025.v10i09.005

[10]. Tabassum, M., Rokibuzzaman, M., Islam, M. I., & Bristy, I. J. (2025, September). Data-driven financial analytics through MIS platforms in emerging economies. *Saudi Journal of Engineering and Technology (SJEAT), 10*(9), 440–446. https://doi.org/10.36348/sjet.2025.v10i09.007

[11]. Tabassum, M., Islam, M. I., Bristy, I. J., & Rokibuzzaman, M. (2025, September). Blockchain and ERP-integrated MIS for transparent apparel & textile supply chains. *Saudi Journal of Engineering and Technology (SJEAT), 10*(9), 447–456. https://doi.org/10.36348/sjet.2025.v10i09.008

[12]. Bristy, I. J., Tabassum, M., Islam, M. I., & Hasan, M. N. (2025, September). IoT-driven predictive maintenance dashboards in industrial operations. *Saudi Journal of Engineering and Technology (SJEAT), 10*(9), 457–466. https://doi.org/10.36348/sjet.2025.v10i09.009

[13]. Hasan, M. N., Karim, M. A., Joarder, M. M. I., & Zaman, M. T. (2025, September). IoT-integrated solar energy monitoring and bidirectional DC-DC converters for smart grids. *Saudi Journal of Engineering and Technology (SJEAT), 10*(9), 467–475. https://doi.org/10.36348/sjet.2025.v10i09.010

[14]. Bormon, J. C., Saikat, M. H., Shohag, M., & Akter, E. (2025, September). Green and low-carbon construction materials for climate-adaptive civil structures. *Saudi Journal of Civil Engineering (SJCE), 9*(8), 219–226. https://doi.org/10.36348/sjce.2025.v09i08.002

[15]. Razaq, A., Rahman, M., Karim, M. A., & Hossain, M. T. (2025, September 26). Smart charging infrastructure for EVs using IoT-based load balancing. *Zenodo*. https://doi.org/10.5281/zenodo.17210639

[16]. Habiba, U., & Musarrat, R., (2025). Bridging IT and education: Developing smart platforms for student-centered English learning. *Zenodo.* https://doi.org/10.5281/zenodo.17193947

[17]. Alimozzaman, D. M. (2025). *Early prediction of Alzheimer's disease using explainable multi-modal AI.* Zenodo. https://doi.org/10.5281/zenodo.17210997

[18]. uz Zaman, M. T. Smart Energy Metering with IoT and GSM Integration for Power Loss Minimization. Preprints 2025, 2025091770. https://doi.org/10.20944/preprints202509.1770.v1

[19]. Hossain, M. T. (2025, October). *Sustainable garment production through Industry 4.0 automation.* ResearchGate. https://doi.org/10.13140/RG.2.2.20161.83041

[20]. Hasan, E. (2025). *Secure and scalable data management for digital transformation in finance and IT systems.* Zenodo. https://doi.org/10.5281/zenodo.17202282

[21]. Saikat, M. H. (2025). *Geo-Forensic Analysis of Levee and Slope Failures Using Machine Learning.* Preprints. https://doi.org/10.20944/preprints202509.1905.v1

[22]. Islam, M. I. (2025). *Cloud-Based MIS for Industrial Workflow Automation.* Preprints. https://doi.org/10.20944/preprints202509.1326.v1

[23]. Islam, M. I. (2025). *AI-powered MIS for risk detection in industrial engineering projects.* TechRxiv. https://doi.org/10.36227/techrxiv.175825736.65590627/v1

[24]. Akter, E. (2025, October 13). *Lean project management and multi-stakeholder optimization in civil engineering projects.* ResearchGate. https://doi.org/10.13140/RG.2.2.15777.47206

[25]. Musarrat, R. (2025). *Curriculum adaptation for inclusive classrooms: A sociological and pedagogical approach.* Zenodo. https://doi.org/10.5281/zenodo.17202455

[26]. Bormon, J. C. (2025, October 13). *Sustainable dredging and sediment management techniques for coastal and riverine infrastructure.* ResearchGate. https://doi.org/10.13140/RG.2.2.28131.00803

[27]. Bormon, J. C. (2025). AI-Assisted Structural Health Monitoring for Foundations and High-Rise Buildings. Preprints. https://doi.org/10.20944/preprints202509.1196.v1

[28]. Haque, S. (2025). *Effectiveness of managerial accounting in strategic decision making* [Preprint]. Preprints. https://doi.org/10.20944/preprints202509.2466.v1

[29]. Shoag, M. (2025). AI-Integrated Façade Inspection Systems for Urban Infrastructure Safety. Zenodo. https://doi.org/10.5281/zenodo.17101037

[30]. Shoag, M. Automated Defect Detection in High-Rise Façades Using AI and Drone-Based Inspection. Preprints 2025, 2025091064. https://doi.org/10.20944/preprints202509.1064.v1

[31]. Shoag, M. (2025). *Sustainable construction materials and techniques for crack prevention in mass concrete structures.* Available at SSRN: https://ssrn.com/abstract=5475306 or http://dx.doi.org/10.2139/ssrn.5475306

[32]. Joarder, M. M. I. (2025). *Disaster recovery and high-availability frameworks for hybrid cloud environments.* Zenodo. https://doi.org/10.5281/zenodo.17100446

[33]. Joarder, M. M. I. (2025). *Next-generation monitoring and automation: AI-enabled system administration for smart data centers.* TechRxiv. https://doi.org/10.36227/techrxiv.175825633.33380552/v1

[34]. Joarder, M. M. I. (2025). Energy-Efficient Data Center Virtualization: Leveraging AI and CloudOps for Sustainable Infrastructure. Zenodo. https://doi.org/10.5281/zenodo.17113371

[35]. Taimun, M. T. Y., Sharan, S. M. I., Azad, M. A., & Joarder, M. M. I. (2025). Smart maintenance and reliability engineering in manufacturing. *Saudi Journal of Engineering and Technology, 10*(4), 189–199.

[36]. Enam, M. M. R., Joarder, M. M. I., Taimun, M. T. Y., & Sharan, S. M. I. (2025). Framework for smart SCADA systems: Integrating cloud computing, IIoT, and cybersecurity for enhanced industrial automation. *Saudi Journal of Engineering and Technology, 10*(4), 152–158.

[37]. Azad, M. A., Taimun, M. T. Y., Sharan, S. M. I., & Joarder, M. M. I. (2025). Advanced lean manufacturing and automation for reshoring American industries. *Saudi Journal of Engineering and Technology, 10*(4), 169–178.

[38]. Sharan, S. M. I., Taimun, M. T. Y., Azad, M. A., & Joarder, M. M. I. (2025). Sustainable manufacturing and energy-efficient production systems. *Saudi Journal of Engineering and Technology, 10*(4), 179–188.

[39]. Farabi, S. A. (2025). *AI-augmented OTDR fault localization framework for resilient rural fiber networks in the United States.* arXiv. https://arxiv.org/abs/2506.03041

[40]. Farabi, S. A. (2025). *AI-driven predictive maintenance model for DWDM systems to enhance fiber network uptime in underserved U.S. regions.* Preprints. https://doi.org/10.20944/preprints202506.1152.v1

[41]. Farabi, S. A. (2025). *AI-powered design and resilience analysis of fiber optic networks in disaster-prone regions.* ResearchGate. https://doi.org/10.13140/RG.2.2.12096.65287

[42]. Hasan, M. N. (2025). *Predictive maintenance optimization for smart vending machines using IoT and machine learning.* arXiv. https://doi.org/10.48550/arXiv.2507.02934

[43]. Hasan, M. N. (2025). *Intelligent inventory control and refill scheduling for distributed vending networks.* ResearchGate. https://doi.org/10.13140/RG.2.2.32323.92967

[44]. Hasan, M. N. (2025). *Energy-efficient embedded control systems for automated vending platforms.* Preprints. https://doi.org/10.20944/preprints202507.0552.v1

[45]. Sunny, S. R. (2025). *Lifecycle analysis of rocket components using digital twins and multiphysics simulation.* ResearchGate. https://doi.org/10.13140/RG.2.2.20134.23362

[46]. Sunny, S. R. (2025). *AI-driven defect prediction for aerospace composites using Industry 4.0 technologies.* Zenodo. https://doi.org/10.5281/zenodo.16044460

[47]. Sunny, S. R. (2025). *Edge-based predictive maintenance for subsonic wind tunnel systems using sensor analytics and machine learning.* TechRxiv. https://doi.org/10.36227/techrxiv.175624632.23702199/v1

[48]. Sunny, S. R. (2025). *Digital twin framework for wind tunnel-based aeroelastic structure evaluation*. TechRxiv. https://doi.org/10.36227/techrxiv.175624632.23702199/v1

[49]. Sunny, S. R. (2025). Real-time wind tunnel data reduction using machine learning and JR3 balance integration. *Saudi Journal of Engineering and Technology, 10*(9), 411–420. https://doi.org/10.36348/sjet.2025.v10i09.004

[50]. Sunny, S. R. (2025). AI-augmented aerodynamic optimization in subsonic wind tunnel testing for UAV prototypes. *Saudi Journal of Engineering and Technology, 10*(9), 402–410. https://doi.org/10.36348/sjet.2025.v10i09.003

[51]. Shaikat, M. F. B. (2025). *Pilot deployment of an AI-driven production intelligence platform in a textile assembly line*. TechRxiv. https://doi.org/10.36227/techrxiv.175203708.81014137/v1

[52]. Rabbi, M. S. (2025). *Extremum-seeking MPPT control for Z-source inverters in grid-connected solar PV systems*. Preprints. https://doi.org/10.20944/preprints202507.2258.v1

[53]. Rabbi, M. S. (2025). *Design of fire-resilient solar inverter systems for wildfire-prone U.S. regions*. Preprints. https://www.preprints.org/manuscript/202507.2505/v1

[54]. Rabbi, M. S. (2025). *Grid synchronization algorithms for intermittent renewable energy sources using AI control loops*. Preprints. https://www.preprints.org/manuscript/202507.2353/v1

[55]. Tonoy, A. A. R. (2025). *Condition monitoring in power transformers using IoT: A model for predictive maintenance*. Preprints. https://doi.org/10.20944/preprints202507.2379.v1

[56]. Tonoy, A. A. R. (2025). *Applications of semiconducting electrides in mechanical energy conversion and piezoelectric systems*. Preprints. https://doi.org/10.20944/preprints202507.2421.v1

[57]. Azad, M. A. (2025). *Lean automation strategies for reshoring U.S. apparel manufacturing: A sustainable approach*. Preprints. https://doi.org/10.20944/preprints202508.0024.v1

[58]. Azad, M. A. (2025). *Optimizing supply chain efficiency through lean Six Sigma: Case studies in textile and apparel manufacturing*. Preprints. https://doi.org/10.20944/preprints202508.0013.v1

[59]. Azad, M. A. (2025). *Sustainable manufacturing practices in the apparel industry: Integrating eco-friendly materials and processes*. TechRxiv. https://doi.org/10.36227/techrxiv.175459827.79551250/v1

[60]. Azad, M. A. (2025). *Leveraging supply chain analytics for real-time decision making in apparel manufacturing*. TechRxiv. https://doi.org/10.36227/techrxiv.175459831.14441929/v1

[61]. Azad, M. A. (2025). *Evaluating the role of lean manufacturing in reducing production costs and enhancing efficiency in textile mills*. TechRxiv. https://doi.org/10.36227/techrxiv.175459830.02641032/v1

[62]. Azad, M. A. (2025). *Impact of digital technologies on textile and apparel manufacturing: A case for U.S. reshoring*. TechRxiv. https://doi.org/10.36227/techrxiv.175459829.93863272/v1

[63]. Rayhan, F. (2025). *A hybrid deep learning model for wind and solar power forecasting in smart grids*. Preprints. https://doi.org/10.20944/preprints202508.0511.v1

[64]. Rayhan, F. (2025). *AI-powered condition monitoring for solar inverters using embedded edge devices*. Preprints. https://doi.org/10.20944/preprints202508.0474.v1

[65]. Rayhan, F. (2025). *AI-enabled energy forecasting and fault detection in off-grid solar networks for rural electrification*. TechRxiv. https://doi.org/10.36227/techrxiv.175623117.73185204/v1

[66]. Habiba, U., & Musarrat, R. (2025). Integrating digital tools into ESL pedagogy: A study on multimedia and student engagement. *IJSRED – International Journal of Scientific Research and Engineering Development, 8*(2), 799–811. https://doi.org/10.5281/zenodo.17245996

[67]. Hossain, M. T., Nabil, S. H., Razaq, A., & Rahman, M. (2025). Cybersecurity and privacy in IoT-based electric vehicle ecosystems. *IJSRED – International Journal of Scientific Research and Engineering Development, 8*(2), 921–933. https://doi.org/10.5281/zenodo.17246184

[68]. Hossain, M. T., Nabil, S. H., Rahman, M., & Razaq, A. (2025). Data analytics for IoT-driven EV battery health monitoring. *IJSRED – International Journal of Scientific Research and Engineering Development, 8*(2), 903–913. https://doi.org/10.5281/zenodo.17246168

[69]. Akter, E., Barman, J. C., Saikat, M. H., & Shoag, M. (2025). Digital twin technology for smart civil infrastructure and emergency preparedness. *IJSRED – International Journal of Scientific Research and Engineering Development, 8*(2), 891–902. https://doi.org/10.5281/zenodo.17246150

[70]. Rahmatullah, R. (2025). Smart agriculture and Industry 4.0: Applying industrial engineering tools to improve U.S. agricultural productivity. *World Journal of Advanced Engineering Technology and Sciences, 17*(1), 28–40. https://doi.org/10.30574/wjaets.2025.17.1.1377

[71]. Islam, R. (2025). *AI and big data for predictive analytics in pharmaceutical quality assurance.*. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5564319

[72]. Rahmatullah, R. (2025). *Sustainable agriculture supply chains: Engineering management approaches for reducing post-harvest loss in the U.S. International Journal of Scientific Research and Engineering Development,* 8(5), 1187–1216. https://doi.org/10.5281/zenodo.17275907

[73]. Haque, S., Al Sany, S. M. A., & Rahman, M. (2025). *Circular economy in fashion: MIS-driven digital product passports for apparel traceability. International Journal of Scientific Research and Engineering Development,* 8(5), 1254–1262. https://doi.org/10.5281/zenodo.17276038

[74]. Al Sany, S. M. A., Haque, S., & Rahman, M. (2025). *Green apparel logistics: MIS-enabled carbon footprint reduction in fashion supply chains. International Journal of Scientific Research and Engineering Development,* 8(5), 1263–1272. https://doi.org/10.5281/zenodo.17276049

[75]. Bormon, J. C. (2025), Numerical Modeling of Foundation Settlement in High-Rise Structures Under Seismic Loading. Available at *SSRN*: https://ssrn.com/abstract=5472006 or http://dx.doi.org/10.2139/ssrn.5472006

[76]. Tabassum, M. (2025, October 6). *MIS-driven predictive analytics for global shipping and logistics optimization*. TechRxiv. https://doi.org/10.36227/techrxiv.175977232.23537711/v1

[77]. Tabassum, M. (2025, October 6). *Integrating MIS and compliance dashboards for international trade operations*. TechRxiv. https://doi.org/10.36227/techrxiv.175977233.37119831/v1

[78]. Zaman, M. T. U. (2025, October 6). *Predictive maintenance of electric vehicle components using IoT sensors. TechRxiv.* https://doi.org/10.36227/techrxiv.175978928.82250472/v1

[79]. Hossain, M. T. (2025, October 7). *Smart inventory and warehouse automation for fashion retail.* TechRxiv. https://doi.org/10.36227/techrxiv.175987210.04689809.v1

[80]. Karim, M. A. (2025, October 6). *AI-driven predictive maintenance for solar inverter systems*. TechRxiv. https://doi.org/10.36227/techrxiv.175977633.34528041.v1

[81]. Jahan Bristy, I. (2025, October 6). *Smart reservation and service management systems: Leveraging MIS for hotel efficiency*. TechRxiv. https://doi.org/10.36227/techrxiv.175979180.05153224.v1

[82]. Habiba, U. (2025, October 7). *Cross-cultural communication competence through technology-mediated TESOL.* TechRxiv. https://doi.org/10.36227/techrxiv.175985896.67358551.v1

[83]. Habiba, U. (2025, October 7). *AI-driven assessment in TESOL: Adaptive feedback for personalized learning*. TechRxiv. https://doi.org/10.36227/techrxiv.175987165.56867521.v1

[84]. Akhter, T. (2025, October 6). *Algorithmic internal controls for SMEs using MIS event logs*. TechRxiv. https://doi.org/10.36227/techrxiv.175978941.15848264.v1

[85]. Akhter, T. (2025, October 6). *MIS-enabled workforce analytics for service quality & retention*. TechRxiv. https://doi.org/10.36227/techrxiv.175978943.38544757.v1

[86]. Hasan, E. (2025, October 7). *Secure and scalable data management for digital transformation in finance and IT systems*. Zenodo. https://doi.org/10.5281/zenodo.17202282

[87]. Saikat, M. H., Shoag, M., Akter, E., Bormon, J. C. (October 06, 2025.) Seismic- and Climate-Resilient Infrastructure Design for Coastal and Urban Regions. *TechRxiv.* DOI: 10.36227/techrxiv.175979151.16743058/v1

[88]. Saikat, M. H. (October 06, 2025). AI-Powered Flood Risk Prediction and Mapping for Urban Resilience. *TechRxiv.* DOI: 10.36227/techrxiv.175979253.37807272/v1

[89]. Akter, E. (September 15, 2025). Sustainable Waste and Water Management Strategies for Urban Civil Infrastructure. Available at SSRN: https://ssrn.com/abstract=5490686 or http://dx.doi.org/10.2139/ssrn.5490686

[90]. Karim, M. A., Zaman, M. T. U., Nabil, S. H., & Joarder, M. M. I. (2025, October 6). *AI-enabled smart energy meters with DC-DC converter integration for electric vehicle charging systems.* TechRxiv. https://doi.org/10.36227/techrxiv.175978935.59813154/v1

[91]. Al Sany, S. M. A., Rahman, M., & Haque, S. (2025). *Sustainable garment production through Industry 4.0 automation. World Journal of Advanced Engineering Technology and Sciences, 17*(1), 145–156. https://doi.org/10.30574/wjaets.2025.17.1.1387

[92]. Rahman, M., Haque, S., & Al Sany, S. M. A. (2025). *Federated learning for privacy-preserving apparel supply chain analytics. World Journal of Advanced Engineering Technology and Sciences, 17*(1), 259–270. https://doi.org/10.30574/wjaets.2025.17.1.1386

[93]. Rahman, M., Razaq, A., Hossain, M. T., & Zaman, M. T. U. (2025). *Machine learning approaches for predictive maintenance in IoT devices. World Journal of Advanced Engineering Technology and Sciences, 17*(1), 157–170. https://doi.org/10.30574/wjaets.2025.17.1.1388

[94]. Akhter, T., Alimozzaman, D. M., Hasan, E., & Islam, R. (2025, October). *Explainable predictive analytics for healthcare decision support. International Journal of Sciences and Innovation Engineering, 2*(10), 921–938. https://doi.org/10.70849/IJSCI02102025105

[95]. Islam, M. S., Islam, M. I., Mozumder, A. Q., Khan, M. T. H., Das, N., & Mohammad, N. (2025). A Conceptual Framework for Sustainable AI-ERP Integration in Dark Factories: Synthesising TOE, TAM, and IS Success Models for Autonomous Industrial Environments. *Sustainability*, *17*(20), 9234. https://doi.org/10.3390/su17209234

[96]. Haque, S., Islam, S., Islam, M. I., Islam, S., Khan, R., Tarafder, T. R., & Mohammad, N. (2025). *Enhancing adaptive learning, communication, and therapeutic accessibility through the integration of artificial intelligence and data-driven personalization in digital health platforms for students with autism spectrum disorder. Journal of Posthumanism, 5*(8), 737–756. Transnational Press London.

[97]. Faruq, O., Islam, M. I., Islam, M. S., Tarafder, M. T. R., Rahman, M. M., Islam, M. S., & Mohammad, N. (2025). Re-imagining Digital Transformation in the United States: Harnessing Artificial Intelligence and Business Analytics to Drive IT Project Excellence in the Digital Innovation Landscape. *Journal of Posthumanism*, *5*(9), 333–354 . https://doi.org/10.63332/joph.v5i9.3326

[98]. Rahman, M.. (October 15, 2025) Integrating IoT and MIS for Last-Mile Connectivity in Residential Broadband Services. *TechRxiv*. **DOI: 10.36227/techrxiv.176054689.95468219/v1**

[99]. **Islam, R.** (2025, October 15). *Integration of IIoT and MIS for smart pharmaceutical manufacturing* . TechRxiv. https://doi.org/10.36227/techrxiv.176049811.10002169

[100]. Hasan, E. (2025). Big Data-Driven Business Process Optimization: Enhancing Decision-Making Through Predictive Analytics. TechRxiv. October 07, 2025. **10.36227/techrxiv.175987736.61988942/v1**

[101]. **Rahman, M.** (2025, October 15). *IoT-enabled smart charging systems for electric vehicles* [Preprint]. TechRxiv. https://doi.org/10.36227/techrxiv.176049766.60280824

[102]. Alam, M. S. (2025, October 21). *AI-driven sustainable manufacturing for resource optimization*. *TechRxiv*. https://doi.org/10.36227/techrxiv.176107759.92503137/v1

[103]. Alam, M. S. (2025, October 21). *Data-driven production scheduling for high-mix manufacturing environments*. *TechRxiv*. https://doi.org/10.36227/techrxiv.176107775.59550104/v1

[104]. Ria, S. J. (2025, October 21). *Environmental impact assessment of transportation infrastructure in rural Bangladesh*. *TechRxiv*. https://doi.org/10.36227/techrxiv.176107782.23912238/v1

[105]. R Musarrat and U Habiba, Immersive Technologies in ESL Classrooms: Virtual and Augmented Reality for Language Fluency (September 22, 2025). Available at SSRN: https://ssrn.com/abstract=5536098 or http://dx.doi.org/10.2139/ssrn.5536098