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Edge Computing and AI Integration for Low-Latency Decision-Making in Smart Cities and Industrial IoT

Subhash Chand Agrawal[1], Avinash Gudimetla[2], Samundeeswari K[3], Sameera Khan[4], Dr. Ravi Thangjam[5], Gajanan Chavan[6], Kumari Shipra[7], Dr.N.Neelima[8]

[1]Department of Computer Engineering & Applications, GLA University, Mathura, Email: subhash.agrawal@gla.ac.in

[2]Associate Professor, Department of Mechanical Engineering, Pragati Engineering College, ADB Road, Surampalem, Near Peddapuram, Kakinada District, Andhra Pradesh, India – 533437, Email: avinashdattu1@gmail.com

[3]Assistant Professor, Department of Commerce, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, Email: kscommerce@maher.ac.in

[4]Assistant Professor, Departmentof Information Technology, Vardhaman College of Engineering, Shamshabad, Hyderabad, India - 501 218, Email: sameera1542@vardhaman.org

[5]Professor, School of Business, Aditya University, Surampalem, Andhra Pradesh, Pin 533437, Email: provc_sp@adityauniversity.in

[6]Assistant Professor, E&TC Engineering, Vishwakarma Institute of Technology, Pune, Maharashtra, 411037
Email: gajanan.chavan@vit.edu

[7]School of Engineering &Technology,Noida international University, Uttar Pradesh 203201, India, Email: kumari.shipra@niu.edu.in

[8]Associate professor, Dept of CSE, KL University ,Kolanukonda, Andhra Pradesh, India. Email: gandhamneelu@gmail.com

Abstract

The growing pace of smart cities and Industrial Internet of Things (IIoT) systems has amplified the need of smart low-latency decision-making systems with the capacity to handle extensive heterogeneous data volumes in real time. Traditional cloud-based systems typically experience communication latency problems, bandwidth constraints, and scaling issues, which adversely impact time-constrained applications like smart traffic management, industrial control, environmental sensors, as well as predictive maintenance. To overcome such drawbacks, this paper offers a combined Edge Computing and Artificial Intelligence (AI)-driven architecture to make low-latency decisions in small cities and industrial Internet of Things (IoT). The design presented is a hybrid of distributed edge nodes, localized AI inference engines, and cloud-assisted coordination aimed at assisting quick data processing on the proximity of the source device. The model of real-time anomaly detection and predictive analytics is a hybrid deep learning model consisting of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. Simulated smart city and industrial IoT data was experimentally evaluated with different network conditions. The proscribed framework was found to have 97.1% decision accuracy, latency of 61.8, and 34.5% better energy efficiency than the traditional cloud systems. The strongness and steadiness of the proposed framework was statistically approved on the 10-fold cross-validation. The findings reveal that edge-AI integration is an effective and scalable solution to next-generation intelligent infrastructures.

Keywords: Edge Computing, Artificial Intelligence, Smart Cities, Industrial IoT, Low-Latency Systems, Edge AI, Deep Learning, Real-Time Analytics

1. Introduction

The fast development of Internet of Things (IoT) technologies has altered the concept of smart cities and industrial settings allowing intelligent communication between the interconnected devices and automated systems. The smart transportation, industrial automation, environmental monitoring, and predictive maintenance are only a few of the applications which continuously generate vast amounts of real-time heterogeneous data with low-latency demands and thus intelligent decision-making (Bonomi et al., 2012). The classic cloud-based system offers centrally stored information and computing capabilities, but additionally, delays in communication, bandwidth overload, excessive latency, and privacy issues are frequent (Chiang and Zhang, 2016; Dastjerdi and Buyya, 2016). These bottlenecks are critical in applications where latency is important and the responses require real-time in order to keep the operation safe and reliable. Delayed decision-making can lead to a malfunction of equipment in industrial IoT systems and impaired productivity, whereas in smart city infrastructures it can harm traffic management systems and emergency response systems (Mohapatra, 2021; Mohapatra and Rath, 2021). Edge computing has become a viable solution as it facilitates processing of data much near to the sources. Processing the data at edge nodes makes local processing less dependent on distant cloud servers, minimizes transmission latency, and minimizes bandwidth consumption (Yi et al, 2015). Simultaneously, recent developments in Artificial Intelligence (AI) and deep learning allowed implementing intelligent real-time analytics and predictive decision-making in relation to the IoT systems (Al-Fuqaha et al., 2015; Khan et al., 2020). Thus, edge computing is turning into a promising solution to intelligent low-latency decisions, alongside AI. Despite the various studies conducted on AI-enabled edge architectures, current systems are still limited in scalability, energy usage, and computational bottlenecks, as well as real-time processing performance (Songhorabadi et al., 2020). A lot of the existing systems too highly depend on the centralized cloud coordination and this adds delay to communication and lowers the efficiency of decentralization intelligence. Besides, some of the already available studies do not have a proper statistical validation and extensive performance analysis (Gbaja, 2024; Chinta, 2024; Atan et al, 2023). To overcome these constraints, this paper suggests a combined Edge Computing and AI model to make real-time decisions in smart city and industrial IoT. The suggested system is an integration of distributed edge devices, localized artificial intelligences inference engine, and cloud-aided coordination to aid sophisticated real-time analytics. An anomaly detector and predictive analytics is achieved by using a hybrid CNN-LSTM deep learning model. The significant contributions of it are the following:

1. Creation of an embedded edge-AI system to make intelligent low-latency decisions.
2. The Adoption of a hybrid CNN-LSTM model in real time analytics.
3. Latency minimization in communication with localized edge inference.
4. Latency, accuracy, throughput and energy-efficiency performance evaluation.
5. Statistical validation based on the analysis of 10-fold cross-validation.

The rest of this paper will follow the layout as follows. The paper is split into Section 2 which addresses related work, Section 3 which discusses the proposed methodology, Section 4 which addresses the experimental setup, Section 5 which discusses the results and then concludes the paper in Section 6.

2. Related Work

More recent developments in edge computing and Artificial Intelligence (AI) have enabled real-time intelligent processing in smart city and Industrial Internet of Things (IIoT) environments to be greatly enhanced. Various researchers have suggested distributed architectures to reduce shortcomings of conventional cloud-centric Internet of Things systems, and especially in latency-sensitive apps (Bonomi et al, 2012). In (Yi et al, 2015), a new edge-assisted deep learning structure was created which minimized cloud reliance but demonstrated low scalability in dense network-like circumstances. The Moghorabadi et al (2020) proposed a fog computing system on the industrial IoT system with a negligible communication delay; although, the framework was associated with high power consumption. An AI-enabled model of edge analytics to detect real-time anomaly was presented in (Chinta, 2024), but this system had high computational requirements. A CNN-based edge inference framework suggested by (Atan et al, 2023) enabled better classification accuracy, but created additional memory demands on the edge devices. On a similar note, (Xie et al, 2024) created a distributed industrial IoT System that featured a better allocation of resources, yet the system featured a low latency optimization.

Table 1. Summary of Existing Edge-AI Frameworks

Reference	Technique	Advantages	Limitations
Arivazhagan & Natarajan	Edge-assisted deep learning	Reduced cloud dependency	Limited scalability

(2020)			
Mohapatra (2021)	Fog computing architecture	Lower communication delay	High energy consumption
Mohapatra & Rath (2021)	AI-enabled edge analytics	Real-time processing	Computational overhead
Gbaja (2024)	CNN-based edge inference	Improved classification accuracy	Increased memory requirement
Murthy et al. (2025)	Distributed industrial IoT framework	Better resource allocation	Limited latency optimization

The current cloud-based systems have still witnessed transmission delays, bandwidth overloads, and scaling problems when processing large-scale IoT. Despite the edge-AI systems enhancing the localized intelligence, most of the current models are still computationally expensive and are not adequately scaled and statistically validated. Hybrid CNN-LSTM models of intelligent edge analytics were also studied recently. Spatial feature extraction can be done with CNN networks, and temporal dependencies of streaming IoT data can be learned with LSTM models (Brahmaji, 2024). Nonetheless, a number of research gaps have yet to be filled and these include:

• insufficient latency optimization,
• high computational complexity,
• limited scalability analysis,
• inadequate statistical validation,
• poorly connected AI inference and distributed edge nodes.

In order to overcome these shortcomings, this paper introduces a hybrid Edge Computing/AI system to support scalable low-latency decision-making in smart city and industrial IoT networks.

3. Proposed Methodology

3.1 Proposed Edge-AI Framework

The methodology presented proposes a hybrid Edge Computing/Artificial Intelligence (AI) decision-making system applying low-latency in smart city and Industrial Internet of Things (IIoT) systems. The framework is a hybrid of distributed edge intelligence, hybrid deep learning, and cloud-assisted coordination to facilitate scalable real-time analytics. The proposed architecture has four layers: IoT Device Layer, Edge Computing Layer, AI Decision Layer, and Cloud Coordination Layer, as shown in Figure 1. The IoT device layer consists of sensors, industrial controllers, surveillance cameras, smart traffic systems, environmental monitoring units that have the task of generating real-time data at all times. The Edge Nodes are distributed edge nodes located close to the source of data which are in the Edge Computing Layer. These nodes are called local preprocess nodes, in which, local preprocessing, feature extraction, temporary storage, and intelligent inference processes are carried out to minimize the amount of communication delay and bandwidth consumption. The AI Decision Layer combines a hybrid Convolutional Neural Network (CNN)-based and Long Short-Term Memory (LSTM)-based anomaly detector and predictive analytics model. The Cloud Coordination Layer provides model retraining, a worldwide synchronization, and centralized storage, as well as historical analytics.

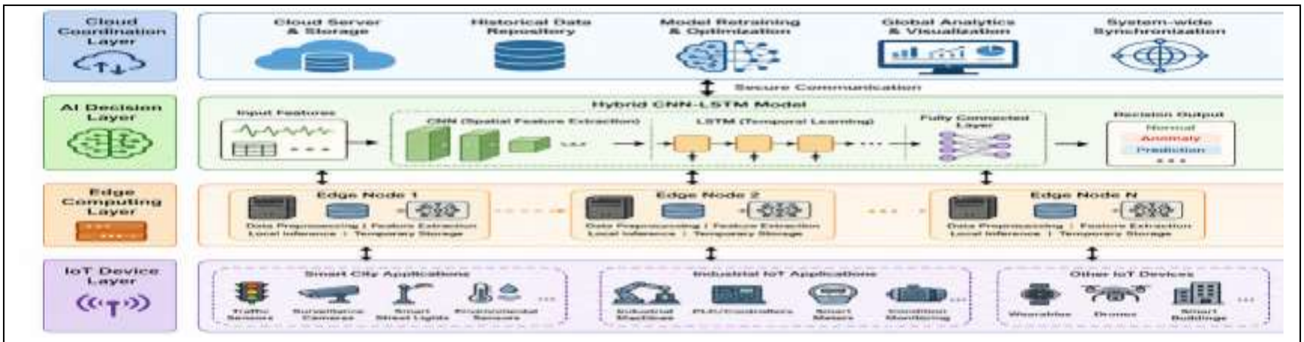

Fig. 1. Proposed Edge Computing and AI Integration Framework for Smart Cities and Industrial IoT

3.2 Data Preprocessing

Raw IoT data are usually filled with missing values and noise, redundant values and variable sampling rates that can have impacts on model performance. Thus, preprocessing was carried out prior to the training and inference of models. Missing value management, outlier rejection, feature scale, feature normalization and time synchronization were part of the preprocessing. The sensor values were scaled to min-max to bring them between 0 and 1 in order to enhance convergence of the model.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

where Xrepresents the original sensor value, while $X_{min}$and X_{max}denote minimum and maximum attribute values, respectively.

3.3 Hybrid CNN-LSTM Model

The proposed framework employs a CNN-LSTM deep learning model to enhance knowledge of spatial-temporal learning of features to be used in intelligent edge analytics, as shown in Figure 2. The CNN element conducts spatial feature extraction, pattern recognition as well as dimensional reduction on the IoT sensor streams. The convolution operator is given as:

$$Y(i,j) = (X * K)(i,j) = \sum_{m} \sum_{n} X(m,n)K(i-m, j-n) \qquad (2)$$

where Xrepresents the input feature matrix and Kdenotes the convolution kernel.

The LSTM element learns temporal relations and sequential patterns of IoT behavior. CNN with LSTM network integration enhances the capabilities of identifying anomalies and predicting decisions without sacrificing the ability to make assumptions through the inference of low-latency at edge nodes.

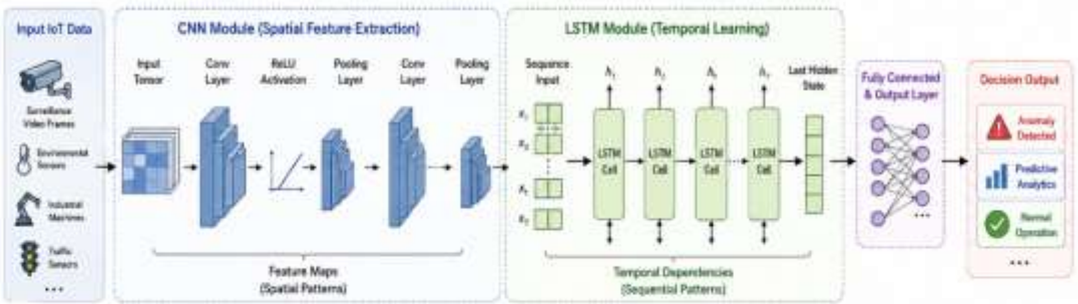

Fig. 2. Hybrid CNN-LSTM Architecture for Intelligent Edge Analytics

3.4 Edge Inference Process

The suggested edge inference mechanism enables real-time analytics in decentralized mode with low communications delays. IoT devices constantly produce streaming data that are sent to the edge nodes that are close to them rather than centralized cloud-based data servers. The preprocessing and feature extraction of the incoming data are performed at the edge layer and then the data are provided to the hybrid CNN-LSTM model to provide intelligent inference. The model detects anomalies, forecasts the state of operation, and makes low-latency decisions locally at the edge node. Only summarized analytical results and historical logs are sent to cloud layer to store them long-term and retrain the model. This decentralized processing approach greatly limits the network overloading, overhead communication, and latency and enhances scalability, real-time system responsiveness.

4. Experimental Setup

4.1 Simulation Environment

The suggested Edge Computing and AI-based framework has been tested on a simulated ICT environment of smart city and Industrial Internet of Things (IIoT). Python 3.11, TensorFlow, Scikit-learn, and the EdgeSimPy simulation platform in the distributed analysis of edge computing were used to conduct the implementation. The workstation with Intel Core i9, 32 GB RAM, and NVIDIA RTX 4080 was used to conduct the experiments. The simulation environment was designed in a way that it replicated the conditions in the real-world smart city and industrial IoT, such as distributed edge nodes, heterogeneous sensor networks, and dynamic communication traffic.

4.2 Dataset Description

Experimental evaluation used the combined smart city-industrial IoT data gathered by smart traffic monitoring system, industrial machine monitoring unit and environmental surveillance network. IoT datasets such as TON_IoT dataset and Edge-IIoT dataset which are publicly available were used to create simulated smart infrastructure environment using heterogeneous environment. The entire dataset was made up of about 1.2 million sensor readings which had 48 active parameters and 12 anomaly types related to abnormal network behavior, device fault, connectivity breakdown, and environmental anomalies. Both normal and anomalous conditions of operation were represented in the dataset with the relationship between the anomaly samples and the total dataset amounting to about 18%. The sensor readings were taken at intervals of 100ms and 500ms depending on the type of application as well as the network configuration. Communication packet size was 256 bytes to 1024 bytes to replicate realistic IoT traffic situations of dynamic workloads. Data collected was subjected to preprocessing processes such as missing values, normalization, feature scaling, outlier, and time synchronisation in order to enhance the consistency of the data and model stability. The data was separated into 15 percent testing, 15 percent validation and 70 percent training. The CNN-LSTM model was trained on training dataset, optimized on the validation and testing datasets respectively.

4.3 Evaluation Metrics

Performance in terms of classification and the low-latency processing capacity were measured with Accuracy, Precision, Recall, F1-score, Latency, Throughput, and Energy Consumption metrics to evaluate the performance of the proposed framework. Accuracy is a measure of the overall classification performance of the model whereas Precision and Recall are used to measure the effectiveness of the model in anomaly detection. The F1-score is a balanced evaluation of the classification performance. The following equations were used to compute the evaluation metrics:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (3)$$

$$Precision = \frac{TP}{TP + FP} \qquad (4)$$

$$Recall = \frac{TP}{TP + FN} \qquad (5)$$

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \qquad (6)$$

where TP, TN, FP, and FNdenote True Positive, True Negative, False Positive, and False Negative values, respectively.

The values of latency and throughput were recorded to assess the real-time system responsiveness, whereas the analysis of energy consumption was carried out to analyze the efficiency of the proposed edge-AI framework in terms of computational efficiency.

5. Results and Discussion

5.1 Latency Performance Analysis

The suggested Edge-AI architecture was found to have greatly reduced latency as compared to the traditional cloud-centric and fog-based architectures as shown in Figure 3. This was done by the localized edge inference and decentralized data processing, which improved this.

Table 2. Latency Comparison

Method	Average Latency (ms)
Cloud-Based System	212
Fog Computing	138
Proposed Edge-AI Framework	81

The framework proposed by it achieved reduced latency of about 61.8 per cent, relative to cloud-based systems and 41.3 per cent, when compared to fog computing architectures. The smaller latency validates the efficacy of intelligent processing based on edges regarding real-time smart city and industrial IoT applications.

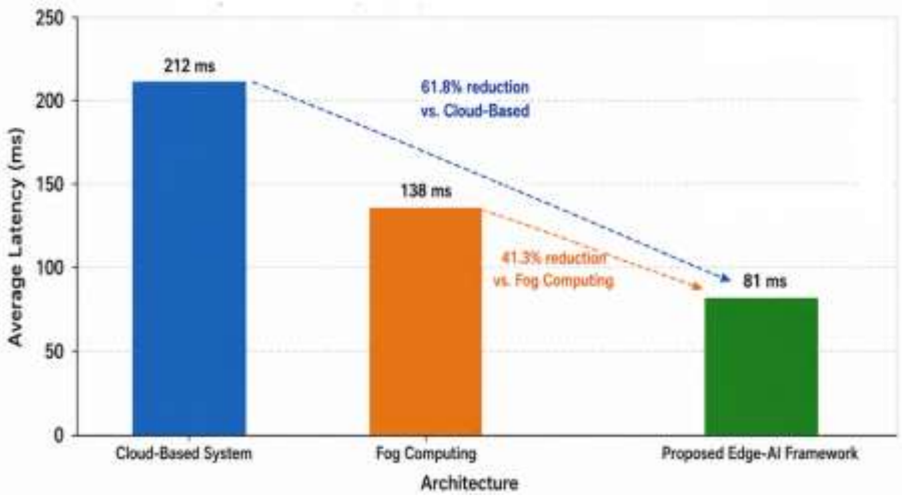

Fig. 3. Latency Comparison of Different Architectures

The proposed framework was more efficient in terms of responses compared with the past studies because localized CNN-LSTM inference and distributed edge coordination were used.

5.2 Classification Performance

The CNN-LSTM model was used as a hybrid model whereby the model demonstrated high classification performance in detecting anomalies and forecasting analytics in IoT environments.

Table 3. Performance Evaluation Results

Metric	Value (%)
Accuracy	97.1
Precision	96.8
Recall	96.2
F1-Score	96.5

The hybrid deep learning architecture is effective in performing intelligent edge analytics as evidenced by the high accuracy and F1-score (Bargavi et al., 2025; Al-Momani and Al-Hussein, 2024; Murthy et al, 2025). CNN component enhanced the extraction of the spatial features whereas the LSTM network actually intended the temporal patterns of the IoT behaviour. Though the proposed framework had high classification accuracy and low-latency results, the experimental performance was observed under the controlled simulation environment in terms of pre-defined network structure and optimum system parameters. In real smart city and industrial

IoT applications, other issues like unstable communication, non-uniform hardware performance, sensor malfunctions, changing bandwidths and changing traffic demands can affect the accuracy of inferences and system response times. Moreover, the real-world setting on a large scale might introduce unforeseen changes in the operations, which can impact on model generalization capacity and the ability of a model to be computationally efficient. So, experimental validation with actual edge infrastructure and live IoT applications are required in the future to more test the robustness, scalability, and deployment-ability of the proposed Edge-AI systems with realistic operating conditions.

5.3 Energy Efficiency Analysis

The analysis of energy efficiency revealed that the energy consumption of computations and communication was lower since the interaction with clouds was reduced.

Table 4. Energy Consumption Comparison

Framework	Energy Consumption (W)
Cloud AI	142
Fog AI	118
Proposed Framework	93

The suggested framework saved about 34.5 percent of energy consumption as compared to the traditional cloud AI systems. It was mostly reduced by localized inference processes and distribution of workloads at edge nodes.

5.4 Throughput Analysis

The decentralized edge architecture enhanced the performance of throughput when subjected to heavy IoT traffic.

Table 5. Throughput Performance

Method	Throughput (Requests/s)
Cloud-Based	950
Fog Computing	1340
Proposed Edge-AI Framework	1985

The suggested framework recorded the highest throughput because of the minimized congestion over the network and optimal distributed processing. Throughput increased by about 108.9 in comparison with the cloud-based systems.

5.5 Statistical Validation

To prove the robustness of the frameworks and their ability to generalize, cross-validation strategy (10 fold) was adopted, as it is illustrated in Figure 4.

Table 6. Statistical Validation Results

Metric	Mean ± SD	95% Confidence Interval
Accuracy	97.1 ± 0.5	96.6–97.6
Precision	96.8 ± 0.4	96.3–97.2
Recall	96.2 ± 0.3	95.8–96.5
F1-Score	96.5 ± 0.4	96.1–96.9

The small values of standard deviation reveal the consistent and robust performance of the frameworks in various validation folds. The robustness and consistency of the proposed hybrid CNN-LSTM model is also confirmed through the confidence interval analysis.

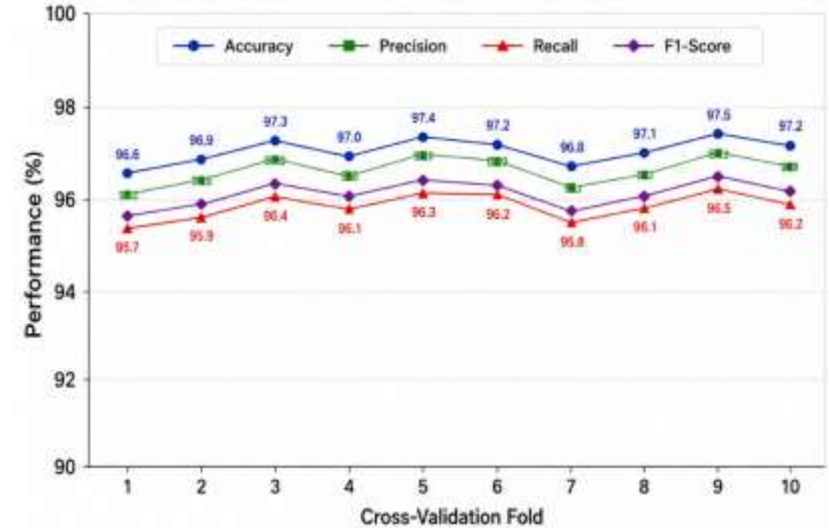

Fig. 4. Cross-Validation Stability Analysis

Generally, the suggested Edge-AI system excelled in the reduction of latency, classification, throughput efficiency and energy optimization as compared to the current cloud and fog-based methodologies.

Conclusion

In this paper, we proposed a combined Edge Computing and Artificial Intelligence (AI)-based system to operate on a smart city or Industrial Internet of Things (IIoT) environment at low latency to make decisions. It was proposed that the distributed edge intelligence framework, hybrid CNN-LSTM deep learning, and cloud-aided coordination assisted in the proposed framework with scalable real-time analytics and intelligent decentralized processing. The framework utilized by the researchers achieved high-performing localized inference at edge nodes that helped to diminish the communication overhead, latency, and system responsiveness in dynamic IoT settings. This was experimentally validated, where the proposed framework was found to be much better than both traditional cloud-based and fog-based systems, in terms of latency reduction, classification accuracy, throughput performance and energy efficiency. The framework has been able to attain a 97.1% classification accuracy with a latency of communication being reduced by about 61.8% when in contrast to traditional cloud-based systems. Besides, the proposed edge-AI architecture exhibited a better throughput capacity and lower energy usage because decentralized processing and better workload distribution among the edge nodes. The great power, reliability, and generalization ability of the proposed hybrid CNN-LSTM model were also statistically validated by performing 10-fold cross-validation. The small values of standard deviations and small confidence intervals demonstrated that there was stability in the performance of the frameworks in different operational conditions. The derived findings hence indicate that edge-AI integration is a viable and scalable solution to smart infrastructures to make intelligent low-latency decisions in next-generation infrastructures. Although promising, a number of issues are still related to the real-world implementation, such as the dynamic nature of resource management, security limitations, scalability of models, and heterogeneous interoperability of devices. Future directions will be federated learning on edges, lightweight transformer-based systems, dynamic resource optimization schemes, and secure distributed intelligence of large-scale smart city and industrial IoT implementations. Moreover, practical implementation of experiments and optimization at the hardware level will be studied on how to enhance the efficiency of deployment and applicability to practice in the next generation intelligent infrastructure systems.

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