IoT-Driven Information Acquisition and Processing Architecture for Real-Time Systems

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ABSTRACT

Through the use of various information and communication technologies (ICT), connected and autonomous cars have the potential to improve traffic safety. In order to model these signs, conventional traffic elements like driver, vehicle, road, and surroundings must be taken into account. In the end, traffic safety indications can be shown to drivers in an appropriate aggregate form to draw their attention and persuade them to make choices that will prevent and lessen traffic accidents. Massive amounts of real-time data have been produced as a result of the Internet of Things' (IoT) rapid expansion, necessitating effective data collection, processing, and analysis. The latency, scalability, as well as reliability necessities for real-time applications are difficult for traditional centralised architectures to achieve. In order to support real-time systems, this work presents an IoT-driven information gathering and processing architecture that integrates cloud-based analytics, edge computing, and sensor networks. The suggested design guarantees scalability as well as data reliability while enabling low-latency data collecting, instantaneous processing and intelligent decision-making. The design is appropriate for time-sensitive applications including smart medical care, industrial automation, and smart transportation systems since experimental evaluation shows improved response time, decreased network overhead, and increased system performance.

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1. INTRODUCTION

The Internet of Things' (IoT) quick development has revolutionised information engineering by making it possible to collect enormous amounts of data in real time from a variety of heterogeneous devices, including sensors, actuators, and smart objects. Smart healthcare, automation in industries, intelligent transportation [1], and innovative urban infrastructures are just a few of the time-sensitive uses for these IoT-enabled systems. Traditional centralised information processing architectures frequently fall short of meeting the demands of such applications, which include fast decision-making, low-latency data processing, and effective information acquisition.

The susceptibility of systems to the effects of seismic forces remains a persistent source of challenge in the discipline of civil engineering. As a solution to this issue, integrating technologies who might be linked to the global web of things (IoT) has emerged as a potentially effective way to fortify buildings against seismic threats. It is becoming clear that real-time monitoring capabilities and a paradigm shift in the way we approach construction and maintenance are provided by the marriage of IoT plus structural design [2]. IoT in the construction industry is expected to reach USD 16 billion by 2024, representing an amazing compound annual growth rate (CAGR) of 26.0%. The use of the Internet of Things in production is expanding rapidly worldwide. In the context of earthquake resilience, this is particularly true. The increasing use of sensors in construction tracking systems is an excellent example of this trend. Between 2017 and 2024, the global market for monitoring structural health is predicted to grow at a compound yearly growth rate of 17.9%. The fact that IoT-based early warning systems, such as the shake alert tsunami early caution system created by the US Geological Survey, are crucial in reducing the amount of damage caused by seismic events by providing crucial seconds to minutes of information is especially noteworthy.

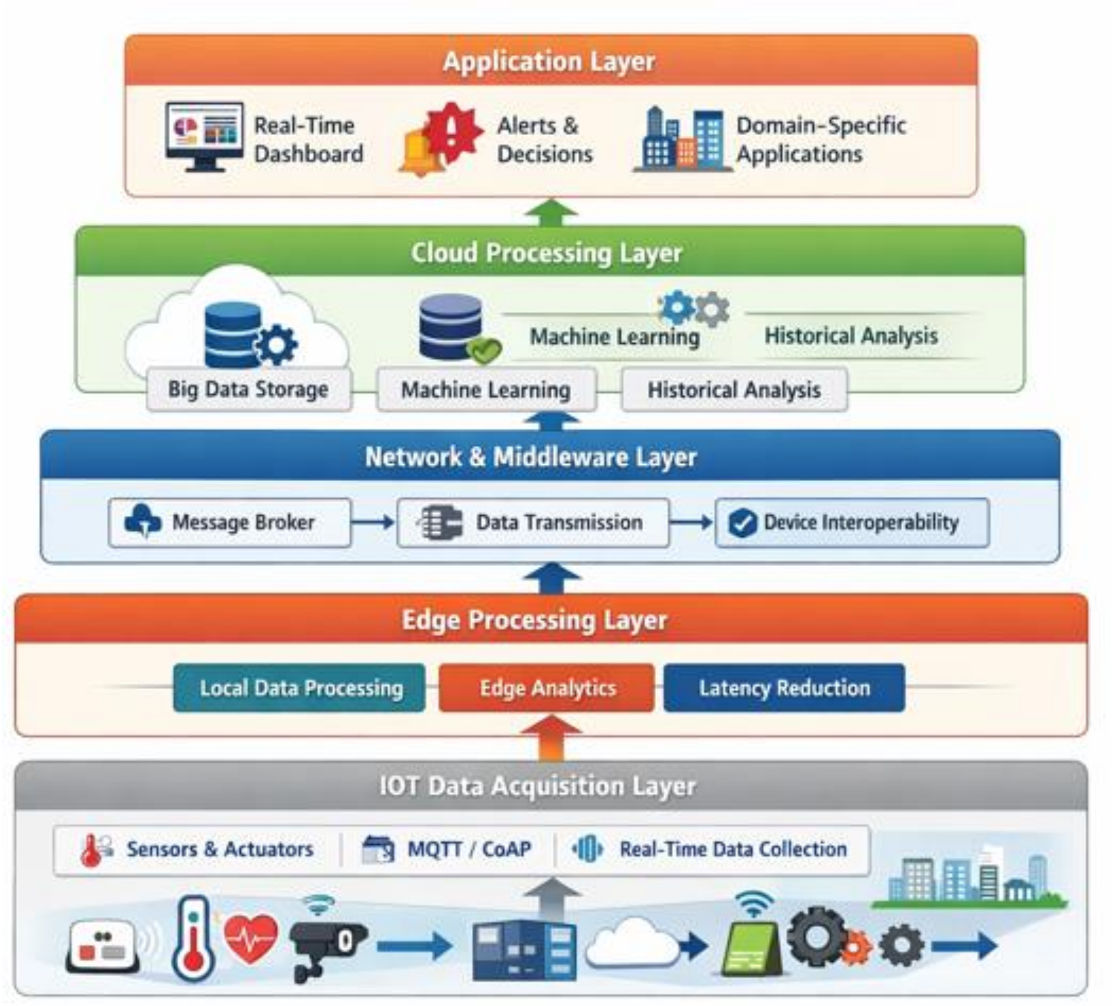

Figure 1. IoT-Driven Information Acquisition and Processing Architecture for Real-Time Systems

1.1 Problem Statement

Even though IoT technology have advanced significantly, applying current information processing frameworks to real-time systems presents a number of important hurdles. Due to their heavy reliance on centralised data processing, traditional cloud-centric systems have scalability issues, high connection latency, and increasing network congestion. Furthermore, bandwidth and processing resources are severely strained by the ongoing production of enormous data streams from dispersed IoT devices. These restrictions make them unsuitable for sensitive to latency real-time applications because they lead to delayed responses, decreased system reliability, more inefficient use of available resources [3]. A reliable, scalable, and low-latency architecture for information processing and acquisition is therefore desperately needed in order to support real-time Internet of Things-based applications.

1.2 Major Contributions

An IoT-driven architecture for information processing and acquisition that is suited for real-time systems is presented in this study. The following is a summary of this work's primary contributions:

1. To enable effective real-time information flow, a layered IoT-driven architecture was proposed that combines data collecting, edge handling, network middleware, cloud analysis, and application layers.
2. By processing important data closer to the source, edge-based information preprocessing techniques were introduced to lower latency, minimise network overhead, and enhance real-time responsiveness.
3. Outperformed conventional cloud-centric methods in terms of response speed, scalability, and bandwidth utilisation through experimental evaluation.

1.3 Paper Organization

This is how the rest of the paper is structured. In Section 2, relevant research on real-time system designs and IoT-based information processing is reviewed. The suggested IoT-driven information collecting and processing architecture is thoroughly explained in Section 3. The experimental setup and system implementation are presented in Section 4. The results and performance evaluation are covered in Section 5.

2. LITERATURE REVIEW

Business process operation and monitoring can be greatly enhanced by adding IoT capabilities to Business Process Management Systems [4]. However, it can be difficult to offer comprehensive support for IoT-driven process modelling, execution, and monitoring. The IoT features (such asynchronicity & parallelism) of IoT-driven operations cannot be fully met by current process modelling and process executing languages, like BPMN 2.0. In this paper, we introduce BPMNE4IoT, a comprehensive framework for IoT-driven process modelling, execution, and monitoring. In order to achieve the intended IoT recognition of business processes, we present a number of artefacts and events centred on the BPMN 2.0 metamodel.

Better traffic safety is made possible by data gathered utilising technologies like the Internet of Things (IoT) based on particular safety indications [5]. In order to model these signs, conventional traffic elements like driver, vehicle, road, and surroundings must be taken into account. In the end, traffic safety indications can be shown to drivers in an appropriate aggregate form to draw their attention and persuade them to make choices that will prevent and lessen traffic accidents. Current driving risk evaluation models often take into account a small number of signs pertaining to specific drivers & their psycho-physical capacities, which are crucial for engaging in traffic. An improved evaluation of driving danger and a wider range of traffic safety indicators are made possible by data gathered utilising IoT infrastructure in conjunction with shared computing and cloud technologies.

To enable bidirectional data flow, IoT-driven a digital twin models depend on strong frameworks made up of networked sensors [6], edge computing hardware, and cloud-based platforms. The digital twin can accurately depict the state of the physical system thanks to real-time data processing and acquisition, providing a thorough understanding of manufacturing processes. Manufacturers can use this capability to model different situations, carry out root cause investigations, and spot possible inefficiencies or equipment malfunctions before they happen. With a focus on reducing latency and guaranteeing interoperability across various industrial ecosystems, the study clarifies the technical necessities for creating such systems, particularly integrating data pipelines, model synchronisation, and system scalability.

The goal of integrating IoT with SCM is to use smart technologies to improve supply chain network tracking and control [7]. Real-time monitoring and decision-making throughout the whole supply chain are made easier by this connection. Workflow modelling and Internet of Things technology are used by the framework known as Smart Supply Chain Management (SSCM) to intelligently track products in real time along the supply chain. Predetermined supply chain operations are monitored by SSCM, a machine-learning event-driven system that facilitates dependable, immediate decision-making. With workflow modelling used for the planning and assessment of knowledge and task flow through the supply chain, the suggested method focuses on tackling supply chain features in a real-time setting.

The framework positioned Lean principles as the method foundation that drives decreased waste and flow stability, CPS as an adaptive control layer that ensures feedback precision, and IoT as the info backbone that enables real-time sensing. Regression, mediated, and moderation approaches were used to analyse quantitative data in order to assess the causal relationships between IoT data quantity, CPS responsiveness, on Lean performance results [8]. The findings showed that IoT data synchronisation and dependability greatly increased CPS availability, which in turn improved machine utilisation, takt adherence, and first-pass yield. CPS responsiveness also served as a complete mediator among IoT integration & Lean efficiency. The study also found that the association between operations results and CPS responsiveness was mitigated by lean maturity, suggesting that process discipline increased the advantages of digital transformation.

After examining current IoT-based and AI-based trash management systems and automated in smart cities, the current study suggested an updated waste disposal architecture of the system design. The suggested system design uses Internet of Things (IoT) technology to automate municipal trash disposal in smarter metropolitan areas [9]. Notification messages are sent based on sensor data about the dustbin's state, like in the full or empty. To ensure that waste is removed on time, the notifications are delivered simultaneously to the waste carriers vehicle driver and the municipality administration. The suggested system design is a crucial step in reducing municipal trash in smart cities and offers municipalities looking to revamp their waste collection procedures a scalable and flexible solution.

3. METHODS AND MATERIAL

The materials and design process for the suggested IoT-driven information processing and acquisition architecture for current systems are covered in this part. In order to facilitate prompt decision-making, the methodical flow starts with real-time data collecting from dispersed IoT devices, moves on to data extraction and engineering features [10], and ends with edge-based processed and cloud-level analytics.

3.1 Data Collection

A network of diverse IoT sensors installed in an immediate tracking setting is used to collect data. Whatever the application domain, the sensors are in charge of continuously recording raw data like moisture, temperature, motion, or physiological signals. Low-power microcontrollers are installed in each sensor node, and lightweight communication protocols like MQTT or CoAP are used to connect to the edge layer. These protocols were chosen because of the appropriateness for real-time data transfer, low overhead, and dependability. The gathered data streams are sent to the edge processors for prompt processing after being time-tagged at the source to maintain temporal integrity. While reducing delay in transmission and energy consumption [11], this decentralised data collecting method guarantees continuous data availability.

3.2 Data Extraction and Preprocessing

Data extraction and preparation procedures are performed to convert the unstructured sensor data into a format that can be used once it has been received at the outermost point processing layer. The process of data extraction entails separating pertinent data fields from packets of data that arrive and removing duplicate or distorted records brought on by connection faults or sensor noise. To enhance data quality and consistency, preprocessing methods like noise filtering, normalisation, and handling missing values are used [12]. These procedures are necessary to guarantee that only accurate and significant data is delivered for additional examination. Preparation at the edge layer greatly reduces needless data transfer to the cloud, which lowers bandwidth consumption and boosts system responsiveness.

3.3 Feature Extraction

In order to extract useful characteristics from pre-processed information streams, feature extraction is carried out at the edge layer. The system collects domain-relevant information, such as median, variance, peak standards, rate of shifts, or threshold-related indications over a moving time window, rather than sending raw data [13]. These characteristics preserve important real-time information while efficiently summarising the underlying pattern in the sensor data. By acting as condensed representation of the data itself, the extracted characteristics provide quicker processing and lower computing overhead. When managing massive amounts of IoT data, our feature-based method guarantees scalability and improves real-time performance.

3.4 Edge-Based Processing Using Threshold-Based Decision Technique

At the edge processing layer, a threshold-based decision approach is used to facilitate real-time decision-making. This method finds abnormal or critical circumstances by comparing extracted feature values to predetermined threshold limits. System needs, past observations, or domain-specific limitations are used to calculate threshold values. The system doesn't wait for cloud-level processing to initiate local alerts or actions when feature values above the specified thresholds. In situations where speed is of the essence, our edge-based decision technique greatly lowers latency and permits quick reactions. Summarised feature information is sent to the cloud layer for additional analysis & long-term storage of non-critical data.

3.5 Cloud-Level Analytics and Storage

The cloud processing layer conducts sophisticated analytics, including trend analysis & historical pattern evaluation, after receiving feature-level data from several edge nodes. Cloud infrastructure facilitates machine learning systems for predictive analysis and offers scalable memory for long-term data retention. By fine-tuning threshold values, enhancing analytical models, and assisting with strategic decision-making, processing of clouds contributes significantly to system optimisation even though it is not directly involved in decision-making. Combining edge and processing clouds guarantees a well-balanced architecture that satisfies long-term and real-time analytical needs.

3.6 Output and Application Layer Integration

The application layer receives the finished products of the suggested technique, where they are used to create real-time reports, alerts, and control actions. The application layer shows the state of the system and gives users or controlled automation useful information. The suggested approach guarantees effective information gathering, prompt processing, and dependable system efficiency in real-time IoT contexts by fusing cloud-based intelligence with real-time edge judgements.

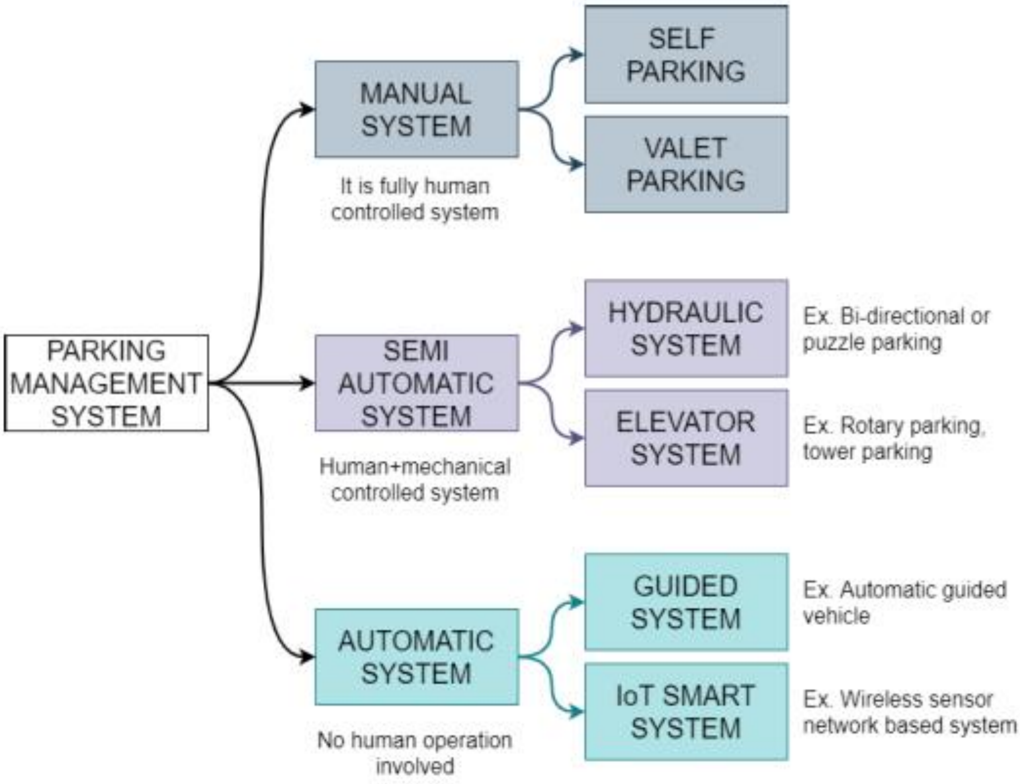

Figure 2. Classification of parking management system

The three types of parking systems are automatic, semi-automatic, and manual. Manual systems are entirely controlled by humans. Manual systems include self-parking and valet parking. When using self-parking, the driver looks for a parking space while driving. Valet parking, on the other hand, involves someone else parking on the driver's behalf. On the other hand, both humans and machines can operate a semi-automatic system. Examples of this kind of system include lift parking and hydraulic parking. Lastly, the machines have complete control over the automatic system. An example parking system classification is depicted in Figure 2 [14].

By linking and automating numerous smart gadgets, the Internet of Things (IoT) significantly contributes to the comfort and ease of our lives. Sensors are used in IoT-driven systems to gather data. The gathered data is then processed by integrating these sensors with some programmable circuitry. The information processed is then saved and distributed to an authorised user over a network. A driver must physically look for open parking spaces when using a manual parking system. Nonetheless, an innovative system can make it simple for the driver to locate pertinent parking-related information, such as i) Details regarding parking spaces that are available, ii) Online booking and payment, iii) A navigation system that operates automatically iv) Automated control of interior lighting, v) Security and monitoring, and vi) automated access control.

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

The implementation specifics of the suggested IoT-driven information collecting and processing architecture are presented in this section, together with a discussion of the experimental findings used to assess its efficacy in real-time settings. In comparison to traditional cloud-centric methods, implementation focuses on verifying the performance gains made possible by edge-based data processing & feature-level transmission.

4.1 System Implementation

IoT sensor nodes, cutting-edge computing devices, & cloud infrastructure were used to build the suggested design. Sensor nodes were set up to continuously gather data in real time and send it to the edge processor layer using the MQTT protocol. A lightweight processing unit that could perform threshold-based decision logic, feature extraction, and preprocessing in real time was used to implement the edge layer. In order to keep processed data and carry out historical analysis, the cloud layer was implemented utilising a scalable virtual environment. At the application layer, an online dashboard was created to provide performance data, alarms, and system status. This implementation maintained low latency & scalability while guaranteeing smooth communication between all architectural layers.

4.2 Experimental Setup

Experiments with different data loads & network circumstances were carried out to assess system performance. In order to evaluate the system, the number for active IoT nodes with sensors was progressively increased while latency, bandwidth usage, and system throughput were tracked. In order to replicate real-world operational situations, a threshold for edge-based choices were established using historical observations. To demonstrate the advantages of the suggested strategy, performance data gathered during testing were contrasted with a starting point cloud-centric IoT infrastructure.

Table 1. Experimental Setup Parameters

Parameter	**Value**
Number of IoT Sensors	10 – 100
Communication Protocol	MQTT
Edge Processing Unit	Single-board computer
Cloud Platform	Virtualized cloud server

Data Sampling Rate	1 sample/sec
Decision Technique	Threshold-based

The arrangement of parameters utilised for the experimental evaluation are compiled in Table 1.

4.3 Performance Metrics

End-to-end latency, bandwidth utilisation, and system throughput were chosen as the three primary performance measures for assessment. The time it takes for data to go from sensors acquisition to decision-making is measured by end-to-end latency. While throughput shows how many data packets are processed per second, bandwidth utilisation shows how much data is sent across the network. These indicators are essential for evaluating the effectiveness of the system in real time.

Table 2. Latency Comparison (ms)

Number of Sensors	**Cloud-Centric Architecture**	**Proposed Architecture**
10	420	180
30	610	240
50	820	310
100	1240	420

Table 2 demonstrates how edge-based processing in the suggested architecture greatly lowers latency.

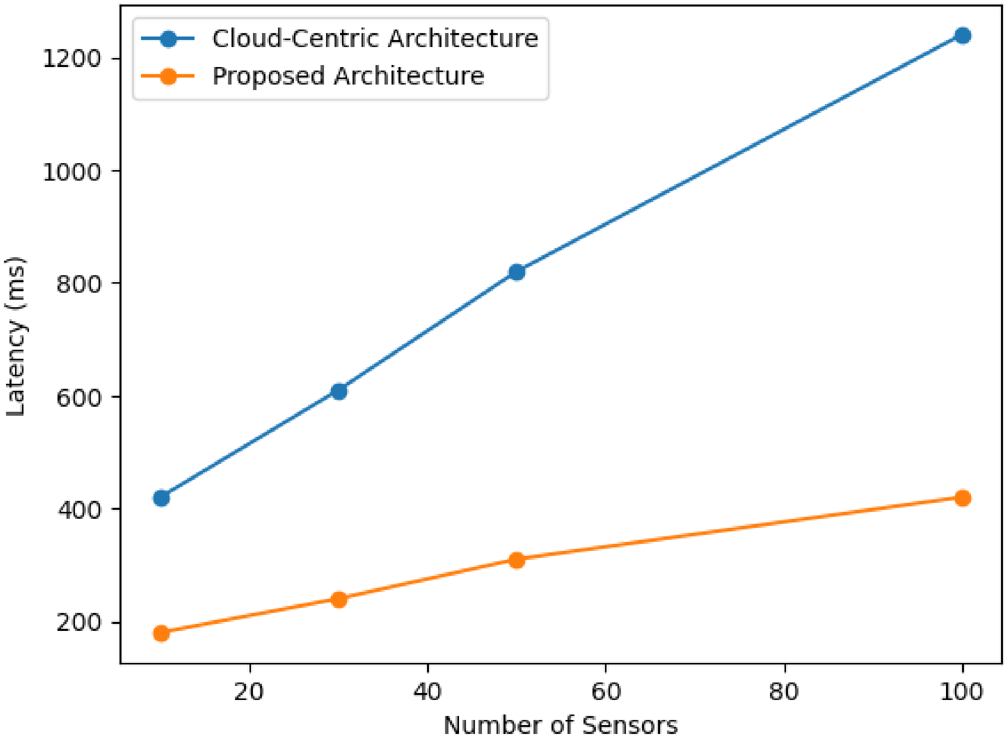

Figure 3. End-to-End Latency vs Number of Sensors

A line graph in Figure 3where the y-axis represents latency (ms) and the x-axis represents the number of sensors. In comparison to the cloud-centric paradigm, the suggested architecture continuously exhibits lower latency, and the difference grows with the number of sensors.

4.4 Bandwidth Utilization Analysis

The effectiveness of feature-level data transfer was assessed by analysing bandwidth utilisation. The suggested architecture significantly reduces network demand by transmitting derived features rather than raw sensor data. As the size for the IoT network grows, this decrease becomes more noticeable. The bandwidth efficiency attained by extracting features at the edge is shown in Table 3.

Table 3. Bandwidth Utilization (MB/min)

Number of Sensors	**Cloud-Centric**	**Proposed**
10	18.5	7.2
30	42.6	15.8
50	71.3	24.6
100	130.5	46.1

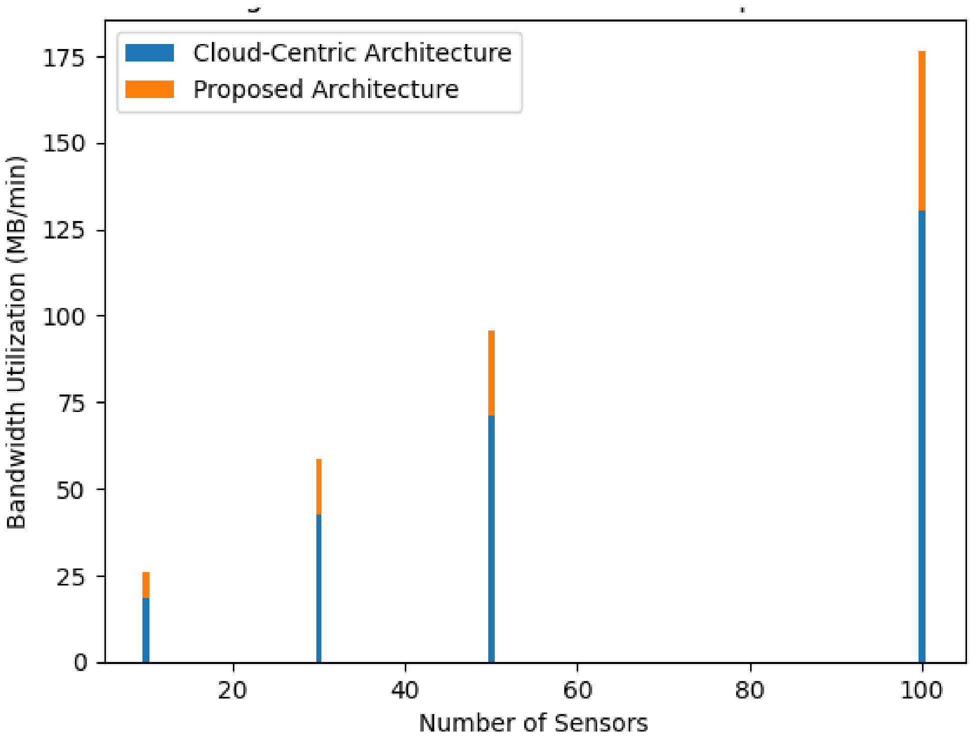

Figure 4. Bandwidth Utilization Comparison

A bar graph in Figure 4 that contrasts the two designs' bandwidth usage for various sensor counts. There is a noticeable decrease in bandwidth consumption with the suggested architecture.

4.5 Throughput and System Scalability

The flexibility of the suggested architecture was assessed by measuring system throughput. The system can manage greater rate of data without experiencing performance loss because to edge-based preprocessing, according to the results. Stable performance even under high loads is ensured by the capability to process data locally.

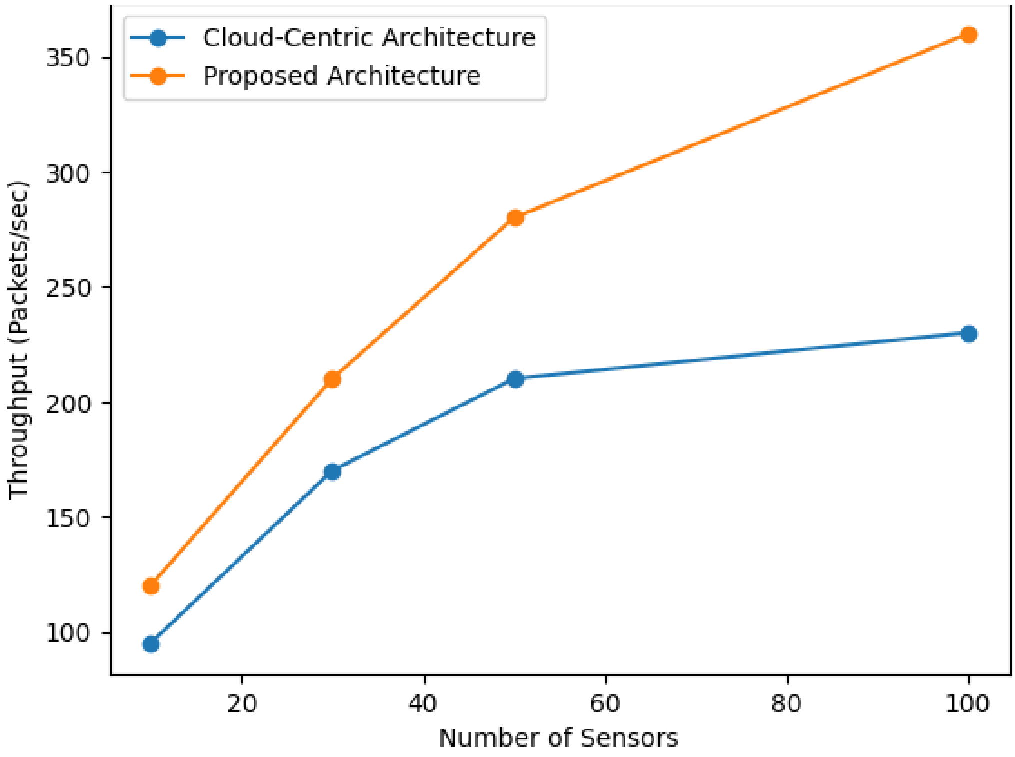

Figure 5. System Throughput vs Number of Sensors

A line graph in Figure 5 that plots the number of sensors against throughput (packets/sec). While the cloud-centric system exhibits saturation under heavy load, the suggested design sustains a consistent increase in throughput.

4.6 Result Discussion

The experimental findings unequivocally show that, in real-time circumstances, the suggested IoT-driven collecting data and processing architecture performs better than conventional cloud-centric systems. Throughput gains, bandwidth efficiency, and latency reduction confirm how well edge computing and feature-level data transfer work together. Because of these enhancements, the suggested architecture is ideal for time-sensitive Internet of Things applications where scalability and quick decision-making are crucial.

5. CONCLUSION

In order to overcome the shortcomings of conventional cloud-centric methods and support real-time systems, this article introduced an IoT-driven data gathering and processing architecture. To guarantee low latency and effective information flow, the suggested architecture combines edge-level processing, feature extraction, threshold-based decision-making, and IoT-based data gathering. The technology greatly lowers end-to-end latency & network bandwidth utilisation while enhancing overall system adaptability by processing crucial data more near the source. Comparing the suggested architecture to traditional architectures, experimental results show that it performs better in terms of reaction time, bandwidth utilisation, and throughput. These results confirm that edge computing and feature-level data transmission work well together for real-time Internet of Things applications. The suggested architecture offers a scalable and adaptable solution appropriate for a variety of time-sensitive fields, including intelligent transportation systems, automated manufacturing, and smart healthcare.

Future Scope

Even though the suggested architecture shows encouraging outcomes, there are a number of research avenues that might be investigated to improve its capabilities. In order to facilitate adaptive and predictive decision-making, future research can concentrate on incorporating cutting-edge machine learning and deep learning approaches at the edge layer. Reinforcement learning-based dynamic threshold optimisation can be used to increase system accuracy in a variety of operating scenarios. In distributed IoT systems, blockchain technology can also improve data security, honesty, and trust. Additionally, the architecture may be expanded to facilitate federated learning, which maintains data privacy while enabling cooperative training models across edge nodes. Moreover, system robustness, efficiency in energy use, and interoperability under diverse IoT ecosystems may be evaluated through extensive real-life deployments and cross-domain assessments. The suggested architecture's suitability for next-generation actual time IoT systems will be further strengthened by these extensions.

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