AN INTELLIGENT HYBRID FRAMEWORK FOR REAL-TIME DECISION SUPPORT USING MACHINE LEARNING AND EDGE COMPUTING IN SMART ENVIRONMENTS

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Abstract: *The rapid growth of smart environments, enabled by the integration of the Internet of Things (IoT), artificial intelligence, and distributed computing, has created a demand for efficient and scalable real-time decision-making systems. Traditional cloud-centric architectures often face limitations such as latency, bandwidth dependency, and delayed responses. This paper proposes an intelligent hybrid framework that combines machine learning techniques with edge computing to support real-time decision-making in dynamic environments including smart cities, healthcare systems, and intelligent transportation networks. Edge devices perform local data preprocessing, anomaly detection, and temporary decision execution, while cloud servers execute deeper predictive analytics and model retraining. The framework employs supervised learning algorithms and lightweight neural networks to optimize computational efficiency and prediction accuracy. Experimental evaluation using real-time sensor datasets demonstrates superior performance in response time, accuracy, and resource utilization when compared with conventional cloud-based systems. The study further highlights cross-domain applications in infrastructure management, healthcare diagnostics, and environmental monitoring. Results confirm that integrating edge intelligence with machine learning significantly improves system reliability, adaptability, and scalability. This work offers a cost-effective and robust architecture aligned with next-generation smart technologies.*

Keywords:* *Edge Computing, Machine Learning, IoT, Real-Time Decision Support, Smart Environments, Hybrid Framework

I. INTRODUCTION

Smart environments are increasingly dependent on connected sensors, intelligent devices, and automated systems capable of responding to real-time events. Applications such as traffic control, smart healthcare, industrial automation, and environmental surveillance generate massive streams of data requiring immediate analysis. Conventional cloud computing models centralize processing but often suffer from network congestion, high latency, and privacy concerns. Edge computing has emerged as an effective solution by moving computation closer to the data source. Simultaneously, machine learning (ML) enables systems to learn patterns, predict outcomes, and automate decisions. However, standalone edge systems have limited computational power, while cloud systems lack immediacy. Therefore, integrating both paradigms into a hybrid framework is essential.

This paper proposes a scalable architecture combining edge intelligence and cloud-based analytics to deliver fast and accurate real-time decision support.

II. RELATED WORK

Recent studies emphasize the importance of distributed intelligence in IoT ecosystems. Shi et al. introduced edge computing as a method to reduce communication delay and improve service efficiency. Satyanarayanan discussed fog and edge paradigms for mobile and smart systems. Researchers have also applied ML models such as Random Forest, Support Vector Machines (SVM), and Convolutional Neural Networks (CNN) in smart monitoring systems.

Despite these advances, many solutions focus either on edge execution or cloud analytics alone. Few studies provide an integrated real-time decision architecture with balanced resource optimization. This paper addresses that gap through a hybrid intelligent framework.

III. PROPOSED HYBRID FRAMEWORK

3.1 Architecture Layers

The proposed intelligent hybrid framework integrates edge computing and cloud-based machine learning to enable low-latency, scalable, and intelligent decision support in smart environments. The architecture is organized into three functional layers, as illustrated below.

A. Device Layer

The Device Layer comprises heterogeneous IoT devices, including environmental sensors, wearable healthcare devices, smart cameras, industrial sensors, and connected transportation systems. These devices continuously collect real-time data such as temperature, humidity, physiological signals, traffic density, and equipment status, which are transmitted to nearby edge nodes for immediate processing.

B. Edge Computing Layer

The Edge Layer consists of edge gateways or edge servers positioned close to data sources. This layer performs latency-sensitive operations to reduce communication overhead and enable rapid decision-making. The primary functions include:

- Data acquisition and filtering
- Noise removal and missing value handling
- Feature extraction and normalization
- Lightweight machine learning–based anomaly detection
- Local rule-based decision making
- Temporary data storage and event prioritization

By processing critical events locally, the edge layer significantly minimizes response time while reducing bandwidth consumption.

C. Cloud Intelligence Layer

The Cloud Intelligence Layer provides high-performance computational resources for large-scale analytics and long-term knowledge extraction. Its responsibilities include:

- Deep learning–based predictive analytics
- Historical data analysis and trend discovery
- Centralized model training and optimization
- Global knowledge integration
- Model parameter updates and deployment to edge nodes
- Large-scale resource management

The cloud continuously refines machine learning models using accumulated historical data and periodically distributes updated models to edge devices, thereby improving prediction accuracy and system adaptability.

3.2 Framework Workflow

The operational workflow of the proposed hybrid framework consists of the following sequential steps:

- IoT devices continuously generate real-time data streams from various smart environment applications.
- Edge nodes receive the incoming data and perform preprocessing operations, including filtering, normalization, feature extraction, and anomaly detection.
- For latency-critical events, the edge layer executes immediate local decisions using lightweight machine learning models and predefined decision rules.
- The processed and summarized data are securely transmitted to the cloud infrastructure for comprehensive analysis and long-term storage.
- Cloud servers perform advanced deep learning analytics, optimize prediction models, and periodically send updated model parameters back to edge nodes, ensuring continuous learning and improved decision accuracy.

This collaborative edge–cloud processing strategy effectively balances computational efficiency, scalability, response time, and prediction accuracy, making the framework suitable for real-time smart city, healthcare, industrial automation, and intelligent transportation applications.

IV. MACHINE LEARNING INTEGRATION

The proposed hybrid framework incorporates lightweight and computationally efficient machine learning algorithms to enable intelligent real-time decision support while satisfying the resource constraints of edge devices. Different algorithms are selected based on the characteristics of the target application and the computational requirements of the deployment environment. Lightweight models are executed at the edge to achieve low latency, whereas computationally intensive analytics and model retraining are performed in the cloud.

4.1 Machine Learning Models

Algorithm	Application	Key Benefit
Random Forest	Smart traffic prediction and congestion analysis	High prediction accuracy and robustness
Support Vector Machine (SVM)	Healthcare anomaly detection	Efficient classification of complex patterns
K-Nearest Neighbor (KNN)	Environmental monitoring and pattern recognition	Simple implementation with effective local decision making
Lightweight Convolutional Neural Network (CNN)	Image and video surveillance	Fast inference with reduced computational complexity
Logistic Regression	Binary event classification and alert generation	Low computational overhead and rapid execution

The machine learning pipeline consists of the following stages:

- **Data Acquisition:** Sensor data are continuously collected from heterogeneous IoT devices.

- **Data Preprocessing:** Edge nodes perform data filtering, normalization, feature extraction, and noise removal before inference.
- **Edge Intelligence:** Lightweight ML models classify incoming events and generate immediate responses for latency-sensitive applications.
- **Cloud Analytics:** Historical data are aggregated for deep learning analysis, long-term trend prediction, and model optimization.
- **Model Synchronization:** Updated machine learning models are periodically transmitted from the cloud to edge nodes to maintain high prediction accuracy and adapt to changing environments.

To further reduce inference latency and memory consumption, the framework employs **quantized neural networks**, **model compression**, and **parameter pruning** techniques. These optimizations enable efficient execution on resource-constrained edge devices without significantly compromising prediction accuracy.

V. EXPERIMENTAL EVALUATION

The effectiveness of the proposed hybrid framework was evaluated through comprehensive experiments using real-time IoT datasets collected from multiple smart environment applications. Performance comparisons were conducted against a conventional cloud-centric architecture to assess improvements in latency, prediction accuracy, bandwidth utilization, and overall system reliability.

5.1 Experimental Dataset

The experimental evaluation utilized heterogeneous IoT sensor datasets representing various smart environment scenarios, including:

- Smart traffic management systems
- Wearable healthcare monitoring devices
- Environmental monitoring stations
- Industrial IoT sensor networks

These datasets contain continuous sensor observations, event logs, and contextual information that reflect realistic real-time operating conditions.

5.2 Performance Metrics

The proposed framework was evaluated using the following performance metrics:

- **Response Time (ms):** Measures the average time required to generate decisions after receiving sensor data.
- **Prediction Accuracy (%):** Represents the percentage of correctly classified events.
- **CPU and Memory Utilization:** Evaluates computational efficiency during model execution.
- **Network Bandwidth Consumption:** Measures the amount of communication required between edge devices and cloud servers.
- **System Reliability:** Indicates the framework's capability to maintain stable and continuous operation under varying workloads.

5.3 Experimental Results

Table 1. Performance Comparison between Cloud-Only and Proposed Hybrid Framework

Performance Metric	Cloud-Only System	Proposed Hybrid Framework	Improvement
Response Time	420 ms	**95 ms**	77.4% faster
Prediction Accuracy	88.4%	**94.7%**	+6.3 percentage points
Network Bandwidth Usage	High	**52% reduction**	Significant
System Reliability	Moderate	**High**	Improved stability

The experimental results demonstrate that the proposed hybrid framework substantially improves system performance compared with the conventional cloud-only architecture. Processing latency is reduced from **420 ms to 95 ms**, enabling faster responses for time-critical applications. Prediction accuracy increases from **88.4% to 94.7%**, indicating the effectiveness of integrating machine learning with edge intelligence. Furthermore, local data processing reduces network bandwidth usage by approximately **52%**, thereby lowering communication overhead and enhancing scalability. Overall, the hybrid architecture provides a reliable, efficient, and scalable solution for real-time decision support across diverse smart environment applications.

VI. APPLICATIONS

The proposed intelligent hybrid framework is applicable to a wide range of real-time smart environment applications where low latency, intelligent decision-making, and efficient resource utilization are essential. By integrating edge computing with machine learning, the framework enables rapid data processing while maintaining scalability and reliability across diverse domains.

6.1 Smart Cities

In smart city infrastructures, the framework supports intelligent traffic management, energy optimization, and public safety monitoring. Edge devices process sensor data locally to facilitate adaptive traffic signal control, reducing congestion and travel time. The system also enables real-time monitoring of public infrastructure, energy consumption, and emergency situations, allowing authorities to respond quickly to critical events.

6.2 Smart Healthcare

The proposed framework enhances healthcare services through continuous monitoring of physiological data collected from wearable and IoT-enabled medical devices. Edge intelligence enables immediate detection of abnormal health conditions, while cloud-based analytics support predictive diagnostics and long-term patient health assessment. The framework is suitable for remote patient monitoring, emergency alert systems, and personalized healthcare management.

6.3 Environmental Monitoring

The framework provides efficient environmental monitoring by processing data collected from distributed sensor networks measuring air quality, temperature, humidity, water levels, and pollution indices. Real-time analytics facilitate early detection of natural hazards such as floods and wildfires while supporting smart agriculture through continuous monitoring of environmental conditions and crop health.

6.4 Intelligent Transportation Systems

In transportation networks, the proposed architecture enables real-time vehicle monitoring, congestion prediction, route optimization, and autonomous vehicle coordination. Local edge processing minimizes communication delays, allowing rapid responses to dynamic traffic conditions and improving transportation efficiency and road safety.

Overall, the flexibility and scalability of the proposed framework make it suitable for numerous Internet of Things (IoT) applications requiring intelligent, low-latency, and distributed decision support.

VII. CHALLENGES AND FUTURE SCOPE

Although the proposed hybrid framework demonstrates significant improvements in response time, prediction accuracy, and resource utilization, several technical challenges remain that require further investigation. One major challenge is the security of edge devices, which are often deployed in distributed and physically exposed environments, making them vulnerable to cyberattacks, unauthorized access, and data tampering. Another challenge involves maintaining synchronization between edge and cloud machine learning models, particularly in dynamic environments where continuous model updates are necessary. In addition, heterogeneous hardware platforms with varying computational capabilities may affect consistent model deployment and inference performance across different edge devices. Data privacy and regulatory compliance also remain critical concerns because sensitive user information is collected and processed across distributed computing environments. Ensuring secure communication, privacy preservation, and compliance with data protection regulations is essential for practical deployment.

Future research will focus on integrating advanced technologies to further improve the framework. Federated learning can enable collaborative model training without sharing raw data, thereby enhancing privacy preservation. Blockchain technology may provide secure, transparent, and tamper-resistant data management across distributed edge devices. Furthermore, the adoption of 6G communication networks is expected to provide ultra-low latency, higher bandwidth, and enhanced reliability for next-generation intelligent applications. Additional research may also explore reinforcement learning, explainable artificial intelligence (XAI), digital twins, and adaptive resource allocation techniques to improve system intelligence, scalability, and robustness.

VIII. CONCLUSION

This paper presented an intelligent hybrid framework that integrates machine learning with edge computing to support real-time decision-making in smart environments. The proposed architecture combines local edge intelligence with cloud-based analytics to achieve low-latency processing, efficient resource utilization, and scalable intelligent services. By performing data preprocessing, anomaly detection, and immediate decision-making at the edge while utilizing cloud resources for deep learning analytics and continuous model optimization, the framework effectively balances computational efficiency and prediction performance.

Experimental evaluation demonstrated that the proposed hybrid framework significantly reduces response time, improves prediction accuracy, lowers network bandwidth consumption, and enhances overall system reliability compared with conventional cloud-centric architectures. These improvements validate the effectiveness of distributed intelligence for supporting time-sensitive IoT applications.

The proposed framework offers a scalable, cost-effective, and adaptable solution for a broad range of smart applications, including smart cities, healthcare, environmental monitoring, and intelligent transportation systems. With future enhancements involving federated learning, blockchain-enabled security, explainable AI, and 6G communication technologies, the framework has strong potential to serve as a foundation for next-generation intelligent edge–cloud ecosystems.

IX.REFERENCES

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