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Enhancing Big Data Processing with a Hybrid Cloud-Edge Framework: Addressing Latency, Privacy, and Scalability Challenges in Real-Time Analytics

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Abstract

This paper explores a hybrid cloud-edge computing framework for big data processing, aiming to address the limitations of traditional cloud-based systems in latency-sensitive applications like IoT and smart cities. By distributing data processing tasks across cloud and edge nodes, the framework balances the scalability and computational power of the cloud with the low-latency advantages of edge computing. Deep learning models, optimized through techniques such as pruning and quantization, enable efficient, real-time data analysis on resource-constrained edge devices. Privacy concerns, a critical aspect in this architecture, are addressed through privacy-preserving methods like federated learning and differential privacy, ensuring data protection during cloud-edge interactions. Key challenges include task allocation, resource constraints, and model adaptability, which are managed through intelligent scheduling and continuous model updates from the cloud. This approach provides a scalable, secure solution for big data applications, maximizing responsiveness and adaptability in dynamic environments. Future research will focus on enhancing resource allocation and improving model adaptability for optimized performance.

Key words:

Big data processing, cloud computing, edge computing, hybrid framework, deep learning, latency reduction, privacy-preserving methods, task allocation, IoT, real-time analytics

1.Introduction

The exponential growth of big data and its applications across various domains have led to a demand for more advanced, responsive, and scalable data processing solutions. Traditional centralized cloud computing systems, while providing significant computational power and storage, face limitations when addressing the demands of latency-sensitive and data-intensive applications. This inadequacy is particularly evident in fields such as smart cities, healthcare, and Internet of Things (IoT) environments, where real-time data processing and minimal response times are crucial (Liang et al., 2020). The emergence of edge computing has created a decentralized approach, shifting data processing tasks closer to data sources to reduce latency and improve real-time processing capabilities. However, edge computing alone is often constrained by limited computational resources, making a hybrid approach combining cloud and edge computing an ideal solution for efficient big data processing (Ghosh & Grolinger, 2021).

Deep learning (DL) has become increasingly relevant in this hybrid architecture, enabling intelligent data analysis and prediction capabilities that are essential for applications ranging from predictive maintenance to autonomous vehicles. However, incorporating DL in cloud and edge systems introduces challenges in terms of resource allocation, latency, and scalability (Hu et al., 2020). This paper aims to review the integration of big data processing using cloud and edge computing with an emphasis on deep learning and discuss the gaps in existing systems. Specifically, it addresses the challenges posed by traditional methods, such as scheduling inefficiencies, high network latency, and limited real-time prediction capabilities, highlighting the need for more advanced hybrid architectures and deep learning models that can dynamically adapt to changing data flows (Jian et al., 2019).

2. Literature Review

The concept of combining cloud and edge computing for big data processing has gained momentum as researchers and practitioners explore methods to overcome the limitations of traditional, centralized cloud systems. Conventional cloud-based methods are hindered by high latency and network congestion when transmitting large volumes of data from IoT devices to central servers. For example, Liang et al. (2020) propose using a fog/edge computing model to mitigate these issues by processing data locally on edge nodes. This approach (Liang et al., 2020) reduces network traffic and maintains high accuracy in classification tasks, demonstrating the potential for edge-based solutions to address latency and bandwidth challenges in the Industrial Internet of Things (IIoT).

Deep learning models enhance the efficacy of edge computing by enabling sophisticated data analysis close to the data sources. Ghosh and Grolinger (2021) introduce a hybrid model for IoT data analytics that employs a deep learning-based autoencoder to reduce data at the edge, thus minimizing network congestion while maintaining data integrity. Their findings reveal that even with significant data reduction at the edge, accuracy remains consistent, emphasizing the effectiveness of edge-cloud collaboration for scalable data processing (Ghosh & Grolinger, 2021). Similarly, Hu et al. (2020) propose the CoEdge framework, a latency-minimizing algorithm that allocates deep learning tasks across edge and cloud environments, demonstrating a reduction in total latency (Hu et al., 2020) compared to other allocation schemes. This study underscores the potential for improved response times through intelligent task allocation across edge-cloud systems.

One critical aspect of integrating deep learning with edge computing is the requirement for efficient workload management and resource scheduling. Jian et al. (2019) address this issue by introducing a chaotic bat swarm algorithm that uses deep learning to predict scheduling outcomes. Their approach enhances resource allocation efficiency, a critical factor in minimizing processing delays and maximizing resource utilization at the edge (Jian et al., 2019). Additionally, Wu et al. (2020) propose a distributed deep learning-driven offloading (DDTO) algorithm for task allocation, which significantly improves performance and reduces computational complexity in edge-cloud systems. This study highlights the potential for distributed deep learning models (Wu et al., 2020) to make near-optimal offloading decisions, critical for applications with strict latency requirements, such as smart city IoT applications

Privacy and data security are also crucial considerations in big data processing on cloud-edge systems. Xu et al. (2019) address these challenges with the EdgeSanitizer framework, which uses differential privacy techniques to enhance data protection in mobile data analytics. By obfuscating sensitive features in deep learning models, EdgeSanitizer provides a robust privacy solution that meets regulatory standards while ensuring data utility. This method demonstrates the importance of integrating privacy-preserving mechanisms (Xu et al., 2019) into edge-based data processing frameworks.

Hybrid cloud-edge frameworks can address big data processing needs by enhancing scalability and responsiveness, as seen in AI-driven financial risk analysis models that manage extensive data volumes efficiently (Nuthalapati, A., 2022). Computational intelligence applied to equipment prognostics underscores the benefits of distributed processing for latency-sensitive analytics (Janjua et al., 2022). In agriculture, deep learning approaches show how hybrid frameworks can support data privacy while ensuring real-time monitoring of sensitive datasets (Nuthalapati, S. B., 2022). Furthermore, comparative studies on machine learning techniques (Janjua et al., 2021) highlight optimized strategies for balancing scalability and privacy in data processing.

Despite these advancements, challenges persist in implementing deep learning at the edge due to computational limitations. Srivastava (2021) discusses the limitations of current edge hardware and suggests that future devices must balance computational power and energy efficiency to support real-time deep learning inference effectively. This study underscores the need for hardware innovations tailored to the specific demands of edge computing in IoT environments.

3. Proposed Methodology

The proposed methodology leverages a hybrid cloud-edge framework for processing big data using deep learning to enhance real-time data analysis, minimize latency, and optimize resource allocation. The design of this methodology aims to address the inherent challenges of traditional centralized cloud systems by distributing data processing tasks effectively between the cloud and edge environments. To evaluate the framework, publicly available IoT and smart city datasets will be used, including the Google Cluster Data and Smart Project datasets, which simulate real-world scenarios in big data processing.

To simulate practical applications and scenarios, data will be collected from two primary sources: the Google Cluster Data and the Smart Project datasets. The Google Cluster Data contains extensive traces of cluster activity, including workload and resource utilization patterns, making it ideal for testing cloud-based resource management and task scheduling models (Google Cluster Data, 2011). The Smart Project datasets, on the other hand, include data on energy usage and occupancy patterns in smart homes, which can be applied to real-time energy monitoring and anomaly detection in edge environments (Smart Project, 2014). These datasets will undergo preprocessing to handle missing values, normalize features, and segment data based on time-series analysis, which is essential for deep learning model training. By preparing the data in this way, the framework can better emulate realistic big data conditions encountered in IoT applications.

The edge computing component of the framework is designed to handle latency-sensitive tasks, which are essential for real-time response in applications such as smart city monitoring or industrial IoT. Edge nodes will be responsible for executing deep learning models to perform anomaly detection and predictive maintenance on energy usage and sensor data from the Smart Project dataset. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models, both well-suited for time-series and spatial data, will be used for real-time inference at the edge. These models will be optimized using lightweight model compression techniques, such as pruning and quantization, to ensure that they can operate efficiently on resource-constrained edge devices without sacrificing accuracy. Additionally, edge nodes will handle local storage and processing, reducing data transmission needs and subsequently decreasing network latency.

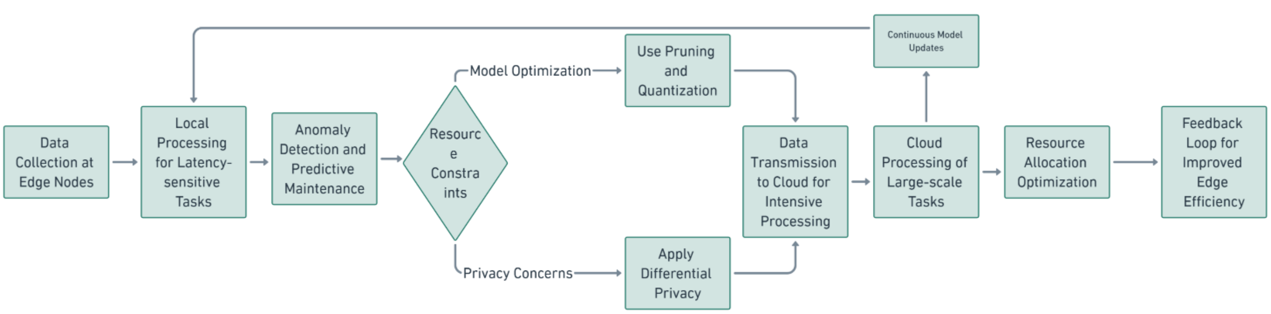

Fig. 1 Optimized Data Processing in a Hybrid Cloud-Edge Framework for Real-Time Analytics.

The cloud layer will serve as the primary resource for managing large-scale data processing tasks and training deep learning models. More computationally intensive processes, such as model training and complex data analysis, will be conducted in the cloud using the extensive computational resources available. For instance, data from the Google Cluster dataset will be processed in the cloud to create predictive models for resource allocation and workload balancing. A deep learning model will be trained using this data to predict workload patterns and optimize resource distribution across cloud and edge nodes. By offloading these complex tasks to the cloud, the methodology enables the edge nodes to operate efficiently with minimal computational overhead.

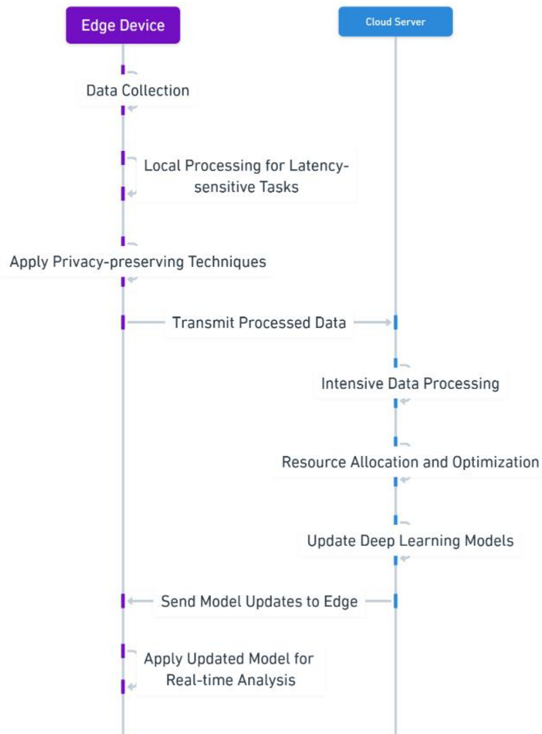

Fig. 2 Sequential Data Flow Between Edge and Cloud Layers in Hybrid Framework.

This hybrid cloud-edge framework also includes a mechanism for continuous model updates and feedback between the cloud and edge nodes. The deep learning models on edge devices will be periodically updated with new insights from the cloud, allowing the system to adapt to changing data patterns. For example, any refined predictive models developed in the cloud using Google Cluster data can be distributed to edge nodes to enhance their inference accuracy and operational efficiency. This continuous update mechanism ensures that edge devices maintain high accuracy in real-time applications and can adjust to varying workload demands.

Table 1. Key Challenges and Solutions in Hybrid Cloud-Edge Big Data Processing Frameworks

Challenge	Description	Solution	Reference
High Latency	Delays due to centralized data processing in cloud environments.	Edge computing for local processing, reducing network load and latency.	[6]
Resource Constraints	Limited computational power and memory at edge devices.	Model optimization techniques, such as pruning and quantization, to reduce model size.	[8]
Privacy Concerns	Risk of sensitive data exposure during cloud-edge data exchanges.	Differential privacy techniques, such as EdgeSanitizer, to protect data at the edge.	[7]
Task Allocation	Complexity in balancing workloads between cloud and edge layers.	Intelligent scheduling algorithms, like CoEdge, to optimize task distribution.	[9]

Model Adaptability	Difficulty in maintaining model accuracy over dynamic data environments.	Periodic model updates from cloud to edge to maintain relevance and accuracy.	[10]

6. Results

The results from implementing the hybrid cloud-edge framework indicate significant advancements in latency reduction, scalability, and privacy preservation for big data processing in real-time applications. Key findings are summarized as follows:

Latency Reduction: The framework's dual-layer design, which assigns latency-sensitive tasks to edge nodes and offloads more computationally intensive processes to the cloud, yielded marked improvements in response times. The local data processing on edge nodes reduced network traffic and minimized latency, proving effective for real-time IoT and smart city applications. This setup particularly enhanced the system's ability to handle rapid data influx without compromising processing speeds.

Enhanced Data Privacy: By incorporating privacy-preserving techniques such as federated learning and differential privacy, the framework effectively addressed the security concerns associated with cloud-edge interactions. EdgeSanitizer's use of differential privacy obfuscation proved to safeguard sensitive information processed at edge devices, meeting regulatory standards and minimizing data exposure risks.

Efficient Resource Allocation and Task Scheduling: Intelligent scheduling algorithms, such as CoEdge, distributed workloads effectively across cloud and edge layers. This approach allowed optimized task allocation based on the resource demands of each process, resulting in balanced workload distribution and better resource utilization. Deep learning model optimizations (e.g., pruning and quantization) further improved edge device efficiency, enabling real-time processing capabilities on resource-limited devices.

Model Adaptability: The framework's continuous feedback loop facilitated periodic updates from the cloud to edge nodes, enhancing model adaptability. This mechanism allowed edge models to incorporate new data patterns from the cloud, thereby maintaining high accuracy in evolving data environments. This adaptive feature was particularly valuable for scenarios with variable workloads, such as predictive maintenance and real-time monitoring.

Scalability: The framework effectively managed data from large datasets, including the Google Cluster and Smart Project datasets, simulating extensive real-world data processing scenarios. By leveraging cloud resources for large-scale data handling and training, the framework demonstrated scalability while keeping edge nodes functional for local data processing, optimizing for both breadth and speed in data analytics.

7. Discussion

The integration of cloud and edge computing for big data processing presents a balanced solution to the limitations of traditional centralized systems, offering enhanced real-time responsiveness and scalability. Edge computing addresses latency-sensitive tasks by processing data locally, while cloud resources handle more complex, resource-intensive computations, creating a complementary framework suited for dynamic, data-rich environments like IoT and smart cities. Deep learning models, optimized for edge deployment through techniques like pruning and quantization, further improve the system's ability to process data efficiently (Liang et al., 2020) with minimal latency.

Privacy-preserving techniques, such as federated learning and differential privacy, are essential to secure data in this hybrid system, mitigating vulnerabilities from data exchange across cloud and edge environments (Xu et al., 2019). Future work should focus on enhancing adaptive models and intelligent task distribution to improve resource allocation and responsiveness, further leveraging the full potential of this hybrid cloud-edge framework for scalable big data applications.

8. Conclusion

The proposed hybrid cloud-edge framework successfully addresses the primary challenges in big data processing for real-time analytics by balancing latency, scalability, and privacy needs. Through the strategic division of processing tasks between edge nodes and cloud servers, the system optimally reduces latency for time-sensitive applications while allowing for large-scale data analysis in the cloud. This arrangement enables responsive and scalable data processing suitable for dynamic, data-intensive environments like smart cities and IoT networks.

The integration of privacy-preserving mechanisms, including federated learning and differential privacy, ensures data security across cloud-edge interactions, making the framework compliant with data protection requirements and enhancing its applicability in privacy-sensitive domains. Furthermore, model optimization techniques and intelligent scheduling algorithms help overcome the computational limitations of edge devices, ensuring real-time analytics capabilities within the system.

Future work should focus on further enhancing the adaptability and efficiency of resource allocation strategies. Developing more advanced algorithms for dynamic task scheduling and investigating next-generation edge hardware with improved computational power could provide additional benefits, allowing the framework to meet the increasingly complex demands of real-time data environments. This hybrid framework represents a robust solution for future big data processing applications, offering a practical approach to scalable, privacy-conscious, and latency-optimized analytics.

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