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Improving Accuracy of Sensor Data by Frequent Pattern Mining Algorithm Using Edge Computing

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Abstract

Sensor data plays a crucial role in various applications, including industrial automation, environmental monitoring, and healthcare. However, the accuracy of sensor data can be adversely affected by factors such as noise, latency, and data transmission issues in existing systems. This study focuses on identifying the disadvantages associated with current sensor data collection and analysis methods and explores the use of frequent pattern mining to enhance data accuracy. The research presents a comprehensive overview of Edge computing in conjunction with sensor systems and the Internet of Things, highlighting the complexities in processing sensor data using conventional methods and the advantages of employing frequent pattern mining. The study concludes that the utilization of frequent pattern mining in edge sensor data processing offers optimized response time, resource utilization, and better scalability. It is also capable of handling the massive amount of data generated from sensors and mobile devices in the Internet of Things.

Keywords: Sensor data, Latency, Noise filtering, Real-time applications, Data Accuracy

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1. Introduction

In the recent era of the Internet of Things, sensors play a major role, providing solutions to a wide range of real-world problems. Examples of such applications include smart cities, healthcare systems, buildings, transportation, and environments. However, real-time IoT sensor data presents various obstacles, such as a deluge of unclean sensor data and high resource consumption costs. The work of the IoT sensor network goes beyond collecting sensor data; it also involves processing and decision-making. The raw sensor data collected often contains unwanted information, leading to high resource utilization and computational costs, resulting in inaccuracies [11]. Figure 1 below illustrates the basic steps involved in the collection and processing of IoT sensor networks.

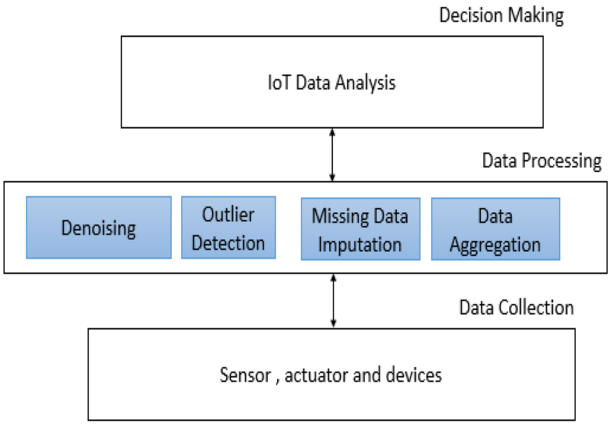

Figure 1. Basic Steps of Sensor Data Collection

As sensor data is inherently susceptible to inaccuracies caused by environmental factors, device faults, and communication disruptions, these errors can compromise data integrity, leading to incorrect interpretations and decisions in systems relying on sensor inputs. Furthermore, conventional sensor data collection and processing systems often experience high latency, causing delayed decision-making and hindering real-time applications. Network congestion and intermittent connectivity can further degrade the accuracy of sensor data, resulting in unreliable results. Additionally, traditional data processing methods may not effectively filter out noise and anomalies from sensor data, contributing to inaccuracies in the generated information. The centralized nature of data processing can also lead to increased operational costs, requiring substantial bandwidth and computational resources.

To overcome such issues the Frequent Pattern Mining a data mining technique that seeks to identify repeating patterns, correlations, or links within datasets can be used. When applied to sensor data, this algorithm seeks to find patterns that repeat over time, thereby providing significant insights into the underlying dynamics of the physical world. By finding consistent patterns, the algorithm helps to filter out noise and improve the signal-to-noise ratio in sensor data. Frequent pattern mining can be applied in a range of real-world scenarios. It is commonly used in supermarkets for tasks such as optimizing sales, product positioning, defining promotion rules, and facilitating text search. This technology finds application in wireless sensor networks, especially in smart homes where sensors are attached to human bodies or household goods. Additionally, it proves beneficial in applications that require thorough monitoring of critical situations or hazards, such as gas leaks, fires, and explosions. Frequent patterns can play a crucial role in tracking the activities of dementia patients. This approach is particularly valuable for assessing functional deterioration in dementia patients by continuously monitoring their daily activities in a smart environment [12]. The below flowchart in figure .2 shows the use of frequency pattern mining in the sensors.

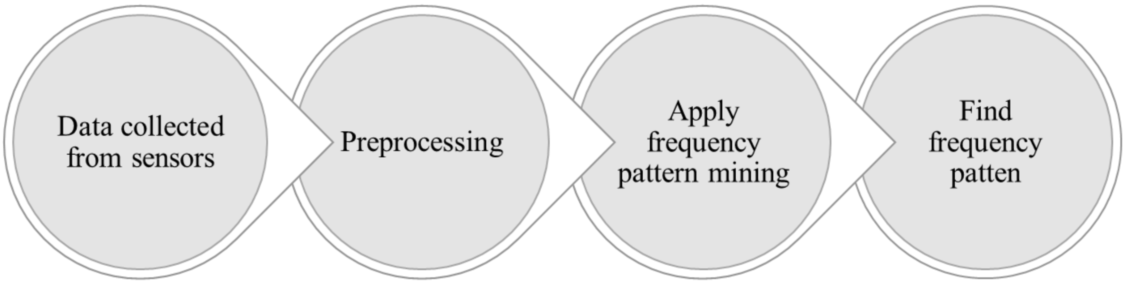

Figure 2. Basic Flow Diagram of Frequency Pattern Mining. [13]

This study aims in exploring the Integration of Frequent Pattern Mining algorithms at the edge which enables real-time analysis and decision-making, as patterns are identified and acted upon locally. This approach not only ensures timely responses but also reduces the need for extensive data transfer, making it particularly beneficial for resource-constrained IoT devices. The Figure.3 below shows the details of the pattern mining research

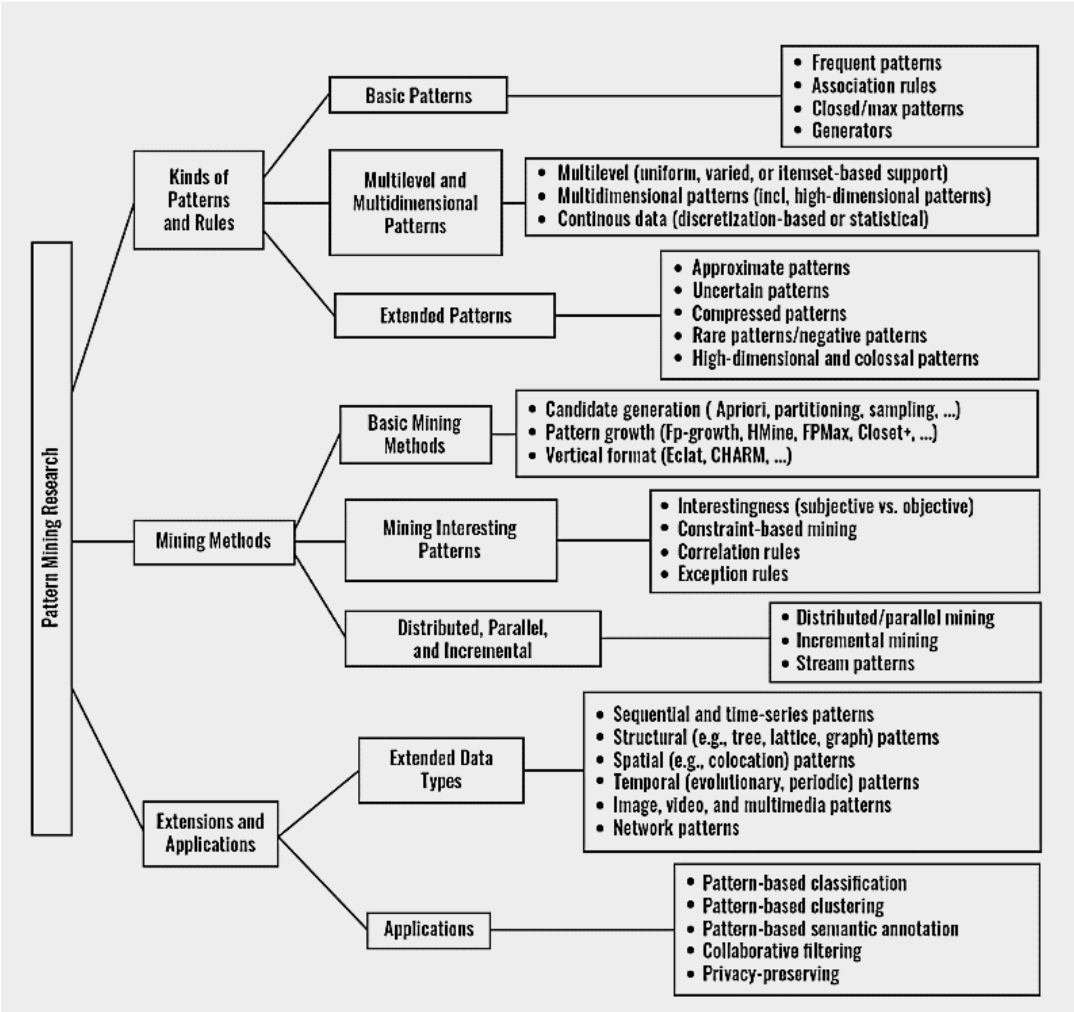

Figure 3. Pattern Mining Research [14]

The primary aim of the study is to explore the different edge computing methods that uses the frequency pattern mining and present it as a potential solution to overcome the disadvantages of the conventional methods that do not employ frequency pattern mining.

2. Literature Review

Ananda et al. [1] in his proposed work detail the rapid proliferation of connected devices, encompassing wearables, smartphones, and sensors, has led to an unprecedented surge in data traversing networks, primarily driven by the Internet of Things (IoT). However, the conventional approach of transferring IoT data to centralized systems, typically the cloud, for processing and machine learning (ML) tasks introduces latency and escalates network traffic. In response to these challenges, edge computing emerges as a viable solution by bringing processing capabilities closer to the network edge and data sources. Despite its potential, the limited computational capacity of edge computing poses constraints, particularly for complex ML tasks.

This article proposes an innovative approach to integrate edge and cloud computing for IoT data analytics, aiming to harness the advantages of both paradigms. The strategy involves leveraging edge nodes strategically to minimize data transfer, with a focus on grouping sensors based on location for proximity-based processing. The study employs feature learning, utilizing deep learning techniques, such as autoencoders (AEs), to enhance data processing on edge nodes. Furthermore, the article explores similarity-based processing and introduces the concept of using edge-based encoders and cloud-based decoders for efficient data analysis.

A critical aspect addressed in the literature survey is the burgeoning field of IoT and its role in enabling smart systems across various domains, ranging from healthcare to smart cities. Despite the transformative potential of IoT, the computational limitations of edge devices, such as sensors, have confined them to data transmission, primarily to more powerful centralized systems. This data transfer paradigm not only induces latency but also contributes to increased network traffic. Consequently, there is a growing recognition of the need for integrated solutions that combine edge and cloud computing to optimize data analytics while reducing latency and network congestion.

The study introduces a novel methodology, employing autoencoders, edge computing, and the PCA (Principal Component Analysis) algorithm, to address the challenges posed by the existing data processing models. The objective is to minimize network traffic and latency by strategically distributing computational tasks between edge nodes and the cloud. The evaluation focuses on human activity recognition (HAR) from sensor data, considering different approaches, including location-based and similarity-based scenarios. The findings underscore the potential for substantial data reduction, up to 80%, without compromising accuracy, particularly when employing large sliding windows in the preprocessing step.

The integration of edge and cloud computing for IoT data analytics emerges as a promising avenue to enhance efficiency, reduce latency, and optimize network traffic. The study's contributions lie in its innovative approach to leveraging edge nodes, employing feature learning through autoencoders, and evaluating diverse scenarios for sensor data grouping. The results demonstrate the feasibility of significantly reducing data on the edge without compromising the accuracy of ML tasks, signaling a transformative direction for IoT data analytics.

Michele et al. [2] presented a concise and precise explanation of these computing paradigms and their interrelationships has been lacking in the literature, posing a challenge for newcomers to the field. This work aims to address this gap by serving as a comprehensive resource for researchers entering this domain. The authors commence by presenting the evolution of contemporary computing paradigms and associated research interests. Subsequently, they meticulously delve into each paradigm, elucidating its core concepts and establishing connections with others.

The foundational paradigm, cloud computing, originally conceived to facilitate "computing as a utility," gained prominence until the advent of IoT, which highlighted the limitations of a centralized approach. The rise of edge computing aimed to extend the power of the cloud to the network's edge, addressing issues like latency and connectivity. Various implementations, including Mobile Cloud Computing (MCC) and Mobile Edge Computing (MEC), emerged under the broader umbrella of edge computing.

Fog computing, as the culmination of edge computing principles, emerged to provide a comprehensive architecture dispersing resources along the Cloud-to-Things continuum. It transcends being a mere addition to the Cloud, serving as a vital intermediary enhancing the interaction between the Cloud and IoT. Despite its potential, research on fog and edge computing is still in its early stages, and the literature continually evolves, presenting new perspectives on these paradigms.

Hesham El-Sayed et al [3] in his paper explores the challenges of current centralized infrastructure in wireless networks and IoT applications, anticipating increased difficulties related to network dynamics. In response, edge computing (EC) is proposed to optimize resource utilization and enable the development of innovative applications, moving processing power to network peripheries. EC proves effective in reducing response times and saving network resources, particularly evident in smart applications like traffic lights, cities, grids, and cars. A comparative analysis with cloud computing demonstrates EC's superior performance in various network properties, establishing its effectiveness. Future research directions and challenges in EC system implementation are discussed.

Additionally, the paper highlights EC as a paradigm shift for mission-critical applications, emphasizing its remarkable performance in real-time data analysis, scalability, and enhanced quality of service. Projections suggest EC's transformative impact across industries, with major players investing in EC services. The decentralized architecture of EC facilitates autonomous decision-making at the edge, addressing network overhead and security concerns. Integration with other wireless networks further enhances decision-making speed. Comparisons with traditional cloud computing standards underscore EC and fog computing's improved quality of service for IoT applications.

The conclusion emphasizes the reliability of EC and fog computing compared to traditional cloud computing, despite the associated implementation costs. It stresses the need for strategic technology planning and testing to meet the evolving requirements of IoT applications in the future. Overall, the paper provides a comprehensive overview of EC's potential, its comparison with existing standards, and the imperative for careful technology selection to meet the demands of emerging IoT applications.

Patrick McEnroe et al [4] in his article explores the synergy between unmanned aerial vehicles (UAVs/drones), Internet of Things (IoT) applications, and the latest 5G mobile networks. It emphasizes the pivotal role of artificial intelligence (AI) technologies, particularly computer vision and path planning, in enhancing UAV-based IoT applications. Low latency and energy consumption requirements pose challenges for the current cloud-based AI paradigm, leading to the proposal of edge AI, which executes AI algorithms on-device or on edge servers close to users.

UAVs, or drones, are described as pilotless aircraft operated by onboard computers or ground control, gaining popularity in military and civil IoT applications. Civil applications discussed include drone light shows, delivery systems, precision agriculture, infrastructure inspection, search and rescue operations, and serving as aerial wireless base stations. The role of edge computing and edge AI in optimizing UAV effectiveness and IoT applications is highlighted, illustrating their potential in handling technical challenges and improving UAV capabilities.

The fusion of edge computing and AI, termed edge AI, is explored in the context of UAVs, leveraging the benefits of lower latency, higher reliability, improved security and privacy, reduced costs, and energy consumption. The article clarifies the distinction between edge computing and edge AI, emphasizing the capability of edge AI to execute AI algorithms at the network's edge. Researchers interested in the convergence of edge AI and UAVs are encouraged to utilize this survey article as a valuable resource, given the increasing significance of this intersection.

Ruikun Luo in his study discusses the design problems of Edge Server Networks (ESNs) in Mobile Edge Computing (MEC), focusing on the trade-off between network building cost and network density. MEC deploys edge servers to base stations to provide cloud-like computing and storage capabilities, which are critical for achieving low latency requirements at the network edge. The Edge Server Network Design (ESND) problem is introduced and formulated as a restricted optimization problem, which demonstrates its NP-hardness. The work presents two approaches: ESND-O, an optimal integer programming approach for small-scale issues, and ESND-A, an efficient approximation approach for large-scale problems. Extensive trials prove the effectiveness and efficiency of ESND-O and ESND-A on a real-world dataset, comparing their performance to four comparable techniques.

The explosive growth of mobile and IoT services has led to a surge in mobile traffic, making MEC, with its edge computing capabilities, crucial for meeting low latency and resource consumption challenges. The collaborative nature of ESNs, formed by geographically adjacent edge servers, facilitates efficient resource sharing, contributing to improved service performance. While current studies focus on optimizing edge server placement, ESND addresses the undervalued aspect of ESN design, emphasizing the impact of network density on collaborative edge server performance.

ESND considers the geographic distances between edge servers to measure construction costs, acknowledging the challenge of balancing network density and construction budgets for Edge Infrastructure Providers (EIPs). The paper contributes to the understanding of ESND and provides solutions for achieving the optimal trade-off between network density and construction costs, enhancing the design of advanced ESN construction solutions. Future research directions are highlighted, focusing on network robustness and the interplay between network service performance and construction costs in ESND.

Yuxuan Sun et al [6] in his e paper addresses the challenges of mobility management (MM) in the integration of mobile edge computing (MEC) with ultra-dense networking (UDN) and presents a user-centric energy-aware mobility management (EMM) scheme. The scheme optimizes delay considering both computation and radio access, taking into account the user's long-term energy consumption constraint. Leveraging multi-armed bandit theory and Lyapunov optimization, EMM operates efficiently with incomplete system state information and performs online without requiring future system state information. Theoretical analysis demonstrates a bounded deviation in energy consumption and delay performance compared to an oracle solution with precise future system information. The proposed algorithm handles scenarios where candidate base stations (BSs) randomly turn on and off during task offloading.

The integration of UDN and MEC is highlighted as a key deployment scenario, enhancing network capacity and offering low-latency services for applications like connected cars, video analysis, augmented reality, and IoT. The EMM algorithms maximize delay performance while adhering to user energy constraints, showcasing near-optimal results in simulations. Future research considerations include cooperative computing among BSs and MM schemes for high-mobility scenarios.

Yuyi Mao et al [7]. in his paper delves into the intricate details of MEC system elements, including communications, computation tasks, and the computational capabilities of both mobile devices and MEC servers. Modeling approaches are discussed to evaluate the performance of MEC systems in terms of latency and energy consumption. The review extends to recent studies on resource management for MEC under various system architectures, covering aspects like computation offloading, joint radio-and computational resource allocation, MEC server scheduling, and multi-server cooperation and selection.

In addition to research challenges, the paper examines common use cases for MEC applications and highlights ongoing industry standardization efforts. This holistic overview serves as a valuable resource for researchers, practitioners, and industry professionals interested in gaining insights into the evolving landscape of MEC, offering a roadmap for future advancements in the field.

Badr Eddine Mada et al [8] The escalating demand for live streaming services has necessitated the development of effective live transcoding solutions, emphasizing Quality of Experience (QoE) for a large user base. This paper proposes a framework architecture based on the ESTI-NFV model, leveraging multiple cloud domains for transcoding and streaming Virtual Network Functions (VNFs). Adhering to the ESTI-NFV model ensures the adaptability of the virtual delivery platform, dynamically scaling in response to changing end-user demands to optimize costs. The framework aims to maintain QoE while reducing expenses by managing virtual live transcoding and streaming VNFs across diverse cloud domains. Experimental benchmarking of transcoding and streaming VNFs with variant resource configurations has been conducted to inform the development of an intelligent algorithm. This algorithm, to be incorporated into the proposed framework, will optimize the management of transcoding and streaming VNFs based on acquired benchmarking results. Live streaming's increasing popularity and traffic dominance necessitate scalable, available, and maintainable transcoding solutions, and the proposed framework addresses these requirements by leveraging cloud domains and intelligent algorithms. Future work involves creating an algorithm using optimization strategies such as convex optimization, linear integer programming, and game theory to enhance decision-making at the orchestrator level.

Live transcoding, crucial for meeting the surging demand in live streaming services, is addressed in this paper through a proposed framework built on the ESTI-NFV model. By utilizing multiple cloud domains for Virtual Network Function (VNF) transcoding and streaming, the framework ensures flexibility, dynamically scaling to changing user demands while adhering to the ESTI-NFV model. The focus is on enhancing Quality of Experience (QoE) while optimizing costs. A key contribution is the management of transcoding and streaming VNFs across diverse cloud domains, aiming to balance QoE and cost-effectiveness. The framework's development is informed by experimental benchmarking of transcoding and streaming VNFs under varying resource configurations.

Live streaming's unprecedented popularity underscores the importance of scalable, available, and maintainable transcoding solutions. The proposed framework addresses these requisites by leveraging cloud domains and integrating an intelligent algorithm. The algorithm, shaped by benchmarking outcomes, aims to optimize transcoding and streaming VNF management within the framework. The paper's forward-looking approach involves further algorithm refinement, incorporating optimization strategies like convex optimization, linear integer programming, and game theory. This approach aligns with the anticipated growth in live streaming, where scalable, cost-effective transcoding solutions are essential for maintaining superior QoE.

Tarik Taleb et al [9] in his paper delves into the role of the ETSI MEC Industry Specification Group (ISG), initiated in 2014, in standardizing and promoting edge-cloud computing within mobile networks. It explores the potential benefits of MEC for various stakeholders, including mobile network operators, application developers, and over-the-top players. MEC's ability to reduce latency is identified as a key advantage, opening avenues for services such as mobile serious gaming, IoT/M2M, and 4K UHD video.

The discussion extends to the fundamental enablers of MEC, encompassing network slicing, software-defined networking (SDN), network function virtualization (NFV), and virtualization technologies like virtual machines and containers. Orchestrator deployment options and considerations are thoroughly examined, providing insights into standalone services, service mobility, cooperative networks, and service optimization.

The paper concludes with an exhaustive state-of-the-art study on edge-cloud computing, highlighting its impact on various applications and presenting open research challenges in the MEC landscape. Overall, MEC emerges as a transformative technology poised to reshape mobile communications, with ongoing efforts in standardization and research paving the way for its future applications and advancements.

Liangzhi Li, et al [10] in his paper addresses the challenge of handling massive data generated by sensors in industrial productions, focusing on manufacturing inspection for defect identification. In response to the Industry 4.0 trend, the authors propose a deep learning-based classification model designed to enhance the accuracy of defect detection in smart industries.

The growth of IoT devices in factories necessitates the efficient processing of large volumes of real-time data, particularly in scenarios with multiple assembly lines.

Within the context of Industry 4.0, characterized by automation and data-centric approaches, AI techniques like deep learning play a pivotal role. The adoption of IoT-enabled devices in smart factories provides valuable data for AI applications, with a specific focus on autonomous manufacturing inspection. The paper emphasizes the challenges arising from the increasing data size as vision sensors are deployed across production lines to reduce reliance on human workers.

To address the computing efficiency bottleneck, the authors introduce DeepIns, a manufacturing inspection system with three modules: server-side computing, backend communication, and fog-side computing. Fog computing, with its computation offloading capability, is highlighted as a solution to enhance computing efficiency in real-time inspection systems. The fog-side computing module includes an early-exit feature to reduce response latency and network traffic, providing quick classification results.

The proposed system employs deep models to analyze sensor-captured images, identifying defective products and indicating the degree of defects. Leveraging fog computing, the system achieves real-time capabilities and efficiently manages large datasets by offloading computation to fog nodes, thereby alleviating the central server's overload. Simulations validate the system's reliability, effectiveness, and superior performance compared to certain tested methods.

Looking ahead, the authors plan to conduct classification and regression experiments on various production types and refine the offloading strategy to incorporate multiple fog devices into deep model computation simultaneously. This ongoing research aims to enhance the overall operating efficiency of fog-based deep learning applications in smart industries. The Table .1 below present the key findings of the research.

Table 1. Comparative Table

Ref. No	Methodology	Merits	Demerits
[1]	Feature Learning with Deep Learning,Data Reduction,and Evaluation on Human Activity Recognition.	Reduced Data Transfer, Improved Efficiency, Maintained Accuracy	Complexity , Scalability and Resource Allocation
[2]	Identifying Open Challenges and Future Directions	Comprehensive Understanding, Clarity and Neatness and Highlighting Relationship s.	Depth of Exploration and Open Challenge s and Future Directions
[3]	Application of EC in IoT	Problem Solving, Practical Application and Research Validation	Lack of Specifics, Limited Details on Challenge s and Data and Sample Size
[4]	Evaluation of UAV Applications and Assessment of AI Technologies	Comprehensive Analysis and Practical Focus.	Lack of Specifics, Limited Discussion of Challenge s and Focus on Edge AI
[7]	Research Thrust in MEC	Identification of Research Directions	Lack of Specific Details and Limited Exploration of Standardization.
[8]	ESTI-NFVModel Integration	Quality of Experience (QoE)Enhancement and Cost Reduction.	Complexity and Resource Management
[9]	MECOrchestration and MEC Reference Architecture and Deployment Scenarios.	Comprehensive Coverage, Practical Implications and Multi-tenancy and Standardization.	Lack of Specific Findings and Depth of Coverage.
[10]	Deep Learning Model and Fog Computing.	Dual Assessment and Efficiency Enhancement	Lack of Specific Results and Limited Technical Details.

The use of frequency pattern algorithms in the edge computing offers several advantages some of them are list in the Table .2 below

Table 2. Advantages of Frequency Pattern Mining in Edge Computing

Advantages of Frequency pattern Mining in Edge computing	**Real-Time Analysis**
Advantages of Frequency pattern Mining in Edge computing	Reduced Latency
	Lower Data Transfer Requirements
	Improved Resource Utilization
	Enhanced Data Accuracy with Frequent Pattern Mining
	Scalability
	Optimized Response Time
	Decentralized Processing
	Adaptability to Edge Devices
	Cost Efficiency
	Privacy Preservation

3. Discussion

Edge Computing enables local devices to interpret sensor data in real time, allowing for faster analysis and decision-making. This is critical for applications that require quick reactions. By processing data locally at the edge, latency is reduced. This is especially useful in applications where minimal latency is required, such as industrial automation or crucial healthcare monitoring. Edge Computing lowers the need to send vast amounts of raw sensor data to centralized servers. This minimization of data transport requirements increases bandwidth efficiency and minimizes network stress. Edge devices can efficiently use local computational resources to process sensor data, hence optimizing resource use. This is particularly critical for devices with minimal computing power[11]. Frequent Pattern Mining algorithms look for recurrent patterns in datasets to help filter out noise and useless information from sensor data. This leads to higher accuracy in spotting important patterns and relationships. The combination of Frequent Pattern Mining with Edge Computing enables scalability to handle larger datasets and an increasing number of connected devices. This scalability is critical in the context of the Internet of Things. Localized processing of sensor data at the edge leads to faster response times. This is especially useful for applications that demand rapid decision-making, such as self-driving cars or smart grid systems [12]. Edge computing spreads computational duties across edge devices, resulting in a decentralized processing architecture. This improves the system's resilience, fault tolerance, and overall reliability. Frequent Pattern Mining techniques can be customized and optimized for use on edge devices, ensuring compatibility with a wide range of IoT devices and sensors. Localized processing eliminates the need for substantial data transmission and centralized server architecture, potentially resulting in cost savings on bandwidth and server maintenance. Data analysis at the edge protects sensitive information's privacy by minimizing the quantity of data transported to centralized servers. As a result, integrating Frequent Pattern Mining techniques with Edge Computing not only enhances sensor data accuracy but also addresses issues of latency, data transfer, resource consumption, and scalability, making it ideal for dynamic and time-sensitive applications [13].

As indicated in Table 1 above, frequency pattern mining-based edge devices encounter challenges related to limited computational power, latency in data processing, scalability, resource allocation, and management issues, as well as limited network connectivity. These challenges may lead to issues such as difficulties in implementing complex algorithms like Frequent Pattern Mining, delays in processing data, and disruptions in the timely transfer of processed data. To address these circumstances, future researchers must optimize and streamline the Frequent Pattern Mining algorithm for efficient resource utilization. They should consider offloading intensive computations to more powerful edge devices or utilizing cloud resources when necessary. Implementing distributed computing strategies is essential to handle scalability, which may involve parallelizing computations across multiple edge devices or utilizing cloud resources for large-scale processing. Additionally, optimizing algorithms and processing pipelines for minimal latency, prioritizing critical tasks, and leveraging parallel processing techniques will improve response times. To mitigate network unavailability, implementing local storage and buffering mechanisms on edge devices is recommended. Furthermore, utilizing edge-to-edge communication, when possible, can reduce reliance on centralized servers

4. Conclusion

In conclusion, the combination of Frequent Pattern Mining techniques with Edge Computing emerges as a game-changing approach for improving sensor data accuracy. The survey revealed several advantages of this integration, including real-time analysis, reduced latency, enhanced resource utilization, and increased scalability. By leveraging the processing capabilities of edge devices and the pattern recognition finesse of Frequent Pattern Mining, this strategy not only ensures quick responses but also alleviates network constraints by minimizing data transfer to centralized servers. However, challenges such as limited computational capacity on edge devices and scalability issues require innovative solutions. Future research should focus on algorithmic optimization, efficient offloading of computations to powerful devices or cloud resources, and the application of distributed computing methodologies. Prioritizing key tasks, parallelizing calculations, and mitigating network unavailability through local storage techniques are critical to success. This integration not only improves sensor data accuracy, but it also establishes the foundation for a dynamic and scalable architecture. Looking ahead, continued exploration and refinement in these domains have the potential to impact the trajectory of sensor data processing, supporting innovation and applications across a wide range of industries in our rapidly changing technological landscape.

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