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Emerging Applications of Artificial Intelligence in Edge Computing: A Comprehensive Review

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ABSTRACT

Edge computing, coupled with Artificial Intelligence (AI), represents a paradigm shift in data processing, enabling real-time analytics and decision-making at the source. By distributing computation closer to the data origin, this integration addresses the critical challenges of latency, bandwidth, and privacy, which traditional cloud-centric systems face. AI algorithms deployed on Edge devices enable localized intelligence, facilitating transformative advancements in domains such as healthcare, smart cities, industrial automation, and autonomous systems. This review comprehensively examines the synergistic relationship between AI and Edge computing, highlighting key applications, challenges, and future research opportunities. Moreover, we emphasize the critical need for lightweight AI models, energy-efficient systems, and robust security measures to fully harness the potential of Edge AI in an increasingly connected world.

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1. INTRODUCTION

The exponential growth in data generation, coupled with the rapid proliferation of Internet of Things (IoT) devices, has profoundly influenced the computing landscape [1]-[3]. Traditional centralized cloud computing, while robust, struggles to meet the demands of low-latency processing, bandwidth efficiency, and stringent privacy requirements [4]-[6]. To address these challenges, Edge computing has emerged as a transformative paradigm, shifting data processing closer to the source of data generation—the Edge of the network. By reducing the dependence on centralized infrastructure, Edge computing enhances responsiveness, ensures better privacy, and optimizes resource utilization [7]-[10].

Artificial intelligence, with its unparalleled capabilities in data-driven decision-making, predictive analytics, and pattern recognition, has become an integral component of modern technological solutions. The fusion of AI with Edge computing creates a powerful framework for real-time intelligence, enabling applications ranging from autonomous vehicles and industrial automation to personalized healthcare and smart urban environments. Edge-based AI systems can process vast amounts of data locally, eliminating the need for continuous data transmission to centralized servers and enabling immediate actionable insights [10]-[14].

With the advent of Edge computing, computational power may now be located closer to the location where data is gener- ated. In contrast to typical cloud computing, Edge computing works by doing computations close to mobile devices, sensors, and data sources. This makes data processing faster and more effective, which appeals to a variety of businesses. Researchers and experts have different definitions for Edge computing. Some describe it as a mode of computing where data from the cloud represents services, while data going back represents the Internet of Things (IoT) [15]-[16]. Others see it as a computing model that places resources like small data centers or fog nodes closer to devices or sensors. In simple terms, Edge computing combines computing, storage, and networking resources that are physically or network-wise closer to users, providing services for various applications [3]. Edge computing is improved further through the integration of networking, computation, storage, and applications at the Edge, according to the China Edge Computing Industry Alliance [4]. This connection enables the provision of intelligent services that handle operations performed in real-time, optimization of data management, intelligence of the application, privacy and security concerns. In simple terms, Edge computing refers to the process of relocating networking, storage, and com- puting resources from the cloud to the network's Edge [19]-[23]. As a result, it may offer intelligent services that satisfy the demands of the IT sector for quick connections, real-time operations, effective data processing, and improved security and privacy. Because of this, there is a lot of interest in and research being done on Edge computing.

In this survey paper, we focus on exploring the applications of Edge computing in areas like Internet of Medical Things [17]-[18], cognitive systems, AI on Edge computing, as well as its use in smart homes and smart cities [26]-[30]. Additionally, we discuss the challenges faced in adopting Edge computing [24]-[25]. By examining these applications and challenges in simple terms, we aim to provide a comprehensive overview of the potential and limitations of Edge computing.

The paper is structured as follows: Section II reviews the related literature, Section III describes the materials and methods used, Section IV presents the results and discussion, and finally, Section V concludes the study.

2. OVERVIEW

This section provides an overview of the Edge computing and applications that discussed in this survey paper, focusing on the current applications in the field of Edge Computing. These applications represent a diverse range of domains and highlight the extensive utility and potential of Edge computing technology.

2.1 Overview of Edge Computing:

A. Definition and Key Features:

Edge computing involves processing data at or near the source of generation, reducing the dependency on centralized servers. Key features include low latency, enhanced security, and real-time processing.

B. Architecture of Edge Computing:

The architecture comprises three layers:

i. Edge Devices: Sensors, cameras, and IoT devices generating data.
ii. Edge Gateways: Intermediate devices that preprocess and route data.
iii. Cloud: Centralized storage and analytics for non-time-critical tasks.

C. Benefits and Limitations:

i. Benefits: Reduced latency, improved data security, and bandwidth optimization.
ii. Limitations: Limited computational power and potential interoperability challenges.

2.2 Emerging Areas of Edge Computing:

A. Internet of Medical Things:

The IoMT is an application of various technologies in the medical industry [5]. Various sophisticated technologies include IoT, identifying an object's position, radio frequency identification (RFID), and using transducers, along with mobile devices and network communication, to facilitate communication and connectivity between patients, medical professionals, healthcare facilities, and medical devices. Healthcare services are intended to be made more intelligent, automated, and digital via the IoMT.

B. Cognitive Edge Computing:

The act of acquiring information and understanding men- tally through thought and experience is referred to as cognitive Edge computing [6]. The use of specific technologies to mimic human behaviors and decisions to complete a particular task is known as cognitive computing.

C. Smart Home/Smart City:

The definition of a smart home or city is the use of IOT to gather, process, and integrate data so that we can use our mobile devices to operate various devices. Smart cities and households can respond intelligently to a variety of needs, such as everyday subsistence and environmental preservation.

D. AI on Edge Computing:

A new flavor of computing that combines both architectural kinds of computing was introduced in addition to computing on the Edge and computing in the cloud. The main benefits of architectural styles are included in this. The use of specialized hardware created to speed up the performance of the operations has made it possible for what is known as Specialized Edge architecture to be implemented.

3. APPLICATIONS OF EDGE COMPUTING

3.1 Edge Computing in IoMT:

To send medical data from terminal equipment to a distant cloud, the IoMT uses cloud computing technology. The data is processed by the cloud, which then transmits the results to the terminal devices. However, uploading medical equipment's growing volume of data to the cloud presents difficulties. This puts a lot of strain on the cloud, increasing energy use and causing delays because of the enormous burden. Cloud computing by itself is insufficient to overcome these issues. The ability to successfully increase cloud computing capacity and use dispersed computing resources will determine how quickly medical cloud IoT develops. In this case, processing computer operations at the network's Edge is accomplished through Edge computing [8]. By utilizing resources that are positioned closer to the data source, Edge computing can satisfy computational demands [9]. An Architecture of IoMT is shown in Figure 1.

A) Architecture of Edge Computing in IoMT: There are three layers in the architecture [18] and these layers work together to enable efficient data collection, processing, and analysis in medical IoT systems.

i. *Terminal Layer:* Sensors, wearables, and RFID tags are just a few of the IoT components that make up this layer in the medical industry. It oversees gathering information from these neighbourhood devices and sending it up to the Edge computer layer. Wired or wireless connections are used to transfer the data as input modes.
ii. *Edge Computing Layer:* The Edge computing layer is established as an Edge node network between the terminal equipment and the cloud. These Edge nodes could be routers and gateways on a network, or they could be intelligent terminals like smartphones and tablets. They offer network, storage, and computing services for the gathered data. A network can be

made more flexible and responsive by placing Edge nodes close to the terminal equipment, such as hospitals and clinics. Edge nodes can process data locally, which speeds up request processing and improves security by minimizing long distance transmission. data transmission. Processed data is regularly pushed to the cloud for further evaluation and archiving.

iii. *Cloud Computing Layer:* This layer provides primary data processing facility. An extensive computer, storage, and network infrastructure is needed to process, summarize, and provide persistent data archiving the data transferred by the above layer. Additionally, the cloud makes it easier to dynamically adapt and distribute Edge computing resources according to network conditions, which raises the standard of delay-sensitive services the Edge nodes provide. IoMT's Edge computing design has several advantages. As a result, delays are decreased, and the security of sensitive medical data is improved. It also enables real-time and responsive data processing at the Edge. Edge computing reduces energy consumption and boosts overall system performance by offloading computational workload from the cloud. Applications include Remote Patient Monitoring, Health Monitoring Architectures, Medical Augmented Reality (AR)/ Virtual Reality (VR), Micro Cloud Computing (MCC), Virtual Sensors/ Fog Computing, Collaboration between Edge and Cloud Computing.

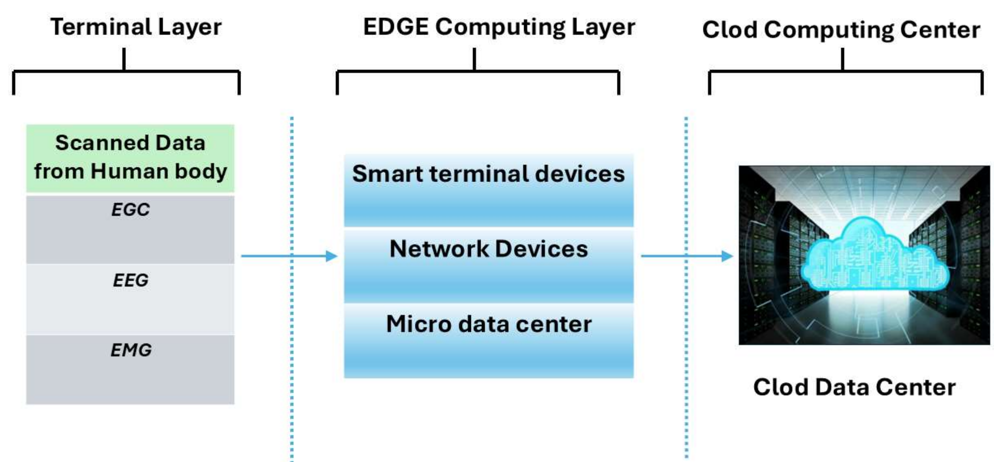

Figure 1. Representation for Architecture of IoMT.

3.2 Cognitive Edge Computing:

"Edge as Infrastructure resources-centric" was the main topic of this study. Here, they provide information on the methods now in use to keep an eye on the hardware resources for Edge computing. To determine the hardware metrics that affect the performance of the Edge application the admin knowlEdge and predefined thresholds are typically utilized to discover and resolve issues when monitoring hardware metrics [6]. Applying the appropriate fixes and having knowlEdge of row metrics frequently requires reverse engineering and is prone to human mistakes.

A crucial component of the process is keeping track of all the datacenter components on which the apps depend. The cost of keeping the service agreement in effect is high. Decisions are based on the logs accumulated daily, coupled with the application data and network data, making threshold-based monitoring obsolete. Making a choice about the hardware should be based on a thorough understanding of all the data. Big data and machine learning are used to validate any missed trends and do analytics on the current data to support human insights.

i. *Edge Resource Monitoring:* The main advantage of combining Edge and cloud computing is that real time decisions can be taken right at the data source. In general, the Edge devices are used in architectures where a high variety of requests are being sent. It is the responsibility of the Edge device to monitor and scale these requests to maintain a consistent service delivery. Machine Learning models are implemented at the Edge for estimating if there is any service that needs to be checked.

ii. *Archiving Cognitive Edge Computing through Machine Learning:* Cognition is practically implemented in the Edge devices by using machine learning algorithms capability to crunch large datasets and find the hidden patterns and information.

3.3 Smart City and Smart Home:

i. *Smart Home:* The implementation of IoT in the home environment is crucial as it is necessary to deploy inexpensive wireless sensors and controllers throughout various areas, including rooms, pipes, floors, and walls. These devices would produce a large quantity of data, and it is ideal for this data to be mostly used inside the home due to data consumption pressure and privacy protection concerns. As a result, the cloud computing paradigm is less suited for smart homes. But when it comes to creating a smart house, Edge computing is the best option. Devices can be readily connected to and operated locally by deploying an Edge gateway with a specific Edge operating system (EdgeOS) within the home. EdgeOS allows for the deployment of services for better administration and delivery, as well as the local processing of data to ease the strain on the internet's bandwidth. Figure 2 provides the pictorial representation on how EdgeOS is implemented in Smart Home and how the data is collected from different sources and communicated through different layers.

ii. *Smart City:* The Edge computing paradigm is highly scalable, allowing for flexible expansion from individual homes to larger communities or even as a city. This paradigm emphasizes the need for computing to occur near the data source. Figure 3 represents an exaple overivew of Edge collaboration in smart city scenario. Considering the characteristics of Edge computing, it can be an ideal platform for smart cities, as below.

Large Data Quantity: Smart cities with a population of one million people are projected to generate a staggering amount of data [14]. Handling such massive data volumes through centralized cloud data centers would impose a heavy workload. Edge computing offers a practical remedy by handling data processing at the network's Edge, reducing the load on the central cloud infrastructure.

Low Latency: This methodology is well versed for applications that require low and predictable latency, such as health emergencies or public safety scenarios. By enabling data processing at the Edge, minimizes the duration of data transmission and simplifies the architecture of the network. In contrast to gathering data and making judgments just at the central cloud, decisions and diagnoses can be made and distributed from the network's Edge, leading to more effective operations.

Location Awareness: Edge computing surpasses cloud computing in applications that rely on spatial information, such as the administration of transportation and utility. Edge computing allows for the collection and processing of data based on a certain location, eliminating the need for transportation to the cloud. This location awareness capability enhances the efficiency and effectiveness of applications in various domains.

Many IoT devices employ the characteristics of both Edge and cloud-based computing. This study's primary goal was to carry out an empirical investigation into the practicality of combining server class performance with an emphasis on AI workloads using a hardware-accelerated specialized Edge layer and to determine the energy, price, and performance advantages of using Edge hardware accelerators. Additionally, it assessed the impact of conventional Edge nodes in comparison to raw and normalized performance and offered suggestions for how IoT applications might make use of distributed and divided processing. A small group of single-board computing Pi-class nodes with Intel Movidius NCS2 VPU, Google

Edge TPU, Nvidia Jetson Nano GPUs and Nvidia TX2 GPU were employed for the arrangement. Processing images, detecting objects, and picking up keywords made up their workday. The results of the trials showed that server CPU and GPU are outperformed by Edge accelerators in terms of normalized performance. The findings also suggest that for some workloads, the special Edge clusters might take the place of x86 Edge clusters. The price is comparable to doing things the old-fashioned manner, but it is frequently less expensive than using many little GPUs. One of the main difficulties of using Edge-based solutions can be addressed by these Edge nodes, which appear to be ideal for environments with limited power and space.

A key point to be noted here is that if the run-time architecture is not memory efficient, concurrencies do often require more device memory. However, by forcefully optimising the run-time architecture and using strategies like shifting models from host memory and quantizing model parameters, devices with fewer resources can support an extensive amount of parallelism.

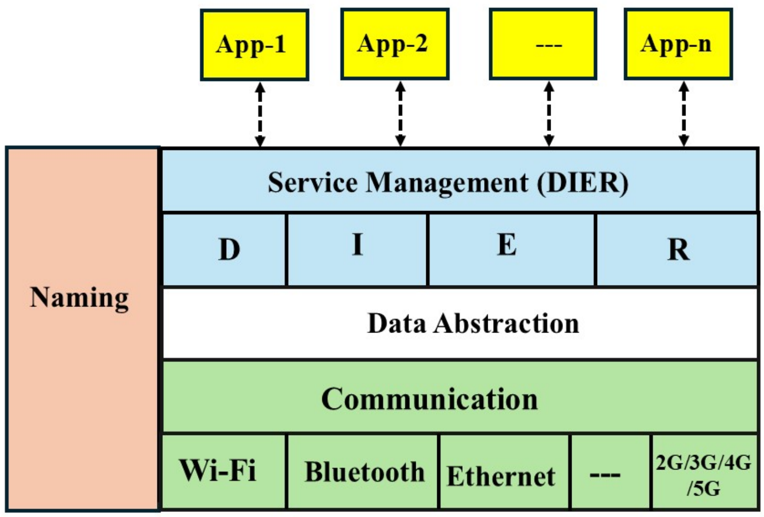

Figure 2. Smart Home Architecture- Edge OS.

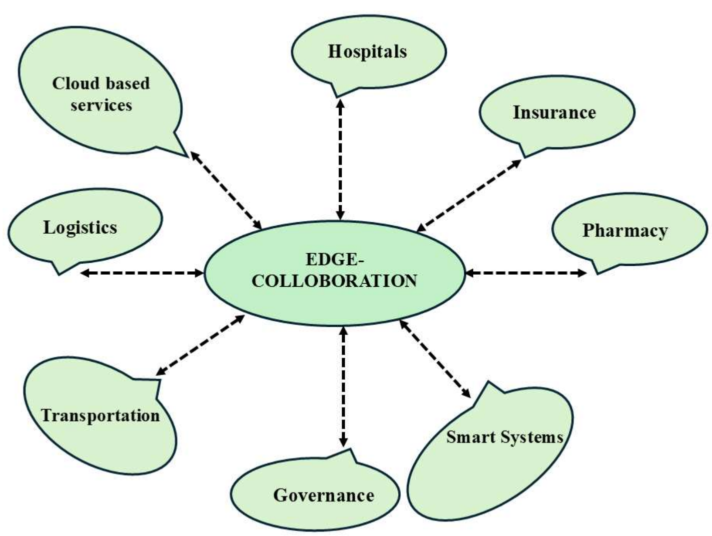

Figure 3. Representation of Edge collaboration in smart city scenario.

4. CHALLENGES IN EDGE COMPUTING

4. 1 Service Management:

There are four essential aspects that must be supported for service management at the network's Edge.

a) Differentiation: With the increasing deployment of IoT services at the Edge, it is crucial to prioritize different services based on their importance.
b) Extensibility: The dynamic nature of IoT devices poses challenges in terms of adding new devices to existing services or replacing worn-out devices.
c) Isolation: In the event of application failures or crashes, the entire system should not be affected.
d) Reliability: From the views of service, system, and data, reliability is a major concern at the network's Edge.
    - From a service perspective, it is important to not only maintain current services but also provide appropriate actions when nodes or components fail.
    - From a system perspective, maintaining the network topology and enabling status and diagnosis information exchange between components and Edge OS is crucial.
    - From a data perspective, reliability challenges arise due to data sensing and communication. IoT devices can fail or report low-fidelity data under unreliable conditions. Further research and development are needed to overcome the open challenges related to reliability in Edge computing.

4.2 Privacy and Security:

Protecting user privacy [21] and guaranteeing data security [22] are crucial functions at the network's Edge. IoT in homes can expose sensitive information through the sensed usage data, which raises challenges in maintaining privacy.

Privacy and Security Awareness: All parties involved, including service providers, programmers of systems and applications, and end users, must be aware of the privacy and security dangers at the network's Edge. Many Wi-Fi networks and devices remain unsecure [23], leaving user data vulnerable to unauthorized access.

Ownership of Collected Data: Data collected from Edge devices should ideally remain at the Edge, allowing users to retain ownership and control over their data. By storing data locally, users can decide whether to share it with service providers.

Lack of Efficient Tools: The Edge environment poses resource constraints and dynamic network conditions, requiring efficient tools for data privacy and security. Current security methods may be resource intensive and unsuitable for resource constrained Edge devices. Addressing these challenges will contribute to enhancing privacy protection and data security at the Edge of the network, allowing users to have more control over their personal information and fostering secure and trusted IoT deployments.

4.3 Optimization Metrics:

Edge computing has multiple layers. Hence, workload allocation is a significant challenge [24]. Here are some metrics.

Latency: Latency plays a crucial role in real-time and interactive applications [25]. Computationally intensive tasks WAN delays can impact real-time behavior. To reduce latency, it is beneficial to complete the workload at the nearest layer with sufficient computation capability.

Bandwidth: High bandwidth can reduce transmission time, especially for large data such as videos. Establishing high-bandwidth wireless access for short-distance transmissions can improve latency and transmission reliability. In smart home environments, handling data at the home gateway through high-speed transmission methods, such as Wi-Fi, can enhance latency and save bandwidth. Preprocessing data at the Edge reduces data size and conserves bandwidth, benefiting both users and the overall network.

4. 4 Computational Resource Constraints:

Edge devices, such as IoT sensors, cameras, and embedded systems, are often limited in terms of processing power, memory, and storage. These constraints make it challenging to deploy complex AI models, which typically require high computational resources to execute inference and training tasks effectively. The lack of powerful hardware restricts the deployment of advanced deep learning architectures, such as convolutional neural networks (CNNs) or transformers, which demand significant resources. Additionally, frequent updates or retraining of AI models are impractical on resource-constrained devices, leading to potential model obsolescence and reduced accuracy over time. Strategies to overcome these constraints include designing lightweight AI models, utilizing hardware accelerators like GPUs or TPUs, and employing model compression techniques such as pruning and quantization. Despite these advancements, balancing model performance and resource consumption remains a significant hurdle.

4. 5 Security and Privacy Concerns:

Although Edge computing mitigates some privacy risks by processing data locally, it also introduces unique security challenges. Edge devices, often deployed in uncontrolled environments, are susceptible to physical tampering, unauthorized access, and data breaches. The distributed nature of Edge systems creates a larger attack surface, increasing the likelihood of cyberattacks such as man-in-the-middle attacks, distributed denial of service (DDoS) attacks, and ransomware.
Privacy concerns also arise due to sensitive data being processed locally. For instance, AI applications in healthcare or smart homes involve personal and confidential information, making robust data protection mechanisms essential. Implementing encryption, secure boot processes, trusted execution environments (TEEs), and regular firmware updates are some approaches to address these issues. However, ensuring robust security without compromising performance remains an ongoing challenge.

4. 6 Data Management at the Edge:

The decentralized nature of Edge computing introduces complexities in managing, processing, and storing data locally. Edge devices generate massive amounts of heterogeneous data, often at high velocities, which necessitates efficient data management frameworks. Challenges include handling real-time data streams, ensuring data consistency, and integrating data from diverse sources for holistic analytics. Additionally, Edge devices often lack the storage capacity to retain data for extended periods, leading to data loss or incomplete historical records. Implementing efficient data compression, real-time data filtering, and prioritization techniques can alleviate these challenges. However, these solutions often require a delicate balance to avoid overburdening the limited computational resources of Edge devices.

4. 7 Interoperability and Scalability Issues:

The Edge ecosystem is characterized by diverse hardware, software, and communication protocols, resulting in interoperability challenges. Different manufacturers adopt proprietary standards for their devices, making it difficult to integrate and manage heterogeneous systems within a unified framework. This lack of standardization impedes the seamless deployment and scalability of Edge AI solutions across different environments. Scalability is another concern, as the growing number of Edge devices in large-scale deployments exacerbates the complexity of network management and coordination. Resource allocation, load balancing, and synchronization among devices require efficient orchestration mechanisms. Emerging solutions such as containerization, microservices, and Edge-native platforms aim to address these issues but are still evolving.

5. CONCLUSION

This survey on the applications of AI in Edge Computing has provided an overview of the dynamic capabilities of Edge Computing along with its uses, and the challenges that coexist with it. Edge Computing enables real-time processing of data and making decisions right at the origin of data, supports low- latency by eliminating the need for extra computing resources like cloud, and increases efficiency of the application at the Edge. In other words, it moves complex computation and data storage closer to the Edge of the network Edge Computing when integrated with powerful ML and AI algorithms enhances the way data is processed and analysed right at the point of data origin. This eliminates the Edge node's dependency on central servers or clouds which would further adhere in reducing the overall congestion in the network and present real-time results with low latency. In addition to low latency, the gross utilization of the cloud would be reduced by performing important computations right at the Edge and reserving the cloud for processing any low priority tasks and letting the Edge devices handle the important tasks.

Along with the aforementioned capabilities of the Edge com- puting, it also comes with certain challenges. These challenges may include issues with managing the data and it's definition, network connectivity and dependability, privacy and security concerns and the limitations that comes up setting up the resources on the Edge. It is therefore crucial to address all these problems to make sure the effective utilization of this technology and resources. The capabilities of this sophisticated technology involve transforming data processing, data analysis, allowing real-time decision making and accelerate the performance of parallel devices and systems. The power of Edge Computing can be applied in creating potent, intelligent, and connected cluster of applications and networks by carefully analyzing its capabilities, including the challenges and proactively working on providing creative and cutting Edge solutions.

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