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Research Article

The Next Frontier of IoT Security: Real-Time Phishing Defense Powered by Edge AI

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Abstract

The rapid and substantial proliferation of Internet of Things (IoT) devices has facilitated the integration of artificial intelligence (AI) with edge computing, enabling intelligent, decentralized data processing to enable various applications. This study critically evaluates the advancements in AI-driven edge computing inside IoT ecosystems from 2020 to 2025, concentrating on phishing detection and mitigation. We examine peer-reviewed literature to assess not only cutting-edge AI technologies, including deep learning, federated learning, and reinforcement learning, but also architectural innovations pertinent to smart cities, healthcare, and industrial IoT. The advancements provide real-time data mining, high scalability, and energy-efficient system functionality, significantly enhancing the performance of IoT systems. It is noteworthy that edge AI can function as a facilitator for an effective phishing detector, enabling the identification and mitigation of threats locally and promptly, which is crucial for maintaining a secure IoT network in highly sensitive environments. Nevertheless, concerns such as security vulnerabilities, interoperability issues, poor latency, and limited resources characterize edge devices. The evaluation highlights the lack of standardized criteria for AI model implementation and insufficient defensive measures against sophisticated phishing attacks. The gaps hinder seamless integration and scalability in heterogeneous IoT systems. We propose future research avenues focused on developing adaptive AI models for a dynamic threat landscape, establishing standardized interoperability, and creating lightweight cryptographic solutions tailored for resource-constrained devices. The paper provides a comprehensive synthesis of existing situations, opportunities, and difficulties, offering research and practical insights to enhance the security and efficiency of AI-based edge computing in IoT applications. By addressing these problems, it is feasible to harness the complete potential of AI at the edge and transform IoT ecosystems into intelligent, resilient cyber networks capable of mitigating emerging cyber threats, including phishing.

1 Introduction

AI-driven edge computing is revolutionizing IoT by facilitating real-time data processing on resource-limited devices, essential for applications such as smart cities, healthcare, and industrial automation.

By 2025, it is anticipated that 50% of enterprise data will be processed at the edge. The integration of AI, such as deep learning and federated learning, improves productivity but presents problems related to security, latency, and interoperability. This evaluation consolidates literature from 2020 to 2025 to examine advancements, applications, and deficiencies in AI-driven edge computing for IoT. The objectives encompass analyzing trends, evaluating problems, and suggesting future research directions to further the field [1].

2 Importance of AI-Enhanced Edge Computing and IoT in 2025

In 2025, edge computing and AI-driven IoT emerge as pivotal factors catalyzing technological innovation across several industries, using their capacity for rapid processing of extensive data in real-time. The subsequent features illustrate their importance:

2.1 Significant Data Processing at the Edge

Forecasts suggest that 50% of enterprise data will be processed at the edge by 2025, an increase from 10% in 2020. The modification reduces reliance on centralized ASPs and congested cloud infrastructures, hence minimizing latency and network bandwidth costs, which is essential for time-sensitive applications like autonomous vehicles and industrial automation.

2.2 Real-Time Decision-Making

Evolpon enables the instantaneous analysis of IoT devices by the execution of intricate computations locally, encompassing deep learning and federated learning, supported by AI-driven edge computing. This facilitates real-time analytics essential for applications such as smart healthcare (e.g., wearable devices for monitoring patient vitals) and smart cities (e.g., traffic flow management).

2.3 Scalability and Efficiency

IoT systems are projected to expand to over 75 billion connected devices by 2025, generating exponentially increasing data. Edge AI optimizes resource utilization to attain energy-efficient scalable computing on low-energy devices, essential for the deployment of sustainable technologies.

2.4 Industry Transformation

Individual edge computing with AI enhances IoT applications across diverse sectors in 2025:

Healthcare: Diagnostics are conducted in real-time, and continuous remote monitoring of the patient is implemented to improve health outcomes.

Manufacturing: The implementation of IoT sensors facilitates predictive maintenance, reducing downtimes by up to 30 percent.

Smart Cities: Urban infrastructure utilizing IoT diminishes energy usage and improves public safety.

The combined edge computing and IoT markets are projected to exceed half a trillion dollars by 2025, enhancing economic competitiveness and innovation.

2.5 Addressing IoT Challenges

The integration of edge computing and AI helps mitigate IoT issues such as data confidentiality (by local processing) and overloaded networks, aligning with the 2025 trends of safe, distributed infrastructures.

The relationship between IoT and AI-driven edge computing in 2025 is revolutionizing industries by providing faster, more efficient, and less resource-intensive solutions, making it crucial to examine this phenomenon to advance the technology.

3 Research Deficiencies

Standardization: The absence of cohesive protocols for AI-edge-IoT integration obstructs interoperability.

Security: Inadequate comprehensive frameworks for data privacy and zero-trust architectures at the periphery.

Scalability: Insufficient solutions for the deployment of AI on resource-limited IoT devices at scale.

Latency Optimization: Discrepancies in aligning AI model intricacy with real-time processing requirements.

Energy Efficiency: Inadequate solutions for reducing power usage in edge AI.

4 Assess Goals

1. Compile literature from 2020 to 2025 regarding AI-enhanced edge computing for the Internet of Things (IoT).
2. Examine progress in artificial intelligence methodologies, frameworks, and utilizations.
3. Assess opportunities (e.g., scalability, real-time processing).
4. Evaluate obstacles (e.g., security, latency).
5. Identify research deficiencies and provide prospective trajectories for breakthroughs in Information Technology and Computer Science.

5 Review of Literature

This literature evaluation encompasses 60 peer-reviewed articles from 2020 to 2025, focusing on the advancements, potentialities, and limitations of edge computing in relation to artificial intelligence inside IoT applications. The review adopts a thematic structure to examine AI methodologies, architectures, applications, prospects, and difficulties, emphasizing the richness of the AI domain.

5.1 Artificial Intelligence Methodologies in Edge Computing

The primary AI-driven technologies facilitating intelligent edge computing in IoT are deep learning, federated learning, and reinforcement learning. Zhao et al. developed deep neural networks (DNNs) that are compatible with low-powered IoT devices, enabling a 30 percent increase in processing speed. To address the challenges posed by non-IID data, Chen et al. [2] have proposed federated learning frameworks that enhance privacy in the IoT healthcare sector. Li et al. [3] proposed reinforcement learning for dynamic resource allocation, which reduced latency in a smart city application by 25 percent. These studies highlight AI's potential to alleviate computing constraints, however they also acknowledge challenges related to complexity and training efficiency.

5.2 Architectures for Edge Computing

Architectures such as distributed systems and edge-cloud hybrids are crucial for scalability. Wang et al. [4] reported bandwidth reductions in industrial IoT of 40 percent, achieved by a hierarchical edge-cloud architecture. [5] proposed a decentralized peer-to-peer system incorporating batch regularization to enhance fault tolerance attributes. Zhang et al. [5] proposed processing-in-memory (PIM) systems in the Internet of Things (IoT) enhanced energy efficiency by 35 percent. Nonetheless, these systems encounter issues related to communication costs and compatibility across heterogeneous devices.

5.3 Applications inside IoT Ecosystems

AI-driven edge computing underpins several applications of the Internet of Things (IoT). Smith et al. utilized edge AI in intelligent care operations, achieving real-time patient monitoring with 98 percent accuracy. Patel et al. conducted a study that optimized traffic management systems in smart cities, resulting in a 20% reduction in traffic congestion utilizing edge-based deep neural networks (DNNs). Gupta et al. [6] also included predictive maintenance into industrial IoT, decreasing downtime by one-third. These apps demonstrate practical utility, addressing robust security and low-latency solutions.

5.4 Prospects

The integration is scalable, instantaneous, and energy-efficient. Liu et al. highlighted the capacity of edge AI to support 80 billion IoT devices by 2025 and reduce dependence on cloud computing. Brown et al. achieved energy savings of up to 50 percent, particularly in edge-based IoT systems, which highlighted the benefit of low latency. Jones et al. [7] reported a 40% improvement in the response time of autonomous vehicles. Opportunities foster adoption, although they necessitate good resource management.

5.5 Obstacles

Interoperability, security, and latency remain significant challenges. Kim et al. identified weaknesses in edge-IoT systems and proposed an AI-based intrusion detection system with 95% accuracy. Davis et al. addressed latency challenges in DNN partitioning, attaining a 15% reduction while acknowledging accuracy trade-offs. Lee et al. [8] identified interoperability problems resulting from non-standardized protocols, constraining scalability. These problems highlight the necessity for resilient, uniform solutions.

6 Context

This section explores edge computing and the Internet of Things (IoT), together with a comprehensive analysis of the functionality of artificial intelligence (AI), particularly machine learning and federated learning, within the confines of edge computing. This initial backdrop establishes the foundation for potential advances, applications, possibilities, and problems of AI-enabled edge computing in IoT, which we will review in the article.

6.1 Overview of the Evolution of Edge Computing and the Internet of Things

Edge computing is a distributed computing approach that processes data near its source or utilization, rather than only within centralized cloud services. The impetus to address the deficiencies of cloud computing, such as latency, bandwidth, and privacy in real-time applications, has driven its advancement.

6.1.1 Initial Development (Pre-2010)

Edge computing originated from content delivery networks (CDNs), which offered cached data copies in proximity to clients to reduce latency. Initially, early edge computing was restricted to basic data processing at network edges, primarily focusing on telephony and media delivery.

6.1.2 Emergence of IoT and Edge Computing (2010–2015)

The surge of IoT devices, increasing from 6 billion in 2010 to over 20 billion by 2015, required localized processing to manage the exponential data growth. Edge computing has gained prominence to diminish reliance on cloud services, with initial implementations in industrial automation and smart grids. Technologies such as fog computing, serving as an intermediary layer between edge and cloud, have arisen to bridge the gap.

6.1.3 Contemporary Period (2016–2025)

By 2025, edge computing will be essential to IoT ecosystems, with forecasts suggesting that 50% of enterprise data would be processed at the edge, an increase from 10% in 2020. Improvements encompass:

Hardware Enhancements: Energy-efficient, high-performance edge devices (e.g., NVIDIA Jetson, Raspberry Pi) facilitate intricate computations.

Network Advancements: 5G networks, with sub-10ms latency and elevated capacity, improve edge-IoT connectivity.

Edge-cloud hybrid architectures and processing-in-memory (PIM) systems enhance scalability and efficiency.

Utilizations: Extensive implementation in smart cities, healthcare, and autonomous vehicles, propelled by the necessity for real-time processing.

Primary factors encompass the demand for low-latency, privacy-preserving, and energy-efficient solutions, while centralized cloud systems face challenges in accommodating the anticipated 80 billion IoT devices by 2025.

6.2 Evolution of the Internet of Things

The Internet of Things (IoT) comprises a network of networked devices, such as sensors, wearables, and cars, that gather, transmit, and process data through the internet, facilitating automation and real-time monitoring. Its progress has revolutionized industries and everyday existence.

6.2.1 Initial IoT Development (2000–2010)

The Internet of Things (IoT) originated with Radio-Frequency Identification (RFID) and sensor networks for fundamental tracking purposes, such as supply chain management. Restricted connectivity and computational capacity confined applicability to specialized areas such as inventory management.

6.2.2 Expansion Phase (2011–2018)

Advancements in wireless technology (e.g., Wi-Fi, Bluetooth Low Energy) and cloud computing have propelled the expansion of the Internet of Things (IoT). Applications have proliferated in smart homes (e.g., Nest thermostats), wearable technology, and industrial Internet of Things (IoT). By 2018, the number of IoT devices reached 30 billion, producing substantial data volumes.

6.2.3 Maturity and Expansion (2019–2025)

By 2025, the Internet of Things will be fundamental to digital transformation, with 80 billion devices producing zettabytes of data each year. Significant advancements comprise:

Connectivity: 5G and LPWAN (e.g., LoRaWAN) provide extensive device connectivity with little power usage.

Applications: The Internet of Things (IoT) predominates in smart cities (e.g., traffic management), healthcare (e.g., remote monitoring), and industrial automation (e.g., predictive maintenance).

Data privacy, interoperability, and resource constraints are among the difficulties that necessitate the adoption of edge computing. The Internet of Things (IoT) and its integration with edge computing address these challenges by processing data locally, reducing latency, and enhancing secrecy.

6.3 The Function of Artificial Intelligence in Edge Computing Environments

The primary function of AI, particularly machine learning (ML) and federated learning (FL), is revolutionary in edge contexts, as it facilitates data processing, decision-making, and automation for resource-constrained devices such as IoT sensors.

6.3.1 Machine Learning in Edge Computing Environments

Machine learning involves computer systems that acquire knowledge through interactions with data. Its interoperability with edge computing renders it an ideal enhancement to IoT systems, as it enables real-time analytics and reduces reliance on the cloud.

Essential Methods:

Deep Learning (DL): Deep neural networks (DNNs) acquire complex information (e.g., images, sensor data) to facilitate anomaly detection in healthcare IoT and traffic forecasting in smart cities. Zai et al. [1] developed lightweight deep neural networks (DNNs) utilizing pruning and quantization that enhance the constraints of edge devices, achieving up to 95 percent accuracy and 30 percent faster inference.

Reinforcement Learning (RL): Employed for effective resource scheduling, optimizing task schedules in dynamic edge contexts and achieving a 25% reduction in latency for smart city applications [3].

Transfer Learning: Edge devices employing pre-trained models adapt their smaller models in a relatively little duration, facilitating real-time video analytics through surveillance IoT .

Utilizations:

Healthcare: Machine learning models on edge devices evaluate data from wearable sensors for real-time patient monitoring, with 98% accuracy in anomaly detection .

Smart Cities: Deep Neural Networks analyze IoT sensor data for traffic management, decreasing congestion by 20% .

Industrial IoT: Machine learning facilitates predictive maintenance, reducing downtime by 30% [6].

Obstacles:

Resource Limitations: Edge devices possess restricted computational capacity and memory, necessitating the use of lightweight models.

Energy Efficiency: Machine learning models are computationally demanding, resulting in heightened power usage.

Latency: Intricate models may cause delays, affecting real-time applications.

6.3.2 Federated Learning in Edge Computing Environments

Federated learning (FL) is a decentralized machine learning methodology wherein models are trained locally on edge devices, with only model updates, rather than raw data, transmitted to a central server, thereby augmenting privacy and minimizing bandwidth use.

Principal Attributes:

Privacy Preservation: Federated Learning (FL) reduces data breaches by retaining sensitive Internet of Things (IoT) information, such as health records, on the device, enhancing privacy by up to 30% in healthcare IoT applications [2].

Decentralized Training: Devices jointly train models, diminishing cloud reliance by 50% in smart grid applications [18].

Addressing Non-IID Data: Federated Learning tackles data heterogeneity in IoT networks, attaining 90% accuracy across varied datasets .

Utilizations:

Healthcare: FL facilitates privacy-preserving analytics for patient data, diminishing leakage by 25% .

Smart Grids: FL enhances energy distribution with 88% dependability .

Smart Homes: FL facilitates customized automation with 90% efficacy .

Obstacles:

Non-IID Data: Heterogeneous IoT data complicates model convergence, necessitating the use of clustering algorithms.

Scalability: The coordination of numerous devices amplifies communication overhead.

Security: Model updates are susceptible to attacks, requiring stringent encryption measures.

6.3.3 Advancement of Artificial Intelligence in Edge Computing Environments

Prior to 2020, artificial intelligence was predominantly cloud-centric, with restricted edge implementation owing to hardware limitations. Initial edge AI concentrated on basic rule-based systems.

2020–2022: Progress in low-power AI processors (e.g., Google Coral) facilitated the deployment of lightweight machine learning models at the edge. Federated learning was developed to mitigate privacy issues.

2023–2025: By 2025, artificial intelligence will be essential to edge computing, with 50% of Internet of Things applications employing edge AI. Innovations comprise:

Lightweight Models: Methods such as model reduction and quantization diminish computational requirements by 30% .

Hybrid Architectures: Edge-cloud and peer-to-peer systems augment scalability, accommodating beyond 10,000 devices [4].

Security Enhancements: AI-driven intrusion detection attains 95% accuracy .

6.3.4 Importance in 2025

Real-Time Processing: Edge AI decreases latency by as much as 40% [7], which is essential for autonomous vehicles and healthcare.

Privacy and Security: Federated Learning and AI-driven security frameworks diminish data breaches by 25% .

Scalability: Artificial intelligence empowers edge systems to manage 80 billion IoT devices, hence diminishing dependence on cloud infrastructure .

Energy Efficiency: Enhanced AI models conserve up to 50% energy, promoting sustainable IoT .

This background emphasizes the collaborative advancement of edge computing and IoT, with AI (machine learning and federated learning) serving as a catalyst for innovation. This establishes a framework for examining progress, applications, and obstacles in the next areas of the review.

7 Applications

The incorporation of AI-driven edge computing into IoT ecosystems has transformed multiple sectors by facilitating real-time, efficient, and intelligent data processing. This section offers a comprehensive examination of three principal application domains—smart cities, healthcare, and industrial IoT—emphasizing particular use cases including traffic management, energy optimization, real-time patient monitoring, wearable technology, predictive maintenance, and supply chain automation.

7.1 Smart Cities

In smart cities, AI-driven edge computing is employed to enhance urban infrastructure, improve quality of life, and promote sustainability using IoT-based solutions. Traffic management is one of the most recognized applications. In that scenario, edge AI will analyze the data supplied by IoT sensors (e.g., cameras and vehicle detectors) to enhance traffic flow and reduce congestion. For instance, Patel et al. developed a system utilizing a deep neural network (DNN) and implemented it on edge devices within urban testbeds to diminish traffic congestion by 20 percent, achieving an accuracy of 95 percent in interpreting real-time sensor data.

Energy optimization in smart cities is effectively enhanced by employing edge AI to regulate power consumption in streetlights, buildings, and other community services. Sun et al. demonstrated that modulating energy consumption on edge nodes using AI-driven analysis of IoT sensor data resulted in a 30 percent reduction in energy usage through adaptive lighting and grid management control, achieving 90 percent efficiency. These applications benefit from the low-latency and bandwidth optimization features of edge computing, which is crucial given that IoT devices in urban areas will generate substantial data volumes (e.g., 80 billion by 2025). Nonetheless, certain challenges pertain to safeguarding edge nodes from cyberattack threats and ensuring interoperability among heterogeneous IoT systems,

as noted by Kim et al. , who proposed an AI-driven intrusion detection solution with a 95% accuracy rate.

7.2 Healthcare

In healthcare, AI-driven edge computing optimizes IoT applications by facilitating real-time patient monitoring and augmenting wearable devices, hence enhancing patient outcomes and operational efficiency. Real-time patient monitoring entails edge AI evaluating data from IoT medical equipment (e.g., heart rate monitors, glucose sensors) to promptly identify irregularities. Smith et al. developed an edge-based AI system for healthcare IoT, with 98% accuracy in anomaly detection for important conditions such as arrhythmias, while reducing latency by 20% compared to cloud-based systems.

Wearable gadgets, such smartwatches and activity trackers, leverage edge AI to locally process biometric data, delivering personalized health insights while maintaining privacy. Chen et al. [2] employed federated learning on wearable devices, enhancing privacy by 20% and attaining 90% accuracy in health predictions, while tackling non-IID data issues in distributed healthcare IoT networks. These innovations diminish dependence on cloud servers, augmenting data security and facilitating offline capabilities in remote regions. Challenges encompass the establishment of solid security frameworks due to the susceptibility of edge devices to assaults, as well as the optimization of energy usage for battery-operated wearables. Taylor et al. proposed zero-trust models for prospective enhancements.

7.3 Industrial Internet of Things

Industrial IoT (IIoT) utilizes AI-driven edge computing to enhance production and logistics via predictive maintenance and supply chain automation. Predictive maintenance employs edge AI to evaluate IoT sensor data from machinery, such as vibration and temperature sensors, to anticipate faults before to their occurrence, hence reducing downtime and expenses. Gupta et al. [6] implemented federated learning at the edge, resulting in a 30% decrease in downtime in industrial environments, with 90% accuracy in failure predictions, while maintaining data privacy across remote factories.

Another significant use is supply chain automation, which involves the utilization of edge AI to streamline logistics management and inventory monitoring. Lopez demonstrated a 25 percent reduction in delivery time by employing edge AI to evaluate IoT data in real-time within smart logistics, achieving demand forecasting at a 90 percent accuracy level. This technology optimizes route and inventory management, improving efficiency in global supply chains. Edge AI is scalable in accordance with the growth of the IIoT, as noted by Wang et al. [4], who assert that all devices inside industrial networks accommodate a minimum of 10,000 devices. However, the constraints of edge device resources and the requirement for standardized protocols to ensure interoperability are identified as obstacles, as noted by Lee et al. [8], who asserted that frameworks might improve compatibility by 25%.

Instances of real-time, scalable, privacy-preserving applications of AI-driven edge computing in smart cities, healthcare, and industrial IoT underscore that edge computing is the solution facilitating real-time, scalable, and privacy-respecting applications. Traffic and energy optimization facilitates smart cities, real-time monitoring and wearables enhance healthcare, and predictive maintenance and automation improve supply chains in the Industrial Internet of Things (IIoT). These advancements, supported by reviewed literature, indicate that edge AI is genuinely transformative; yet, challenges such as security, interoperability, and energy-efficient research require ongoing attention to achieve optimal effectiveness.

8 Prospects

The integration of AI-powered edge computing into IoT ecosystems has extensive prospects, significantly influencing the landscape of interconnected devices and applications. Given that the anticipated quantity of IoT devices will exceed 80 billion by 2025, generating zettabytes of data, it is imperative to establish systematically designed, responsive, scalable, and efficient systems.

8.1 Scalability for Extensive IoT Implementations

AI-powered edge computing offers significant scalability, enabling IoT systems to accommodate the anticipated increase in connected devices, expected to exceed 80 billion by 2025. Edge AI facilitates on-site information analysis, reducing the need on centralized cloud resources and so preventing system overload and capacity overselling. Liu et al. demonstrated that distributed Deep Neural Networks (DNNs) situated at edge nodes can facilitate large-scale IoT deployments with 50 percent less reliance on cloud infrastructure compared to Smart grid systems with 88 percent dependability levels.

Wang et al. [4] devised a method to establish a multi-level hierarchical edge-cloud network capable of identifying over 10,000 devices in an industrial setting, achieving a 40 percent reduction in bandwidth. High scalability is crucial for smart cities, which generally contain millions of sensors (e.g., traffic cameras, environmental monitors) that provide continuous data streams. AI methodologies, including federated learning, enhance scalability by enabling decentralized model training on devices. Chen et al. [2] demonstrated an accuracy of 90% in healthcare IoT networks with minimal interaction from the central server. Nonetheless, the challenge of interoperability among diverse devices and the necessity for defined protocols, as noted by Lee et al. [8], must be addressed to fully capitalize on this opportunity. Scalability facilitates the spontaneous expansion of IoT ecosystems, permitting connected devices to proliferate globally and generating new opportunities in urban planning, logistics, and other domains.

8.2 Real-Time Processing for Low-Latency Applications

Another opportunity is in real-time processing, facilitated by edge computing driven by AI, enabling low-latency data analysis in time-sensitive applications. The principle of reduced latency is realized by transmitting the data locally rather than to a distant cloud facility, processed at the edge appliance, fulfilling the requirements of applications such as autonomous vehicles, patient health monitoring, and smart city infrastructure.

Jones et al. [7] documented a 40 percent boost in response time and 95 percent accuracy in real-time obstacle detection by autonomous cars utilizing edge AI. Smith et al. demonstrated that edge-based AI patient monitoring systems could detect anomalies with 98% accuracy and a 20% reduction in latency compared to cloud-based systems, facilitating quick alerts for problems such as heart arrhythmias. Similarly, Patel et al. shown that edge AI reduces traffic management latency by 20 percent in smart cities, achieving 95 percent optimum signal corrections.

Alternative methods to reduce latency include reinforcement learning [3] and DNN partitioning , achieving a 25% and 15% reduction in latency, respectively, through dynamic resource allocation and computational task division.

8.3 Improvements in Cost and Energy Efficiency

Enhancements in cost and energy efficiency represent a significant opportunity, as AI-enabled edge computing will reduce operational expenses and energy costs, rendering IoT deployments more sustainable and economically feasible. Edge computing diminishes the need on cloud infrastructure and high-bandwidth networks, thereby reducing operational expenditures by processing data locally.

Brown et al. assert that smart house IoT systems utilizing lightweight AI models can achieve up to 50 percent energy savings and demonstrate 90 percent efficacy in automated tasks. Similarly, Huang et al. demonstrated that energy usage in common IoT applications dropped by 40 percent with the implementation of optimized edge designs, representing a sustainable design for large-scale networks. Gupta et al. [6] shown that in industrial IoT, predictive maintenance utilizing edge AI applications reduces organizational downtime by 30 percent and maintenance expenses by 25 percent in a manufacturing context.

Processing-in-memory (PIM) architectures [5] enhance energy efficiency in smart homes by an additional 35%, enabling more complex AI applications to operate on low-power devices. Nguyen et al. reported economic benefits, including a 20% reduction in costs for the smart grid through the application of swarm intelligence to maximize resources.

9 Obstacles

The implementation of AI-driven edge computing in IoT settings may yield transformative advantages; yet, it is accompanied by significant challenges that must be addressed to ensure ubiquity and efficacy. As IoT applications are projected to rise to 80 billion devices by 2025, the resulting vast quantities of data will highlight the challenges associated with edge computing.

9.1 Security: Data Privacy and Zero Trust Frameworks

A significant concern in AI-enabled edge computing on IoT devices is security, particularly with privacy protection and the implementation of an effective security framework, such as zero-trust architecture. The IoT devices (e.g., sensors, wearables) monitor critical sensitive data (health records, geolocation, etc.), rendering them prime targets for technology-facilitated crimes.

Kim et al. proposed an AI-driven intrusion detection system for smart city IoT networks, achieving 95 percent accuracy in threat identification; nevertheless, false positives were identified as a limitation, necessitating further adjustments. Similarly, Chen et al. [2] indicated that federated learning enhances data privacy security in healthcare IoT by an additional 20-30 percent through on-device storage of critical information; nevertheless, the updates transmitted across the network may be vulnerable to assaults, including model poisoning.

Smith et al. suggest integrating zero-trust models inside healthcare IoT to mitigate hazards, but with an increase in computational overhead by 15%. Taylor et al. asserted that scalable zero-trust frameworks are essential, as current solutions are inadequate for managing the diversity of edge devices.

9.2 Latency: Reconciling Velocity and Precision

In AI-enabled edge computing, latency is a significant concern, and end-to-end latency requirements are escalating daily due to the proliferation of IoT applications, like autonomous vehicles and real-time patient monitoring. Edge computing reduces latency by performing processing locally, yet intricate AI models, such as deep neural networks (DNNs), often induce delays due to their computational demands.

Davis et al. examined DNN partitioning to get 88 percent accuracy and reduce latency by 15 percent in healthcare IoT contexts, noting trade-offs due to model division between edge and cloud, which led to a reduction in precision. Similarly, Li et al. [3] utilized reinforcement learning to enhance resource allocation in smart city IoT, achieving a 25% reduction in latency; however, they noted that the most intricate models fail to meet sub-millisecond demands in applications like autonomous driving.

Wu et al. have proposed dynamic DNN splitting, which achieves a 20% reduction in latency, however the decrease in accuracy appears negligible. These results underscore the need of employing lightweight AI algorithms and adaptive techniques that provide low-latency assurances without sacrificing dependability, particularly in time-sensitive IoT applications.

9.3 Interoperability: Absence of Standardized Protocols

Interoperability presents a considerable difficulty owing to the absence of established protocols for AI-driven edge computing across IoT ecosystems. Ensuring smooth communication and data exchange among billions of heterogeneous devices, including as sensors, gateways, and wearables from many manufacturers, is complex.

Lee et al. [8] introduced an interoperability framework that enhances compatibility by 25% in generic IoT systems, while also highlighting that non-standardized protocols restrict scalability across various networks. Wang et al. [4] observed that hierarchical edge-cloud systems can accommodate over 10,000 devices and encounter compatibility issues due to proprietary protocols, resulting in a 20 percent increase in deployment costs. devices utilize disparate data formats, as indicated by Chen et al. [2], who documented a 10% decline in performance in non-IID data contexts. The absence of standardized protocols complicates the installation of AI models on edge devices, hence diminishing the potential for large-scale IoT deployments. Future studies should focus on developing open standards

and protocols to facilitate interoperability, as Park et al. recommended adaptive clustering to mitigate compatibility issues.

9.4 Resource Limitations: Insufficient Computational Capacity for Edge Devices

The primary obstacle to deploying AI in IoT devices is resource constraints, particularly regarding computational power and memory at the network's edge. IoT sensors and other wearable devices are edge devices that are typically limited in capabilities, including low-power processors and storage, rendering more complicated AI frameworks such as DNNs impractical.

Zai et al. [1] addressed this issue by developing lightweight deep neural networks using pruning and quantization, achieving a 30 percent increase in inference speed and 95 percent accuracy on healthcare wearables, however retraining remains a costly endeavor. Zhang et al. [5] demonstrated that processing-in-memory (PIM) architectures do not enhance energy efficiency, although they indicated a 35% energy-frequency efficiency of PIM systems in smart homes, albeit constrained by hardware complexity.

Gupta et al. [6] assert that 90% accuracy in federated learning for industrial IoT predictive maintenance is compromised by resource constraints, since it requires 20% more memory than typically available on edge computers. In the context of smart home IoT, Brown et al. exhibited merely 50% energy savings with their lightweight AI model, which pales in comparison to competitors achieving 90-99% energy savings.

These limits necessitate innovative solutions, including model compression, energy-efficient algorithms, and hardware acceleration. Patel et al. [14] have recognized that the creation of low-power AI models would prolong the lifespan of AI-enabled devices, a consideration that future research should focus on to mitigate resource limitations.

The challenges of security, latency, interoperability, and resource constraints significantly impact the implementation of AI-driven edge computing in the IoT. Security considerations, including data privacy and the necessity for zero-trust models, necessitate the implementation of power-efficient, intelligent protection for susceptible edge devices. Latency concerns need compromises between speed and accuracy, particularly in time-sensitive applications. The standardization of protocols has also contributed to interoperability difficulties, which impedes a seamless integration process across diverse IoT ecosystems. The implementation of intricate AI models is limited by resource limits, necessitating advancements in lightweight algorithms and technology. The difficulties highlighted by the examined literature underscore the necessity for more research to enhance the reliability, scalability, and efficacy of AI-driven edge computing in the Internet of Things.

10 Discussion

The integration of AI-driven edge computing into IoT systems represents a paradigm shift, as IoT is projected to generate an estimated 80 billion devices by 2025. The literature review of 60 peer-reviewed articles (2020-2025) examines the primary trends and inconsistencies, identifies significant research gaps, and outlines future research directions to advance the field of AI-based edge computing in relation to the IoT. This discussion can facilitate the formation of a comprehensive understanding of the current position in the area and delineate the trajectory of the outstanding issues.

10.1 Integrating Trends in the Literature

The literature reveals several significant trends in AI-enabled edge computing inside IoT, demonstrating rapid technology and application progress. A significant driving force is the use of lightweight AI, encompassing deep neural networks (DNNs) and optimized networks that have undergone pruning and quantization, enabling execution on the limited resources of edge devices. Zai et al. [1] demonstrated that a 30 percent acceleration may be attained with 95 percent accuracy in healthcare IoT, indicating that intricate AI models need not necessitate extensive centralization.

Another trend is federated learning (FL), particularly in contexts where data privacy is paramount, such as healthcare and smart grids. A study by Chen et al. [2] demonstrates a corresponding enhance-

ment in data privacy of 20-30 percent when utilizing locally trained models on edge devices. The edge-cloud hybrid structure, as articulated by Wang et al. [4], enhances scalability by reducing bandwidth consumption by 40%, hence facilitating extensive IoT deployments.

The capacity for real-time processing is emerging as a significant trend, with Jones et al. [7] illustrating a 40% reduction in the response time of an autonomous vehicle, indicating the applicability of edge AI in low-latency scenarios. Furthermore, heightened focus is directed towards energy efficiency, with Brown et al. and Huang et al. documenting energy reductions of 50 percent and 40 percent, respectively, through the utilization of lightweight AI and processing-in-memory (PIM) architecture.

These trends indicate a progression towards decentralized, efficient, and privacy-respecting IoT systems, facilitated by edge-based AI advancements. Nonetheless, literature emphasizes the necessity of adequate security and interoperability solutions to sustain the enhancement of these developments.

10.2 Prospective Trajectory

To address these gaps and discrepancies, several future study topics are proposed:

Hybrid AI Models: Research may develop hybrid AI models that mix lightweight deep neural networks with reinforcement learning or federated learning to achieve a compromise between accuracy and latency. Performance in real-time applications, such as autonomous driving, could be enhanced by the synergistic integration of adaptive pruning [1] and dynamic partitioning .

Edge-Native Protocols: The development of standardized, edge-native protocols is the paramount scientific endeavor to improve interoperability. Future study may focus on open-source frameworks that are compatible with various IoT devices, enhancing cost-efficiency and scalability, as suggested by Lee et al. [8].

Scalable Security Frameworks: There is a necessity for lightweight security frameworks utilizing artificial intelligence, such as optimized zero-trust models with diminished complexity. Kim et al. proposed model adjustment to minimize false positives, and subsequent research may explore decentralized encryption in edge devices.

Energy-Efficient Hardware and Algorithms: Enhanced hardware, such as next-generation PIM architectures [5], along with algorithms designed for ultra-low-power devices [14], may address resource constraints.

Decentralized Federated Learning: Chen et al. [2] proposed enhancements to Federated Learning in non-IID data and extensive networks through the implementation of adaptive clustering and peer-to-peer aggregation to reduce communication demands.

Real-Time Optimization: The investigation of dynamic AI model optimization, encompassing adaptive reinforcement learning [3], will diminish latency while maintaining accuracy.

These recommendations will remove current limitations and foster the advancement of AI-driven edge computing inside the IoT sector. The application cases, foundational components, and integration into the infrastructure are examined and synthesized as primary trends, encompassing lightweight AI, federated learning, and edge-cloud architectures, facilitating the development of scalable, efficient, and low-latency IoT systems. The intricacy of the domain is demonstrated by inconsistencies in latency-accuracy trade-offs, scalability-resource limitations, and security-efficiency conflicts. The failure to identify answers in security frameworks and standardization, energy efficiency, scalable federated learning, and latency optimization underscores the need for localized innovation to bridge this research gap. Proposed future paths and emerging trends, including hybrid AI-based systems, edge-native protocols, and scalable security models, offer a pathway to realize the potential of AI-driven edge computing in transforming IoT ecosystems by 2025 and potentially beyond.

11 Conclusion

The review paper "Advances in AI-Powered Edge Computing for IoT Applications: Opportunities and Challenges" synthesizes the present state of the topic, drawing from 60 peer-reviewed articles published between 2020 and 2025. The last section encapsulates the principal findings and contributions of the literature review, further elucidating how AI-driven edge computing within IoT ecosystems might be

revolutionary. It emphasizes the significance of these findings for allied fields, including information technology (IT) and computer science (CS), and their pertinence to industry stakeholders.

11.1 Principal Insights and Contributions

The literature analysis clearly indicates that AI-driven edge computing is a pivotal factor in the advancement of next-generation IoT systems, with IoT devices projected to exceed 80 billion by 2025, leading to challenges associated with centralized cloud infrastructure. Other major insights are the new techniques to develop lightweight AI models, including deep neural networks (DNNs) optimized by pruning and quantization that exhibit up to 30% faster inference with at least 95% accuracy on resource-constrained devices, as illustrated by Zai et al. [1].

Federated learning (FL) has emerged as a cornerstone for privacy-preserving applications, improving data privacy by 20–30% in healthcare and smart grid IoT [2]. Edge-cloud hybrid architectures and processing-in-memory (PIM) systems enhance scalability and energy efficiency, supporting 10,000+ devices and reducing bandwidth usage by 40%, according to Wang et al. [4]. Applications in smart cities (e.g., 20% congestion reduction), healthcare (e.g., 98% anomaly detection accuracy), and industrial IoT (e.g., 30% downtime reduction [6]), underscore the real-world impact of edge AI.

Opportunities such as scalability, real-time processing (15–40% latency reduction), and cost/energy efficiency (up to 50% energy savings) highlight the potential for large-scale, sustainable IoT deployments. Nonetheless, issues such as security risks, latency-accuracy trade-offs, absence of established protocols, and resource limitations demand continuous research. The review contributes by aggregating trends, noting inconsistencies (e.g., scalability versus resource limitations), and proposing future possibilities, including hybrid AI models and edge-native protocols, to solve deficiencies in security frameworks and standardization.

11.2 Implications for Information Technology and Computer Science

The conclusions have significant ramifications for IT and CS, impacting research agendas and instructional programs. The new edge computing paradigm necessitates innovative approaches to network administration, security, and resource orchestration. The improvement of AI-driven intrusion detection systems, achieving a 95 percent accuracy rate , underscores the imperative for groundbreaking advancements in cybersecurity research to protect edge devices.

Algorithm optimization in resource-constrained environments is a significant subject within computer science, as seen by the focus on lightweight AI models, federated learning, and reinforcement learning. The lack of established protocols necessitates the examination of interoperable frameworks, a critical issue that computer science must answer to ensure seamless incorporation into IoT networks. The review emphasizes the importance of interdisciplinary approaches, specifically the integration of AI, distributed systems, and hardware design, particularly PIM architectures.

Academically, the findings indicate a necessity to update computer science curricula to equip students with knowledge in edge AI, federated learning, and IoT-specific security, reflecting new industry requirements. Proposed future trends, including hybrid AI models, edge-native protocols, and scalable federated learning, also offer significant opportunities for IT and computer science researchers to foster innovation in addressing the challenges posed by extensive IoT ecosystems.

11.3 Implications for Industry

AI-driven edge computing possesses significant potential across various industries, enhancing efficiency, reducing costs, and facilitating the provision of innovative services, albeit accompanied by challenges that may be mitigated through strategic investments. In smart cities, edge AI's capacity to diminish traffic congestion by 20% and energy consumption by 30% allows municipalities to enhance urban living and sustainability; however, deployment necessitates robust security frameworks to combat cyber threats.

In healthcare, real-time patient monitoring with 98% accuracy and privacy-preserving wearables can transform patient care, yet industries must tackle battery life and data security to ensure reliability.

Industrial IoT benefits from predictive maintenance, achieving a 30% reduction in downtime, and supply chain automation drives efficiency and productivity, but resource constraints and interoperability issues demand investment in lightweight AI and standardized protocols.

The cost and energy efficiency gains make edge AI economically viable, particularly for large-scale deployments, but high initial hardware costs remain a barrier. Industries must collaborate with academia to develop scalable security solutions and open standards, as suggested to accelerate adoption. The projected $500 billion market for edge computing and IoT by 2025 underscores the economic incentive for industries to invest in edge AI infrastructure, positioning them to capitalize on emerging opportunities in smart cities, healthcare, and manufacturing.

In conclusion, this review provides a comprehensive synthesis of the advancements, applications, opportunities, and challenges of AI-powered edge computing in IoT, offering key insights into its transformative potential. Contributions include a detailed analysis of lightweight AI, federated learning, scalable architectures, and real-world applications, alongside identification of critical gaps in security, standardization, and resource optimization. The implications for IT/CS highlight the need for advanced research in algorithms, security, and interoperability, while industry stakeholders are poised to leverage edge AI for efficiency and innovation, provided they address deployment challenges. By proposing future directions like hybrid AI models and edge-native protocols, this review lays the groundwork for advancing AI-powered edge computing, ensuring it meets the demands of a connected, intelligent world by 2025 and beyond.

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