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Research Article

AI-Driven Resilience: Enhancing Critical Infrastructure with Edge Computing

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Abstract

The advancement of AI technology in recent times has brought about significant transformations in people's lives. AI workloads are moving from dispersed edge systems to centralised cloud infrastructures thanks to edge computing, creating a new paradigm known as edge AI. Critical Infrastructures (CIs) functionality becomes essential for the welfare and growth of society and the functioning of governments. There are many different kinds of disruptions that might affect these interdependent infrastructures, which include electricity, communications, healthcare, and transportation. These centralised architectures of historic design fail to cope with the current latency, scale, and requirements of real-time CIs. A potential strategy to improve CI resilience is the combination of AI with Edge Computing (EC). Distributed intelligence is offered by edge AI, which means implementing AI capabilities at the network edge. This reduces latency and bandwidth utilisation, improves privacy, and allows for real-time reaction. Data is processed closer to the source. This study presents a comprehensive overview of how AI and EC are transforming CI management, documenting their benefits and exploring factors that determine CI resilience. By leveraging Edge AI, CIs can become more adaptive, efficient, and secure, ensuring operational continuity even under disruptive conditions. The key contributions of this paper include promoting Edge-AI as a scalable and efficient solution for improving CI resilience by reducing central server loads, enhancing energy efficiency, and facilitating real-time decision-making.

Keywords: *Critical Infrastructure, Edge Computing, Artificial Intelligence, Edge-AI*

1. Introduction

The physical and conceptual relevance of a nation's critical infrastructures (CIs) makes them paramount in the modern era [1]. Crucially, CIs are essential for government operations, economic progress, and the general welfare [2]. Typical CIs are such important assets as energy supply (oil, gas, electricity), information and communication technologies (telecommunication, navigation), nuclear industry, water supply, medical facilities (hospital, medicine, vaccines), financial sector (banks, insurance), civil administration (executive, legislative, and judiciary bodies and facilities), and the function of transportation (road, railway, and aerospace). CIs are always found to be highly intertwined and closely connected [3]. This indicates that other CIs' operations are crucial to the functioning of the first CI [4][5]. Critical infrastructures are becoming more and more important to our daily lives, and as a result, the demands placed on these industries to meet the ever-increasing demand for goods and services are always pushing the envelope of complexity.

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The underlying circumstances that these infrastructures rely on are also always changing[6]. It has recently been crucial for several governments to construct robust CI systems that would guarantee the continuous operation of a nation's economy, due to the complex interdependencies of CIs networks. Traditional centralised systems often struggle to meet the demands of modern CI, particularly in terms of latency, scalability, and real-time processing needs.

In response to these challenges, the integration of AI and EC has gained significant attention as a robust solution to enhance CI resilience. "Edge AI" is allowing distributed intelligence with devices at the network's periphery via the integration of AI capabilities there. It aims to facilitate data-driven application adaptation, enhance network connection, and make it possible to create AI pipelines with quality objectives. Edge AI integrates intelligence and analysis with a wide range of networked systems and devices for data processing, caching, and gathering. It makes it possible to integrate data collecting and analysis in a broad range of innovative and promising applications[7]. This fusion of EC and AI is shown below in Figure 1.

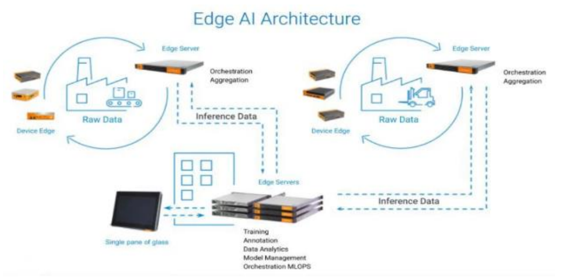

Fig. 1. Architecture of Edge-AI

EC and AI work together to run AI algorithms on consumers' devices. This results in real-time apps, decreased latency, and energy economy. With this integration, data can be processed, and decisions can be made in real time right at the source, drastically reducing latency and bandwidth use. Autonomous cars, industrial IoT, smart home systems, etc., may all benefit from the heightened intelligence and responsiveness made possible by integrating AI with edge computing. Organisations may drive innovation across multiple industries by employing edge AI to gain improved efficiency, increased privacy, and quicker insights[8][9]. In order to circumvent problems with privacy and network connection that plague cloud-based processing for the IoT, AI functions embedded at the edge may be used. Efficiency and security in wireless networks are improved by the deployment of AI at the edge, which boosts latency-sensitive tasks and decreases network congestion[10].

There are many reasons to combine AI with edge computing, but the most important ones are the growing requirement for real-time data processing and the difficulties associated with using centralised cloud computing. Conventional cloud-centric models are finding it harder and harder to deal with problems like latency, bandwidth limitations, and major data privacy concerns as the number of connected devices continues to climb exponentially and data volume continues to skyrocket. As an advocate for data processing at the edge, edge AI is emerging as a critical component in overcoming these obstacles. This change not only improves applications' responsiveness to real-time data inputs but also reduces latency by reducing dependency on distant cloud infrastructures. In order to improve vital infrastructure and power next-gen technologies that need immediate data analysis and decision-making, this paradigm change is especially important. The following research paper contributions are:

- This study provides a comprehensive overview of how edge computing and AI are transforming critical infrastructure.
- The study documents the benefits of edge computing and artificial intelligence when combined.
- This research explores the impact of various factors on determining the resilience of critical infrastructure
- This research promotes Edge-AI as a scalable and efficient solution, reducing central server loads and bandwidth usage and improving energy efficiency.

A. Organization of the paper

The remainder of this essay continues as Section II gives an overview of critical infrastructure and discusses the complementary roles that EC and AI play in it. Sections III and IV go into detail about how resilient critical infrastructure is, what factors go into determining it, and the main advantages of integrating EC with AI. Section V reviews the literature and identifies research gaps based on a variety of research papers; the final section concludes this work and offers recommendations for future work.

2. Resilience of Critical Infrastructure

A critical infrastructure system's resilience may be defined as the capacity to withstand and recover quickly from disruptions, as well as to adapt to new circumstances. Developing and enhancing the resilience of any group of subsystems in critical infrastructure is an arduous process that demands well-defined starting and end points in addition to substantial investment of time and monetary resources. A critical infrastructure system's subsystems' resilience may be defined in terms of these broader circumstances. The primary starting point may be seen as the establishment of the management process (Figure 2) for safeguarding essential infrastructure components, which make up the foundation for enhancing resilience.

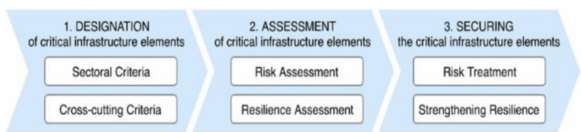

Fig. 2. Management process for protecting critical infrastructure elements

B. Factors Determining Critical Infrastructure Resilience.

There are three categories of elements that come together to generate critical infrastructure subsystem resilience: Things that influence resilience (threats or resilience-enhancing tools), things that restrict resilience (legislative oversight of infrastructure operations or a lack of funding), and things that decide resilience (i.e., technical and organisational resilience variables and components) [11]. Figure 3 depicts the elements and factors that influence the robustness of vital infrastructure. The technical and physical protection of components, as well as the management of the organisation, are the two primary factors that influence the resilience of a critical infrastructure system [12].

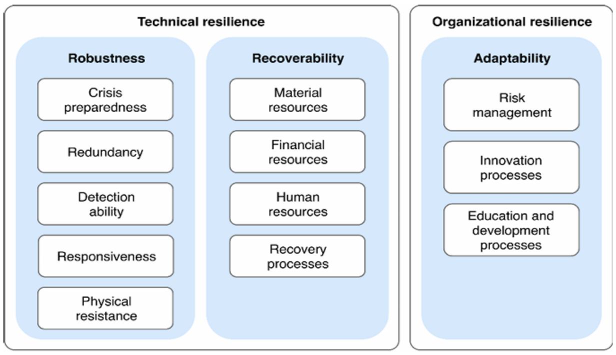

Fig. 3. components and variables determining the resilience of critical infrastructure

Individual element protection, both technically and physically, is the first topic to be discussed. Technical resilience, which emphasises durability and recoverability, is defined by these two qualities. Managing an organisation is the second component. The degree to which an organisation's internal operations aim to provide the best possible environment for the adaptation of essential infrastructure components to disruptive events determines this kind of resilience, which is called organisational resilience [13][14].

3. Building Resilient Infrastructure with Ai Technology

In the face of escalating natural disasters, climate change, and other disruptive events, constructing resilient infrastructure has become paramount. Artificial Intelligence (AI) has emerged as a disruptive technology in civil infrastructure development and management through the provision of novel technologies that would improve general resilience. Predictive analytics can be deemed the most impactful of all AI applications to build infrastructure sustainability [15][16]. AI algorithms can process extensive datasets from various sources to foresee potential failures and vulnerabilities within infrastructure systems. For instance, by analysing historical weather data, sensor inputs from infrastructure, and environmental factors, AI can forecast the impact of extreme weather events on bridges, roads, and buildings[17][18]. This capacity for prediction also helps prevent maintenance and necessary interventions and thereby greatly minimises the possibility of failure. The application of AI-driven predictive analytics is particularly crucial in the realm of climate resilience, where anticipating and mitigating the effects of climate change on infrastructure is vital[19]. Table I. shows the building resilient infrastructure with AI technology.

Table 1. Building resilient infrastructure with AI technology

Sr. No.	Aspect	Description	Technologies
1	Predictive Maintenance	Utilising AI to forecast maintenance needs for infrastructure, minimising disruptions and extending asset lifespan	Machine Learning, IoT Sensors, Predictive Analytics
2	Disaster Response and Recovery	Implementing AI-driven solutions for efficient response and recovery post natural disasters, reducing impact and downtime.	Drones, Simulation Models, Natural Language Processing (NLP) for crisis communication
3	Climate Resilience	Applying AI to evaluate and mitigate climate risks, ensuring infrastructure durability against environmental changes.	Climate Modeling AI, Remote Sensing, Data Analytics
4	Smart Cities	Integrating AI in urban infrastructure for better resource management, traffic control, and energy efficiency.	IoT, Smart Grid Technology, AIpowered Traffic Management Systems
5	Structural Health Monitoring	Continuous infrastructure health monitoring with AI to detect and address potential issues before they become critical.	Sensor Networks, Anomaly Detection AI, Big Data Analytics
6	Energy Efficiency	Optimising energy usage and incorporating renewable energy in infrastructure through AI for enhanced sustainability	AI-based Energy Management Systems, Renewable Energy Forecasting AI, Smart Grid Technology
7	Supply Chain Resilience	Utilising AI to predict and mitigate supply chain disruptions, ensuring timely availability of materials and resources	Supply Chain Analytics, Demand Forecasting AI, Blockchain for Supply Chain Transparency
8	Autonomous Construction	Employing AI and robotics in construction to enhance safety, efficiency, and precision.	Robotics, AI-driven Construction Management Software, Autonomous Vehicles and Machinery
9	Cybersecurity	Protecting infrastructure from cyber threats using advanced AI techniques.	AI-based Threat Detection, CyberPhysical Security Systems, Machine Learning for Anomaly Detection
10	Enhanced Decision Making	Leveraging AI tools for data-driven decision-making in infrastructure planning, design, and management.	Decision Support Systems, AI-driven Planning Tools, Advanced Data Visualization
11	Water Management	Implementing AI for efficient water resource management and infrastructure resilience against floods and droughts.	AI-based Flood Prediction Models, Smart Irrigation Systems, AI-powered Water Quality Monitoring
12	Sustainability and Green Building	Utilising AI technologies to design and maintain sustainable and environmentally friendly infrastructure.	Environmental Impact Assessment AI, Sustainable Material Selection Algorithms, Green Building Certification AI

4. Ai-Driven Resilience: The Role of Edge Computing

The following areas are providing the AI-Driven Resilience: The Role of Edge Computing

A. Distributed Decision-Making

Currently, the legacy cloud-based systems may experience the latency issue because of network choking or occurrence of link failure which is inconceivable in dealing with SCADA systems. Distributed AI at the edge provides autonomous and independent command and control keeping devices active when the core networking system is offline. This is very useful in smart grid systems or possibly the self-driven transport system where timely control is required to sustain continuity of service as well as safety.

B. Predictive Maintenance and Self-Healing Systems

Additionally, the AI models can operate at the periphery to monitor the condition of infrastructure components that are being upgraded, such as turbines in power plants, water pipelines, and railway tracks, prior to their complete failure. Algorithms for condition-based monitoring in an area, enabled by machine learning, are used by operators to organize maintenance activities before system failures, thus preventing system downtimes and high costs on maintenance. Also, the opportunity is given to start self-repair actions or, for example, redirect resources and further systems to maintain performance on the desired level.

C. Enhanced Cybersecurity

As more and more of our infrastructure goes online, the potential for a cyber-attack becomes much greater. Edge computing enhances security by only sending data to central networks to a minimal extent thus minimizing the circulation of such important data. AI models also in deployment at the edge can therefore identify and counteract security threats such as viruses or attempts at hacking through a perpetual analysis of network, user and system activity. They enhance the shielding strategy in order to strengthen structures against such invasions.

D. Optimized Resource Management

Energy and water management are the areas of high importance in critical infrastructure, and the efficiency in combination with sustainability aspects are highly desired. There is also the ability to manage resources in real-time using edge AI applications due to the fact that data on usage, demand and supply are well gotten. For instance, in smart grids AI at the edge can negotiate electricity loads, renewable energy sources and proactively manage power distribution to prevent failures or overloads. Likewise, in water supply line, AI can enhance the supply analysis and control; availability being its counterpart of scarcity.

5. Ai-Driven Edge Computing in Critical Infrastructure

The following areas are providing the AI-driven edge computing in critical infrastructure

A. Smart Grids

As mentioned above, AI implemented on the edge of the grid allows for instantaneous reactive and proactive protection against blackouts, overloads, and faulty equipment. The AI could preemptively know the amount of demand for energy and also balance the renewable energy mixes to allow the grid to consistently and efficiently deliver power to homes.

B. Transportation Network

In smart transportation, which includes self-driving cars and smart railways among others, the AI at the edge is suitable for real-time route determination, traffic regulation and safety control. Some of the categories are traffic motions, road surfaces, or possible threats that can be felt by self-driving cars and make decisions immediately. With the help of edge computing, these systems may continue to function at peak efficiency even while disconnected from widely used networks.

C. Healthcare Systems

In healthcare for instance edge computing improves the health infrastructure by allowing constant surveillance of patients and responding to any calamity on real-time mode. AI models in smart end-points may include: monitoring vital signs, detecting signs of an impending medical emergency, triggering preventive alarms or action. This ensures round-the-clock care, which is particularly important in disaster-stricken or rural locations where centralised services are not always available.

D. Water and Waste Management

The AI enabled edge computing can keep track and operation of water supply and treatment facilities, distribution networks, and waste management systems. Considering the water quality and flow rate as well as the climate conditions AI models can diagnose leaks, contamination and failures of equipment and respond with appropriate measures to protect the water supply.

E. Telecommunications

In telecommunications, edge computing allows for the deployment of AI-powered 5G networks that can dynamically manage bandwidth, optimise traffic flow, and ensure the resilience of communication networks during peak loads or natural disasters. AI at the edge ensures that mission-critical communications are maintained even in the event of central network disruptions.

6. Benefits of Integrating Artificial Intelligence with Edge Computing

There is an obvious junction between AI and edge computing, thus their merging is not surprising. Edge computing is concerned with coordinating a network of nearby servers and devices to handle data produced at the network's periphery, whereas artificial intelligence is an attempt to imitate human intelligence in computers via data learning.

In addition to the standard advantages of edge computing, such as lower bandwidth usage and low latency, there are additional mutual benefits to moving AI to the edge.

A. Data Generated at the Network Edge Need AI to Fully Unlock Their Potential

As the quantity and variety of mobile and IoT devices continues to soar, there is a constant stream of massive amounts of multimodal data (e.g., audio, images, and video) about the physical environment perceived by these devices. Due to its capacity to swiftly analyse such massive data volumes and derive insights for good decision-making, AI will be practically required in this context.

B. Edge Computing Can Prosper AI with Richer Data and Application Scenarios

One potential use case for edge computing is enabling high-performance AI processing by bringing computing power closer to the data generating source, rather than the cloud data centre, thereby achieving low-latency data processing.

C. AI Democratization Requires Edge Computing as a Key Infrastructure

In this regard, edge computing clearly outperforms cloud computing. To start, edge servers are physically closer to end users, data sources, and devices than cloud datacenters. As a second point, edge computing is more accessible and less expensive than cloud computing. Lastly, AI application scenarios might be more varied with edge computing compared to cloud computing. These benefits highlight the importance of edge computing as a tool for ubiquitous AI.

D. Edge Computing Can Be Popularized with AI Applications

The only practical method that can fulfil these stringent criteria is computing at the edge. Referring back to the previous history of edge computing, it is anticipated that new artificial intelligence applications from industries like IIoT, smart robots, smart cities, and smart homes would be instrumental in the widespread adoption of edge computing. Reason being, edge computing is a good fit for the computationally and energetically demanding, privacy-and delay-sensitive, practical applications that make up a large portion of AI in mobile and IoT contexts [20]

7. Literature Review

This section explores the existing body of work in the field of AI-driven resilience for enhancing critical infrastructure with edge computing. Also, Table II. provide the Summary of literature review.

In this study, Kamruzzaman, (2021) a number of researches that were published between 2016 and 2021 are considered. Prisma is a flowchart that depicts the selecting process. It has been discovered that these growing healthcare issues may be resolved by using AI, ML, DL, Edge AI, the IoT, 6G, and cloud computing. However, these most recent developments have also improved the results in a small number of places. Both the patient's and the healthcare professionals' perspectives on the difficulties have been successfully resolved as a consequence of these implications[21].

In this study, Fu et al., (2020) they introduce Astraea, a revolutionary framework for deploying AI services that can automatically transform an uncooked AI model into RESTful web services at edge nodes. The findings of the experiments demonstrate that Astraea can deploy a common AI model at edge nodes in less than two minutes, and that this model outperforms the previous approach by 2Sx to 110x[22].

This study, Kumar, Karthik and Nair, (2020) seeks to provide a comprehensive analysis of the performance indicators at the central server and at the edge devices after each federation step. The goal of their early release of the study findings is to stimulate interest in this new field among researchers by offering a potential remedy for the inherent latency of existing ML techniques as well as a means of addressing privacy issues about user data. Potential real-world applications for our paper's results include EMR based ML technologies, which protect privacy[23].

In this study, Kum et al., (2020) It is suggested to implement an AI Service Architecture for an Edge Device in order to make the AI service itself accessible. Pre- and post-processing, in addition to the model, are all part of the AI as a service that the suggested architecture offers. As it incorporates all the methods that make up an AI service, the suggested architecture offers easier ways to deploy an AI method to devices on the edge. In addition, it is well-suited for microservice design since it specifies interfaces for configuring and accessing the AI service[24].

In this study, Liang, Shenoy and Irwin, (2020) we conduct an experimental comparison of conventional edge and cloud computing, as well as specialised edge systems constructed employing edge accelerators, to determine their advantages and disadvantages. By running AI workloads on modern edge accelerators, we were able to demonstrate that these devices can match, and often outperform, more conventional edge and cloud servers when power and cost are taken into account [25].

This study, Lin et al., (2019) suggests an IoT platform that uses peer-to-peer (P2P) knowledge exchanges to facilitate the trading of knowledge at the edge. As a starting step, we suggest a knowledge market implementation architecture. They also create a novel consensus method for proof of trade, smart contracts, and a cryptographic currency called knowledge coin as part of our knowledge consortium blockchain, which will allow for efficient and safe market knowledge administration and trading. An additional proposal is a knowledge pricing technique that is not reliant on cooperative games and incorporates market incentives. They have shown the efficacy and safety of our knowledge market via performance simulations and security analyses, and we have shown the incentive impacts of our knowledge pricing method. We are unaware of any previous proposals for an incentive-based P2P knowledge market in edge-AI-enabled environments [26].

Table 2. Summary of literature review in the field of enhancing critical infrastructure using Edge-AI

Study	Key Contributions	Technologies/Methods	Performance Metrics	Limitations	Future Work
[21]	Overview of AI, ML, DL, Edge AI, IoT, 6G, and cloud computing applied to healthcare	AI, ML, DL, Edge AI, IoT, 6G, Cloud Computing	Successful outcomes from patient and healthcare professional perspectives	Limited areas of healthcare explored	Further exploration of other areas in healthcare, applying these technologies on a larger scale with more diverse datasets.
[22]	Astraea: AI model to RESTful web services at edge nodes	Edge AI, RESTful web services	25x to 110x performance improvement in AI model deployment	Early stage with limited real-world validation	Extend Astraea's application to more diverse AI models and edge devices and test performance in real-world environments.
[23]	Holistic analysis of performance metrics at edge devices and central servers	Federated Learning, Edge AI, Privacy-Preserving ML	Addressed data privacy and reduced latency in EMR ML apps	Early publication of future research are needed	Validate findings in larger federated networks and apply them to other privacy-sensitive applications beyond EMR.
[24]	AI Service Architecture for pre-processing, post-processing, and model deployment	Edge AI, Microservice Architecture	More intuitive AI service integration for edge devices	Needs real-world application and testing	Develop more flexible configurations for diverse AI models and edge environments; improve scalability and security.
[25]	Performance comparison of edge accelerators vs traditional edge/cloud computing	Edge Accelerators, Cloud Computing	Edge accelerators often perform better when normalised for power and cost	May not generalise across all workloads	Explore new edge accelerators and extend comparisons to more complex AI workloads and real-time applications.
[26]	P2P knowledge market with blockchain for knowledge trading in IoT	P2P Knowledge Market, Blockchain, Cryptographic Currency (Knowledge Coin), Smart Contracts	Secure, efficient knowledge trading and incentive effects are shown in simulations	First-time implementation lacks real-world deployment	Expand to real-world trials, enhance blockchain scalability, and develop more advanced consensus and pricing strategies.

Conclusion and Future Work

The combination of Artificial Intelligence and Edge Computing as the solution gives a reliable and extensible way of improving the protection of Critical Infrastructures. Edge AI processing helps to reduce latency, control the usage of resources and perform real-time and distributed decision-making, as well as predictive maintenance and security for Edge AI systems. These benefits are crucial for resolving the dependencies that are present in critical infrastructures and for maintaining their constant operational continuity regardless of the situation that is present, including one that would be normal business operations. Using the example of smart grids, auto-mobile transport systems, healthcare and other critical verticals, Edge AI proves that it is capable of providing Innovation and Better Efficiency with High Security & High Reliability. The following paper establishes Edge AI as a crucial solution in overcoming the drawbacks of centralised cloud and improving CI robustness. More future work will be directed towards building more sophisticated Edge AI models that enhance infrastructure hardiness using next-gen technologies like 5G and quantum computing.

Future work will center on investigating newer AI paradigms and techniques and their possibilities to be implemented at the edge for attending superior real-time decisions in the critical infrastructures. This includes exploring the possibilities of secure federated learning for model updating across different nodes, examining possibilities of effective deployment of edge AI for various CI sectors, as well as discussing the question of achieving compatibility with heterogeneous terminal devices. Furthermore, future work will focus on the fusion of edge AI with quantum computing in order to enhance performance and anti-fragility, specifically for diverse large-scale infrastructure systems in the context of high-risk scenarios.

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