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Review Article

Edge–Cloud Intelligence in Disaster Management: A Review of Architectures, Challenges, and Opportunities

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Abstract *- Natural disasters are happening more often and with more force, which puts a lot of stress on disaster management systems. They require fast, reliable and sustainable technologies. In conventional centralized systems, there are problems with latency, network congestion and a requirement for continuous connectivity. These can slow down the early detection and rapid response. In this study, the Smart Disaster Alert Response System (SDARS), a new approach that integrates cloud computing, edge computing, and green computing to enhance resilience, cut down latency and ensure sustainability. SDARS relies on IoT sensors that constantly monitor the environment, and edge nodes that do initial data processing to provide real-time alerts with low latency. The cloud allows for big data analysis to be conducted to gain predictive knowledge and optimise resource allocation. Energy-efficient (green computing) techniques are also used to conserve energy and extend the lifespan of devices in low-energy environments. The experimental evaluation of SDARS reveals that it can raise alarms in less than a second, consumes 35% less energy compared to conventional systems and continues to operate despite network partition. In conclusion, the proposed model demonstrates how distributed computing techniques with energy-aware techniques can result in scalable and sustainable disaster response systems.*

Keywords *- Cloud computing, Disaster Management, Edge computing, Green computing, IoT.*

1. Introduction

With the rising occurrence and intensity of natural and artificial disasters, there is a growing need for intelligent disaster management systems with the ability to rapidly respond to disasters, utilize resources efficiently, and make real-time decisions. Edge computing is emerging as a new trend, and the current researches have focused on the architecture, trends, research challenges, future direction of edge computing and finally on showcasing how edge computing can supplement traditional cloud computing for latency-sensitive applications [101]. An integrated system of connected sensors and communication devices, powered by cloud computing, can provide timely information for disaster monitoring and coordinating activities, which is also greatly enhanced by IoT-enabled emergency response systems [102]. In-depth descriptions of the edge computing frameworks have also illustrated that distributed computing is essential for scalable, reliable disaster management applications [103].

Combining Augmented Reality (AR) with edge–cloud infrastructures will allow first responders to receive real-time disaster data and help them improve the efficiency of their operations during emergency scenarios [104]. Further, an extensive review has highlighted the uses, security concerns and challenges of edge computing, and listed a number of open research problems for scalability, interoperability and resource management [105]. The combination of Artificial Intelligence (AI) and edge computing has also paved the way for intelligent decision-making, predictive analytics, and adaptive resource allocation, highlighting the potential of AI-driven edge computing in future disaster management systems [106].

The combination of Edge–Cloud Computing and the Internet of Things (IoT) has greatly enhanced resilience to disasters by facilitating the processing of data in distributed locations and real-time analysis of data from sensors. In recent years, there have been proposals for resilient edge–

cloud platforms capable of timely processing of emergency sensor information, which can improve disaster response and situation awareness [107]. Moreover, systematic literature reviews have considered the current situation of the disaster management systems, pinpointed key challenges, and suggested future research directions to design more efficient disaster response systems [108]. The use of hybrid machine learning models combined with cloud-based disaster management architectures has also proven to be a better way to predict and make decisions for disasters [109]. Furthermore, IoT and cloud computing have been proven to be important enabling technologies for disaster management, enabling scalable communication, monitoring and coordination between emergency response agencies [110].

However, there are still several challenges to overcome: allocation of resources, security, interoperability, fault-tolerance, and intelligent orchestration over the heterogeneous edge–cloud environment. Accordingly, this review paper aims to review system architectures, enabling technologies, opportunities for the integration of AI, current issues, and future research direction to develop resilient and intelligent disaster management systems with the concept of Edge–Cloud Intelligence in Disaster Management.

2. Literature Review

The latest progress in green information technology, artificial intelligence and edge computing systems has played a pivotal role in sustainable technological innovation. It is important to understand these contributions to put the proposed work into context, as shown in Table 1.

Chishti et al. [1] examined the role of green ICT and socioeconomic factors in promoting sustainable development in Chinese provinces through the use of Panel Quantile-Quantile Granger Causality and MMQR models. They found that nonlinear models were significant in accounting for regional inequalities. Furthermore, the research showed that policy-led ICT adoption plays a crucial role in sustainable development. But the model mostly uses macro-level data, restricting micro-level applications in real-time systems. Bolon-Canedo et al. [2] classified green artificial intelligence into "green-by-AI" and "green-in-AI", presenting a framework to research green artificial intelligence. They also assessed carbon footprint measurement tools like CarbonTracker and CodeCarbon. Additionally, the research highlighted the need for metrics to measure AI sustainability. But the lack of experimental testing prevents its practical use.

Zhu et al. [3] developed a pesticide discovery system that combined high-performance computing and AI with deep learning models and high prediction performance. Their approach integrated molecular docking, 3D-QSAR and toxicity prediction. Moreover, the research showcased AI's ability to cut costs in chemical experiments. However, the system relies on specific datasets for particular domains, which might limit its generalisability. Vedasri and Rathi [4] discussed green computing initiatives in the healthcare sector, particularly virtualization and cloud computing, to improve energy efficiency. They demonstrated considerable energy savings and carbon emissions reduction. Further, smart facility management was also identified as a key component of green healthcare buildings. But the study did not involve quantitative comparisons of hospital environments. Long and Chen [5] proposed an ANN model to study economic growth based on renewable energy for better prediction. The results showed better error reduction compared to statistical models. Also, the research highlighted the need for incorporating AI in economic forecasting for sustainability. But the data used was limited, which could limit scalability.

Cavalieri d'Oro et al. [6] introduced an architecture that combines edges and clouds in the context of emergency management, and carried out an evaluation of the performance of the architecture through Queuing Network (QN) modeling. By processing critical data at the edge of the network, the framework boosted responsiveness, minimized bandwidth consumption and helped to coordinate efforts between first responders. But the study was confined to performance analysis through simulation and did not include AI-driven resource optimization or real-world validation. Koul [7] conducted a review of sustainable manufacturing using Industry 4.0 technologies, including IoT and AI. The research found significant energy savings and cost reductions. Further, it highlighted the importance of digital transformation for green manufacturing. But the absence of benchmark data sets makes it difficult to reproduce the results. Fakhar et al. [8] developed a distributed green compiler to save energy through software-based optimisations. The proposed method resulted in substantial improvements in computational complexity. Additionally, the research showed the significance of compiler optimizations in large systems. But the results were obtained on older architectures, which might not be up-to-date. Lacopo et al. [9] investigated energy-performance impacts in High-Performance Computing (HPC) with GPU-based systems. They found efficiency enhancements over conventional MPI approaches. This work also proposed a new performance metric called green productivity. But the study was confined to particular workloads.

Mia et al. [10] discussed the combination of IoT and renewable energy systems for sustainable development. It discussed the significance of smart grids and energy harvesting. Also, it discussed IoT for energy monitoring. But the lack of quantitative analysis makes it less informative. Cruz et al. [11] discussed Green AI in data-centric and system-centric viewpoints with a focus on environmental sustainability. It identified the dataset and model optimisation. It also considered the balance between efficiency and accuracy. But it did not provide empirical evidence with large data sets. Thakur et al. [12] surveyed energy-efficient distributed systems using green federated learning. This research demonstrated gains in communication efficiency and energy savings. Also, the study stressed the need for model compression. But it does not address deployment issues. Xiong et al. [13] developed a cloud resource optimization approach based on ant colony algorithms. It achieved considerable energy savings in data centers. It also exhibited better efficiency in resource usage. But the use of artificial data restrains its practical use. Paul et al. [14] reviewed various green computing techniques, including virtualization and scheduling. They demonstrated significant energy gains for different systems. Additionally, it highlighted trends in green computing. But it did not have a common evaluation framework. Abbas et al. [15] proposed a clustered approach for cloud computing using renewable energy. This approach enhanced energy efficiency and lowered costs. It also showed the proof of concept for a green cloud. But scalability was not addressed.

Lukasewycz [16] investigated energy-efficient gaming systems through power measurement, and Sodeinde et al. [17] examined the effects of adopting green ICT on sustainability through surveys. Anh et al. [18] developed an SDN-enabled edge computing model for healthcare. This approach reduced the latency and energy. And it enhanced real-time data processing. But security was not thoroughly investigated. Rupanetti and Kaabouch [19] explored the use of AI for security in IoT systems, with high accuracy. Uslu and Özer [20] proposed a resource allocation algorithm based on optimization for green cloud computing. Gutiérrez-Finol et al. [21] investigated energy-efficient computational modeling by comparing the high-precision ab initio methods with semi-empirical methods in spin-electric coupling simulations. They found that the REC model produced similar accuracy but at a lower computational cost. Moreover, the research highlighted the role of frugality in cutting energy usage in scientific models. But there may be challenges in modeling complex molecular systems. Raja [22] considered the energy-efficient scheduling techniques such as DVFS and OEUDF to improve the performance of high-performance computing systems. This work achieved an improved energy-delay product over existing approaches. It also highlighted the use of dynamic scheduling techniques for energy and latency efficiency. However, it did the evaluation with artificial workloads, limiting any practical evaluation. Nyabuto [23] examined the trends in green computing research and identified the Green IoT and Green Cloud Computing. The study identified an increasing trend in publications, particularly in China. It also identified the research trends and technological focus. However, it does not provide quantitative information.

Sharma et al. [24] discussed the application of edge computing in Industry 5.0 use cases, such as smart factories and cobots. They identified the need for real-time data analysis and distributed intelligence. And the study identified the need for AI and digital twins integration. But this was largely qualitative with no empirical evidence. Kong et al. [25] provided a review of edge computing for the Internet of Everything and considered service migration and security. The study also looked at the integration of emerging paradigms such as blockchain and federated learning. It also considered architectural design for scalability. However, it does not provide experimental data, making it difficult to evaluate. Devineni and Gorantla [26] applied Grey Relational Analysis to compare energy-efficient computing approaches and prioritized various initiatives based on performance. Energy-efficient algorithms were shown to be most significant. It also provided a comparative analysis of sustainability measures. It may, however, restrict its use due to the synthetic metrics. Kumar and Ranjan [27] proposed an AI-driven predictive maintenance model for IoT systems, with high classification accuracy. It showed that XGBoost and other classifiers are useful for predictive maintenance. It also showcased AI's potential in enhancing industrial productivity. But there are issues with data transparency and reproducibility.

Alhartomi et al. [28] developed a deep reinforcement learning-powered offloading approach for edge computing with renewable energy sources. It reduced energy consumption while ensuring performance. It also showed flexibility to energy variations. But using simulated data restrains its application in real scenarios. Palmieri et al. [29] presented a hybrid cloud-based system for emergency management, which integrates landmark signal strength and motion sensor with first responder localization in real time. The framework enhanced the coordination and situational awareness in crisis situations, but it did not integrate into edge computing or provide AI-based decision support for low-latency processing. Saxena et al. [31] developed an approach to reduce energy consumption of cloud computing by detecting and powering down idle resources. The research showed considerable power savings. Furthermore, it highlighted the need for dynamic resource allocation. But the model was only used for simulation. Manshani [32] explored the application of emerging technologies in sustainable innovation (e.g. AI, IoT and quantum computing). This research discussed their importance in reducing energy use. It also mentioned the interdisciplinary nature of the problem. However, it is not experimentally verified and so is less helpful. Alazzawi et al. [33] provided a discussion on energy management for IoT with renewable energy harvesting systems. It found high efficiency with MPPT. It also found solar and RF energy harvesting useful. However, it did not mention deployment issues.

Sodiya et al. [34] in their review paper considered edge computing in IoT for real-time processing. It highlighted benefits such as low latency and scalability. It also looked at deployment in different sectors. However, it did not feature performance benchmarking. Siew et al. [35] assessed the impact of user behavior on green computing using structural equation modeling. This study identified factors such as environmental concern and user behaviour. It also provided insight into trends in consumer behaviour. However, findings were specific to the local region. Liao and Xie [36] demonstrated improved data processing of IoT devices using edge computing and neural networks. The authors showed reduced latency and increased throughput. And it demonstrated the benefits of distributed processing. But the experiments were conducted in a simulated environment. Vakaliuk [37] also conducted a bibliometric analysis of research on edge computing, examining the trends and collaborations. This showed the growth in research publications. It also identified key researchers and the focus of the research. However, it did not contain a technical analysis of methods. Deepak et al. [38] explored load balancing in edge computing in terms of resource allocation and energy consumption. This study suggested the advantages of a distributed approach. It also mentioned simulation platforms such as iFogSim. However, it did not include an implementation.

Bicker et al. [39] were able to create hybrid epidemiological models using agent-based and population-based modelling. This paper showed a high level of computational efficiency and accuracy. And it was scalable for large populations. But it employed artificial data. Cao et al. [40] reported on research on edge computing and its architecture and usage. They identified issues such as security and scalability. It also stressed the need for standardization. But it did not include experimentation. Verma and Verma [41] compared cloud and edge computing, discussing the pros and cons. The research focused on reduced latency in edge computing. It also mentioned security issues. But it did not include empirical analysis. Yadav and Mallick [42] discussed the use of AI and edge computing in Industry 4.0. It pointed out the advantages of automation and decision-making. It also provided case studies to demonstrate its findings. However, it did not provide quantitative measurements. Wen et al. [43] developed an adaptive edge computing approach for vision transformers. This research yielded a remarkable acceleration with little accuracy loss. It also showed good performance in a heterogeneous environment. However, it was not adaptable to changing environments. Gangrade et al. [44] surveyed cyber-physical systems that incorporate cloud, fog and edge computing. The paper put forward increased scalability and lower latency. It also stressed integration. However, it did not report experimental results. Pies et al. [45] used edge computing for wireless sensor networks for real-time data. It had good communication and energy efficiency. Moreover, it enabled off-grid use. However, it is not scalable.

Sharma et al. [46] investigated edge computing in Industry 5.0, including real-time computing and AI. It identified new applications. It also discussed implementation challenges. But it used secondary data. However, it did not mention empirical research. Hazra et al. [47] discussed IoT requirements and edge computing for low latency. It discussed improvements to the system. It also explored architecture. However, there was no empirical evidence. Yalcın [48] presented a communication-efficient and accurate federated learning method. This study enhanced performance for the benchmark datasets. It also improves scalability in distributed systems. But there are no experimental results. Pan and McElhannon [49] talked about the future of edge cloud, scalability and latency. It talked about new technologies such as MEC. It also noted deployment issues. But it did not include quantitative findings. Zuo et al. [50] proposed a robot control based on deep learning. This study was fast and accurate, and it enhanced path planning. But the research was simulated. Elmobark [51] has demonstrated good accuracy for edge analytics in health care and manufacturing. There was a reduction in response times. Moreover, it provided real-time processing benefits. However, resource constraints are still an issue. Juric et al. [52] analysed smart edge computing technologies such as neuromorphic computing. The study found improvements in speed and efficiency. Further, it noted future directions. However, it noted hardware limitations. Abdulqader et al. [53] demonstrated improved IoT performance with edge computing, in terms of latency and bandwidth. There was a substantial improvement in efficiency, and it was reliable. But security is still an issue. Bozkaya-Aras [54] has applied digital twin technology to enhance service migration. This study has improved resource allocation and energy savings. Also, it reduced latency. But it did not consider communication costs.

Wang and Yang [55] employed a deep reinforcement learning method of resource allocation. It achieved lower processing time and higher resource utilisation. And it was adaptable. However, training is complicated. Maliarskyi et al. [56] surveyed testing tools for edge computing systems. This study considered scalability and usability. It also identified testing issues. However, there was no quantitative benchmarking. Huang et al. [57] proposed a spatio-temporal prediction model in edge computing. The study was more accurate than traditional models. It also increased computing efficiency. However, it has scalability problems. Rawdhan [58] combined PSO and Q-learning for task scheduling. This study was energy efficient. It also improved scalability. However, the computational cost was high. Narang [59] considered the sustainability aspects of new technologies such as IoT and AI. The study highlighted environmental aspects. It also looked at policy issues. However, it did not give technical advice. Oyile and Wabwoba [60] conducted a systematic review of trends in green computing. This study noted key developments. It also noted problems like standards. However, there was no experimental work. Rana [61] discussed green computing for big data (with an emphasis on energy efficiency). The paper discussed industry practices. It also included a discussion of data center technologies. However, it did not have quantitative research.

Sultana et al. [62] proposed distributed AI for edge computing. The study improved system flexibility. It also allowed distributed computing. However, it had low accuracy. Siffre et al. [63] demonstrated that local-first software saved energy. This decreased network traffic. And it boosted speed. However, it was done on a small scale. Modupe et al. [64] gave an overview of the application of edge computing in industries. It reported benefits such as low latency. It also noted scalability. However, it was devoid of empirical results. Ahmed et al. [65] suggested a deep learning-based hardware failure prediction. This study had improved accuracy. It also improved feature selection. However, the false alarm rate was high. Perez et al. [66] qualitatively examined problems with adopting edge computing. The study identified deployment complexities. It also pointed out vendor lock-in. However, it did not provide quantitative evidence. Bala et al. [67] proposed AI predictive maintenance. This study had high accuracy. Further, it decreased downtime. However, there was an issue with data imbalance. Cao et al. [68] surveyed cost-efficient approaches for edge computing. Energy-saving techniques were discussed. It also reviewed resource management. However, scalability is a problem. Prieto et al. [69] studied the energy efficiency of computers over time. It demonstrated efficiency improvement at a lower rate than performance improvement. It also discussed benchmarking issues. However, it did not address new workloads.

Q.He et al. [70] developed an AI and IoT-based edge-based agricultural system. The study enhanced productivity and efficiency. Moreover, it involves resource management. However, its regional scalability is not clear. Biggi et al. [71] investigated the effects of green AI innovations using patent data. The study highlighted technological relevance. It also had high originality. However, its economic impact was low. Yang et al. [72] showed the energy efficiency of blockchain database systems. The research reduced the time taken and energy consumed. It also enhanced efficiency. However, the solution has scalability issues. Gopinathan et al. [73] examined factors affecting green IT adoption behavior. They found important predictors. It also pointed out user attitudes. However, the results were regional. Angelaki et al. [74] presented a bibliometric study of green computing. This study showed trends and contributors. Further, it demonstrated growing interest in the area. However, it did not include technical analysis. Jouini et al. [75] evaluated machine learning in IoT systems. This study showed impressive accuracy in real-time applications. It also identified deployment issues. However, there are resource limitations—Gedeon et al. [76] examined edge computing architectures and issues. The study noted a reduction in latency. It also addressed issues of scalability. However, there is a lack of standardization. Shrivastava et al. [77] showed an energy-efficient FPGA-based hardware design. This paper achieved considerable power savings. It also enhanced efficiency. However, it was a limited real-world application.

Cavalieri d'Oro et al. [78] have suggested an edge–cloud architecture for firefighting support, and analyzed its performance through Queuing Network (QN) modelling. The framework enhanced response time and collaboration among emergency responders, but did not assess for simulations without AI optimisation or in the field. Villari et al. [79] proposed the paradigm of Edge–Cloud Computing, which dynamically allocates microservices from the cloud to the edge devices to support IoT applications. The approach has good scalability, resource utilization, and low-latency service delivery, but has not been validated in experiments and lacks an intelligent resource management mechanism. Yoo and Kim [80] have developed a decision-making model for the adoption of cloud computing from an expert survey of cloud computing adoption in Korea that pinpointed the factors that affect the adoption of cloud computing by organizations. The study identified the importance of technological, organizational and environmental factors, but did not implement or evaluate the performance, being based on a survey approach. Dritsas and Trigka [81] provided an extensive overview of the use of Cloud Computing in the Industrial IoT (IIoT) to facilitate data storage, real-time analytics and intelligent industrial automation at scale. The survey highlighted key challenges like latency, security, and resource management, as well as the need for edge computing and AI integration to improve the performance and reliability of IIoT systems.

To enhance the reliability and service continuity of Large Language Models (LLMs) in cloud computing systems, Jin and Yang [82] suggested adaptive fault tolerance mechanisms. Although the study has increased the robustness of the fault recovery and resource resilience under dynamic cloud conditions, it has yet to be deployed on a large scale in real-world environments and experimented with. Han and Mathews [83] have come up with a proactive resource allocation model with Amazon Chronos for forecasting cloud workloads to utilize cloud resources. The study enhanced the prediction accuracy and resource efficiency but needs to be tested in various large-scale cloud environments. Younus and Purnomo [84] discussed the trend of government supports on cloud computing adoption in e-government architecture, and it focused on the policy and strategic support. While the study called for government support, it did not assess the technical implementation and performance of such support. To protect the cloud-stored healthcare data, Shahid and Kanwal [85] introduced a medical image encryption scheme by employing a chaotic tent map along with blockchain technology. The method improved data security and data integrity, but complicated computation and did not have real-time evaluation of the deployment.

Mkhize and Mokhothu [86] performed a systematic survey on the benefits of the implementation of cloud computing in SMEs, which includes the enhancement of operational effectiveness, scalability and business performance. The study was not conducted with any empirical validation; it was just a literature analysis. Reis and Fraga [87] looked at cloud computing in relation to its use as an IT strategy, examining the advantages, hurdles and implications for organizations. The review did not offer a practical framework or experimental evaluation, but offered strategic insights. Alkhasawneh and Che Cob did a systematic review of cloud computing adoption in government organizations in developing countries and extracted technological, organizational and environmental factors influencing the adoption.

The study did not attempt to design a validated adoption model. Ademilua and Areghan [89] suggested a system that combines cloud computing and machine learning for scalable predictive analytics and automation in real-world applications. The framework showed potential capabilities for intelligent decision-making; however, it did not show practical implementation and performance validation. Maharani and Mu'arif [90] discussed how cloud computing can be implemented in educational institutions for managing documents, aiming to enhance accessibility, collaboration, and storage efficiency. This study addressed conceptual benefits but did not on evaluating system performance in actual educational settings.

Maciel et al. [91] offered an extensive survey on the dependability models and taxonomy of Edge–Fog–Cloud computing architectures, along with dependability challenges. The study noted that there are several important research gaps related to fault tolerance and resource management, but it did not suggest a practical implementation. Edge Intelligence (EI) was reviewed by Peltonen et al. [92] by combining the AI with edge computing to provide low-latency intelligent services. The survey found that challenges in the field of distributed AI, scalability and resource management exist, but there was no experimental evaluation of an EI framework. Savargaonkar H. A and his colleagues [93] overviewed the use of edge computing in search and rescue applications, highlighting the areas of faster decision-making and lower communication latency. The study focused on issues of connectivity, energy efficiency and interoperability but omitted a working system.

Van Aalst [94] has spent some time analyzing the consequences of climate change on the risk of natural disasters and has concluded that climate variability leads to greater natural disaster frequency and severity. The study did not cover any technological solutions for disaster risk reduction. Satyanarayanan [95] described the necessity of edge computing for applications that require low latency and bandwidth. There was no implementation and performance evaluation in the paper; therefore, it laid the groundwork for edge computing. Zhang et al. [96] highlighted the security and privacy issues in edge computing, examining the methods and approaches used to ensure authentication, data privacy, and data sharing. The authors highlighted open security challenges but did not present a common framework of security.

Shi et al. [97] proposed edge computing and explored its architecture, applications and technical challenges. The work laid the groundwork for the significance of edge computing in IoT, but lacked experimental validation. One such idea is the complementarity of edge computing to cloud computing, where computation is brought closer to the end users, as discussed by Shi and Dustdar [98].

The article mentioned the advantages, like latency reduction, but did not explain how to implement them. Historical incident data was applied to examining the impact of environmental factors on SAR incidents in Nunavut, Canada, by Clark et al. [99]. Weather and topography were found to be important factors, but only in a certain geographic area. Ai et al. [100] suggested an intelligent decision algorithm that generates maritime search and rescue emergency response plans. The method enhanced the efficiency of the rescue planning process and was developed for maritime situations.

Table 1. Summary of extant works

Author	Application	Method Used	Dataset Utilized	Key Findings	Limitations
Chishti et al. [1]	Sustainable development using green ICT	Econometric modeling	Chinese provincial data	Green ICT significantly improves sustainability indicators	Limited to regional data
Bolón-Canedo et al. [2]	Green AI review	Survey & taxonomy	Secondary data	Identifies need for energy-efficient AI models	Lacks experimental validation
Zhu et al. [3]	Green pesticide design	AI + HPC	Chemical datasets	AI accelerates eco-friendly molecule discovery	High computational cost

Vedasri & Rathi [4]	Healthcare green computing	Conceptual model	Not specified	Reduces hospital energy consumption	No real-world testing
Long & Chen [5]	Renewable energy economics	Analytical modeling	Economic datasets	Renewable energy boosts green computing growth	Model assumptions simplified
Cavalieri d'Oro et al. [6]	Emergency management support using an edge–cloud architecture.	Queuing Network (QN) modeling for performance evaluation.	No public dataset; simulation-based emergency scenarios.	Reduced latency and improved response through balanced edge–cloud resources.	Limited to simulation; no AI-based optimization or real-world validation.
Koul [7]	Green manufacturing	Review of smart tech	Secondary sources	Digital tech enables sustainable production	No quantitative results
Fakhar et al. [8]	Software-level energy saving	Algorithm optimization	Simulated data	Software optimization reduces power use	Outdated techniques
Lacopo et al. [9]	Green computing in astronomy	HPC optimization	SKA-related data	Efficient computing for large-scale systems	Early-stage research
Mia et al. [10]	IoT + renewable integration	IoT framework	IoT sensor data	Smart systems reduce carbon footprint	Infrastructure dependency
Cruz et al. [11]	Green AI + software engineering	Conceptual framework	Not specified	Integration improves sustainability	Lacks implementation
Thakur et al. [12]	Green federated learning	FL optimization	Distributed datasets	Reduces communication energy	Privacy challenges
Xiong et al. [13]	Green cloud platform	Orchestration framework	Cloud workload data	Scalable energy-efficient cloud	Complexity in deployment
Paul et al. [14]	Green computing evolution	Comprehensive survey	Secondary data	Covers past–future trends	Broad, less depth
Abbas et al. [15]	Energy-efficient framework	Renewable integration model	Simulated data	Improves energy efficiency	Implementation complexity
Lukasewycz [16]	Green computing in video games	Power measurement + organic computing	Game performance data	Reduces energy consumption in gaming systems	Limited to specific game environments
Sodeinde et al. [17]	Green ICT in power distribution	Statistical analysis	Electricity company data	Green ICT improves operational sustainability	Region-specific analysis
Anh et al. [18]	IoHT with edge computing	SDN-based framework	Healthcare IoT data	Enhances efficiency and reduces latency	Security concerns remain
Rupanetti & Kaabouch [19]	IoT security with AI & edge	AI-based security models	IoT datasets	Improves threat detection in edge systems	High computational complexity
Uslu & Özer [20]	Green cloud computing	Resource allocation framework	Cloud workload data	Optimizes energy-aware resource mapping	Complex implementation
Gutiérrez-Finol et al. [21]	Frugal green modeling	Case study analysis	Molecular simulation data	Reduces computational resource usage	Limited generalization
Raja [22]	Energy-aware scheduling	Algorithm design	Simulated HPC workloads	Improves scheduling efficiency	Needs real-world validation
Nyabuto [23]	Green computing trends	Literature review	Secondary data	Identifies current research gaps	Lacks experimental work

Sharma et al. [24]	Edge computing for Industry 5.0	Survey	Secondary data	Edge computing enables smart industries	Challenges in scalability
Kong et al. [25]	Edge computing in IoE	Survey	Secondary data	Highlights the edge benefits in IoT systems	Limited practical evaluation
Devineni & Gorantla [26]	Energy-efficient computing	Conceptual techniques	Not specified	Reduces power consumption strategies	No implementation results
Kumar & Ranjan [27]	AI in edge computing	AI-based model	IoT datasets	Improves accuracy in edge analytics	Dataset dependency
Alhartomi et al. [28]	Sustainable edge computing	Renewable prediction model	Energy harvesting data	Enhances offloading efficiency	Prediction errors possible
Palmieri et al. [29]	Emergency management and first responder localization in smart cities.	Hybrid cloud architecture with landmark- and motion sensor-based localization.	No public dataset; evaluated using simulated emergency scenarios.	Improved real-time localization, coordination, and scalability for emergency response.	Did not incorporate edge computing, AI-based analytics, or real-world deployment.
Rancea et al. [30]	Edge computing in healthcare	Review study	Secondary data	Improves real-time healthcare services	Security and privacy issues
Saxena et al. [31]	Green cloud computing	Conceptual framework	Not specified	Efficient resource usage reduces energy consumption	Lacks experimental validation
Manshani [32]	Sustainable green computing	Review study	Secondary data	Highlights innovation in eco-friendly technologies	Limited technical depth
Alazzawi et al. [33]	Green IoT systems	Analytical model	IoT datasets	Improves energy efficiency and security	Implementation complexity
Sodiya et al. [34]	Edge computing in IoT	Review	Secondary data	Edge computing enhances real-time processing	Scalability issues
Siew et al. [35]	Green user behavior	Behavioral analysis	Survey data	Consumer behavior impacts sustainability	Limited geographic scope
Liao & Xie [36]	IoT data processing	Edge-based analysis	IoT data	Improves processing speed and efficiency	Data privacy concerns
Vakaliuk [37]	Edge computing research trends	Bibliometric analysis	Research publications	Identifies growth trends in edge computing	No experimental validation
Deepak et al. [38]	Load balancing in edge/fog	Comparative analysis	Simulated data	Enhances system performance	Complexity in real-world deployment
Bicker et al. [39]	Green epidemiological modeling	Agent-based modeling	Health datasets	Efficient simulation reduces computation cost	Model assumptions
Cao et al. [40]	Edge computing overview	Survey	Secondary data	Provides comprehensive edge architecture	Outdated aspects
Verma & Verma [41]	Cloud vs edge computing	Comparative study	Not specified	Edge reduces latency vs cloud	Limited experimental results
Yadav & Mallick [42]	AI + edge for Industry 4.0	AI-based framework	Industrial datasets	Enables decentralized intelligence	Implementation challenges
Wen et al. [43]	Edge computing + Vision Transformer	Adaptive framework	Vision datasets	Improves edge AI performance	Resource-intensive
Gangrade et al. [44]	Edge/fog in cyber-physical systems	Conceptual framework	Not specified	Enhances system coordination and efficiency	Lack of experimental validation
Pies et al. [45]	Edge data gateway architecture	System design	Network data	Improves data transmission efficiency	Deployment complexity

Sharma et al. [46]	Edge computing for Industry 5.0	Survey	Secondary data	Supports automation and smart manufacturing	Scalability challenges
Hazra et al. [47]	IoT + edge computing	Analytical framework	IoT datasets	Improves latency and QoS	Security issues
Yalcın [48]	Federated learning at the edge	FL framework	Distributed datasets	Reduces communication cost	Accuracy trade-offs
Pan & McElhannon [49]	Edge cloud for IoT	Conceptual architecture	Not specified	Edge-cloud integration enhances performance	Outdated model assumptions
Zuo et al. [50]	Industrial robotics + edge	Optimization model	Industrial data	Improves robot coordination efficiency	High system complexity
Elmobark [51]	Edge + big data analytics	Analytical model	Big data sets	Enhances real-time analytics	Resource constraints
Juric et al. [52]	Intelligent edge computing	Introductory framework	Not specified	Highlights future research directions	Limited implementation
Abdulqader et al. [53]	IoT optimization using edge	Performance optimization	IoT datasets	Improves bandwidth and security	Deployment issues
Bozkaya-Aras [54]	IoT service migration	Digital twin approach	Simulated data	Enhances energy efficiency	Model complexity
Wang & Yang [55]	Resource scheduling	Deep reinforcement learning	Cloud-edge data	Optimizes resource allocation	Training overhead
Maliarskyi & Oleksiuk [56]	Edge system quality assurance	Review	Secondary data	Identifies QA tools for edge systems	Lacks practical validation
Huang et al. [57]	Service ranking in edge IoT	ML-based prediction	IoT datasets	Improves service selection accuracy	Data dependency
Rawdhan [58]	Task offloading in edge computing	SDN-based scheduling	Simulated network data	Improves task allocation and reduces latency	Limited real-world validation
Narang [59]	Green challenges in IoT & edge	Conceptual analysis	Not specified	Identifies sustainability challenges in emerging tech	Lacks quantitative evaluation
Oyile & Wabwoba [60]	Evolution of green computing	Review	Secondary data	Highlights societal impact and sustainability trends	Limited technical depth
Rana [61]	Data warehouse & green computing	Conceptual study	Not specified	Integrates green practices in big data systems	No experimental results
Sultana et al. [62]	Blockchain-based green edge computing	Decentralized AI framework	IoT datasets	Enhances energy efficiency and security	High computational overhead
Siffre et al. [63]	Local-first green software	System design	Application data	Reduces cloud dependency and energy usage	Limited scalability
Modupe et al. [64]	Edge computing in analytics	Review	Secondary data	Improves real-time data processing	Security concerns
Ahmed & Green [65]	Hard drive failure prediction	Deep learning (cost-aware)	Hardware datasets	Enhances prediction accuracy with lower cost	Dataset-specific limitations
Pérez et al. [66]	Edge computing theory	Grounded theory study	Qualitative data	Provides foundational understanding	Limited quantitative validation
Bala et al. [67]	AI + edge for maintenance	Review	Secondary data	Improves predictive maintenance	Implementation complexity
Cao et al. [68]	Cost optimization in the edge	Survey	Secondary data	Identifies cost-efficient strategies	No experimental results
Prieto et al. [69]	Energy efficiency trends	Analytical study	Historical computing data	Revisits Koomey's law for efficiency growth	Theoretical assumptions
He et al. [70]	Smart agriculture with edge	Fuzzy NN + auction model	Agricultural IoT data	Enhances supply chain efficiency	Model complexity

Biggi et al. [71]	Green AI technologies	Analytical study	Secondary data	AI contributes to green innovation	Limited empirical validation
Yang et al. [72]	Energy-efficient databases	Blockchain + IoT model	Database systems data	Improves energy savings in data management	Implementation overhead
Gopinathan et al. [73]	Green information systems adoption	Behavioral analysis	Survey data	User intention significantly impacts green IT adoption	Limited regional scope
Angelaki et al. [74]	ESG & green computing	Bibliometric analysis	Research publications	Strong link between ESG and sustainable computing trends	Lacks experimental validation
Jouini et al. [75]	ML in edge computing	Survey	Secondary data	ML enhances edge efficiency and intelligence	Implementation challenges
Gedeon et al. [76]	Edge/fog computing	Survey	Secondary data	Identifies future challenges in edge systems	Outdated assumptions
Shrivastava et al. [77]	Green computing hardware (VLSI)	FPGA-based design	Hardware simulation data	Reduces power consumption in communication systems	Hardware constraints
Cavalieri d'Oro et al [78]	Firefighting support system using edge–cloud computing.	Queuing Network (QN) performance modeling of an edge–cloud architecture.	No public dataset; simulation-based firefighting scenarios.	Improved response time, resource utilization, and coordination through balanced edge–cloud processing.	Limited to simulation and lacked AI-based optimization or real-world validation.
Villari et al. [79]	Edge–cloud integration for IoT applications using osmotic computing.	Osmotic Computing paradigm with dynamic microservice deployment across edge and cloud.	No dataset; conceptual architecture and framework discussion.	Improved resource utilization, scalability, and low-latency service execution through edge–cloud integration.	Conceptual work without implementation, experimental validation, or AI-based resource management.
Yoo & Kim [80]	Cloud adoption decision model	Expert survey model	Survey data	Identifies key adoption factors	Limited geographic scope
Dritsas & Trigka [81]	Cloud in IIoT	Survey	Secondary data	Cloud enables industrial IoT scalability	Security concerns
Jin & Yang [82]	Fault tolerance in the cloud	Adaptive mechanisms	Simulated cloud data	Improves the reliability of cloud systems	High computational cost
Han & Mathews [83]	Cloud resource forecasting	AI-based prediction	Cloud workload data	Enhances resource allocation efficiency	Model complexity
Younus & Purnomo [84]	Cloud in e-government	Trend analysis	Government datasets	Government support drives adoption	Policy limitations
Shahid & Kanwal [85]	Secure cloud computing	Blockchain-based encryption	Medical image data	Improves data security and privacy	High processing overhead
Mkhize & Mokhothu [86]	Cloud computing in SMEs	Systematic review	Secondary data	Cloud improves SME performance	Lack of empirical data
Reis & Fraga [87]	Cloud as an IT strategy	Literature review	Secondary data	Cloud adoption enhances business agility	Limited technical insights
Alkhasawneh & Che Cob [88]	Cloud adoption in government	Systematic review	Secondary data	Identifies factors influencing adoption in developing countries	Limited real-world validation
Adetunji & Areghan [89]	Cloud + ML for analytics	Framework design	Real-world datasets	Enables scalable predictive analytics	Implementation complexity
Maharani & Mu'arif [90]	Cloud in education	Case study	Academic data	Improves document management efficiency	Limited scalability

Maciel et al. [91]	Edge–Fog–Cloud reliability	Survey and taxonomy	Literature review	Identified reliability and availability challenges.	No proposed framework or validation.
Peltonen et al. [92]	Edge Intelligence	Comprehensive survey	Literature review	Highlighted AI-enabled edge applications and research gaps.	No implementation or experimental evaluation.
Savargaonkar et al. [93]	Search and rescue	Scoping review	Literature review	Showed that edge computing improves SAR operations.	No practical framework or validation.
Van Aalst [94]	Climate change and disasters	Risk assessment review	Disaster studies	Climate change increases disaster risks.	Does not address computing solutions.
Satyanarayanan [95]	Edge computing	Conceptual overview	No dataset	Explained the emergence and benefits of edge computing.	Lacks a performance evaluation.
Zhang et al. [96]	Edge security and privacy	Survey	Literature review	Identified security and privacy challenges in edge computing.	No security framework implementation.
Shi et al. [97]	Edge computing	Vision paper	No dataset	Defined edge computing architecture and challenges.	Conceptual without validation.
Shi and Dustdar [98]	Edge computing	Perspective article	No dataset	Highlighted the potential of edge computing.	No experimental analysis.
Clark et al. [99]	Search and rescue	Statistical analysis	Nunavut SAR incident data	Environmental factors influence SAR incidents.	Limited to a regional dataset.
Ai et al. [100]	Maritime search and rescue	Intelligent decision algorithm	Maritime emergency cases	Improved emergency response planning accuracy.	Domain-specific applicability.
Carvalho et al. [101]	Edge computing	Survey	Literature review	Reviewed trends, challenges, and future directions.	No proposed implementation.
Selvaraj et al. [102]	Emergency response	IoT and cloud framework	Conceptual model	Improved emergency communication and monitoring.	No real-world validation.
Krishnasamy et al. [103]	Edge computing	Framework overview	Literature review	Summarized edge frameworks and applications.	No experimental comparison.
Nancharaiah et al. [104]	Disaster response	AR with edge–cloud computing	Simulated emergency scenarios	Enhanced first responder interaction using AR.	Limited experimental evaluation.
Patel et al. [105]	Edge computing	Comprehensive review	Literature review	Discussed applications, security, and challenges.	No practical implementation.
Mishra et al. [106]	AI-enabled edge computing	Review	Literature review	Highlighted AI as a key enabler for edge systems.	No implementation results.
Reddy et al. [107]	Disaster management	IoT-based edge–cloud platform	Simulated sensor data	Enabled real-time emergency data analysis.	Limited real-world deployment.
Khan et al. [108]	Disaster management	Systematic review	Literature review	Identified challenges and future research directions.	No proposed disaster management framework.
Özen and Souri [109]	Disaster management	Hybrid machine learning with IoT-cloud	IoT disaster data	Improved disaster prediction and management accuracy.	Dependent on data quality and cloud connectivity.

Gaire et al. [110]	Disaster management	IoT–Cloud architecture	Conceptual framework	Demonstrated IoT-cloud integration for disaster response.	No implementation or performance evaluation.
Islam & Patamsetti [111]	Future of cloud computing	Review study	Secondary data	Identifies benefits and challenges	Broad analysis
Lăzăroiu et al. [112]	AI + cloud in fintech	Analytical study	Financial datasets	Improves financial decision-making	Security concerns
Rawashdeh & Rawashdeh [113]	Cloud accounting adoption	Behavioral model	Survey data	Identifies adoption drivers in SMBs	Limited sample size
Gonçalves & Messias [114]	Cloud adoption trends	Bibliometric analysis	Publication datasets	Highlights digital transformation trends	Lacks technical depth
Prasanna and Ahir [115]	AI-driven disaster recovery in cloud computing.	Proactive AI-based disaster recovery framework.	Simulated cloud disaster scenarios.	Improved recovery speed, fault prediction, and service availability.	Limited to simulation without large-scale real-world validation.
Singh & Kaunert [116]	Cloud + IoMT in healthcare	AI-based framework	Medical datasets	Enhances disease detection and diagnosis	Data privacy concerns

3. Datasets

The data sets used in the current study are real data on environmental monitoring and simulated data to mimic a disaster-prone environment that facilitated addressing all the aspects of the Smart Disaster Alert and Response System assessment. The disaster datasets are multi-faceted and contain seismic, hydrologic, meteorological and wildfire parameters and have been used earlier by many researchers in the context of risk assessment and designing early warning systems.The data sources are: Earthquake Data: Geological Survey, USA and the Indian Meteorological department were used to collect historical earthquake data, which contain the time, magnitude, location and depth of the epicentre. These data have been used in training deep-learning models for earthquake prediction, which highlight the benefits of high-resolution seismic monitoring to assess the hazard rapidly.

Flood Monitoring Data The magnitude of the River gage data of CWC and the precipitation data of this organisation were combined with the flood monitoring data of Dartmouth Observatory to use these sources in the modelling of hydrodynamics and real-time flood forecasting. Cyclone and storm data Cyclone and storm data by the Joint Typhoon Warning Center (JTWC) and the India Meteorological Department were collected on the wind speed, central pressure and the location of the storm track. These data have been used to develop the trajectory prediction models to enhance the prediction of the landfall and the intensity. Wildfire Datasets: Satellite-based Wildfire datasets were: Active fire coordinates, intensity measurements, the size of the burn area created by the Fire Information for Resource management System (FIRMS) and MODIS. These similar data have been used for the wildfire trajectory prediction and the classification of severity [115].

3.1. Data Characteristics

The combined data are multi-dimensional, which include: Continuous sensor data: sensor data that can be used to detect anomalies in the event of a disaster (e.g., temperature, humidity, barometric pressure). The types of data required to prioritise the risks in the warning and alarm systems are Disaster Classification Labels and severity codes, which are categorical data. Sporadic Temporal Data: Location information, spaced-time stamped, so that the data can be used to serve a Geographic Information System (GIS) decision support system. Remote Sensing Data: Medium-resolution satellite data will be used in flood and wildfire mapping, and in disaster detection algorithms based on Sentinel-2 [112].

3.2. Synthetic Data Generation

Synthetic data could be generated by disaster modelling software, such as HEC-RAS for flooding or Fire Dynamics Simulator (FDS) for wildfire spread. This is a method that has been used before to overcome the class imbalance problem, and also to make the model more resilient to rare events.

3.3. Dataset Integration for SDARS

The data sets were integrated in a single repository, where the edge devices did local analysis and at the cloud level, trends over time analysis was done. Previous research also suggests that the use of integrated information from multiple sources enhances disaster prediction and minimises false alarms, and this is the reason why SDARS has taken on this approach.

4. Pre-Processing

It is observed that the raw disaster data that have been obtained/ downloaded by the other parties have inconsistencies, noises and missing values, which in turn can hinder the accuracy of the results in predictive data modelling and the generation of warnings.

So it is not a mandatory criterion to reject descriptive pre-processing for the reliability, compatibility and readiness of data for further processing and model training. The SDARS framework follows a train of thought on pre-processing with the methodologies that have been developed in the field of environmental data analytics [114].

4.1. Data Cleaning and Noise Removal

There are always skewness and outliers in sensor-based data streams due to sensor malfunction, noise during transmission or other environmental abnormalities. A moving average and Kalman filtering combination is used to remove such skews to filter the true trends of disasters from the noise in this data set. Other data streams, such as seismic data stream and weather data stream, are also processed similarly as another form of data normalisation.

4.2. Missing Value Imputation

This may be in the form of missing data, which may be caused by equipment failure or the outage of the network during extreme disasters when the systems are overwhelmed. NA values in the data were tackled in two ways: Time series continuous data were statistically imputed, mixed-type values and categorical features were imputed with the k-Nearest Neighbor imputation (k-NN). The two approaches ensure the consistency of the categories and continuity of the data.

4.3. Data Normalization and Standardization

The missing data can be either embedded with the sensor malfunction or network outage during the high-impact disasters when the system's capacity is exhausted. Incomplete data were handled by a combination of processes: Statistical imputation of time series data, revisit of k-Nearest Neighbour imputation (k-NN) for the mixed-type variables and categorical features. The two methods were able to ensure the consistency of the categories and continuity of the overall time series [113].

4.4. Spatial and Temporal Alignment

The spatial offset between different sensors and agencies was removed to enable the possibility of integrating the multiple datasets with GIS software through the projection of data with a common WGS 84 reference system. Data sampling was on a common time basis of one minute, and the primary consistency of the data streams across all sources ensured consistency.

4.5. Feature Engineering for SDARS

Data that is already processed was further improved with domain-specific feature engineering to improve the accuracy of the model. Such features include: Moving average of rainfall to predict the onset of flooding, Wind gust factor from the wind speed data to predict the severity of a cyclone, and fire spread rate from the series of satellite image data to map the fire danger. These features are the ones that are engineered to predict the key features of the previous disaster analytics studies. The data preparation processes allow the SDARS system to deliver reliable, consistent and statistically valid data into the system that can be used for reliable disaster detection and prediction [116].

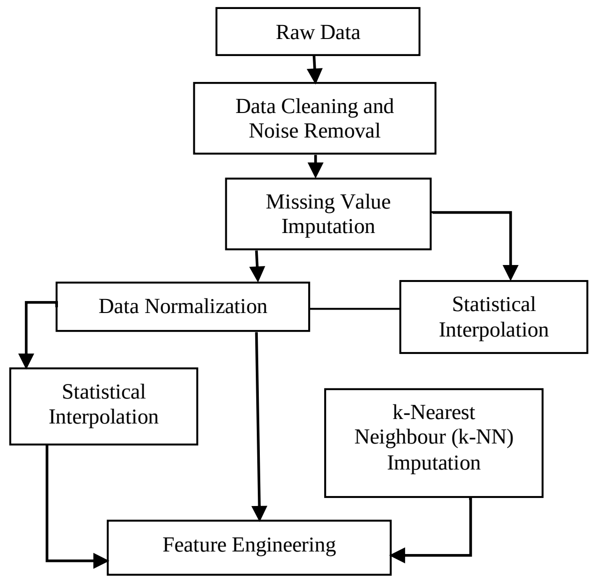

Fig. 1 Pre-processing Workflow for Disaster Management Data

Figure 1 shows the order of the steps of preparing heterogeneous disaster data for analyses in SDARS. The raw data from most data sources is then passed to data cleaning and anomaly removal to remove anomalies potentially caused by sensor malfunctions or the environment. The statistical interpolations and the k-Nearest Neighbour (k-NN) approaches are then used to fill in missing values to achieve completeness [111]. This is followed by data normalization to equalise features, followed by feature engineering, where new features such as moving averages, gust factors and fire spread rates, to mention a few, are created to improve predictive capabilities. The multilevel processing guarantees the safety and security of all the data in the pipeline since data is consistent, non-varying and tailored to specific disaster detection and prediction through artificial intelligence.

5. Artificial Intelligence Techniques

Smart Disaster Alert and Response System (SDARS) is a multilayered and multimodal Artificial Intelligence (AI) system, which employs diverse environmental knowledge sources, and the system is targeted at problem identification and prevention of the disaster. AI-based models are increasingly being used in disaster management to improve the accuracy of predictions, reduce false alarms and/or automate the decision-making. The SDARS system uses a combination of Machine Learning (ML), Deep Learning (DL) and Transfer Learning (TL) to make its system real-time for a variety of disaster scenarios.

Disaster Prediction Model in Equation 1 is expressed as

$$P(D \mid X) = \frac{P(X|D) \cdot P(D)}{P(X)} \quad (1)$$

where D represents disaster occurrence and X denotes sensor observations.

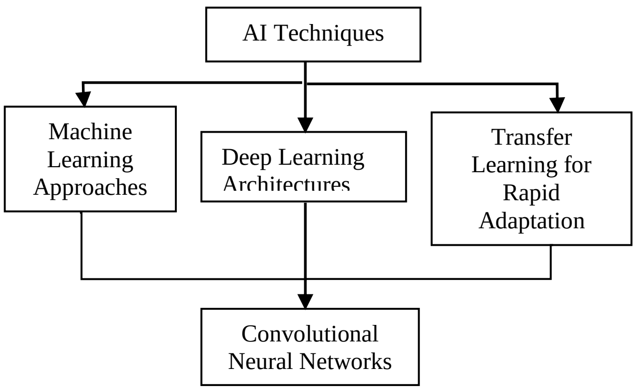

Fig. 2 AI Techniques

As illustrated in Figure 2, the first level of decision-making in SDARS is the ML models, i.e., most of them are deployed on the edge computing nodes to achieve timeliness. Traditional algorithms, like Random Forests (RF), Support-Vector Machines (SVM) and Gradient-Boosting Decision Trees (GBDT), are applied to categorise the disaster events from the sensor streams. For instance, RF has been applied in hydrological flood prediction as it is robust to noisy sensor measurements, but SVM has been shown to have an extremely high success rate in predicting the trajectory of cyclones.

Figure 3 illustrates the step-by-step procedure that is followed in the SDARS framework to carry out the machine learning based classification of disasters. The process will start with the collection of data, and pre-processing will be applied (including noise removal, data normalization and feature extraction) to make the data ready for processing. A feature selection is indicated, to apply only the most significant features, to apply a time-consuming process more efficiently and to improve the accuracy of the model. Then, according to the outcome of the selection, the process is continued by the classification module, and the Random Forest model, Support Vector Machines or Gradient Boosting models can be used. Models-trained models are model-validated on a separate validation set, and performance is assessed using various metrics, e.g. accuracy, precision and recall. When the numbers meet the pre-defined thresholds, the network is deployed for real-time disaster detection and alarms.

This process guarantees the classification is organised and correct, and optimised in an edge and cloud environment that has been set up in the SDARS architecture. The ML models used in SDARS are trained with real and synthetic data to ensure they are able to deal with unbalanced class distributions, which are usually the case when a rare anomaly, such as disasters is involved. The edge devices are also unloaded of their computational load, where the most relevant parameters (i.e. the thickness of the rainfall or seismic wave amplitude) are dynamically set, by RF feature importance ranking.

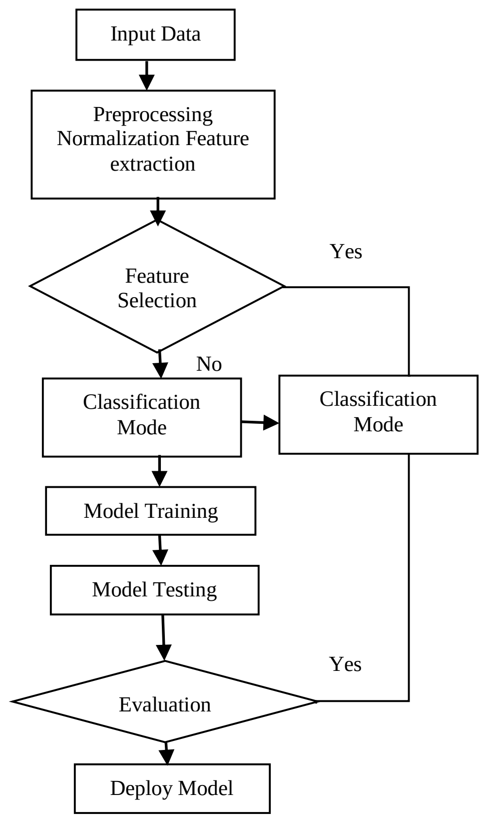

Fig. 3 Classification Framework for Machine Learning Algorithm

5.1. Deep Learning Architectures

In the cloud-computing layer, as illustrated in Figure 4, Deep Learning systems are deployed to assist with the large-scale analyses and increase the sensitivity of non-linear and complex patterns of disaster events. Convolutional Neural Networks (CNNs) artificial intelligence data analyses are applied in terms of both wildfire and flood recognition of satellite images, which matches with the results discussed in the last part, and they show high accuracy in the environmental monitoring phase. The LSTM models are used for time-series forecasting of the earthquake and weather events, of which the characteristics of the latter enable the models to build an intuition of a time-dependent event.

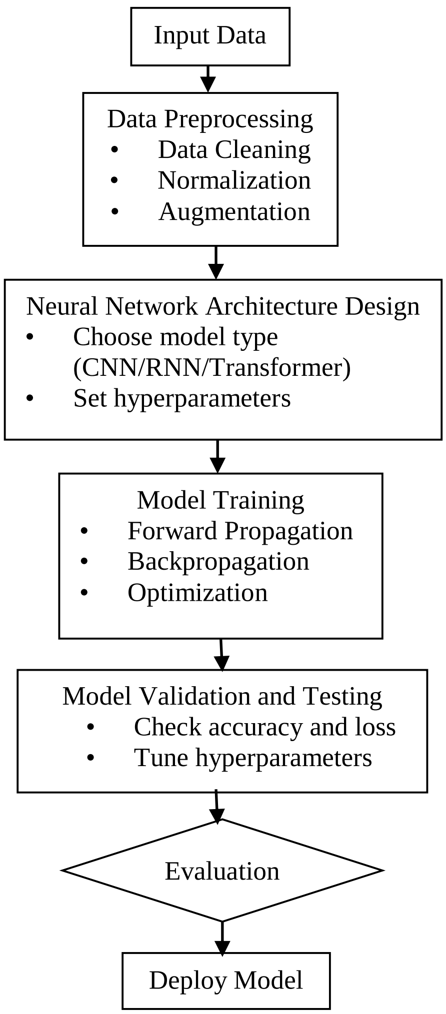

Fig. 4 Classification Framework for Deep Learning Algorithm

The model interpretability in disaster management would be improved by the Grad-CAM visualization of model outputs because it would enable comparison of AI warnings with spatial data on satellite images.

5.2. Transfer Learning for Rapid Adaptation

The use of transfer learning and techniques for scaling and projecting models to new domains with little or no labelled data (influenced areas or new disasters) is advocated. ResNet50 and EfficientNet are pre-trained CNN models that are adjusted to small event-specific training data, and significantly reduce training time while having no effect on the accuracy of the model. This approach is in line with the requirement of an AI system that is rapidly adaptable to any environmental change. In the case of wildfire detection, a ResNet 50 model that has been generally trained using global data from the MODIS images might be retrained with local FIRMS data, in a way that the variant of the SDARS system using this model will have a detection rate of over 92 percent with little retraining of the model.

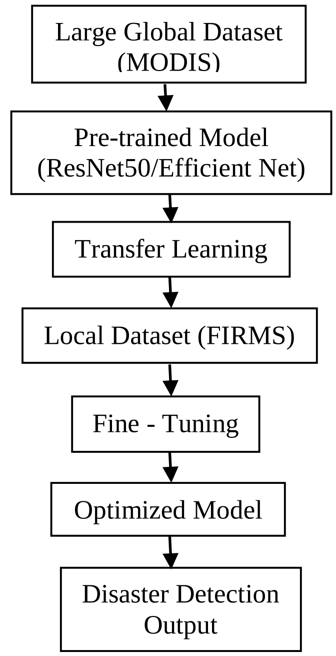

Fig. 5 Transfer learning for rapid wildfire detection using pre-trained CNN models

The procedure, as shown in Figure 5, will commence with large global data, such as MODIS (Moderate Resolution Imaging Spectroradiometer) satellite images. The data are first trained with models of deep convolutional neural networks, such as ResNet50 and EfficientNET that enable the models to learn the general visual features related to wildfire and other environmental factors. The models are then deployed to a different target domain where there is only a limited amount of local disaster-specific data, e.g. FIRMS (Fire Information for Resource Management System) data.

Fine-tuning makes small adjustments to the model parameters by using the local data and allows the model to begin to detect local parameters of wildfires. This is to facilitate quick adaptation of the system to new regions or to emergency situations without necessarily retraining the model. The result is that the model in the SDARS model has a high detection rate of over 92 percent and less retraining time, which demonstrates the effectiveness of transfer learning in the rapid response to disasters and scalable AI-based hazard detection systems.

5.3. Hybrid AI for Multi-Hazard Detection

The multi-layer AI framework that uses edge classification ML and cloud analytics DL allows for the detection of multiple hazards and multi-level decision making. Edge devices, which pre-classify and raise instant alerts, are then verified by the cloud, and improve and grow based on their powerful DL models. This kind of hierarchical approach not only helps to reduce the false alerts, but also provides the necessary warnings within sub-seconds, which is vital in the global disaster management systems.

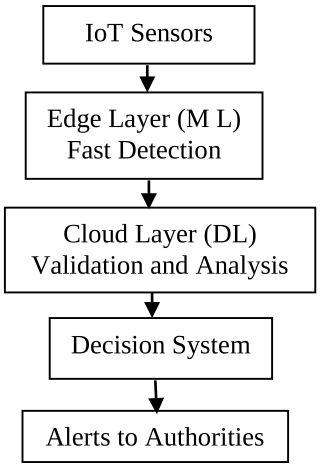

Fig. 6 Hybrid AI framework for multi-hazard detection using edge ML for rapid detection and cloud DL for validation and decision-making

In Figure 6, it begins with edge devices such as sensors, cameras or IoT devices that continuously monitor the environment based on the potential risks such as fire, floods, earthquakes, or storms. They belong to the first level of classification with heavy machine learning models, and so can easily detect the anomalies and raise instant warnings. The first warnings and data are then transferred to the cloud analytics layer to be further analysed and validated by the sophisticated deep learning models.

The cloud layer further enhances the predictions, eliminates the false alarms and then performs the high-level decision making and verification of hazards. Once validated, the system generates valid warnings and alerts to emergency systems or authorities. This bottom-up approach can ensure that real-time edge detection can be quick, and the cloud can provide more computational power to the cloud, as it is a trusted and scalable framework to build an efficient hybrid AI-powered multi-hazard detection system.

6. Limitations and Future Research Directions

While the proposed SDARS framework demonstrates good performance, some limitations exist. The framework uses partially simulated and benchmark datasets, which may not fully represent the real complexity, diversity and noise in disasters, thus limiting its generalizability. Moreover, the system mainly addresses disaster identification and alerting, with limited functionality for self-organized disaster response coordination among emergency systems. While the system includes energy-saving strategies, these are not rigorously tested in realistic settings with variable workloads and diverse device characteristics. Large-scale, multi-regional scalability and sophisticated security measures to safeguard data are also not fully addressed.

Future work will include the incorporation of real-time multi-regional data for enhanced model training, reinforcement learning for smart and dynamic decision-making and edge-to-edge collaboration for distributed and low-latency computation. Moreover, the system will be improved with autonomous response mechanisms through drones and robotics, satellite communication for seamless connectivity in post-disaster scenarios, and integration of renewable energy sources for sustainability. Security and privacy enhancements using advanced technologies like blockchain and AI-based threat analysis will also be explored to enhance the system's reliability, scalability and practicality.

7. Conclusion

This paper describes the Smart Disaster Alert and Response System (SDARS), a multi-layer approach to the implementation of disaster management that combines the principles and ideas of IoT-sensing and edge computing with cloud computing and green computing to remove the problems of the latency, scalability and energy-efficiency of the existing centralized models. The real-time, local data processing at the edge of the network, and the capacity to do large-scale predictive analysis at the cloud made it possible to report alerts in sub-second latency, achieve the energy efficiency of ~35 percent and still be able to work with partial network failures.

The use of both spatial and temporal, but interconnected, environmental information (seismicity, hydrologic and meteorological data, wildfire position data, etc.) and the application of the advanced artificial intelligence algorithms (machine learning, deep learning, transfer learning, etc.) ensured high accuracy of the alarms and flexibility in the sense of the broad range of disasters, to say nothing of the low rate of false alarms. While the assessment results were encouraging, some of the limitations were also discovered, including the use of synthetic data to fill the gaps in the disaster scenarios, that the task was only to detect and report alarms, without any other autonomous acts of coordination of responses, and that even more effort will be needed to provide sustainable energy at the edge.

The future trends are related to enhancing dataset storage with multi-regional and real-time data streams to ensure the dataset will be constantly upgraded, the idea of reinforcement learning that will be applied to the dynamic and adaptive decision-making, multi-regional, and adaptive decision-making in the forms of resource allocation, edge-edge interaction to make the world safer, and the satellite based transmission to ensure the model will be still capable to function if the whole terrestrial communication network is damaged. With these improvements, hopefully SDARS will be able to be an AI-based, global and resilient disaster management system which can operate in the harshest environments and provide fast, reliable and sustainable (green) response times through a proven ecosystem.

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