Review

Comparative Analysis of Edge-Enabled AI–IoT Healthcare Systems: Toward the Most Effective Predictive Model

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Abstract

The combination of the Artificial Intelligence (AI), the Internet of Things (IoT), and the Internet of Medical Things (IoMT) is driving current developments in the field of intelligent healthcare systems, thus, enabling the continuous, real-time, and remote monitoring of patients. The traditional cloud-based healthcare infrastructure, however, is riddled with latency, bandwidth, scaling, and increased risks to the privacy of data, all of which decrease their efficiency in time-intensive clinical settings. To address these drawbacks, this study performs a comparative analysis of edge-based AI-IoT healthcare systems, in which the most useful predictive model is determined to be deployed on clinical scenarios in real time. Various machine-learning and deep-learning frameworks have been tested on hybrid edge-cloud systems using ECG data gathered by IoT and the performance indices included prediction accuracy, latency, computation efficiency, and edge-feasibility. Table 1 enumerates the results of applying the convolutional neural network (CNN)-based models, showing that they have higher performance, achieving around 99 percent success on arrhythmia detection, with low latency that makes them an option of implementing them in the form of edge devices. Comparatively, a three-layer-based monitoring setup based on the concept of combining IoT devices with a hybrid CNN-UUGRU model achieves 97.7 percent accuracy on public datasets and can be used to partition edge-cloud tasks and mobile-based notifications, but at slightly reduced predictive accuracy. Although benchmark results are strong, the enduring weaknesses are linked to reliance on clean and non-clinical datasets and lack of a thorough test of robustness, privacy, and extended deployment. Comprehensively, it can be indicated that CNN-based models provide the best balance in terms of accuracy,

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real-time performance, and edge feasibility; thus, its significant potential in scalable, patient-centered, and reliable edge-enabled AI-IoT healthcare systems, especially regarding real-time arrhythmia screening.

Keywords: Internet of Medical Things (IoMT), Smart Healthcare Systems, Healthcare Data Privacy, Real-time Monitoring, Wearable Sensors, AI-Driven Analytics

I. INTRODUCTION

Over the last few years, the combination of Artificial Intelligence (AI) and the Internet of Things (IoT) turned the sphere of healthcare into a more intelligent, connected, and patient-oriented one. The rise in chronic illnesses, ageing world, and the general need to be watched constantly on matters related to health has compounded the rate of uptake of smart healthcare systems [1]. The conventional model hospital-based care is usually insufficient in terms of delivering medical care in time particularly to the aged or to the remote patient. Hence, it may be expected that smart-based healthcare, integrating wearable sensors, IoT-based infrastructure, and AI-driven analytics, will become a promising solution in enhancing the early diagnosis of the disease, individual treatment, and patient safety [2]. The topicality of this discipline is supported by the trends in digital medicine across the world today. This publication growth is also visible in Fig. 1, which shows an increasing concentration of AI–IoT healthcare studies in 2024–2025. With the World Health Organization stipulating such a high number of elderly patients growing fast, which makes up 2.1 billion people by the year 2050, there are new challenges of healthcare systems like real-time monitoring of patients and prevention of diseases [3]. Existing healthcare systems cannot cope with all these issues because of the insufficient resources, geographical limitations, and the unavailability of individualized monitoring systems. This results in the increased demand to integrate smart, interrelated networks that gather and process biomedical data in real-time so that physicians could make correct and prompt choices [4].

Although systems have advanced fast, the current systems are faced with a number of challenges that include, latency in data transmission, low interoperability, and inadequate dependability of wearable devices [5]. Furthermore, the issue of privacy and data-security is also a constant barrier in the implementation of AI-IoT healthcare systems on a large scale [6]. So, authors suggest new constructs of edge or fog computing and blockchain systems in order to provide safe and real time data management [7]. To demonstrate it, Baucas et al. (2023) proposed a federated learning and blockchain-based platform of the building of a fog-IoT that permits the execution of computations at the wearable level but keeps users confidential [8]. This model shows how centralized storage of healthcare data in healthcare has transitioned to the distributed, privacy-protecting structures.

What is another important component of the problem is the necessity of reliability and resilience in healthcare systems. Rudimentary monitoring technologies are typically unrelated, which reduces their ability to look at various conditions of health, which are interconnected. To counter this, Healthcare 5.0 technologies can make reliable, resilient, and personalized choices to provide continuity of service and autonomous decision-making [9]. These systems will be able to identify unfavorable conditions, reestablish the functionality automatically, and adjust the treatment plans based on the unique genetic, behavioral or environmental factors of patients. The COVID-19 pandemic has also brought additional weight to value AI-IoT convergence in the medical care. The AI-based IoT applications have played a significant role in identifying the patterns of infections, enabling telemedicine, and automating non-contact health monitoring [10]. These uses made it clear that smart digital health systems can not only decrease the amount of physical contact between patients and healthcare providers but can also guarantee quick responses and mass disease monitoring. This led to the adoption of such solutions in the healthcare system of many countries. According to the recent research, AI and IoT have great pluses in the areas of diagnostic accuracy and treatment efficacy. Mansour et al. (2021) developed an AI-IoT disease-diagnosis model based on deep learning and optimization algorithms, in which the accuracy was over 96 per cent in classifying heart diseases and diabetes. Likewise, Zahid et al. (2022) came up with an adaptive and sustainable IoT-based healthcare model to maintain a real-time data processing and energy efficiency in medical sensors. The innovations presented above show how AI-IoT integration has the potential to transform the sphere of diagnostic and monitoring in smart scenarios of healthcare industry.

Nevertheless, with this technological advancement, there are still many gaps in research. Medical devices are heterogeneous, lack standardization, and are unable to be scaled to be extensively used. Further, moral and legal issues of data sharing and algorithmic transparency are persisting to become impediments to global level implementation. Thus, recent literature is concerned with the formulation of complex schemes that will strike a balance in terms of efficiency and reliability, not to mention ethical accountability.

To sum up, the unification of AI and IoT technologies is a breakthrough into the realm of proactive, preventative, and personalized healthcare. The contemporary work environment attempts to fill deficiencies of the conventional systems through improved connections, accuracy, and decision-making in real time. Thus, the analysis of AI-IoT-based smart healthcare has been relevant to a large extent because it has solutions to the world-wide problems, including population aging, handling chronic diseases, and accessibility of healthcare.

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The recent convergence of edge computing, the Internet of Things, and artificial intelligence (AI) has changed the way healthcare systems monitor and assist patients. Thanks to wearable and sensor-based Internet of Things devices that allow continuous data collection, doctors and patients can now stay connected even outside hospital settings. Mansour et al. [11] developed a low-cost Internet of Things prototype that uses Arduino sensors to assess heart rate, grip strength, and sleep to aid stroke patients in their home-based recovery. Wang et al. [12] demonstrated the potential of wearable technology in rehabilitation by creating a smart knee sleeve that gathers motion data in real time and sends it to the cloud.

Making these systems more intelligent and effective was the aim of other researchers. Hassan et al. [13] introduced an edge-based AI system integrating deep and reinforcement learning to accelerate healthcare data processing and minimize network latency. This idea was further developed by Li et al. [14] with UniTS, a deep-learning model for real-time anomaly identification in wearable sensor data intended for low-power devices. An IEEE study [15] described a CNN-based arrhythmia detection system that links IoT devices with edge and cloud layers to balance accuracy and response time, while ElSayed et al. [16] suggested a zero-trust AI model to identify ransomware and DDoS attacks in healthcare IoT networks.

Overall, these studies highlight how combining AI and the Internet of Things will transform healthcare through the possibility of quicker, more intelligent, and more individualized therapy. The majority of these systems, however, are still in the early phases of development and are frequently tested with tiny sample sizes or few trials. To assess how well they continue to work in actual healthcare settings, improve patient confidentiality and data privacy, and guarantee thorough clinical validation, more study is required. By addressing these issues, future developments will be able to fully realize the potential of AI and IoT technology to provide safer, more efficient, and patient-centered healthcare.

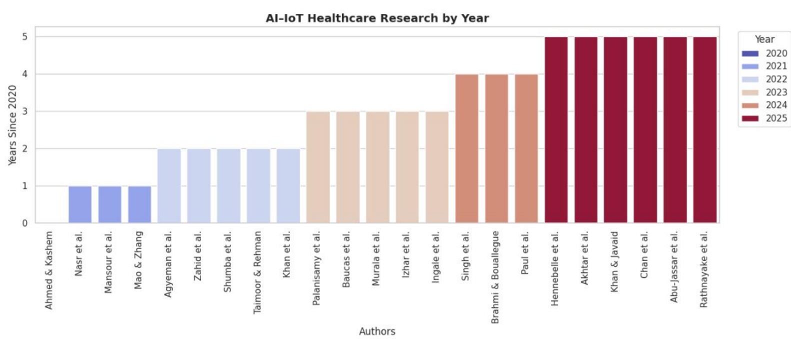

Fig. 1. The chronological distribution of AI-IoT healthcare research from 2020 to 2025 demonstrates the upward trend in publications. An earlier study (2020–2022) focused on the basic principles of IoT–AI integration, while more recent studies (2023–2025) emphasize advanced applications like edge computing, predictive analytics, and wearable health monitoring systems.

TABLE I: Comparative Analysis of Existing AI–IoT Healthcare Research

Research work	Key Findings	Pros	Cons
Zahid et al., 2022	Proposed an AI-based adaptive routing and resource-control algorithm to improve energy efficiency in IoT-enabled healthcare.	Unified routing and rate regulation; clear evaluation setup.	No hardware/clinical validation; real-world data absent.
Mansour et al., 2021	k Built a hybrid AI–IoT diagnosis pipeline with CSO–LSTM for cardiovascular/diabetes detection.	End-to-end sensor-to-cloud design; 96–97% accuracy; practical IoT constraints considered.	Relies on simulated IoT data; limited privacy analysis; no clinician-in-the-loop study.

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Research work	Key Findings	Pros	Cons
Abu-Jassar et al., 2025	ESP32-based Remote Patient Monitoring with AWS IoT Core for real-time streaming and dashboards.	Reproducible hardware–software stack; working cloud prototype.	Only lab-tested; no clinical/security assessment; lacks quantitative latency metrics.
Paul et al., 2024	Lightweight ConvLSTM skeleton-HAR for medical events with real-time IoT alerts.	High accuracy on standard datasets; skeleton data improves privacy.	Limited population diversity; camera-surveillance ethics not fully addressed.
Ahmed & Kashem, 2020	Low-cost IoT+ML (DT, LR, SVM) to predict maternal health risk levels.	Replicable for low-resource settings; inexpensive sensing.	Small dataset; little discussion of consent/security; no long-term deployment.
Baucas et al., 2023	Fog–IoT platform using federated learning and blockchain for privacy-preserving predictions.	Combines FL + blockchain; hardware demo on Raspberry Pi.	Focus on feasibility over accuracy; no clinical or energy benchmarks.
Khan et al., 2022	Systematic review of AI–IoT for COVID-19; highlights deep learning, fog, blockchain for detection/tracing.	Comprehensive taxonomy; interpretable ML; trend analysis.	No empirical validation; limited quantitative evaluation.
Ingale et al., 2023	AI–IoT framework for continuous monitoring with real-time analytics and cloud dashboards.	Improved responsiveness and automation; clear system layering.	Minimal comparative evaluation; scalability not measured.
Taimoor & Rehman, 2022	Survey of Healthcare 5.0 focusing on reliability, resilience, personalization via AI/IoT and blockchain.	Clear three-layer HIoT taxonomy; security threats/countermeasures mapped.	No implementation; lacks empirical metrics.
Shumba et al., 2022	Review of IoT/AI critical-care architectures with edge intelligence and piezoelectric sensing.	Modular low-latency design; privacy-aware on-device processing.	No hardware validation; performance mostly qualitative.
Palanisamy et al., 2023	Three-tier monitoring (IoT + CNN–UUGRU) achieving 97.7% on public data; mobile API for alerts.	High accuracy; efficient edge–cloud split; end-user layer included.	Non-clinical dataset; lacks field deployment; no long-term analysis.
Nasr et al., 2021	Review of AI–IoT–Edge–Blockchain for smart healthcare and AAL systems.	Broad technology coverage; identifies real-time security needs.	Conceptual synthesis; no standardized benchmarks or pilots.
Singh et al., 2024	AAL review mapping CNN/LSTM/RF to elderly-care sensors; calls for multimodal fusion and edge inference.	Comprehensive taxonomy; emphasizes edge-assisted AAL.	Limited real-world data; privacy/interoperability underexplored.
Zahid et al., 2022	Chipless RFID for passive health tracking; compares tag designs and read-range sensitivity.	Battery-free low-cost sensing; detailed hardware review.	No AI/analytics integration; data protection not addressed.
Murala et al., 2023	"MedMetaverse" combining AI, blockchain, wearables for chronic care and consented data sharing.	Strong data-governance stance; decentralized identity/consent.	Conceptual; no latency/energy evaluation; no pilot deployment.
Izhar et al., 2023	IoT–Edge hybrid: $>$70% latency and $\sim$68% bandwidth reduction with $>$95% accuracy; lightweight security/validation.	Measured edge gains; real devices; privacy-by-locality.	No power-aging model; limited device/network heterogeneity.

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Research work	Key Findings	Pros	Cons
Brahmi & Bouallegue, 2024	Digital Twins over 6G (URLLC/slicing) for proactive monitoring and predictive interventions.	Actionable 6G-twin architecture for telemedicine.	No deployment data; cost/security trade-offs open.
Agyeman et al., 2022	CNN arrhythmia detection for IoT ECG with $\sim$99% accuracy; discusses edge feasibility.	Strong benchmark results; real-time screening potential.	Clean-data bias; robustness/privacy not fully studied.
Akhtar et al., 2025	An AI-IoT conceptual framework of predictive assistance and real-time monitoring.	Remote care can make use of AI-IoT workflow, which is understandable and suitable.	No metrics, no research, and no respect to privacy.
Khan & Javaid, 2025	Simulated AI–IoT telehealth system using wearables and cloud analytics.	Improves diagnostic speed; considers security.	Simulation only; unclear device compatibility; privacy gaps.
Chan et al., 2025	The accuracy of IoT + AI cardiac prediction in obese youth is $\sim$90%.	improves model accuracy through the use of clinical sensing.	Minimal testing, simple models, and a small sample size.
Mao & Zhang, 2021	Neural networks and confidence filtering are used in this IoT-AI consultation platform.	Faster consultations; new confidence scoring.	limited attention to privacy, no clinical trials, and simulated data.
Hennebelle et al., 2025	To predict diabetes, the SmartEdge edge-cloud system uses ensemble machine learning.	Strong modeling; favorable latency-accuracy results	Disregard for privacy, simulated data, and benchmark-only testing.
Rathnayake et al., 2025	An examination of wearable AI with an emphasis on sensors and edge inference	Discusses FL + low-power ideas and current trends.	Little practical application and little discussion of regulations.
Mansour et al., 2021	Developed a low-cost IoT prototype using Arduino Nano 33 BLE with sensors for heart rate, grip strength, steps, and sleep to support home-based stroke rehabilitation.	Low-cost, easy to replicate; demonstrates practical IoT use for remote monitoring; transparent testing procedure.	Only three participants; lacks statistical validation and privacy framework; short-term testing only.
Hassan et al., 2021	Proposed an edge-intelligence framework combining deep and reinforcement learning for distributed healthcare analytics, reducing latency and bandwidth load.	Comprehensive review of 15 studies; well-defined edge-AI architecture; addresses delay reduction and scalability.	Conceptual only—no prototype; omits network loss and real deployment; limited data security discussion.
Li et al., 2025	Introduced UniTS, a unified deep-learning model for anomaly detection in wearable sensor data, enabling real-time inference on edge or wearable devices.	Strong empirical evaluation; high F1 and low-latency detection; optimized for limited hardware.	Relies on synthetic anomalies; no clinical or real-patient validation; interpretability not explored.
Wang et al., 2018	Designed an IoT-enabled smart knee sleeve for real-time motion capture and cloud-based rehabilitation feedback.	Demonstrates feasible wearable prototype; enhances patient engagement; achieves accurate motion sensing.	Small sample; restricted to knee movement; no AI analytics or strong privacy analysis.

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Research work	Key Findings	Pros	Cons
ElSayed et al., 2024	Proposed a zero-trust ML-based architecture using the CICIoT2023 dataset to detect DDoS and ransomware attacks in healthcare IoT networks.	High detection accuracy (93.6%); energy-efficient and scalable; validated on real datasets.	No real hospital deployment; limited ethical assessment; lacks blockchain/federated learning integration.
[Anonymous, IEEE], 2023	Presented CNN-based arrhythmia classification integrated with IoT devices through a layered edge–cloud system to balance accuracy and latency.	Comprehensive hardware–AI integration; practical performance evaluation using benchmark datasets; system-level analysis.	Restricted access limits reproducibility; unclear implementation details; lacks diverse environment validation.

Table I summarizes the most representative AI–IoT healthcare studies published between 2018 and 2025. The comparison highlights a clear shift from cloud-centric architectures toward hybrid edge–cloud and fog-based solutions [2], [6], [43]. Studies such as Mansour et al. [2] and Palanisamy et al. [38] demonstrate that integrating edge intelligence significantly reduces latency while maintaining high diagnostic accuracy.

II. Experimental Approaches in AI–IoT Healthcare Monitoring

The experimental designs in most of the reviewed studies involved wearable devices and smart sensors that had the ability to detect human motion and physiological indicators.An experiment, e.g., involved a portable neural-based system to identify leg movement. The subjects were also fitted with a knee sleeve that had a stretch sensor and a smaller accelerometer attached to it to measure the minute change in motion and muscle motion.

Another survey utilized a vision-based device, which consisted of cameras and pose estimation algorithms to project the body joint concerning movements in two and three dimensions. The subjects were asked to do some simple tasks like walking, sitting or some therapy exercises with the system monitoring and computing the joint trajectories, to decrease the effect of minor motion and the fluctuations of camera errors.To enhance reliability, the researchers used correction measures, minimizing the effects of minor motion, and the camera error values. This framework allowed physical activity to be monitored during physiotherapy and rehabilitation and it was also inevitable to do this with accuracy and in real-time.

Multiple other works used medical sensors in the form of ECG, temperature, and oxygen saturation sensor and transmitted the local data feed to bog or edge devices to do preliminary analysis and then transfer the processed information to cloud servers to do an in-depth analysis. This mixed arrangement greatly lowered the communication latency and enabled quicker identification of uncommon body physiological patterns.

In another architecture, the IoT gateways were used to ensure the transfer of physiological data e.g. heart rate, blood pressure and temperature to cloud platforms.Here, artificial intelligence models used the data to evaluate possible health risk and issue alerts when abnormal conditions were found. Such architecture allowed tracking their health without the strain of local devices as well as offered a scalable solution to remote medical supervision.

There were studies that investigated hybrid IoT-edge architectures in which the data processing operations were shared among the local and the cloud elements to find the balance between accuracy and latency. The signals recorded by wearable sensors (ECG and photoplethysmography (PPG)) were partially processed on local devices to identify the relevant features and the summarized data were then migrated to the cloud servers to make the final evaluation and assessments.

To collect the data, the studies utilized either publicly available data or the measurements taken in the case of real experiments with wearable devices. The measurable parameters were usually, motion, acceleration, temperature, heart rate and other physiological measurements. All the signals were marked by the type of activity of the participant, i.e. walking, resting or exercising. The data were preprocessed (noise filter, signal normalization, and missing or corrupted value correction) prior to analysis.

Most researchers used machine learning in order to analyze data and determine the trends and predict the outcomes. The overall workflow was feature extraction such as frequency or intensity, labeling using models such as decision trees, support vectors, or deep neural networks, followed by their aggregation on cloud servers to provide deep analysis.Aggregation of the results of multiple sensors was referred to as edge fusion since it enhanced the accuracy and the reliability.

The methodology also involved statistical validation so that to assess the performance of the models the studies commonly used k-fold cross-validation to separate data into training and testing. Quality of prediction was measured by accuracy, precision, recall,

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F1-score, and ROC curves. Response time and energy used during specific experiments were also noted to determine the system efficiency when comparing models paired tests like t-test were conducted to determine whether there was any significant difference between observed results or not.

The researches were founded on a number of assumptions. The assumption made was that all sensors were calibrated properly, the wireless communication would be stable and the same environment conditions such as lighting where the camera-based systems were used would be consistent across the experiments.It was also assumed that the datasets would be representative of real-life human behaviour and that sufficient amount of training data would allow the various algorithms to generalize to similar real life conditions.

On the whole, the integrated findings of the research indicate that IoT, wearable technology, and intelligent computing can be complementary and complement each other to improve the healthcare system monitoring. These frameworks are known to lead to lower latency, better accuracy, and enhanced responsive health measurements; however, most of the experiments were realized in controlled conditions with a small number of subjects, which means that large clinical studies are required. Nevertheless, these solutions provide a good basis of the creation of the next-generation smart healthcare and activity recognition systems.

III. Results and Discussion

This part unites and synthesizes the key lessons discovered in the chosen articles on AI-, IoT-, and edge-enabled healthcare systems. Rather than reiterating the initial numerical findings, the point here is to see how larger trends can be traced, how various methodological decisions arrived at the findings and what these findings (taken together) can tell us regarding the future of intelligent medical technologies. To make the discussion easier, it is divided into several thematic sections: overall findings, comparison to the previous research, the remaining limitations, causal and forward-looking interpretations, and a series of deductive conclusions based on the literature.

Findings and Interpretation This subsections provide the research content of the study and its interpretations. One of the similar motifs present in the analyzed literature is that the integration of artificial intelligence and IoT and edge computing leads to significantly more responsive and reliable health monitoring systems. Papers that used some sort of on-device or near-device computation either lightweight neural models or local feature extraction or event-based data transmission were seen to have unmistakable advantages in speed and immediacy of medical feedback. These systems could detect the physiological changes faster by offloading part of the computational load onto the device and therefore, they did not rely on remote servers and bad network connectivity. Such responsiveness is of particular significance in conditions, like cardiac surveillance or mobility evaluation, where responsiveness directly affects clinical significance. The existence of several other contributions, especially those defining Digital Twin concepts or healthcare structures consistent with future 6G technologies, explains how a synchronized representation of the patient can be exploited to predict health problems and make active supervision. Although most of these designs are on paper, they provide an outline of a possible very bright future where virtual models could be the key point in the decision-making cycles. Equally, blockchain-based works, such as the MedMetaverse proposal, are more focused on the management of identity and traceability of data. These initiatives are a reaction to the long history of mistrust of medical systems, lack of transparency, and data sovereignty. Studies that explored the low power sensing technologies including chipless RFID have demonstrated that massive health monitoring does not have to have enormous overhead in hardware. Simultaneously, these methods highlight some of the trade-offs: being very cheap and energy-efficient, these types of sensors do not provide the necessary level of intelligence to make a local decision or may provide limited native protection to sensitive information. Conversely, research on deep learning to perform tasks such as arrhythmia showed that the state of the art level of accuracy could be achieved. Nevertheless, these developments have their limitations, the most obvious one being the fact that they still depend on good connectivity and computing power. Altogether, the discussed publications reflect the current trend of switching to less centralized, cloud-based pipelines to more distributed healthcare systems. Hybrid methods of AI-IoT-Edge seem to be the most sensible trade-offs in terms of the latency, energy usage, and privacy protection. However, they also clarify that designing such systems should be met with keen consideration of size of the model, ability of the devices used, communication protocols and end-to-end data security.

Comparison with Prior Studies When examining the literature on a broader scale it is noticeable on how the field has progressed through time. Early systems themselves, particularly those founded on RFID sensing, were aimed at hardware simplicity, low cost and broad deployability. These early measures formed the basis of the more advanced solutions that ensued afterwards where sensors, communication modules and analytical algorithms were closely combined. The most current studies of Digital Twins and multimodal fusion prove that the integration of various types of sensors (e.g., ECG, PPG, motion) can contribute to a great improvement of the monitoring strength. Despite the fact that a wide consensus on decentralized processing is that the latency

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is minimized and responsiveness is enhanced, there is a great difference in the extent to which the studies were able to provide validity to their projections. Theoretical solutions like the MedMetaverse or 6G-enabled Digital Twins have interesting concepts but fail to test their hypotheses experimentally. Conversely, more concrete implementations of IoT-Edge data fusion or CNN-based arrhythmia recognition are available, but usually under constrained test conditions. These place the works together can indicate that the meaningful progress lies in balancing three essential items: the model that is lightweight enough to be operational on the edge devices, communication protocols adjusting to the varying conditions of the network, and system designs that take into account energy consumption and long-term operation.

Limitations of Existing Research Although the mentioned literature presents some impressive progress, there are still a number of limitations that are widespread in research. The experimentation often is based on the relativity small datasets or groups of participants that cannot be considered the complete representation of the existing clinical groups. Consequently, it is hard to determine how effective such systems could be in the less homogenous or predictable conditions. The other common problem is the testing conditions themselves: laboratory or semi-controlled environments can be used to make accurate measurements but cannot be used to model the noise, interruptions, and variability found in real world use. The challenge of hardware diversity is another. The behaviour of different sensor types, microcontrollers, and communication modules in practice can sometimes be incredibly different, and it is not always possible to compare results across studies or repeat them reliably. Secondly, despite several frameworks raising issues about security and privacy systems, many of them are at a conceptual level, i.e. they do not look into how these systems will survive real-life threats. The long-term factors, including battery degradation, persistent power consumption, and effects of the environment on the sensor quality, are mostly not part of the current analysis. Furthermore, one can observe certain causal and speculative insights that are absent in the extensive literature concerning the topic of the study.

Causal and Speculative Insights In addition to that, some causal and speculative insights can be identified that do not exist in the comprehensive literature on the subject matter of the study. Although there is a variety of methodologies, there are a number of plausible causal relationships that can be inferred based on the literature. Making inferences on the device or close to it of course shortens the path of data which consequently lowers communication delays. Local feature extraction prior to transmission reduces data to be transmitted thereby reducing network load as well as the total system energy. The preservation of raw biosignals on the device has its own privacy benefits as well, as it prevents the exposure of sensitive data to other networks. These results indicate that the advantages of distributed AI are not only associated with architectural decisions, but also with core characteristics of data flow, computation, and risk exposure. In the future, there seem to be a few directions that are particularly promising. Federated learning may enable edge devices to customize their models dynamically without transmitting raw data to centralized servers, which will mitigate the issues of personalization and privacy.

IV. Conclusion and Future Work

This paper gives a comparison of edge based AI-iot medical system of arrhythmia detection in ECG graph with specific focus on predictive accuracy and edge viability. As the findings presented in the Table 1 reveals, models based on convolutional neural network (CNN) are always the best in terms of performance with up to 99 per cent accuracy and the low latency allows them to be deployed in real time to detect edges. All these features make the CNN the best predictor model of the considered methods in the IoT-based cardiac monitoring and early arrhythmia detection. However, despite the meticulously designed three-layer architecture integrating IoT devices with the hybrid CNNUUGRU framework with high accuracy (97.7 percent), which proves to be highly functional, it has practical merits in terms of dividing the edge-cloud tasks and executing user alerts with the mobile API. However, its predictive precision is a bit less accurate as compared to that of standalone CNN models. In addition, the two methods are fundamentally founded on clean and publicly accessible data, which creates the risk of bias and limits the ability to generalize it to real-world clinical settings. The absence of field deployment over time, intensive testing of reliability in the harsh environment, and a detailed assessment of privacy and security represent a big gap in research. All in all, the results show that CNN-based models offer the best trade-off of predictive accuracy, computational efficiency, and real-time edge practicability. Further studies must focus on testing these models with clinical data, making them resistant to data noise and variability, and deploying privacy-sensitive functions to enable secure, scalable, and reliable to deploy edge-enabled AI-IoT healthcare platforms.

In conclusion, the present paper has examined the current AI-inspired IoT and IoMT architectures with a specific emphasis placed on the hybrid edge-cloud computing architectures that are intended to solve the shortcomings of the conventional centralized healthcare systems. The discussion proved that federated learning, lightweight AI models,and edge intelligence could be used to promote the system responsiveness, data privacy, and personalized decision-making in smart healthcare settings significantly. Nonetheless, a number of critical issues, such as the inability to ensure the interoperability between gadgets, safe and efficient information processing, energy limitations in wearables, and the compromise between the processing power and the accuracy of the

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models, have not been resolved yet. Thus, the future paradigm of research must be to create decentralized, flexible, and patient-centered IoMT systems, which guarantee trustfulness and scalability and also investigate privacy-conserving AI solutions, sustainable wearable technologies, and universally applicable standards of real-time medical systems worldwide. In general, the paper indicates that there is an increased need to have decentralized, privacy-conscious, and highly efficient IoMT architectures that can enable credible and real-time healthcare delivery.

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