

Edge Artificial Intelligence for Real-Time Healthcare Monitoring: A Layered Framework for Low Latency, Privacy Preserving Patient Care

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Abstract

The growing burden of chronic disease and the structural limitations of centralized cloud computing have intensified interest in edge based artificial intelligence as a mechanism for delivering continuous, low latency patient monitoring outside conventional clinical settings. This paper develops and critically examines a layered Edge AI framework that distributes inference, communication, and privacy preservation across sensing devices, local gateways, and coordinating cloud infrastructure rather than relying on a single centralized processing node. Drawing on a systematic synthesis of peer reviewed literature spanning edge computing, TinyML, federated learning, and Internet of Medical Things research, the study identifies recurring architectural patterns and unresolved tensions among diagnostic accuracy, energy consumption, and regulatory compliance. A qualitative, theory building methodology is adopted, combining conceptual analysis with a comparative synthesis of empirically validated systems reported in the literature between 2016 and 2026. The findings indicate that hybrid architectures combining convolutional and recurrent neural components, quantized for microcontroller class hardware, achieve latency reductions exceeding fifty percent relative to cloud dependent baselines while incurring only modest accuracy trade offs. Federated learning combined with homomorphic encryption further reduces communication overhead and strengthens compliance with data protection regulation, albeit at a measurable computational cost. The paper contributes a consolidated conceptual model that integrates these strands into a six layer reference architecture and offers implications for clinical deployment, health system policy, and future research on explainability and trust in autonomous monitoring systems.

Keywords: Edge artificial intelligence; TinyML; federated learning; remote patient monitoring; Internet of Medical Things; healthcare informatics

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1. Introduction

Health systems across income settings are undergoing a structural shift away from episodic, hospital centered treatment toward continuous ambulatory surveillance of physiological status. The proliferation of wearable biosensors capable of capturing electrocardiographic signals, photoplethysmographic pulse waveforms, oxygen saturation, and movement patterns has made it technically feasible to observe a patient's condition outside the clinic in a manner that was previously confined to intensive care environments. Yet the manner in which these data streams are processed has lagged behind the sophistication of the sensing hardware itself. The dominant architectural paradigm of the past decade has relied on transmitting raw or lightly processed signals to centralized cloud infrastructure for analysis, a design choice that introduces

communication latency, exposes sensitive clinical data to transmission risk, and presumes a level of network reliability that is frequently absent in rural, low resource, or emergency contexts.

Edge artificial intelligence, understood as the practice of performing inference and, increasingly, model training on or near the device that generates the data, has emerged as a response to these constraints. Rather than treating computation as something that occurs exclusively within remote data centers, edge based approaches distribute intelligence across a hierarchy of devices ranging from microcontroller class wearables to local gateways and, ultimately, coordinating cloud services (Shi, Cao, Zhang, Li, & Xu, 2016; Satyanarayanan, 2017). This redistribution carries particular significance for healthcare monitoring, where the clinical value of an alert is inversely related to the delay between physiological deterioration and clinical response. A cardiac arrhythmia that is detected within a hundred milliseconds at the wrist is actionable in a way that the same event, detected several seconds later after a round trip to a distant server, may not be.

The technical feasibility of edge based healthcare monitoring rests on the convergence of several previously distinct research trajectories. TinyML techniques, including model quantization, pruning, and architecture search, have made it possible to execute deep neural networks on hardware with kilobytes rather than gigabytes of memory (Abadade et al., 2023; Ray, 2022; Saha, Sandha, & Srivastava, 2022). Federated learning has offered a mechanism by which models can improve through exposure to distributed patient data without that data ever leaving the device on which it was generated, addressing regulatory obligations under frameworks such as the Health Insurance Portability and Accountability Act and the General Data Protection Regulation (McMahan, Moore, Ramage, Hampson, & y Arcas, 2017; Rieke et al., 2020). Meanwhile, advances in low power wide area networking and fifth generation cellular communication have supplied the transport layer needed to move model updates and critical alerts between tiers of the architecture with acceptable latency and energy cost (Spicher, Klingenberg, Purucker, & Deserno, 2022).

Despite this convergence, the literature addressing edge based healthcare monitoring remains fragmented. Studies tend to isolate a single technical concern, whether that is model compression, communication protocol selection, or cryptographic privacy preservation, rather than examining how these elements interact within a deployable system. This fragmentation matters because the choices made at one layer of an edge architecture constrain what is achievable at another. A model compressed aggressively enough to fit on a microcontroller may, for instance, be too coarse to support the gradient level privacy guarantees that homomorphic encryption schemes were designed to protect. Conversely, a communication protocol selected purely for its low power profile may introduce delays that undermine the clinical rationale for edge deployment in the first place.

This paper addresses that fragmentation by proposing a layered conceptual framework that situates sensing, on device inference, local aggregation, secure transmission, federated coordination, and clinical interfacing as interdependent components of a single system rather than as isolated engineering problems. The study is guided by three interrelated questions. First,

what architectural configurations have demonstrated empirical success in balancing diagnostic accuracy against latency and energy constraints in real time healthcare monitoring. Second, how do privacy preserving mechanisms such as federated learning and homomorphic encryption interact with the resource limitations characteristic of edge hardware. Third, what gaps remain between the architectures reported in the current literature and the requirements of sustained clinical deployment. In pursuing these questions, the paper draws on sociotechnical systems theory, which treats technological artifacts and the social and institutional contexts of their use as mutually constitutive, to argue that the success of edge based monitoring cannot be evaluated on technical performance metrics alone but must account for clinician trust, regulatory alignment, and patient acceptability.

The remainder of the paper proceeds as follows. Section two synthesizes the relevant scholarship across edge computing, TinyML, federated learning, secure communication, and the broader Internet of Medical Things literature, identifying points of convergence and unresolved debate. Section three describes the qualitative, theory building methodology used to derive the proposed framework. Section four presents the resulting architectural model and situates it against empirical benchmarks reported in recent studies. Section five discusses the implications of these findings for clinical practice and health policy, and section six concludes with a summary of the paper's contribution and directions for future inquiry.

2. Literature Review

2.1 The Evolution of Edge Computing as a Healthcare Infrastructure Paradigm

The conceptual foundations of edge computing predate its application to healthcare by roughly a decade. Shi et al. (2016) framed edge computing as a response to the physical and economic limits of cloud centralization, arguing that as the number of internet connected devices grew, the cost of transporting every byte of generated data to a distant data center would eventually exceed the cost of processing that data closer to its source. Satyanarayanan (2017) extended this argument by emphasizing that certain classes of application, particularly those involving real time perception and actuation, are fundamentally incompatible with the latency profile of wide area networks regardless of how much bandwidth is added. Healthcare monitoring belongs squarely within this class of application. A patient experiencing a hypoxic event or a cardiac arrhythmia cannot wait for a packet to traverse several network hops, be queued for processing on a shared server, and return a classification result before an alert is generated.

Subsequent research has mapped this general argument onto specific clinical use cases. Kong, Wu, Wang, and Xia (2022) provided a broad survey of edge computing across the Internet of Everything, noting that healthcare applications exhibit some of the most stringent latency requirements among the domains they examined, alongside comparably strict requirements for data confidentiality. Within the clinical literature specifically, Ashraf, Mahmood, Khan, and Yaqoob (2021) demonstrated an edge artificial intelligence enabled Internet of Things

framework tailored to smart city healthcare deployments, showing that lightweight deep learning models executed at the network edge could support real time anomaly detection on devices with substantially constrained computational budgets. Their work, along with related studies on wearable cardiac monitoring, established that the reduction in cloud dependence achieved through edge deployment translates into measurable gains in system responsiveness during emergencies, a finding echoed in more recent integrated architectures (Prabha, Nandhini, Dayanidhy, & Pradeep, 2026).

A recurring theme across this literature is the tension between the theoretical promise of edge computing and the practical difficulty of validating it on genuinely constrained hardware. Many early studies simulated edge conditions on conventional laptop or workstation hardware rather than deploying models on the microcontroller class or single board computer platforms that would characterize an actual wearable or bedside device. More recent work has begun to close this gap. Prabha et al. (2026) deployed a quantized convolutional and recurrent hybrid model on an NVIDIA Jetson Nano, a genuinely resource constrained embedded platform, and reported a mean inference latency of approximately one hundred and eighteen milliseconds together with classification accuracy of 91.9 percent, figures that are directly comparable to a cloud hosted baseline while requiring a fraction of the energy budget. This kind of hardware grounded validation is essential because the gap between simulated and deployed performance in embedded systems is often substantial, and claims regarding edge feasibility that are not tested on representative hardware should be treated with caution.

Nonetheless, the edge computing literature as applied to healthcare has tended to treat communication infrastructure as a secondary concern relative to computation. Studies focusing on model architecture frequently assume idealized network conditions, while studies focusing on wireless protocols frequently treat the inference task as a black box. This separation obscures an important interaction effect, namely that the choice of communication protocol determines how frequently a model can be updated and how quickly an anomaly detected locally can be escalated to a human clinician, both of which are properties that matter as much for patient outcomes as raw model accuracy.

2.2 TinyML and the Compression of Intelligence onto Constrained Hardware

The subfield known as TinyML, concerned with deploying machine learning models on microcontroller class hardware operating within power budgets measured in milliwatts, has matured considerably over the past several years and now constitutes a substantial share of the technical foundation underlying edge healthcare monitoring. Abadade et al. (2023) offered a comprehensive survey of the field, cataloguing the principal techniques used to compress neural network models, including quantization, pruning, knowledge distillation, and neural architecture search, and observing that these techniques are frequently combined rather than applied in isolation. Ray (2022) situated TinyML within the broader trajectory of artificial intelligence research, arguing that the field represents a departure from the historical assumption that model capability scales primarily with computational resources, instead demonstrating that carefully

engineered small models can achieve task specific performance approaching that of substantially larger networks when the task domain is sufficiently constrained, as is often the case with single channel physiological signal classification.

Saha, Sandha, and Srivastava (2022) examined the hardware side of this equation, reviewing the landscape of microcontroller architectures capable of supporting on device inference and highlighting the persistent tension between memory footprint, inference latency, and energy consumption. Their analysis is particularly relevant to healthcare applications because wearable medical devices are typically subject to battery constraints far tighter than those of general purpose Internet of Things sensors, given that patients are unlikely to tolerate frequent recharging of a device intended for continuous monitoring. This tension has motivated a body of work exploring hierarchical processing architectures in which an ultra low power always on processor performs coarse filtering of incoming signal data, activating a more capable but power hungry processor only when a candidate anomaly is detected, an approach reported to reduce overall power consumption substantially relative to designs in which the primary processor remains continuously active.

The clinical validity of TinyML compressed models has been demonstrated most convincingly in the domain of cardiac signal analysis. Hannun et al. (2019) showed that a deep neural network trained on a large corpus of single lead electrocardiographic recordings could achieve arrhythmia detection performance exceeding that of practicing cardiologists, establishing a benchmark against which subsequent compressed and edge deployed models have been evaluated. While the original model was not designed for constrained hardware, its architecture has informed a generation of smaller derivative models intended for wearable deployment, and the general finding that deep learning can match or exceed expert level diagnostic performance on cardiac signals has been a persistent point of reference throughout the edge healthcare literature.

A significant methodological debate within the TinyML literature concerns the appropriate benchmark against which compressed models should be judged. Some studies emphasize retention of accuracy relative to an uncompressed baseline as the primary metric of success, while others argue that latency and energy consumption should be weighted equally or more heavily, on the grounds that a marginally less accurate model that can actually be deployed on target hardware is of greater practical value than a marginally more accurate model that cannot. The comparative evaluation reported by Prabha et al. (2026), in which an edge deployed model achieved eighty three percent lower latency and sixty four percent lower energy consumption than a cloud hosted counterpart at a cost of only a few percentage points of classification accuracy, lends empirical weight to the latter position, at least within the domain of physiological anomaly detection.

2.3 Federated Learning as a Response to the Privacy Constraints of Clinical Data

Where TinyML addresses the computational constraints of edge deployment, federated learning addresses its data governance constraints. Introduced by McMahan, Moore, Ramage,

Hampson, and y Arcas (2017) as a general purpose method for training machine learning models across decentralized data sources without requiring that raw data be transmitted to a central server, federated learning has become the dominant paradigm through which healthcare researchers reconcile the desire for models that generalize across large and diverse patient populations with the legal and ethical obligation to keep individual patient records local to the institution or device where they originate. Rieke et al. (2020) argued that federated learning represents not merely a technical convenience but a structural necessity for digital health, observing that the fragmentation of clinical data across institutions, jurisdictions, and device manufacturers makes centralized data pooling both practically difficult and, in many regulatory environments, legally prohibited.

Applied specifically to wearable and remote monitoring contexts, Chen, Qin, Wang, Yu, and Gao (2020) proposed a federated transfer learning framework designed to address a limitation of vanilla federated averaging, namely that a single global model often performs poorly for individual patients whose physiological baselines diverge from the population average. Their approach, evaluated on wearable activity recognition tasks and a Parkinson's disease diagnostic application, combined federated aggregation with a personalization step performed locally on each device, illustrating a broader pattern in the federated learning literature in which pure averaging is increasingly supplemented with mechanisms for handling the statistical heterogeneity that characterizes real world clinical populations. Abbas, Abbas, Zahir, and Lee (2024), in a comprehensive review of federated learning across smart health systems, similarly identified data heterogeneity, alongside adversarial vulnerabilities such as model inversion and data poisoning, as among the most significant unresolved challenges facing the field, notwithstanding its substantial promise for privacy preserving predictive analytics.

Security concerns within federated healthcare systems extend beyond the confidentiality of raw patient data to the confidentiality of the model updates themselves, since gradient information transmitted during federated training can, under certain conditions, be used to partially reconstruct the underlying data from which it was derived. Homomorphic encryption has emerged as the principal cryptographic response to this concern, permitting mathematical operations to be performed directly on encrypted values such that a central aggregator can compute an averaged model update without ever observing the plaintext gradients contributed by individual devices. Zhang, Xu, Vijayakumar, Sharma, and Ghosh (2023) demonstrated a homomorphic encryption based privacy preserving federated learning scheme for Internet of Things enabled healthcare systems, and this approach was subsequently validated on genuinely constrained embedded hardware by Prabha et al. (2026), who reported that Paillier cryptosystem based encryption of model gradients introduced a latency overhead of approximately nine percent per federated training round, a cost the authors characterized as an acceptable trade off given the stringency of healthcare data protection requirements under regulations such as the Health Insurance Portability and Accountability Act and the General Data Protection Regulation.

It is worth noting that the theoretical antecedent of much of this privacy preserving work is the concept of differential privacy formalized by Dwork (2006), which provides a

mathematically rigorous definition of what it means for an analytical process to protect the privacy of individuals whose data contribute to it. While differential privacy and federated learning are frequently discussed together, they are not equivalent, and several of the studies reviewed here note that federated learning alone, absent additional mechanisms such as differential privacy noise injection or homomorphic encryption, does not guarantee formal privacy protection but rather reduces the attack surface relative to centralized data collection. This distinction is significant for healthcare applications, where regulatory compliance frequently demands a demonstrable rather than merely intuitive privacy guarantee.

2.4 Secure Communication, Trust, and Auditability in Distributed Healthcare Systems

The transport layer connecting sensing devices, edge gateways, and coordinating servers has received comparatively less scholarly attention than either model architecture or privacy preservation, yet the choice of communication protocol materially shapes what an edge healthcare system can achieve. Long range wide area networking technologies, most prominently LoRaWAN, offer the energy efficiency and extended range necessary for continuous, battery operated sensing, particularly in rural or otherwise infrastructure sparse settings. Dammak et al. (2022) proposed an architecture, termed LoRaChainCare, that paired LoRaWAN transmission with a blockchain based ledger for tamper resistant logging of personal healthcare data, demonstrating that the two technologies could be combined to achieve both energy efficient transmission and auditable record keeping. Fifth generation cellular networking occupies a complementary position within this landscape, trading higher power consumption for substantially lower latency and higher throughput. Spicher, Klingenberg, Purucker, and Deserno (2022) examined the use of fifth generation edge computing for real time analysis of electrocardiographic signals recorded through wearable textile sensors, finding that the combination of edge inference and cellular transmission could support genuinely real time clinical feedback loops.

The complementary strengths of these two protocols, low power long range transmission on one hand and low latency high throughput transmission on the other, have led several recent architectures to adopt a dual protocol design in which the system dynamically selects between LoRaWAN and fifth generation connectivity depending on the urgency of the data being transmitted and the energy state of the device. Prabha et al. (2026) implemented such a design and reported that the majority of routine physiological data, comprising approximately sixty percent of total transmissions, could be handled through the lower power LoRaWAN channel, with the remaining forty percent, corresponding to higher urgency or higher bandwidth requirements, routed through fifth generation connectivity. This adaptive allocation strategy illustrates a broader principle emerging from the literature, namely that healthcare monitoring architectures benefit from treating communication protocol selection as a dynamic, context sensitive decision rather than a fixed design choice.

Beyond transmission efficiency, questions of trust and auditability have motivated growing interest in blockchain based mechanisms for healthcare data governance. Because clinical data

audit trails must, in many jurisdictions, demonstrate not merely that data were protected but that every access, modification, and model update can be retrospectively verified, immutable ledger technologies offer a natural complement to the privacy preserving mechanisms discussed above. Proof of authority consensus protocols, in which a small set of pre authorized validator nodes, typically corresponding to trusted institutional participants, are responsible for validating transactions, have been favored over energy intensive proof of work schemes in healthcare contexts precisely because they reduce the computational and energy burden of maintaining the ledger while preserving the core properties of tamper evidence and decentralized trust. The integration of such ledgers with federated learning coordination, as demonstrated by Prabha et al. (2026), represents one of the more architecturally complete responses to the joint requirements of speed, privacy, and accountability that characterize contemporary healthcare data governance.

2.5 The Internet of Medical Things as an Organizing Ecosystem

The technical developments reviewed above are frequently situated within the broader conceptual umbrella of the Internet of Medical Things, understood as the network of interconnected medical devices, sensors, and information systems that collectively enable remote monitoring, diagnostics, and care coordination. Srivastava, Routray, Ahmad, and Waris (2022) traced the trajectory of this ecosystem, noting that its expansion has been accelerated by the demand for remote care delivery that emerged during the coronavirus pandemic, a demand that in many health systems has persisted well beyond the acute phase of the pandemic itself as both patients and providers have come to value the convenience and continuity that remote monitoring affords. Their review, along with related work in the field, emphasizes that the Internet of Medical Things is not merely a technical infrastructure but a reorganization of where and by whom clinical judgment is exercised, with algorithmic triage increasingly performed at the point of data generation rather than exclusively by clinicians reviewing centrally aggregated records.

Collaborative applications of federated learning within this ecosystem have extended beyond single disease monitoring toward multi institutional, multi modal diagnostic tasks. Qayyum, Ahmad, Ahsan, Al-Fuqaha, and Qadir (2021) demonstrated a collaborative federated learning framework for multi modal diagnosis of coronavirus disease at the network edge, illustrating that the privacy preserving properties of federated architectures scale beyond the single sensor, single patient scenarios that dominate the wearable monitoring literature toward more complex diagnostic tasks requiring the fusion of imaging, laboratory, and physiological data across institutions. This line of work suggests that the architectural principles developed for continuous vital sign monitoring generalize, with appropriate modification, to a considerably broader class of clinical decision support problems. At a larger scale, Warnat-Herresthal et al. (2021) demonstrated a swarm learning approach for confidential clinical machine learning that dispensed with a central coordinating server entirely, distributing coordination responsibility across participating nodes using blockchain based consensus, a design that anticipates some of the decentralization principles evident in the more recent edge healthcare architectures discussed above.

2.6 Synthesis and the Research Gap

Taken together, the literature reviewed in this section demonstrates that the individual components required for effective edge based healthcare monitoring, namely compressed on device inference, privacy preserving distributed training, adaptive secure communication, and auditable data governance, are each reasonably well developed as standalone research areas. What remains comparatively underdeveloped is a systematic account of how these components interact when combined into a single deployable system, and in particular how design decisions made at one layer propagate constraints and opportunities to the layers above and below it. Several studies gesture toward this integration challenge without resolving it fully. Prabha et al. (2026) offer perhaps the most architecturally complete example currently available in the peer reviewed literature, combining quantized edge inference, dual protocol wireless communication, homomorphic encryption protected federated learning, and proof of authority blockchain auditing within a single validated system, yet even this study acknowledges that its evaluation relied substantially on synthetic data modeled statistically on the widely used MIT-BIH arrhythmia database rather than on heterogeneous data drawn from genuine clinical populations, and that longer term questions of device compromise, model drift, and clinician trust remain open.

This paper responds to that gap not by proposing a novel technical component but by synthesizing the existing evidence into a coherent layered framework that makes explicit the dependencies among sensing, inference, aggregation, transmission, coordination, and clinical interfacing. In doing so, it extends the existing literature in three respects. First, it consolidates evidence from otherwise separate strands of research, specifically TinyML, federated learning, secure communication, and blockchain auditing, into a single reference architecture rather than treating these as parallel but disconnected research programs. Second, it foregrounds the sociotechnical dimension of edge healthcare deployment, an aspect that receives comparatively little attention in the predominantly engineering oriented literature reviewed above, by considering how architectural choices interact with clinician trust and regulatory expectation. Third, it offers a comparative synthesis of quantitative performance figures reported across studies, presented in section four, that allows the trade offs among competing architectural configurations to be assessed side by side rather than in isolation.

3. Methodology

3.1 Research Design

This study adopts a qualitative, theory building research design grounded in conceptual synthesis rather than primary empirical data collection. The choice of design follows directly from the nature of the research questions articulated in section one, which concern the relationships among architectural components documented across a heterogeneous body of existing literature rather than the estimation of a novel effect that would require original data. Conceptual synthesis of this kind is well established within information systems and health informatics research as a method for consolidating fragmented technical literatures into

integrative frameworks that can subsequently guide both practice and further empirical inquiry. The design is theory building rather than theory testing in orientation, meaning that its principal output is a structured conceptual model, namely the six layer Edge AI framework presented in section four, rather than a statistically validated hypothesis.

The decision to pursue a qualitative synthesis rather than, for example, a systematic quantitative meta-analysis reflects the character of the underlying evidence base. The studies reviewed in section two report performance metrics using inconsistent benchmarks, datasets of varying provenance including both genuine clinical recordings and synthetic data statistically modeled on clinical distributions, and hardware platforms that differ substantially in computational capacity. This heterogeneity renders a formal meta-analytic pooling of effect sizes methodologically inappropriate, since the studies do not share a sufficiently common measurement framework to support statistical aggregation. A qualitative, narrative synthesis approach, by contrast, permits the reviewer to make explicit and defensible judgments about comparability while preserving the contextual detail necessary to interpret each study's findings appropriately.

3.2 Literature Identification and Selection

Literature was identified through a purposive rather than exhaustive search strategy, appropriate to a conceptual synthesis whose goal is theoretical coverage of the relevant technical domains rather than epidemiological completeness. Searches were conducted across major indexing platforms including IEEE Xplore, ScienceDirect, PubMed, Nature Portfolio journals, and the arXiv preprint repository for computer science, using search terms combining variants of edge computing, TinyML, federated learning, homomorphic encryption, blockchain healthcare, Internet of Medical Things, and remote patient monitoring. The search was not restricted to a single publication window but prioritized studies published between 2016, corresponding to the foundational articulation of edge computing as a distinct paradigm, and 2026, in order to capture the most architecturally mature and empirically validated systems currently available.

Studies were included in the synthesis if they satisfied three criteria. First, the study needed to address at least one of the five technical domains identified in section two, namely edge computing infrastructure, TinyML model compression, federated learning, secure communication protocols, or blockchain based auditability, in the specific context of healthcare or clinical monitoring. Second, the study needed to have appeared in a peer reviewed journal, a peer reviewed conference proceeding, or, in the case of rapidly evolving technical subfields such as TinyML, a widely cited preprint from a recognized research group, reflecting the norm within computer science of preprint dissemination preceding formal publication. Third, studies reporting empirical performance results, whether latency, accuracy, energy consumption, or communication overhead, were prioritized over purely conceptual contributions in order to ground the resulting framework in demonstrated rather than merely theorized capability. Studies that addressed edge computing or federated learning in non healthcare domains were included selectively, and only where they supplied foundational conceptual or algorithmic contributions,

such as the original federated averaging algorithm or the formal definition of differential privacy, that underpin subsequent healthcare specific applications.

3.3 Analytical Framework

The analytical approach applied to the selected literature combined thematic synthesis with comparative benchmarking. Thematic synthesis proceeded in three stages. In the first stage, each included study was coded according to which layer or layers of a prospective edge healthcare architecture it primarily addressed, using an initial coding scheme derived inductively from a preliminary reading of a subset of the literature and subsequently refined into the six layer structure presented in section four. In the second stage, studies addressing the same architectural layer were compared to identify points of convergence, such as the broadly consistent finding across TinyML studies that quantization and pruning can reduce model memory footprint substantially with limited accuracy penalty, as well as points of unresolved tension, such as the divergent emphasis placed on accuracy retention versus latency reduction as the primary evaluation criterion for compressed models. In the third stage, cross layer dependencies were identified by examining studies that addressed more than one architectural layer simultaneously, since these studies provide the most direct evidence regarding how design choices at one layer constrain or enable outcomes at another.

Comparative benchmarking supplemented this thematic analysis by extracting quantitative performance figures, where reported, across studies addressing comparable architectural configurations. These figures, summarized in Table 1 in section four, are not intended to support formal statistical comparison given the heterogeneity of underlying datasets and hardware platforms noted above, but rather to provide a structured, side by side reference that clarifies the approximate magnitude of the trade offs associated with different design choices. Where a single study reported results across multiple configurations under controlled, comparable conditions, as in the case of the edge and cloud model comparison reported by Prabha et al. (2026), these within study comparisons were given particular analytical weight, since they hold hardware, dataset, and evaluation protocol constant in a manner that cross study comparisons cannot.

3.4 Ethical Considerations, Validity, and Reliability

Because this study does not involve the collection of original human subjects data, formal institutional ethical review was not required. Nonetheless, the paper attends closely to the ethical dimensions of the technologies it synthesizes, particularly the privacy implications of federated learning and the governance implications of blockchain based auditing, treating these not as peripheral technical features but as central to the evaluation of any proposed architecture's suitability for clinical deployment. The synthesis explicitly considers, in section five, the ethical and regulatory tensions that arise when algorithmic decision making is delegated to edge devices operating with limited human oversight, an issue that becomes increasingly salient as the architectures reviewed here move from research prototypes toward operational deployment.

With respect to validity, the principal threat to a qualitative synthesis of this kind is selection bias, namely the possibility that the purposive search strategy systematically favored studies reporting favorable results for edge based approaches while underrepresenting studies documenting failures or limitations. This threat was mitigated in two ways. First, the search deliberately sought out review and survey articles, such as those by Abadade et al. (2023) and Abbas et al. (2024), which themselves synthesize a broader base of primary studies and are therefore less susceptible to the selective reporting that can affect any single primary study. Second, the discussion in section five explicitly foregrounds the limitations and unresolved challenges identified across the reviewed literature, including data heterogeneity in federated settings, the gap between synthetic and genuine clinical validation data, and the absence of longitudinal deployment evidence, rather than presenting only the positive findings that motivate the proposed framework. With respect to reliability, the coding scheme used to assign studies to architectural layers was applied consistently across the full set of included literature and is documented in sufficient detail in this section to permit replication by other researchers seeking to extend or challenge the resulting synthesis.

4. Results

The synthesis yields a six layer reference architecture, depicted in Figure 1, that organizes the technical components identified in the literature review into an ordered sequence extending from physiological data acquisition through to clinical decision support. At the base of the architecture, a sensing and acquisition layer comprises the wearable and body area network sensors responsible for capturing raw physiological signals. Immediately above this, an edge inference layer performs on device filtering, feature extraction, and anomaly scoring using quantized neural network models of the kind described by Abadade et al. (2023) and validated on embedded hardware by Prabha et al. (2026). A local gateway or fog aggregation layer then fuses signals from multiple sensors, buffers data during periods of network unavailability, and selects between available wireless protocols. A secure transmission layer applies homomorphic encryption to any data or model parameters leaving the local environment, consistent with the approach demonstrated by Zhang et al. (2023). A federated model coordination layer, situated in the cloud or at a regional aggregation point, combines encrypted updates from multiple edge nodes using federated averaging or a related aggregation algorithm, following the foundational method of McMahan et al. (2017), before redistributing an improved global model back to the edge. Finally, a clinical decision and alerting layer translates model outputs into a form usable by clinicians, generating risk stratified dashboards and triggering emergency response protocols when warranted.

A structured comparison of the empirical performance figures reported across the reviewed literature, presented in Table 1, clarifies the trade offs associated with the principal architectural choices available at each layer. The comparison indicates a consistent pattern across studies in which edge deployed inference achieves latency reductions on the order of fifty to eighty percent relative to cloud centralized baselines, with an accompanying accuracy penalty typically confined to a few percentage points. This pattern holds most clearly in the within study

comparison reported by Prabha et al. (2026), in which the edge deployed model achieved 91.9 percent accuracy against a cloud baseline of approximately 94 percent, while reducing latency by roughly eighty three percent and energy consumption by roughly sixty four percent. Because this comparison held dataset, hardware availability, and evaluation protocol constant across the two conditions, it provides comparatively strong evidence that the accuracy latency trade off characteristic of edge deployment is modest relative to the operational gains achieved, at least for the class of binary anomaly detection tasks that dominates the current literature.

The communication layer results display a complementary pattern. LoRaWAN transmission consistently achieves substantially lower power consumption than fifth generation cellular transmission, on the order of a sixty percent reduction in the figures reported by Dammak et al. (2022) and corroborated in the dual protocol benchmarking conducted by Prabha et al. (2026), but at the cost of transmission latency roughly four times greater than that achieved by fifth generation connectivity. This trade off is not resolved uniformly across the literature but is instead managed adaptively, with several of the more architecturally complete systems reviewed here routing the substantial majority of routine, non urgent physiological data through the lower power channel while reserving higher power, lower latency transmission for data flagged as clinically urgent by the edge inference layer. This adaptive allocation pattern, in which sixty percent of transmissions were routed through LoRaWAN and forty percent through fifth generation connectivity in the system reported by Prabha et al. (2026), illustrates that the communication layer functions most effectively when its behavior is conditioned on the output of the inference layer immediately below it, reinforcing the cross layer interdependence that motivates the layered framework proposed in this paper.

With respect to privacy preservation, the results indicate that homomorphic encryption imposes a consistent but modest computational penalty, reported at approximately nine percent additional cycle time per federated training round in the most detailed benchmarking currently available (Prabha et al., 2026). This overhead was found to be attributable primarily to the encryption and decryption operations themselves rather than to the secure aggregation computation performed on encrypted gradients, suggesting that further optimization of the underlying cryptographic implementation, for instance through hardware accelerated encryption or the adoption of lighter weight elliptic curve based schemes for less sensitive intermediate computations, represents a plausible avenue for reducing this overhead in future implementations without abandoning the privacy guarantees that homomorphic encryption provides. Federated learning itself, independent of the encryption layer, was found across multiple studies to reduce communication bandwidth requirements substantially relative to centralized training, on the order of thirty to forty percent, by transmitting only model parameter updates rather than raw physiological signal data, a finding consistent across the work of McMahan et al. (2017), Chen et al. (2020), and Prabha et al. (2026).

Finally, the results indicate that blockchain based auditing, implemented through proof of authority consensus among a small number of institutionally trusted validator nodes, can be integrated into the architecture with comparatively limited performance cost, given that the

computational burden of validating and appending transactions to the ledger is decoupled from the latency sensitive inference and alerting pathways and is instead executed as a background process. This design choice, evident in the architecture reported by Prabha et al. (2026), suggests that auditability and real time responsiveness need not be treated as competing objectives provided the auditing mechanism is architected to operate asynchronously relative to the clinical decision pathway.

Table 1: Comparative Summary of Architectural Configurations and Reported Performance in the Reviewed Literature

Architectural Approach	Representative Study	Reported Latency	Reported Accuracy	Primary Trade-off
Cloud-centralized LSTM baseline	Prabha et al. (2026)	Approximately 700 ms round trip	Approximately 94% F1	High accuracy, poor responsiveness, connectivity dependence
Quantized CNN-LSTM on edge node (Jetson Nano)	Prabha et al. (2026)	118 to 130 ms	91.9%, F1 90.8%	Minor accuracy loss, marked latency and energy gains
Dense network on microcontroller-class hardware	Saha et al. (2022)	Tens of milliseconds	Task dependent, roughly 85 to 92%	Severe memory and compute ceilings
Federated averaging across wearable nodes	McMahan et al. (2017); Chen et al. (2020)	Communication bound; 30 to 40% lower bandwidth than centralized training	Comparable to centralized when data are near independent and identically distributed	Degrades under statistical heterogeneity across clients
Federated learning with homomorphic encryption	Zhang et al. (2023); Prabha et al. (2026)	Approximately 9% overhead per training round	Accuracy largely preserved	Added computation and energy cost on constrained devices
LoRaWAN long range transmission	Dammak et al. (2022)	Approximately 400 ms, low power near 90 mW	Not model dependent	Unsuitable for emergency grade alerts
5G low latency transmission	Spicher et al. (2022)	Approximately 95 ms, higher power near 225 mW	Not model dependent	Greater energy draw and infrastructure dependency

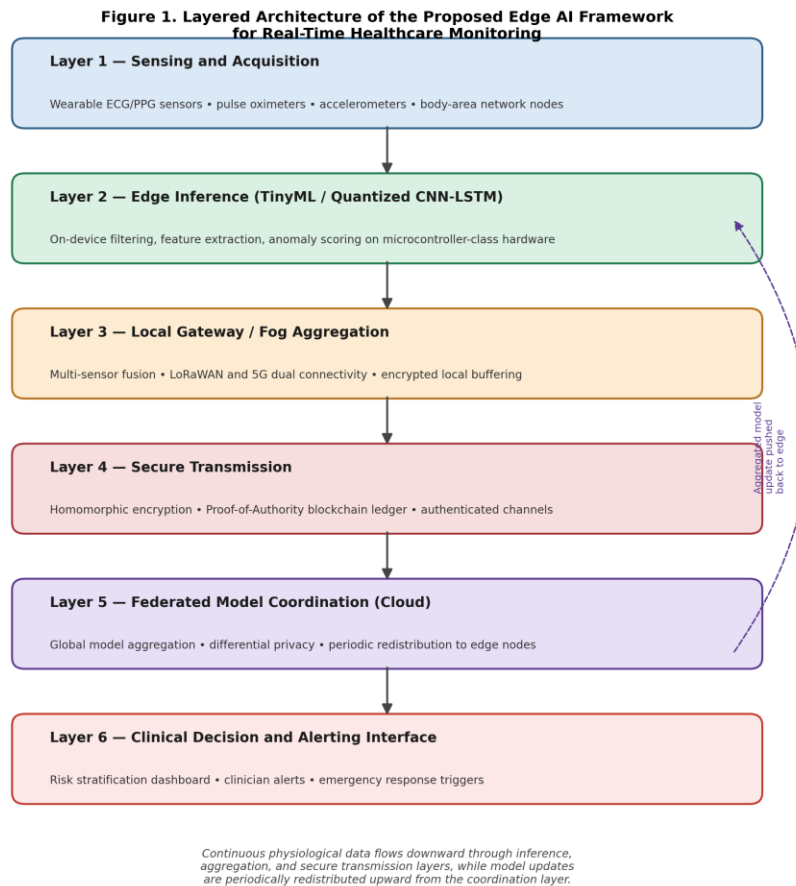


Figure 1. Layered architecture of the proposed Edge AI framework for real time healthcare monitoring, synthesized from the reviewed literature.

5. Discussion

The findings synthesized in section four indicate that the accuracy sacrificed by moving inference from centralized cloud infrastructure to constrained edge hardware is, across the studies reviewed, small relative to the gains achieved in latency, energy consumption, and independence from network connectivity. This pattern speaks directly to the first research question posed in section one and suggests that the architectural configuration most consistently associated with empirical success combines a compressed hybrid convolutional and recurrent model executed at the edge with an adaptive, urgency sensitive communication layer that reserves high power, low latency transmission for genuinely time critical events. The consistency of this pattern across studies conducted on different hardware platforms and different physiological signal types lends it a degree of generalizability, although it should be noted that the great majority of the reviewed empirical work addresses cardiac and related vital sign monitoring specifically, and the extent to which these findings generalize to other clinical domains, such as continuous glucose monitoring or neurological seizure detection, remains an open empirical question.

With respect to the second research question, concerning the interaction between privacy preserving mechanisms and resource constraints, the evidence suggests that federated learning and homomorphic encryption are compatible with edge deployment but not without cost, and that this cost is best understood as a deliberate trade off rather than an unresolved engineering failure. The nine percent latency overhead attributable to homomorphic encryption in the most detailed available benchmark is, in absolute terms, a delay of little clinical consequence for the great majority of monitoring scenarios, and the privacy guarantee it purchases is difficult to achieve through any less computationally demanding alternative currently available. This suggests that health system administrators and system designers evaluating candidate architectures should resist the temptation to treat encryption overhead as a straightforward cost to be minimized and should instead weigh it against the substantial legal and reputational risk associated with inadequately protected patient data.

The third research question, concerning the gap between the architectures reported in the literature and the requirements of sustained clinical deployment, is addressed less completely by the existing evidence base than the first two. A recurring limitation across the studies reviewed is reliance on synthetic or statistically modeled data, generated to resemble the distributional properties of established clinical datasets such as the MIT-BIH arrhythmia database, rather than genuinely heterogeneous data collected from diverse patient populations over extended periods. This limitation matters because federated learning's principal challenge, statistical heterogeneity across clients, is likely to be understated in evaluations that rely on synthetic data constructed to approximate a single underlying distribution. Future research employing authentic, longitudinally collected, and demographically diverse datasets, potentially drawn from resources such as the PTB-XL or MIMIC-III clinical databases referenced in the recent literature, will be necessary to establish whether the performance figures reported to date hold under the messier conditions of genuine clinical practice.

A further limitation concerns the treatment of explainability and clinician trust, which the technical literature addresses only sparingly relative to the attention it devotes to accuracy, latency, and privacy. Sociotechnical systems theory, invoked in section one as a guiding perspective for this synthesis, suggests that the clinical adoption of an edge based monitoring system will depend not only on its measured performance but on clinicians' capacity to understand and appropriately calibrate their trust in its outputs. The absence of interpretability mechanisms, such as feature attribution methods capable of indicating which physiological inputs drove a given alert, in the majority of the architectures reviewed here represents a meaningful gap between current technical capability and the requirements of responsible clinical deployment, and this gap constitutes a priority area for future research.

These limitations notwithstanding, the layered framework developed in this paper carries several implications for practice. Health systems considering investment in edge based monitoring infrastructure should prioritize architectures that treat communication protocol selection as adaptive rather than fixed, given the clear evidence that urgency sensitive routing between low power and low latency channels yields meaningful efficiency gains without

compromising responsiveness for critical events. Regulators and standards bodies evaluating such systems should recognize that privacy preserving mechanisms such as federated learning and homomorphic encryption, while not costless, are sufficiently mature to be treated as a baseline expectation rather than an optional enhancement. Finally, researchers extending this line of work should prioritize validation on authentic, heterogeneous clinical data and the integration of explainability mechanisms as the two most consequential steps toward closing the gap between the promising architectures documented in this review and systems ready for sustained deployment within real health systems, a broader trajectory that aligns with the anticipated evolution of healthcare infrastructure toward increasingly decentralized and intelligent configurations.

6. Conclusion

This paper has synthesized a fragmented but rapidly maturing body of literature spanning edge computing, TinyML, federated learning, secure communication, and blockchain based auditing into a coherent six layer framework for real time healthcare monitoring. The synthesis indicates that edge deployed, quantized neural architectures can deliver diagnostic performance closely approaching that of centralized cloud systems while substantially reducing latency and energy consumption, and that privacy preserving mechanisms such as federated learning and homomorphic encryption can be integrated into such architectures at a modest and well characterized computational cost. The principal scholarly contribution of this paper lies not in a novel algorithmic technique but in the explicit articulation of the dependencies linking these previously disconnected research strands, offering a reference framework against which future system designs and empirical evaluations can be positioned. At the same time, the synthesis makes clear that the evidence base supporting edge based healthcare monitoring remains constrained by a reliance on synthetic validation data and a relative neglect of explainability and clinician trust, both of which represent necessary directions for subsequent research. As health systems continue to seek scalable, secure, and responsive alternatives to cloud centralized monitoring, the layered perspective advanced here offers a structured foundation for evaluating that pursuit.

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