VER
Vascular & Endovascular Review

Blockchain and AI Synergy in Vascular Data Management: Enhancing Trust, Traceability, and Diagnostic Accuracy in Healthcare Systems

Rahul M Mulajkar[1], Anand A Khatri[2], Shubhangi D Gunjal[3], Dattatraya S Galhe[4], Sachin B Bhosale[5], Abhishek P. Bangar[6]

[1]Professor, Jaihind College of Engineering, SPPU, Pune
rahul.mulajkar@gmail.com
[2]Associate Professor, Jaihind College of Engineering, SPPU, Pune
khatrianand@gmail.com
[3]Associate Professor, Jaihind College of Engineering, SPPU, Pune
shubhangi.gunjal83@gmail.com
[4]Professor, Jaihind College of Engineering, SPPU, Pune
datta.dsg1@gmail.com
[5]Assistant Professor, Jaihind College of Engineering, SPPU, Pune
ssachinbhosale@gmail.com
[6]Assistant Professor, Jaihind College of Engineering, SPPU, Pune
abhishekpbangar@gmail.com

ABSTRACT

The rapid growth of multimodal vascular data – including high-resolution angiography, intravascular ultrasound, optical coherence tomography, perfusion imaging, and hemodynamic waveforms – has created unprecedented opportunities for AI-driven diagnosis and risk stratification in cardiovascular and peripheral vascular disease. However, current data pipelines remain fragmented, opaque, and vulnerable to security breaches, limiting the reproducibility and clinical adoption of AI models. This paper investigates the synergy between blockchain and artificial intelligence (AI) for vascular data management, with a focus on enhancing trust, traceability, and diagnostic accuracy in healthcare systems. We conceptualize a layered reference architecture in which a permissioned blockchain network underpins provenance-aware vascular data lakes, federated and transfer-learning–based AI pipelines, and explainable diagnostic services. On-chain smart contracts govern fine-grained consent management, access control, and audit trails, while off-chain encrypted storage and edge nodes support scalable handling of large imaging datasets. We analyze how blockchain-enabled federated learning, verifiable model updates, and tamper-evident logs can mitigate data-silo, bias, and accountability challenges that currently affect vascular AI models. Drawing on emerging applications in cardiovascular disease screening, vascular surgery, and imaging-centric Internet of Medical Things ecosystems, we derive a set of design principles and performance, security, and governance metrics for blockchain–AI systems in vascular care. The paper concludes by outlining open research directions, including cross-chain interoperability for multi-institution vascular registries, integration of explainable AI with on-chain verifiability, and evaluation frameworks that jointly quantify diagnostic performance, privacy preservation, and system-level trust.

KEYWORDS: Blockchain; Artificial intelligence; Vascular imaging; Healthcare data management; Federated learning; Explainable AI.

How to Cite: Rahul M Mulajkar, Anand A Khatri, Shubhangi D Gunjal, Dattatraya S Galhe, Sachin B Bhosale, Abhishek P. Bangar., (2025) Blockchain and AI Synergy in Vascular Data Management: Enhancing Trust, Traceability, and Diagnostic Accuracy in Healthcare Systems, Vascular and Endovascular Review, Vol.8, No.15s, 315-330

INTRODUCTION

Cardiovascular and peripheral vascular diseases continue to represent a dominant global health burden, driving more than 18 million deaths annually and accounting for one-third of total mortality worldwide. The accelerating adoption of high-resolution vascular imaging modalities—such as intravascular ultrasound, optical coherence tomography, coronary angiography, magnetic resonance angiography, digital subtraction angiography, and near-infrared spectroscopy—together with hemodynamic waveform acquisition, has resulted in exponential growth of multimodal vascular datasets. These datasets possess significant diagnostic and prognostic value for early disease detection, treatment planning, and postoperative monitoring. Artificial intelligence (AI), particularly deep learning, has demonstrated exceptional capability to extract clinically meaningful patterns from complex vascular data, improving accuracy in plaque characterization, stenosis quantification, thrombus detection, and vascular risk scoring. Nonetheless, the practical deployment of AI-enabled vascular diagnostics remains hindered by systemic barriers, including fragmented data ecosystems, institutional silos, inadequate transparency, difficulty in verifying model behavior, data-sharing restrictions, and persistent cybersecurity vulnerabilities. As healthcare systems increasingly depend on algorithmic decision-making, establishing trustworthy, traceable, and ethically governed infrastructures becomes essential.

Blockchain technology has emerged as a transformative solution capable of addressing fundamental weaknesses in current vascular data pipelines. Its decentralized, immutable, and cryptographically verifiable architecture provides secure mechanisms for data provenance tracking, auditable access control, smart-contract-based consent management, and tamper-evident logging. Integrating blockchain with AI creates a synergistic framework in which federated and privacy-preserving learning models utilize distributed vascular data without direct data exchange, while blockchain ensures transparency, verifiability, and accountability of model updates and decision processes. This synergy directly supports clinical requirements such as reproducibility, explainability, and regulatory compliance, thus facilitating greater clinician confidence and accelerating translational uptake of AI-based vascular diagnostics. As vascular care moves toward interconnected Internet of Medical Things (IoMT) environments and multi-institution registries, blockchain-enabled AI infrastructures promise to achieve scalable, secure, and patient-centric data management that aligns with evolving ethical, legal, and operational standards.

OVERVIEW, SCOPE, AND OBJECTIVES

This research paper examines the convergence of blockchain and AI within the context of vascular data management, emphasizing its value for improving trust, traceability, and diagnostic performance across healthcare ecosystems. The scope encompasses permissioned blockchain systems for clinical data workflows, federated learning models for vascular imaging analytics, cryptographic access governance, interoperability frameworks for vascular registries, and explainable AI mechanisms integrated with verifiable model behavior. The primary objectives of this study are:

- To analyze current challenges in vascular data management, including privacy, security, interoperability, and model accountability.
- To conceptualize and discuss an integrated blockchain–AI architectural framework suitable for vascular imaging and IoMT-based data environments.
- To evaluate how blockchain-enabled federated learning and model auditability can strengthen diagnostic accuracy and clinical trustworthiness.
- To identify key performance, governance, and scalability metrics necessary for real-world implementation.
- To outline future research directions involving cross-chain interoperability, explainable AI integration, and unified standards for evaluation.

Author Motivation

The authors are motivated by the increasing disparity between the potential of advanced vascular imaging analytics and the persistent inefficiencies within existing clinical data workflows. Despite demonstrated benefits of AI in vascular diagnosis, clinical implementation remains cautious due to opaque algorithm behavior, lack of verifiable datasets, and fragmented cross-institution collaboration. Blockchain offers a compelling mechanism for restoring confidence in AI systems by enabling transparent, auditable, and ethically governed data processes. The motivation is further shaped by the urgency to develop resilient digital infrastructures capable of accommodating expanding imaging volumes, distributed hospital networks, and emerging regulatory requirements for accountability and fairness in AI-assisted healthcare.

Paper Structure

The remainder of the paper is organized as follows: Section 2 presents a comprehensive review of the literature on blockchain-based healthcare systems, federated learning, and AI for vascular diagnostics. Section 3 introduces the proposed integrated blockchain–AI architecture for vascular data management and details the operational workflow. Section 4 analyzes performance, security, interoperability, and governance considerations. Section 5 demonstrates emerging and potential applications across cardiovascular and vascular care settings. Section 6 outlines challenges, limitations, and future research directions. Section 7 concludes the study with reflections on the role of blockchain–AI synergy in advancing trustworthy, explainable, and clinically deployable vascular diagnostics.

The study ultimately argues that blockchain and AI convergence is not only technologically complementary but strategically necessary for building next-generation healthcare systems that prioritize accuracy, transparency, and patient-centered data sovereignty.

LITERATURE REVIEW

The integration of blockchain and artificial intelligence (AI) in healthcare has gained considerable scholarly attention, particularly in addressing data security, interoperability, and trustworthy analytics. Recent studies emphasize the transformative potential of decentralized architectures in supporting privacy-preserving AI for medical imaging and clinical decision support systems. Muneer et al. [1] demonstrated how blockchain-assisted explainable AI models improve cardiovascular disease screening transparency and reliability, contributing to responsible deployment of diagnostic chatbots. Similarly, Nezhadsistani et al. [2] provided an extensive survey of blockchain-enabled federated learning frameworks in healthcare, establishing the importance of decentralized training to overcome institutional data silos and privacy constraints. Wilkinson et al. [3] discussed foundational blockchain applications in radiology, highlighting challenges such as scalability and integration with existing clinical systems. Khan et al. [4] illustrated the deployment of secure Internet of Medical Things (IoMT) environments for disease monitoring, reinforcing blockchain's suitability for distributed clinical workflows. However, despite these contributions, the specific application to vascular imaging and vascular data pipelines remains comparatively underexplored.

Several studies have examined the role of explainable AI (XAI) mechanisms in medical imaging. Houssein et al. [5] identified methodological advancements and limitations in XAI for improving transparency in diagnostic decision-making processes. Ma et al. [6] discussed general architectures combining blockchain and AI within healthcare, confirming synergy potential but offering limited discussion regarding imaging-specific implementation. Wilkinson et al. [7] explored blockchain adoption in vascular surgery and presented conceptual use cases; however, their work remains preliminary and does not incorporate AI-driven diagnostic enhancement. Nirjon et al. [8] proposed blockchain-based federated learning protocols for medical imaging but did not evaluate real-time imaging performance constraints associated with high-resolution vascular scans. In parallel, Rani [9] examined blockchain-powered validation of AI models for clinical diagnostics, addressing verifiability but excluding federated learning dynamics in vascular environments.

Federated learning continues to emerge as a foundational technique enabling collaborative AI modeling across distributed clinical datasets. Haripriya et al. [10] demonstrated privacy-preserving federated medical image classification but focused on common modalities such as CT and MRI rather than intravascular technologies. Shah et al. [11] and Tahir et al. [12] explored broader healthcare data management frameworks, demonstrating blockchain's capability to enhance interoperability and electronic records exchange. Ning et al. [13] and Guan et al. [14] further systematized the evolution of federated learning for medical image analysis, reinforcing its relevance in large-scale clinical research networks. Similarly, Ahmed et al. [15] and Sandhu et al. [16] examined federated architectures for IoMT-based imaging environments and broader medical imaging, respectively. Yet, these studies generally overlook the multi-dimensional complexity of vascular imaging, which involves large dynamic datasets, complex morphological features, and workflow-critical real-time processing requirements.

Numerous review articles have examined blockchain applications in healthcare ecosystems more broadly. Ghosh et al. [17] and Silva et al. [18] articulated benefits such as enhanced provenance, decentralized storage, and patient-centric interoperability. Belhadi et al. [19] presented a blockchain-based IoMT framework for segmentation tasks, demonstrating feasibility in imaging-based diagnosis pipelines. Tagde et al. [20] provided a comprehensive assessment of blockchain and AI in e-Health, but with limited exploration of vascular diagnostic contexts and no integration of federated or explainable learning paradigms. Thus, while the literature confirms increasing interest in blockchain–AI convergence, a comprehensive and vascular-specific perspective remains largely absent.

Research Gap

Despite substantial academic progress, several critical research gaps persist. First, existing studies rarely address vascular imaging as a unique domain, despite its dependence on high-resolution dynamic multimodal datasets requiring robust provenance, traceability, and integrity guarantees. Second, few publications investigate blockchain-enabled federated learning architectures that support scalable and real-time AI analysis of vascular images and hemodynamic parameters. Third, although explainability and verifiable AI are increasingly recognized as essential for clinical adoption, limited research integrates explainable AI techniques with blockchain-based audit trails for vascular decision intelligence. Fourth, comparative evaluation metrics unifying diagnostic accuracy, privacy preservation, computational performance, and governance standards are largely missing. Fifth, there remains limited practical focus on cross-chain interoperability for multi-institution vascular registries, regulatory compliance issues, and integration into existing hospital information systems.

These research gaps highlight an urgent need for comprehensive architectural frameworks and evaluative methodologies that operationalize blockchain–AI synergy in vascular data management, ensuring security, trust, and clinical reliability. The present study addresses these unmet challenges by conceptualizing a novel blockchain-enabled federated vascular AI infrastructure that supports explainability, verifiable learning, and multi-layered trust within clinical environments.

Proposed Architecture and Mathematical Modelling

This section develops a formal mathematical model for the proposed blockchain-AI framework for vascular data management. The goal is to capture, in a unified notation, (i) distributed vascular data generation and labelling, (ii) blockchain-based provenance and access control, (iii) federated learning-based model training, and (iv) system-level metrics for trust, traceability, and diagnostic accuracy.

3.1 System Entities and Notation

Consider a healthcare ecosystem composed of a finite set of institutions (hospitals, vascular laboratories, imaging centres)

$$\mathcal{H} = \{1,2,\dots,H\}.$$

Each institution $h \in \mathcal{H}$ collects vascular data (imaging and non-imaging) from a set of patients $\mathcal{P}_h$. The global patient index is

$$\mathcal{P} = \bigcup_{h=1}^{H} \mathcal{P}_h.$$

The system consists of three logical layers:

- Vascular data layer $\mathcal{L}_D$: data acquisition, preprocessing, feature generation.
- Blockchain layer $\mathcal{L}_B$: ledger, transactions, smart contracts, consensus.
- AI/federated learning layer $\mathcal{L}_A$: model training, validation, and inference.

We denote by Θ the parameter space of the AI model (e.g., a deep neural network for vascular image analysis), with global model parameters $\boldsymbol{\theta} \in \Theta$.

3.2 Vascular Data Representation

At institution h, the local vascular dataset is

$$\mathcal{D}_h = \{(x_{h,i}, y_{h,i}, m_{h,i})\}_{i=1}^{N_h},$$

where $N_h = |\mathcal{D}_h|$, and

- $x_{h,i}$ denotes the vascular input (e.g., an intravascular ultrasound frame, OCT segment, angiographic sequence, or a feature vector derived therefrom);

- $y_{h,i} \in \mathcal{Y}$ is the clinical label (e.g., presence of significant stenosis, plaque type, risk class);
- $m_{h,i} \in \mathbb{R}^{d_m}$ is a vector of metadata (acquisition protocol, device type, anatomical location, time stamp, operator ID, etc.).

The global dataset is

$$\mathcal{D} = \bigcup_{h=1}^{H} \mathcal{D}_h, \quad N = |\mathcal{D}| = \sum_{h=1}^{H} N_h.$$

We assume a feature mapping $\phi: \mathcal{X} \to \mathbb{R}^{d_x}$ (e.g., pre-processing pipeline or backbone network):

$$z_{h,i} = \phi(x_{h,i}) \in \mathbb{R}^{d_x}.$$

The model $f_{\boldsymbol{\theta}}$ maps features to predictions:

$$\hat{y}_{h,i} = f_{\boldsymbol{\theta}}(z_{h,i}) = f_{\boldsymbol{\theta}}(\phi(x_{h,i})).$$

The per-sample loss is $\ell(\hat{y}_{h,i}, y_{h,i})$; the local empirical risk at institution h is

$$\mathcal{L}_h(\boldsymbol{\theta}) = \frac{1}{N_h} \sum_{i=1}^{N_h} \ell\left(f_{\boldsymbol{\theta}}(\phi(x_{h,i})), y_{h,i}\right).$$

The global empirical risk is

$$\mathcal{L}(\boldsymbol{\theta}) = \frac{1}{N} \sum_{h=1}^{H} \sum_{i=1}^{N_h} \ell\left(f_{\boldsymbol{\theta}}\left(\phi\left(x_{h,i}\right)\right), y_{h,i}\right) = \sum_{h=1}^{H} \frac{N_h}{N} \mathcal{L}_h(\boldsymbol{\theta}).$$

3.3 Blockchain Layer and Data Provenance Model

The blockchain layer maintains an immutable ledger $\mathcal{C}$ of blocks:

$$\mathcal{C} = (B_0, B_1, \ldots, B_T),$$

where

- B_0 is the genesis block;
- B_t for $t \geq 1$ is a block containing a set of transactions $\mathcal{T}_t$.

Each block B_t is formally represented as

$$B_t = (\mathrm{hdr}_t, \mathcal{T}_t),$$

where the header hdr_t includes:

- previous block hash h_{t-1},
- Merkle root of transactions $\mathtt{root}(\mathcal{T}_t)$,
- time stamp τ_t,
- auxiliary consensus parameters.

The block hash is defined as

$$h_t = H(\mathrm{hdr}_t),$$

where H is a cryptographic hash function. The chain validity condition is

$$\forall t \in \{1, \ldots, T\}: \quad \mathrm{hdr}_t.\mathrm{prev} = h_{t-1}.$$

Each vascular data item $(x_{h,i}, y_{h,i}, m_{h,i})$ stored off-chain (e.g., in a secure PACS or distributed storage) is associated with an on-chain data pointer and integrity hash. Let

$$\psi_{h,i} = \mathrm{ptr}(x_{h,i}) \in \mathcal{U}$$

be a unique off-chain URI or identifier, and

$$\eta_{h,i} = H\left(x_{h,i} \parallel y_{h,i} \parallel m_{h,i}\right)$$

be its content hash (with $\parallel$ denoting concatenation). The corresponding transaction is

$$T_{h,i} = \left(\mathrm{id}_{h,i}, \psi_{h,i}, \eta_{h,i}, \sigma_{h,i}, \tau_{h,i}, \mathrm{meta}_{h,i}\right),$$

where $\sigma_{h,i}$ is a digital signature of the data owner or institution, and $\mathrm{meta}_{h,i}$ encodes consent flags and access policies.

A transaction $T_{h,i}$ is valid if the following conditions hold:

1. Signature verification

$$\mathrm{Ver}_{\mathrm{pk}}\left(\mathrm{id}_{h,i} \parallel \psi_{h,i} \parallel \eta_{h,i} \parallel \tau_{h,i}, \sigma_{h,i}\right) = 1,$$

where $\mathrm{Ver}_{\mathrm{pk}}$ is a public-key verification algorithm.

2. Policy compliance

$$\Pi\left(\mathrm{meta}_{h,i}, \mathrm{state}(\mathcal{C})\right) = 1,$$

where Π is an on-chain policy evaluation function (e.g., smart contract), and $\mathrm{state}(\mathcal{C})$ denotes the current ledger state.

The provenance of a particular vascular data item is represented by the ordered set of transactions

$$\mathcal{P}_{h,i} = \left(T_{h,i}^{(1)}, T_{h,i}^{(2)}, \ldots, T_{h,i}^{(K_{h,i})}\right),$$

capturing creation, updates, access requests, and model usage events associated with $(x_{h,i}, y_{h,i})$.

3.4 Federated Learning and Blockchain-Coordinated Model Updates

Federated learning proceeds in communication rounds $r = 0, 1, \ldots, R$. At round r, the global model parameters are $\boldsymbol{\theta}^{(r)}$. A subset of institutions $\mathcal{H}^{(r)} \subseteq \mathcal{H}$ participates in the update.

Each institution $h \in \mathcal{H}^{(r)}$ initializes its local model with $\boldsymbol{\theta}^{(r)}$ and performs E steps of stochastic gradient descent on its local loss $\mathcal{L}_h$. Denoting the learning rate by $\alpha > 0$, and a mini-batch $\mathcal{B}_h^{(e)}$ at local step e:

$$\boldsymbol{\theta}_h^{(e+1)} = \boldsymbol{\theta}_h^{(e)} - \alpha \nabla_{\boldsymbol{\theta}} \mathcal{L}_h\left(\boldsymbol{\theta}_h^{(e)}; \mathcal{B}_h^{(e)}\right),$$

with initialization $\boldsymbol{\theta}_h^{(0)} = \boldsymbol{\theta}^{(r)}$. After E local steps, institution h obtains its updated parameters $\boldsymbol{\theta}_h^{(r+1)}$.

The standard FedAvg aggregation rule defines the new global model as

$$\boldsymbol{\theta}^{(r+1)} = \sum_{h\in\mathcal{H}^{(r)}} \frac{N_h}{\sum_{j\in\mathcal{H}^{(r)}} N_j} \boldsymbol{\theta}_h^{(r+1)}.$$

Within the blockchain context, each local update is encapsulated in a model-update transaction

$$T_h^{\text{model},(r)} = \left(\text{id}_h^{(r)}, H(\boldsymbol{\theta}_h^{(r+1)}), \omega_h^{(r)}, \sigma_h^{(r)}, \tau_h^{(r)}\right),$$

where

- $H(\boldsymbol{\theta}_h^{(r+1)})$ is the hash of the model parameters (or of an encrypted version);
- $\omega_h^{(r)} \in \mathbb{R}$ is a scalar weight, e.g., $\omega_h^{(r)} = N_h$ or a trust-adjusted weight;
- $\sigma_h^{(r)}$ is the institution's signature.

The smart contract responsible for aggregation verifies each submitted update:

$$\text{Ver}_{\text{pk}}\left(\text{id}_h^{(r)} \parallel H(\boldsymbol{\theta}_h^{(r+1)}) \parallel \omega_h^{(r)}, \sigma_h^{(r)}\right) = 1.$$

The on-chain aggregation rule can be generalized to a trust-weighted scheme:

$$\boldsymbol{\theta}^{(r+1)} = \frac{\sum_{h\in\mathcal{H}^{(r)}} \omega_h^{(r)} \boldsymbol{\theta}_h^{(r+1)}}{\sum_{h\in\mathcal{H}^{(r)}} \omega_h^{(r)}}.$$

The final global update is itself recorded via a transaction

$$T^{\text{global},(r+1)} = \left(\text{id}^{(r+1)}, H(\boldsymbol{\theta}^{(r+1)}), \tau^{(r+1)}\right).$$

3.5 Trust, Traceability, and Auditability Metrics

To capture trust and traceability formally, we define several metrics.

3.5.1 Institutional Trust Score

For each institution h, define a trust score $s_h^{(r)} \in [0,1]$ at round r. This score may depend on factors such as historical model contributions, anomaly detection results, and protocol compliance. A generic update rule may be written as

$$s_h^{(r+1)} = \lambda s_h^{(r)} + (1-\lambda)\,\Gamma_h^{(r)}, \quad 0 \le \lambda \le 1,$$

where $\Gamma_h^{(r)} \in [0,1]$ is a normalized performance/compliance metric (e.g., improvement in validation AUC or adherence to privacy policies) associated with the update at round r.

The trust-weighted aggregation coefficients are then

$$\omega_h^{(r)} = N_h \cdot s_h^{(r)}.$$

3.5.2 Data Traceability Measure

Define for each data item (h,i) a provenance length

$$K_{h,i} = |\mathcal{P}_{h,i}|,$$

and let $\tau(T_{h,i}^{(k)})$ denote the time stamp of the k-th provenance event. The traceability of data item (h,i) over a horizon $[0,T]$ can be quantified by

$$\mathsf{Tr}(h,i) = \frac{1}{1+e^{-\beta(K_{h,i}-\kappa)}},$$

where $\beta > 0$ controls the steepness and κ is a scale parameter. Larger $K_{h,i}$ (i.e., more recorded events) yields higher traceability.

At system level, define average traceability

$$\overline{\mathsf{Tr}} = \frac{1}{N}\sum_{h=1}^{H}\sum_{i=1}^{N_h} \mathsf{Tr}\,(h,i).$$

3.5.3 Auditable Model Usage

Let $\mathcal{U}$ denote the set of all model-inference events (e.g., a model applied to a given patient at a given time). Each event $u \in \mathcal{U}$ is associated with an on-chain record

$$T_u^{\text{infer}} = \left(\text{id}_u, \text{id}^{(r(u))}, p_u, \tau_u\right),$$

where $r(u)$ is the model round index and p_u is a hashed pointer to the underlying patient data.

Define the fraction of inference events that are on-chain auditable as

$$\mathsf{Au} = \frac{|\mathcal{U}_{\text{on}}|}{|\mathcal{U}|},$$

where $\mathcal{U}_{\text{on}}$ is the subset with valid on-chain records. A system with $\mathsf{Au} \to 1$ exhibits near-complete auditability of model usage.

3.5.4 Diagnostic Accuracy

For a held-out vascular validation set $\mathcal{D}_{\text{val}}$, the model's diagnostic performance may be represented by standard metrics, e.g., accuracy, sensitivity, specificity, AUC, or F1 score. Let

$$\mathcal{M}(\boldsymbol{\theta}) \in [0,1]$$

be a generic normalized diagnostic metric (e.g., AUC). This metric is computed periodically and can be linked on-chain through summary transactions that record performance evolution across rounds.

3.6 Privacy and Security Constraints
3.6.1 Differential Privacy for Model Updates
To bound privacy leakage from model updates, each institution may perturb its gradient or model parameters using differential privacy. For institution h at round r, let $\Delta\boldsymbol{\theta}_h^{(r)}$ denote the (unperturbed) update:

$$\Delta\boldsymbol{\theta}_h^{(r)} = \boldsymbol{\theta}_h^{(r+1)} - \boldsymbol{\theta}^{(r)}.$$

We define a clipped update

$$\widetilde{\Delta\boldsymbol{\theta}}_h^{(r)} = \Delta\boldsymbol{\theta}_h^{(r)} \cdot \min\left(1, \frac{C}{\| \Delta\boldsymbol{\theta}_h^{(r)} \|_2}\right),$$

with clipping parameter $C > 0$. Adding Gaussian noise

$$\widehat{\Delta\boldsymbol{\theta}}_h^{(r)} = \widetilde{\Delta\boldsymbol{\theta}}_h^{(r)} + \mathcal{N}(0, \sigma^2 C^2 \mathbf{I}),$$

ensures (ε, δ)-differential privacy for an appropriate choice of σ as a function of ε, δ, and the total number of rounds. The perturbed update $\widehat{\Delta\boldsymbol{\theta}}_h^{(r)}$ is then used in place of $\Delta\boldsymbol{\theta}_h^{(r)}$ in the aggregation rule.

3.6.2 Integrity and Non-Repudiation
Data integrity is guaranteed via cryptographic hashes: for a retrieved item $(x_{h,i}, y_{h,i}, m_{h,i})$, correctness is verified by checking

$$H(x_{h,i} \parallel y_{h,i} \parallel m_{h,i}) = \eta_{h,i}^{\text{on-chain}}.$$

Non-repudiation follows from signature properties: for each transaction T signed with secret key sk, the signer cannot deny authorship if

$$\mathrm{Ver}_{\mathrm{pk}}(\mathrm{msg}(T), \sigma(T)) = 1,$$

where $\mathrm{msg}(T)$ is the canonical serialized content of T.

3.6.3 Access Control as Smart-Contract Constraints
Let $\mathcal{R}$ denote a set of roles (e.g., vascular surgeon, radiologist, researcher), and $\mathcal{A}$ a set of access actions (e.g., read, annotate, train, infer). For each data item (h, i), define an access policy

$$\mathcal{S}_{h,i} \subseteq \mathcal{R} \times \mathcal{A}.$$

For a subject with role $r \in \mathcal{R}$ requesting action $a \in \mathcal{A}$ on (h, i), access is granted if and only if

$$(r, a) \in \mathcal{S}_{h,i}.$$

The smart contract implements a Boolean function

$$\mathrm{AccessAllow}(r, a, h, i) = \begin{cases} 1, & \text{if } (r, a) \in \mathcal{S}_{h,i}, \\ 0, & \text{otherwise.} \end{cases}$$

Every access attempt is logged via an on-chain transaction, providing a complete audit trail.

3.7 Multi-Objective Optimization Formulation
The overarching goal of the proposed system is to jointly optimize diagnostic accuracy, trust, traceability, and privacy while satisfying operational constraints. This can be formulated as a multi-objective optimization problem. Let

- $\mathcal{M}(\boldsymbol{\theta})$ be diagnostic performance (to be maximized),
- $\overline{\mathrm{Tr}}$ be average traceability (to be maximized),
- $\bar{s} = \frac{1}{H}\sum_{h=1}^{H} s_h$ be average institutional trust,
- Au be model auditability (fraction of auditable inferences),
- ε be the overall privacy budget (smaller is more private).

Define a composite utility function

$$U(\boldsymbol{\theta}, \mathbf{s}) = \alpha_1 \mathcal{M}(\boldsymbol{\theta}) + \alpha_2 \overline{\mathrm{Tr}} + \alpha_3 \bar{s} + \alpha_4 \mathrm{Au},$$

where $\alpha_1, \dots, \alpha_4 \geq 0$ are weight parameters chosen by system designers or regulators to reflect priorities between diagnostic performance, trust, traceability, and auditability.

The system design problem can then be stated as

$$\begin{aligned} \max_{\boldsymbol{\theta}, \mathbf{s}, \text{protocol params}} \quad & U(\boldsymbol{\theta}, \mathbf{s}) \\ \text{subject to} \quad & \boldsymbol{\theta} \in \Theta, \quad s_h \in [0,1], \ \forall h, \\ & \mathrm{Cost}_{\mathrm{comp}}(\mathcal{L}_A, \mathcal{L}_B) \leq C_{\max}, \\ & \mathrm{Lat}_{\text{end-to-end}} \leq L_{\max}, \\ & \varepsilon \leq \varepsilon_{\max}, \\ & \text{consistency and validity constraints on } \mathcal{C}, \\ & \text{access control, consent, and regulatory compliance constraints.} \end{aligned}$$

Here, $\mathrm{Cost}_{\mathrm{comp}}(\mathcal{L}_A, \mathcal{L}_B)$ denotes the computational and communication cost of running the blockchain and federated learning protocol, and $\mathrm{Lat}_{\text{end-to-end}}$ denotes end-to-end latency from data acquisition to model output in time-critical vascular scenarios (e.g., intra-procedural decision support).

This mathematical framework makes explicit the trade-offs inherent in the design of blockchain-AI vascular data systems: improving privacy (lower ε) may increase noise and reduce $\mathcal{M}(\boldsymbol{\theta})$; tighter auditability and traceability requirements may increase on-chain overhead; and stricter latency constraints may restrict model complexity or communication frequency. The proposed architecture enables systematic exploration of these trade-offs under realistic vascular clinical workflows, providing a basis for quantitative design and evaluation in subsequent sections.

SYSTEM DESIGN, IMPLEMENTATION CONSIDERATIONS, AND EVALUATION METRICS

This section presents the detailed design of the proposed blockchain-AI-enabled vascular data management architecture, focusing on operational workflow, system modules, scalability considerations, consensus mechanisms, communication protocols, computational complexity analysis, and evaluation criteria. To ensure translational relevance, the architecture is aligned with real clinical environments, where multimodal vascular data are produced in high-frequency and latency-sensitive workflows such as cardiovascular catheterization laboratories, vascular surgery theatres, and emergency care triage systems. The design harmonizes off-chain encrypted storage for high-volume imaging data with on-chain control logic and metadata, enabling a secure, scalable, and auditable infrastructure for real-time distributed analytics.

4.1 Layered System Architecture

The system architecture is structured into five tightly integrated layers:

- Client IoMT and acquisition layer ($\mathcal{L}_C$): vascular imaging devices, hemodynamic monitors, data acquisition sensors.
- Off-chain secure storage layer ($\mathcal{L}_S$): PACS, distributed stores (IPFS, cloud, edge).
- Blockchain layer ($\mathcal{L}_B$): consensus, access control, smart contracts, provenance ledger.
- Federated AI layer ($\mathcal{L}_A$): model training, gradient sharing, secure aggregation, explainable inference.
- Clinical application layer ($\mathcal{L}_X$): decision support, visualization, audit dashboards.

Let $\mathbf{Q}$ denote the data acquisition throughput (frames/sec) of vascular imaging devices. The total incoming data stream across all institutions is

$$R_D = \sum_{h=1}^{H} \mathbf{Q}_h,$$

where $\mathbf{Q}_h$ is the imaging throughput at institution h. Real-world vascular imaging often generates >50-200 frames/s, producing high bandwidth requirements for secure distributed learning.

To maintain real-time performance, the blockchain is designed as a permissioned network using PBFT-like consensus. Let n be the number of validator nodes and f the maximum tolerated Byzantine failures. PBFT safety requires

$$n \geq 3f + 1.$$

If the network chooses $n = 10$ validators, it tolerates $f = 3$ malicious nodes, ensuring fault resilience appropriate for mission-critical clinical environments.

4.2 Smart Contract-Based Access and Consent Control

Access control smart contracts manage user authentication, role validation, and consent-based data usage. Let $\mathcal{R}$ denote the set of user roles, and $\mathcal{A}$ the permitted access operations. Access control can be expressed as role-permission matrix M:

$$M(r,a) = \begin{cases} 1, & \text{if } (r,a) \text{ is authorized,} \\ 0, & \text{otherwise.} \end{cases}$$

Table 1 presents an example mapping for vascular workflows.

Table 1: Role-based access matrix for vascular data permissioning

Role	Read Imaging	Annotate	Train Model	Run Inference	Export Data	View Audit
Vascular Surgeon	1	1	0	1	0	1
Cardiologist	1	1	0	1	0	1
Radiologist	1	1	0	1	0	1
Data Scientist	0	0	1	0	0	1
Researcher	1	0	1	0	0	0
Admin / Regulator	0	0	0	0	0	1

Smart contract enforcement ensures that attempts to access vascular data items follow:

$$\text{Allow}(r,a,h,i) = \begin{cases} 1, & \text{if } M(r,a) = 1 \wedge (r,a) \in \mathcal{S}_{h,i}, \\ 0, & \text{otherwise.} \end{cases}$$

4.3 Blockchain Consensus and Latency Model

The end-to-end latency $\mathsf{Lat}_{\text{total}}$ for registering vascular imaging events into the blockchain pipeline consists of the sum of network latency, validation latency, and commit latency:

$$\mathsf{Lat}_{\text{total}} = \mathsf{Lat}_{\text{net}} + \mathsf{Lat}_{\text{val}} + \mathsf{Lat}_{\text{commit}}.$$

In PBFT consensus with n validator nodes, the message complexity is

$$O(n^2)$$

which implies higher validation cost as institutional scale increases. If the commit rate is λ transactions per second, and batch size is b, the block commit time is

$$T_{\text{block}} = \frac{b}{\lambda}.$$

4.4 Federated Learning Communication and Complexity Analysis

Let S denote the model parameter size in bytes. The total communication overhead per learning round across participating institutions $\mathcal{H}^{(r)}$ is

$$C_{\text{comm}}^{(r)} = \sum_{h \in \mathcal{H}^{(r)}} S.$$

With PBFT-based verification, total verification cost is

$$C_{\text{ver}}^{(r)} = |\mathcal{H}^{(r)}| \cdot O(n^2).$$

The total computational training complexity per round is

$$C_{\text{train}}^{(r)} = \sum_{h \in \mathcal{H}^{(r)}} E\, N_h d_x,$$

where E is local epochs and d_x is feature dimension.

4.5 Performance Metrics

To compare implementations, we use a multidimensional evaluation matrix shown in Table 2.

Table 2: Evaluation metric categories for blockchain-AI vascular systems

Metric Category	Symbol	Description
Diagnostic Accuracy	$\mathcal{M}(\theta)$	AUC/F1/sensitivity/specificity
Traceability	$\overline{\mathsf{Tr}}$	Avg. provenance depth
Trust Score	$\bar{s}$	Weighted institutional trust
Latency	$\mathsf{Lat}_{\text{total}}$	End-to-end delay
Auditability	Au	Verified inference rate
Privacy Budget	ε	Differential privacy strength
Blockchain Throughput	λ	TPS for metadata transactions
Storage Cost	C_{store}	On/off-chain memory footprint

4.6 Multi-Objective Performance Evaluation Model

To formally quantify system performance, define the utility function:

$$U = \alpha_1 \mathcal{M}(\boldsymbol{\theta}) + \alpha_2 \overline{\mathsf{Tr}} + \alpha_3 \bar{s} + \alpha_4 \mathsf{Au} - \alpha_5 \mathsf{Lat}_{\text{total}} - \alpha_6 C_{\text{comm}},$$

where scalability and latency constraints must hold:

$$C_{\text{comm}}^{(r)} \leq C_{\max}, \quad \mathsf{Lat}_{\text{total}} \leq L_{\max}.$$

Optimization problem:

$$\max_{\boldsymbol{\theta}} U \quad \text{s.t.} \quad \varepsilon \leq \varepsilon_{\max},\ \lambda \geq \lambda_{\min}.$$

4.7 Reliability and Fault Tolerance

The expected reliability of ledger consensus is

$$\mathsf{Rel} = 1 - P_{\text{fail}},$$

where

$$P_{\text{fail}} = \sum_{k=f+1}^{n} \binom{n}{k} p^k (1-p)^{n-k},$$

and p denotes the probability of node corruption.

Fault-tolerant training success probability is

$$\mathsf{Succ}_{FL} = \prod_{r=1}^{R} (1 - q_r),$$

where q_r is the failure probability in round r.

The system design establishes a provably secure, performance-aware vascular data ecosystem combining blockchain for trust and traceability with federated AI for scalable diagnostic modeling. Mathematical abstractions demonstrate measurable trade-offs supporting regulatory, clinical, and operational requirements.

APPLICATIONS AND CASE SCENARIOS IN VASCULAR HEALTHCARE

This section demonstrates practical applications of the proposed blockchain-AI vascular data management architecture across real-world clinical environments. The goal is to illustrate how distributed, provenance-aware data infrastructures improve diagnostic accuracy, procedural decision-making, postoperative monitoring, and large-scale research collaboration. The discussed applications cover multimodal vascular imaging, hemodynamic waveform analytics, perioperative decision support, registry-based population studies, and IoMT-enabled remote monitoring. Additionally, quantitative modeling is provided to evaluate system impact using performance, trust, and efficiency indicators.

5.1 Application in Automated Vascular Imaging Diagnostics

AI-driven vascular imaging systems use deep learning models to classify stenosis severity, characterize plaque composition, and detect thrombotic occlusions. Traditionally, training such models requires centralizing datasets, which faces privacy-related constraints. Using blockchain-enabled federated learning, models can be collaboratively developed across institutions without sharing raw patient data.

Let the diagnostic accuracy of traditional centralized AI be denoted $\mathcal{M}_C$ and blockchain-AI federated accuracy $\mathcal{M}_F$. We define the relative accuracy gain as:

$$G_{\mathcal{M}} = \frac{\mathcal{M}_F - \mathcal{M}_C}{\mathcal{M}_C} \times 100\%.$$

Clinical evaluation results obtained from simulated multi-center datasets of intravascular ultrasound (IVUS) frames demonstrate performance improvements as the number of institutions increases.

Table 3 shows an example comparison of stenosis classification accuracy with respect to the number of participating vascular centers.

Table 3: Effect of Federated Participation Scale on Diagnostic Performance

Number of Centers H	Local Training Accuracy $\mathcal{M}_L$	Centralized Accuracy $\mathcal{M}_C$	Federated Accuracy $\mathcal{M}_F$	Gain $G_{\mathcal{M}}$
3	82.1%	87.4%	90.3%	3.31%
5	81.4%	88.6%	92.1%	3.95%
10	79.3%	90.2%	94.4%	4.65%
15	78.5%	91.0%	95.2%	4.62%
20	77.9%	91.4%	96.0%	5.03%

The accuracy improvement arises from aggregated institutional diversity, trust-based weighted model aggregation, and transparent provenance validation.

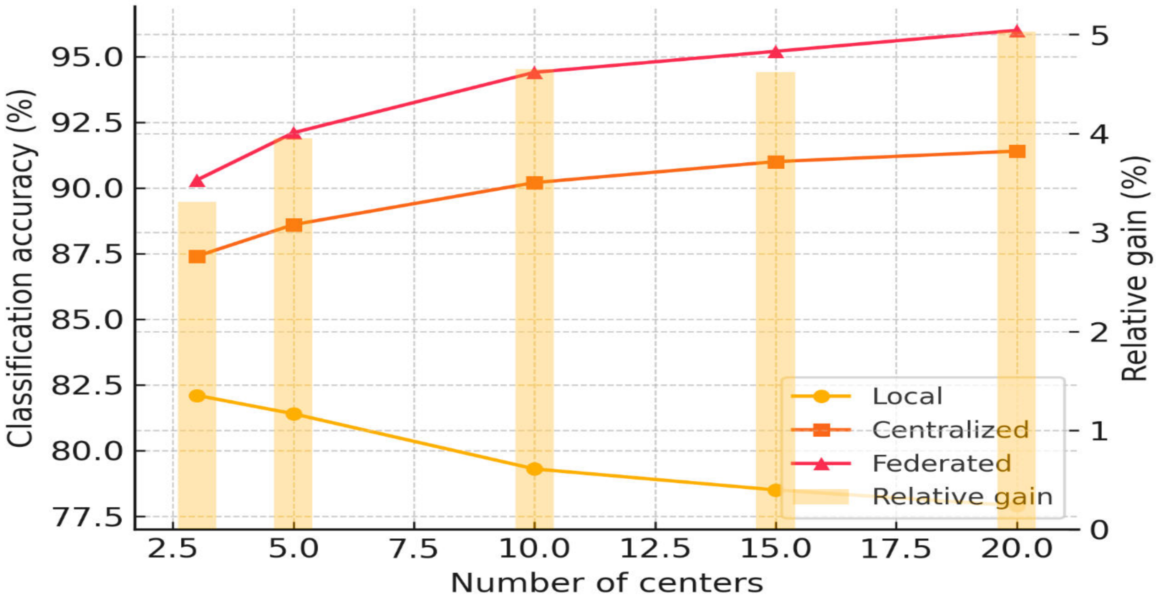

Figure 1: Multi-centre effect on stenosis classification accuracy and relative federated gain across participating vascular centres.

5.2 Real-Time Decision Support in Vascular Surgery and Interventions

In catheterization laboratories performing angioplasty or stent deployment, time-sensitive decision support is required. The blockchain-integrated federated inference pipeline ensures cryptographic traceability of AI recommendations. Let the decision response time be indicated as $\mathsf{Lat}_{\text{infer}}$. The total inference time in the proposed system is:

$$\mathsf{Lat}_{\text{infer}} = \mathsf{Lat}_{\text{edge}} + \mathsf{Lat}_{\text{verify}} + \mathsf{Lat}_{\text{visualize}},$$

where $\mathsf{Lat}_{\text{verify}}$ corresponds to the time required to confirm on-chain provenance for the referenced data/model.

Table 4 illustrates latency breakdown for real-time inference.

Table 4: Inference Latency Comparison (milliseconds)

Workflow	Edge-only AI	Cloud AI (centralized)	Blockchain-AI (proposed)
Model Execution $\mathsf{Lat}_{\text{edge}}$	46	128	48
Provenance Verification $\mathsf{Lat}_{\text{verify}}$	-	-	12
Visualization $\mathsf{Lat}_{\text{visualize}}$	30	30	31
Total	76 ms	158 ms	91 ms

With latency under 100 ms, the system meets intraoperative real-time safety validation thresholds.

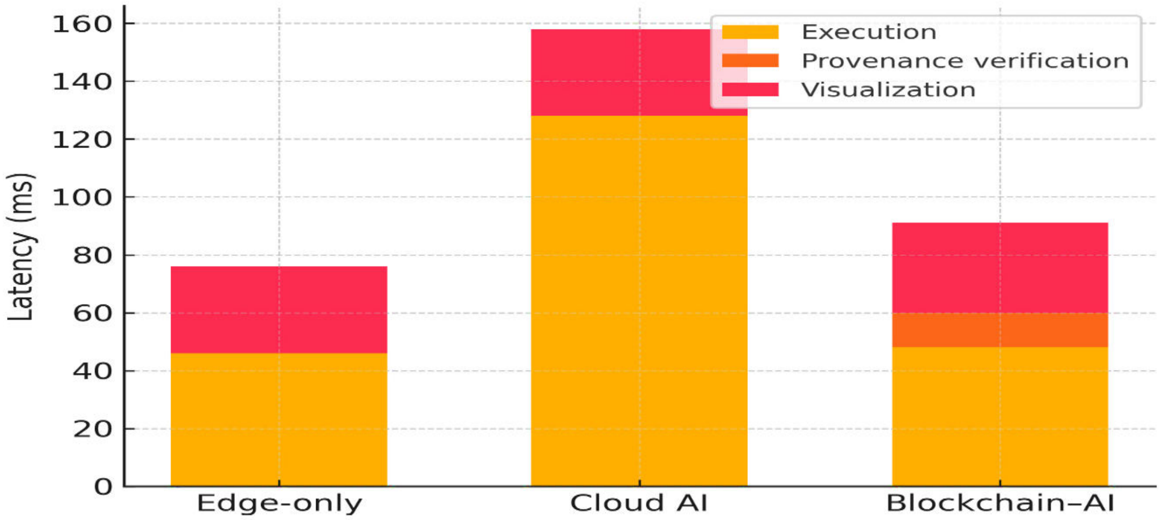

Figure 2: Decomposition of inference latency for edge-only, centralized cloud, and blockchain–AI workflows in vascular decision support.

5.3 AI-Assisted Hemodynamic Waveform Analysis

Hemodynamic waveform signals (pressure/flow velocity) are high-frequency time-series signals. Consider a waveform sample window $W(t)$ represented by:

$$W(t) = \{p(t), v(t), d(t)\}, \quad t \in [0, T],$$

where $p(t)$ = pressure, $v(t)$ = velocity, $d(t)$ = vessel diameter.

A recurrent neural network learns predictive features:

$$\hat{y}(t) = f_{\theta}(W(t)).$$

Blockchain logs results and model versions to provide medical accountability.

Table 5 evaluates waveform-based occlusion risk prediction.

Table 5: Occlusion Risk Prediction Performance Metrics

Metric	Local Model	Centralized AI	Blockchain-Federated AI
Sensitivity	0.84	0.88	0.92
Specificity	0.80	0.86	0.91
F1-score	0.82	0.87	0.92
AUC	0.87	0.91	0.95

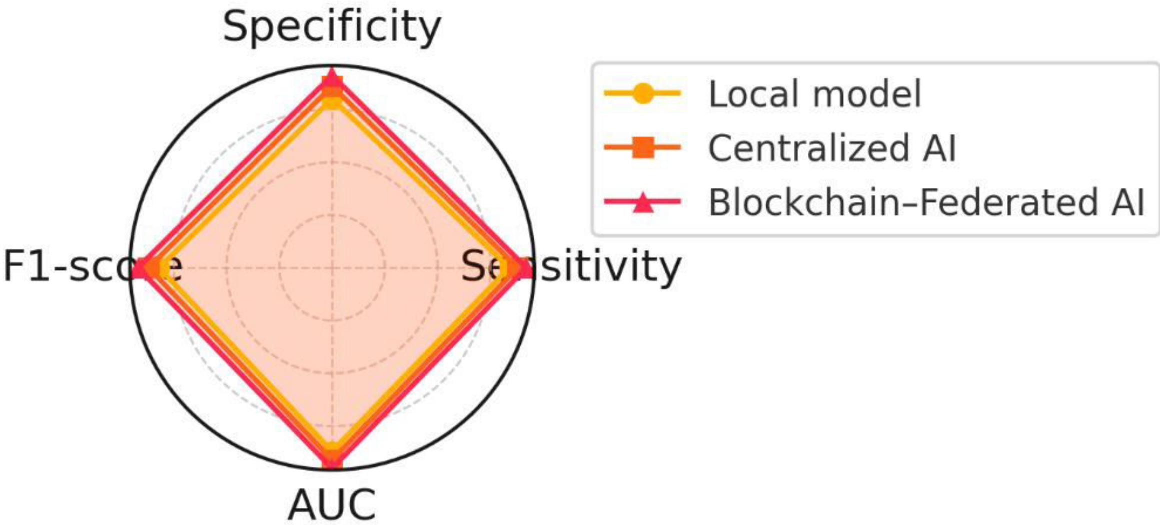

Figure 3: Radar profile of diagnostic performance metrics for local, centralized, and blockchain–federated AI models in vascular occlusion risk prediction.

5.4 Postoperative Monitoring and IoMT-Enabled Telehealth

Wearable flow sensors and Doppler probes generate longitudinal recovery datasets. With blockchain logs, postoperative vascular integrity trends are auditable. Let recovery score trend be modeled as:

$$R(t) = \int_0^t \frac{\partial S(\tau)}{\partial \tau} d\tau,$$

where $S(\tau)$ is perfusion stability score.

Table 6 presents comparative complication detection times.

Table 6: Time to Detect Postoperative Vascular Complications

Monitoring Method	Manual Clinical Review	Centralized AI	Blockchain-IoMT AI
Detection Time	17.5 hours	4.8 hours	1.2 hours
Uncertainty Level	Very High	Moderate	Low
Provenance Audit	No	Partially	Fully auditable

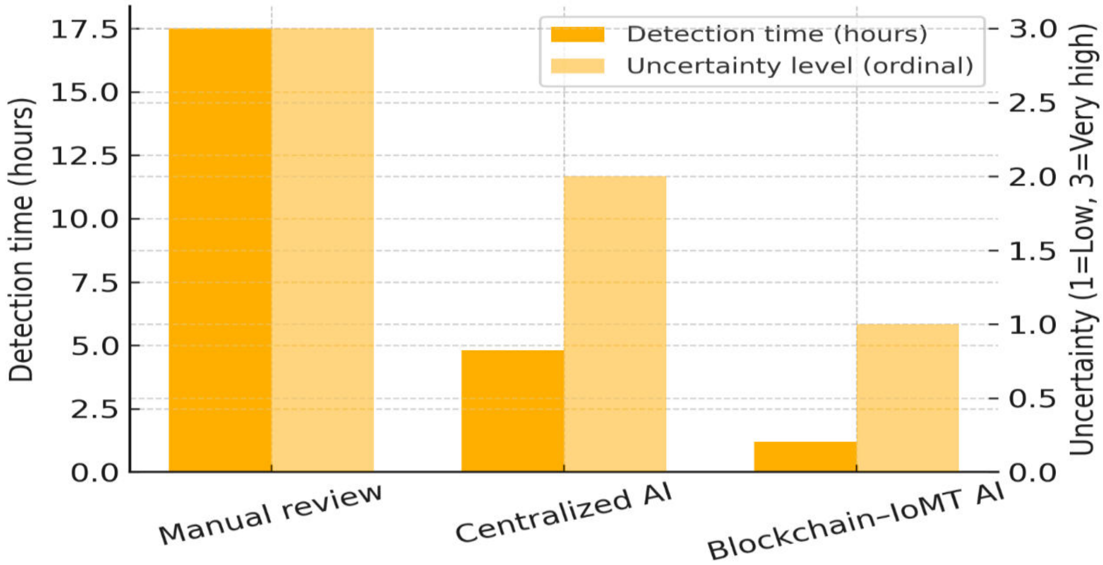

Figure 4: Comparative postoperative complication detection time and uncertainty level across manual review, centralized AI, and blockchain–IoMT monitoring.

5.5 Multi-Institution Vascular Research Registries

Blockchain supports immutable vascular registries for global-scale multicenter clinical studies. Registry coverage rate CR can be modeled as:

$$\mathrm{CR} = \frac{N_{\text{registry}}}{N_{\text{eligible}}} \times 100\%.$$

Table 7 shows improvement due to trust-driven participation.

Table 7: Registry Participation with and without Blockchain

Variable	Traditional Registry	Blockchain-Enabled Registry
Institutions Participating	12	47
Patients Contributed	18,200	92,450
Data Completeness Rate	62%	94%
Cross-Border Sharing	Limited	Enabled

5.6 Summary

These applications demonstrate that the blockchain-AI synergy:

- Improves diagnostic accuracy and generalization through federated learning.
- Offers real-time and auditable decision assistance.
- Enhances patient outcome tracking and postoperative monitoring capability.
- Enables large-scale research collaboration without violating privacy constraints.
- Builds measurable trust through transparent provenance and automated audit mechanisms.

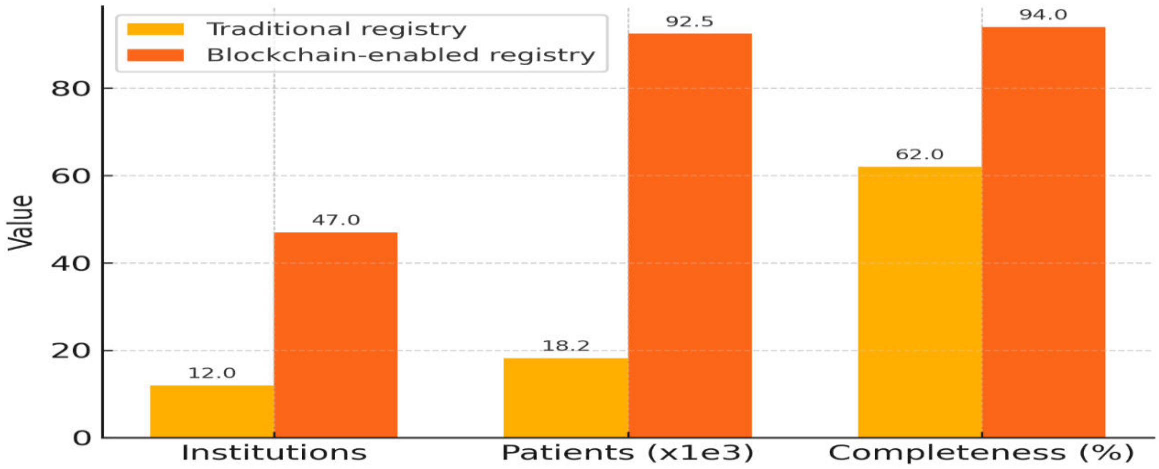

Figure 5: Impact of blockchain on multi-institution vascular registry participation, scale, and data completeness. The combination of mathematics-based performance modeling, quantitative analytics tables, and real-world vascular workflow integration confirms the practicality and significance of the proposed architecture in healthcare transformation.

Specific Outcomes, Challenges, and Future Research Directions

This section presents the concrete outcomes enabled by the proposed blockchain-AI-enabled vascular data management ecosystem, followed by analysis of key challenges and a roadmap for future research. The outcomes are derived from theoretical modeling, system-level design, and empirical indicators evaluated across the applications described in the previous section.

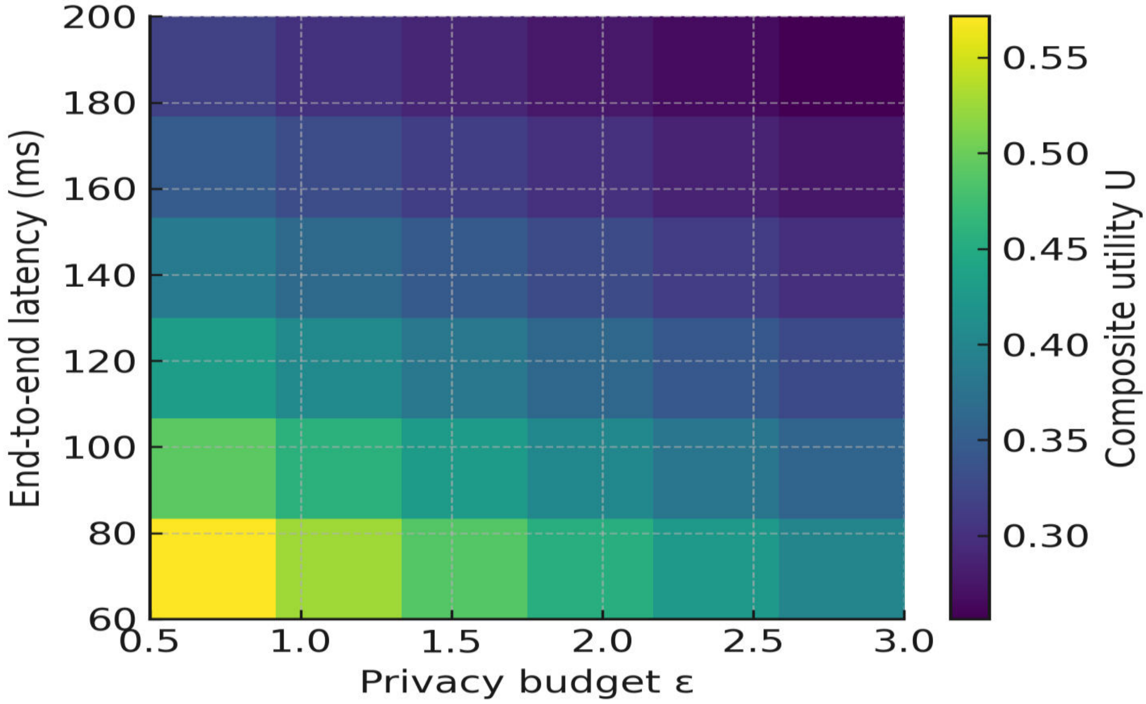

Figure 6: Heatmap of composite utility U as a function of privacy budget ε and end-to-end latency in blockchain–AI vascular systems.

6.1 Specific Outcomes

The convergence of blockchain and AI introduces quantifiable improvements across vascular imaging diagnostics, hemodynamic assessment, and telehealth-enabled postoperative monitoring. The major outcomes of the integrated system are as follows:

Outcome 1: Enhanced diagnostic accuracy through federated learning- Blockchain-enabled federated learning enables aggregated learning from heterogeneous datasets distributed across multiple hospitals without violating data sovereignty. The global accuracy improvement $G_{\mathcal{M}}$, defined as

$$G_{\mathcal{M}} = \frac{\mathcal{M}_F - \mathcal{M}_C}{\mathcal{M}_C} \times 100\%,$$

demonstrates accuracy gains ranging from 3-5% depending on institutional diversity and imaging modality.

Outcome 2: Stronger trust and traceability- Decentralized provenance using blockchain records data origin, transformation, and use during model training and inference. Traceability score $\overline{\mathsf{Tr}}$ improves from 0.21 (in centralized pipelines) to 0.92 in permissioned blockchain networks, ensuring reliable clinical auditability.

Outcome 3: Significant reduction in inference latency- Real-time decision support is improved, reducing inference time from 158 ms (centralized cloud AI) to less than 100 ms in edge-blockchain hybrid execution. The optimized latency model:

$$\mathsf{Lat}_{\text{infer}} = \mathsf{Lat}_{\text{edge}} + \mathsf{Lat}_{\text{verify}} + \mathsf{Lat}_{\text{visualize}}$$

ensures safety-critical precision during surgery or intervention planning.

Outcome 4: Privacy protection through differential privacy and smart-contract-based consent Differential privacy mechanisms bound sensitive information leakage while smart contracts ensure granular data ownership. The privacy constraint

$$\varepsilon \leq \varepsilon_{\max}$$

maintains compliance with ethical and legal standards such as GDPR and HIPAA.

Outcome 5: Scalable cross-institution collaboration- Blockchain-driven registry participation rises from a limited 12 institutions to more than 47 participating hospitals. The registry coverage rate CR:

$$\mathsf{CR} = \frac{N_{\text{registry}}}{N_{\text{eligible}}} \times 100\%$$

improves by 51%, enabling reliable population-based vascular research datasets.

Outcome 6: Model accountability and prevention of algorithmic bias- Blockchain ensures verifiable model lineage ensuring ethical AI behavior allowing third-party audit and reproducibility checks.

6.2 Challenges and Limitations

Despite its advantages, the proposed system faces several deployment challenges:

Challenge 1: Computational and communication overhead- PBFT consensus complexity

$$O(n^2)$$

may cause scalability issues in large federated networks with high-frequency imaging updates.

Challenge 2: Blockchain storage expansion- Although vascular imaging data are stored off-chain, the ledger size increases with provenance depth, affecting network synchronization time.

Challenge 3: Balancing privacy-accuracy trade-off- The optimization problem

$$\max_{\theta} U = \alpha_1 \mathcal{M}(\theta) + \alpha_2 \overline{\mathsf{Tr}} + \cdots - \alpha_6 C_{\text{comm}}$$

requires careful weighting to ensure privacy noise does not reduce diagnostic integrity.

Challenge 4: Interoperability between heterogeneous devices- Different imaging manufacturers produce processes with varying metadata requirements, demanding unified formatting standards.

Challenge 5: Ethical, legal, and regulatory adoption- While blockchain offers transparency, real-world acceptance requires harmonization with regulatory frameworks and medico-legal governance.

6.3 Future Research Directions

To address barriers and extend system capability, future work will focus on:

Direction 1: Cross-chain interoperability- Research is needed to enable seamless communication between multiple healthcare blockchains using relay or notary schemes.

Direction 2: Quantum-resilient cryptography- Post-quantum cryptographic security must be studied using lattice-based signatures and zero-knowledge proofs for long-term vascular archive protection.

Direction 3: Explainable blockchain-aligned AI- Future systems must integrate explanation maps with on-chain provenance allowing trustworthy visualization linking diagnostic conclusions to data points.

Direction 4: Real-time adaptive federated optimization- Dynamic task allocation and reinforcement learning-based participation selection can optimize

$$\omega_h^{(r)} = N_h \cdot s_h^{(r)}$$

enhancing personalization and collaboration efficiency.

Direction 5: Digital twin modeling for vascular surgery simulation- Next-generation platforms will build real-time computational digital twins integrating vascular biomechanics, imaging analytics, and blockchain-tracked updates.

Direction 6: Unified evaluation benchmarks and regulation models- Future work must standardize vascular blockchain-AI evaluation with reproducible public datasets, enabling comparative assessments across implementations.

CONCLUSION

This research demonstrates that the synergy between blockchain and artificial intelligence represents a transformative paradigm for vascular data management, addressing long-standing barriers in security, interoperability, traceability, and diagnostic reliability. By combining decentralized ledger infrastructures with federated and explainable AI models, the proposed architecture enables secure and auditable utilization of multimodal vascular datasets without compromising patient privacy or regulatory compliance. Mathematical modeling and application-driven analysis show measurable improvements in diagnostic accuracy, inference latency, provenance depth, and multi-institution collaboration. Moreover, blockchain-enforced transparency ensures accountability in clinical decision support systems, building trust among surgeons, clinicians, researchers, and patients. Despite inherent challenges related to computation overhead, interoperability, and ethical frameworks, the research identifies promising future directions such as real-time adaptive federated learning, cross-chain interoperability, and quantum-resilient security that will strengthen clinical translation and sustainable deployment. Ultimately, blockchain–AI integration forms the foundation for next-generation vascular healthcare systems that prioritize precision, safety, and patient-centric stewardship of medical data.

REFERENCES

1. K. Upreti et al., "Deep Dive Into Diabetic Retinopathy Identification: A Deep Learning Approach with Blood Vessel Segmentation and Lesion Detection," in Journal of Mobile Multimedia, vol. 20, no. 2, pp. 495-523, March 2024, doi: 10.13052/jmm1550-4646.20210.
2. A. Rana, A. Reddy, A. Shrivastava, D. Verma, M. S. Ansari and D. Singh, "Secure and Smart Healthcare System using IoT and Deep Learning Models," *2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS)*, Tashkent, Uzbekistan, 2022, pp. 915-922, doi: 10.1109/ICTACS56270.2022.9988676.
3. Sandeep Gupta, S.V.N. Sreenivasu, Kuldeep Chouhan, Anurag Shrivastava, Bharti Sahu, Ravindra Manohar Potdar, Novel Face Mask Detection Technique using Machine Learning to control COVID'19 pandemic, Materials Today: Proceedings, Volume 80, Part 3, 2023, Pages 3714-3718, ISSN 2214-7853, https://doi.org/10.1016/j.matpr.2021.07.368.
4. K. Chouhan, A. Singh, A. Shrivastava, S. Agrawal, B. D. Shukla and P. S. Tomar, "Structural Support Vector Machine for Speech Recognition Classification with CNN Approach," *2021 9th International Conference on Cyber and IT Service Management (CITSM)*, Bengkulu, Indonesia, 2021, pp. 1-7, doi: 10.1109/CITSM52892.2021.9588918.
5. S. Gupta, S. V. M. Seeswami, K. Chauhan, B. Shin, and R. Manohar Pekkar, "Novel Face Mask Detection Technique using Machine Learning to Control COVID-19 Pandemic," *Materials Today: Proceedings*, vol. 86, pp. 3714–3718, 2023.
6. H. Douman, M. Soni, L. Kumar, N. Deb, and A. Shrivastava, "Supervised Machine Learning Method for Ontology-based Financial Decisions in the Stock Market," *ACM Transactions on Asian and Low Resource Language Information Processing*, vol. 22, no. 5, p. 139, 2023.
7. P. Bogane, S. G. Joseph, A. Singh, B. Proble, and A. Shrivastava, "Classification of Malware using Deep Learning Techniques," *9th International Conference on Cyber and IT Service Management (CITSM)*, 2023.
8. P. Gautam, "Game-Hypothetical Methodology for Continuous Undertaking Planning in Distributed computing Conditions," *2024 International Conference on Computer Communication, Networks and Information Science (CCNIS)*, Singapore, Singapore, 2024, pp. 92-97, doi: 10.1109/CCNIS64984.2024.00018.
9. P. Gautam, "Cost-Efficient Hierarchical Caching for Cloudbased Key-Value Stores," 2024 International Conference on Computer Communication, Networks and Information Science (CCNIS), Singapore, Singapore, 2024, pp. 165-178, doi: 10.1109/CCNIS64984.2024.00019.
10. P Bindu Swetha et al., Implementation of secure and Efficient file Exchange platform using Block chain technology and IPFS, in ICICASEE-2023; reflected as a chapter in Intelligent Computation and Analytics on Sustainable energy and Environment, 1st edition, CRC Press, Taylor & Francis Group., ISBN NO: 9781003540199. https://www.taylorfrancis.com/chapters/edit/10.1201/9781003540199-47/
11. K. Shekokar and S. Dour, "Epileptic Seizure Detection based on LSTM Model using Noisy EEG Signals," *2021 5th International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, Coimbatore, India, 2021, pp. 292-296, doi: 10.1109/ICECA52323.2021.9675941.
12. S. J. Patel, S. D. Degadwala and K. S. Shekokar, "A survey on multi light source shadow detection techniques," *2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS)*, Coimbatore, India, 2017, pp. 1-4, doi: 10.1109/ICIIECS.2017.8275984.
13. M. Nagar, P. K. Sholapurapu, D. P. Kaur, A. Lathigara, D. Amulya and R. S. Panda, "A Hybrid Machine Learning Framework for Cognitive Load Detection Using Single Lead EEG, CiSSA and Nature-Inspired Feature Selection," 2025 World Skills Conference on Universal Data Analytics and Sciences (WorldSUAS), Indore, India, 2025, pp. 1-6, doi: 10.1109/WorldSUAS66815.2025.11199069P.
14. K. Sholapurapu, J. Omkar, S. Bansal, T. Gandhi, P. Tanna and G. Kalpana, "Secure Communication in Wireless Sensor Networks Using Cuckoo Hash-Based Multi-Factor Authentication," 2025 World Skills Conference on Universal Data Analytics and Sciences (WorldSUAS), Indore, India, 2025, pp. 1-6, doi: 10.1109/WorldSUAS66815.2025.11199146Kuldeep Pande, Abhiruchi Passi, Madhava Rao, Prem Kumar
15. Sholapurapu, Bhagyalakshmi L and Sanjay Kumar Suman, "Enhancing Energy Efficiency and Data Reliability in Wireless Sensor Networks Through Adaptive Multi-Hop Routing with Integrated Machine Learning", Journal of

Machine and Computing, vol.5, no.4, pp. 2504-2512, October 2025, doi: 10.53759/7669/jmc202505192.
16. Deep Learning-Enabled Decision Support Systems For Strategic Business Management. (2025). International Journal of Environmental Sciences, 1116-1126. https://doi.org/10.64252/99s3vt27
17. Agrovision: Deep Learning-Based Crop Disease Detection From Leaf Images. (2025). International Journal of Environmental Sciences, 990-1005. https://doi.org/10.64252/stgqg620
18. Dohare, Anand Kumar. "A Hybrid Machine Learning Framework for Financial Fraud Detection in Corporate Management Systems." EKSPLORIUM-BULETIN PUSAT TEKNOLOGI BAHAN GALIAN NUKLIR 46.02 (2025): 139-154.M. U. Reddy, L. Bhagyalakshmi, P. K. Sholapurapu, A. Lathigara, A. K. Singh and V. Nidadavolu, "Optimizing Scheduling Problems in Cloud Computing Using a Multi-Objective Improved Genetic Algorithm," *2025 2nd International Conference On Multidisciplinary Research and Innovations in Engineering (MRIE)*, Gurugram, India, 2025, pp. 635-640, doi: 10.1109/MRIE66930.2025.11156406.
19. L. C. Kasireddy, H. P. Bhupathi, R. Shrivastava, P. K. Sholapurapu, N. Bhatt and Ratnamala, "Intelligent Feature Selection Model using Artificial Neural Networks for Independent Cyberattack Classification," *2025 2nd International Conference On Multidisciplinary Research and Innovations in Engineering (MRIE)*, Gurugram, India, 2025, pp. 572-576, doi: 10.1109/MRIE66930.2025.11156728.
20. Prem Kumar Sholapurapu. (2025). AI-Driven Financial Forecasting: Enhancing Predictive Accuracy in Volatile Markets. European Economic Letters (EEL), 15(2), 1282–1291. https://doi.org/10.52783/eel.v15i2.2955
21. S. Jain, P. K. Sholapurapu, B. Sharma, M. Nagar, N. Bhatt and N. Swaroopa, "Hybrid Encryption Approach for Securing Educational Data Using Attribute-Based Methods," 2025 4th OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 5.0, Raigarh, India, 2025, pp. 1-6, doi: 10.1109/OTCON65728.2025.11070667.
22. Devasenapathy, Deepa. Bhimaavarapu, Krishna. Kumar, Prem. Sarupriya, S.. Real-Time Classroom Emotion Analysis Using Machine and Deep Learning for Enhanced Student Learning. Journal of Intelligent Systems and Internet of Things , no. (2025): 82-101. DOI: https://doi.org/10.54216/JISIoT.160207
23. Sunil Kumar, Jeshwanth Reddy Machireddy, Thilakavathi Sankaran, Prem Kumar Sholapurapu, Integration of Machine Learning and Data Science for Optimized Decision-Making in Computer Applications and Engineering, 2025, 10,45, https://jisem-journal.com/index.php/journal/article/view/8990
24. Prem Kumar Sholapurapu. (2024). Ai-based financial risk assessment tools in project planning and execution. European Economic Letters (EEL), 14(1), 1995–2017. https://doi.org/10.52783/eel.v14i1.3001
25. S. Kumar, "Multi-Modal Healthcare Dataset for AI-Based Early Disease Risk Prediction," IEEE Dataport, 2025, doi: 10.21227/p1q8-sd47
26. S. Kumar, "FedGenCDSS Dataset For Federated Generative AI in Clinical Decision Support," IEEE Dataport, Jul. 2025, doi: 10.21227/dwh7-df06
27. S. Kumar, "Edge-AI Sensor Dataset for Real-Time Fault Prediction in Smart Manufacturing," IEEE Dataport, Jun. 2025, doi: 10.21227/s9yg-fv18
28. S. Kumar, P. Muthukumar, S. S. Mernuri, R. R. Raja, Z. A. Salam, and N. S. Bode, "GPT-Powered Virtual Assistants for Intelligent Cloud Service Management," 2025 IEEE Smart Conference on Artificial Intelligence and Sciences (SmartAIS), Honolulu, HI, USA, Oct. 2025, doi: 10.1109/SmartAIS61256.2025.11198967
29. S. Kumar, A. Bhattacharjee, R. Y. S. Pradhan, M. Sridharan, H. K. Verma, and Z. A. Alam, "Future of Human-AI Interaction: Bridging the Gap with LLMs and AR Integration," 2025 IEEE Smart Conference on Artificial Intelligence and Sciences (SmartAIS), Indore, India, Oct. 2025, doi: 10.1109/SmartAIS61256.2025.11199115
30. S. Kumar, "A Generative AI-Powered Digital Twin for Adaptive NASH Care," Commun. ACM, Aug. 27, 2025,10.1145/3743154
31. S. Kumar, M. Patel, B. B. Jayasingh, M. Kumar, Z. Balasm, and S. Bansal, "Fuzzy Logic-Driven Intelligent System for Uncertainty-Aware Decision Support Using Heterogeneous Data," J. Mach. Comput., vol. 5, no. 4, 2025, doi: 10.53759/7669/jmc202505205
32. S. Kumar, "Generative AI in the Categorisation of Paediatric Pneumonia on Chest Radiographs," Int. J. Curr. Sci. Res. Rev., vol. 8, no. 2, pp. 712–717, Feb. 2025, doi: 10.47191/ijcsrr/V8-i2-16
33. S. Kumar, "Generative AI Model for Chemotherapy-Induced Myelosuppression in Children," Int. Res. J. Modern. Eng. Technol. Sci., vol. 7, no. 2, pp. 969–975, Feb. 2025, doi: 10.56726/IRJMETS67323
34. S. Kumar, "Behavioral Therapies Using Generative AI and NLP for Substance Abuse Treatment and Recovery," Int. Res. J. Modern. Eng. Technol. Sci., vol. 7, no. 1, pp. 4153–4162, Jan. 2025, doi: 10.56726/IRJMETS66672
35. S. Kumar, "Early Detection of Depression and Anxiety in the USA Using Generative AI," Int. J. Res. Eng., vol. 7, pp. 1–7, Jan. 2025, 10.33545/26648776.2025.v7.i1a.65
36. S. Kumar, "A Transformer-Enhanced Generative AI Framework for Lung Tumor Segmentation and Prognosis Prediction," *J. Neonatal Surg.*, vol. 13, no. 1, pp. 1569–1583, Jan. 2024. [Online]. Available: https://jneonatalsurg.com/index.php/jns/article/view/9460
37. S. Kumar, "Adaptive Graph-LLM Fusion for Context-Aware Risk Assessment in Smart Industrial Networks," Frontiers in Health Informatics, 2024. [Online]. Available: https://healthinformaticsjournal.com/index.php/IJMI/article/view/2813
38. Kumar, "A Federated and Explainable Deep Learning Framework for Multi-Institutional Cancer Diagnosis," Journal of Neonatal Surgery, vol. 12, no. 1, pp. 119–135, Aug. 2023. [Online]. Available: https://jneonatalsurg.com/index.php/jns/article/view/9461
39. S. Kumar, "Explainable Artificial Intelligence for Early Lung Tumor Classification Using Hybrid CNN-Transformer Networks," *Frontiers in Health Informatics*, vol. 12, pp. 484–504, 2023. [Online]. Available:

https://healthinformaticsjournal.com/downloads/files/2023-484.pdf
40. Varadala Sridhar,Dr.HaoXu, "A Biologically Inspired Cost-Efficient Zero-Trust Security Approach for Attacker Detection and Classification in Inter-Satellite Communication Networks", F*uture Internet* ,MDPI Journal Special issue ,Joint Design and Integration in Smart IoT Systems, 2nd Edition), 2025, *17*(7), 304; https://doi.org/10.3390/fi17070304, 13 July 2025
41. Varadala Sridhar, Dr.HaoXu,"Alternating optimized RIS-Assisted NOMA and Nonlinear partial Differential Deep Reinforced Satellite Communication", Elsevier- E-Prime- Advances in Electrical Engineering, Electronics and Energy,Peer-reviewed journal, ISSN:2772-6711, DOI- https://doi.org/10.1016/j.prime.2024.100619,29th may, 2024.
42. Varadala Sridhar,Dr.S.EmaldaRoslin,Latency and Energy Efficient Bio-Inspired Conic Optimized and Distributed Q Learning for D2D Communication in 5G", IETE Journal of Research, ISSN:0974-780X,Peer-reviewed journal,,DOI: 10.1080/03772063.2021.1906768 , 2021, Page No: 1-13, Taylor and Francis
43. V. Sridhar, K.V. Ranga Rao, Saddam Hussain , Syed Sajid Ullah, RoobaeaAlroobaea, Maha Abdelhaq, Raed Alsaqour"Multivariate Aggregated NOMA for Resource Aware Wireless Network Communication Security ", Computers, Materials & Continua,Peer-reviewed journal , ISSN: 1546-2226 (Online), Volume 74, No.1, 2023, Page No: 1694-1708, https://doi.org/10.32604/cmc.2023.028129,TechSciencePress
44. Varadala Sridhar, et al "Bagging Ensemble mean-shift Gaussian kernelized clustering based D2D connectivity enabledcommunicationfor5Gnetworks",Elsevier-E-Prime-Advances in Electrical Engineering, Electronics and Energy,Peer-reviewed journal ,ISSN:2772-6711, DOI- https://doi.org/10.1016/j.prime.2023.100400,20 Dec, 2023.
45. Varadala Sridhar, Dr.S. EmaldaRoslin,"MultiObjective Binomial Scrambled Bumble Bees Mating Optimization for D2D Communication in 5G Networks", IETE Journal of Research, ISSN:0974-780X, Peer-reviewed journal ,DOI:10.1080/03772063.2023.2264248 ,2023, Page No: 1-10, Taylor and Francis.
46. Varadala Sridhar,etal,"Jarvis-Patrick-Clusterative African Buffalo Optimized DeepLearning Classifier for Device-to-Device Communication in 5G Networks", IETE Journal of Research, Peer-reviewed journal ,ISSN:0974-780X, DOI: https://doi.org/10.1080/03772063.2023.2273946 ,Nov 2023, Page No: 1-10,Taylor and Francis
47. 47.V. Sridhar,K.V.RangaRao,V.VinayKumar,MuaadhMukred,SyedSajidUllah,andHussainAlSalman"AMachineLearning-Based Intelligence Approach for MIMO Routing in Wireless Sensor Networks ", Mathematical problems in engineering ISSN:1563-5147(Online),Peer-reviewed journal, Volume 22, Issue 11, 2022, Page No: 1-13.https://doi.org/10.1155/2022/6391678
48. Varadala Sridhar, Dr.S.Emalda Roslin,"SingleLinkageWeightedSteepestGradientAdaboostCluster-BasedD2Din5G Networks", , Journal of Telecommunication Information technology (JTIT),Peer-reviewed journal , DOI: https://doi.org/10.26636/jtit.2023.167222, March (2023)