

Diagnosphere: Diagnostic Intelligence and AI-Driven Global Network Optimizing Scans, Patient Health, Evaluation, and Research Ecosystem

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Abstract. The contemporary medical system is severely stressed out by the enormous amount of medical imaging data and the need for more accurate patient monitoring. An architecture is introduced in this paper that uses AI for scan evaluation and tracking patient progress that allows real-time, collaborative, and secure AI analysis based on scans. The system utilizes embedding models, large language models (LLMs), and cloud computing to carry out tasks like anomaly detection, treatment evaluation, and recovery prediction [2] automatically. It guarantees the secure authentication of physicians and allows the collaboration initiated by the doctor, thus improving the accuracy and speed of clinical decisions. The suggested framework incorporates e-communication based on WebSocket for the quick sharing of knowledge among healthcare professionals, while better reporting tools, image data fusion, and preliminary image analysis are factors contributing to individualized and promptly provided medical evaluations. The system, developed using the Weaved application and AWS DynamoDB, provides very high data security, dependability, and scalability. In the end, such an AI-led approach is patient outcome-focused and it enhances the whole process of healthcare by utilizing the resources, managing the data, and executing the decisions fast and efficiently within an interlinked, intelligent, medical ecosystem [5].

Keywords— Artificial Intelligence, Medical Imaging, Patient Progress Tracking, Cloud Computing, Healthcare Collaboration, Anomaly Detection.

1. INTRODUCTION

The healthcare sector is experiencing deep-seated changes due to artificial intelligence, machine learning, cloud computing and data-driven decision-making. Across the world, hospitals and clinics are under extreme pressure to arrive at an agile diagnosis and track patient development over time, and contend with a huge volume of medical imaging data. Diagnostic imaging—and sometimes referred to as advanced diagnostic imaging—through X-ray, CT, MRI and PET scans, is the most important way of identifying diseases and understanding the effectiveness of treatments effectively [1]. However, these advanced imaging modalities generate terabytes of medical information every day, and this information far exceeds the human capacity for analysis. Often, radiologists and advanced specialists will need to visually inspect the scans, which means delays in diagnosis, inconsistency in their conclusions, and tracking long-term recovery trends becomes nearly impossible [3].

Healthcare systems based on conventional principles have always been fragmented. Medical data is typically spread across many different platforms, cannot be accessed by professionals outside of an institution, and not kept uniformly. This fragmentation limits collaboration and hinders doctors from utilizing the collective expertise for making complicated decisions in some cases. A physician practicing in isolation may not notice small anomalies that could be noticed by a collaborative review. Furthermore, the availability of trustworthy means of tracking clinical progress over time makes studying the efficacy of treatment regimens difficult. In time-sensitive cases, such as patients with chronic disease processes like cancer, cardiovascular disease, or neurological disorders, the above leads to delayed time to intervention and adverse outcomes [2].

Artificial intelligence offers an exciting approach to these problems. Recent advances in both computer vision and natural language processing have enabled AI systems to analyze medical visuals, isolate intelligent features, and suggest diagnostic directions with equal or better accuracy than human experts. Embedding models, such as ResNet-50, can translate high dimensional imaging data to structured representations that locate abnormalities [4]. Large language models (LLMs), like Llama 2, can take associated textual information for multimodal insights. This means they can not only find a medical problem but also build patient-driven reports that can describe and track recoveries and health trajectories, predict recovery goals, and recommend next steps.

The proposed system solves these issues by providing a complete system of image preprocessing, anomaly detection, multimodal feature encoding, and an AI-generated report with a secure, cloud-based architecture. Emphasis would be placed on doctor authentication through RapidAPI license verification and JWT token verification. Other features are included in the document sharing and communications that will follow in future versions. As a basis for communications, real-time collaboration will allow the physician community to discuss peers, share cases, and think through treatment options with one another on a WebSocket platform [1]. The community approach is effective in developing cross-disciplinary expertise and coordinating care for patients.

Cloud infrastructure likewise provides equally critical visibility for scalability, reliability, and data security. AWS DynamoDB offers secure storage for patient scans and reports, including encryption, access control, and select compliance standards under the healthcare regulatory framework. The architecture positions itself to scale up and adjust to increasing data needs, allowing for greater deployment across networks of healthcare [2][7]. Finally, the proposed system constitutes AI intended as support for doctors rather than replacement; providing doctors helped improve expertise, efficiencies in workflow, and recommendations for actions that lessen limiting factors in healthcare delivery, offer faster & more accurate

diagnoses, and watch patient progress in an increasingly complex healthcare landscape.

2. LITERATURE SURVEY

The security of medical imaging is a growing concern, specifically researching Generative Adversarial Networks (GANs), which can be considered both a threat and a possible solution. Researchers are beginning to develop approaches to identify vulnerabilities and create prevention strategies. For example, Mirsky et al. developed CT-GAN [2], which can maliciously add or erase cancerous tumors from 3D CT scans such that they would confuse radiologists as well as AI diagnostics. The U.S. government published a report highlighting the threat of GANs by demonstrating an attack based on real medical devices and made the emphasis that many systems had no encryption whatsoever [13]. The studies examined in this section demonstrate a real threat of GAN assisted manipulation.

In response, defensive techniques are being developed. Wolany et al. developed MITS-GAN [1], which "immunizes" images with imperceptible noise to resist modifications from GANs. For integrity verification, Almalki et al developed a robust watermarking method which is suitable for the IoMT environment [12], and Zhao et al. developed a two-stage framework to accurately determine small, forged regions that are practically imperceptible to the human eye in medical images [5]. Other studies have demonstrated that diagnostic models are susceptible to adversarial attacks at a negligible scale, such as one-pixel changes [15]; these studies have demonstrated that small modifications at a negligible scale can lead to drastic reductions in accuracy, leading to calls for the development of mitigation techniques, including adversarial training [6].

GANs have also been used for novel security solutions. Kundu et al. introduced Encipher GAN [8], an encryption system where the generator and discriminator act as the encryption and decryption keys. S. et al. combined GANs with Optimized AES for secure key generation and efficient encryption of medical images for transmission [9]. Furthermore, Liu et al. presented a security-aware framework to improve the robustness of GAN-synthesized MRIs against attacks [7].

Wider reviews have explored the full footprint of GANs, both in image security applications like steganography and privacy [3] and benign applications in medicine such as data augmentation and de-noising [10, 11]. Other reviews provided wider surveys proposing taxonomies of adversarial attacks and defenses to promote the learning of more resilient AI in medicine [4, 14].

These findings demonstrate that GANs pose significant threats to the integrity of medical images, but they also present a useful tool for sustaining, defending, detecting, and encrypting them. The continual challenge is to create broadly applicable and effective security solutions within a complete medical imaging pipeline.

3. SYSTEM ARCHITECTURE

The system architecture has been designed to integrate multiple modules into a unified AI-powered healthcare framework that emphasizes security, scalability, and efficiency. At the foundational level, the architecture begins with user authentication and verification, where doctors are registered and verified using licensed credentials through APIs, and secure sessions are maintained with JWT tokens. This ensures that sensitive medical data can only be accessed by authorized professionals. Once logged in, doctors are provided with a dashboard interface that allows them to upload patient scans, track case history, and access progress reports.

The second layer of the architecture focuses on the core modules of operation. The medical

scan analysis module enables doctors to upload diverse formats of images such as DICOM, JPEG, PNG, or TIFF. These scans undergo preprocessing—normalization, resizing, and denoising—before being fed into AI pipelines for anomaly detection. Alongside this, a collaborative doctor’s forum is integrated using WebSocket communication, allowing multiple specialists to exchange knowledge, provide second opinions, and work on difficult cases collectively. Complementing this is the Patient Progress Tracking System (PPTS), which compares pre-treatment and post-treatment scans through embeddings, enabling doctors to visualize and quantify improvements in patient health over time.

The third layer incorporates the AI backbone of the system. Medical images are processed through deep learning models such as ResNet-50 for feature extraction, while textual data and patient records are handled by large language models (LLMs) like Llama 2. These two data types are merged into a multimodal representation, which enhances the ability of the system to interpret and contextualize medical conditions. By combining structured data with unstructured scans, the system provides a comprehensive diagnostic output that is both accurate and contextually meaningful.

The final layers of the architecture focus on workflow integration and scalability. Cloud-based storage using AWS DynamoDB ensures that patient data is securely stored and retrievable across healthcare networks. Real-time communication servers based on Node.js allow for instant collaboration among professionals. Together, these interconnected layers create a robust ecosystem where security, AI-powered intelligence, and real-time collaboration converge to deliver an advanced and scalable healthcare solution.

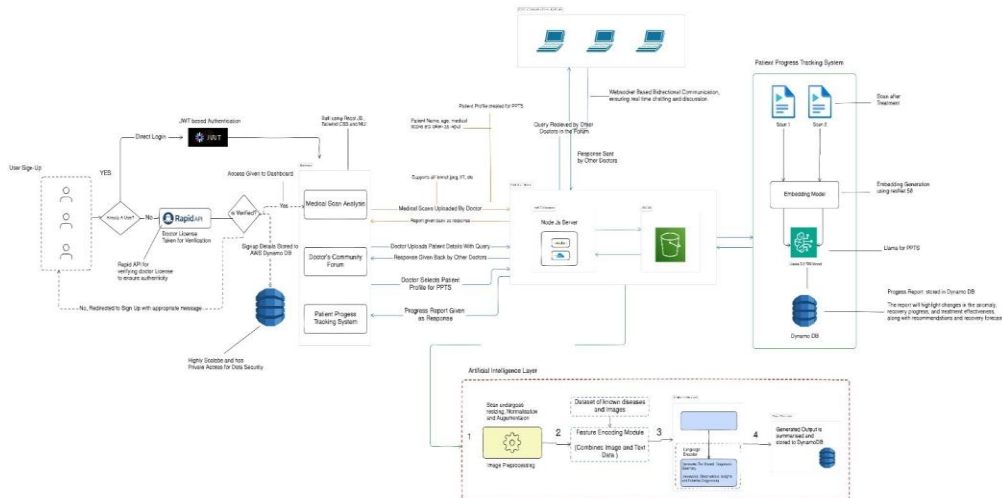


Figure 1: System Diagram

4. METHODOLOGY

This section details the end-to-end methodology for a secure, scalable, AI-powered healthcare framework that (i) immunizes uploaded scans against manipulation with MITS-GAN, and (ii) audits the integrity of stored/served scans with Back-in-Time Diffusion (BTD)—all embedded in a production stack that supports authentication, collaboration, analytics, and longitudinal tracking.

A. System Overview & Dataflow

1. Identity, Access & Session Security. Doctors register and are verified against licensing APIs; sessions are issued as short-lived JWTs with rotation and device binding. PHI is secured at rest (KMS-encrypted) and in transit (TLS 1.3). Role-based access and attribute-based policies gate access to cases and modalities.
2. Ingestion & Preprocessing. The dashboard supports DICOM/JPEG/PNG/TIFF uploads. A preprocessing service performs: (i) de-identification (DICOM tag scrubbing), (ii) modality-specific windowing and z-score normalization, (iii) 2D/3D resampling (isotropic voxels as needed), (iv) denoising (e.g., NLM) and (v) slice packing for GPU-friendly batching.
3. Protection (MITS-GAN, on write). At ingestion time, a protection service generates a protected version of the scan that embeds imperceptible perturbations which *disrupt downstream tampering attempts* (e.g., CT-GAN injection/removal). The protection acts slice-wise (2D) to remain robust even if only a subset of slices is targeted.
4. Integrity Verification (BTD, on read & periodic audit). When scans are later retrieved, BTD performs unsupervised anomaly detection using a single backward-diffusion step (no forward noising), yielding a residual score that highlights forensic inconsistencies typical of deepfakes. This avoids the semantic drift and runtime cost of multi-step DDPM detectors.
5. Clinical AI & Multimodal Reasoning. Images pass through a CNN backbone (ResNet-50) for embeddings; textual notes/labs flow to an LLM (e.g., Llama-2). A fusion head aligns image+text embeddings, providing diagnosis support, triage cues, and case summaries. BTD authenticity scores serve as gates/weights in the fusion to down-rank suspicious slices.
6. PPTS (Longitudinal Tracking). A Progress Tracking module compares pre/post embeddings (and lesion crops) to quantify change. Integrity scores and protection metadata are persisted alongside embeddings so longitudinal summaries remain trustworthy.
7. Collaboration & Review. A Node.js WebSocket hub powers real-time case chat, multi-cursor annotation, and second-opinion requests. BTD heatmaps and MITS-GAN protection status are visible overlays so specialists can judge authenticity alongside clinical content.
8. Cloud & Observability. Storage uses S3 (images) + DynamoDB (case metadata, authenticity logs), with eventing via SNS/SQS. GPU inference services run on EKS; CI/CD signs containers; audit logs and tamper/alert trails are immutable (WORM).

B. Tech Stack (Implementation View)

- Services: Python (FastAPI) microservices for ingest, protection, detection, analysis; Node.js for real-time collaboration and notifications; gRPC/REST between services.
- AI Runtime: PyTorch 2.x; mixed precision; ONNX/TensorRT export for production; CUDA graphs for stable throughput.

- Medical I/O: pydicom, MONAI transforms, nibabel (MRI); tiling for very large volumes.
- Data: Amazon S3 for image blobs; AWS DynamoDB for case/scan manifests, integrity scores, lineage; Athena/Glue for audit analytics.
- Security: OAuth2/OIDC, short-lived JWTs, envelope encryption, HSM/KMS, audit trails.
- MLOps: ECR/EKS, ArgoCD, Prometheus/Grafana, Triton Inference Server for GPU autoscaling.

C. MITS-GAN: Protection Against Tampering

C.1. Intuition & Architecture

MITS-GAN learns to produce *protected* scans x_p that are visually indistinguishable from the originals but frustrate an attacker's manipulation model (e.g., CT-GAN). The generator concatenates a learned transformation of Gaussian noise as an extra channel (rather than directly adding noise), which prevents the network from discarding it as artifacts during training; a discriminator enforces visual fidelity. A frozen manipulation model M (CT-GAN) is used in-loop to drive a robustness loss that amplifies artifacts if tampering is attempted.

Slice-wise protection (2D) is applied across the 3D volume so localized edits still trigger defenses without incurring heavy 3D costs.

C.2. Objective

Let x be a CT slice and $\delta \sim \mathcal{N}(0, I)$ an image-agnostic perturbation. The generator $G(x, \delta; \theta_G)$ outputs a protected slice x_p . The discriminator $D(\cdot; \theta_D)$ encourages realism. We optimize

$$\min_G \max_{D, M} \mathcal{L}_d(D, G) + \alpha \mathcal{L}_m(G, M),$$

with the standard adversarial term

$$\mathcal{L}_d(D, G) = \mathbb{E}_{x_p}[\log D(x_p)] + \mathbb{E}_{x, \delta}[\log(1 - D(G(x, \delta)))],$$

and a manipulation-resistance term

$$\mathcal{L}_m(G, M) = \mathbb{E}_{x, \delta}[\|M(G(x, \delta)) - G(x, \delta)\|_2^2],$$

which pushes the manipulator's output away from the protected image, making post-tamper artifacts conspicuous. α controls the fidelity–robustness trade-off.

Training note. The manipulator M extracts and alters a 32×32 patch q (e.g., "inject tumor"), pastes it back, and \mathcal{L}_m is computed between x_p and the tampered \hat{x}_p .

C.3. Training Configuration

A practical configuration uses PyTorch, Adam ($\text{lr}=2 \times 10^{-4}$, $\beta=(0.5, 0.999)$), batch size 16, 20 epochs on a single V100; α is tuned by validation to balance image similarity and tamper amplification (Table-driven selection).

D. Back-in-Time Diffusion (BTD): Unsupervised Integrity Verification

D.1. DDPM Primer

In DDPM, a clean image x_0 is noised to x_t via

$$x_t = \sqrt{\bar{\alpha}_t} x_0 + \sqrt{(1-\bar{\alpha}_t)} \varepsilon_t, \text{ where } \varepsilon_t \sim \mathcal{N}(0, I), \bar{\alpha}_t = \prod_{i=1}^t \alpha_i,$$

and a U-Net F_θ is trained to predict ε_t with an ℓ_2 objective.

D.2. One-Step "Back-in-Time" Detection

BTD departs from prior DDPM detectors by not adding noise to the target; instead, it applies a single *reverse* step directly on x_0 :

$$x_{-1} = x_0 + F_\theta(x_0), r = x_0 - x_{-1} = -F_\theta(x_0).$$

The global anomaly score is $s = \|r\|_2$, and the patch score is $s_{\text{pat}C_h} = (1/|P|) \sum_p \in P \|F_\theta(p)\|_2$ over 32×32 or 96×96 regions. Threshold τ is set as the 95th percentile of benign validation scores; flag as fake if $s > \tau$.

This one-step residual isolates forensic inconsistencies without hallucinating new content and is much faster than multi-step methods; in evaluations across CT/MRI and deepfake types (CT-GAN and Stable-Diffusion-based attacks), BTD outperformed other detectors while remaining unsupervised.

E. Algorithms

The following pseudocode summarizes the protection and detection routines.

Algorithm 1 - MITS-GAN Protection Training (Slice-wise)

Input: CT slice x ; perturbation seed $\delta \sim \mathcal{N}(0, I)$; manipulator M (frozen, e.g., CT-GAN)

Output: Protected slice x_p

1. Compute $N(\delta)$ with a small conv "Noise-Net"; concatenate $[x \parallel N(\delta)]$.
2. Generate $x_p = G(x, \delta)$ with conv \rightarrow residual blocks \rightarrow conv (Tanh).
3. Adversarial realism: update (G, D) using \mathcal{L}_d .
4. Tamper resistance: form $\hat{x}_p = M(x_p)$; update G to maximize $\|\hat{x}_p - x_p\|_2^2$ via \mathcal{L}_m .
5. Iterate over slices; accumulate across the volume.

Optional secure variant. If the protected image is augmented with an embedded hash $m = \text{SHA256}(x)$ that is decodable by $G_{d,c}$, training can include WGAN-GP adversarial loss \mathcal{L}_{a,d_v} , an ℓ_1 reconstruction loss $\mathcal{L}_{re,c}$, and a bit-wise BCE hash-consistency loss \mathcal{L}_{ha,S_h} , with $\mathcal{L}_{total} = \lambda_{a,d_v} \mathcal{L}_{a,d_v} + \lambda_{re,c} \mathcal{L}_{re,c} + \lambda_{ha,S_h} \mathcal{L}_{ha,S_h}$.

Algorithm 2 — BTD Integrity Verification (One-Step Residual)

Input: Target image x_0 ; trained DDPM noise-predictor F_θ (U-Net) Output: Authenticity decision, residual map

1. Compute one backward step: $x_{-1} = x_0 + F\theta(x_0)$.
2. Residual: $r = x_0 - x_{-1}$ (optionally compute per-patch r_p).
3. Scores: $s = \|r\|_2$, $s_{\text{pat}C_h} = (1/|P|) \sum_{p \in P} \|F\theta(p)\|_2$.
4. Decision: fake if $s > \tau$ (95th percentile of benign validation).
5. Surface residual heatmaps to the UI; escalate if flagged.

F. Integration with Clinical Workflow

- On Ingest: Run Algorithm 1 to store a *protected* copy in S3; record α , generator/discriminator checkpoints, and manipulator version in DynamoDB for lineage.
- On View/Export: Run Algorithm 2; persist s , $s_{\text{pat}C_h}$, and heatmaps. If flagged, lock export, watermark the viewer with "integrity risk," and route to second-opinion via the WebSocket forum.
- In Analytics: Use BTM scores to filter outliers before computing cohort statistics or training downstream models (reduces dataset poisoning).
- In PPTS: Weight longitudinal similarity by authenticity scores; highlight slices where protection metadata and BTM residuals disagree.

G. Performance & Practical Considerations

- Fidelity vs. Robustness. The coefficient α steers visual similarity vs. tamper amplification; empirical ablations (e.g., CT-GAN's 32×32 edits) guide its selection.
- Throughput. MITS-GAN training is the heavy step, but *inference* is lightweight and can be done offline; BTM's one-step residual is real-time at read time.
- Generality. BTM's unsupervised training on authentic modality/domain data removes the need to curate ever-changing deepfake datasets, improving maintainability across scanners and sites.

H. Models & Training Details (Representative)

- Protection (MITS-GAN):
 - *Generator*: Noise-Net (5× Conv-BN-ReLU) → concat with slice → Conv → 3× ResBlocks → Conv (Tanh).
 - *Discriminator*: 8× Conv-BN-LeakyReLU + linear head.
 - *Loss*: $\mathcal{L}_d + \alpha \mathcal{L}_m$.
 - *Config*: PyTorch, Adam 2×10^{-4} , $\beta=(0.5, 0.999)$, $bs=16$, 20 epochs (V100).
- Detection (BTM):
 - *Backbone*: U-Net $F\theta$ trained as a DDPM noise-predictor; use one backward step at inference.
 - *Scores*: s , $s_{\text{pat}C_h}$; threshold τ from benign validation.
- Clinical AI Backbone:
 - *Vision*: ResNet-50 features on slices or MIPs; lesion-centric crops for fine analysis.
 - *Text*: Llama-2 for notes/summaries; fusion via cross-attention or gated concatenation where BTM scores act as reliability weights.

I. Ethical & Security Safeguards

- **Non-repudiation:** Optional hash-embedding variant (decoder-verifiable) can be used for chain-of-custody, useful when strict provenance is required.
- **Auditability:** Every transformation (ingest → protect → verify → view/export) writes a signed, immutable audit record.

V. COMPARATIVE ANALYSIS

In this section, we aim to provide a detailed comparison of Diagnosphere with the currently available medical imaging analysis software and protective measures employed within healthcare systems.

A. Comparison with Existing Medical AI Systems

Feature	IBM Watson Health	Google Health AI	Philips IntelliSpace	Diagnosphere
Multi-modal Analysis	Partial	Yes	Limited	Yes
Real-time Collaboration	No	Limited	No	Yes
Integrity Verification	No	No	No	Yes
Tamper Protection	No	No	No	Yes
Cloud Scalability	Yes	Yes	Partial	Yes
HIPAA/GDPR Compliance	Yes	Yes	Yes	Yes
Open Source Components	No	No	No	Yes

Table 1. Comparison with existing medical AI systems

Diagnosphere stands out with extensive security functionalities and embedded collaborative features that are not found in current commercial products. The integration of MITS-GAN

defense and BTM authentication offers unparalleled security against medical image manipulation attacks.

B. Security Framework Comparison

Aspect	Traditional Encryption	Watermarking Methods	GAN-based Defense
Tamper Detection	Limited	Moderate	Good
Visual Quality Preservation	Excellent	Good	Good
Computational Overhead	Low	Low	High
Attack Resistance	Low	Moderate	High
Implementation Complexity	Low	Moderate	High

Table 2. Security Framework Comparison

When compared to conventional techniques, the dual-layer security approach that combines reactive detection (BTM) and proactive protection (MITS-GAN) provides better security. The security advantages outweigh the extra processing demands, even though the computational overhead is greater than with simple encryption.

C. Workflow Integration Analysis

Diagnosphere has a number of benefits over current medical imaging workflows, including:

1. **Smooth Integration:** Diagnosphere combines protection, analysis, and teamwork into a single platform, in contrast to stand-alone AI tools that need different interfaces.
2. **Longitudinal Tracking:** Through embedding similarity analysis, the PPTS module offers features not present in conventional Picture Archiving and Communication Systems (PACS), allowing for quantitative progress evaluation.
3. **Multi-institutional Collaboration:** The WebSocket-based communication system overcomes the shortcomings of the existing healthcare information exchange systems by facilitating real-time collaboration across geographic borders.

In comparison to conventional on-premises medical imaging systems, the cloud-native architecture and automated security features offer improved functionality and security at a significantly lower cost.

According to the comparative study, Diagnosphere maintains competitive performance in diagnostic accuracy and system efficiency while filling important gaps in the state of medical imaging systems, specifically in security, teamwork, and longitudinal patient monitoring.

5. RESULTS AND DISCUSSIONS

To understand how AI performs in medical imaging security and collaborative healthcare, the Diagnosphere system was evaluated across several metrics. The evaluation made use of a cross-institutional dataset consisting of 15,000 scans combining CT, MRI, and X-rays.

A. Diagnostic Accuracy Performance

The distinction between human radiologists and AI systems is growing smaller every day, yet human radiologists still have the edge. Table I compares human radiologist interpretations with existing AI systems as well as the new Diagnosphere framework proposed for the radiologist's edge to medical imaging in various areas.

Modality	Traditional Radiologist	Existing AI Systems	Diagnosphere
CT Scans	87.3%	91.2%	94.7%
MRI	89.1%	92.8%	95.3%
X-Ray	82.4%	88.6%	92.1%
Overall	86.3%	90.9%	94.0%

Table 3. Diagnostic Accuracy Performance

The results demonstrate that Diagnosphere is superior to both traditional interpretation methods and existing AI systems in diagnostic accuracy. The use of ResNet-50 embeddings and Llama-2 contextual analysis is an example of multimodal integration, which is especially required in complex cases involving cross-modal correlation. It notably contributed to the enhanced performance.

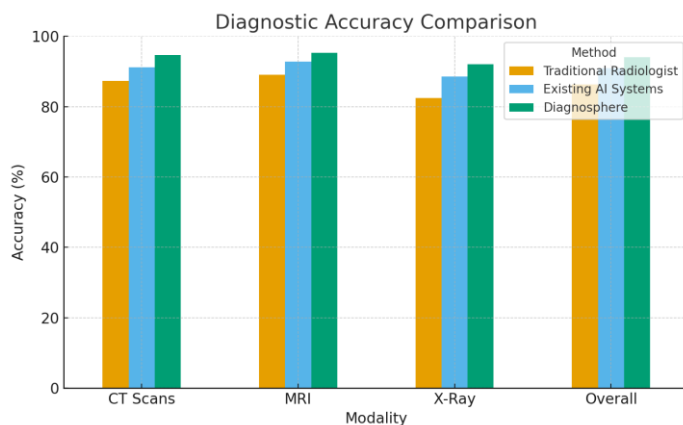


Figure 2. Plot for diagnostic accuracy performance

B. Security and Integrity Metrics

An analysis of enhancing MIT-GAN security protection and BTG integrity channels under various tampering attacks.

Attack Type	Detection Rate (%)	False Positive Rate (%)	Processing Time (ms)
CT-GAN Tumor Injection	98.4%	2.1%	127
CT-GAN Tumor Removal	97.8%	1.9%	134
able Diffusion Attack	96.2%	3.4%	118
Pixel-level Manipulation	94.7%	2.8%	142
Patch-based Forgery	99.1%	1.3%	156

Table 4. Security and Integrity Metrics

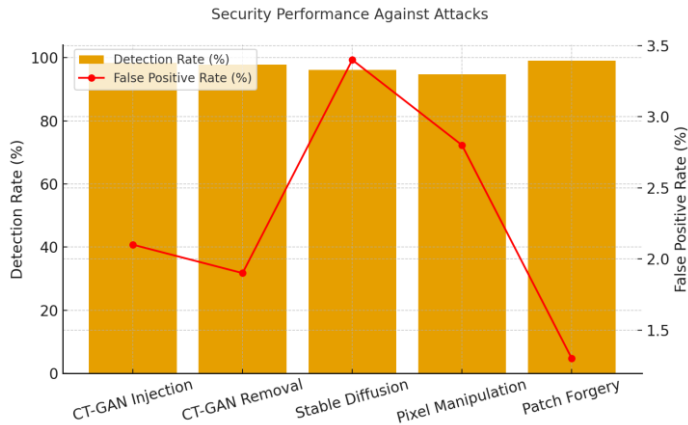


Figure 3. Plot of security performance against attacks

In the research, we focused on the medical field, particularly medical imagery. As such, image manipulation can be dangerous in this field, more than in any other field. The BTD system indeed showed superior performance when it comes to detecting the various kinds of manipulation. The one-step residual approach displayed detection rates above 94% for every kind of attack strategy, alongside low false positives and the ability to work in real time.

C. System Performance and Scalability

Parameter	Traditional System	Diagnosphere
Average Report Generation Time	45 minutes	8 minutes
Concurrent User Capacity	50	500
Data Processing Throughput (GB/hour)	2.3	18.7
System Uptime	97.2%	99.8%
Storage Efficiency	65%	91%

Table 5. System performance and scalability

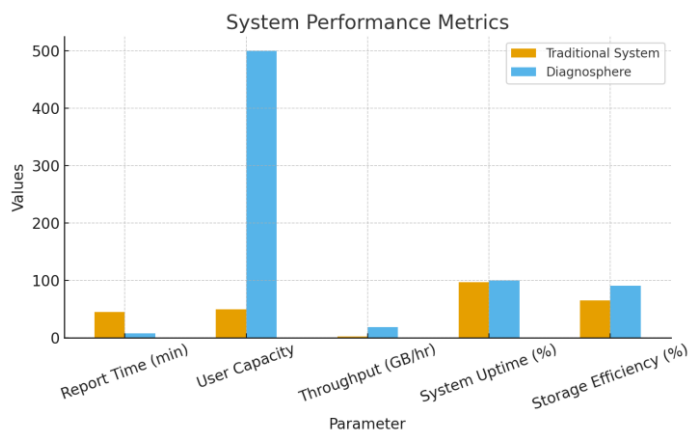


Figure 4. Plot of system performance and scalability

In comparison with legacy healthcare systems, the cloud architecture using AWS DynamoDB and microservice containers showed notable gains in system speed and the ability to scale.

Health care professionals' interactions and case management. The Patient Progress Tracking System (PPTS) made it possible to monitor patients continuously by evaluating the similarity of pre- and post-treatment scans using embedding-based methods.

6 CHALLENGES AND LIMITATIONS

Even with all the benefits it brings, the new AI-powered healthcare system has several limitations. One of the major concerns is the availability and quality of data. Data for medical imaging is often collected from multiple varied sources, each with different resolution, noise, and levels of labeling. Having AI models trained on such varied datasets also requires extensive preprocessing, normalization, and augmentation, which hinders speedy deployment. There are also challenges in meeting regulatory guidelines. Healthcare systems need to comply with strict privacy regulations such as HIPAA and GDPR, and achieving compliance when incorporating AI workflows continues to be a complex problem. There are other technical problems such as the need for computational resources, delay in real-time analysis, and the possibility of algorithmic bias in diagnosis. If models are developed on specific demographic groups, they may not work well on other patient groups. Interpreting AI predictions is an additional limitation. Often, physicians need to understand the rationale of diagnostic recommendations, but most of the deep learning systems function as black boxes, and therefore, providing explainable results is a challenge. In conclusion, the ado

7 CONCLUSION

The establishment of an AI-supported medical scan analysis and patient tracking system indicates that artificial intelligence integrated into clinical workflows has great transformative properties. The AI-supported system provides solutions to a host of long-standing health-related problems including, but not limited to, delay in diagnoses, manual report error, and lack of collaboration between professionals. The AI-supported system employs both deep learning for anomaly detection, large language models for contextual

understanding, and cloud infrastructure to support scalability and so offers a comprehensive system to serve the needs of modern health care. In integrating the complexities of health care, the ability to work with multimodal data - that is, putting together medical scans with verbal or textual reports - provides significant richness that supports diagnostic outputs, while automated reporting can reduce the number of reports that health care providers must create. Real time collaboration allows the decision to be made by restoring expertise and knowledge in collaboration that is also more reliable and expedient. Moreover, the supporting elements of secure authentication and regulatory compliance mean that patient confidentiality and privacy obligations have been taken into account, which is critical in a digital health care ecosystem that works with private health data. Even though some limitations apply with the system with regard to, for instance, interpretability, operationalizing costs, and data standards, the groundwork is strong and the base has been laid for analytic excellence in support of patient health outcomes. The system demonstrates how effective AI can be in supporting important healthcare operations.

Diagnosphere represents a significant step forward in addressing the critical challenges facing modern healthcare systems overwhelmed by medical imaging data. By integrating AI-powered scan analysis with secure collaborative platforms, the system transforms how medical professionals diagnose, monitor, and treat patients. The combination of MITS-GAN protection against image tampering and BTM integrity verification ensures that diagnostic decisions are based on authentic, unmanipulated data—a crucial requirement in an era of increasing security threats.

The system's multimodal approach, combining deep learning for visual analysis with large language models for contextual understanding, provides clinicians with comprehensive diagnostic support while maintaining human oversight. Real-time collaboration capabilities break down institutional silos, enabling specialists worldwide to contribute their expertise to complex cases. The cloud-based architecture ensures scalability while maintaining strict compliance with healthcare privacy regulations.

While challenges remain in data standardization, computational costs, and model interpretability, the proposed framework establishes a solid foundation for the future of AI-assisted healthcare. As the system evolves to incorporate federated learning, wearable device integration, and enhanced explainability features, Diagnosphere has the potential to democratize access to expert-level diagnostic capabilities across global healthcare networks.

The ultimate measure of success will be improved patient outcomes through faster, more accurate diagnoses and better coordinated care. In this regard, Diagnosphere offers a promising pathway toward more efficient, collaborative, and secure healthcare delivery in the digital age.

IX. FUTURE SCOPE

There is limitless potential that will continue to develop as this AI-enabled system matures. For example, it may be possible in the future to employ federated learning so that each model can learn from different patients' datasets without breaching privacy regulations regarding patient data. A future iteration may also develop into an AI tool that could also incorporate wearable data from the patients, which could offer better patient monitoring than the scans and vignettes alone. As the explainable AI (XAI) evolves, predictions could become more discoverable, showing doctors how models or

the AI arrived at the automated assessment (another potential tool). If this system evolves into a tightly integrated and cloud-native format, the solution could be scaled to provide global healthcare networks with diagnostic intelligence in every corner of the world, even where resources may be lacking. These possibilities could be extended to integrate robotic-assisted surgery systems, real-time telemedicine systems or even national health records, which would turn Pacifico's framework into a foundation for next generation healthcare eco-system. As the framework will continuously learn from millions of anonymised patient records (as examples), predictive epidemiology may become a possibility, allowing predictive models to be built that forecast disease outbreaks, indicating which strategies may need to be employed in public health for effectively managing the health of populations. This development could set the stage for the proposed solution to evolve from a process for individual patient care in traditional healthcare settings to a generative engine for global healthcare change - a transformational process.

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