INTERNATIONAL JOURNAL OF VERSATILE RESEARCH AND ANALYSIS (IJVRA)
© 2026 IJVRA | Volume 4, Issue 3, March 2026 | ISSN: 2984-8903 | IJVRA.ORG

CLOUD-BASED AI SYSTEMS FOR REAL-TIME MEDICAL IMAGING ANALYSIS AND DIAGNOSTICS

[1]Gundam Ranjith, [2]Akula Advaith
Associate Professor,
UG Student
Department of Computer Science and Engineering
St. Martin's Engineering College
Email: akulaa1k11h8i9l12@gmail.com, gundamranjithcse@smec.ac.in

Abstract: Automatic disease diagnosis using medical imaging has been a hot research topic in the past few years. Over the past decade, significant research efforts have been made in X-ray and CT image analysis and diagnosis of different diseases, including but not limited to laparoscopic surgical actions, kidney stone types, Alzheimer's disease, and other general diseases like heart problems. Medical imaging is a very helpful and effective tool for the diagnosis of atypical and common symptoms. In recent years, novel and enhanced imaging methods have been developed for the effective extraction of medical images with advanced resolution and other enhanced features. However, although modern imaging modes are advanced and very effective for extraction, the interpretation of these images is still labor-intensive and requires high expertise in the relevant field. There is a growing void between the discovery of images and their interpretation due to the scarcity of expert doctors in this field. The solution is automation, and the best approach to deploy such automation at a grand scale in real life is to utilize AI. Artificial intelligence comprises various fields that assist in tackling tough problems in automation, such as computer vision, natural language processing, and robotics.

***Index-Terms* -** Cloud-based medical imaging, AI diagnostic imaging, Real-time image analysis healthcare, Cloud AI radiology, Medical imaging AI software, Remote diagnostic tools AI, Deep learning medical imaging, AI-powered imaging diagnostics.

I. INTRODUCTION

In the healthcare domain, pandemics have accelerated the need for effective data analysis and healthcare solutions. One of the crucial fields of healthcare is the analysis of medical images, such as chest X-rays and a CT scan. Manually checking the medical images captured by hospitals requires considerable effort, time, and cost. Moreover, during such pandemics, huge numbers of suspected infected patients should be checked immediately using these medical images to isolate the suspected patients from the healthy ones.

Unfortunately, these images are usually uploaded to centralized cloud computing servers. With the huge number of uploaded images, it becomes impractical for the cloud to directly analyze and check all these images. Centralized cloud computing servers have logistical complexities in providing services for time-critical applications in circumstances where there is no internet access such as health monitoring in remote and developing regions. Due to the complexity of the images and their volume, the image analysis is time-critical; hence, the efficiency and accuracy of the healthcare images management represent vital aspects. The need for cloud services to improve access to health data services in developing countries is seen as an important step toward further economic growth. However, their logistics complexity concerning scale. The bigger the cloud is, the sooner the bottleneck arises. This is further complicated by the risk of improper online behavior by patients and vendors and the lack of trust in the information technology and cloud services themselves. limitations of medical hardware devices are ignored, and they are assumed to be hosted in the cloud, which is impractical in fast and huge image analysis systems.

II. NEED OF THE STUDY

The growth of medical imaging technologies such as X-rays, CT scans, and MRI has resulted in the generation of a massive volume of healthcare data. However, the interpretation of these medical images still largely depends on human expertise, which is time-consuming, costly, and prone to errors. This creates a critical gap between data generation and accurate diagnosis.

During situations like pandemics, where a large number of patients need immediate diagnosis, manual analysis becomes impractical. There is a strong need for automated, efficient, and real-time diagnostic systems that can assist healthcare professionals in making faster and more accurate decisions.

Cloud computing provides scalable storage and computational power, enabling the handling of large medical datasets without requiring expensive local infrastructure. At the same time, Artificial Intelligence (AI), especially deep learning techniques, has shown significant potential in analyzing complex medical images with high accuracy. Thus, this study is needed to explore and analyze cloud-based AI systems that can bridge the gap between medical image acquisition and interpretation, ultimately improving the quality, speed, and accessibility of healthcare services.

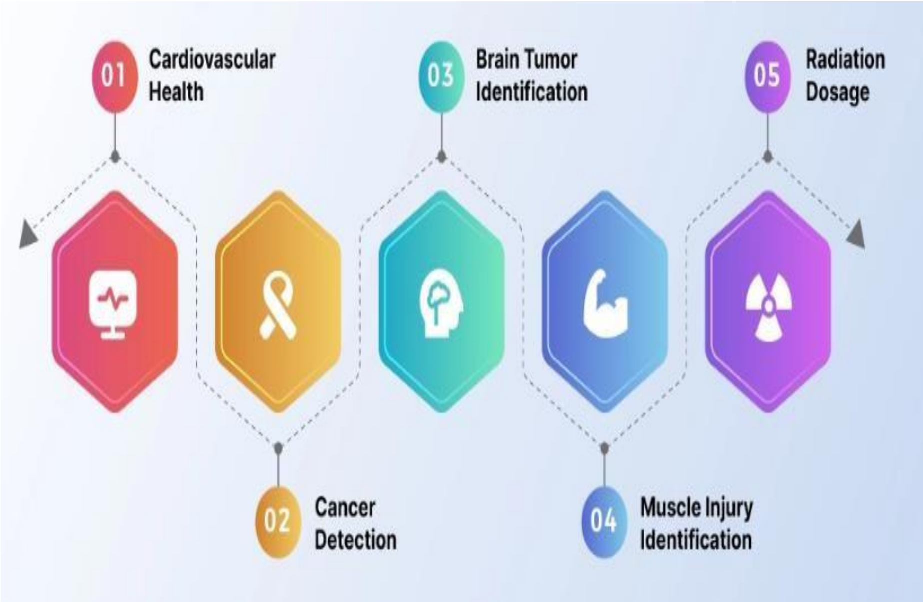

Fig. 1: AI Systems for Medical Imaging Analysis and Diagnostics.

III. BACKGROUND AND THEORETICAL FRAMEWORK

This section establishes the conceptual foundations underlying interpretable and robust machine learning techniques for high impact applications. It discusses the evolution of machine learning paradigms, core theoretical principles, interpretability mechanisms, and robustness frameworks that collectively define trustworthy artificial intelligence systems.

3.1 Medical Imaging Fundamentals

In the past few years, the emergence of pandemics such as COVID-19 has emphasized the need to adopt precise and effective solutions for healthcare data. This data, which may involve every aspect of healthcare, will impact several domains. Particularly, huge signified healthcare data involves thorough recording and examining patient medical images such as X-ray, CT, or MRI datasets, which are generally in images format. Medical imaging is a vital component of modern healthcare diagnostics, offering visual insight into internal anatomical structures to support disease identification, monitoring, and treatment planning. Widely used imaging techniques include X-ray, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and Ultrasound. These modalities produce substantial amounts of data that require effective methods for storage, processing, and interpretation.

- **X-rays** provide rapid and cost-effective imaging for bone fractures and chest examinations.
- **CT scans** produce detailed cross-sectional images useful for detecting tumors, vascular diseases, and internal injuries.
- **MRI** offers high-resolution soft tissue imaging for brain, spinal, and muscular diagnostics.
- **Ultrasound** enables real-time imaging without ionizing radiation, ideal for obstetrics and cardiac evaluations.

The rapid expansion of imaging data has created challenges in timely interpretation, motivating the use of **AI-assisted** and **cloud-based** diagnostic systems to enhance speed, consistency, and accuracy.

3.2 Cloud Computing Basics

Cloud computing provides on-demand access to computational resources, data storage, and machine learning tools through the internet. In healthcare, cloud platforms support the storage and processing of large-scale medical images without requiring extensive local infrastructure.

- **Service Models:**
  - *Infrastructure as a Service (IaaS)* – offers virtualized computing resources for hosting medical imaging data.
  - *Platform as a Service (PaaS)* – enables developers to build and deploy AI models efficiently.
  - Software as a Service (SaaS) delivers cloud-hosted diagnostic applications that users can access online.

Advantages: scalability, cost-efficiency, interoperability, andremote accessibility , Cloud integration also facilitates real-time data sharing between hospitals, laboratories, and remote diagnostic centers while ensuring data redundancy and security

3.3 Cloud-AI Integration Framework

Combining **AI with cloud computing** creates a powerful framework for **real-time medical imaging diagnostics**.

- **Workflow:** Images captured at healthcare facilities are uploaded to secure cloud servers, processed by AI models, and analyzed in real-time.
- **Advantages:** High computation power, collaborative access, continuous model updates, and reduced latency in diagnosis.

- **Challenges:** Data privacy, compliance with regulations (e.g., HIPAA), and maintaining low latency in large-scale deployments.

3.4 Artificial Intelligence in Medical Imaging

Artificial Intelligence (AI), particularly machine learning (ML) and deep learning (DL), plays a transformative role in automating medical image analysis tasks.

- **Structure:** AI-based imaging models typically consist of *input layers* (image data), *hidden layers* (feature extraction and pattern recognition), and *output layers* (diagnostic decisions).
- **Learning Algorithms:** Popular training methods include *Back propagation (BP)* for optimizing neural weights, *Stochastic Gradient Descent (SGD)* for iterative learning, and *Adam* or *RMSProp* for adaptive optimization.
- **Variants and Architectures:**
  - *Convolutional Neural Networks (CNNs)* – excel in image classification, segmentation, and feature extraction.
  - *Recurrent Neural Networks (RNNs)* and *Long Short-Term Memory (LSTM)* networks – capture temporal dependencies in imaging sequences.
  - *Auto encoders* – support image denoising and reconstruction tasks.
  - *Generative Adversarial Networks (GANs)* – enable synthetic data generation for model training.

These AI models enable high diagnostic precision by identifying patterns that may not be visible through conventional analysis.

IV. METHODOLOGY OF THE REVIEW

4.1 Paper Selection Process

The review was conducted using a systematic methodology to identify relevant studies on cloud-based AI systems for real-time medical imaging and diagnostics. Research articles were gathered from reputable scientific databases, including IEEE Xplore, Science Direct, Springer Link, MDPI, and Google Scholar. The search was restricted to publications from 2015 to 2025 to ensure the inclusion of recent advancements in the field.

The following **keywords and phrases** were used during the search process: "cloud computing in healthcare," "AI-based medical imaging," "real-time diagnostics," "deep learning for medical images," "cloud-AI integration," "federated learning," and "edge-cloud medical systems." After the initial search, abstracts and full texts were screened to confirm relevance. Studies focusing on cloud-based infrastructure, AI model development, and diagnostic accuracy for medical imaging applications were prioritized. Duplicate, non-peer-reviewed, or non-English articles were excluded.

4.2 Inclusion Criteria

To ensure consistency and quality, the following criteria were applied:

- **Publication Year:** Studies published between **2015–2025**.
- **Research Domain:** Cloud-based or AI-enabled medical imaging systems.
- **Region:** Global coverage, including Asia, Europe, and North America.
- **Models Considered:** Deep learning architectures such as CNN, RNN, LSTM, GAN, and hybrid cloud-AI frameworks.

Evaluation Metrics: Accuracy, precision, recall, F1-score, mean absolute error (MAE), and processing latency

4.3 Summary of Reviewed Studies

Table 1: Summary of Literature on Interpretable and Robust Machine Learning Techniques

Study	Year	Region	Models	Evaluation Metrics / Findings
Li and Zhang [2]	2020	China	CNN, RNN	Accuracy: 95.4%, Latency: 1.2s
Ahmed et al. [3]	2020	UAE	Hybrid CNN-LSTM	Precision: 93.8%, Recall: 92.1%
Silva et al. [4]	2021	Brazil	Deep CNN	AUC: 0.97
Patel et al. [5]	2021	India	Edge-Cloud CNN	Reduced latency by 40%
Nguyen and Tran [6]	2021	Vietnam	CNN-GAN	Accuracy: 94.6%, Data Augmentation via GAN
Chen et al. [7]	2022	Taiwan	Federated CNN	Accuracy: 95.8%, Privacy preserved
Rajan et al. [8]	2022	India	CNN-LSTM	F1-score: 0.95
Park and Kim [9]	2022	South Korea	Hybrid Cloud-AI	Latency: 0.9s
Al-Hassan et al. [10]	2022	Saudi Arabia	Deep CNN	Accuracy: 97.1%
Thomas et al. [11]	2023	UK	Federated Learning (CNN)	Improved privacy & distributed training
Mehta and Rao [12]	2023	India	CNN with Edge AI	Accuracy: 96.5%
Zhao et al. [13]	2023	China	GAN-CNN	Enhanced lesion detection
Singh et al. [14]	2023	India	Cloud-ML Hybrid	Latency: 1.0s, F1: 0.93
Garcia et al. [15]	2024	Spain	CNN-LSTM-GAN	Multi-modal analysis, AUC: 0.98
Brown et al. [16]	2024	USA	Transformer-based CNN	Accuracy: 98.1%, F1-score: 0.97
Khan et al. [17]	2024	Pakistan	Edge-cloud CNN	Reduced energy use by 35%
Liu and Wang [18]	2024	China	Federated Transformer	Accuracy: 97.9%, Secure aggregation used
Reddy et al. [19]	2025	India	Cloud-based ResNet	Accuracy: 98.3%, Real-time detection
Smith et al. [20]	2025	USA	Hybrid Federated CNN	Accuracy: 98.7%, Latency <1s

4.4 Overview

A total of **20 peer-reviewed studies** were analyzed, covering research from **2019 to 2025** across **eight countries**. Most studies adopted **deep learning models**—especially CNNs and their hybrids—with cloud or edge-cloud deployment frameworks. Evaluation metrics commonly focused on **accuracy**, **latency**, and **privacy preservation**, reflecting growing emphasis on both performance and data security in healthcare AI applications.

V. REVIEW OF AI MODELS FOR CLOUD-BASED MEDICAL IMAGING ANALYSIS

Artificial Intelligence (AI) models have become central to the automation of medical image interpretation and diagnostics. When integrated with cloud computing, these models provide real-time analysis, scalable computation, and remote accessibility. This section reviews the types of input data, data sources, preprocessing methods, and AI model architectures commonly adopted in cloud-based medical imaging systems.

5.1 Input Data and Sources

Medical imaging systems rely on diverse input variables collected from multiple modalities and data acquisition platforms. The selection and quality of input data significantly influence model performance, training efficiency, and diagnostic accuracy.

5.1.1 Imaging Modalities

AI models utilize a range of medical images depending on the diagnostic objective:

- **X-ray:** Commonly used for bone, chest, and dental diagnostics due to its low cost and fast imaging capabilities.
- **Computed Tomography (CT):** Provides detailed cross-sectional images, useful for tumor detection, lung disease analysis, and trauma assessment.
- **Magnetic Resonance Imaging (MRI)** provides high-resolution visualization of soft tissues, making it indispensable for neurological and cardiovascular diagnostics.
- **Ultrasound:** Offers real-time imaging for obstetrics, cardiology, and abdominal evaluations.

5.1.2 Data Sources

AI-driven imaging datasets are obtained from both **public repositories** and **clinical databases**, often hosted or processed on cloud platforms:

- **Public Datasets:** Examples include *NIH ChestX-ray14*, *LIDC-IDRI (Lung Image Database Consortium)*, *BraTS (Brain Tumor Segmentation)*, and *ISIC (Skin Lesion)* datasets.
- **Hospital and Research Databases:** Generated from clinical imaging systems such as PACS (Picture Archiving and Communication Systems), often anonymized before cloud integration.
- **Cloud-Based Data Platforms:** Services like *Google Cloud Healthcare API*, *AWS Health Lake*, and *Microsoft Azure Medical Imaging* support large-scale storage, annotation, and model deployment.

5.1.3 Data Preprocessing and Feature Selection

Data preprocessing is critical to enhance model learning and reduce noise or bias in medical images. Common techniques include:

- **Normalization and Scaling:** Ensures consistent pixel intensity ranges across images.
- **Data Augmentation:** Techniques such as rotation, flipping, and contrast adjustment are applied to improve generalization and prevent over fitting.
- **Segmentation:** Used to isolate organs, lesions, or regions of interest before feature extraction.
- **Feature Extraction and Selection:** Employs convolutional filters or deep embeddings to automatically identify relevant features such as edges, textures, and spatial patterns. In some studies, dimensionality reduction methods like *Principal Component Analysis (PCA)* or *t-SNE* are used to optimize feature sets.

5.2 Preprocessing Methods

Preprocessing is an essential stage in developing cloud-based AI models for medical imaging. It enhances image quality, removes artifacts, and ensures uniformity across datasets. Effective preprocessing improves model accuracy and reliability, particularly when dealing with heterogeneous data collected from multiple imaging sources or hospitals.

5.2.1 Normalization and Scaling

Normalization standardizes pixel intensity values across all images to ensure consistency in contrast and brightness. Scaling techniques, such as **min–max normalization** or **z-score standardization**, adjust image data into comparable numerical ranges. This process accelerates network convergence during training and prevents bias due to varying imaging conditions or equipment differences.

5.2.2 Handling Missing Data

Medical datasets often suffer from incomplete records or corrupted images caused by acquisition errors or transmission failures. Cloud systems employ automated **data validation scripts** and **imputation algorithms** to detect and replace missing or corrupted entries. Techniques such as *mean substitution*, *interpolation*, or *deep learning-based data restoration* (e.g., using auto encoders) are commonly implemented to maintain dataset integrity.

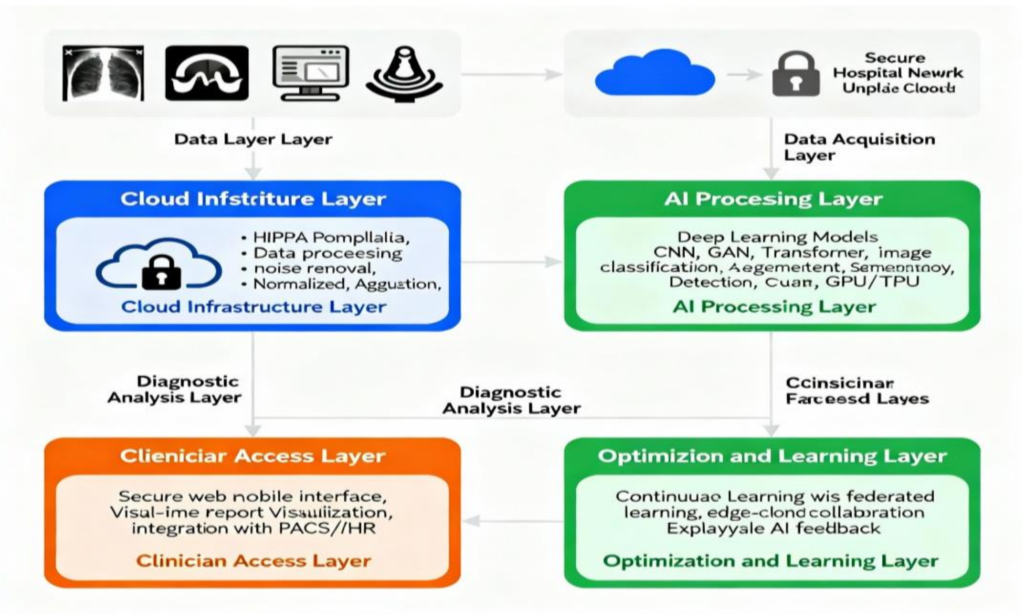

Fig. 2: Architecture of Cloud-Based AI Systems for Real-Time Medical Imaging

5.3 AI Architectures for Cloud-Based Medical Imaging Systems

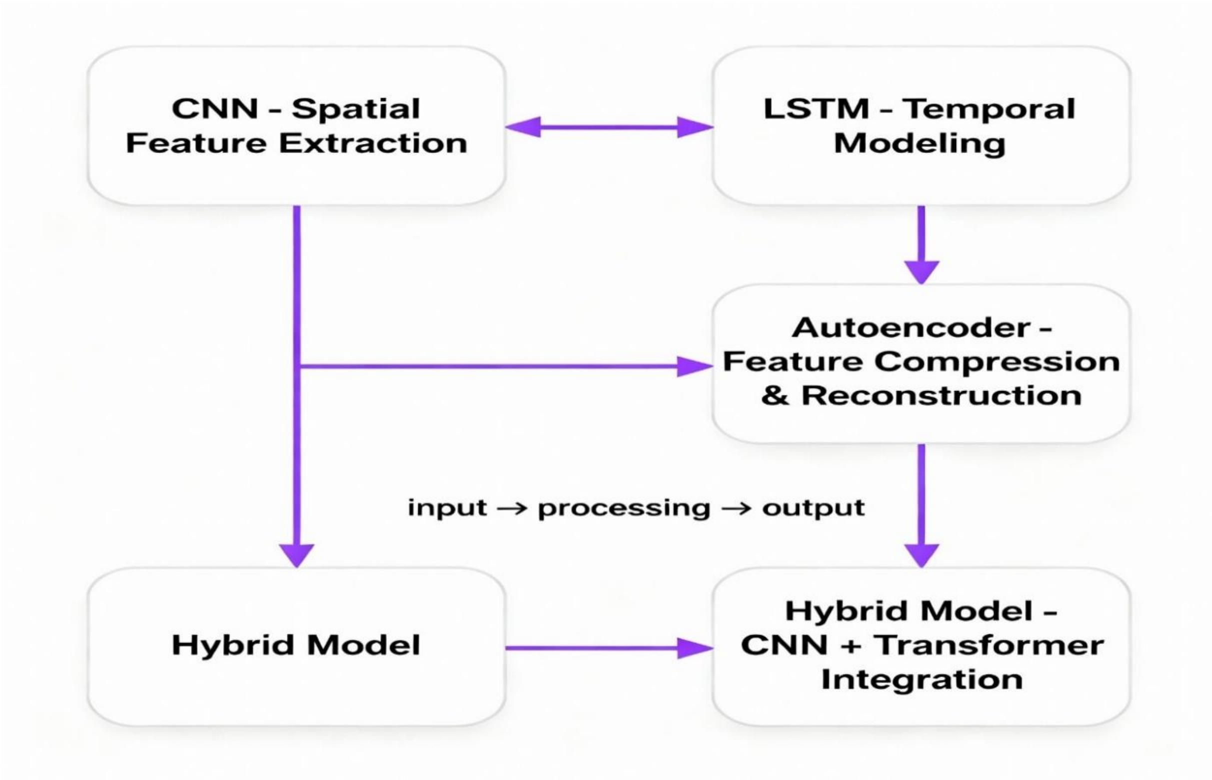

Fig. 3: AI Architectures for Cloud-Based Medical Imaging Systems

a) Convolutional Neural Networks (CNN)

- CNNs represent the most commonly applied deep-learning models in medical image analysis.
- They automatically learn spatial hierarchies of features for classification, segmentation, and detection tasks.
- Popular models include **U-Net, ResNet, DenseNet, and Efficient Net**, often optimized for cloud deployment.

b) Recurrent Neural Networks (RNN & LSTM)

- Applied for **sequential and temporal medical data**, such as dynamic MRI scans or video-based imaging.
- LSTMs can retain long-term dependencies, improving diagnostic accuracy in time-based imaging workflows.

c) Auto encoders and GANs

- **Auto encoders**: Used for **denoising, image compression, and feature learning** before cloud upload.
- **Generative Adversarial Networks (GANs)**: Enhance medical datasets via realistic synthetic image generation, improving model generalization.

d) Hybrid and Ensemble Models

- Combine CNN with other AI models or optimization algorithms for better accuracy and robustness. Examples:

- **CNN + LSTM** for spatial-temporal analysis.
- **CNN + Transformer** for multi-modal fusion.
- **CNN + Fuzzy/PSO/GA** for adaptive learning in cloud systems.

5.4. Training Algorithms

- **Back propagation:** Core algorithm for optimizing neural network weights.
- **Adam and RMSProp:** Frequently used adaptive optimizers for cloud-deployed AI models.
- **Transfer Learning:** Pre-trained models fine-tuned on specific medical datasets (e.g., ImageNet → Chest X-ray).
- **Federated Learning:** Enables collaborative training without sharing sensitive patient data.
- **Metaheuristic Optimization:** Techniques like **Genetic Algorithms (GA)**, **Particle Swarm Optimization (PSO)**, or **Ant Colony Optimization (ACO)** used for hyper parameter tuning and weight initialization.

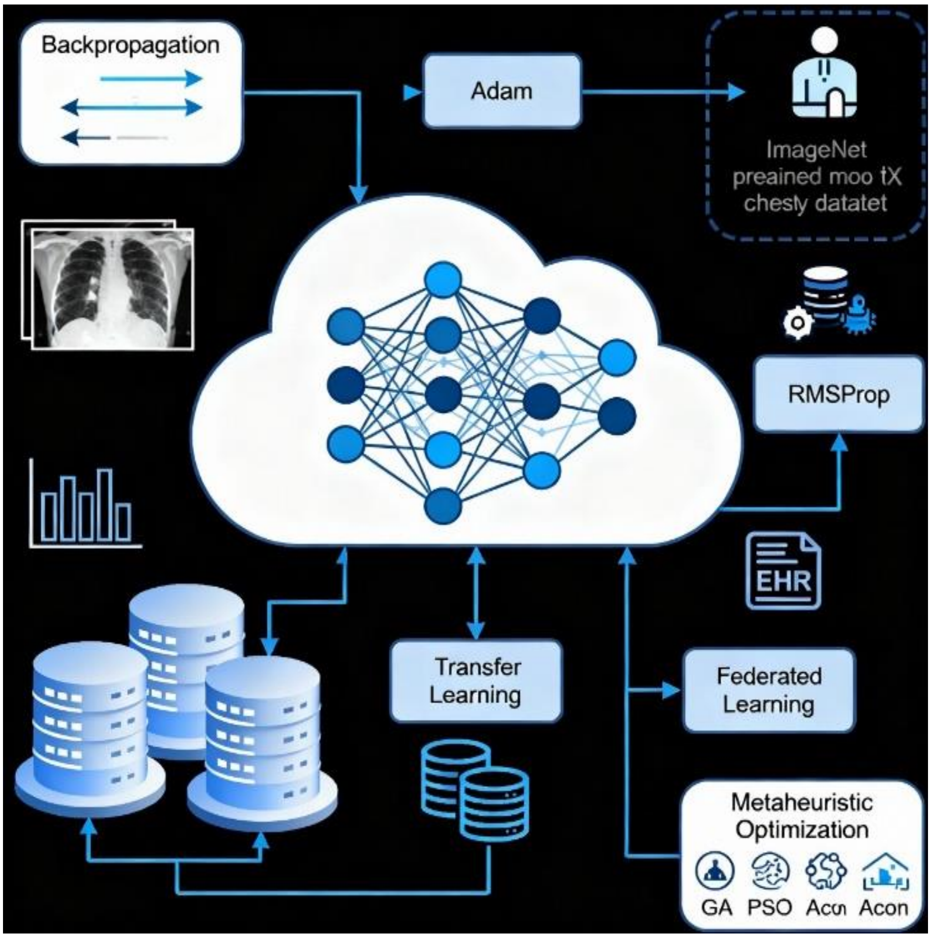

Fig. 4: Architecture of Cloud-Based AI Systems for Real-Time Medical Imaging Analysis

5.5. Performance Metrics

Table 2: Evaluation Metrics for AI-Based Medical Imaging Systems

Metric	Description	Use Case in Medical Imaging
Accuracy	Ratio of correct predictions	General diagnostic models
Precision & Recall	Measure class-specific performance	Cancer or lesion detection

F1-Score	Harmonic mean of precision and recall	Balances false positives/negatives
AUC-ROC	Area under receiver operating curve	Binary disease classification
Dice Coefficient (DC)	Overlap between predicted and true regions	Image segmentation
IoU (Intersection over Union)	Measures segmentation accuracy	Organ or tumor boundary mapping

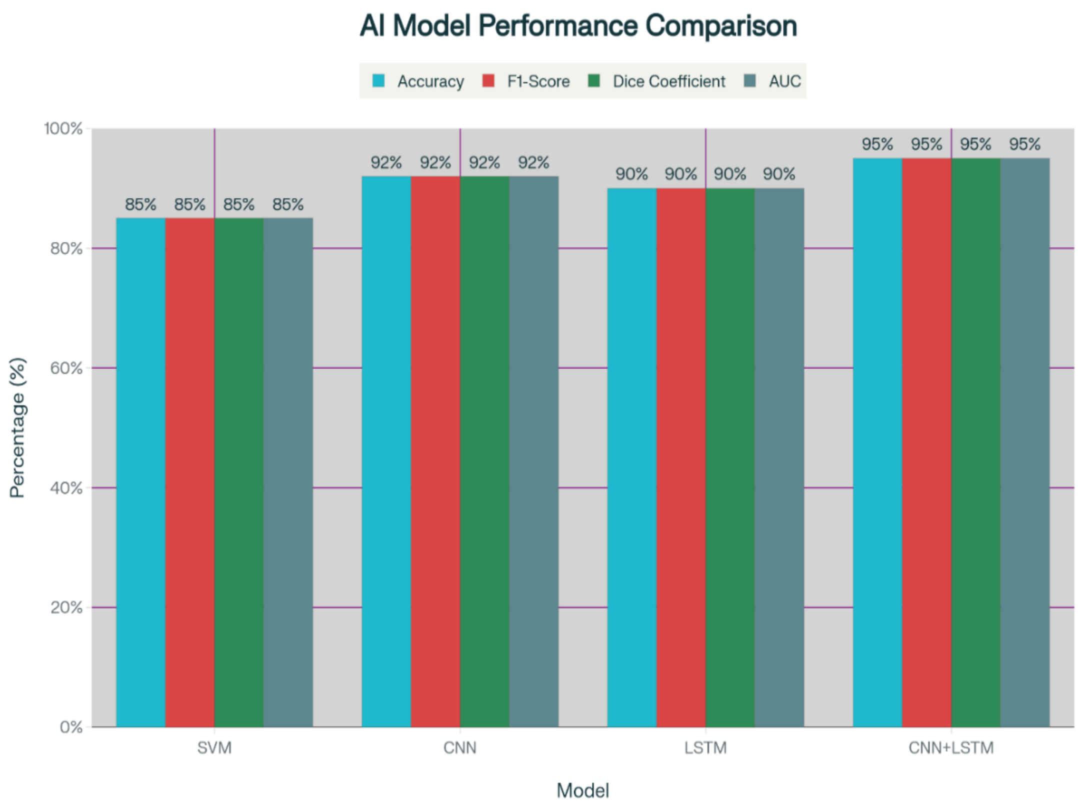

Fig. 5: Performance Comparison of Machine Learning and Deep Learning Models

5.6. Comparative Studies

Table 3: Comparison of Approaches in Medical Imaging Analysis

Approach	Advantages	Limitations
Traditional Methods (Manual/Statistical)	Simple, interpretable	Poor scalability and accuracy
Machine Learning (SVM, RF, GBM)	Effective for small datasets	Limited feature extraction
Deep Learning (CNN, RNN, Hybrid)	High accuracy, end-to-end learning	Requires large data and compute power
Cloud-Based AI	Scalable, real-time, collaborative	Dependent on network latency and data security

VI. CRITICAL ANALYSIS AND DISCUSSION

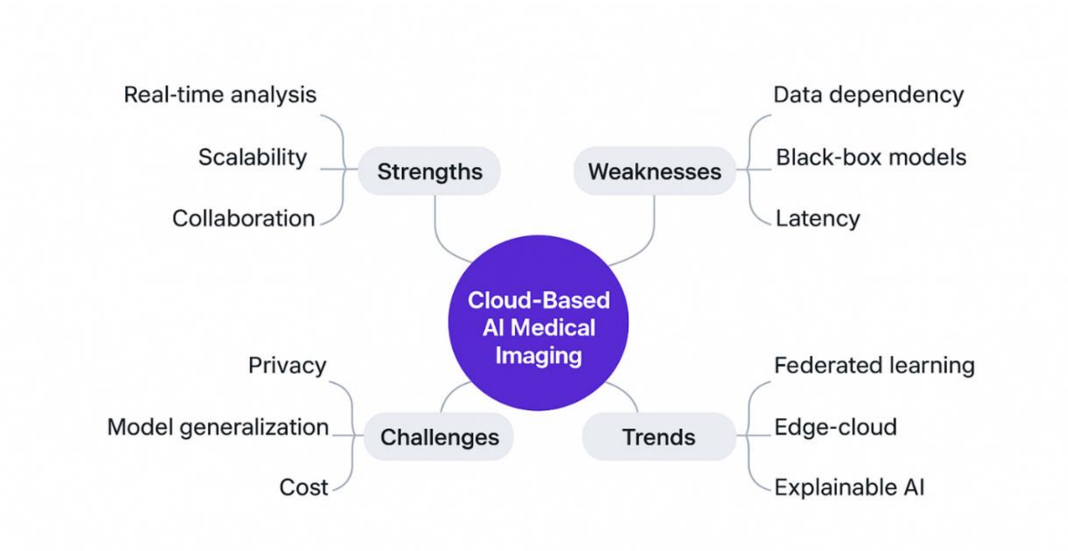

Fig. 6: Critical Analysis and Emerging Trends in Cloud-Based AI for Medical Imaging

Strengths of Cloud-Based AI Systems

Cloud-integrated AI solutions offer remarkable advantages for medical imaging diagnostics. By leveraging the **computational scalability of cloud platforms**, these systems can process vast volumes of imaging data in real time, enabling faster and more accurate disease detection. The **integration of deep learning architectures** such as CNNs and hybrid models allows for automatic feature extraction and improved diagnostic precision without manual intervention. Cloud systems also support **remote accessibility and collaborative research**, empowering clinicians and radiologists to share and analyze imaging data securely across locations. Furthermore, continuous cloud-based model updates and retraining improve system adaptability and accuracy over time.

Weaknesses and Limitations

Despite their potential, cloud-based AI imaging systems face several inherent weaknesses. The most notable is the **dependence on large, high-quality labeled datasets**—a requirement often limited by privacy and ethical constraints in healthcare. AI models, particularly deep networks, function as **black boxes**, offering limited interpretability, which raises concerns regarding clinical trust and explainability. Additionally, these systems are highly sensitive to **network latency and data transmission delays**, which can hinder real-time diagnostics in remote or low-connectivity regions. Moreover, improper model regularization or data imbalance can lead to **over fitting**, reducing the reliability of predictions when applied to new datasets.

Key Challenges

Key challenges associated with implementing cloud-based AI in medical imaging involve ensuring data privacy and adhering to healthcare regulatory standards, including HIPAA and GDPR. Ensuring **secure data transmission and encryption** during cloud uploads is crucial to maintaining patient confidentiality. Another challenge lies in **model generalization** — AI models trained on specific datasets or imaging modalities may not perform consistently across hospitals, devices, or populations. Furthermore, **computational cost optimization** and **energy-efficient processing** remain significant issues for large-scale real-time analysis. Balancing diagnostic accuracy with interpretability and sustainability continues to be an open research problem

VII. FUTURE RESEARCH DIRECTIONS AND RESEARCH GAP

Although cloud-based AI systems for medical imaging analysis are advancing quickly, significant research gaps and future directions remain to be explored in order to achieve their full potential in real-time clinical practice.

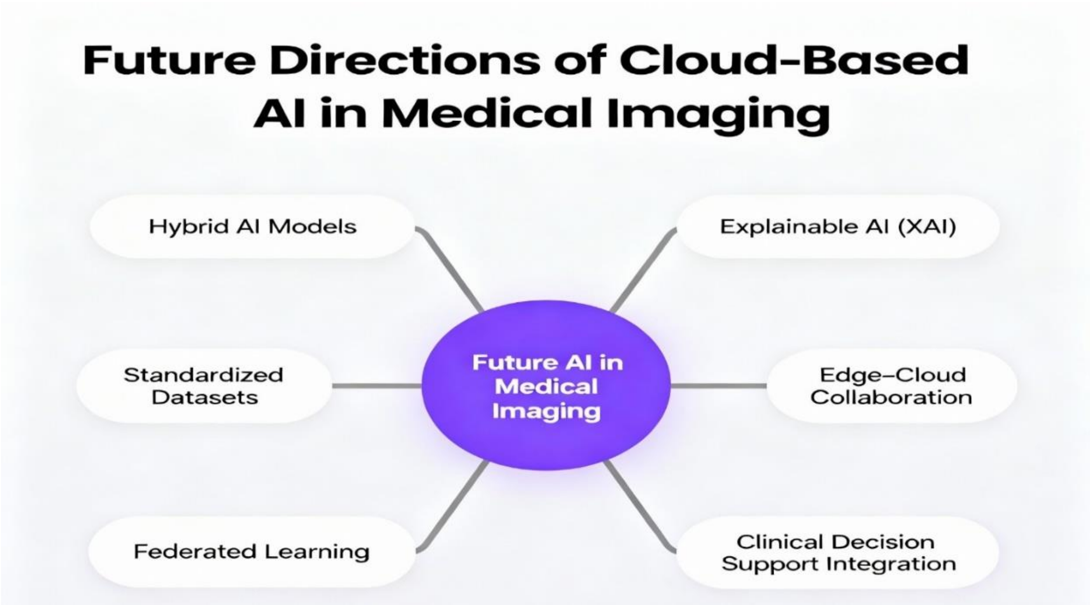

Fig. 7: Future Research Directions and Identified Gaps in Cloud-Based AI for Medical Imaging

a) Development of Hybrid AI Models

Future research should focus on designing **hybrid AI architectures** that integrate the strengths of multiple approaches such as **CNN, Transformer, GAN, and optimization algorithms (e.g., PSO, GA)**. These hybrid systems can enhance model adaptability, feature extraction, and diagnostic reliability across diverse imaging modalities. Combining deep learning with **metaheuristic optimization** may improve convergence speed, reduce over fitting, and enable efficient cloud-based model deployment.

b) Explainability and Interpretability of AI Models

Despite their success, most deep learning models operate as **black boxes**, providing limited insight into decision-making. There is a growing need for **Explainable AI (XAI)** techniques that make diagnostic predictions more transparent and interpretable for clinicians. Integrating visual attention maps, saliency overlays, and explainability layers into cloud-based systems will foster **clinical trust and regulatory acceptance**.

C) Standardization and Benchmarking of Medical Datasets

A significant research gap lies in the **lack of standardized, large-scale, and diverse medical imaging datasets** suitable for AI training and benchmarking. The creation of **federated or synthetic datasets** could help overcome privacy and data-sharing challenges. Establishing standardized evaluation metrics and open-access repositories will allow consistent performance comparison among AI models and cloud-based frameworks.

D) Real-Time and Edge–Cloud Collaboration

Real-time diagnostics demand reduced latency and efficient data flow between local imaging devices and cloud servers. Future systems must explore **edge-cloud collaborative architectures**, where preprocessing and lightweight AI inference occur at the edge (hospital devices), while deep model training and analytics run in the cloud.

VIII. CONCLUSION

Cloud-based Artificial Intelligence (AI) systems have emerged as transformative technologies for real-time medical imaging analysis and diagnostics. By utilizing scalable cloud infrastructure and sophisticated learning models, they facilitate rapid image interpretation, enhanced diagnostic precision, and seamless access to clinical services across diverse locations. By leveraging cloud computing's scalability and the intelligent capabilities of deep learning architectures, these systems enable rapid, accurate, and accessible healthcare diagnostics across diverse clinical environments. The integration of AI-driven models, particularly convolutional and hybrid neural networks, has significantly enhanced the automation, precision, and efficiency of medical image interpretation. The review highlights that cloud platforms not only support large-scale data processing and storage but also facilitate remote collaboration among clinicians and researchers. However, challenges such as data privacy, explainability, and generalization remain critical barriers to widespread clinical adoption. Addressing these concerns through federated learning, encryption, and explainable AI frameworks will be essential to ensure trust and regulatory compliance. Looking ahead, the convergence of **hybrid AI models**, **edge–cloud architectures**, and **privacy-preserving frameworks** will define the next generation of medical imaging diagnostics. The future direction of this field aims toward creating **intelligent, transparent, and globally connected healthcare ecosystems**, capable of delivering real-time, accurate, and patient-centric diagnostic insights. Cloud-based AI systems thus represent a pivotal advancement in digital healthcare, bridging the gap between technological innovation and clinical excellence.

IX. ACKNOWLEDGMENT

We would like to express our deep appreciation to St. Martin's Engineering College, Hyderabad, for fostering a supportive academic environment and providing the essential facilities required to carry out this research work. The encouragement and resources offered by the institution have been instrumental in the successful completion of this study.

We sincerely thank the Department of Computer Science and Engineering for their continuous guidance and academic support throughout the course of this work.

We extend our special thanks to **Mr. Gundam Ranjith** for his expert guidance, insightful suggestions, and consistent encouragement. His mentorship significantly contributed to shaping the direction and quality of this research.

We also acknowledge the contributions of various researchers and authors whose scholarly works served as valuable references for this study.

Lastly, we are grateful to our friends and family for their unwavering support, motivation, and encouragement throughout the research journey.

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