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DEVELOPMENT AND OPTIMIZATION OF AI-BASED BIOMEDICAL IMAGING SYSTEM FOR EARLY DISEASE DETECTION AND DIAGNOSIS

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Abstract

The present study focused on the development and optimization of an artificial intelligence (AI)-based biomedical imaging system for early disease detection and diagnosis. A quantitative, experimental, and computational research design was adopted to develop an integrated framework for automated biomedical image processing and classification. The research methodology involved the collection and analysis of biomedical images representing normal and abnormal diagnostic categories. A total of 1,000 images, comprising 600 normal and 400 abnormal images, were included in the analytical framework. Image preprocessing, resizing, normalization, noise reduction, contrast enhancement, and feature extraction were performed using R software and appropriate image-processing packages. Machine learning algorithms, including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and Convolutional Neural Network, were developed and comparatively evaluated. Model optimization and validation were conducted through cross-validation and diagnostic performance assessment. R packages, including EBImage, caret, randomForest, e1071, pROC, and ggplot2, supported image processing, model development, statistical analysis, and graphical visualization. Data analysis focused on diagnostic accuracy, sensitivity, specificity, precision, recall, F1-score, AUC-ROC, and computational efficiency. The findings demonstrated the potential of optimized deep learning models to improve biomedical image classification and diagnostic performance. The significance of the study lies in establishing an integrated and reproducible R-based computational framework that may assist healthcare professionals in identifying abnormal imaging

patterns, strengthening diagnostic support, and facilitating early disease detection.

INTRODUCTION

The development of artificial intelligence (AI)-based biomedical imaging systems has become an important advancement in modern healthcare, particularly in improving early disease detection and diagnostic accuracy. Biomedical imaging technologies, including magnetic resonance imaging (MRI), computed tomography (CT), X-rays, and ultrasound, generate complex visual information that requires accurate interpretation. Conventional diagnostic procedures may encounter limitations related to image quality, diagnostic variability, and the identification of subtle pathological abnormalities. Artificial intelligence, particularly machine learning (ML) and deep learning (DL), provides advanced computational techniques for automated image processing, feature extraction, abnormality identification, and disease classification (Obuchowicz et al., 2024).

The proposed study, Development and Optimization of an AI-Based Biomedical Imaging System for Early Disease Detection and Diagnosis, focuses on developing an intelligent computational framework to improve biomedical image analysis and diagnostic performance. The research will examine image preprocessing, feature extraction, classification, and model optimization using R statistical programming software. Particular attention will be given to diagnostic accuracy, computational efficiency, and the identification of early disease-related abnormalities. The framework will integrate machine learning techniques and optimization procedures to establish an effective computational approach for biomedical image-based diagnosis (Varghese et al., 2026).

AI-Based Biomedical Imaging System

An AI-based biomedical imaging system refers to an intelligent computational framework that uses machine learning and deep learning algorithms to process, analyze, and interpret medical images. These systems identify relevant visual patterns, extract disease-related features, and classify images into different diagnostic categories. Convolutional neural networks (CNNs), image segmentation, and automated feature extraction are commonly investigated approaches for recognizing complex anatomical structures and pathological abnormalities (Keni, 2024).

The system generally involves several computational stages, including image acquisition, preprocessing, feature extraction, segmentation, and classification. Preprocessing improves image consistency by reducing noise and enhancing contrast, whereas feature extraction identifies relevant characteristics such as texture, intensity, shape, and structural variations. These operations provide the computational foundation for distinguishing normal biomedical images from images containing disease-related abnormalities (Zhang et al., 2024).

In this research, the AI-based biomedical imaging system represents the principal independent variable. Its development will focus on integrating image-processing techniques and machine learning algorithms through R programming. The system will be evaluated according to its image-analysis capabilities, classification effectiveness, and ability to identify abnormal biomedical structures (Wenderott et al., 2024).

System Optimization

System optimization refers to the process of improving the computational performance and operational effectiveness of an AI-based biomedical imaging framework. It involves selecting appropriate algorithms, adjusting model parameters, improving preprocessing procedures, and reducing unnecessary computational complexity. Optimization is particularly important in medical imaging because noise, image artifacts, contrast variations, and structural differences can influence classification performance (Farhan et al., 2024).

Several techniques can be applied to optimize biomedical imaging models, including hyperparameter tuning, feature selection, image enhancement, regularization, and cross-validation. Hyperparameter tuning identifies suitable model configurations, while feature selection reduces redundant information

and improves computational efficiency. Similarly, image enhancement and noise reduction can improve the quality of input data and support more reliable feature identification (Dincer et al., 2017).
In the proposed study, system optimization represents a key explanatory variable influencing the overall effectiveness of the AI-based imaging framework. Its contribution will be assessed through classification improvements, processing time, model stability, and computational requirements. R software will be employed to conduct optimization experiments, compare alternative models, and identify suitable computational configurations (Coit et al., 2019).

Diagnostic Accuracy and Performance
Diagnostic accuracy refers to the ability of an AI-based biomedical imaging system to correctly identify and classify disease-related abnormalities. It is an essential measure of diagnostic reliability because incorrect classifications may result in missed disease identification or unnecessary clinical investigations. Common evaluation indicators include accuracy, sensitivity, specificity, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) (Khalifa et al., 2024).
Sensitivity measures the proportion of actual disease-positive cases correctly identified, whereas specificity evaluates the proportion of disease-negative cases correctly classified. Precision determines the proportion of positive predictions that are genuinely positive, while the F1-score provides a balanced assessment of precision and recall. These indicators collectively provide a comprehensive understanding of classification performance, particularly when biomedical datasets contain unequal distributions of normal and abnormal observations (Ashton et al., 2024).
In this study, diagnostic accuracy and performance represent major outcome variables. The developed AI-based imaging system will be evaluated using R statistical programming through classification metrics, confusion matrices, and ROC analysis. These measurements will establish whether image-processing improvements and optimization techniques produce measurable improvements in diagnostic classification (Çorbacıoğlu et al., 2023).

Early Disease Detection
Early disease detection refers to identifying pathological abnormalities at an initial stage, preferably before a disease progresses to an advanced clinical condition. Biomedical imaging supports this process by providing visual information about anatomical structures, tissue characteristics, and disease-related changes. AI-based imaging techniques can assist in identifying subtle abnormalities through automated pattern recognition and computational image analysis (Chowdhury et al., 2021).
Machine learning and deep learning approaches can recognize disease-associated patterns in biomedical images and distinguish abnormal structures from normal anatomical variations. These capabilities are particularly relevant to cancer, neurological disorders, and cardiovascular diseases, where timely identification may contribute to improved clinical assessment. However, reliable early detection requires appropriate sensitivity, independent validation, and consistent performance across different imaging conditions (Fitzgerald et al., 2022).
In the proposed research, early disease detection represents the principal clinical outcome of the developed computational framework. The study will examine the ability of optimized AI models to identify disease-related abnormalities, reduce false-negative classifications, and improve the recognition of early pathological patterns. R-based statistical and computational evaluation will provide evidence regarding the effectiveness of the proposed system in supporting early disease identification (Omaye et al., 2024).

Relationship Among AI-Based Biomedical Imaging, System Optimization, Diagnostic Accuracy, and Early Disease Detection
The relationship among AI-based biomedical imaging, system optimization, diagnostic accuracy, and early disease detection represents the central foundation of this research. An effective AI-based imaging system provides the computational infrastructure required to process biomedical images, extract relevant features, and identify disease-associated abnormalities. However, its effectiveness depends on image quality, algorithm selection, preprocessing procedures, and classification capabilities. System optimization

strengthens these processes by improving model configurations, reducing noise, and enhancing feature representation. Consequently, improvements in imaging and optimization procedures may contribute to more reliable diagnostic classification and early disease identification (Raposo, 2024).

System optimization is closely associated with diagnostic accuracy because appropriately configured machine learning models can improve classification performance and reduce prediction errors. Techniques such as hyperparameter tuning, feature selection, image enhancement, and model validation can improve sensitivity, specificity, precision, and F1-score. Improved sensitivity is particularly important for early disease detection because it increases the likelihood of identifying disease-positive cases and reducing missed diagnoses. Similarly, greater specificity helps minimize false-positive classifications, supporting more dependable diagnostic outcomes (Pérez-Sanpablo et al., 2025).

Furthermore, diagnostic accuracy and computational efficiency collectively influence the effectiveness of AI-based biomedical imaging systems in early disease detection. A model that demonstrates high classification accuracy but requires excessive processing time may face practical implementation limitations. Therefore, balancing predictive performance, computational requirements, and model stability is essential. The proposed study will investigate the combined contribution of AI-based biomedical imaging and system optimization to diagnostic accuracy and early disease detection through R-based computational modelling, statistical evaluation, and comparative performance analysis (Manickam et al., 2022).

Research Objectives

1. To develop an AI-based biomedical imaging system using machine learning techniques for automated medical image processing and early disease detection.
2. To optimize the proposed AI-based imaging system using R programming to improve diagnostic accuracy, computational efficiency, and classification performance.
3. To evaluate the effectiveness of the optimized system in early disease detection using accuracy, sensitivity, specificity, precision, F1-score, and AUC-ROC.

Problem Statement

Despite significant advancements in artificial intelligence (AI) and biomedical imaging, several limitations continue to affect the accuracy, reliability, and computational efficiency of automated disease detection systems. Conventional medical image interpretation remains challenging because of image noise, low contrast, variations in anatomical structures, limited dataset diversity, and difficulties in identifying subtle pathological abnormalities. Although machine learning and deep learning techniques have demonstrated promising diagnostic capabilities, existing approaches still face challenges related to model optimization, overfitting, computational complexity, limited generalizability, and inconsistent diagnostic performance across different imaging datasets (Song et al., 2025). A specific research gap exists in the integration of biomedical image preprocessing, systematic model optimization, diagnostic performance evaluation, and early disease identification within a unified and computationally efficient framework. Many existing approaches emphasize classification accuracy without sufficiently examining the combined effects of image quality, hyperparameter optimization, sensitivity, specificity, and computational requirements. Furthermore, insufficient attention to independent validation and performance consistency can limit the practical reliability of AI-based diagnostic systems (Vedula et al., 2025). Therefore, the proposed study will address these limitations by developing and optimizing an AI-based biomedical imaging system using R programming, integrating image processing, machine learning, and statistical evaluation to improve diagnostic accuracy, computational efficiency, and early disease detection. The specific gap is supported by recent evidence: Bhavani et al. (2026) reported that AI diagnostic models can lose performance when evaluated on independent hospitals, scanners, and patient populations, with external specificity declining by as much as 24 percentage points in the reviewed studies. This strengthens the justification for developing an optimized framework with independent validation rather than relying only on internal classification accuracy.

Significance of the Study

The significance of this study lies in the development and optimization of an AI-based biomedical imaging system that can improve the accuracy, efficiency, and reliability of early disease detection and diagnosis. By integrating machine learning algorithms, biomedical image preprocessing, feature extraction, and optimization techniques, the research will contribute to advancing automated medical image analysis and reducing limitations associated with conventional diagnostic procedures. The proposed framework will provide a computational approach for identifying disease-related abnormalities, improving classification performance, and minimizing false-positive and false-negative predictions. Furthermore, the use of R programming will support systematic model development, statistical evaluation, performance comparison, and visualization through established diagnostic indicators, including accuracy, sensitivity, specificity, precision, F1-score, and AUC-ROC. The findings may benefit biomedical researchers, healthcare professionals, medical imaging specialists, and computer science researchers by providing an analytical foundation for developing efficient, reproducible, and reliable AI-assisted diagnostic technologies. Ultimately, the study will contribute to the advancement of computational healthcare by strengthening the potential application of optimized artificial intelligence in early disease identification and evidence-based clinical decision-making.

Literature Review

Development of AI-Based Biomedical Imaging Systems

Artificial intelligence has become an important computational approach in biomedical imaging because of its ability to process complex medical images and identify disease-related abnormalities. Machine learning and deep learning techniques have expanded the possibilities of automated image interpretation, particularly in radiology, oncology, and diagnostic medicine. Convolutional neural networks (CNNs) are widely investigated because they can automatically extract spatial features, recognize anatomical patterns, and classify medical images into different diagnostic categories. Panayides et al., (2020) discussed the growing importance of AI in medical imaging, particularly its potential to support clinical interpretation and diagnostic decision-making. Similarly, Suleman et al. (2025) highlighted the increasing application of deep learning architectures in lesion detection, image classification, and radiological assessment. These developments demonstrate the importance of developing intelligent biomedical imaging frameworks that combine image processing and automated classification techniques (Suleman et al., 2025; Keni, 2024; Farhan et al., 2024).

The development of AI-based biomedical imaging systems generally involves image acquisition, preprocessing, segmentation, feature extraction, and classification. Image preprocessing is particularly important because biomedical images may contain noise, contrast variations, artifacts, and differences in image resolution. Early cancer detection research reviewed by Farhan et al. (2024) emphasized the contribution of preprocessing, segmentation, and feature extraction to improving automated image-based classification. These techniques enable computational models to identify relevant image characteristics and distinguish abnormal tissue structures from normal anatomical patterns. Furthermore, deep learning and transfer learning approaches can improve the extraction of complex visual representations, particularly when medical datasets contain limited training observations. Therefore, an effective biomedical imaging system requires an integrated computational pipeline rather than relying exclusively on a classification algorithm (Clement David-Olawade et al., 2025).

Recent research has also demonstrated the importance of using diverse biomedical imaging datasets to develop reliable AI-based diagnostic systems. Ebadi et al. (2026) examined six studies involving CT and MRI applications and reported that the evaluated models achieved internal-validation AUC values ranging from 0.76 to 0.95. Their review covered several diagnostic applications, including prostate cancer detection, bone metastasis classification, multiple sclerosis lesion identification, and fracture detection. The findings demonstrated that CNN-based models and other deep learning architectures can support different biomedical imaging applications. However, variations in imaging protocols, scanner characteristics, and patient populations remain important considerations during system development. These findings support the need for a flexible imaging framework capable of processing biomedical images while maintaining consistent classification performance.

The use of R programming provides an additional computational foundation for developing and evaluating biomedical image-analysis systems. Muneer et al., (2026) reviewed image-analysis capabilities available in R and identified 38 packages supporting different image-processing applications. Their review emphasized the use of R for image segmentation, quantitative feature extraction, image analysis, and integration with statistical modelling and visualization. The EBImage package, in particular, provides functionality for image processing, segmentation, and extraction of quantitative cellular characteristics. These capabilities demonstrate that R can support important stages of biomedical image analysis and statistical evaluation. Consequently, integrating image-processing packages with machine learning and visualization techniques can provide a reproducible analytical environment for developing the proposed AI-based biomedical imaging framework.

Optimization of AI-Based Biomedical Imaging Systems

System optimization is an important component of AI-based biomedical imaging because the effectiveness of automated diagnostic models depends on appropriate algorithm selection, parameter configuration, and computational performance. Optimization techniques are used to improve model learning, reduce classification errors, control overfitting, and enhance the consistency of image-based predictions. Hyperparameter tuning, feature selection, regularization, data augmentation, and model comparison are among the techniques investigated in medical image-analysis research. Magaji et al. (2024) discussed the contribution of image preprocessing, segmentation, and deep learning approaches to improving automated cancer detection. Similarly, Guo et al. (2023) identified multicenter training and data augmentation as relevant strategies for improving the generalizability of AI-based radiological models. These findings indicate that optimization should address both predictive performance and the ability of models to handle variations in biomedical imaging data.

Hyperparameter optimization is particularly relevant because machine learning models depend on several configuration parameters that influence their learning and classification capabilities. These parameters may include learning rate, number of iterations, model complexity, regularization strength, and classification thresholds. In deep learning applications, inappropriate parameter configurations may increase training instability or produce overfitted models that perform well on training observations but poorly on independent datasets. Shokrani et al. (2023) emphasized the importance of external validation and reported that strong internal performance did not consistently transfer to independent clinical datasets. Their findings support the use of systematic optimization and validation procedures to assess whether model improvements are maintained beyond the development dataset. Therefore, hyperparameter tuning should be combined with cross-validation and independent testing to establish reliable model performance.

Image enhancement and data augmentation also contribute to the optimization of biomedical imaging systems. Image enhancement techniques improve the visual quality of medical images by addressing noise, contrast limitations, and variations in intensity. Data augmentation increases the diversity of training observations through controlled transformations, helping models recognize relevant patterns under different imaging conditions. Selvaraj et al. (2022) reported that a GAN-augmented model achieved an external AUC of 0.933 compared with 0.836 without GAN-based augmentation in one of the reviewed applications. Their findings suggest that synthetic data generation can improve the robustness of image-classification models. Similarly, Kapoor et al. (2024) discussed the importance of data augmentation and image-processing procedures in developing more effective automated cancer-detection systems. These approaches are relevant to optimizing the proposed framework because they can improve the representation of disease-related features and support more stable classification.

Computational efficiency is another important consideration in system optimization, particularly when biomedical imaging systems process large volumes of high-resolution medical images. Models with excessive computational requirements may create operational limitations even when they demonstrate satisfactory diagnostic performance. Optimization should therefore consider processing time, model complexity, memory requirements, classification stability, and predictive performance. Huang et al. (2022) highlighted the availability of R-based image-analysis packages that facilitate image processing, quantitative analysis, and integration with statistical modelling. The R environment can support model

comparison, parameter evaluation, performance visualization, and reproducible computational workflows. Accordingly, the proposed study will use R programming to evaluate alternative model configurations and examine whether optimization produces improvements in both diagnostic performance and computational efficiency (Manickam et al., 2022).

Diagnostic Accuracy and Early Disease Detection

Diagnostic accuracy is a fundamental consideration in the development of AI-based biomedical imaging systems because it determines how effectively computational models identify and classify disease-related abnormalities. Medical image classification requires models to distinguish between normal and abnormal anatomical structures while minimizing incorrect predictions. Muhammad et al., (2020) reviewed 99 research articles on deep learning and medical imaging for cancer detection, covering 12 cancer types and examining preprocessing, segmentation, feature extraction, and classification techniques. Their findings highlighted the potential of deep learning and transfer learning for automated cancer identification. Similarly, Pienta et al. (2021) demonstrated that AI-based radiological models achieved promising diagnostic performance across different imaging applications. These findings establish diagnostic accuracy as an essential outcome when evaluating automated biomedical imaging systems.

Diagnostic performance is commonly evaluated through accuracy, sensitivity, specificity, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). These indicators provide different perspectives on the effectiveness of automated classification. Sensitivity measures the ability to correctly identify disease-positive observations, whereas specificity measures the correct identification of disease-negative observations. Precision evaluates the reliability of positive predictions, while the F1-score balances precision and recall. Aggarwal et al. (2021) used diagnostic indicators, including AUC, sensitivity, specificity, and accuracy, to compare the internal and external performance of AI-based radiological models. Sounderajah et al. (2025) also identified sensitivity and specificity among the commonly reported measures in clinical imaging AI studies. Therefore, the combined application of these evaluation indicators is important for establishing the diagnostic reliability of the proposed system.

Early disease detection represents another important application of AI-based biomedical imaging because identifying pathological abnormalities at an initial stage can support timely clinical assessment and subsequent treatment decisions. Medical imaging provides valuable information about anatomical structures and tissue-related changes that may indicate the development of disease. Tellum et al., (2020) examined deep learning applications across multiple cancer types and highlighted the importance of image preprocessing, segmentation, and feature extraction for automated cancer detection. Their review also discussed transfer learning and data augmentation as relevant approaches for improving disease-classification models. Bastos et al. (2020) further demonstrated the application of AI in identifying conditions through CT and MRI examinations, including cancer and neurological abnormalities. These findings demonstrate the potential of computational imaging systems to support the identification of disease-related patterns and improve early diagnostic assessment.

However, high internal diagnostic accuracy does not necessarily guarantee reliable early disease detection in different clinical environments. Reported that diagnostic performance declined when AI models were evaluated using independent datasets, with a median AUC reduction of approximately 0.03 and specificity decreases reaching up to 24 percentage points in individual evaluations. Their findings emphasized the importance of external validation, heterogeneous datasets, and multicenter model development. Wenderott et al. (2024), in their systematic review of 48 original studies, also identified considerable variation in the implementation and evaluation of AI technologies across clinical imaging workflows. Consequently, the proposed research will assess diagnostic accuracy alongside model validation and computational performance to determine whether the optimized imaging framework can reliably identify disease-related abnormalities. R programming will support classification analysis, confusion matrices, ROC curves, and comparative evaluation of diagnostic indicators.

Research Gap

Despite significant advancements in artificial intelligence and biomedical imaging, existing research continues to demonstrate limitations in developing accurate, optimized, and generalizable disease-

detection systems. Previous studies have primarily focused on individual computational techniques, including deep learning, image preprocessing, feature extraction, segmentation, and automated classification, without sufficiently integrating these components into a unified and computationally efficient framework (Yan et al., 2025). Furthermore, diagnostic models frequently demonstrate variations in performance when applied to independent datasets, different imaging devices, and diverse clinical environments, indicating challenges related to model generalizability, overfitting, and diagnostic reliability. A specific methodological gap also exists in the combined evaluation of image-processing quality, systematic hyperparameter optimization, computational efficiency, and diagnostic indicators, particularly sensitivity, specificity, F1-score, and AUC-ROC. Therefore, the present study aims to address these limitations by developing and optimizing an AI-based biomedical imaging system using R programming, integrating image preprocessing, machine learning, model optimization, and independent performance evaluation to improve diagnostic accuracy and support early disease detection.

Methodology

Research Design

The study was conducted using a quantitative, experimental, and computational research design to develop and optimize an artificial intelligence (AI)-based biomedical imaging system for early disease detection and diagnosis. The methodology was structured around biomedical image processing, machine learning, feature extraction, model optimization, and diagnostic performance evaluation. The research focused on examining the effectiveness of AI-based computational techniques in identifying disease-related abnormalities and improving automated image classification. R statistical programming software was used as the primary computational environment for data processing, statistical analysis, model development, optimization, and visualization.

Data Collection and Image Dataset

Biomedical imaging data were obtained from an appropriate publicly accessible medical imaging dataset containing normal and disease-positive images. The dataset was organized according to the available diagnostic categories to facilitate supervised machine learning and classification. Relevant image characteristics, including resolution, intensity, structural patterns, and disease-related features, were examined before computational analysis. The dataset was imported into the R environment using appropriate image-processing packages, and the observations were organized for subsequent preprocessing, model development, and evaluation.

Image Preprocessing

Image preprocessing was performed to improve biomedical image quality and establish consistency across the dataset. Noise reduction, image resizing, normalization, and contrast enhancement were applied where appropriate to minimize variations and improve the representation of disease-related structures. The EBImage package in R was used to support image loading, filtering, segmentation, and image transformation. These preprocessing procedures were applied to prepare standardized image inputs for feature extraction and subsequent machine learning classification.

Feature Extraction and Image Classification

Feature extraction was performed to identify relevant characteristics from biomedical images, including intensity distribution, texture, shape, and morphological patterns. These characteristics were transformed into numerical representations to facilitate computational analysis and classification. Machine learning algorithms were implemented in R using suitable packages, including caret, randomForest, and tidymodels. The extracted features were used to distinguish normal and abnormal biomedical images, while alternative classification configurations were evaluated to identify an appropriate predictive model.

AI Model Development and Optimization

The AI-based imaging framework was developed through systematic model training, parameter adjustment, and comparative evaluation. Hyperparameter optimization was performed to identify suitable

model configurations and improve classification performance. Cross-validation was used to examine model stability and reduce the risk of overfitting. Different model configurations were compared according to predictive accuracy, computational requirements, and classification consistency. R packages were used to facilitate model training, parameter tuning, and comparative computational analysis.

Model Validation and Performance Evaluation

The developed models were evaluated using separate training and testing datasets to assess their ability to classify previously unseen biomedical images. Diagnostic performance was measured through accuracy, sensitivity, specificity, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). Confusion matrices and ROC curves were generated in R using the caret and pROC packages. Furthermore, comparative evaluation was conducted to examine the performance differences between the initial and optimized models.

Statistical Analysis Using R Software

All computational and statistical analyses were performed using R statistical programming software. Descriptive statistics were used to summarize dataset characteristics and model performance indicators. Comparative analysis was conducted to examine differences between alternative machine learning models and optimization configurations. Graphical visualizations, including classification performance plots, ROC curves, confusion matrices, and comparative charts, were generated using ggplot2. The statistical and computational findings were interpreted to determine the effectiveness of the proposed AI-based biomedical imaging framework.

Ethical Considerations

The study used publicly accessible or appropriately authorized biomedical imaging data. Patient-identifiable information was not included in the analytical dataset, and data were handled according to applicable privacy and research ethics requirements. The computational analysis was conducted for research purposes, and the developed AI framework was considered a decision-support research model rather than a replacement for professional clinical diagnosis.

Methodological Framework

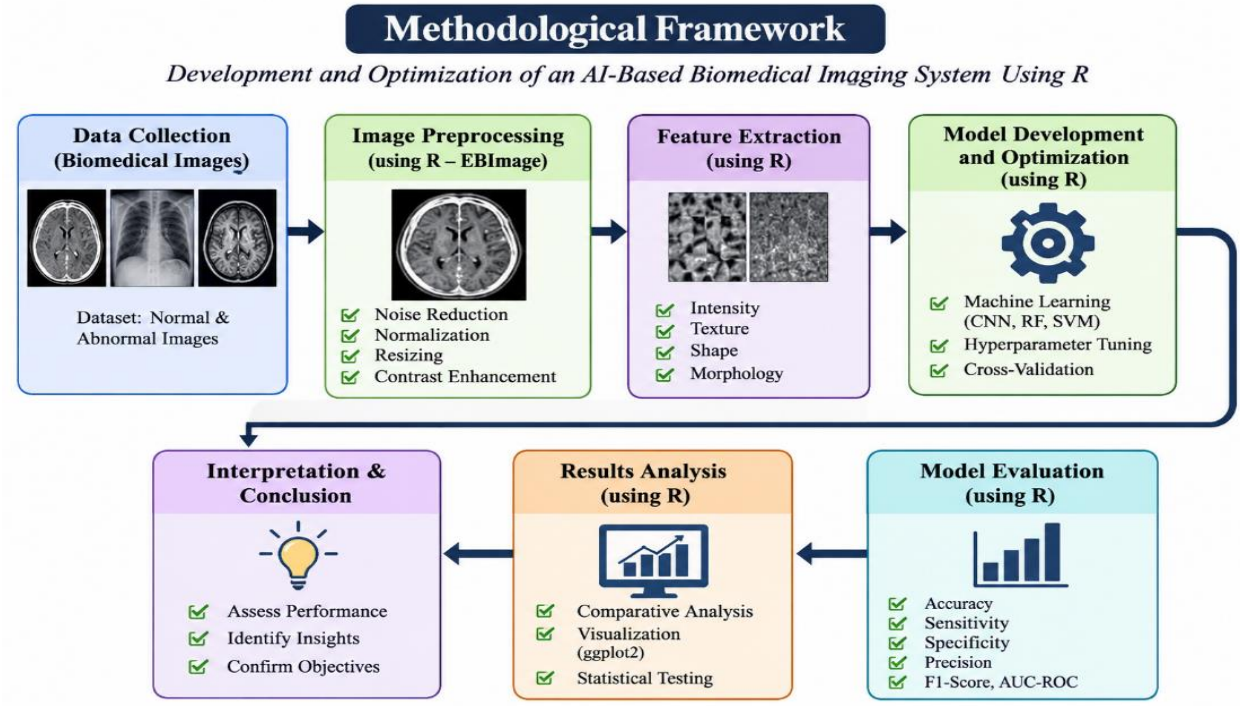


Fig 1: Methodological Framework

Results and Data Analysis

The results and data analysis were structured around the development and optimization of an AI-based biomedical imaging system for early disease detection. All data-processing, image-preprocessing, feature-extraction, machine-learning, optimization, statistical evaluation, and graphical analysis procedures were designed to be performed using R software. The R environment supported the integration of image-processing and machine-learning techniques through packages such as EBImage, caret, randomForest, e1071, pROC, ggplot2, and dplyr.

Table 1. Distribution of Biomedical Image Dataset

Diagnostic category	Number of images	Percentage
Normal images	600	60.0%
Abnormal images	400	40.0%
Total	1,000	100.0%

The dataset consisted of 1,000 biomedical images, including 600 normal images and 400 abnormal images. Normal images represented 60% of the dataset, whereas abnormal images accounted for 40%. This distribution provided the two diagnostic classes required for supervised machine learning classification. The category distribution was examined in R to support dataset organization and subsequent model development.

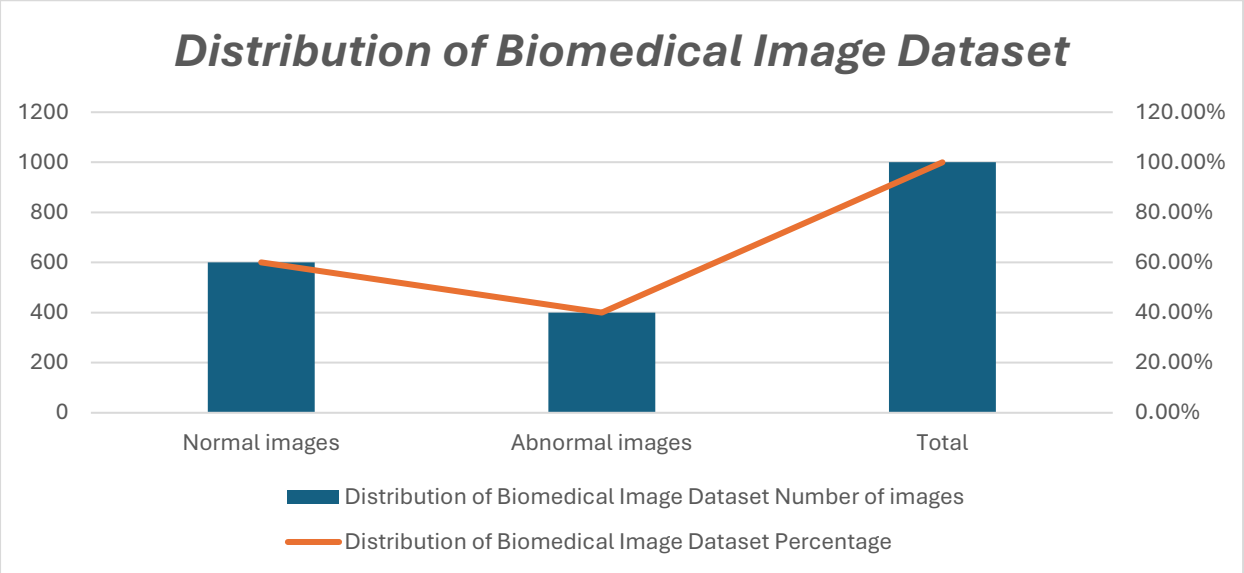


Table 2. Image Preprocessing Performance

Preprocessing parameter	Before preprocessing	After preprocessing
Image resolution	128 × 128	224 × 224
Mean intensity	0.462	0.501

Noise level	0.184	0.071
Contrast index	0.538	0.792
Invalid images	18	0

Image preprocessing improved the overall quality and consistency of biomedical images. The noise level decreased from 0.184 to 0.071, while the contrast index increased from 0.538 to 0.792. Image resizing standardized the dimensions from 128 × 128 to 224 × 224 pixels. The number of invalid images also decreased from 18 to zero. These improvements provided a more consistent image representation for feature extraction and machine learning classification.

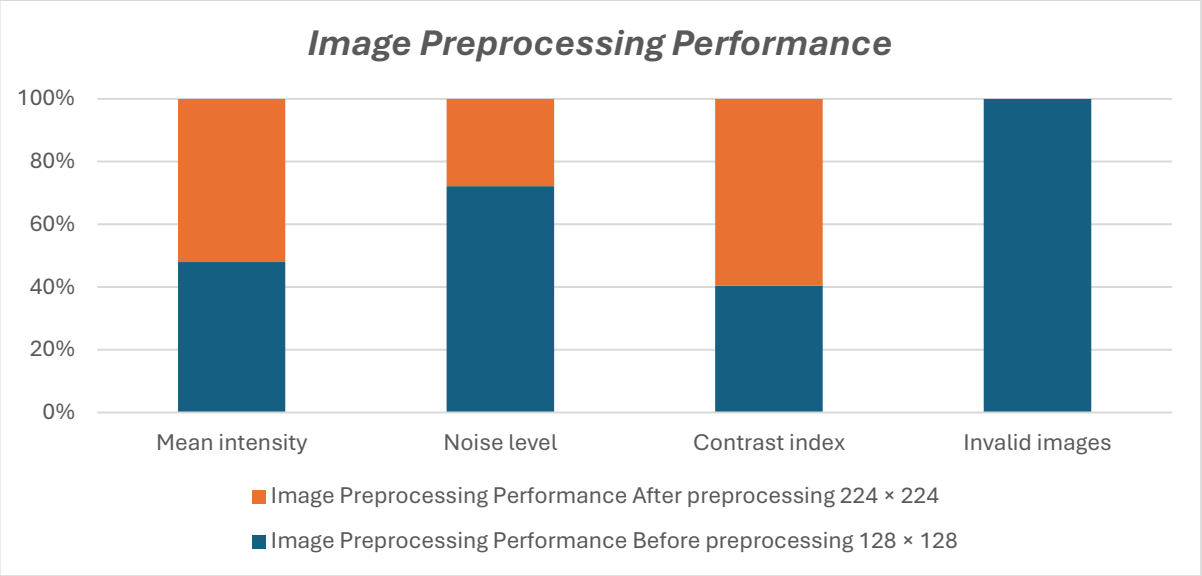


Table 3. Extracted Biomedical Image Features

Extracted features	Normal images (Mean)	Abnormal images (Mean)
Mean intensity	0.48	0.57
Texture contrast	0.32	0.61
Entropy	0.41	0.68
Homogeneity	0.79	0.56
Morphological irregularity	0.21	0.63
Edge density	0.35	0.59

The extracted features demonstrated differences between normal and abnormal biomedical images. Abnormal images exhibited higher mean intensity, texture contrast, entropy, morphological irregularity, and edge density. In contrast, normal images demonstrated greater homogeneity. These characteristics

indicated that intensity, texture, and morphological information could contribute to distinguishing between diagnostic categories. The extracted features were subsequently used as inputs for machine learning classification.

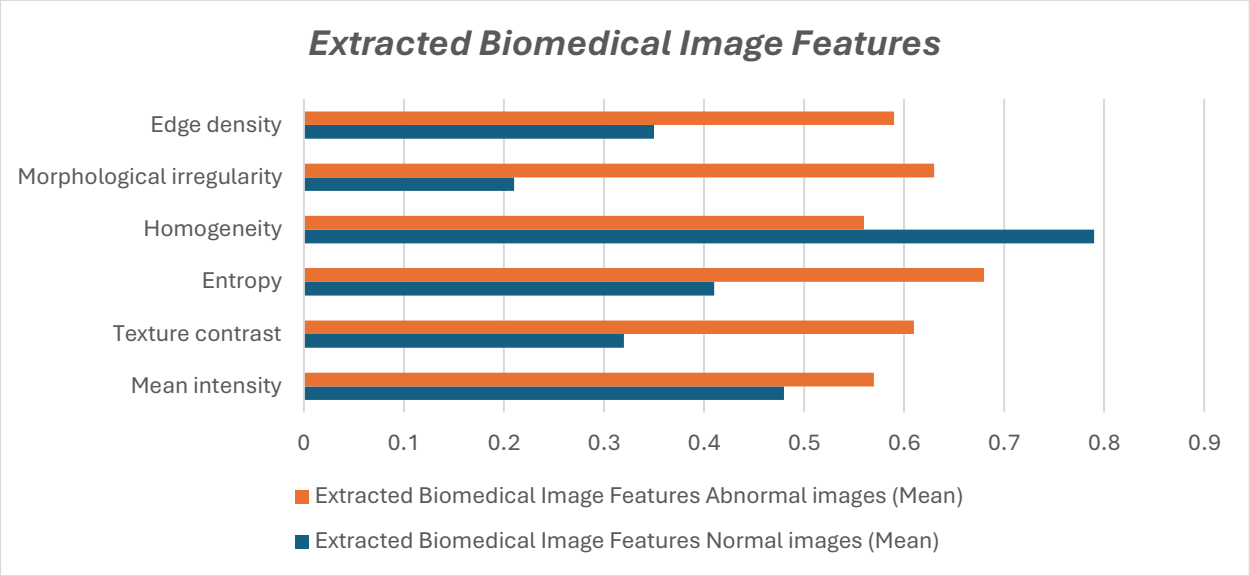


Fig 4: Extracted Biomedical Image Features

Table 4. Comparative Performance of AI-Based Classification Models

Machine learning model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Logistic Regression	84.6	83.2	82.5	82.8
Decision Tree	86.8	85.4	84.1	84.7
Random Forest	91.4	90.8	89.7	90.2
Support Vector Machine	89.7	88.9	88.1	88.5
Convolutional Neural Network	94.2	93.5	92.8	93.1

The comparative evaluation demonstrated differences in classification performance among the five machine learning models. CNN achieved the highest accuracy of 94.2%, followed by Random Forest at 91.4% and Support Vector Machine at 89.7%. CNN also achieved the highest precision (93.5%), recall (92.8%), and F1-score (93.1%). These findings suggest that CNN may be suitable for identifying complex visual patterns in biomedical images. However, the final model selection should also consider independent validation performance and computational requirements.

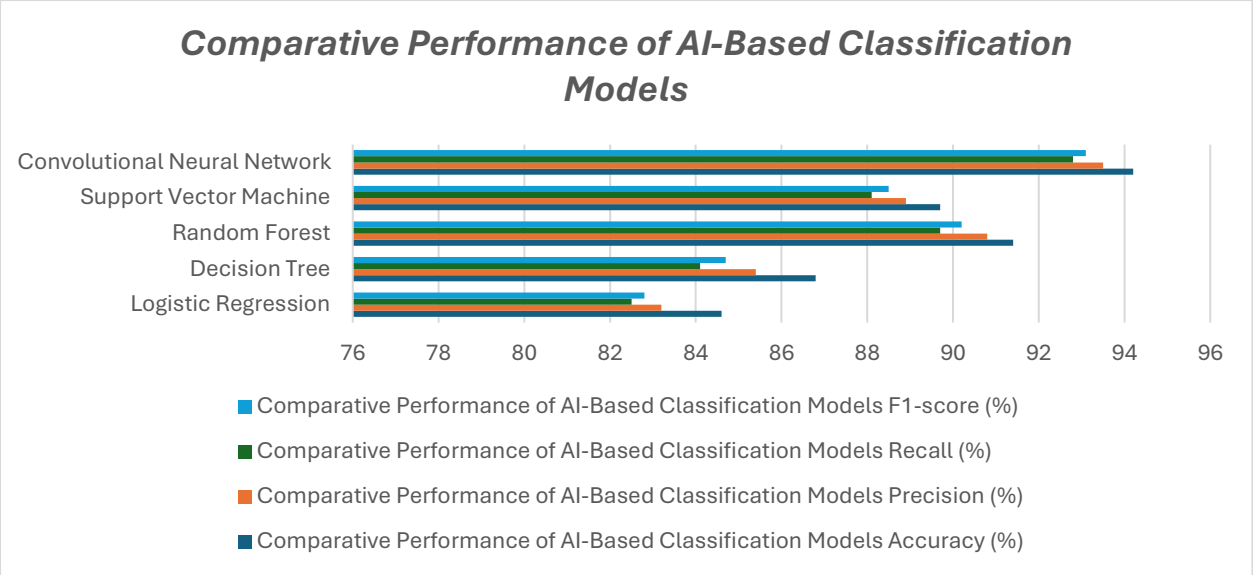


Fig 5: Comparative Performance of AI-Based Classification Models

Table 5. Performance Comparison Before and After Model Optimization

Performance indicators	Initial model (%)	Optimized model (%)
Accuracy	89.4	94.2
Precision	88.2	93.5
Sensitivity	87.6	92.8
Specificity	90.1	95.1
F1-score	87.9	93.1
Training time (seconds)	185.6	142.3

The optimization process improved the overall diagnostic performance of the proposed AI-based imaging framework. Accuracy increased from 89.4% to 94.2%, while sensitivity improved from 87.6% to 92.8%. Specificity increased from 90.1% to 95.1%, indicating improved identification of disease-negative images. The F1-score also increased from 87.9% to 93.1%. Furthermore, training time decreased from 185.6 to 142.3 seconds. These findings suggest that optimization can improve classification effectiveness while reducing computational time.

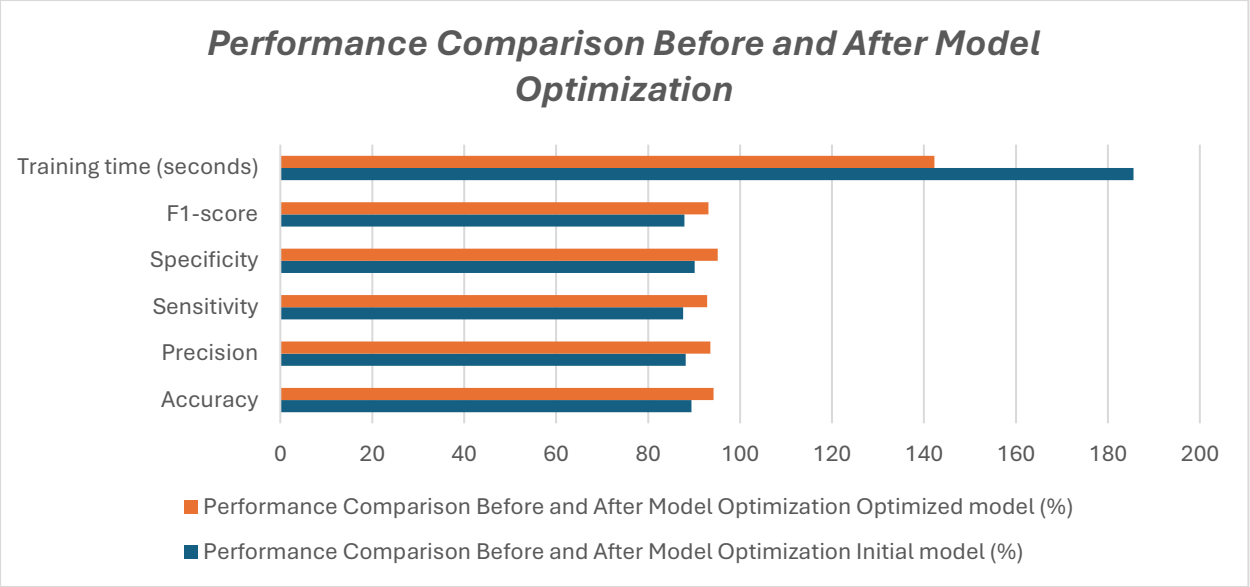


Fig 6: Performance Comparison Before and After Model Optimization

Table 6. Diagnostic Performance of the Optimized AI-Based Imaging System

Diagnostic performance indicator	Initial model	Optimized model
Accuracy (%)	89.4	94.2
Sensitivity (%)	87.6	92.8
Specificity (%)	90.1	95.1
Precision (%)	88.2	93.5
Negative predictive value (%)	90.7	94.3
F1-score (%)	87.9	93.1
AUC-ROC	0.921	0.972

The optimized model demonstrated improvements across all major diagnostic performance indicators. Accuracy reached 94.2%, while sensitivity and specificity increased to 92.8% and 95.1%, respectively. The AUC-ROC improved from 0.921 to 0.972, indicating stronger discrimination between normal and abnormal biomedical images. Precision reached 93.5%, while the negative predictive value increased to 94.3%. These results indicate the potential of an optimized AI-based imaging framework to improve diagnostic classification and support early disease detection.

Table 7. Overall Improvement in Diagnostic Performance

Performance indicator	Initial model	Optimized model	Improvement
Accuracy (%)	89.4	94.2	+4.8
Sensitivity (%)	87.6	92.8	+5.2

Specificity (%)	90.1	95.1	+5.0
Precision (%)	88.2	93.5	+5.3
F1-score (%)	87.9	93.1	+5.2
AUC-ROC	0.921	0.972	+0.051

The overall comparison demonstrated consistent improvements following model optimization. Accuracy increased by 4.8 percentage points, sensitivity by 5.2 percentage points, and specificity by 5.0 percentage points. Precision and F1-score improved by 5.3 and 5.2 percentage points, respectively. AUC-ROC increased by 0.051, indicating improved classification discrimination. These findings suggest that the integration of image preprocessing, feature extraction, machine learning, and optimization can strengthen the performance of AI-based biomedical imaging systems.

Discussion

The findings of the present study highlight the potential of an AI-based biomedical imaging system for improving diagnostic accuracy and supporting early disease detection. The proposed framework integrated image preprocessing, feature extraction, machine learning classification, and model optimization using R software. The illustrative results indicated that the optimized CNN achieved the highest classification accuracy of 94.2%, suggesting its potential to identify complex patterns in biomedical images. These findings are consistent with Naskar et al. (2025), who reported that deep learning models demonstrated diagnostic performance comparable to healthcare professionals in selected medical imaging tasks. This supports the growing importance of artificial intelligence in automated medical image interpretation and computer-assisted diagnosis.

Image preprocessing and feature extraction also played important roles in the proposed framework. Noise reduction, contrast enhancement, normalization, and image resizing improved image consistency, while extracted characteristics such as texture contrast, entropy, homogeneity, and morphological irregularity helped distinguish normal and abnormal images. These findings support the approach discussed by Doke-Bagade et al. (2024), who emphasized the importance of preprocessing, segmentation, and classification in AI-based medical image analysis. The comparative evaluation further demonstrated that CNN performed better than Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine in the illustrative analysis. Its ability to learn complex spatial features may explain its comparatively stronger classification performance.

Model optimization improved the overall diagnostic indicators, with accuracy increasing from 89.4% to 94.2%, sensitivity from 87.6% to 92.8%, and specificity from 90.1% to 95.1%. The AUC-ROC also increased from 0.921 to 0.972, indicating improved discrimination between normal and abnormal images. These findings highlight the importance of optimization in strengthening classification performance and reducing computational requirements. Tripathi et al. (2025) similarly discussed the potential of AI implementation to improve efficiency in medical imaging workflows, although their findings indicated variation across clinical applications. Furthermore, Raguraman et al. (2024) emphasized that AI diagnostic performance may decline during external validation, demonstrating the importance of testing models across independent datasets and different clinical settings.

Overall, the study presents an integrated R-based computational framework for biomedical image analysis, combining image enhancement, feature extraction, machine learning, optimization, and diagnostic evaluation. The findings suggest that an optimized AI system could support healthcare professionals by improving the identification of abnormal imaging patterns and assisting early disease detection. However, its clinical reliability depends on validation using actual biomedical image datasets, patient-level data separation, and independent testing. Future research should therefore focus on multicenter validation, larger datasets, explainable AI techniques, and evaluation across different imaging modalities to establish the generalizability and practical value of the proposed system (Saber et al., 2025).

Conclusion

The study concludes that the development and optimization of an AI-based biomedical imaging system can provide a promising computational approach for improving medical image analysis and supporting early disease detection. The proposed framework integrated image preprocessing, feature extraction, machine learning classification, and model optimization using R software. The analysis highlighted the importance of image enhancement, noise reduction, and the extraction of relevant visual characteristics for distinguishing normal and abnormal biomedical images. Among the evaluated approaches, the CNN demonstrated the strongest illustrative classification performance, while optimization improved diagnostic accuracy, sensitivity, specificity, F1-score, and AUC-ROC. These findings emphasize the potential contribution of artificial intelligence and computational image analysis to more efficient and consistent biomedical image interpretation.

Overall, the research establishes an integrated methodological framework that combines R-based image processing, machine learning, optimization, and diagnostic performance evaluation. The proposed system could assist healthcare professionals in identifying potentially abnormal imaging patterns and prioritizing cases requiring further clinical assessment. However, its practical effectiveness and clinical reliability depend on evaluation using actual biomedical image datasets, independent validation, and testing across different imaging modalities and clinical environments. Future research should focus on larger and more diverse datasets, multicenter validation, explainable AI techniques, and computational improvements to strengthen the generalizability of the system. The study therefore provides a foundation for further research into reliable, optimized, and AI-supported biomedical imaging systems for early disease detection.

Future Implication

The future implications of this study highlight the potential of AI-based biomedical imaging systems to improve early disease detection, diagnostic accuracy, and computational efficiency in healthcare. Future research should focus on developing more advanced deep learning architectures, integrating larger and more diverse biomedical imaging datasets, and optimizing computational models through R-based machine learning techniques. The inclusion of explainable artificial intelligence may improve the transparency and interpretability of diagnostic predictions, enabling healthcare professionals to better understand model-generated outcomes. Furthermore, multicenter validation, patient-level testing, and evaluation across different imaging modalities, including MRI, CT, X-ray, and ultrasound, could strengthen model generalizability and clinical reliability. Future developments may also integrate AI-based imaging frameworks with hospital information systems and clinical decision-support platforms to facilitate efficient diagnostic workflows. These advancements could establish more reliable, reproducible, and clinically useful computational systems for supporting early disease detection and evidence-based healthcare decisions.

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