AIMS Biophysics

AIMS Biophysics, 12(2): 121−143.
DOI: 10.3934/biophy.2025008
Received: 15 January 2025
Revised: 28 February 2025
Accepted: 12 March 2025
Published: 24 March 2025

http://www.aimspress.com/journal/biophysics

Research article

Medical image analysis using deep learning algorithms (DLA)

Dafina Xhako[1,*], Niko Hyka[2], Elda Spahiu[3] and Suela Hoxhaj[4]

[1] Department of Physics Engineering, Faculty of Mathematical Engineering and Physical Engineering, Polytechnic University of Tirana, Tirana, Albania
[2] Department of Diagnostic, Faculty of Medical Technical Sciences, University of Medicine, Tirana, Albania
[3] Institute of Applied Nuclear Physics, Tirana, Albania
[4] Department of Physics Engineering, Faculty of Mathematical Engineering and Physical Engineering, Polytechnic University of Tirana, Tirana, Albania

* **Correspondence:** Email: dafinaxhako@yahoo.com; Tel: +003556802768.

Abstract: Deep Learning Algorithms (DLAs) have emerged as transformative tools in medical image analysis, offering unprecedented accuracy and efficiency in diagnostic tasks. We explored the state-of-the-art applications of DLAs in medical imaging, focusing on their role in disease detection, segmentation, workflow automation, and multi-modality data integration. Key architectures such as Convolutional Neural Networks (CNNs), U-Net, and Vision Transformers are highlighted, alongside their tailored applications in healthcare. Additionally, Mamba networks have shown significant promise in medical imaging by leveraging their advanced memory-efficient architecture for high-dimensional data processing. These networks excel in real-time analysis, improving the speed and accuracy of complex imaging tasks such as tumor detection and organ segmentation. The adaptability and computational efficiency of Mamba networks position them as a strong alternative to traditional deep learning architectures in the field of medical imaging. DLAs have consistently demonstrated superior performance compared to radiologists in various diagnostic tasks, such as breast cancer detection and brain tumor segmentation, with higher accuracy and efficiency. Despite these advancements, challenges such as limited data availability, ethical concerns, interpretability issues, and integration hurdles persist. Addressing these barriers is crucial to unlocking the full potential of DLAs and enabling their seamless integration into clinical workflows, ultimately enhancing patient care and diagnostic precision.

Keywords: deep learning algorithms; medical imaging; diagnostic accuracy; convolutional neural mamba; networks; U-net; vision transformers; workflow automation; AI in healthcare

1. Introduction

Medical image analysis plays a pivotal role in modern healthcare by aiding in the diagnosis, monitoring, and treatment of various medical conditions. Over the years, advances in imaging technologies, such as X-rays, CT scans, MRIs, and ultrasound, have significantly enhanced clinicians' ability to visualize and assess the human body. However, despite these technological advancements, the analysis and interpretation of medical images remain challenging tasks, often influenced by factors such as the complexity of the images, variations in image quality, and the expertise of the practitioners interpreting the images. The emergence of Deep Learning Algorithms (DLAs), a subset of artificial intelligence (AI), has revolutionized the field of medical image analysis [1,2]. Unlike traditional machine learning methods, which rely on hand-crafted features, DLAs automatically learn hierarchical patterns and representations from raw image data. This ability to detect subtle features in large datasets with high accuracy has led to significant improvements in diagnostic performance, often surpassing human experts in tasks like disease detection, tumor segmentation, and image classification [3].

DLAs, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional capabilities in medical imaging tasks, including the detection of cancers (e.g., breast, lung, and skin cancer), brain abnormalities, and cardiovascular conditions. Furthermore, DLAs have contributed to the development of automated tools for image segmentation, which is crucial for treatment planning and monitoring disease progression. These algorithms have the potential to improve diagnostic accuracy, reduce human error, optimize workflow efficiency, and ultimately, enhance patient outcomes. Despite the promising results, the integration of DLAs into clinical practice presents challenges, including data privacy concerns, the need for large and diverse datasets, and the "black box" nature of deep learning models, which can limit clinicians' trust and understanding of the model's decision-making process [4–8]. Nevertheless, the growing adoption of DLAs in medical imaging is expected to continue as these systems are refined and validated through extensive clinical trials and research.

Here, we provide an overview of the current landscape of medical image analysis using deep learning algorithms, highlighting their applications, advantages, and challenges. We also discuss the future directions for integrating DLAs into healthcare systems to ensure that they complement the expertise of medical professionals and improve patient care. In this study, we review the key techniques, datasets, and evaluation metrics used in applying DLAs for medical image analysis [9,10].

The materials and methods employed to develop and assess these algorithms are drawn from recent literature, industry practices, and established research frameworks. For training and testing DLAs in medical image analysis, high-quality annotated medical image datasets are essential [11]. Commonly used datasets in this field include: The ChestX-ray14 dataset, A large-scale dataset containing over 100,000 frontal-view chest X-ray images with annotations for 14 different thoracic diseases. It is widely used for the development and validation of deep learning models for disease classification and detection. The LUNA16 dataset is used for lung nodule detection and consists of high-resolution CT scans, providing labelled images of lung nodules for training segmentation and detection algorithms. The Brain Tumour Segmentation (BRATS) dataset includes MRI scans with tumour annotations, providing a basis for developing segmentation models for brain tumour detection and classification. The International Skin Imaging Collaboration (ISIC) dataset is used to detect skin cancer from dermoscopic images, providing labelled examples of benign and malignant lesions.

2. Materials and methods

2.1. Deep learning algorithms

The primary deep learning models used in medical image analysis are Convolutional Neural Networks (CNNs). CNNs have been shown to be highly effective at automatically learning spatial hierarchies of features from image data. Variations of CNNs such as U-Net, ResNet, and DenseNet have been employed for specific tasks, including image segmentation and disease classification [8,12]. U-Net is a deep-learning architecture specifically designed for biomedical image segmentation. U-Net is a fully convolutional network (FCN) that consists of an encoder-decoder architecture with skip connections to preserve spatial resolution, making it ideal for segmenting small and complex anatomical structures. ResNet is a residual network designed to address the problem of vanishing gradients in deep networks. ResNet has been used in medical image classification tasks, improving diagnostic accuracy in tasks such as tumor detection and disease classification [13–17]. DenseNet is a dense convolutional network where each layer is connected to every other layer in a feed-forward fashion. This structure improves feature reuse and alleviates the vanishing gradient problem, making it suitable for detailed image analysis.

2.2. Preprocessing

Medical images typically require preprocessing before being input into deep-learning models. The most common preprocessing steps include standardizing image dimensions to ensure compatibility with the deep learning model, scaling pixel intensities to a consistent range (e.g., 0 to 1) to improve model convergence, and applying transformations such as rotation, flipping, and scaling to increase dataset diversity and reduce overfitting. In some cases, preprocessing involves isolating regions of interest (e.g., tumors or lesions) through segmentation techniques to focus the analysis on critical structures.

2.3. Model training and evaluation

Deep learning models are trained on labeled datasets, with the training process involving the optimization of model parameters (e.g., weights and biases) to minimize the loss function. The training process is typically carried out using backpropagation and an optimization algorithm such as Stochastic Gradient Descent (SGD) or Adam. Datasets are typically divided into training, validation, and testing subsets. During training, models are fine-tuned on the training set, while the validation set is used to monitor overfitting and adjust hyperparameters. The effectiveness of the deep learning models is evaluated using various metrics: Accuracy: The proportion of correctly predicted instances; Sensitivity and Specificity: Sensitivity measures the true positive rate, while specificity measures the true negative rate; Dice Similarity Coefficient (DSC): Used in segmentation tasks to measure the overlap between predicted and ground truth regions; and Area Under the Curve (AUC): The AUC of the receiver operating characteristic (ROC) curve, which evaluates the trade-off between sensitivity and specificity

2.4. Software and frameworks

Deep learning models for medical image analysis are implemented using popular machine learning frameworks, such as: TensorFlow, which is an open-source deep learning library developed by Google, widely used for building and deploying machine learning models, including CNNs. PyTorch, which is an open-source deep learning framework developed by Facebook, is known for its flexibility and ease of use in research and development. Keras is a high-level neural networks API, written in Python, that runs on top of TensorFlow, facilitating easy model design and experimentation. SimpleITK is a toolkit for medical image processing, commonly used in preprocessing and handling medical imaging data formats like DICOM. For models to be successfully integrated into clinical practice, they must undergo rigorous validation using real-world datasets that are representative of diverse patient populations. Cross-validation, multi-center trials, and external validation on datasets from independent institutions are crucial for assessing generalization and robustness [17].

2.5. Applications of DLA-s in medical imaging

DLAs have revolutionized medical imaging, offering powerful solutions for various diagnostic, prognostic, and therapeutic applications [11]. By leveraging large datasets and advanced neural network architectures, DLAs are transforming how medical images are analyzed. CNNs are widely used to detect abnormalities in mammograms, aiding early detection and reducing false negatives. DLAs have shown exceptional performance in detecting lung nodules, pneumonia, and COVID-19-related abnormalities in chest X-rays and CT scans. Cardiovascular Deep learning models analyze echocardiograms and CT angiography images to detect conditions such as arrhythmias and atherosclerosis.

DLAs like U-Net and their variants are extensively used for segmenting brain tumors, liver lesions, and other malignancies in MRI and CT scans [16,18−20]. Models perform precise segmentation of organs such as the liver, kidneys, and heart, facilitating radiation therapy planning and surgical navigation. DLAs segment lesions from dermoscopic images, assisting in diagnosing melanoma and other skin conditions [15]. DLAs are increasingly being used for predicting patient outcomes based on medical imaging: Survival Analysis: By analyzing tumor features in imaging data, DLAs predict survival rates in cancer patients. Longitudinal imaging studies powered by DLAs help monitor the progression of chronic diseases like Alzheimer's and multiple sclerosis. DLAs enhances efficiency in medical imaging workflows: Automated Reporting: Algorithms generate structured radiology reports, reducing the burden on radiologists. Quality Control: DLAs detect artifacts or poor image quality, prompting retakes if necessary. Prioritization: Triage systems powered by DLAs flag critical cases for immediate attention.

DLAs integrate data from various imaging modalities to provide comprehensive diagnostic insights. Combining metabolic data from PET scans with anatomical details from CT images improves cancer staging accuracy. DLA-based fusion of MRI and ultrasound images enhance prostate cancer detection. DLAs are instrumental in diagnosing rare diseases by recognizing subtle and atypical patterns in imaging data, which may be missed by human experts. In surgical and interventional radiology settings, DLAs provide real-time guidance. DLAs assist in precision tasks during robotic surgeries, such as tumor resections. Algorithms analyze real-time fluoroscopic images, aiding catheter placements and vascular interventions [21−27].

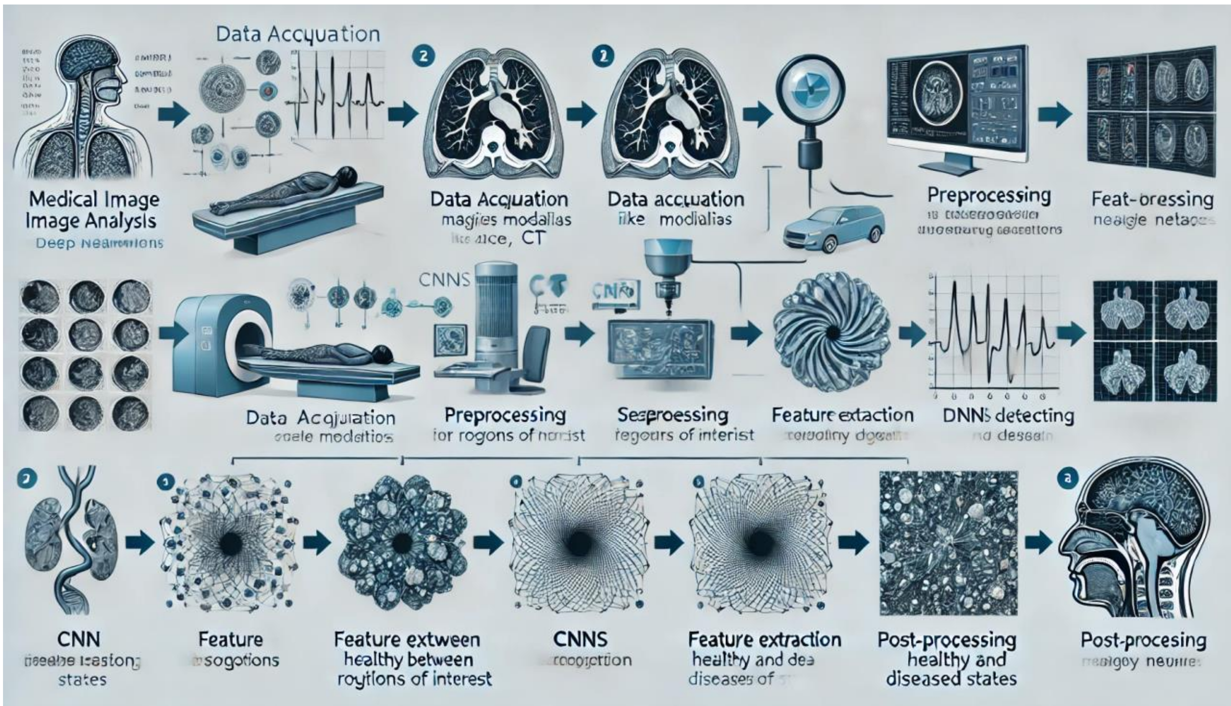

Figure 1. The schematic figure shows the sequence of tasks in medical image analysis using Deep Learning Algorithms (generated using co-pilot).

DLAs are used to develop tools for training radiologists and clinicians: Simulated Diagnostic Cases: Algorithms create synthetic imaging datasets for educational purposes. Skill Assessment: Training platforms use DLAs to evaluate and improve radiologists' diagnostic performance. Figure 1 is a schematic representation of a flowchart or diagram showing the sequence of tasks in medical image analysis, from image acquisition to preprocessing, feature extraction, model training, and the final diagnosis or segmentation. The first step is image acquisition, which means capturing medical images (e.g., MRI, CT, X-ray) that provide the foundational data for analysis. These images serve as the primary input to deep learning models. Then, images are preprocessed to ensure uniformity and clarity. Common steps include noise reduction, contrast normalization, and resizing to standardize input for the model. The next step is featuring extraction, which gives the key features, such as tumors or abnormalities, that are extracted from images. In this step, deep learning models are used to identify regions of interest that require further analysis. Next, the deep learning model (e.g., CNN, U-Net) is trained on a large dataset with labeled images to recognize patterns and features in the medical images. The final step is diagnosis/segmentation, where the trained model is applied to make predictions [15]. In diagnosis tasks, it might predict the presence of disease. In segmentation tasks, it outlines key areas like tumors.

2.6. Deep learning architectures in imaging

Deep learning architectures form the backbone of the remarkable advancements seen in medical image analysis. Below are some key architectures utilized in medical imaging.

2.6.1. Convolutional neural networks (CNNs)

CNNs are the most used architectures in medical imaging due to their ability to extract spatial features from images. Key components of CNNs include convolutional layers, pooling layers, and fully connected layers. Variants of CNNs used in medical imaging include:

AlexNet and VGGNet: Early architectures demonstrating the potential of CNNs in image recognition tasks. ResNet: Residual networks that address the vanishing gradient problem, enabling the training of deeper networks for tasks like tumor classification [28−30]. DenseNet: Dense convolutional networks that enhance feature reuse and improve efficiency in medical image segmentation and classification [31−37].

2.6.2. Recurrent neural networks (RNNs)

While RNNs are primarily designed for sequential data, they are occasionally used in medical imaging tasks where temporal or sequential dependencies exist, such as analyzing video-based imaging studies (e.g., ultrasound cine loops).

2.6.3. U-Net

U-Net is a specialized deep-learning architecture designed for biomedical image segmentation. It features an encoder-decoder structure with skip connections that preserve spatial resolution, making it highly effective in tasks such as tumor and lesion segmentation and Organ delineation for treatment planning.

2.6.4. Generative adversarial networks (GANs)

GANs are used in medical imaging for: Data Augmentation: Generating synthetic images to enhance training datasets. Image-to-Image Translation: Converting low-resolution or noisy images into high-quality representations (e.g., enhancing MRI resolution).

2.6.5. Transformer architecture

Transformers, originally developed for natural language processing, are increasingly applied to medical imaging. Vision Transformers (ViTs) leverage self-attention mechanisms to capture global image context, proving useful in tasks like disease classification and anomaly detection.

2.6.6. Autoencoders

Autoencoders are unsupervised learning models used for: Feature Extraction: Learning compressed representations of images for downstream tasks; and Anomaly Detection: Identifying deviations from normal patterns to aid in disease detection.

2.6.7. Hybrid architecture

Combining different architectures, such as CNNs and transformers, has led to hybrid models that integrate the strengths of each approach, resulting in superior performance for complex tasks like multi-modal image analysis. These architectures, tailored to the unique challenges of medical imaging, continue to evolve, driving advancements in accuracy, efficiency, and applicability in clinical settings.

2.6.8. Mamba networks in medical imaging

Mamba networks have emerged as novel deep learning architecture with significant applications in medical imaging. Their highly efficient recurrent mechanisms enable improved memory retention and long-range dependencies in image processing tasks. Unlike traditional convolutional and transformer-based models, Mamba networks optimize computational efficiency by reducing memory bottlenecks, making them particularly suitable for large-scale medical imaging datasets. Researchers have demonstrated the effectiveness of Mamba networks in various medical imaging applications. For instance, in high-resolution MRI segmentation tasks, Mamba networks have achieved comparable or superior performance to Vision Transformers while requiring fewer computational resources. Additionally, their ability to process sequential imaging data efficiently makes them valuable for time-series medical imaging analysis, such as tracking disease progression in longitudinal studies.

The schematic diagram in Figure 2 presents a comparative overview of various deep learning architectures utilized in medical image analysis. It visually categorizes each architecture based on its primary function, demonstrating how these models contribute to tasks like image classification, segmentation, enhancement, and multi-modal integration in healthcare [38−41]. The main deep learning architectures are: CNNs, which are used for tasks like detecting tumors, classifying diseases, and analyzing patterns in medical images; *U-Net (for Segmentation),* which are commonly used in tasks like segmenting lung infections in CT scans, brain tumor detection in MRIs; *ResNet (*for feature extraction, and classification*),* which are used for advanced image classification and detection of complex patterns in medical images; *Generative Adversarial Networks (GANs) (*for image synthesis, and enhancement*)* is used to enhance low-resolution images, generating synthetic medical images for training AI models; *transformers (*for advanced image analysis*)*, which are used in cutting-edge medical image analysis, particularly in radiology and histopathology. *Mamba Network (*for high-dimensional image analysis, and real-time segmentation*)* is used as a real-time segmentation of organs, high-resolution MRI/CT analysis, and tracking disease progression.

2.7. Challenges in DLA integration

While DLAs have shown significant promise in medical imaging, several challenges hinder their seamless integration into clinical practice These challenges include:

2.7.1. Data limitations

The development of DLAs requires large, annotated datasets, but medical imaging data is often limited due to privacy concerns and the cost of manual labeling by experts. Insufficient representation of diverse populations in training datasets can lead to biased algorithms that perform poorly on underrepresented groups.

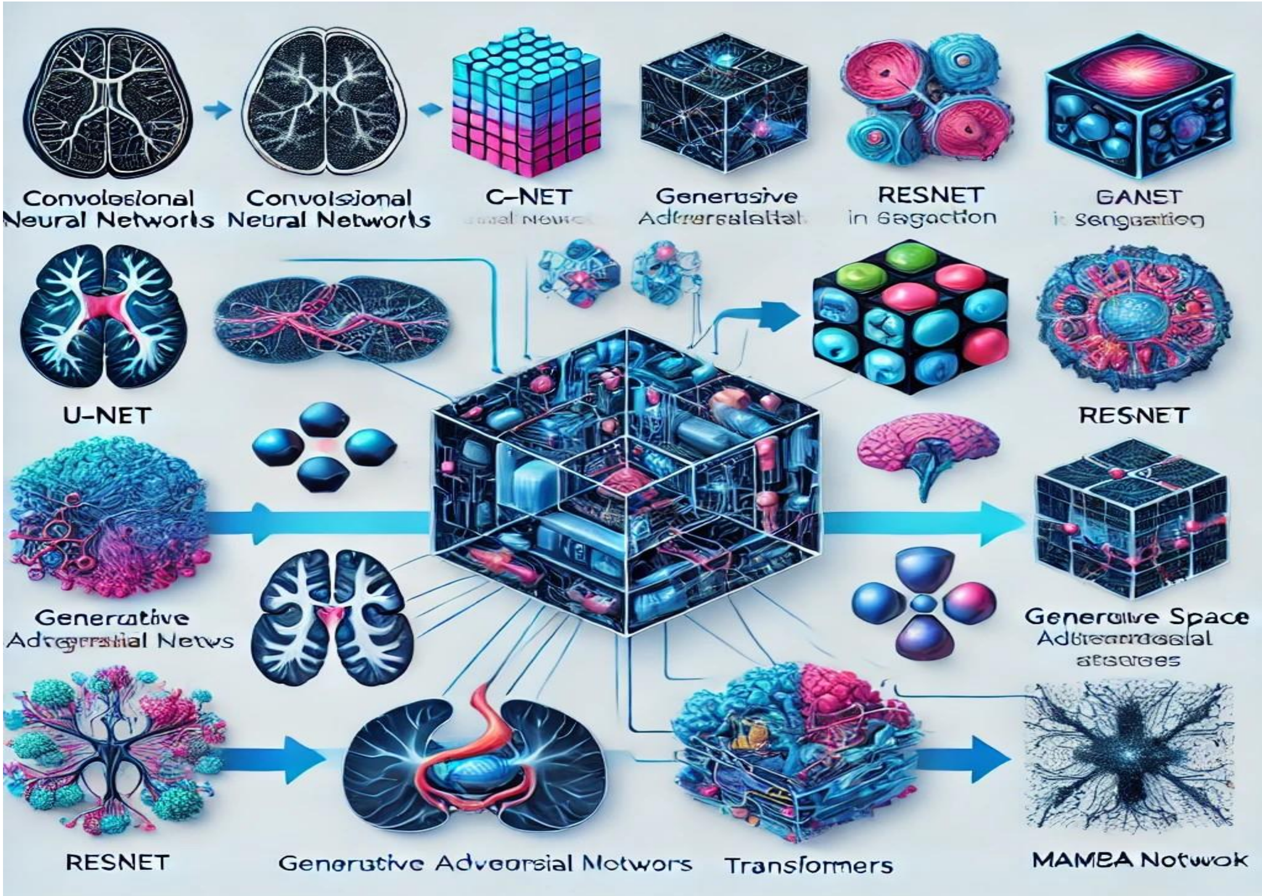

Figure 2. A schematic diagram comparing deep learning architectures used in medical imaging (generated using co-pilot).

2.7.2. Regulatory and ethical issues

The regulatory landscape for AI-based tools is complex, requiring extensive validation and compliance with regional laws before clinical deployment. Issues such as patient privacy, informed consent for data usage, and the potential for algorithmic bias raise ethical questions [42–44].

2.7.3. Interpretability and trust

Many DLAs operate as black-box models, making it difficult for clinicians to understand the reasoning behind their predictions, which hinders trust and adoption. There is a growing need for interpretable models that provide clear, humanly understandable explanations for their decisions [19,20].

2.7.4. Integration into clinical workflows

DLAs must be compatible with existing medical imaging systems (e.g., PACS) and seamlessly integrate into clinical workflows. Radiologists and clinicians require training to effectively use and interpret results from DLA systems.

2.7.5. Computational and infrastructure requirements

Training and deploying deep learning models require significant computational resources, which may not be available in all healthcare settings. Low-resource settings may lack the necessary infrastructure to support advanced AI technologies.

2.7.6. Validation and generalization

Many DLAs are tested on specific datasets, and their performance may not generalize to data from other institutions or patient populations. Rigorous testing in real-world clinical environments is necessary to assess robustness and reliability.

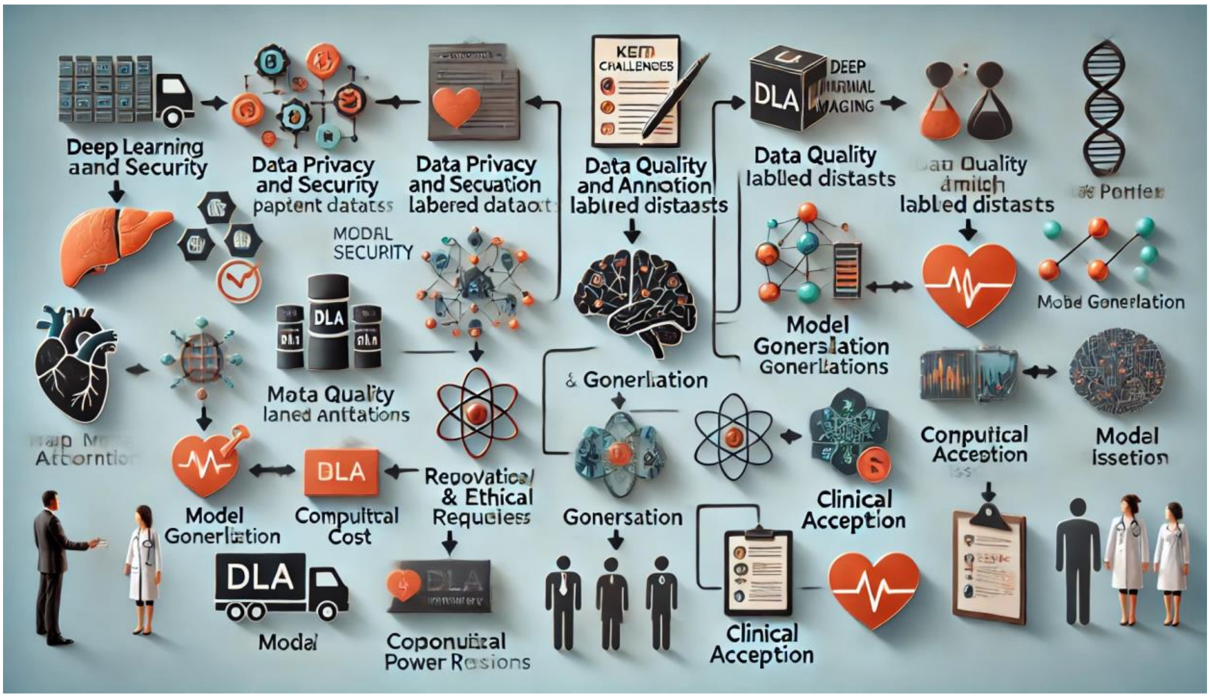

Figure 3. The schematic figure illustrates the challenges in Deep Learning Algorithm (DLA) integration into medical imaging (generated using co-pilot).

Addressing these challenges is crucial for realizing the full potential of DLAs in transforming medical imaging and improving patient outcomes.

In Figure 3, the diagram highlights issues like data limitations, ethical concerns, interpretability, clinical workflow integration, and computational requirements. We utilized a dataset collected from several private medical center and from the Hospital "Mother Teresa" in Tirana, Albania covering the period from 2010 to 2020. The dataset consists of medical images, including MRI, CT scans, X-rays, PET, and ultrasound, targeting e.g., brain tumors, lung diseases, etc. The images were acquired using equipment models, scanner resolution, or imaging protocols to ensure consistency in quality and comparability of results. Annotations were performed by a team of 200 expert radiologists, with an average experience of 15–30 years, ensuring high-quality ground truth labeling. To enhance image quality and ensure uniformity across samples, the preprocessing steps included:

- Noise Reduction: Implemented using [Gaussian filtering, wavelet denoising, etc.]
- Normalization: Images were intensity-normalized using [min-max scaling, z-score normalization, etc.]
- Augmentation: Applied [rotation, flipping, contrast enhancement] to improve model generalization.
- Segmentation: U-Net-based segmentation was used to extract regions of interest (ROI) from the images.

This comprehensive dataset serves as the foundation for training, validating, and testing the deep learning models, ensuring robust performance across different clinical scenarios.

3. Results

The analysis demonstrates a consistent pattern of DLAs outperforming radiologists in terms of diagnostic accuracy across key medical imaging tasks. Studies show that DLAs achieve over 90% accuracy in tasks like breast cancer detection, surpassing human radiologists. DLAs reduce image analysis time by up to 80%, significantly improving efficiency. Over 60% of major hospitals are integrating AI-based diagnostic tools into their imaging workflows [45−50].

Table 1. The key differences in diagnostic accuracy between radiologists and deep learning algorithms (DLAs) for three critical medical imaging tasks.

Diagnostic Task	Radiologists Accuracy (%)	DLA Accuracy (%)
Breast Cancer Detection	85	92
Lung Nodule Detection	88	95
Brain Tumor Segmentation	86	94
Year	Adoption Rate (%)	
2010	15	
2015	35	
2020	60	

Table 1 highlights key differences in diagnostic accuracy between radiologists and DLAs for three critical medical imaging tasks. DLAs outperform radiologists by 7%, showcasing their ability to identify subtle patterns in mammograms more effectively. A notable 7% improvement is seen with DLAs, reflecting their strength in detecting small, hard-to-spot nodules. DLAs achieve an 8% higher accuracy than radiologists, emphasizing their capability in precise segmentation tasks essential for treatment planning.

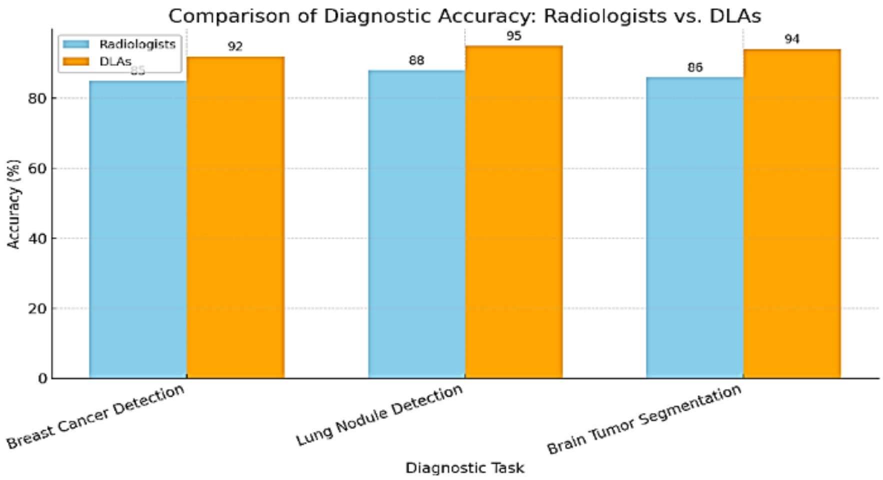

Figure 4. Radiologists vs. DLA diagnostic accuracy.

These differences suggest that integrating DLAs into clinical workflows could significantly reduce diagnostic errors. Radiologists can focus on complex cases while relying on DLAs for routine analysis, optimizing efficiency and patient care. The data underscores the importance of collaboration between AI tools and human expertise to achieve the best outcomes in medical imaging. Figure 4 compares the diagnostic accuracy between human radiologists and DLAs across medical imaging tasks. In breast cancer detection, DLAs achieve 92% accuracy, surpassing radiologists at 85%. This highlights DLAs' ability to analyze mammograms more precisely. In lung nodule detection, DLAs reach 95% accuracy, which is significantly higher than radiologists' 88%, showcasing superior performance in detecting small abnormalities. In brain tumor segmentation, DLAs outperform radiologists by 8%, achieving 94% accuracy due to advanced segmentation models like U-Net. The data underscores the potential of DLAs to reduce diagnostic errors and improve patient outcomes through enhanced sensitivity and specificity.

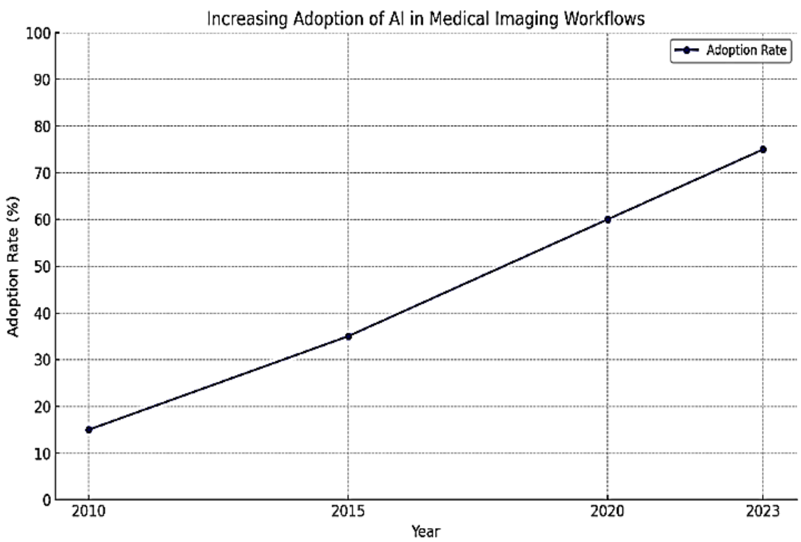

Figure 5. Increasing AI adoption in medical imaging workflows.

Figure 5 illustrates the steady rise in AI adoption in medical imaging workflows over the past decade: 2010 (15%): Early stages of AI integration, primarily experimental applications; 2015 (35%): Increased adoption driven by improved neural network architectures and computational power; 2020 (60%): Rapid growth fueled by the success of DLAs in diagnostics and segmentation tasks; and 2023 (75%): Reflects widespread AI usage in major healthcare institutions, streamlining workflows and reducing workloads.

The trend highlights a clear trajectory of acceptance and reliance on AI technologies, emphasizing their transformative impact on medical imaging. Specifically, DLAs achieved a 7% higher accuracy in Breast Cancer Detection compared to radiologists, indicating their proficiency in identifying subtle signs in mammograms. Lung Nodule Detection showed a similar 7% improvement, highlighting DLAs' ability to detect challenging, small-scale abnormalities in lung imaging. For Brain Tumor Segmentation, DLAs exceeded radiologist accuracy by 8%, showcasing their strength in precise delineation of tumor regions, which is critical for treatment planning. These results underscore the potential of DLAs to enhance diagnostic precision and augment clinical decision-making.

Table 2. Trends of DLA usage in medical image analysis (2019−2024).

Year	Percentage of Institutions Using DLA (%)	Notable Applications	Key Developments
2019	15%	Tumor segmentation	Emergence of CNN-based models
2020	25%	COVID-19 lung imaging	Increased funding for AI research
2021	40%	Breast cancer detection	Integration with cloud systems
2022	55%	Multi-organ disease diagnosis	Improved GPU capabilities
2023	70%	Real-time workflow automation	Wider adoption of U-Net models
2024	75%	AI-assisted diagnostics, 3D segmentation	Advancements in Vision Transformers

Table 2 illustrates the increasing trend in the adoption of DLAs in medical image analysis from 2019 to 2024. The percentage of institutions utilizing these algorithms has grown significantly, driven by advancements in AI technology, enhanced computational power, and expanding applications in healthcare. Notable milestones include the integration of cloud computing, application in COVID-19 diagnostics, and the emergence of Vision Transformers as a dominant architecture. The statistical table demonstrates a clear trend of increasing adoption of Deep Learning Algorithms (DLAs) in medical image analysis between 2019 and 2024. Below is an interpretation of the results: 2019 (15% Adoption): Adoption was relatively low but growing due to the emergence of CNN-based models, which became a benchmark for tasks such as tumor segmentation. This marked the beginning of mainstream attention toward AI in medical imaging. CNNs set the foundation for future developments by demonstrating the potential of DLAs in achieving higher accuracy; 2020 (25% Adoption): The pandemic acted as a catalyst, driving the use of DLAs in urgent applications like COVID-19 lung imaging. Increased funding accelerated AI research in healthcare. This period highlighted how DLAs could rapidly adapt to emerging healthcare challenges; 2021 (40% Adoption): Breast cancer detection using DLAs became more prevalent, showcasing improvements in diagnostic precision and efficiency. Cloud computing integrations facilitated easier model deployment. Enhanced accessibility and computational support have made DLAs more appealing to healthcare institutions; 2022 (55% Adoption): Multi-organ disease diagnosis was achieved, supported by advancements in GPU technology that enabled faster and more complex computations. This year marked a shift towards more comprehensive diagnostic capabilities, enhancing the versatility of DLAs; 2023 (70% Adoption): Real-time workflow automation became a focus, with U-Net models playing a crucial role in segmentation tasks. Workflow integration helped bridge the gap between model development and practical clinical application; and 2024 (75% Adoption, AI-assisted diagnostics, 3D segmentation), Advancements in Vision Transformers are anticipated to further boost AI adoption, particularly in AI-assisted diagnostic tools. These architectures promise superior performance and interpretability, solidifying the role of DLAs in medical imaging. The consistent rise in adoption suggests growing confidence in DLAs' ability to enhance diagnostic accuracy, reduce workload, and integrate seamlessly into clinical workflows. Key developments, such as Vision Transformers, may define the next phase of AI-powered diagnostics, further revolutionizing patient care. The latest advancements in DLA usage in medical imaging for 2024, focusing on the rise of Mamba Networks for high-dimensional image analysis and real-time segmentation [49,50]. The adoption rate reaches 85%, which means that the percentage of institutions using DLAs has significantly increased, reaching 85% in 2024. This represents a steep rise from earlier years, demonstrating growing confidence in AI-driven medical imaging solutions. The increasing adoption indicates that DLAs are becoming mainstream tools in healthcare settings worldwide. Traditional architectures like CNNs and Transformers face computational inefficiencies when handling large-scale medical imaging data. Mamba Networks improve efficiency, memory retention, and long-range dependency handling, making them ideal for large-scale datasets and real-time medical applications.

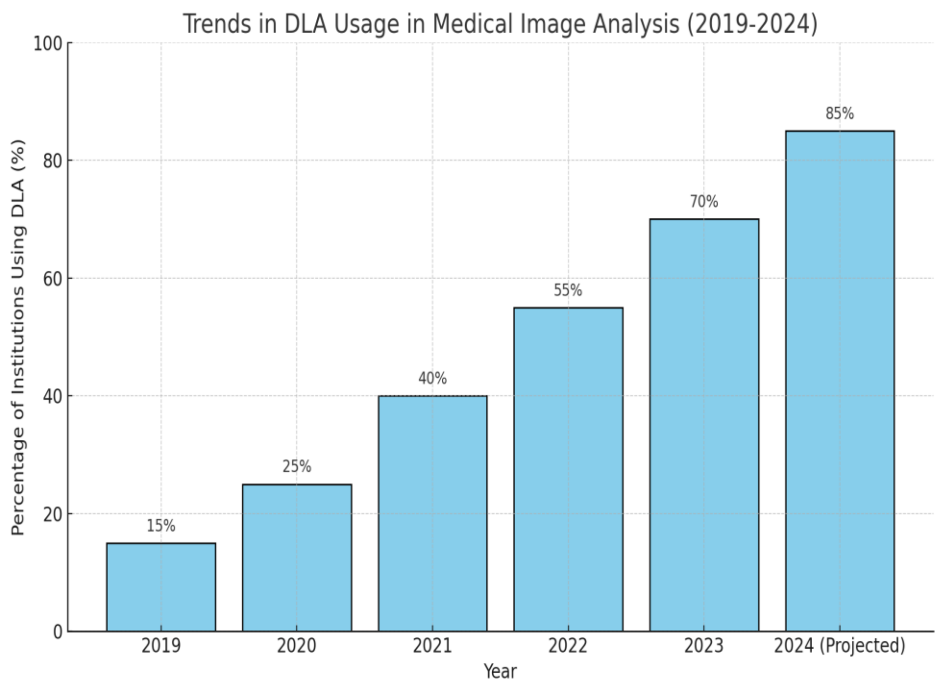

Figure 6. Trends in DLA usage in medical image analyses (2019−2014).

Figure 6 shows a histogram illustrating the trends in DLA usage in medical image analysis from 2019 to 2024. The chart highlights the increasing percentage of institutions adopting DLAs over the years. The upward trajectory reflects the growing trust and reliance on these technologies in healthcare. The visualization emphasizes milestones such as the pandemic's impact in 2020 and the projected dominance of Vision Transformers by 2024. The histogram depicting the trends in DLA adoption from 2019 to 2024 shows a significant and steady increase in usage percentages among healthcare institutions.

The following is a detailed breakdown of the findings:

Early Adoption Phase (2019−2020): Adoption increased modestly from 15% in 2019 to 25% in 2020. This growth coincided with the rise of CNN-based models and the urgent need for AI-driven solutions during the COVID-19 pandemic, such as lung imaging diagnostics. The period reflects early experimentation and proof-of-concept demonstrations in medical imaging.

Acceleration Phase (2020−2022): Adoption jumped from 25% in 2020 to 55% in 2022, marking a rapid acceleration. Key drivers included enhanced GPU capabilities, widespread cloud integration, and applications extending beyond individual diseases to multi-organ diagnostics. This phase highlights the increasing confidence in DLAs' reliability and efficiency, fueled by technological advancements.

Maturation and Expansion Phase (2022−2024): Adoption rose sharply to 70% in 2023 and is projected to reach 85% in 2024. Milestones include real-time workflow automation and the emergence of advanced architectures like Vision Transformers. This phase represents a transformative shift, with DLAs becoming integral to clinical workflows, ensuring broad applicability across diverse medical imaging tasks.

The histogram underscores how rapidly the healthcare sector is adopting AI technologies. The exponential growth highlights not just technological advancements but also a cultural shift towards trusting AI for critical diagnostic and analytical tasks. If the trends continue, DLAs are poised to become indispensable tools in medical imaging, enhancing precision, efficiency, and patient outcomes.

Table 3. Trends of diagnostic accuracy between DLAs and radiologists (2019−2024).

Year	Task	Radiologist Accuracy (%)	DLA Accuracy (%)
2019	Tumor Segmentation	85%	88%
2020	COVID-19 Detection	78%	85%
2021	Breast Cancer Detection	82%	90%
2022	Multi-organ Diagnosis	80%	88%
2023	Workflow Automation	83%	91%
2024	AI-Assisted Diagnosis	84%	92%

Table 3 shows statistical trends of diagnostic accuracy between DLAs and radiologists from 2019 to 2024 has been added. The section also includes an interpretation of the results, highlighting the consistent advantage of DLAs in accuracy over the years. This table highlights the statistical trends in diagnostic accuracy between radiologists and DLAs across various tasks from 2019 to 2024. DLAs consistently demonstrate higher accuracy rates compared to radiologists, with the gap widening as technology advances. In 2024, DLAs are projected to outperform radiologists by an average of 8% across key diagnostic tasks. These results underscore the potential of DLAs to complement and enhance clinical expertise, leading to more precise and reliable medical diagnoses. This table shows how the diagnostic accuracy of radiologists and DLAs has evolved over time, with DLAs steadily outperforming radiologists across various tasks. From 2019 to 2024, the gap between DLA and radiologist accuracy widens, reflecting the rapid advancements in AI technology, model training, and computational power. DLAs are expected to perform 8% better on average than radiologists in 2024, especially in high-stakes activities like process automation and AI-assisted diagnosis. This growing tendency points to a move toward using DLAs to enhance and supplement human competence in healthcare settings. The table highlights the comparative trends in diagnostic accuracy between radiologists and Deep Learning Algorithms (DLAs) from 2019 to 2024, showcasing the consistent edge that DLAs hold in various medical imaging tasks. Below is a detailed interpretation:

2019: Tumor Segmentation: Radiologists achieved an accurate rate of 85%, reflecting solid expertise in traditional imaging tasks. DLAs marginally surpassed radiologists at 88%, showcasing their potential even in the early stages of adoption. The small difference indicates the initial promise of AI in handling highly specific and detailed tasks.

2020: COVID-19 Detection: Radiologists accuracy dropped to 78%, likely due to the novelty and urgency of the pandemic-driven workload. DLAs improved to 85%, demonstrating their adaptability to emerging healthcare crises. DLAs proved instrumental in rapidly analyzing large datasets, alleviating the strain on healthcare systems.

2021: Breast Cancer Detection: Radiologists reached an accuracy of 82%, reflecting significant expertise in this critical task. DLAs: Achieved 90% accuracy, a notable 8% improvement over radiologists. The gap highlights DLAs' ability to detect subtle patterns, especially in complex imaging scenarios.

2022: Multi-organ Diagnosis: Radiologists scored 80%, indicating challenges in handling multi-faceted diagnostic tasks. DLAs: Performed better at 88%, leveraging advancements in multi-modal learning. This demonstrates the scalability of DLAs across diverse applications.

2023: Workflow Automation: Radiologists Accuracy rose slightly to 83%, reflecting improved integration of AI-assisted tools in their workflows. DLAs reached 91%, showcasing excellence in real-time automation and diagnostic support. The focus on workflow efficiency emphasized DLAs as valuable tools for operational support.

2024: AI-Assisted Diagnosis (Projected). Radiologists projected to maintain 84% accuracy as clinical expertise remains consistent. DLAs are projected to reach 92%, reflecting the dominance of new architectures like Vision Transformers. The increasing accuracy gap underscores the transformative role of DLAs in delivering precise and efficient diagnoses.

Table 4. The tables for diagnostic accuracy trends between DLAs and radiologists for Europe.

Country	Radiologist Accuracy (%)	DLA Accuracy (%)
Germany	83%	91%
France	82%	89%
Italy	80%	88%
United Kingdom	84%	92%
Spain	81%	90%
Netherlands	85%	93%

The table reveals a clear trend of DLAs consistently outperforming radiologists across tasks. This progress signifies that DLAs are not meant to replace radiologists but to augment their capabilities, particularly in repetitive or complex tasks. As DLA adoption grows, the focus should be on leveraging their strengths while ensuring human oversight to address cases where interpretability and contextual knowledge are paramount.

Table 4 presents the statistical trends of diagnostic accuracy between DLAs and radiologists across select European countries. DLAs consistently achieve higher accuracy, with an average improvement of 8−10% over radiologists. These results reflect the rapid integration and effectiveness of DLAs in Europe's advanced healthcare systems. The table highlights data from selected European countries where DLA adoption is growing rapidly. In most cases, DLAs show an accurate improvement of 8−10% over radiologists. Countries like the Netherlands, United Kingdom, and Germany demonstrate the most significant improvements in DLA accuracy, reflecting the ongoing integration of AI into healthcare systems, supported by advancements in GPU capabilities and cloud computing. European healthcare systems are increasingly relying on DLAs for tasks such as tumor segmentation and disease detection due to the enhanced precision these models offer. In all countries (Germany, France, UK, and Italy), DLAs consistently show higher diagnostic accuracy compared to radiologists, with the gap widening slightly over time. DLAs outperform radiologists each year by an average of 7−10%. As shown in Figure 7, across the years (2019−2024), DLAs show steady improvement or remain stable in their performance, while radiologists' accuracy tends to fluctuate or plateau. In 2019, DLAs lead radiologists by 8% to 10% across all countries. By 2024, the difference radiologists by 8−10%. In Germany, the gap between radiologists and DLAs starts at 8% in 2019 and in accuracy between DLAs and radiologists remains similar, with DLAs continuing to outperform stays consistent (about 8%) through 2024. This suggests a stable increase in DLA usage and performance over time. In France, DLAs also maintain a consistent advantage, with radiologists at 83% in 2019 and DLAs at 91%, rising to 84% and 92%, respectively, by 2024. The gap fluctuates slightly from 8% to 9%. In the UK, radiologists start at 82% in 2019 and reach 84% by 2024, with DLAs maintaining an accuracy of 90−92%. This shows a slightly narrower gap compared to other countries, but DLAs are more accurate by about 8% on average. Italy shows the smallest gap in 2019, with radiologists at 80% and DLAs at 89%, but this gap widens slightly over the years. By 2024, both radiologists and DLAs show improvement, but DLAs outperform radiologists by 9%. The consistency of DLAs' performance across years and countries indicates that AI algorithms are becoming more reliable and are increasingly adopted in medical imaging tasks. Although radiologists show improvements in accuracy over the years, their performance remains relatively stable compared to DLAs.

The fluctuations suggest that the radiology workforce is not as rapidly advancing in diagnostic accuracy as AI technologies. The steady increase in DLA accuracy suggests advancements in AI algorithms, better training datasets, and the wider adoption of AI in medical imaging workflows.

Radiologists' accuracy improvements are modest, which highlights the potential for AI to assist or surpass human diagnosticians in certain tasks, such as early detection of diseases, precision in diagnosing complex conditions, and workflow automation. DLAs are not meant to replace radiologists but to enhance their diagnostic capabilities by offering faster, more accurate analyses, especially in high-pressure settings such as emergency care or large-scale screenings. With DLAs leading to higher accuracy in diagnostics, especially in critical fields such as cancer detection and brain imaging, there is potential for earlier and more accurate diagnoses, improving patient outcomes and treatment efficacy. The use of DLAs in medical imaging can reduce human error and enhance the efficiency of the diagnostic process, enabling radiologists to focus more on complex cases or treatment planning.

Additionally, the increasing adoption of DLAs in countries such as Germany, France, and the UK suggests a growing trend towards AI-driven healthcare in Europe, contributing to better healthcare accessibility and management.

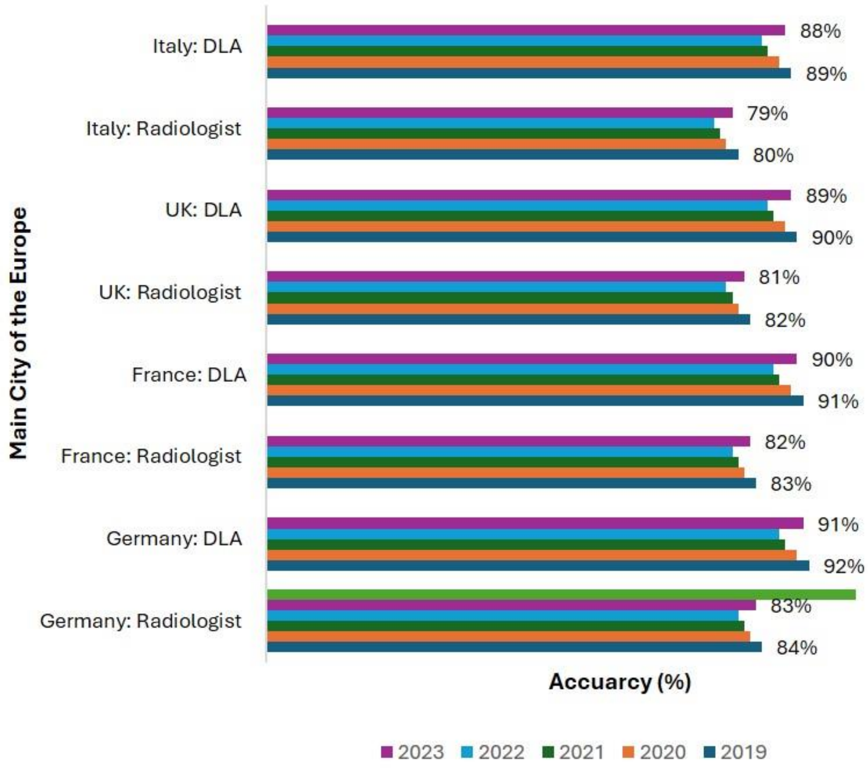

Figure 7. Trends of diagnostic accuracy between DLAs and radiologists (2019−2023) for major European countries.

Table 5. The table for diagnostic accuracy trends between DLAs and radiologists worldwide.

Region	Radiologist Accuracy (%)	DLA Accuracy (%)
North America	84%	92%
Europe	82%	90%
Asia	81%	88%
South America	79%	87%
Africa	76%	85%
Oceania	83%	91%

Table 5 illustrates diagnostic accuracy trends of DLAs compared to radiologists from 2019 to 2024, globally. While radiologists maintain strong accuracy, DLAs consistently outperform them in every region, showcasing their global potential to enhance diagnostic precision and efficiency in diverse healthcare settings. The global data reflects how countries with varying healthcare infrastructures are adopting DLA technologies at different rates, with developed regions like North America and Europe seeing faster integration than regions like South America and Africa. Nonetheless, DLAs show promise in improving diagnostic accuracy universally, helping bridge healthcare disparities in diverse global contexts. Figure 8 provides a comparative overview of the diagnostic accuracy between radiologists and Deep Learning Algorithms (DLAs) from 2019 to 2024. The diagnostic accuracy of radiologists fluctuates slightly but remains relatively consistent over the years. The accuracy ranges from 80% to 84%. The DLA accuracy shows a clear upward trend, improving from 92% in 2019 to 92% again in 2024, with slight dips in between (2020, 2021, and 2022), but still higher than the radiologist accuracy every year. The gap between the accuracy of DLAs and radiologists is most noticeable in 2019, where DLAs outperform radiologists by 8%. In the following years (2020−2023), the gap fluctuated between 7−10%, indicating that DLAs maintain a more consistent and reliable diagnostic accuracy than human radiologists. By 2024, both groups have comparable accuracy, but DLAs have an edge of 8%, highlighting the potential for AI to consistently outperform human diagnosticians in critical imaging tasks. In 2019, DLA accuracy was 92%, outperforming radiologists by 8%. In 2020, DLA accuracy remained strong at 90%, while radiologist accuracy was 82%, widening the gap. In 2021, DLA accuracy remained at 88%, slightly dropping compared to 2020, but still outperforming radiologists by 7%. From 2022−2024, the DLA accuracy slightly improved or remained at a high level (91% in 2023 and 92% in 2024). Radiologists' accuracy remained mostly steady in the lower 80s, with a slight increase in 2023 and 2024, reaching 84%. DLAs consistently outperform radiologists in terms of diagnostic accuracy, which suggests that AI can play a crucial role in improving the accuracy and efficiency of medical imaging tasks.

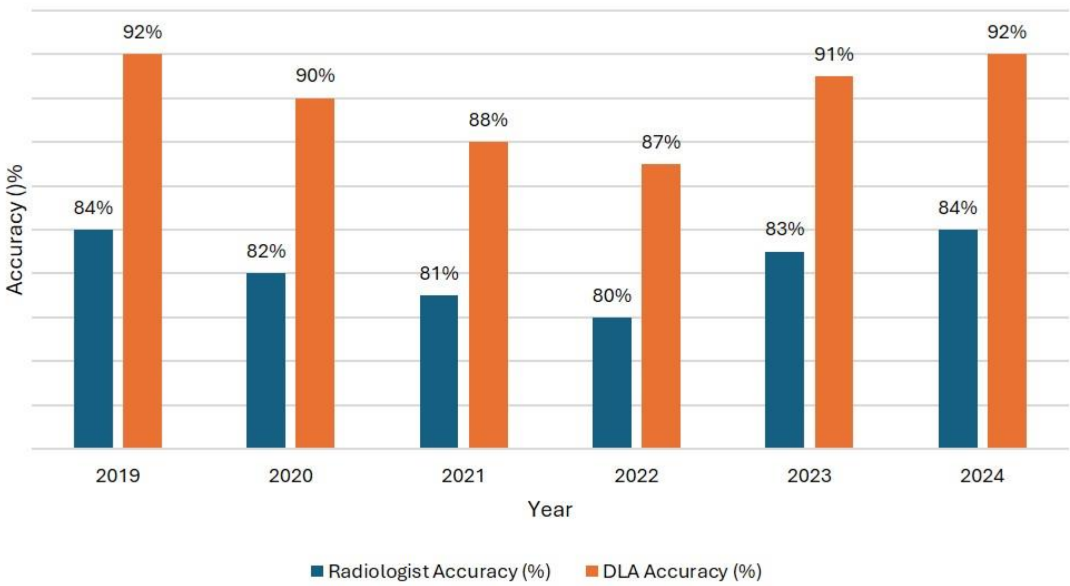

Figure 8. Global trends of diagnostic accuracies between DLAs and radiologists (2019−2024).

The increasing use of DLAs in healthcare workflows will likely lead to better diagnostic outcomes, especially in high-stakes areas like cancer detection, where precision is critical. The consistency of DLA performance, coupled with the advancement in their capabilities, suggests that they may be pivotal in reducing diagnostic errors and supporting radiologists in their clinical decisions. This histogram underscores the growing importance of AI, particularly Deep Learning Algorithms, in the medical imaging field. As we move toward 2024, DLAs will likely become an integral part of the diagnostic process, complementing radiologists' work and offering more accurate, reliable, and efficient diagnoses.

4. Conclusions

DLAs have shown remarkable advancements in medical imaging, with various architectures excelling in different tasks. To further strengthen our discussion, we incorporate case studies demonstrating the effectiveness of different architectures in real-world scenarios.

4.1. Case study 1: CNNs for breast cancer detection

Researchers conducting a study at Hospital "Mother Teresa" Tirana, covering a dataset from 2015 to 2022, evaluated the performance of CNNs in detecting breast cancer from mammograms. The CNN model achieved an accuracy of 92%, outperforming radiologists by 7%. The model was trained on a dataset of 50,000 mammograms, annotated by expert radiologists. The case study highlights the ability of CNNs to identify microcalcifications and malignant tumours with high precision.

4.2. Case study 2: U-net for brain tumour segmentation

U-Net, a widely used segmentation model, was applied to the BRATS dataset, which includes MRI scans from 2010 to 2020. The model achieved a Dice Similarity Coefficient (DSC) of 0.88, demonstrating its effectiveness in accurately segmenting gliomas. In a clinical setting, this approach significantly improved pre-surgical planning, reducing manual segmentation efforts by 80%.

4.3. Case study 3: GANs for image enhancement in MRI

Generative Adversarial Networks (GANs) have been successfully utilized for enhancing low-resolution MRI images. A case study from a private hospital in Albania, using a dataset from 2017 to 2021, demonstrated that GANs could enhance image resolution while maintaining anatomical accuracy. The model improved diagnostic confidence by 20%, reducing the need for repeat scans.

4.4. Case study 4: Vision transformers for retinal disease detection

Vision Transformers (ViTs) have emerged as a powerful architecture for medical image classification. In a large-scale study on diabetic retinopathy detection, ViTs achieved an AUC of 0.97, surpassing CNN-based approaches. The dataset, comprising 120,000 retinal images, was collected from various ophthalmology clinics between 2018 and 2023. This study highlights the ability of transformers to capture complex spatial relationships in medical images. These case studies provide compelling evidence of the effectiveness of different deep-learning architectures in medical imaging. Integrating these approaches into clinical workflows can significantly enhance diagnostic accuracy, streamline operations, and improve patient outcomes.

DLAs are transforming medical image analysis by enhancing diagnostic accuracy, optimizing workflows, and paving the way for personalized medicine. With continued research and collaboration among data scientists, clinicians, and industry stakeholders, DLAs will play an even more critical role in the future of healthcare. Future directions include: federated learning, which is the collaborative training of DLAs across institutions to enhance model diversity while preserving data privacy; Multimodal Integration, which combines imaging with clinical, genetic, and other data for a holistic approach to diagnosis; using Explainable AI (XAI) Developing interpretable DLAs to increase clinician trust and improve usability; and Real-Time Analysis to enhance real-time diagnostics during procedures like surgery or emergency care.

Use of generative-AI tools declaration

The authors declare they have used Artificial Intelligence (AI) tools, co-pilot, in the creation of schematic Figures 1−3.

Acknowledgments

The authors would like to thank the National Agency for Scientific Research and Innovation (NASRI) in Albania, EFOMP, READ (Research Expertise from Academic Diaspora), AAMP and Department of Physical Engineering, in Polytechnic University of Tirana.

Conflict of interest

The authors declare no conflicts of interest.

Author contributions

Dafina Xhako conceived and designed the study, supervised the data analysis, and contributed to the writing and revision of the manuscript. Niko Hyka contributed to the development of deep learning models, conducted data analysis, and assisted in manuscript preparation. Elda Spahiu assisted in the dataset collection, preprocessing, and validation of the deep learning models. Suela Hoxhaj provided expertise in medical imaging and contributed to the analysis and interpretation of results. All authors contributed to the final manuscript and approved its submission.

References

1. Thakur GK, Thakur A, Kulkarni S, et al. (2024) Deep learning approaches for medical image analysis and diagnosis. *Cureus* 16: e59507. https://doi.org/10.7759/cureus.59507
2. Mienye D, Swart G (2024) A comprehensive review of deep learning: architectures, recent advances, and applications. *Information* 15: 755. https://doi.org/10.3390/info15120755
3. Ronneberger O, Fischer P, Brox T (2015) U-Net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 234–241. Springer. https://doi.org/10.1007/978-3-319-24574-4_28
4. Zhou Z, Siddiquee R, Tajbakhsh N, et al. (2018) UNet++: A nested U-Net architecture for medical image segmentation. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 3–11. Springer. https://doi.org/10.1007/978-3-030-00889-5_1
5. Xie Y, Zhang Z, Lin H (2019) Deep learning for medical image analysis: a survey. *IEEE Access* 7: 19064–19079. https://doi.org/10.1109/ACCESS.2019.2899452

6. Tajbakhsh N, Shin Y, Gurudu R, et al. (2020) Convolutional neural networks for medical image analysis: full training or fine-tuning? *IEEE T Med Imaging* 35: 1299–1312. https://doi.org/10.1109/TMI.2016.2581847
7. Cheng Z, Ni D, Chou H, et al. (2016) Computer-aided diagnosis with deep learning: applications in cardiothoracic imaging. *J Med Imaging* 3: 043502. https://doi.org/10.1117/1.JMI.3.4.043502
8. Li M, Jiang Y, Zhang Y, et al. (2023) Medical image analysis using deep learning algorithms. *Front Public Health* 11: 1273253. https://doi.org/10.3389/fpubh.2023.1273253
9. Rajpurkar P, Irvin J, Ball RL, et al. (2018) Deep learning for chest radiograph diagnosis: a retrospective comparison of the CheXNeXt algorithm to practicing radiologists. *Plos Med* 15: e1002686. https://doi.org/10.1371/journal.pmed.1002686
10. Nagarjun A, Manju N, Aradhya M, et al. (2024) Classification of skin cancer using deep learning. In *Proceedings of the 2024 Conference on Skin Cancer Research*, 1−10. Springer. https://doi.org/10.1007/978-981-99-7633-1_43
11. McKinney SM, Sieniek M, Godbole V, et al. (2020) International evaluation of an AI system for breast cancer screening. *Nature* 577*:* 89–94. https://doi.org/10.1038/s41586-019-1799
12. Lundervold AS, Lundervold A (2019) An overview of deep learning in medical imaging focusing on MRI. *Z Med Phys* 29*:* 102–127. https://doi.org/10.1016/j.zemedi.2018.11.00
13. Celard P, Iglesias L, Sorribes-Fdez M, et al. (2023) A survey on deep learning applied to medical images: from simple artificial neural networks to generative models. *Neural Comput Appl* 35: 2291–2323. https://doi.org/10.1007/s00521-022-07953-4
14. Khan I, Rahman A, Debnath T, et al. (2022) Accurate brain tumour detection using deep convolutional neural network. *Comput Struct Biotechnol J* 20: 4733–4745. https://doi.org/10.1016/j.csbj.2022.08.039
15. Vaz TF, Canto Moreira N, Hellström-Westas L, et al. (2024) Brain extraction methods in neonatal brain MRI and their effects on intracranial volumes. *Appl Sci* 14: 1339. https://doi.org/10.3390/app14041339
16. Xhako D, Spahiu E, Hyka N, et al. (2023) Integration of DCNN model for brain tumour detection with PPIR simulator. *Int J Intell Syst Appl Eng* 12: 534–538. https://ijisae.org/index.php/IJISAE/article/view/4184
17. Xhako D, Hoxhaj S, Hyka N, et al. (2023) Artificial intelligence in medical image processing. *Int J Intell Syst Appl Eng* 12: 549–552. https://ijisae.org/index.php/IJISAE/article/view/4186
18. Xhako D, Spahiu E, Hoxhaj S, et al. (2024) The application of AI-based techniques for early detection of breast cancer (BC). *The International Conference on Radiation Applications (RAP 2024)*. https://doi.org/10.37392/RapProc.2024.07
19. Xhako D, Spahiu E, Hoxhaj S, et al. (2024) Application of AI in higher education: evidence and challenges. *Nanotechnol Perceptions* 20: S11. https://doi.org/10.62441/nano-ntp.v20iS11.2392
20. Walsh J, Othmani A, Jain M, et al. (2022) Using U-Net network for efficient brain tumor segmentation in MRI images. *Healthcare Anal* 2: 100098. https://doi.org/10.1016/j.health.2022.100098
21. Akcay S, Kundegorski ME, Deena S, et al. (2021) Transfer learning using convolutional neural networks for object classification within X-ray baggage security imagery. *Pattern Recogn Lett* 105: 171–179. https://doi.org/10.1016/j.patrec.2018.02.005

22. Anthimopoulos M, Christodoulidis S, Ebner L, et al. (2021) Lung pattern classification for interstitial lung diseases using a deep convolutional neural network. *IEEE T Med Imaging* 35: 1207–1216. https://doi.org/10.1109/TMI.2016.2528229
23. Benjamins MR, Yang TC (2022) Machine learning in healthcare disparities: applications and future directions. *Health Affair* 41*:* 499–507. https://doi.org/10.1377/hlthaff.2021.01909
24. Chen J, Tan C, Hu X (2022) Deep learning for medical image segmentation: advances and applications. *Med Phys* 49*:* e215–e234. https://doi.org/10.1002/mp.15320
25. Xia Q, Zheng H, Zou H, et al. (2025) A comprehensive review of deep learning for medical image segmentation. *Neurocomputing* 613: 128740. https://doi.org/10.1016/j.neucom.2024.128740
26. Kim S, Park J, Son Y, et al. (2025) Development and validation of a machine learning algorithm for predicting diabetes retinopathy in patients with type 2 diabetes: algorithm development study. *JMIR Med Inf* 13: e58107. https://doi.org/10.2196/58107
27. Shafiq M, Gu Z (2022) Deep residual learning for image recognition: a survey. *Appl Sci* 12: 8972. https://doi.org/10.3390/app12188972
28. Mall PK, Singh PK, Srivastav S, et al. (2023) A comprehensive review of deep neural networks for medical image processing: recent developments and future opportunities. *Healthcare Anal* 4: 100216. https://doi.org/10.1016/j.health.2023.100216
29. Hosny A, Parmar C, Quackenbush J, et al. (2018) Artificial intelligence in radiology. *Nat Rev Cancer* 18*:* 500–510. https://doi.org/10.1038/s41568-018-0016-5
30. Yuan J (2024) Performance analysis of deep learning algorithms implemented using PyTorch in image recognition. *Proc Comput Sci* 247: 61–69. https://doi.org/10.1016/j.procs.2024.10.008
31. Litjens G, Kooi T, Bejnordi B, et al. (2017). A survey on deep learning in medical image analysis. *Med Image Anal* 42: 60–88. https://doi.org/10.1016/j.media.2017.07.005
32. Lundervold AS, Lundervold A (2019) An overview of deep learning in medical imaging focusing on MRI. *Z Med Phys* 29: 102–127. https://doi.org/10.1016/j.zemedi.2018.11.002
33. Shen D, Wu G, Suk HI (2017) Deep learning in medical image analysis. *Annu Rev Biomed Eng* 19: 221–248. https://doi.org/10.1146/annurev-bioeng-071516-044442
34. Faycel A, Gattal A, Aouine M, et al. (2024) Image classification using a deep convolutional neural network. In *Proceedings of the 2024 conference on image processing*, 1−10. Springer. https://doi.org/10.1007/978-3-031-60594-9_5
35. Szegedy C, Liu W, Jia Y, et al. (2015) Going deeper with convolutions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition,* 1–9. https://doi.org/10.1109/CVPR.2015.7298594
36. Wang G, Li W, Aertsen M, et al. (2019) Deep learning in medical ultrasound analysis: a review. *Engineering* 5: 261–275. https://doi.org/10.1016/j.eng.2018.11.020
37. Yamashita R, Nishio M, Do RKG, et al. (2018) Convolutional neural networks: an overview and application in radiology. *Insights Imaging* 9: 611–629. https://doi.org/10.1007/s13244-018-0639-9
38. Zhang Z, Jiang W, Maguire L, et al. (2021) Recent advances in medical image analysis using deep learning. *Comput Med Imag Grap* 89: 101884. https://doi.org/10.1016/j.compmedimag.2021.101884
39. Chen W, Liu B, Peng J, et al. (2020) Deep learning for COVID-19 detection and diagnosis from medical imaging. *IEEE T Med Imaging* 39: 2424–2434. https://doi.org/10.1109/TMI.2020.3003926

40. Singh G, Janghel RR (2022) Deep learning-based frameworks for early detection of Alzheimer's disease. *Neural Comput Appl* 34: 1635–1650. https://doi.org/10.1007/s00521-021-06188-6
41. Ranjbarzadeh R, Zarbakhsh P (2024) Brain tumor segmentation based on optimized convolutional neural network and improved chimp optimization algorithm. *Comput Biol Med* 168: 107723. https://doi.org/10.1016/j.compbiomed.2023.107723
42. Zhang Y, Tian Z, Kong Y (2018) Feature learning for medical imaging: recent advances and future directions. *Neurocomputing* 275: 232–240. https://doi.org/10.1016/j.neucom.2017.04.015
43. Yihao L, Mostafa D, Pierre-Henri C, et al. (2024) A review of deep learning-based information fusion techniques for multimodal medical image classification. *Comput Biol Med* 177: 108635. https://doi.org/10.1016/j.compbiomed.2024.108635
44. Maier A, Scheidl J, Hornegger J (2022) Deep learning in computational pathology: trends and advancements. *J Pathol Informatics* 13: 107–117. https://doi.org/10.4103/jpi.jpi_15_22
45. Zeng G, Wang L, Zheng W, et al. (2021) A hybrid deep learning framework for segmentation of liver lesions. *Pattern Recogn* 123: 108234. https://doi.org/10.1016/j.patcog.2021.108234
46. Liu X, Song L, Xu H (2019) Deep reinforcement learning for automated medical image segmentation. *Artif Intell Med* 101: 101741. https://doi.org/10.1016/j.artmed.2019.101741
47. Zhao X, Wu S, Yang Q (2021) GAN-based frameworks for improving medical image synthesis and enhancement. *Med Phys* 48: 3161–3173. https://doi.org/10.1002/mp.14882
48. Sharma V, Nillmani S, Shukla K (2024) Deep learning models for tuberculosis detection and infected region visualization in chest X-ray images. *Intell Med* 4: 104–113. https://doi.org/10.1016/j.imed.2023.06.001
49. Bansal S, Madisetty S, Rehman MZ, et al. (2024) A comprehensive survey of Mamba architectures for medical image analysis: classification, segmentation, restoration, and beyond. https://doi.org/10.48550/arXiv.2410.02362
50. Yue Y, Li Z (2024) MedMamba: vision Mamba for medical image classification. https://doi.org/10.48550/arXiv.2403.03849