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Review Article

Advancements in Medical Image Analysis: A Metric-driven review of AI, ML, and DL Methods

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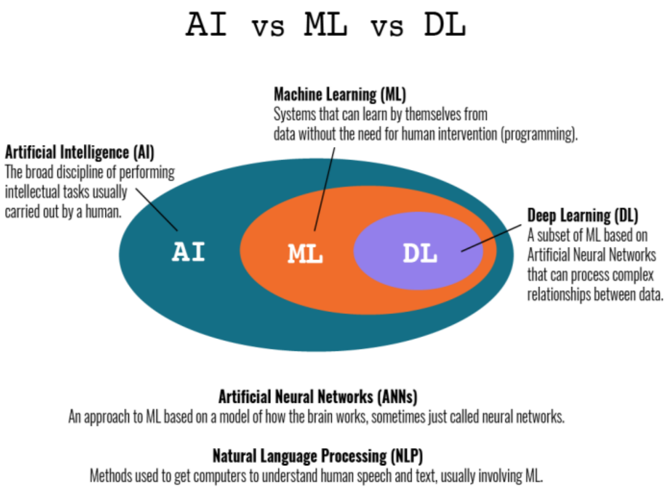
Abstract: The domain of medical image analysis (MIA) within Machine Learning (ML), Artificial Intelligence (AI), and Deep Learning (DL), the significance of employing advanced methods cannot be overstated. Several methods have attained better outcomes in several fields, making it especially noteworthy for MIA in healthcare. The combination of these fields with MIA gives real-time analysis of prior and different databases, comprehensive insights that are important to improve healthcare results, and operational efficacy in the industry. This analysis article of existing literature considers a thorough examination of the most current ML, DL, and AI methods designed to identify the complexities faced in medical healthcare, specifically focusing on the utilization of DL, ML, and AI methods in MIA. The main contribution of this paper is how AI, ML and DL is used in medical field for early disease detection, drug discovery, and robotic-assisted surgeries. Comparative Analysis Based on the Different models and Algorithm is properly defined in this paper. It analysed the different methods, such as convolutional neural networks(CNNs), Support Vector Machine (SVM), Logistic Regression (LR), Decision Tree (DT), etc. This paper review the existing result was analysed, by other authors with a high accuracy achieved with the CNN method of 94%, XGBoost achieved the maximum accuracy of 91%, and Logistic Regression an accuracy of 79% and compared with the existing models.

Keywords: Medical Image Analysis (MIA), Machine Learning (ML), Artificial Intelligence (AI), Deep Learning (DL), Convolutional Neural Networks (CNN)

Graphical Abstract-



1. Introduction

Nowadays, Medical (X-ray, MRI, and CT-Scan) Images are crucial tools in the medical field, offering comprehensive insights into the internal organization and condition of a patient's tissues. They are widely used for diagnosis, treatment strategy, monitoring disease, etc. Basically, the different types of images include X-rays, MRI, ultrasound, nuclear medicine, pathology slides, and ophthalmological images [1]. Traditionally, interpreting these images relies deeply on the capability of medical experts, such as radiologists and pathologists. Various imaging techniques are employed to obtain these medical images, each suited for different clinical purposes. For example, X-rays are often used for bone and chest examinations, CT scans provide comprehensive cross-sectional images, and MRI provides high-contrast medical images of soft tissues. Ultrasound utilizes sound waves for real-time imaging, while nuclear medicine highlights physiological functions. These techniques differ in complexity, resolution, and the type of information they provide [2]. Despite their importance, medical image analysis faces several challenges. High-dimensional data, noise, artifacts, and variability in imaging quality complicate interpretation. The sheer volume of data and the requirement for rapid, precise diagnosis put immense pressure on healthcare professionals. Additionally, manual analysis is time-consuming and subject to human expectation, that may impact diagnostic consistency and treatment outcomes.

To solve these challenges, optimization algorithms have been increasingly applied in medical image analysis. These algorithms improve image enhancement, segmentation, feature extraction, and classification by adjustment metrics to exploit precision and efficacy [3]. Techniques such as gradient descent, genetic algorithms, and Bayesian optimization help automatically identify the best algorithm settings. Optimization also plays a key role in feature selection by reducing dimensionality and focusing on the most relevant image attributes, thus improving model interpretability and robustness. Beyond image processing, optimization methods support healthcare resource allocation, including staff scheduling, supply chain management, and emergency response [4]. These applications ensure efficient use of limited resources while maintaining high-quality patient care. As medical imaging (MI) technology advances, optimization techniques will continue to be integral in enhancing diagnostic precision, workflow efficiency, and personalized treatment strategies.

In parallel, Several domains, such as Artificial Intelligence (AI), especially Machine Learning (ML) and Deep Learning (DL), have developed as a powerful tool to support and improve medical image analysis. ML allows systems to study designs from data and make detection and classification decisions without explicit programming. It encompasses methods, such as supervised, unsupervised, and semi-supervised learning, and often requires domain expertise for feature extraction and optimizing the features [5]. To overcome the limitations of manual feature engineering, DL has gained traction. DL models can automatically extract meaningful features from raw medical images and learn complex representations through multiple layers of abstraction [88]. DL has proven especially valuable in medical domains such as MRI, Radiology, Cardiology, and Neurology.

Several DL architectures, originally developed in computer vision (CV), have been adapted for MIA. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are DL models applied to tasks like segmentation, object detection, classification, and image registration. In addition, unsupervised models, including Restricted Boltzmann Machines (RBMs), Autoencoders, Generative Adversarial Networks (GANs), and Deep Belief Networks (DBNs), are utilized for feature learning and image generation tasks [6]. The applications of DL in MI are visually summarized in Figure 1, which demonstrates how these technologies contribute to various stages of MIA.

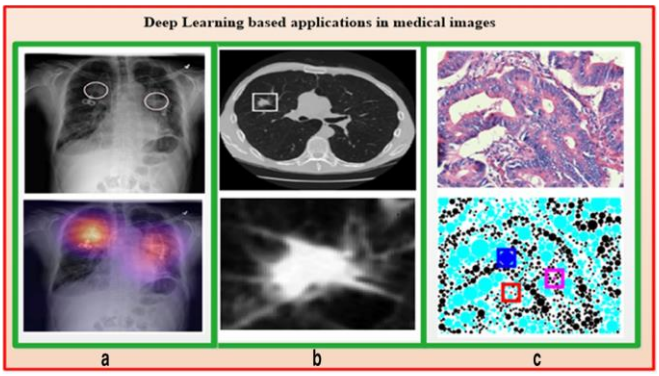


Figure. 1. Different Medial Image Technologies Images [7] [8] [9]

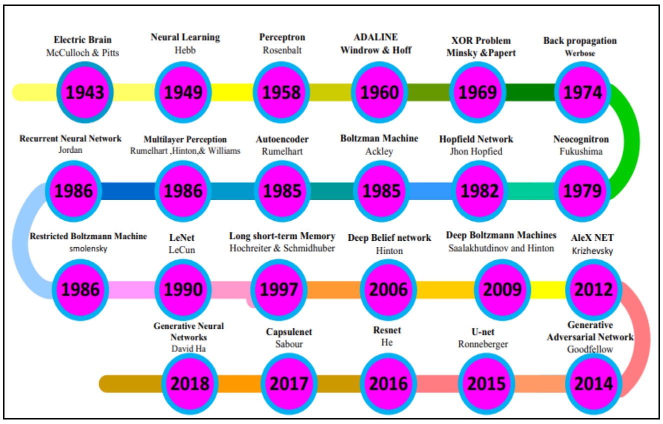


Figure 2 Protests of important growths in the history of NNs [5]

The advance of DL is rooted in decades of progress in neural network research, beginning with early models by McCulloch and Pitts in the 1940s. Milestones such as the Perceptron by Rosenblatt, the ADALINE model by Widrow, and the Neocognitron by Fukushima laid the groundwork for modern architectures. Breakthroughs such as back propagation, CNNs for handwritten digit recognition by LeCun, and Deep Belief Networks by Hinton et al., shaped today's DL systems. These key advancements are depicted in As MI data continues to be produced in complexity and volume, the integration of AI, DL, and optimization algorithms will play a major role in improving diagnostic accuracy, reducing human error, streamlining clinical workflows, and enabling more personalized and data-driven healthcare provision.

Lastly, the addition of optimization techniques and artificial intelligence—particularly DL—has revolutionized MIA by addressing challenges like data complexity, variability, and diagnostic delays. These advancements have enabled automated, accurate, and efficient interpretation of medical images, as illustrated in Figures 1 and 2, marking a significant shift toward more intelligent and scalable healthcare solutions.

The rest of the article is defined as shadows: Section 2 explains the different ML, DL, AI, and Optimization-based Medical Image Analysis (MIA) methods. Section 3 discusses the comparative analysis based on the different methods (AI, ML, and DL). The existing result analysis based on different AI, ML, and DL methods elaborates the different performance metrics, such as accuracy, precision, etc., with other comparison methods.

2. Related Work

Recent developments in medical image processing leverage ML, DL, AI, and optimization methods to improve disease classification and segmentation. ML focuses on feature selection and algorithm design, while DL, particularly CNNs, excels in learning from complex image data. AI integrates these approaches to enable personalized and predictive healthcare. Optimization methods help enhance model accuracy and generalization. Despite promising results, limitations, such as limited data, interpretability, and ethical concerns, endure in key research areas.

2.1 Medical Image Processing Using Machine Learning (ML)

Recent advances in MI processing have increasingly leveraged ML techniques to improve disease detection, segmentation, and classification. Various studies have addressed challenges ranging from feature selection and algorithm design to ethical considerations and clinical applicability, driving meaningful progress in the field. [10] used ML in medical imaging to select the most relevant features for precise detection of disease, though many features were often irrelevant and slowed computation. This research presented a Congruent Feature Selection technique based on similarity and correlation of pixel intensities and textures to improve feature relevance and consistency. The method significantly increased ML performance, precision, boosting accuracy, and training speed by over 10%, while reducing error and selection time by more than 12% compared to existing methods. Another author, [11], aimed to present the role of values specific to medical image analysis. The article defined main technical choices in ML, especially the end-to-end versus separable learning techniques, and presented a clear, organized framework linking these values to technical decisions. By doing so, it sought to deepen the understanding of how philosophical perspectives influenced research design and outcomes. This approach highlighted how the philosophy of science clarified and improved important aspects of MIA research, ultimately guiding better practices in the field. In this study [12] leveraged the K-Nearest Neighbor (KNN) method combined with NNs for effective MI segmentation and classification, utilizing gray-level co-occurrence matrix features. Tested on echocardiographic images, the system showed improved accuracy and performance over existing methods, validated through metrics such as Mean Squared Error, PSNR, and SSIM. Another study, [13] showed great potential to improve patient outcomes; medical image analysis research was hindered by problems, including biased data and research focused more on publication than clinical value. Progress slowed because models often demonstrated limited real-world effectiveness and evaluation flaws. This study examined these barriers, ongoing solutions, and suggested changes in research practices to better align ML with healthcare needs. Meaningful progress required shifting priorities and standards across the field.

2.2 Medical Image Processing Using Deep learning (DL)

Recent studies in MI processing using DL highlight the efficiency of CNNs and transfer learning (TL) for accurate disease diagnosis, while addressing challenges like limited data, model interpretability, and adaptive techniques for improved clinical applications. [14] explored the use of CNNs for diagnosing lung nodules from chest X-rays, indicating high accuracy, sensitivity, etc., on a large annotated database. The results highlighted CNNs' potential to support early lung cancer detection and improve clinical decision-making. While promising, problems such as model interpretability, data privacy, and regulatory compliance remained. The research underscored CNNs' transformative role in diagnostic medicine and emphasized the need for further research to ensure safe and effective clinical adoption. Similarly, [15] aimed to develop an automated method for selecting the most suitable pooling method in CNNs for image fusion tasks; the research based its method on the characteristics of input images. The presented method outperformed traditional approaches, such as DWT, NSCT, and PCA in terms of image superiority parameters (PSNR, MSE, VIF, etc.) and processing time. By enabling adaptive pooling selection, it improved CNN convergence and delivered more consistent performance across different datasets. The results highlighted its potential for generalized multi-modal image fusion, with future scope for integrating newly developed pooling methods. In [16] focused on improving CNN-based classification for medical image analysis, solving problems including limited labeled data and improving performance on large datasets. A high-performing CNN architecture with fully connected layers was designed, which achieved 95.77% accuracy across 24 medical image classes and an average precision of 0.69 on the ROC curve. Calculated using different parameters, such as precision, recall, etc., the system showed strong potential for improving image retrieval and supporting advanced computer-aided diagnosis. [17] investigated the utilize of CNN-based techniques for pneumonia classification using a small chest X-ray dataset, solving issues related to limited labeled data. It compared traditional SVM with ORB features, capsule networks, and CNN-based transfer learning using VGG16 and InceptionV3. The results demonstrated that transfer learning (TL), especially with fine-tuned layers and proper network complexity, outperformed the other methods. Data augmentation proved to be essential for improving model performance. The research concluded that CNN-based approaches, especially transfer learning, were more effective than traditional methods and emphasized the need for future work on reducing overfitting, exploring advanced models, and increasing model interpretability for clinical use.

2.3 Medical Image Processing Using Artificial Intelligence (AI)

AI is converting MI by allowing more precise and efficient analysis of complex medical data. Utilizing advanced methods like deep learning and neural networks, AI increases disease detection, classification, and personalized treatment planning. This integration is reshaping healthcare by improving diagnostic capabilities and supporting better clinical decisions. [18] examined how AI revolutionized analytic imaging by enhancing efficiency, accuracy, and personalized care in healthcare. Analyzing 30 studies, it highlighted AI's roles in increasing operational efficiency, image interpretation, enabling predictive analytics, and supporting clinical decisions. Despite its promise, problems, such as ethical problems, security, and the need for investment and training, remained. The study emphasized the need for ongoing commitment to ethical AI development, professional education, and collaboration to ensure effective clinical integration and equitable healthcare outcomes. Another author, [19] examined he integration of AI in medical imaging, which drove a major transformation in healthcare by enhancing diagnostic accuracy and efficiency. Advanced methods such as DL, CNNs, and GANs enabled faster, more precise detection of abnormalities across various specialties, including radiology and cardiology. AI not only accelerated image interpretation but also supported early detection of disease and personalized treatment strategies, ultimately increasing patient outcomes. This shift underscored AI's serious role in revolutionizing medical diagnosis and determining the future of healthcare. This study, [20], provided a study of medical imaging methods and their use in AI-driven disease classification and segmentation, explaining core AI, ML, and DL concepts. It systematically examined research on AI applications across many anatomical regions, highlighting key findings and emerging trends. The paper emphasized challenges like limited data, model generalization, and interpretability, advocating for hybrid ML-DL techniques that showed strong potential. It also identified medical image synthesis and transfer learning as vital strategies to overcome data scarcity, pointing to promising directions for future research in medical diagnosis. Another study, [21], designed AI models to enable highly accurate medical image diagnosis. This required properly labeled and standardized images that were pre-processed before analysis. To prevent overfitting from limited data, augmentation methods, such as rotation and flipping, were used to expand the datasets. Supervised learning (SL) handled classification and regression, while unsupervised methods solved clustering and generation. CNNs efficiently extracted features for diagnosing diseases across many organs and systems, demonstrating AI's broad capabilities in MI.

2.4 Medical Image Processing Using Optimization Methods

Recent advancements used in medical image processing through optimization techniques. It highlights innovative models and algorithms that enhance disease diagnosis, improve generalization, and address challenges like data privacy and overfitting, demonstrating strong potential for clinical application. In study [22] focused on developing an optimized Medical Image Analysis Model (MIAM) using advanced data augmentation approaches within a CNN framework to enhance disease diagnosis. By integrating 3D and intensity-based augmentations, along with regularization methods like dropout and batch normalization, the model enhanced generalization and reduced overfitting. It was assessed across multiple imaging modalities and diseases, achieving notable gains in accuracy and segmentation performance. These improvements showed their clinical potential, with future work presented to increase explainability, incorporate multi-modal data, and validate outcomes through real-world trials. In study [13], solved problems in medical image classification by exploring a novel CLIP-based approach using multiple CNN and ViT architectures, integrating federated learning for privacy, and applying traditional ML methods to improve generalization. It was tested on brain and skin cancer datasets, where models like MaxViT and ConvNeXt_L demonstrated strong performance, particularly in multimodal and federated settings. The results showed that combining dl with methods like SVM further increased performance on unseen medical data, showing a promising direction for developing privacy-preserving, generalizable medical AI systems. In another research [24] explored that medical image analysis played a vital role in diagnosing and monitoring diseases by allowing detailed examination of internal body structures through imaging data. With developments in DL and computer vision, the field saw improvements in automation, accuracy, and real-time processing. Emerging techniques such as GANs, self-supervised learning, and interpretability approaches opened new research directions. This research focused on optimization methods that enhanced the accuracy, efficiency, and reliability of MIA systems. Lastly, [25] focused on a specific class of robust nonconvex optimization problems where the objective function, given certain parameters, was represented as a difference of convex functions. It established necessary optimality conditions under general assumptions and introduced a sequential robust convex optimization algorithm to solve the problem. The presented method demonstrated global convergence to a stationary point under broad uncertainty conditions. Its application to medical image enhancement confirmed the algorithm's effectiveness through numerical results. Table I provides a comparative overview of recent studies employing various machine learning, deep learning, AI, and optimization methods for medical image analysis. It highlights the datasets used, key limitations, performance metrics, and proposed future research directions, illustrating advances and ongoing challenges in improving diagnostic accuracy, model generalization, privacy, and clinical applicability.

Table 1. Analysis of ML, DL, AI, and Optimization methods in Medical Image Processing

Author & Years	Method Used	Database	Limitations	Performance Metrics	Improvements
Anjum et al., (2024) [10]	Analytical learning paradigm; Congruent Feature Selection Method using similarity and correlation-based features	Dataset with brain, lung, eye scans (multi-organ medical images)	Irrelevant features increase computation time if not filtered; generalizability to other datasets not deeply discussed	Accuracy ↑13.19%, Precision ↑10.69%, Training rate ↑11.06%, Mean error ↓12.56%, Selection time ↓13.56% compared to other models	Apply the method across diverse medical image datasets to validate feature selection performance

Heena et al. (2023) [12]	K-Nearest Neighbor (KNN) for segmentation; neural networks for classification; gray level co-occurrence matrix (GLCM) features for extraction.	Echocardiographic image datasets (Synthetic and Echo)	Limited testing on other medical imaging datasets; needs real-time validation on untrained or diverse datasets.	Accuracy: Synthetic 89%, Echo 88%; Sensitivity: Synthetic 97%, Echo 63%; Specificity: Synthetic 25%, Echo 81%.	Apply algorithm to real-time and other untrained databases for broader applicability; enhance neural network classifier integration..
Varoquaux et al., (2022) [13]	Systematic review of challenges in medical image ML; Evaluates biases, data limitations, and research incentives.	Various public and research-specific medical imaging datasets.	Bias in datasets; real-world clinical impact is minimal; performance plateaus in real-life cohorts; publication-driven development trends.	NA	Promote standardization, unbiased dataset curation, and clinically relevant benchmarking.
K. Desai et al. (2024) [14]	Proprietary CNN model for lung nodule diagnosis from chest X-rays.	Interpretability challenges, data privacy concerns, and regulatory hurdles.	10,000 labeled chest X-ray images (lung nodules).	Accuracy: 94.8%, Sensitivity: 92.1%, Specificity: 96.5%, AUC, Precision, Recall, F1-score	Enhance model interpretability, address privacy/regulatory compliance.
G. J. Trivedi et al. (2022) [15]	CNN with automated pooling for image fusion.	Existing methods are not generalizable across datasets; they are dependent on fixed pooling techniques	Multiple datasets (varied)	PSNR: 36.82, MSE: 0.53, Fusion Factor: 4.62, VIF: 0.91, Avg. Time: 29.66s.	Add new optimal pooling methods; expand to more image fusion applications.
P. Kalyani et al. (2021) [16]	CNN with 3 fully connected layers for medical image classification & retrieval.	Limited precision in retrieval; challenges with multimodal data.	Large multimodal medical image dataset (24 classes).	Accuracy: 95.77%, Avg. ROC Precision: 0.69.	Improve retrieval accuracy; further development of CADe systems.
S. S. Yadav et al. (2019) [17]	Transfer learning with VGG16, InceptionV3, and CapsNet on chest X-ray images for pneumonia classification; baseline with SVM + ORB features; data augmentation applied.	Medical image datasets are small and hard to label- Risk of overfitting with deep networks on small datasets- Model complexity must be balanced: too simple → low accuracy, too complex → overfit- Limited model types tested (e.g., no ResNet or ensemble).	Small chest X-ray dataset.	Normal vs Pneumonia:• Best accuracy: 0.938 (VGG16 v3)• Best specificity: 0.944 (VGG16 v3)• Best recall: 0.939 (VGG16 v3)Bacteria vs Virus:•: • Best accuracy: 0.932 (State-of-art)• Best specificity: 0.917 (VGG16 v3)• Best recall: 0.886 (State-of-art).	Investigate methods to stabilize training in transfer learning (avoid overfitting)- Evaluate stronger models (e.g., ResNetv2, CNN ensembles)- Add visualization for model interpretability and clinical adoption.
Khalifa, M. et al. (2024) [18]	AI in diagnostic imaging (various AI domains)	Various medical imaging datasets.	Ethical concerns, data privacy, need for training & investment.	Accuracy, efficiency, cost-effectiveness.	Ethical guidelines, training, patient-centered AI, and collaborative integration.
Pinto-Coelho, L. et al. (2023) [19]	Deep learning, CNN, GANs	Diverse medical image datasets.	Integration challenges, rapid technology evolution.	Diagnostic accuracy, early detection rates.	Continued innovation and broader AI applications in healthcare.
Azizi, A. et al. (2023) [20]	Hybrid ML and DL approaches	Disease-specific annotated datasets.	Data availability, model generalization, and interpretability.	Classification & segmentation accuracy.	Medical image synthesis, transfer learning, and hybrid model optimization.
Yoon, H. et al. (2019) [21]	Deep learning (CNN), data augmentation	Labeled medical images (various organs).	Overfitting due to limited labeled data.	Classification and regression accuracy.	Improved data augmentation, expanded dataset labeling, and diverse disease diagnosis.

Nwizua Felix Kingsley et al. (2025) [22]	Optimized CNN with 3D/intensity-based augmentation, Dice loss, dropout, and L2 regularization.	MRI, CT scans, X-rays (pneumonia, breast cancer, heart disease, diabetic retinopathy, intracranial hemorrhage).	Data scarcity, model interpretability, and clinical integration.	7.3% classification accuracy, ↑7.0% Dice Score, improved AUC.	Explainable AI, multi-modal integration, clinical validation.
Wu, Y. et al. (2025) [23]	CLIP variant (4 CNNs, 8 ViTs), federated learning, ML integration.	HAM10000, ISIC2018 (brain and skin cancer classification).	Data privacy, domain generalization, and large data requirements.	MaxViT: 87.03% AVG; ConvNeXt_L: F1 = 83.98% in FL model.	Enhance with SVM, improve generalization to unseen domains.
Wang et al. (2023) [24]	GANs, self-supervised learning, and DL optimization methods.	NA	Real-time application needs and interpretability challenges.	Improved automation, accuracy, and multimodal integration.	Advance GANs, increase explainability, and enable real-time systems.
Li, X. et al. (2021) [25]	Robust nonconvex optimization via sequential convex optimization.	NA	Complex nonconvex formulations.	Global convergence to a stationary point, numerical efficiency.	Apply to broader medical image problems.

3. Comparative Analysis Based on the Different AI, Machine Learning, and Deep Learning Models

Nowadays, AI, ML, and DL have become central to technological innovation, widely used to mechanize tasks, generate insights, and handle large-scale data analysis. While they are interrelated—with ML and DL being subsets of AI—they differ significantly in scope, methodology, and complexity. The following subsections explore these distinctions in detail.

3.1 Artificial Intelligence (AI)

It is a self-motivated field in computer science motivated by building machines capable of executing tasks that mimic human cognitive functions. These comprise learning from experience, analyzing environments, making decisions, solving problems, and even exhibiting creativity. AI systems range from modest task automation to complex decision-making applications. A historically significant concept in AI is the Turing Test, proposed by Alan Turing, which evaluates whether a machine can exhibit behavior indistinguishable from a human. Contemporary examples, such as Apple's Siri, demonstrate how AI has evolved to support natural human-computer interaction. AI incorporates various techniques, including rule-based systems and data-driven approaches, to simulate intelligent behavior across diverse applications.

3.2 Machine Learning (ML)

It is an essential subset of AI, primarily focused on identifying patterns within data to allow systems to make forecasts and decisions without being explicitly programmed. It improves over time by learning from data and adjusting to changing conditions. Although many ML algorithms have existed for decades, recent advancements in parallel computing have dramatically expanded their capabilities, allowing them to analyze vast datasets with high efficiency. ML methods are typically classified into:

- **Supervised learning,** which uses labeled datasets to train models on input-output relationships (e.g., classifying images of cats and dogs).
- **Unsupervised learning** analyzes unlabeled data to uncover hidden structures or patterns.

ML models like Decision Trees (DTs) or Support Vector Machines (SVMs) are known for their transparency, offering clear, interpretable decision-making paths. These models are especially useful in scenarios requiring explainability, such as in healthcare or finance.

3.3 Deep Learning (DL)

It is a particular branch of ML that utilizes DNNs composed of multiple layers of interconnected nodes. These layers enable DL models to process data hierarchically, learning increasingly complex features as information moves through each layer.

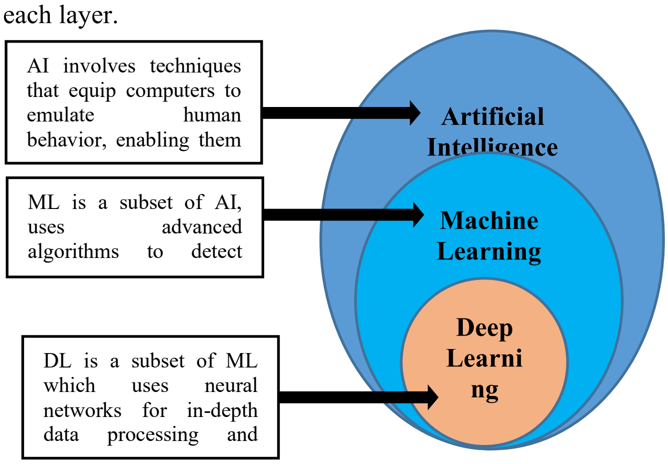


Figure 3. View of AI, ML, and DL [27]

DL excels in working with unbalanced data such as images, audio, and natural language (NL) and powers uses like image and speech recognition, and language translation. While DL has demonstrated remarkable accuracy and performance, it also presents several challenges:

- **Lack of interpretability**: It is difficult to understand how deep models reach decisions due to their complex structure.
- **High computational demands**: DL models require powerful hardware and longer training times compared to traditional ML models.

Despite these challenges, DL's ability to remove deep insights from large and composite databases makes it a critical tool in modern AI development.

Table 2 presents a comprehensive comparison of various models categorized under AI, ML, and DL. Each model is described by its core definition, benefits, drawbacks, and evaluated performance metrics (such as accuracy, precision, etc. The aim is to provide a complete view of traditional and advanced modeling approaches, highlighting their suitability for different tasks such as classification, segmentation, and prediction. While deep learning models like ResNet and CNN offer the highest performance, traditional methods like Logistic Regression (LR) and DTs remain valuable for their interpretability and efficiency in simpler problems.

Table 2. Comparative Overview of Artificial Intelligence (AI) Different Methods

Methods	Definition	Benefits	Drawbacks
Generalized Linear Model [26]	A regression model that handles various types of response distributions beyond normal.	Easy to interpret and fast to train for linear relationships.	Performs poorly on complex, non-linear data.
Gradient Boosted Trees [26]	Builds trees sequentially to correct previous errors using gradients.	Handles non-linear data well and improves accuracy.	It can overfit and requires careful tuning.
KNN [27]	Classifies data based on the closest neighbors in the training set.	Simple, no training time, effective on small datasets.	Slow on large data, sensitive to irrelevant features.
XGBoost [28]	An optimized gradient boosting with regularization and parallel processing.	High accuracy, handles missing data, and reduces overfitting.	Complex tuning and resource-intensive.
Naive Bayes	Probabilistic classifier based on Bayes' theorem, assuming feature independence.	Fast, simple, and it works well with small datasets.	Assumes feature independence (rarely true).
Logistic Regression	Statistical model for binary classification predicting probabilities using a logistic function.	Easy to implement, interpretable coefficients.	Limited to linear relationships.
Decision Tree	Tree-structured model splitting data based on feature thresholds to classify.	Intuitive, interpretable, handles nonlinear data	Prone to overfitting, sensitive to data variations
Random Forest	An ensemble of decision trees built on random subsets of data/features, aggregating predictions.	Reduces overfitting and achieves high accuracy.	Less interpretable than single trees, computationally intensive.
Support Vector Machine	Finds the optimal hyperplane maximizing the margin between classes in the feature space.	Effective in high-dimensional spaces, robust to overfitting.	Can be slow with large datasets, sensitive to kernel and parameter choice.
CNN [29]	A deep learning model that uses convolutional layers to extract spatial features from images.	High accuracy for image classification; automatic feature learning.	Requires large datasets; GPU-intensive.
U-shaped Convolutional Network(U-Net) [30]	Specialized for biomedical image segmentation using a symmetric encoder-decoder architecture.	Works well with limited data; precise segmentation.	Limited use for classification; sensitive to input variability.
Residual Neural Network(ResNet) [31]	Deep neural network using identity shortcut connections to allow very deep architectures.	Very accurate; mitigates the vanishing gradient problem.	More complex architecture; training time is longer.
Densely Connected Convolutional Network(DenseNet) [32]	Each layer connects to all previous layers to improve information flow.	Efficient; fewer parameters and better feature reuse.	High memory use; slower during inference.
GAN (Generative Adversarial Network) [33]	Uses two networks (generator + discriminator) to generate synthetic but realistic data.	Useful for medical image enhancement and augmentation.	Unstable training; requires tuning.

This section delivers a detailed proportional analysis of different AI, ML, and DL models, highlighting their definitions, advantages, limitations, and performance metrics to guide their appropriate use in tasks like classification, prediction, and image segmentation.

4. Existing Result Analysis

This section presents a complete examination of the performance of numerous AI, ML, and DL models constructed on key classification metrics, such as accuracy, precision, etc. The evaluation covers traditional AI algorithms, conventional ML methods, and advanced DL architectures applied across different data complexities and application domains, including image analysis. Through comparative tables and corresponding visualizations, the effectiveness, assets, and restrictions of each model are highlighted, providing visions into their appropriateness for diverse tasks.

Table 3. Performance Comparison of AI Models

Method	Accuracy	Precision	Recall
Generalized Linear Model [26]	79.2%	66.5%	61.8%
Gradient Boosted Trees[26]	75.4%	53%	49.1%
KNN[27]	85%	83.5%	82%
XGBoost [28]	91.5%	89%	88%

Table 3 presents a comparative analysis of AI algorithms, Generalized Linear Model (GLM), Gradient Boosted Trees, KNN, and XGBoost based on their classification presentation metrics. The models are evaluated using accuracy, precision, and recall to assess their efficiency in handling various types of data and complexities. XGBoost demonstrates the highest performance across all metrics, while Gradient Boosted Trees show relatively lower scores.

Figure 4 below shows the performance comparison of AI models (Generalized Linear Model, Gradient Boosted Trees, KNN, and XGBoost) using Accuracy, Precision, and Recall metrics. XGBoost shows the maximum performance through all evaluation parameters, while Gradient Boosted Trees exhibit lower scores in comparison.

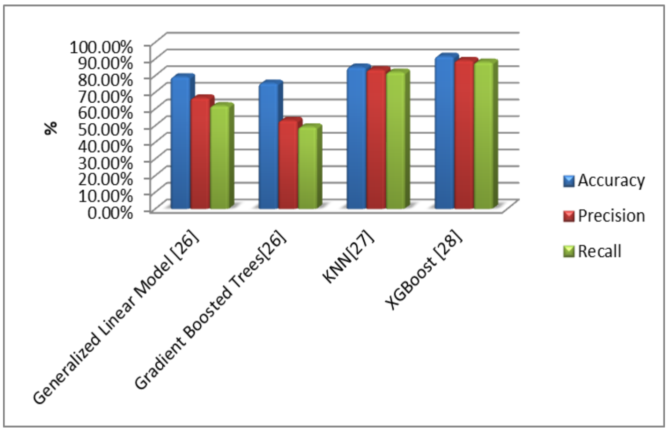


Figure 4. Performance Metrics Comparison of Different AI Classification Models

Table 4. Performance Metrics of Traditional Machine Learning Algorithms

Method	Accuracy	Precision	Recall
Naive Bayes [29]	77.6%	56.5%	55.2%
Logistic Regression [30]	79.2%	73.1%	52.5%
Decision Tree [31]	76.5%	66.0%	44.5%
Random Forest [32]	75.0%	54.9%	49.4%
Support Vector Machine [33]	76.1%	55.8%	48.8%

Table 4 summarizes the performance of traditional ML algorithms, like Naive Bayes (NB), Logistic Regression (LR), DT, Random Forest (RF), and SVM, based on key classification metrics, such as accuracy, precision, and recall. These models are generally faster and easier to interpret compared to advanced ensemble methods, though their performance varies depending on data characteristics. Logistic Regression offers balanced performance with interpretability, while Naive Bayes provides simplicity at the cost of lower recall and precision.

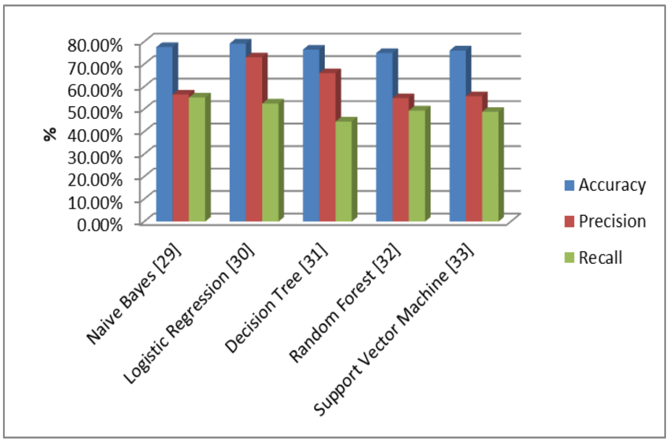


Figure 5. Performance Comparison of Different Machine Learning Models

Figure 5 below compares the different metrics, accuracy, precision, and recall, of various ML techniques, including NB, LR, DT, RF, and SVM methods. The regression model shows the highest precision, while NB and Regression models lead in accuracy. Recall values are generally lower across all models, highlighting potential areas for improvement in sensitivity.

Table 5. Performance Comparison of Deep Learning Models in Image Analysis

Method	Accuracy	Precision	Recall
Convolutional Neural Network (CNN)	94.0%	91.5%	90.0%
U-Net	92.0%	90.0%	87.5%
Residual Neural Network (ResNet)	94.5%	92.5%	91.0%
DenseNet	93.0%	90.0%	88.5%
Generative Adversarial Network (GAN)	88.5%	86.5%	84.0%

Table 5 offers a comparative indication of DL constructions: CNN, U-Net, Residual Neural Network (ResNet), DenseNet, and Generative Adversarial Network (GAN). These methods are evaluated using accuracy, precision, and recall metrics, focusing on tasks such as classification and segmentation, particularly in medical imaging. ResNet and CNN exhibit the highest performance, while U-Net is effective for segmentation even with limited data. GANs offer unique capabilities for data generation but require careful tuning and are less stable during training.

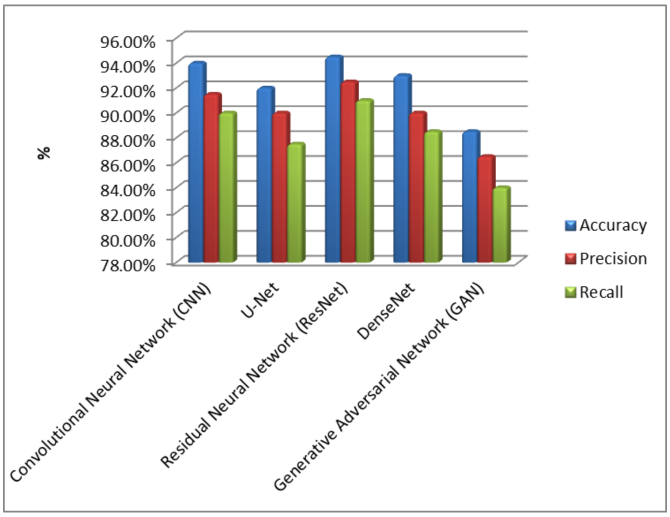


Figure 6. Performance Comparison of Different Deep Learning Models.

Figure 6 below compares the presentation of various DL models, including CNN, U-Net, Residual Neural Networks (ResNet), DenseNet, and Generative Adversarial Networks (GAN). The comparison is based on three metrics, such as accuracy, precision, and recall. ResNet demonstrates the highest accuracy and recall, followed closely by CNN and DenseNet. U-Net shows strong performance, especially in precision, while GAN exhibits slightly lower but still competitive results. Overall, this visualization highlights the superior predictive capabilities of advanced DL architectures in handling composite data tasks.

5. Conclusion

This article concluded that MI is an essential constituent of current healthcare, providing critical insights for diagnosis, treatment strategy, and disease monitoring. The complexity and volume of medical image data pose significant challenges for traditional manual analysis, often resulting in time-consuming processes and potential diagnostic inconsistencies. The integration of optimization algorithms has improved medical image processing by enhancing image quality, automating feature selection, and fine-tuning model parameters to boost accuracy and efficiency. AI, particularly ML and DL, has revolutionized MI analysis by enabling automated, high-precision interpretation of complex images. While traditional AI and ML methods offer interpretability and efficiency in simpler scenarios, deep learning models demonstrate superior performance in handling large, high-dimensional medical image datasets, particularly in classification and segmentation tasks. Though, these advanced models require substantial computational resources and large annotated datasets, and their interpretability remains limited. Overall, the synergy of AI, optimization techniques, and deep learning architectures is driving significant advancements in medical imaging. This integration enhances diagnostic accuracy, accelerates clinical workflows, and supports personalized patient care. As research and technology continue to evolve, these tools will become increasingly vital in delivering scalable, intelligent healthcare solutions. future scope could focus on advance Deep learning models such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for higher efficiency in medical fields.

Authors Contributions
Tejinder Kaur and Manpreet Kaur conceptualized the study, performed the literature survey, analyzed and synthesized the findings, and wrote the manuscript.

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