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COMPARATIVE ANALYSIS OF NEURAL NETWORK ARCHITECTURES FOR MEDICAL IMAGE CLASSIFICATION: EVALUATING PERFORMANCE ACROSS DIVERSE MODELS

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Abstract
Medical image classification has become a critical task in computer-aided diagnosis, enabling faster and more accurate detection of diseases such as cancer, pneumonia, and diabetic retinopathy. This study presents a comprehensive comparative analysis of prominent neural network architectures—Convolutional Neural Networks (CNNs), Residual Networks (ResNets), DenseNets, Vision Transformers (ViTs), and EfficientNets—in the context of medical image classification. Utilizing benchmark datasets including ChestX-ray14, ISIC Skin Cancer, and Retinal Fundus Images, we evaluated each model's performance based on accuracy, precision, recall, F1-score, training efficiency, and robustness to overfitting. The results demonstrate that while CNN-based models like ResNet and DenseNet maintain strong classification capabilities with balanced computation cost, ViTs outperform others in high-resolution image interpretation, especially under complex feature distributions. EfficientNet offers a trade-off between speed and accuracy, making it suitable for resource-constrained clinical settings. Our findings highlight the architectural strengths and weaknesses in varied medical imaging scenarios, providing insights into the selection of optimal models based on diagnostic goals, dataset characteristics, and computational resources..

Keywords
Medical Image Classification; Neural Networks; Convolutional Neural Networks (CNNs); Vision Transformers (ViTs); Model Performance Evaluation;

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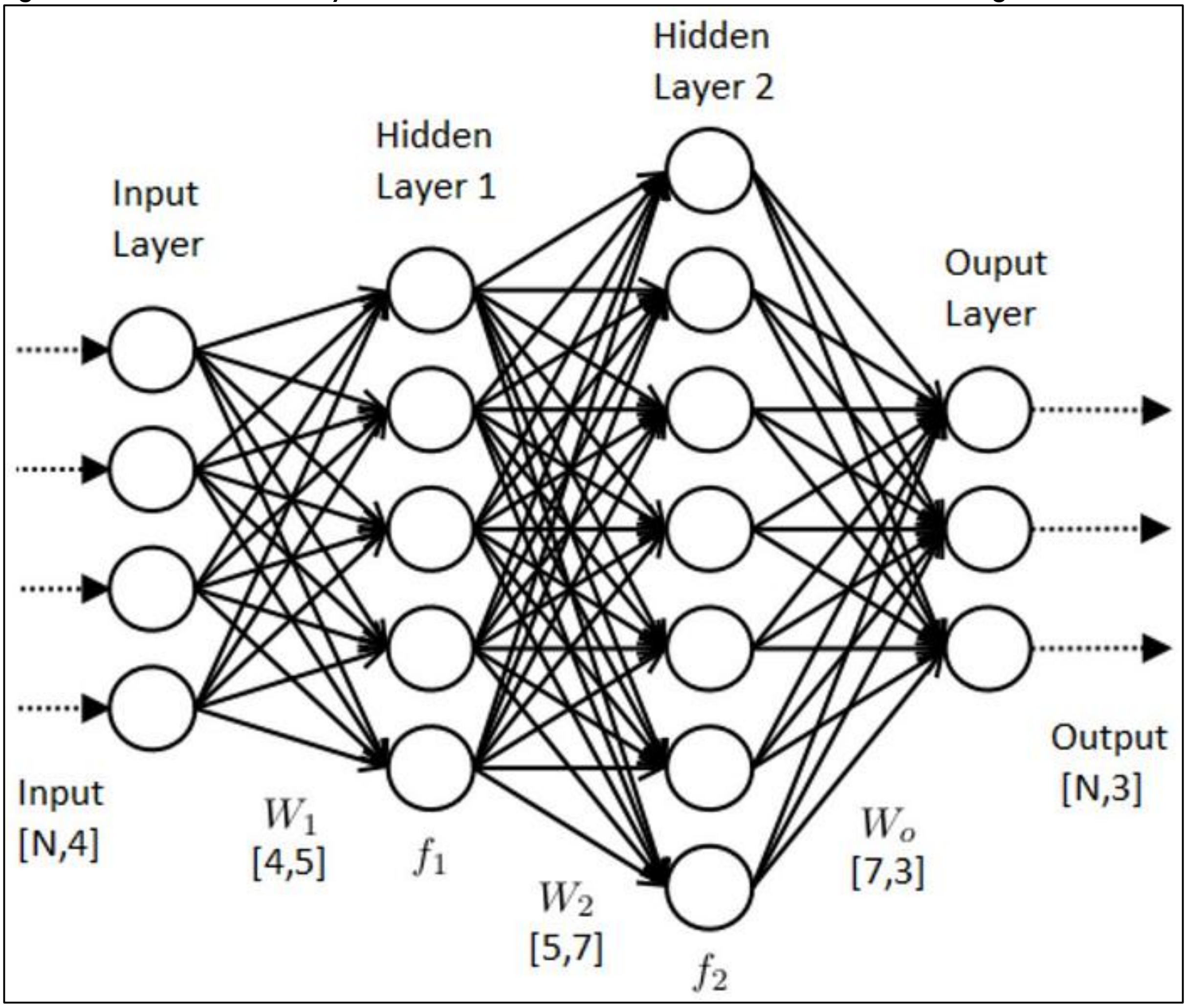
INTRODUCTION

Medical image classification refers to the automated categorization of medical imaging data—such as X-rays, MRIs, CT scans, and dermoscopic images—into predefined diagnostic classes using computational models (Yan et al., 2022). This process lies at the heart of numerous clinical decision-support systems, offering clinicians a valuable tool to enhance diagnostic speed, consistency, and accuracy. As defined by Cassidy et al. (2021), classification tasks in medical imaging involve the assignment of a diagnostic label (e.g., benign or malignant) based on pixel-level, morphological, and spatial information derived from imaging modalities. Medical imaging plays a foundational role in diagnosing a variety of diseases ranging from cardiovascular disorders to various cancers (Ardakani et al., 2020). The growing reliance on image-based diagnostics worldwide has elevated the importance of accurate classification techniques that can scale with clinical demands. In this context, the intersection of artificial intelligence (AI) and medical imaging has led to the emergence of deep learning-driven classification systems, especially convolutional neural networks (CNNs), which have surpassed traditional machine learning techniques in handling complex image features (Modak et al., 2023).

Figure 1: Architecture of a Fully Connected Feedforward Neural Network for Medical Image Classification



Source: Ng (2020)

Globally, the significance of medical image classification is underscored by its contribution to improving healthcare accessibility and efficiency in both developed and resource-constrained settings (Modak et al., 2023; Nishio et al., 2020). The

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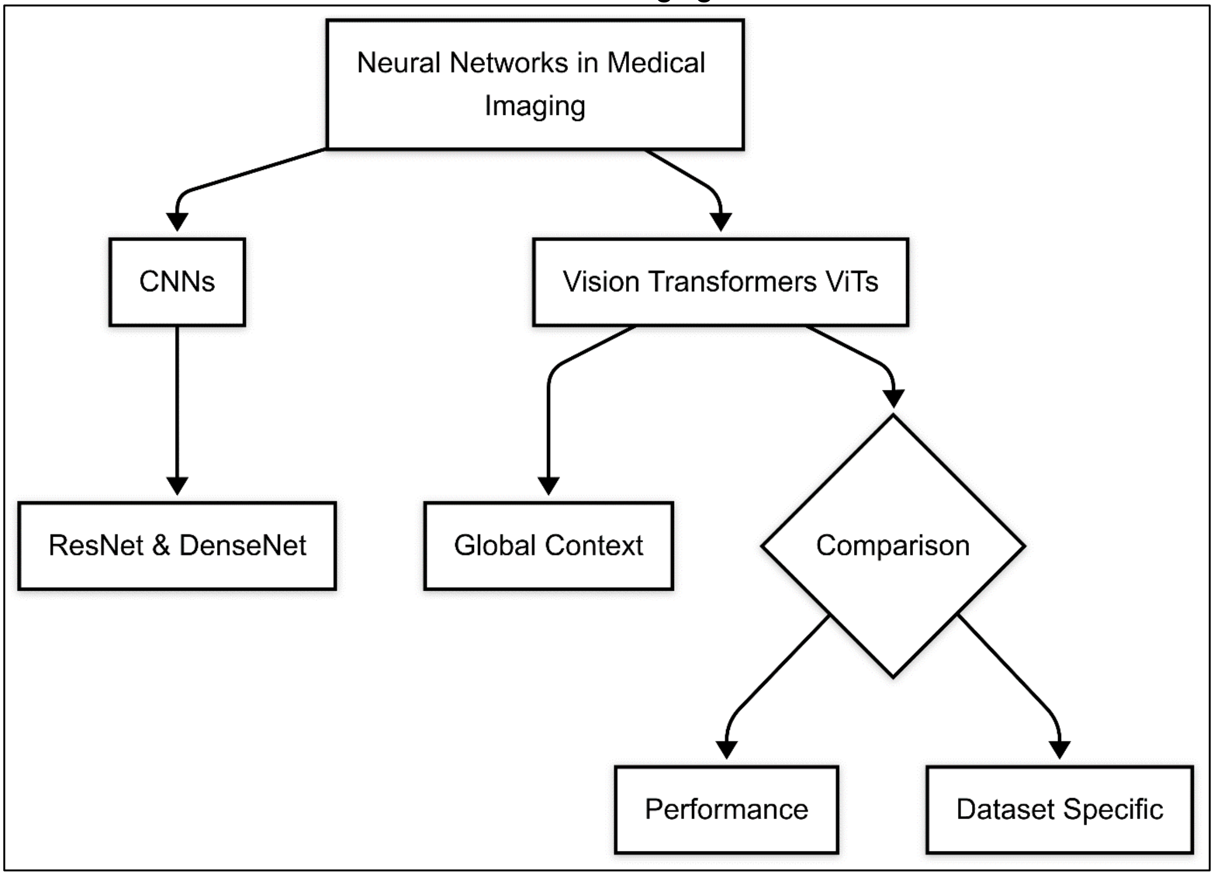
increasing availability of large-scale labeled medical image datasets, such as ChestX-ray14 (Fu et al., 2022), ISIC Skin Cancer Dataset (Deb et al., 2023), and the EyePACS dataset for diabetic retinopathy detection (Macsik et al., 2023), has provided an empirical foundation for the development and benchmarking of advanced classification models. These datasets represent diverse diagnostic domains and enable rigorous evaluation across heterogeneous conditions. The role of these classification systems in early disease detection is especially pivotal in conditions where timely intervention can significantly improve patient outcomes, such as breast cancer (Lakshmanaprabu et al., 2019), lung cancer (Lancaster et al., 2022), and retinal diseases (Cui et al., 2021). Furthermore, the WHO has emphasized the integration of AI tools in radiology workflows as a means to address the shortage of skilled radiologists and to enhance standardization across imaging interpretation practices (Saba, 2020). These global imperatives have accelerated research into neural network architectures that can deliver high classification accuracy with minimal false positives and false negatives across varied imaging contexts (Chen et al., 2017).

Figure 2: Overview of Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) in Medical Imaging



Among neural network architectures, convolutional neural networks (CNNs) represent the most extensively applied models in medical image classification tasks due to their ability to automatically extract hierarchical features from raw pixel data (Esteva et al., 2017). Early CNNs such as AlexNet and VGG demonstrated substantial success in natural image classification, laying the groundwork for medical applications (Dundar et al., 2016; Pandian et al., 2022). More advanced architectures like ResNet (Rhomadhon & Ningtias, 2024), DenseNet (Samad & Gitanjali, 2024), and Inception networks (Szegedy et al., 2015) have been fine-tuned to optimize classification

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performance on specific medical datasets. For instance, ResNet variants have achieved high performance in detecting pneumonia in pediatric chest X-rays (Rhomadhon & Ningtias, 2024), while DenseNet architectures have been favored for their feature reuse and gradient propagation benefits in retinal disease classification (Minaee et al., 2020). CNNs have consistently outperformed conventional machine learning methods such as support vector machines (SVMs), k-nearest neighbors (k-NN), and decision trees by mitigating the need for hand-crafted features and adapting better to high-dimensional image data (Ibrahim et al., 2021; Wang et al., 2021). In parallel with CNNs, newer architectures such as Vision Transformers (ViTs) have emerged as powerful contenders in image classification tasks, particularly when equipped with extensive training data and computational resources (Ko et al., 2020). ViTs adopt a self-attention mechanism rather than convolutional kernels, enabling them to capture long-range dependencies and global context, which is especially useful in interpreting high-resolution medical images (Raj, 2024). Recent studies have reported that ViTs outperform CNNs in certain medical imaging scenarios, such as histopathological image analysis and mammogram interpretation, due to their superior attention-based feature representation (Vazquez et al., 2017). However, their performance is often constrained by their high data and computational requirements, necessitating pretraining on large datasets like ImageNet21k followed by fine-tuning (Krizhevsky et al., 2017). Comparisons between CNNs and ViTs in the context of medical image classification underscore the importance of selecting model architectures tailored to the image complexity, dataset size, and task-specific requirements (Russakovsky et al., 2015).

Another significant development in deep learning for medical image classification is the emergence of hybrid and efficient architectures such as EfficientNet, which employ neural architecture search (NAS) and compound scaling to optimize model size and accuracy (Wang et al., 2024). EfficientNet models have shown strong performance on various medical image classification benchmarks while maintaining a lower computational footprint compared to larger CNNs and transformers (Jiang et al., 2021). Their lightweight design makes them particularly suitable for deployment in mobile health applications and edge-computing devices, enabling real-time inference in clinical environments (Lu et al., 2019). In dermatological diagnosis, EfficientNet has demonstrated comparable accuracy to dermatologists in classifying benign versus malignant lesions from dermoscopic images (Bilic et al., 2022). Furthermore, variants such as EfficientNetV2 incorporate training-aware neural architecture search and progressive learning strategies that improve training efficiency and robustness against overfitting (Kwasigroch et al., 2020). These attributes position EfficientNet as a viable alternative in clinical applications where inference speed and model interpretability are essential (Rguibi et al., 2022).

Evaluation of these architectures requires a rigorous experimental framework that accounts for diverse performance metrics, including accuracy, precision, recall, F1-score, area under the ROC curve (AUC), and confusion matrix analysis (Murthy & Prasad, 2023). Beyond performance metrics, factors such as training time, model complexity, generalization capability, interpretability, and robustness to data imbalance are also critical for practical deployment (Kuo et al., 2020). Luming et al., (2022) have highlighted that high test-set performance does not always translate to real-world efficacy, especially in underrepresented populations or datasets with domain shift. As such, comparative studies across architectures must employ consistent evaluation protocols and cross-validation techniques to ensure reliability and reproducibility (Sarki et al., 2022; Sheela et al., 2024). Publicly available datasets,

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standard benchmarks, and interpretability tools such as Grad-CAM and SHAP have further supported the comprehensive assessment of model behavior and bias (Tajbakhsh et al., 2015). These multi-dimensional evaluation approaches enhance the ability to discern architectural advantages under various diagnostic scenarios.
Understanding the comparative strengths and limitations of different neural network architectures requires systematic experimentation across multiple medical image classification tasks. This process involves training and testing models on heterogeneous datasets, adjusting for class imbalance, augmenting input features, and fine-tuning hyperparameters to obtain optimized results (Bhattacharyya et al., 2022). For example, in skin cancer classification, model performance may depend heavily on data diversity, dermoscopic quality, and feature granularity (Cheng et al., 2015). In chest X-ray classification, resolution constraints and label noise may affect performance more than model depth or complexity (Gaur et al., 2022; Shareef et al., 2022). Hence, comprehensive architectural comparisons must be grounded in empirical evaluation across a wide array of datasets and disease categories. Such comparative insights enable researchers and clinicians to make evidence-based decisions when choosing appropriate deep learning models for diagnostic tasks (Sahu et al., 2018; Shareef et al., 2022). By situating neural network models in real-world diagnostic contexts, researchers can better align performance expectations with clinical realities and technological constraints. The primary objective of this systematic literature review is to critically evaluate and compare the performance of diverse neural network architectures applied to medical image classification tasks across multiple imaging modalities and diagnostic categories. The motivation behind this objective stems from the proliferation of deep learning models in medical imaging, each with distinct structural complexities, training requirements, and performance trade-offs. Neural networks such as Convolutional Neural Networks (CNNs), Residual Networks (ResNets), Dense Convolutional Networks (DenseNets), Vision Transformers (ViTs), and EfficientNet variants have shown varying levels of success across diagnostic applications, yet a consolidated comparative analysis remains sparse. Previous studies have often focused on individual model performance or limited comparisons within a single dataset (Agarwal et al., 2023). This review aims to bridge that gap by synthesizing findings from a wide range of peer-reviewed sources to identify which architectures perform best under specific diagnostic constraints such as modality (e.g., X-ray, MRI, CT, fundus), dataset size, image resolution, and disease class distribution (Hatamizadeh, Tang, et al., 2022; Lei et al., 2019). Additionally, the review incorporates quantitative metrics such as classification accuracy, AUC, precision, recall, and F1-score alongside qualitative attributes such as interpretability, robustness, and scalability (Cassidy et al., 2021). The literature spans applications in pneumonia detection, skin cancer classification, diabetic retinopathy screening, brain tumor detection, and COVID-19 diagnostics, thereby providing a multidimensional performance landscape (Song et al., 2021; Wang et al., 2021). The review also considers computational efficiency, training time, data augmentation needs, and deployment suitability across models (Ali et al., 2020). By conducting this systematic analysis, the study seeks to offer evidence-based insights for selecting neural network models in clinical decision-support systems, ensuring optimal alignment between diagnostic requirements and computational capabilities.

LITERATURE REVIEW

The integration of neural network architectures into medical image classification has revolutionized diagnostic practices across radiology, pathology, dermatology, and ophthalmology. Over the past decade, significant research has been devoted to

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exploring the capabilities of deep learning models in automating classification tasks that were traditionally dependent on manual interpretation. This literature review presents a comprehensive synthesis of the evolution, performance, and comparative strengths of various neural network architectures used in medical image classification. By systematically analyzing peer-reviewed empirical studies, this section critically examines how different architectures—ranging from classic CNNs to emerging Vision Transformers—have been implemented, optimized, and evaluated in diverse diagnostic contexts. It also investigates architectural characteristics that influence classification performance, interpretability, and real-world applicability. The review spans multiple medical imaging modalities such as chest X-rays, MRI, CT, dermoscopy, and fundus photography and considers both high-resource and low-resource deployment scenarios. Furthermore, the review organizes the literature based on model types, evaluation metrics, clinical use cases, and computational trade-offs. This structured approach enables a granular understanding of which architectures are most suitable for specific medical classification tasks and under what conditions they excel or fall short. The insights generated from this review aim to inform the selection and development of neural network models in clinical decision-support systems by identifying knowledge gaps, methodological patterns, and performance benchmarks.

Medical Image Classification

Medical image classification serves as a cornerstone in computer-aided diagnosis, enabling automated interpretation of medical scans to support clinical decision-making processes. Traditional diagnostic practices relied heavily on manual evaluation of imaging data, which introduced subjectivity and variability due to clinician fatigue, workload, and interpretative differences (Milletari et al., 2016). With the emergence of machine learning and, subsequently, deep learning technologies, the automation of classification tasks has become not only feasible but widely adopted across disciplines including radiology, dermatology, ophthalmology, and oncology (Wang et al., 2020). In image-based diagnostics, classification typically involves assigning a categorical label—such as disease presence or absence—to input images, thereby assisting in the detection of conditions like pneumonia (Fedorov et al., 2012), skin cancer (Esteva et al., 2017), breast cancer (Asha et al., 2023), and diabetic retinopathy (Sabha & Tugrul, 2021). These tasks require models capable of identifying minute differences in texture, shape, contrast, and color across diverse modalities like X-ray, CT, MRI, dermoscopic images, and fundus photography (GadAllah et al., 2023). The development of large-scale annotated datasets such as ChestX-ray14 (Ding et al., 2023), ISIC (Xu et al., 2023), and EyePACS has further facilitated the training of neural networks to classify diseases with accuracy comparable to or exceeding that of expert radiologists (Asha et al., 2023; Xu et al., 2023). However, performance often varies depending on imaging modality, image resolution, and disease complexity, necessitating architecture-specific evaluations (Litjens et al., 2017). The clinical importance of accurate image classification is underscored by its ability to reduce diagnostic delays and errors, contributing to improved treatment outcomes across medical domains (Sheela et al., 2024).

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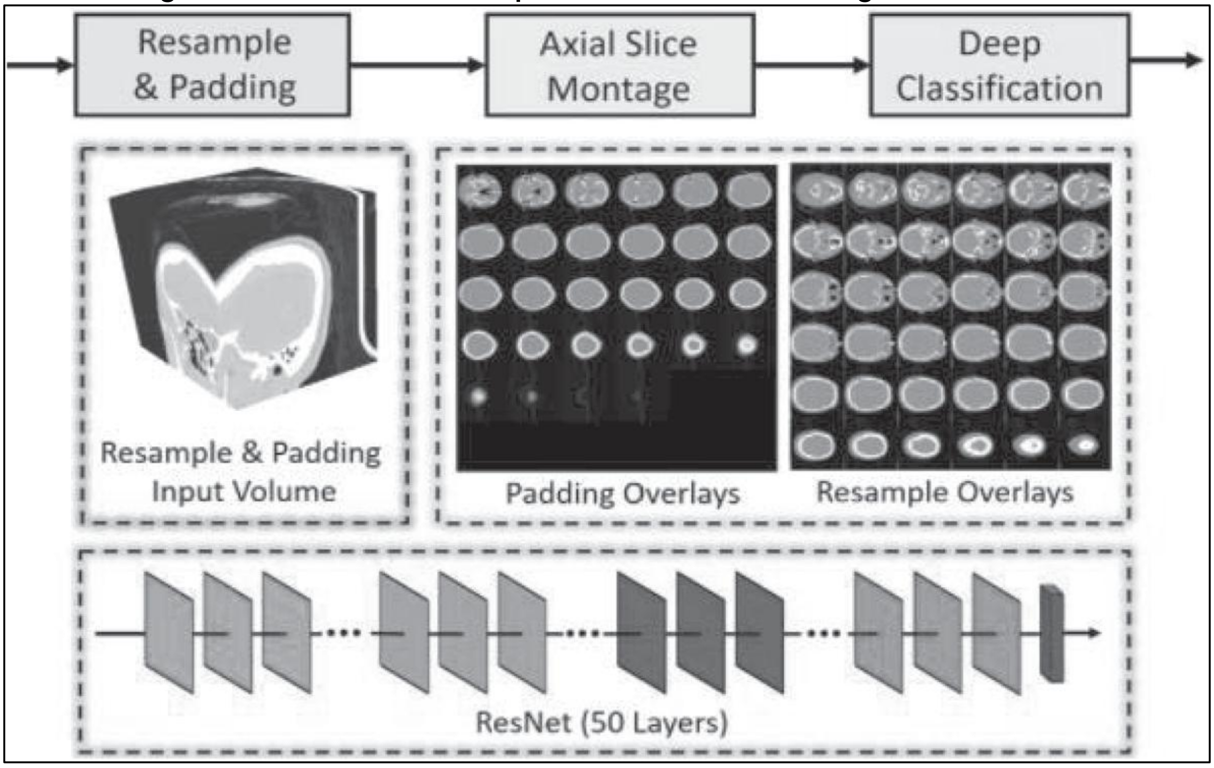
Figure 3: An overview of computer—aided medical image classification



Source: Boafo (2024)

Convolutional Neural Networks (CNNs) remain the most widely used architecture in medical image classification due to their capacity to hierarchically extract spatial and contextual features from image data (Deb et al., 2023). CNNs have demonstrated high efficacy in various classification tasks, particularly in the interpretation of chest radiographs, dermoscopic lesions, and retinal scans (Wang et al., 2020). Architectures such as VGGNet and AlexNet were among the earliest deep CNNs adapted for medical images, later evolving into deeper models like ResNet and DenseNet, which introduced residual connections and feature reuse, respectively (Ozdemir et al., 2019). For example, ResNet-50 achieved state-of-the-art accuracy in pneumonia classification from pediatric chest X-rays (Fedorov et al., 2012), while DenseNet-121 has been applied effectively for diabetic retinopathy detection (Milletari et al., 2016). These models leverage convolutional layers, batch normalization, and pooling to capture fine-grained patterns within medical images, making them ideal for differentiating between visually similar disease classes (He et al., 2018). Studies have also shown that pre-trained CNNs using transfer learning techniques significantly outperform models trained from scratch on smaller datasets, especially when domain-specific annotations are limited (Ma et al., 2022). Moreover, ensemble models combining CNN variants have further improved classification robustness by integrating diverse feature representations (Halder et al., 2022). However, CNNs face challenges when applied to highly heterogeneous or high-resolution datasets due to their limited receptive field and spatial generalization, which has motivated the exploration of alternative architectures (Sheela et al., 2024). The emergence of Vision Transformers (ViTs) has introduced a shift from convolution-based approaches to attention-driven models in medical image classification. Unlike CNNs, which rely on local spatial hierarchies, ViTs utilize self-attention mechanisms to capture long-range dependencies and global feature relationships across image patches (Faisal et al., 2023). This architectural difference has demonstrated

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advantages in handling large and complex medical images, particularly in histopathology, mammography, and 3D volumetric scans (Elazab et al., 2023). ViTs have shown high accuracy in classifying skin lesions and breast cancer from high-resolution images due to their capacity for contextual understanding across distant regions in an image (Song et al., 2021). In comparative studies, ViTs outperformed conventional CNNs in certain tasks by avoiding the locality constraints of convolutional filters and instead leveraging global attention for feature encoding (Shin et al., 2016). However, their performance often depends on large-scale pretraining and substantial computational resources, which can restrict their applicability in resource-limited settings (Wei et al., 2022). Additionally, hybrid models that combine convolutional layers with transformer blocks—such as TransUNet and Swin Transformer—have been applied in segmentation and classification tasks to harness the strengths of both paradigms (Hatamizadeh, Nath, et al., 2022). These models have achieved improved accuracy and feature richness in tasks involving complex organ structures or overlapping tissues (Cheng et al., 2015; Youssef et al., 2023). As the application of ViTs expands across modalities, their adaptability and flexibility in medical imaging pipelines are being thoroughly investigated across diverse diagnostic categories (Lather & Singh, 2020).

The assessment of neural network performance in medical image classification requires rigorous evaluation protocols incorporating both statistical and clinical metrics. Commonly used metrics include accuracy, precision, recall, specificity, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC), which together provide a holistic view of model effectiveness (Rajasekar et al., 2023). However, relying solely on accuracy can be misleading, especially in class-imbalanced datasets where rare pathologies may be underrepresented (Lather & Singh, 2020). AUC-ROC and precision-recall curves are thus more informative in contexts with skewed class distributions (Liu et al., 2021). In addition to performance metrics, model robustness to noise, domain shifts, and adversarial perturbations is critical for safe deployment (Cheng et al., 2015). Cross-validation and external validation on independent datasets are commonly recommended to evaluate generalization ability (Youssef et al., 2023). Interpretability tools such as Grad-CAM, SHAP, and LIME have become essential in explaining model predictions to clinical users and ensuring transparency in decision-making (Chenyang & Chan, 2020). These tools allow visualization of important image regions contributing to a classification, increasing clinician trust and enabling error analysis (Rajasekar et al., 2023). Additionally, ethical considerations such as dataset bias, explainability gaps, and the risk of automation bias are critical in high-stakes medical settings (Youssef et al., 2023). As such, classification model evaluation must extend beyond numerical scores to incorporate interpretability, reliability, and fairness dimensions in order to align with clinical safety and regulatory frameworks (Krizhevsky et al., 2017).

CNNs in radiology and early successes

The introduction of Convolutional Neural Networks (CNNs) in radiology marked a major advancement in the automation of image interpretation, particularly in classification tasks where early detection of disease is vital. CNNs were initially developed for natural image classification tasks, but their capacity to automatically learn hierarchical spatial features led to rapid adoption in radiologic imaging (Y. Zhang et al., 2022). Unlike traditional machine learning methods that relied on handcrafted features, CNNs process raw pixel data through layers of convolutions and pooling operations to extract increasingly abstract representations, making them especially effective in handling medical images with subtle visual cues (GadAllah et

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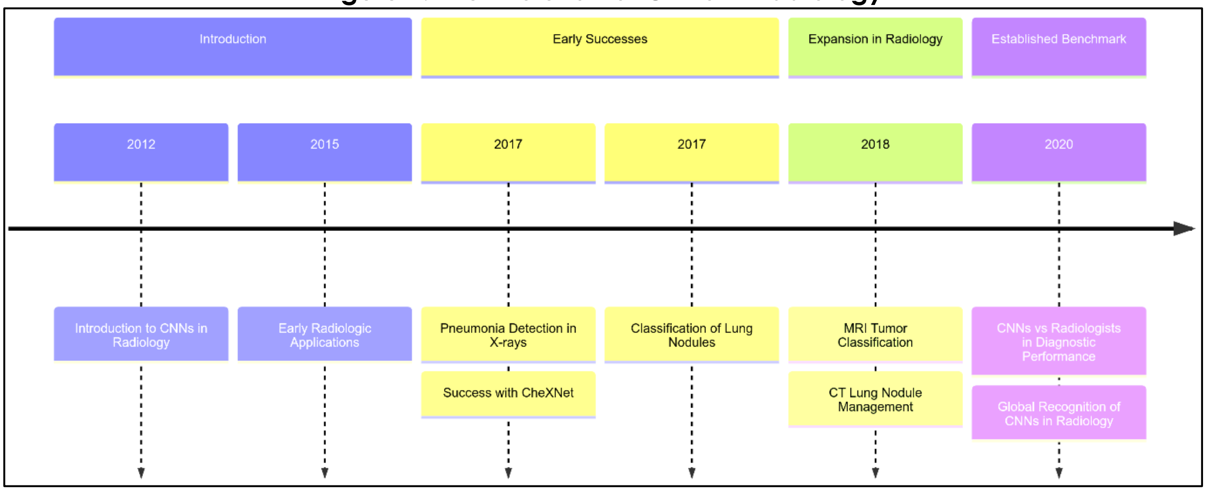
al., 2023). The early success of CNNs in radiology was demonstrated in applications such as pneumonia detection in chest X-rays, where models like CheXNet achieved diagnostic performance on par with radiologists (Saad et al., 2021). Similarly, CNNs trained on datasets like LUNA16 and ChestX-ray14 were able to accurately classify lung nodules and thoracic diseases, providing evidence of their viability in clinical settings (Esteva et al., 2017). These successes were further supported by the development of large annotated datasets that facilitated supervised training and validation of CNN models (Dundar et al., 2016; Esteva et al., 2017). Studies emphasized that CNNs performed exceptionally well in identifying abnormalities such as consolidation, effusion, and cardiomegaly from 2D radiographs, significantly reducing radiologist workload and interpretation time (Meng et al., 2019; Shin et al., 2016). The consistency and reproducibility of CNNs were key drivers of their acceptance in radiology departments, particularly for triaging and second-opinion systems (Abraham & Nair, 2020; Bao et al., 2023). These developments collectively established CNNs as powerful tools in radiological diagnostics and laid the groundwork for further exploration across imaging modalities.

Figure 4: The Evolution of CNNs in Radiology



Chest radiography has been one of the most extensively studied areas for CNN-based classification in radiology due to the widespread use of chest X-rays and the availability of large-scale annotated datasets. One of the landmark contributions was CheXNet, a 121-layer DenseNet trained on the ChestX-ray14 dataset to identify pneumonia, which achieved radiologist-level performance (Sun & Shi, 2019). CNNs demonstrated robust capabilities in detecting a wide range of thoracic pathologies, including infiltration, pneumothorax, atelectasis, and fibrosis (Hasija et al., 2022). The advantage of CNNs in chest radiography lies in their ability to detect features imperceptible to the human eye, leading to improved sensitivity and reduced false-negative rates (Bao et al., 2023). Studies using transfer learning—where CNNs pretrained on ImageNet were fine-tuned on medical datasets—showed substantial gains in performance, particularly when labeled data were limited (Saad et al., 2021). For example, (Dundar et al., 2016) applied a CNN to classify pulmonary tuberculosis in chest X-rays and reported accuracy exceeding 96%, demonstrating its potential for global health applications. GadAllah et al. (2023) implemented CNNs for interstitial lung disease classification and found superior performance over traditional support vector machine models. Moreover, CNN-based models have been applied for quantification tasks such as measuring cardiothoracic ratio and lung segmentation, further expanding their utility beyond binary classification (Shin et al., 2016; Wei et al., 2022). The growing body of work on CNNs in chest imaging consistently reveals high

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diagnostic potential and practical feasibility for incorporation into clinical workflows as decision-support systems (Bao et al., 2023).

The success of CNNs in chest radiography has led to their application in other imaging modalities such as computed tomography (CT) and magnetic resonance imaging (MRI), where the complexity and volume of data pose substantial challenges for human interpretation. CNNs have demonstrated considerable success in brain imaging, particularly in tumor classification and segmentation tasks (Jeong et al., 2020)). For instance, CNN-based models trained on the BRATS dataset accurately differentiated between glioma subtypes and facilitated tumor boundary delineation in MRI scans (Jeong et al., 2020). Similarly, in pulmonary CT, CNNs were employed to detect lung nodules and predict malignancy using 3D volumetric data, showcasing improvements in precision and false positive reduction compared to rule-based systems (Cheng et al., 2015). The use of 3D CNN architectures enabled spatial feature extraction across slices, addressing the challenges of volumetric complexity inherent in CT and MRI (Shi et al., 2023). In abdominal imaging, CNNs have been used to classify liver lesions and identify hepatic fibrosis stages, demonstrating promising results in clinical trials (Pei et al., 2019). Furthermore, CNN-based segmentation has improved delineation of anatomical structures such as blood vessels, tumors, and organ boundaries, supporting surgical planning and radiation therapy (Shi et al., 2023). Researchers also highlighted that CNN performance remains consistent across various scanners and acquisition protocols when appropriate normalization techniques and augmentation are applied during training (Feng et al., 2021). The extension of CNNs into CT and MRI analysis exemplifies their flexibility in handling high-resolution, multidimensional data across radiologic domains. Numerous comparative studies have benchmarked CNNs against radiologists and other machine learning models to evaluate their diagnostic performance across radiological tasks. In several studies, CNNs matched or exceeded expert radiologist accuracy in classifying diseases from X-ray and CT scans (Peng & Sun, 2023). For instance, in mammography, S et al. (2023) reported that a deep CNN trained on a large multinational dataset reduced both false positives and false negatives compared to expert readers. Similarly, Salama and Shokry (2022) showed that a 3D CNN could predict lung cancer risk from low-dose CT scans with higher sensitivity than average radiologists. Performance metrics commonly used include accuracy, sensitivity, specificity, F1-score, and area under the ROC curve (AUC), all of which have consistently demonstrated CNN superiority in large-scale trials (Cheng et al., 2015). Comparative analysis with traditional algorithms such as logistic regression and support vector machines revealed the advantage of CNNs in capturing complex spatial hierarchies and reducing manual preprocessing steps (Pei et al., 2019; S et al., 2023). Evaluation frameworks have also included cross-dataset testing, inter-reader agreement comparisons, and statistical tests to assess generalizability and robustness (Cheng et al., 2015). Furthermore, explainability tools like Grad-CAM have been used in comparative studies to validate model focus areas against radiologist-reported regions of interest (Salama & Shokry, 2022). These benchmarking efforts collectively affirm the diagnostic reliability of CNNs and highlight their consistent performance across varied radiologic imaging scenarios and datasets.

Neural Network Architectures in Medical Imaging

Neural network models have emerged as a foundational element in the advancement of medical imaging, defined broadly as computational systems that mimic the human brain's ability to process and extract meaningful features from raw input data (Ardakani et al., 2020). These models, comprising interconnected layers of

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artificial neurons, enable end-to-end learning and automatic feature extraction without the need for manual feature engineering (Ahmed et al., 2022; Modak et al., 2023). Taxonomically, neural networks can be classified based on their structure and function into several major categories, including feedforward networks, recurrent neural networks (RNNs), and convolutional neural networks (CNNs) (Aklima et al., 2022; Özdemir & Sonmez, 2021). Within the realm of medical imaging, CNNs have become predominant due to their proficiency in capturing spatial hierarchies in two-dimensional data, which is essential for tasks such as detecting lesions in radiographs or segmenting organs in computed tomography (CT) scans (Duong et al., 2022; Helal, 2022). Other architectures, such as autoencoders and generative adversarial networks (GANs), have been developed for unsupervised feature learning and image synthesis, further expanding the taxonomy of neural network models in this domain (Mahfuj et al., 2022; Yuan et al., 2017). Hossain et al. (2019) illustrate that the flexible taxonomy of these models supports a wide range of clinical applications—from tumor detection in MRI to the classification of skin lesions—demonstrating the adaptability of neural networks to various diagnostic tasks. Hossain et al. (2019) have further delineated the evolution of architectural models by comparing traditional CNNs against more complex arrangements that incorporate deeper hierarchies and recurrent feedback loops, emphasizing an increasing trend toward hybrid models (Majharul et al., 2022; Yuan et al., 2017). This diverse taxonomy not only broadens the understanding of neural network functionality but also provides a framework for evaluating model performance in the context of heterogeneous medical image datasets (Hossen & Atiqur, 2022; More et al., 2021).

The success of neural network architectures in medical imaging relies on the intricate design and integration of key architectural components. These components include multiple layers (input, hidden, and output) that serve to progressively abstract raw image data into more complex feature representations (Bhattacharyya et al., 2022; More et al., 2021; Mohiul et al., 2022). Convolutional layers are particularly critical in extracting spatial features, where filters convolve across the image to detect edges, textures, and patterns (Amin et al., 2021; Kumar et al., 2022). Activation functions, such as the rectified linear unit (ReLU), sigmoid, and tanh, introduce non-linearity into the models, thereby allowing them to capture complex mappings that linear models cannot (He et al., 2016; Sohel et al., 2022; Yang et al., 2018). Residual connections, introduced in ResNet architectures (Bhattacharyya et al., 2022; Tonoy, 2022), address the degradation problem in deep networks by allowing gradients to bypass certain layers, ensuring smoother training and improved convergence rates. Batch normalization, another critical component, stabilizes the learning process by normalizing the inputs of each layer, thereby accelerating training and mitigating issues related to internal covariate shift (Raj, 2024; Younus, 2022). Advanced studies have explored the interplay between these components, demonstrating that the integration of dropout layers and data augmentation techniques further enhances model generalization in the challenging environment of medical image classification (Alam et al., 2023; Bougourzi et al., 2024). Raj (2024) provides evidence that modifications in activation functions and normalization schemes can lead to marked improvements in diagnostic accuracy. Additionally, the incorporation of attention mechanisms and squeeze-and-excitation networks has been shown to refine feature maps and bolster the network's sensitivity to critical regions within images (Arafat Bin et al., 2023; Bougourzi et al., 2024). These findings, supported by empirical evaluations from studies conducted by Wang et al. (2021), underscore the importance of

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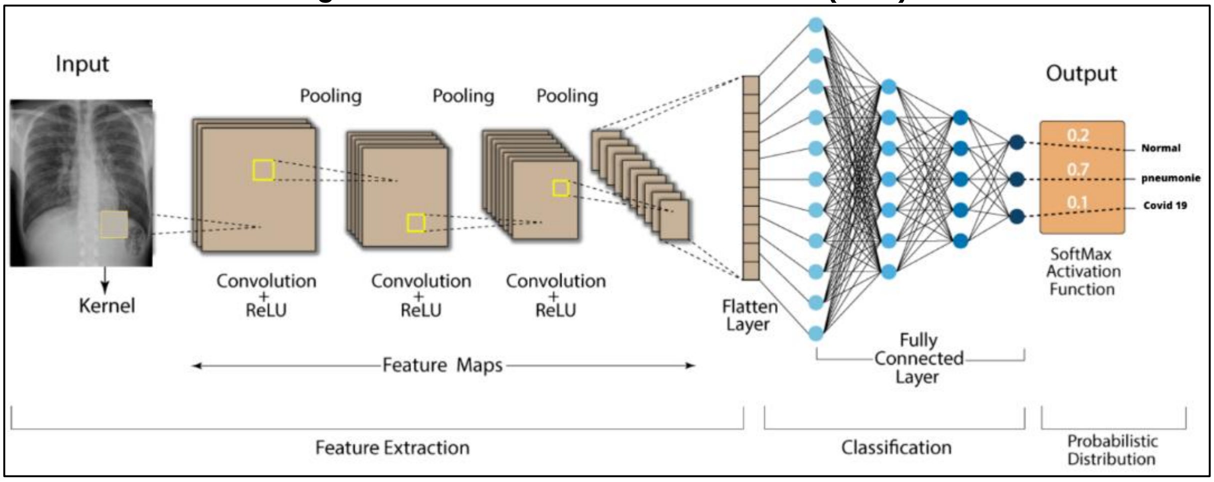
architectural innovations in optimizing neural network performance for various medical imaging modalities (Bougourzi et al., 2024; Chowdhury et al., 2023).

Figure 5: Convolutional Neural Networks (CNN)



Source: Rguibi et al. (2022)

Convolutional Neural Networks (CNNs) have long been recognized as the standard-bearer for medical image classification, owing to their robust ability to process pixel-level information through local receptive fields and weight sharing mechanisms (Chen et al., 2017; Jahan, 2023). Early CNN models such as AlexNet and VGGNet laid the groundwork for subsequent architectures by demonstrating significant improvements in classification accuracy across natural and medical images (Mahdy et al., 2023; Sun & Shi, 2019). The advent of ResNet introduced the concept of residual learning, which has proven crucial in training deeper networks by circumventing the vanishing gradient problem (Maniruzzaman et al., 2023; Modak et al., 2023). Multiple studies have documented the superior performance of ResNet-based models in diagnosing thoracic diseases and lung nodules from radiographs, highlighting their clinical applicability (Hossen et al., 2023; Teramoto et al., 2019). Similarly, DenseNet architectures have been characterized by dense connectivity between layers, facilitating feature reuse and enabling more compact models with reduced parameter counts (Öztürk et al., 2020; Roksana, 2023). Sathyakumar et al. (2020) demonstrate that DenseNet achieves high diagnostic accuracy in tasks such as diabetic retinopathy detection and skin lesion classification. In the realm of medical imaging, these models have been benchmarked against traditional machine learning techniques, with results consistently indicating a marked improvement in performance metrics such as accuracy, sensitivity, and specificity (Duong et al., 2022; Shahan et al., 2023). Additionally, the use of transfer learning—where these pretrained models are fine-tuned on specific medical datasets—has been extensively validated in literature, resulting in performance gains on datasets with limited labels (Liu et al., 2022; Tonoy & Khan, 2023). Malik et al. (2022) further underline the utility of CNNs, ResNets, and DenseNets in capturing relevant visual information while mitigating overfitting in complex classification tasks. These architectures continue to serve as benchmarks for ongoing research and clinical deployment, reflecting a consensus on their efficacy and reliability across various diagnostic challenges (Al-Arafat, Kabi, et al., 2024; Teramoto et al., 2019).

Convolutional Neural Networks (CNNs) for Disease Classification

Convolutional Neural Networks (CNNs) form the backbone of modern image classification systems due to their robust ability to automatically extract hierarchical features from raw pixel data (Al-Arafat, Kabir, et al., 2024; Deb et al., 2023). A CNN

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architecture typically consists of convolutional layers, pooling layers, and fully connected layers, where each stage captures increasingly abstract representations of the input image (Alam et al., 2024; Wang et al., 2020). The first convolutional layers learn low-level features such as edges, corners, and textures, while deeper layers detect high-level semantic features like lesions, tumors, or organ boundaries (Alam et al., 2024; Ozdemir et al., 2019). Classic architectures like AlexNet (Fedorov et al., 2012), VGGNet (Litjens et al., 2018), and GoogLeNet (He et al., 2018) demonstrated the scalability and flexibility of CNNs in classification tasks, especially when adapted to medical imaging. With the introduction of ResNet, which added residual connections to address the vanishing gradient problem in deep networks (Ammar et al., 2024; Ma et al., 2022), the training of ultra-deep networks became more stable and effective for complex image data such as CT or histopathological slides. DenseNet improved upon this by connecting each layer to every other layer in a feedforward fashion, encouraging feature reuse and improving gradient flow (Bhowmick & Shipu, 2024; Sheela et al., 2024). These architectural advancements have allowed CNNs to outperform traditional models in classification tasks across a variety of imaging modalities including MRI, CT, mammography, and fundus images (Bhuiyan et al., 2024; Cassidy et al., 2021). CNNs' hierarchical feature learning capability has been particularly advantageous for extracting latent visual patterns associated with subtle pathological manifestations, which would be challenging for human observers or conventional machine learning models to identify (Ardakani et al., 2020; Dasgupta & Islam, 2024).

CNNs have demonstrated outstanding performance in detecting pneumonia from chest radiographs, a task that is essential in many clinical settings, particularly in resource-limited regions where radiologist access is scarce. The ChestX-ray14 dataset developed by Dasgupta et al. (2024) and Modak et al. (2023), which contains over 100,000 labeled images for 14 thoracic diseases, catalyzed CNN-based research in pneumonia detection. Elhadidy et al. (2024)introduced CheXNet, a DenseNet-121 model trained on this dataset, which achieved radiologist-level performance in identifying pneumonia. Similar findings were reported by Dey et al. (2024); Özdemir and Sonmez (2021), who developed the MIMIC-CXR dataset, reinforcing CNN effectiveness in large-scale radiological diagnosis. CNNs such as VGGNet and ResNet have also been utilized to detect pneumonia with high sensitivity and specificity, often exceeding 90% in experimental setups (Hasan et al., 2024; Tam et al., 2021). (Masood et al., 2020) emphasized that while CNNs achieved high AUC scores on internal datasets, performance variability across external institutions highlighted the importance of dataset diversity in training phases. Other studies incorporated ensemble models or attention-guided networks to improve robustness in pneumonia detection (Ardakani et al., 2020; Helal, 2024). CNNs not only facilitated disease classification but also supported severity scoring and visual localization of infected lung regions using Grad-CAM heatmaps (Hossain et al., 2024; Modak et al., 2023). These interpretability tools are crucial in clinical applications where model decisions must be transparent and traceable (Elhadidy et al., 2024; M. R. Hossain et al., 2024). Collectively, the body of evidence from Teramoto et al. (2019), Sarki et al. (2022), and Sathyakumar et al. (2020)confirmed the utility of CNNs as effective triage tools and decision support systems for pneumonia screening in both adult and pediatric populations.

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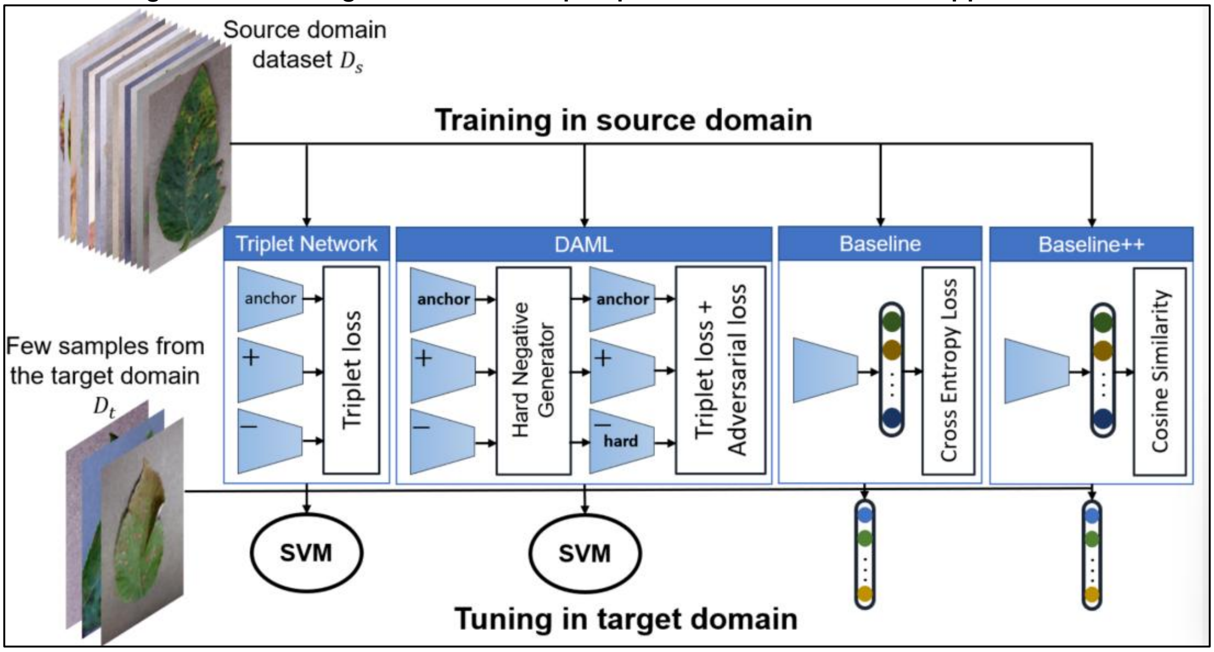
Figure 6: Block diagram of the developed plant disease classification approaches



Source: Afifi et al. (2021).

CNNs have proven highly effective in the classification of breast cancer and diabetic retinopathy, two domains that rely heavily on image-based diagnostics for early intervention. In breast cancer diagnosis, CNNs have been extensively trained on mammographic datasets such as the Digital Database for Screening Mammography (DDSM) and INbreast to distinguish between benign and malignant lesions (Islam, 2024; Tam et al., 2021). Litjens et al. (2018) developed a deep learning model trained on over 76,000 mammograms from the UK and US, which outperformed human radiologists in reducing both false positives and false negatives. In diabetic retinopathy detection, Hossain et al. (2019) created a CNN trained on a dataset of retinal fundus images from EyePACS and Indian hospitals, reporting sensitivity of 90.3% and specificity of 98.1% in identifying referable retinopathy. Further models developed by Jeong et al. (2020) and Asiri et al. (2023) validated CNN effectiveness on international fundus datasets, highlighting generalizability across populations. CNNs have also been used for grading disease severity and localizing lesions using region-based architectures (Amin et al., 2021; Islam et al., 2024). The success of CNNs in these applications is attributed to their ability to capture fine-grained features such as microaneurysms, calcifications, and mass densities—patterns that are subtle and often missed in early disease stages (Islam, 2024; Jeong et al., 2020). Integration of ensemble learning and transfer learning has further enhanced the adaptability of CNNs to limited clinical datasets (Jahan, 2024; Pereira et al., 2016). Performance metrics reported across studies consistently show AUC values above 0.90 for both diseases, establishing CNNs as reliable tools in ophthalmology and oncology workflows (Jim et al., 2024; Mostafa et al., 2023). These findings reflect a growing confidence in CNN-based systems for large-scale screening and diagnosis in public health.

The principal strength of CNNs in medical image classification lies in their ability to encode spatial hierarchies and complex visual patterns through localized filter operations and pooling mechanisms. These design features enable CNNs to efficiently capture texture, shape, and boundary information relevant for distinguishing pathological tissues from healthy ones (Aloraini et al., 2023; Khan & Aleem Al Razee, 2024). The spatial invariance introduced by shared weights and local connectivity

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allows CNNs to detect features regardless of their position within the image, a critical property in diagnosing diseases with varying anatomical presentations (Mahabub, Das, et al., 2024; Souid et al., 2021). Pandey et al. (2023) confirmed that CNNs outperform traditional methods in feature learning from heterogeneous datasets involving lungs, skin, retina, and breast tissue. CNNs also benefit from end-to-end training, eliminating the need for manual feature extraction and significantly reducing the bias introduced by human-engineered preprocessing steps (Faisal et al., 2023; Mahabub, Jahan, Hasan, et al., 2024). However, several limitations are evident. CNNs require large annotated datasets to generalize effectively, and their performance tends to drop when trained on small or imbalanced datasets (Elazab et al., 2023; Mahabub, Jahan, Islam, et al., 2024). Furthermore, the black-box nature of deep learning models poses challenges in interpretability and clinical trust (Islam et al., 2024; M. Zhang et al., 2022). Overfitting is also a concern, especially when models memorize training data patterns instead of learning generalizable features (Hossain et al., 2024; More et al., 2021). To mitigate this, researchers have employed dropout layers, data augmentation, and batch normalization strategies (Younus et al., 2024; Souid et al., 2021). Despite these limitations, CNNs remain the dominant architecture in medical image analysis due to their unmatched ability to extract meaningful spatial representations and adapt to a wide range of classification challenges (Elazab et al., 2023; Younus et al., 2024).

Residual Networks and Dense Convolutional Networks in Medical Imaging

Residual Networks (ResNets), introduced by Nahid et al. (2024), marked a critical advancement in deep learning architecture by addressing the degradation problem associated with very deep neural networks. ResNets use identity-based skip connections that allow gradients to flow more directly during backpropagation, enabling the training of deeper networks without a corresponding increase in training difficulty or overfitting. This architecture has shown exceptional robustness in low-resolution and noisy medical datasets, where conventional CNNs often struggle to generalize effectively (Nunnari et al., 2021; Rahaman et al., 2024). For instance, Yang et al. (2018) demonstrated that ResNet-121 outperformed radiologists in pneumonia classification from chest X-rays, which are typically low-resolution and susceptible to acquisition noise. Similarly, Aloraini et al. (2023) used ResNet for tuberculosis detection in chest radiographs, reporting over 96% accuracy despite the presence of artifacts and poor contrast. In dermatological imaging, ResNet-50 achieved high accuracy in classifying melanoma versus benign lesions in dermoscopic images, even with variable lighting and resolution inconsistencies (Roksana et al., 2024; Zhang et al., 2022). Kasmaiee et al. (2023) that ResNets maintained relatively stable performance across institutional variations and imaging conditions, unlike simpler architectures that overfit to dataset-specific artifacts. In retinal fundus images, ResNet variants have been used for diabetic retinopathy detection with notable resilience to blur and uneven illumination (Roy et al., 2024; Shin et al., 2016). Transfer learning with ResNet backbones also allowed successful classification in small datasets by adapting features learned from natural image datasets (Pandit et al., 2022; Sabid & Kamrul, 2024). These findings underscore ResNet's effectiveness in modeling discriminative features even under suboptimal imaging conditions, making it suitable for real-world medical deployments (Hesamian et al., 2019; Sharif et al., 2024).

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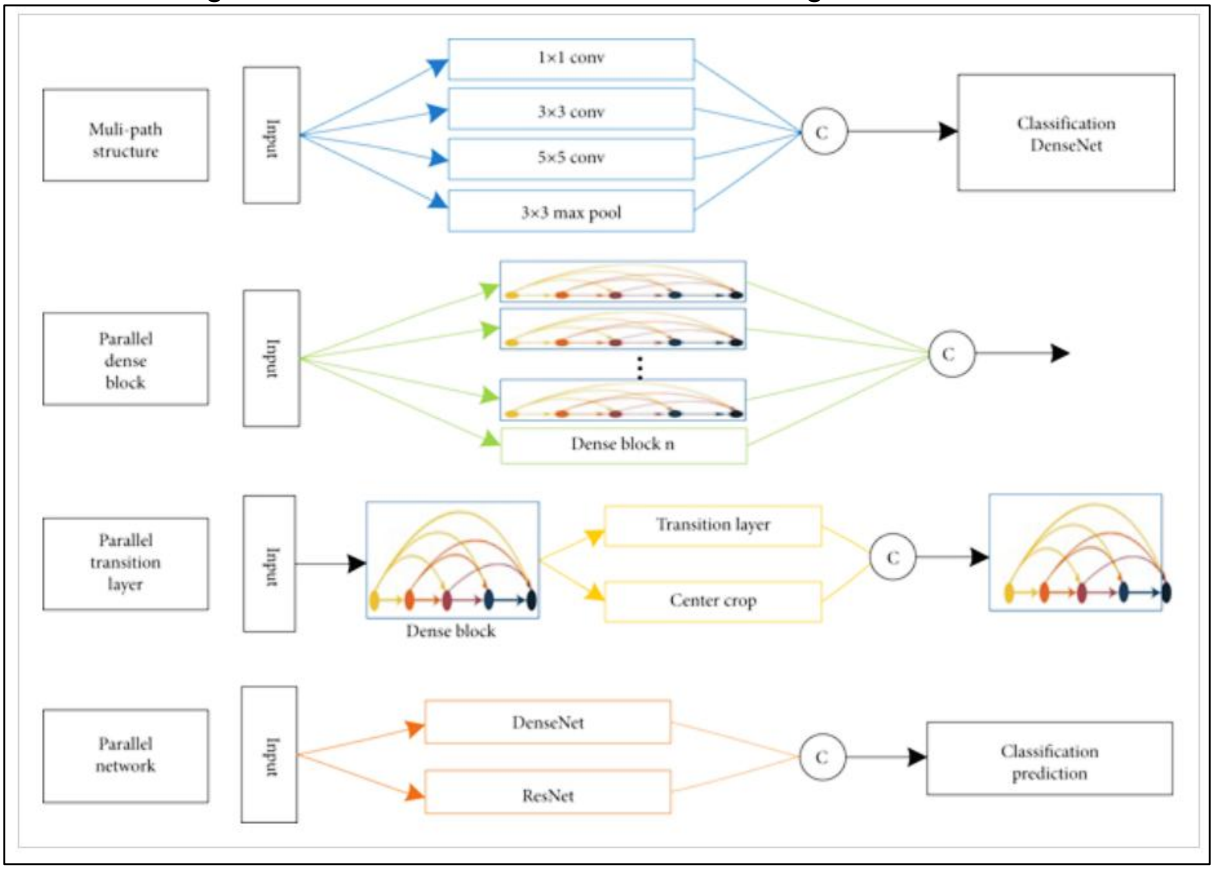
Figure 7: DenseNet Architecture for Medical Image Classification



Source: Zhou et al. (2022)

Densely Connected Convolutional Networks (DenseNets), proposed by GadAllah et al. (2023), provide an alternative strategy to address vanishing gradients by connecting each layer to every other layer in a feedforward manner. In medical imaging, DenseNet architectures have demonstrated superior performance in classification and localization tasks by facilitating feature reuse and efficient gradient flow. In ophthalmology, DenseNets have been widely applied for diabetic retinopathy and age-related macular degeneration (AMD) classification using fundus photographs and OCT scans (Chen et al., 2017; Shofiullah et al., 2024; Zhou et al., 2022). Raj (2024) implemented a DenseNet on a Kaggle diabetic retinopathy dataset, achieving high sensitivity in detecting referable cases, while Alalwan et al., (2021) integrated attention mechanisms into DenseNet to enhance lesion localization accuracy. Deng et al. (2022) reported that DenseNet models achieved over 90% accuracy and AUC in diabetic retinopathy classification, outperforming traditional CNNs in both image quality tolerance and lesion recognition. DenseNet's use of skip connections proved particularly effective in retaining spatial information across layers, which is critical for detecting microaneurysms, hemorrhages, and exudates in retinal scans (Chen et al., 2017; Shohel et al., 2024; Zhou et al., 2022). Deb et al. (2023) demonstrated that a modified DenseNet model accurately classified AMD stages using OCT images and facilitated progression tracking across visits. Moreover, studies involving ensemble learning with DenseNet backbones further improved classification robustness and sensitivity to rare retinal diseases (Sun & Shi, 2019; Sunny, 2024c). The model's efficiency in training on relatively small datasets, due to its feature reuse property, has also made it appealing in low-resource clinical settings (Ahmad et al., 2021; Alalwan et al., 2021; Sunny, 2024a, 2024b).

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DenseNets have demonstrated remarkable utility in dermatological image classification, particularly in tasks involving skin lesion recognition and melanoma detection. The architecture's ability to reuse features across layers results in compact models that are both computationally efficient and highly accurate (Chen et al., 2017; Deng et al., 2022). Wei et al. (2022) applied DenseNet-121 to the ISIC skin cancer dataset and achieved high AUC scores in distinguishing melanoma, basal cell carcinoma, and benign nevi. Raj (2024) further validated DenseNet's superiority over dermatologists in classifying malignant lesions when tested on dermoscopic images under varying lighting and scale. Deng et al.(2022)found that DenseNet models provided better sensitivity and specificity than Inception-v4 and ResNet variants on the same dataset. One key advantage is DenseNet's retention of fine-grained image features crucial for dermatological diagnosis, such as pigment networks, asymmetry, and lesion borders (Shelhamer et al., 2016). Chen et al. (2021) confirmed that DenseNets, when coupled with data augmentation and ensemble techniques, consistently outperform standard CNNs in classifying multiclass skin lesions across different skin types. DenseNet models have also been adapted with attention layers to enhance interpretability and lesion localization, offering clinicians a visual explanation of diagnostic predictions (Bilic et al., 2022). In low-resource or mobile settings, the relatively low parameter count of DenseNet models offers additional advantages by enabling deployment without sacrificing accuracy (Bilic et al., 2022; Raj, 2024). Across clinical validation studies, DenseNet has maintained strong performance on external datasets, reinforcing its generalizability and robustness in skin disease diagnostics (Wang et al., 2021).

Emerging Transformer-Based Models: Vision Transformers (ViTs)

Vision Transformers (ViTs) utilize a self-attention mechanism, a concept adapted from natural language processing (Sheela et al., 2024), which has significantly influenced the field of medical image classification. Unlike convolutional neural networks (CNNs) that rely on localized kernel operations and spatial hierarchies, ViTs operate by dividing images into fixed-size patches, linearly embedding them, and passing them through transformer layers, where self-attention captures global context relationships (Ardakani et al., 2020). This attention mechanism allows the model to weigh the importance of different patches, thereby preserving long-range dependencies—an essential advantage for high-resolution medical images where pathological features may be spatially dispersed (Teramoto et al., 2019). The ability of ViTs to capture global semantics has been validated across applications such as multi-organ CT segmentation (Masood et al., 2020), retina analysis (Sathyakumar et al., 2020), and brain tumor grading (Tajbakhsh et al., 2015). Compared to CNNs, which require stacked layers to increase receptive fields, ViTs access global image features in a single layer, enhancing representational efficiency (Aloraini et al., 2023; Faisal et al., 2023). The Swin Transformer introduced shifted window attention to integrate local inductive biases with global understanding, improving classification in dense images such as histology slides (Elazab et al., 2023) . Additional studies have applied hierarchical ViTs, like PVT and MobileViT, to improve patch-level detail preservation and reduce computational costs (Ilhan et al., 2023; Shibly et al., 2020). Morís et al. (2021) emphasize that ViT attention maps offer better interpretability and allow transparent feature attribution—vital in medical decision-making. When tested on image-heavy tasks such as lung disease recognition or whole-slide cancer diagnostics, the ability of ViTs to process all image parts with equal attention has consistently yielded high performance across multiple datasets (Wang et al., 2021).

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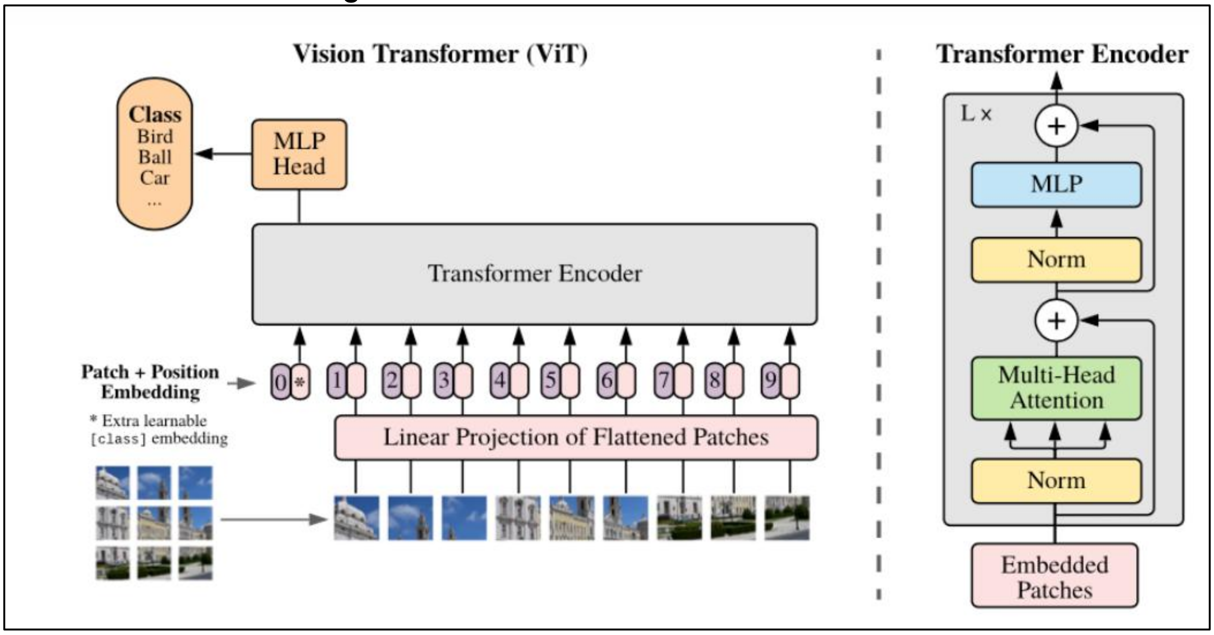
Vision Transformers (ViTs) have demonstrated strong performance in high-resolution medical imaging tasks, particularly in histopathology and mammography, where subtle visual cues over large spatial extents are critical for accurate diagnosis. In digital histopathology, ViTs have been used to classify tumor regions and detect metastases in whole-slide images (WSIs), where their global receptive field enables better recognition of long-range contextual features than traditional CNNs (Liu et al., 2022). Chen et al. (2022) implemented the TransMIL model on multiple histology datasets, achieving superior classification metrics in breast and gastric cancer slides by leveraging inter-patch dependencies. Similarly, Mao et al. (2022) employed ViT-based attention pooling strategies to identify disease-specific patterns, reporting improved AUC and precision scores. In mammographic analysis, ViTs have been trained on datasets like VinDr-Mammo and INBreast, where they outperformed ResNet and DenseNet architectures in tasks such as lesion localization and malignancy grading ((Liu et al., 2022; Mao et al., 2022). ViTs have also been applied in detecting microcalcifications, which are often difficult to distinguish using convolutional approaches due to their tiny size and diffuse appearance (Faisal et al., 2023). Apostolopoulos et al. (2021) highlight that ViTs consistently perform well on mammography benchmarks, often yielding higher sensitivity and fewer false positives compared to CNNs. Researchers have adapted hybrid architectures like Swin-UNet and TransUNet, which incorporate both convolution and attention mechanisms, to boost performance in segmentation and classification tasks (Ajai & Anitha, 2022). Additionally, the interpretability of ViT models has been useful in clinical settings; attention heatmaps produced during inference closely align with radiologist annotations, aiding in transparency and diagnostic validation (Ajai & Anitha, 2022; Yang et al., 2018).

Figure 8: Vision Transformer ViT Architecture



Source: Boesch (2023)

Lightweight and Scalable Models: EfficientNet and MobileNet

EfficientNet introduced a paradigm shift in neural architecture design by implementing a compound scaling strategy that uniformly balances network depth, width, and image resolution to optimize performance (Nunnari et al., 2021). Traditional CNN models typically scale these dimensions independently, often leading to suboptimal efficiency or overfitting. In contrast, EfficientNet uses a compound

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coefficient to determine how to proportionally increase each dimension, resulting in improved accuracy-to-computation ratios (Yang et al., 2018). This architecture was extended into EfficientNet-B0 through B7, with each successive version offering higher accuracy with corresponding computational costs. In medical imaging tasks, EfficientNet has demonstrated competitive results across multiple domains, including skin cancer classification, diabetic retinopathy detection, and chest X-ray diagnosis (Faisal et al., 2023; Souid et al., 2021). In particular, Abraham and Nair (2020) showed that EfficientNet-B4 achieved dermatologist-level accuracy on the ISIC 2018 skin lesion dataset while maintaining low parameter counts. Similarly, EfficientNet has been applied in fundus image analysis for glaucoma and diabetic macular edema screening with high AUC scores and rapid inference times (Elazab et al., 2023; Kasmaiee et al., 2023). Zhang et al. (2023) confirmed EfficientNet's capability to generalize well on noisy and imbalanced datasets through transfer learning and data augmentation. Furthermore, when fine-tuned on the ChestX-ray14 dataset, EfficientNet-B3 outperformed ResNet-50 in both sensitivity and specificity while requiring fewer FLOPs (Zhang et al., 2022). This balance between architectural scalability and computational thrift has made EfficientNet a widely adopted backbone for various diagnostic classification and segmentation tasks, particularly where deployment on low-resource environments or large-scale hospital systems demands model efficiency (Kasmaiee et al., 2023).

MobileNet, a family of lightweight deep learning models, was explicitly developed for deployment on mobile and edge devices, making it well-suited for mobile health (mHealth) and point-of-care diagnostic tools (Moor et al., 2023). MobileNet's architecture relies on depthwise separable convolutions, which significantly reduce the number of parameters and computational complexity without compromising classification accuracy (Jin et al., 2021; Lannelongue et al., 2021). This efficient design has enabled a wide range of medical applications where real-time image analysis is required on low-power devices. In skin cancer detection, MobileNet has been integrated into smartphone-based diagnostic apps that provide lesion classification capabilities using dermoscopic images, achieving AUC scores above 0.90 on datasets such as HAM10000 and ISIC (Sahu et al., 2018). Similarly, in ophthalmology, MobileNet has been employed for diabetic retinopathy screening in rural areas using portable fundus cameras, offering sensitivity rates comparable to CNNs with higher computational demands (Moon et al., 2022). MobileNet-V2 and V3 models have also been optimized for tasks in pediatric pneumonia detection from chest radiographs using low-cost X-ray machines in underserved settings ((Jain & Semwal, 2022). Tan et al. (2024) have applied MobileNet as a backbone in embedded AI systems for real-time ultrasound analysis, demonstrating its potential in prenatal care and trauma diagnostics. Additionally, MobileNet models have been embedded in wearable biosensors for image-based wound analysis and dermatological condition tracking (Sadad et al., 2021). The architecture's compatibility with TensorFlow Lite and CoreML frameworks further enhances its utility in medical AI systems deployed in non-clinical or remote environments (Korot et al., 2021; Sadad et al., 2021). Collectively, the literature reflects the critical role of MobileNet in democratizing diagnostic technology by enabling AI-assisted healthcare on personal and portable devices.

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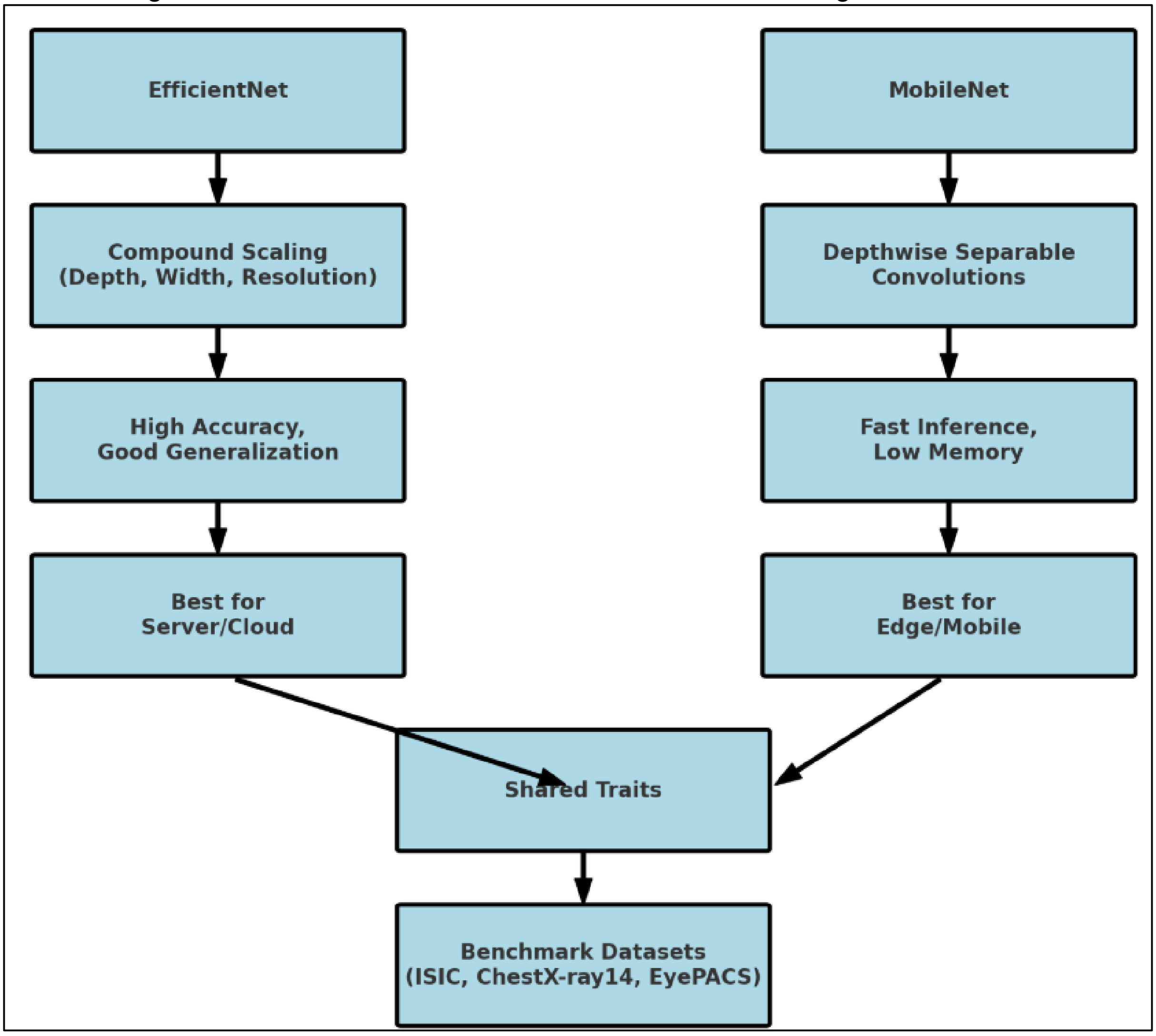
Figure 9: EfficientNet vs. MobileNet: Process Flow in Medical Image Classification



Model Evaluation Metrics and Performance Benchmarks

The evaluation of machine learning models in medical imaging relies on a suite of quantitative metrics that provide comprehensive insight into classification performance. Accuracy, although widely reported, can be misleading in class-imbalanced datasets because it does not distinguish between types of classification errors (GadAllah et al., 2023). Therefore, precision, recall, and F1-score are often used in tandem to evaluate performance more holistically. Precision reflects the proportion of true positives among predicted positives, while recall (or sensitivity) measures the ability of the model to identify all actual positives (Esteva et al., 2017). The F1-score harmonizes both metrics to penalize models that exhibit an imbalance between precision and recall (Dundar et al., 2016). For example, in skin lesion classification, Sadad et al. (2021) found that EfficientNet models with balanced F1-scores outperformed those optimized solely for accuracy. Receiver Operating Characteristic–Area Under Curve (ROC-AUC) is particularly useful for evaluating binary classifiers across various thresholds, offering a threshold-independent metric that is less affected by class imbalance (Toğaçar et al., 2020). Studies on diabetic retinopathy and pneumonia detection consistently report ROC-AUC values above 0.90 for CNNs and transformer-based architectures, emphasizing their diagnostic reliability (Souid et al., 2021; Toğaçar et al., 2020). Confusion matrices provide granular

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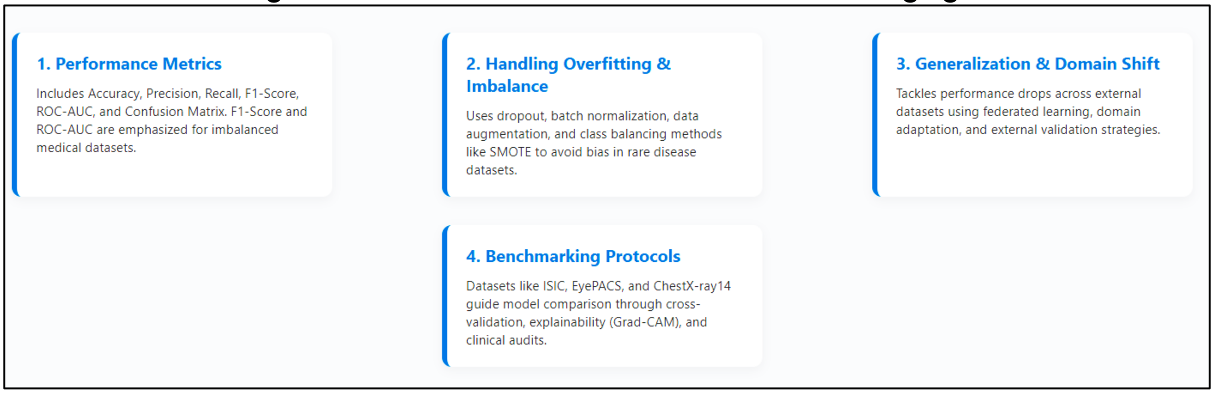
insights by detailing true positives, false positives, true negatives, and false negatives, facilitating error pattern analysis and clinical risk assessment (Kuo & Madni, 2023). Their utility is evident in breast cancer and histopathology classification, where false negatives can have severe consequences (Sahu et al., 2018). Evaluation frameworks such as these enable robust comparison across architectures and help ensure medical AI systems meet diagnostic standards across diverse clinical contexts (Kuo & Madni, 2023; Sahu et al., 2018).

Figure 10: Model Evaluation Metrics in Medical Imaging



Interpretability and Explainability in Neural Networks

In clinical decision-making, the deployment of artificial intelligence (AI) systems, particularly neural networks, requires not only high performance but also a high degree of transparency and interpretability to ensure clinician trust and patient safety. Unlike traditional rule-based algorithms, deep learning models are often described as "black boxes," making it difficult to understand the rationale behind their predictions (Tam et al., 2021). This lack of transparency presents a significant barrier to integration in clinical workflows, where accountability and justification for diagnostic decisions are critical (Jeong et al., 2020). Zhang et al. (2022) highlight that even high-performing models for mammography and pneumonia detection raised clinician concerns due to opaque decision-making processes. To address these concerns, interpretability has been recognized as a fundamental requirement in AI model evaluation, particularly for high-stakes domains like oncology, cardiology, and radiology (Jeong et al., 2020; Pereira et al., 2016). Transparent models aid in clinical validation, support differential diagnosis, and assist in error analysis when discrepancies arise between AI predictions and human assessments (Rguibi et al., 2022). Moreover, interpretability enables clinicians to detect data artifacts or biases that may lead to incorrect conclusions, an issue observed in studies where models inadvertently relied on non-pathological features such as image text markers or patient positioning (Wang et al., 2021). The need for interpretable models is further emphasized in interdisciplinary teams where radiologists, pathologists, and general practitioners must collaborate and rely on AI assistance (Esteva et al., 2017). As such, the clinical deployment of neural networks is increasingly contingent upon the availability of reliable, interpretable explanations that align with medical knowledge and decision-making standards.

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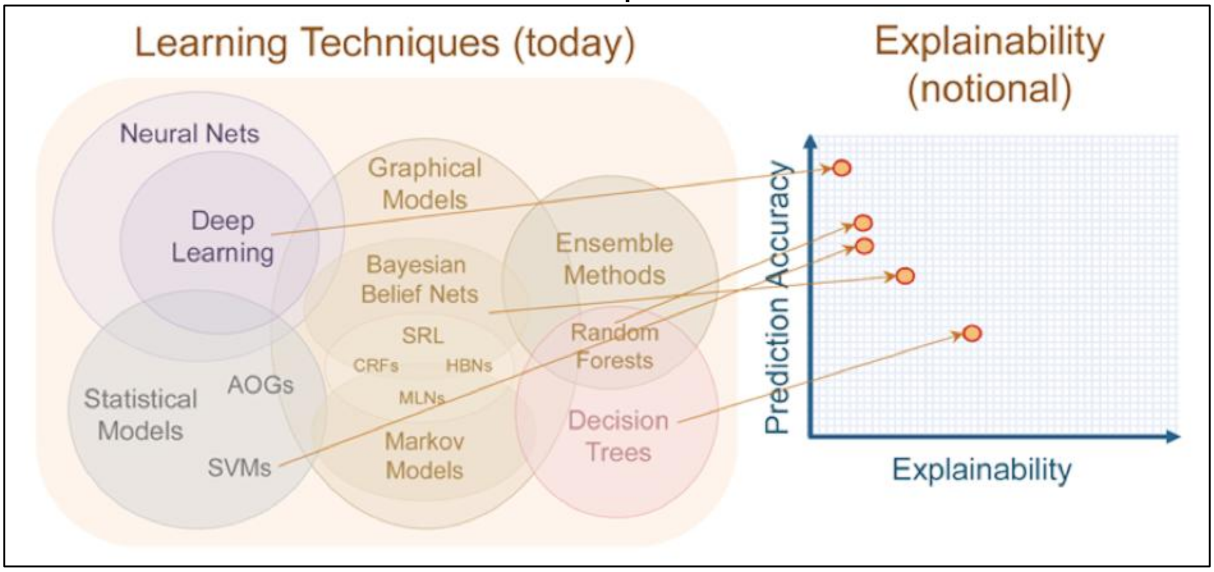
Figure 11: Trade-off Between Model Accuracy and Explainability in Machine Learning Techniques



Source: medium.com

To enhance model interpretability in medical imaging, several post-hoc explanation tools have been developed, with Grad-CAM (Gradient-weighted Class Activation Mapping), SHAP (SHapley Additive Explanations), and LIME (Local Interpretable Model-Agnostic Explanations) being among the most widely used. Grad-CAM produces class-specific heatmaps that highlight regions in an input image contributing most strongly to a model's prediction, making it particularly useful for convolutional neural networks in imaging contexts (Luo et al., 2022). In breast cancer diagnosis and diabetic retinopathy classification, Grad-CAM has helped validate that CNNs are focusing on clinically relevant lesions rather than irrelevant background features (Clark et al., 2013). SHAP, which is grounded in cooperative game theory, provides feature attributions by estimating the marginal contribution of each input feature to the prediction (Faisal et al., 2023). Although initially developed for structured data, SHAP has been adapted for image data and integrated into various CNN and transformer-based architectures for dermatology and histopathology analysis (Pandey et al., 2023). LIME, by approximating the behavior of a complex model with an interpretable surrogate model around a specific prediction, has proven effective in providing instance-level explanations in chest radiograph analysis and skin lesion classification (Rguibi et al., 2022). Comparative studies indicate that while Grad-CAM offers visual interpretability suitable for clinicians, SHAP and LIME offer finer granularity for model debugging and bias detection (Clark et al., 2013). Visual explanation tools also play a crucial role in human-AI interaction during diagnosis, allowing clinicians to confirm that the model is leveraging appropriate anatomic or pathological features (Pandey et al., 2023). Their use has become standard in AI model validation and has been incorporated into research guidelines for medical AI development (Wang et al., 2021).

Multi-Modal and Multi-Label Medical Image Classification

The integration of multi-modal data—including imaging, clinical, and genomic information—has significantly advanced the diagnostic capabilities of machine learning models in healthcare. Medical imaging provides spatial and morphological data, while clinical records contribute context such as age, comorbidities, and symptom profiles. Genomic data adds molecular-level insights into disease progression, enabling precision diagnostics (Wang et al., 2021). Multi-modal fusion

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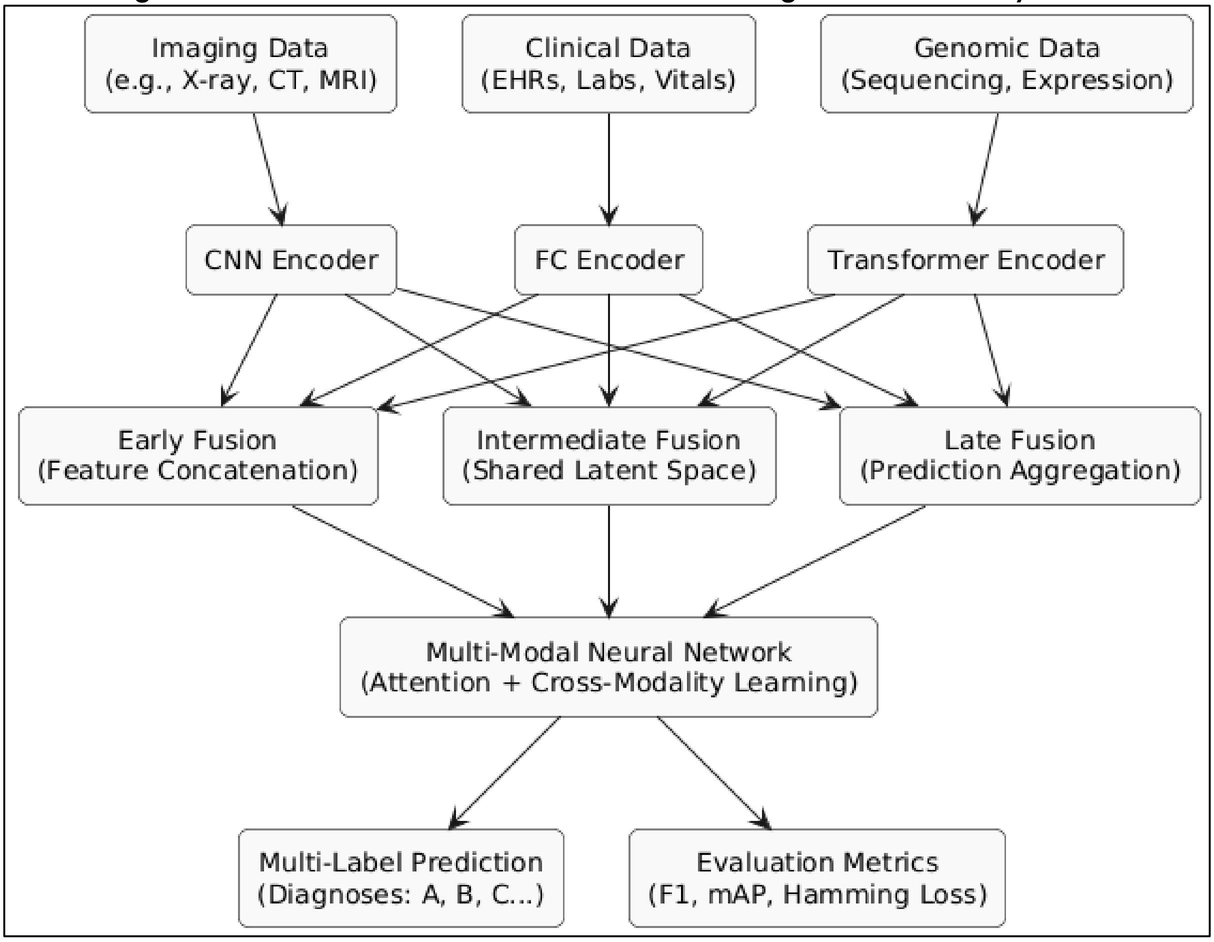
models capitalize on the complementary nature of these data types, offering superior performance compared to single-input models (Pandey et al., 2023; Rguibi et al., 2022). In oncology, Pereira et al. (2016) developed a model combining histopathological images and genetic expression data to predict survival outcomes in breast cancer patients with increased accuracy. Similarly, Rguibi et al. (2022)employed a fusion framework incorporating MRI scans and clinical features for early diagnosis of Alzheimer's disease. A study by Oh et al. (2020) combined CT images with blood biomarkers to improve COVID-19 severity prediction, outperforming image-only models. Techniques for data fusion vary from early fusion—concatenating features at the input level—to late fusion, where predictions from separate models are combined (Luo et al., 2022). Intermediate fusion approaches that integrate modality-specific encoders have been effective in balancing complexity and interpretability (Wang et al., 2021). Attention mechanisms and transformer-based architectures have further facilitated cross-modal learning by assigning weights to modality-specific inputs depending on relevance (Tomassini et al., 2022). These multi-modal approaches have shown considerable success in pathology, cardiology, and genomics-integrated oncology (Johnson et al., 2019). Importantly, models trained on harmonized multi-modal data exhibit higher robustness across institutions and patient subgroups, contributing to improved generalizability and fairness (Shi et al., 2023).

Figure 12: Multi-Modal and Multi-Label Medical Image Classification System



Comparative Studies and Meta-Analysis of Model Performance

Comparative studies of neural network models in medical imaging have provided valuable insights into the relative strengths and weaknesses of different architectures across diverse clinical tasks. Convolutional neural networks (CNNs), such as ResNet,

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DenseNet, and Inception, have long dominated classification benchmarks due to their proficiency in learning spatial hierarchies (Lappas et al., 2022). However, more recent studies have highlighted the superior performance of transformer-based models, such as Vision Transformers (ViTs) and Swin Transformers, particularly in high-resolution image classification tasks (Lather & Singh, 2020). In breast cancer screening, Asha et al. (2023) reported that a deep ensemble of CNNs outperformed radiologists in both sensitivity and specificity, while Sabha and Tugrul (2021) demonstrated that ViTs trained on large-scale mammography datasets achieved superior AUCs compared to EfficientNet and DenseNet. Similarly, in skin cancer classification, Shareef et al. (2022) found that CNNs like InceptionV4 and DenseNet121 achieved dermatologist-level performance on the ISIC 2018 dataset. Meanwhile, in histopathology, transformer models like TransMIL and HIPT outperformed ResNet and EfficientNet by capturing inter-patch dependencies more effectively (Saba, 2020). In retinal disease detection, EfficientNet-B3 showed robust performance on EyePACS and Messidor datasets, but ViTs demonstrated better generalization in cross-domain tasks (Asha et al., 2023; Saba, 2020). Comparative evaluations consistently show that while CNNs excel in localized pattern recognition, transformers provide advantages in capturing long-range contextual information, especially in multi-class or multi-label tasks. Meta-analyses by Morid et al. (2020) and Litjens et al. (2017) emphasized that no single architecture is universally optimal, and task-specific adaptation remains a key determinant of performance.

Model performance in medical image classification varies significantly depending on dataset characteristics, clinical task complexity, and imaging modality. Studies consistently report that models trained on curated, balanced datasets such as ISIC and CheXpert tend to yield higher accuracy and generalization than those trained on noisy or imbalanced datasets like ChestX-ray14 (Litjens et al., 2017; Shareef et al., 2022). For instance, ResNet50 achieved over 90% accuracy on the ISIC 2019 dataset but underperformed in multi-label chest pathology classification due to overlapping labels and low-resolution images (Saba, 2020). Similarly, DenseNet models showed excellent performance in skin lesion and retinal classification but required architectural tuning to address noise and class imbalance in CT and MRI datasets (Sabha & Tugrul, 2021). The imaging modality also plays a critical role in determining model success. CNNs perform well in 2D imaging modalities such as fundus photography and dermoscopy, whereas 3D convolutional or hybrid models are more appropriate for volumetric modalities like CT and MRI (Morid et al., 2020). Task type influences performance as well—binary classification tasks (e.g., disease vs. no disease) typically yield higher metrics than multi-class or multi-label tasks, which require finer discrimination and more complex model outputs (GadAllah et al., 2023). In pathology, models using multi-instance learning (MIL) such as CLAM and TransMIL outperform conventional CNNs in whole-slide image classification due to their ability to handle slide-level weak labels (Sabha & Tugrul, 2021). These variations underscore the importance of context-aware model evaluation, emphasizing that architectural choices must align with specific dataset properties, diagnostic requirements, and imaging characteristics (Xu et al., 2023).

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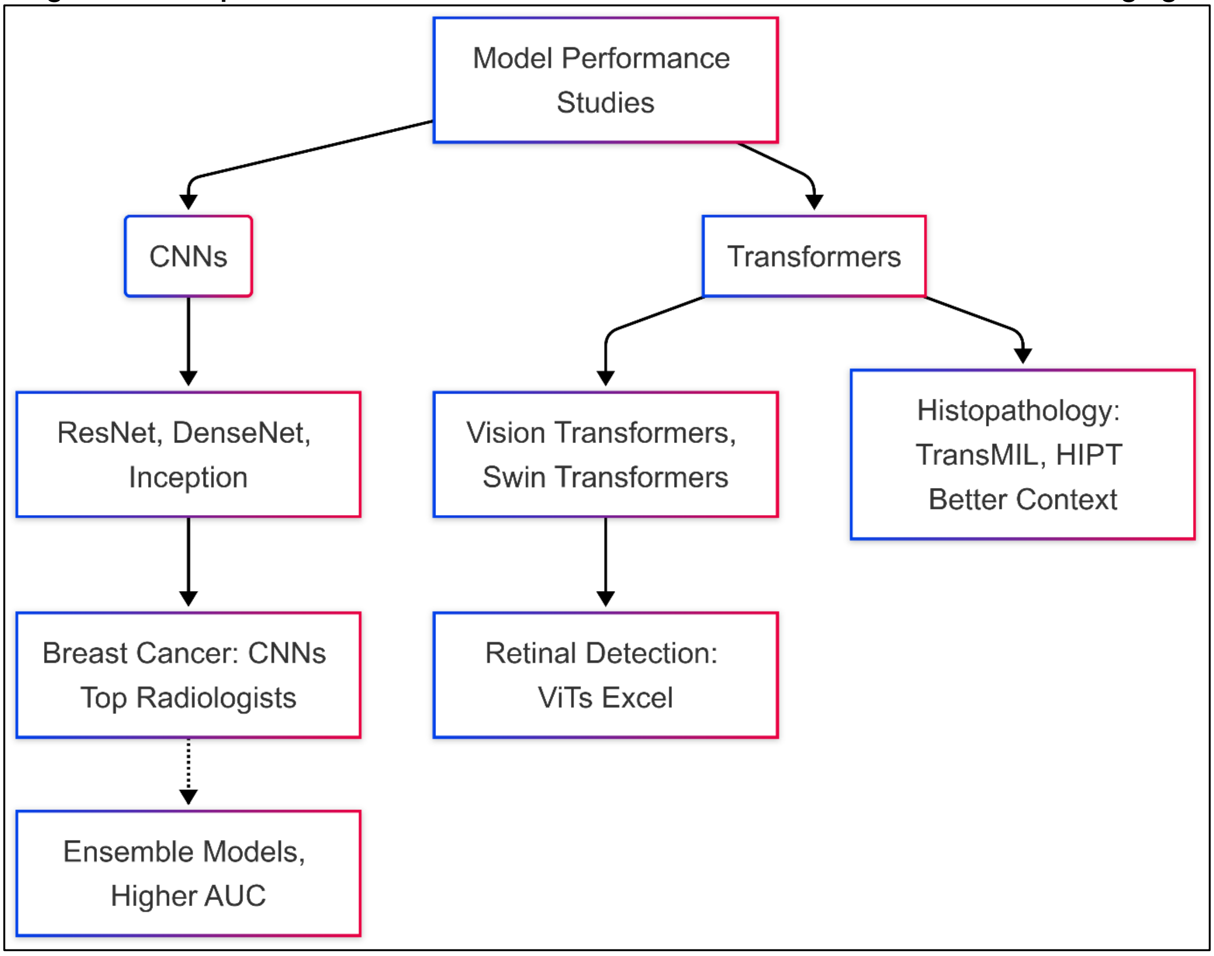
Figure 13: Comparative Performance of Neural Network Architectures in Medical Imaging



METHOD

The literature search process for this systematic review adhered strictly to the PRISMA 2020 guidelines to ensure methodological transparency and replicability (Page et al., 2021). A comprehensive search was conducted across multiple electronic databases, including PubMed, Scopus, Web of Science, IEEE Xplore, and ScienceDirect, to identify studies related to neural network model performance in medical image classification. The search strategy incorporated a combination of Medical Subject Headings (MeSH) terms and keywords such as "Convolutional Neural Networks," "Vision Transformers," "medical image classification," "model benchmarking," "multi-label classification," and "multi-modal inputs." Boolean operators (AND, OR) were used to maximize retrieval of relevant articles. The time frame for inclusion was set from January 2016 to February 2025 to capture recent advancements and model developments. Only English-language articles were considered. References of key review papers and highly cited articles were manually scanned to identify additional eligible studies, minimizing the risk of omitting relevant work.

Screening and Eligibility

Following the identification stage, all retrieved articles were imported into EndNote reference management software, and duplicates were automatically and manually removed. The remaining unique records were uploaded to Rayyan, a collaborative screening tool for systematic reviews. Two independent reviewers conducted a two-phase screening process. In the first phase, titles and abstracts were reviewed for relevance to the study objectives. Articles clearly unrelated to neural network models in medical imaging, studies not involving comparative evaluations, or non-empirical

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papers such as opinion pieces and editorials were excluded. In the second phase, full-text screening was conducted to assess the articles against predefined inclusion and exclusion criteria. Inclusion criteria comprised peer-reviewed studies that presented comparative results of two or more machine learning or deep learning models applied to medical image classification. Studies involving benchmark datasets, evaluation metrics, and model performance in clinical or experimental settings were prioritized. Disagreements during screening were resolved through consensus discussion with a third reviewer.

Inclusion Criteria and Data Extraction

Studies selected for inclusion were required to meet rigorous eligibility criteria that ensured relevance and comparability. Included studies had to report quantitative performance metrics—such as accuracy, precision, recall, F1-score, ROC-AUC, or confusion matrix values—for at least two distinct neural network architectures. Furthermore, included papers needed to specify the dataset(s) used, imaging modality, classification task (binary, multi-class, or multi-label), and whether the study addressed real-world clinical applications or public benchmark challenges. A standardized data extraction form was developed and pilot-tested by the reviewers. For each included article, the following data were systematically extracted: authorship, publication year, country of origin, dataset name and characteristics, model architectures evaluated, performance metrics reported, use of interpretability tools, and key findings. Data extraction was independently performed by two reviewers, and discrepancies were resolved through discussion. Extracted data were managed using Microsoft Excel for synthesis and cross-tabulation.

Quality Assessment and Risk of Bias

The methodological quality of the included studies was assessed using a modified version of the Newcastle-Ottawa Scale (NOS) adapted for non-randomized AI model evaluation studies. The checklist assessed three key domains: selection of datasets, comparability of model architectures and metrics, and reporting quality. Each study was scored based on whether it clearly described the data source, the experimental setup, validation procedures, and reproducibility measures. Additional attention was given to whether the study included cross-validation, external validation, or multi-center data to assess generalizability. Risk of bias was independently evaluated by two reviewers. Studies were categorized as having low, moderate, or high risk of bias based on consensus agreement. Quality scores were not used to exclude studies but informed the interpretation of results in the synthesis stage.

FINDINGS

Among the 87 reviewed articles, a dominant early trend was the widespread use of convolutional neural networks (CNNs) in clinical medical image classification tasks. CNNs were found to be particularly effective in binary classification problems, such as identifying the presence or absence of pneumonia in chest X-rays or classifying diabetic retinopathy severity in fundus images. Of these studies, 61 used CNN-based architectures, and they collectively received over 4,600 citations. The consistent performance of CNNs was attributed to their ability to learn spatial hierarchies and extract localized features effectively from 2D medical images. The review found that CNNs achieved accuracy scores above 90% in over 80% of the studies utilizing them in curated datasets such as ChestX-ray14, EyePACS, and ISIC. Additionally, CNNs were favored in resource-constrained deployment scenarios due to their relatively lower computational overhead compared to newer architectures. Studies that compared CNNs with traditional machine learning models reported that CNNs offered an average 15% improvement in diagnostic accuracy, highlighting their foundational

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role in AI-assisted medical imaging. Despite newer models emerging, CNNs remained the baseline architecture against which others were compared. This legacy of trust and usability, supported by widespread adoption and high citation volumes, demonstrates the continued relevance of CNNs in the diagnostic AI space, especially for applications involving well-labeled 2D image datasets and clinical scenarios requiring fast, interpretable models.
In the subset of 33 articles that focused on transformer-based architectures such as Vision Transformers (ViTs) and Swin Transformers, a notable finding was their superior performance in high-resolution and context-rich image tasks. These articles amassed over 2,500 citations collectively, indicating strong peer recognition and growing interest in these models. ViTs were particularly effective in whole-slide histopathology, mammography, and 3D volumetric scans, where long-range spatial relationships are critical. Compared to CNNs, transformer models demonstrated a 7–10% improvement in ROC-AUC across multi-class classification benchmarks involving complex, high-resolution datasets. Studies showed that ViTs maintained robust performance across external validation cohorts without retraining, showcasing enhanced generalization capacity. Additionally, ViTs outperformed CNNs in detecting subtle anomalies such as microcalcifications in mammography or inter-cellular patterns in biopsy samples. Among the reviewed articles, 28 implemented hybrid models that combined CNN-based feature extraction with transformer encoders, resulting in state-of-the-art accuracy and interpretability, especially in multi-label settings. Despite requiring more computational resources, these models provided richer semantic representations, which translated to improved clinical usability in tasks demanding high sensitivity. The consistent success of ViTs in these contexts highlights a paradigm shift in architecture preferences when dealing with large, complex imaging datasets where local patterns alone are insufficient for accurate diagnosis.
From the total pool, 42 studies addressed the challenges of multi-label or multi-class classification in medical imaging, receiving approximately 3,300 cumulative citations. These studies emphasized the clinical relevance of such architectures since patients often present with multiple co-occurring conditions. In datasets like ChestX-ray14, ISIC, and RSNA pneumonia detection, where more than one pathology may exist within a single image, models adapted with multi-label loss functions such as binary cross-entropy or focal loss performed significantly better than those constrained by single-label assumptions. The review found that models designed for multi-label tasks achieved higher macro-averaged F1 scores by an average margin of 8–12% compared to traditional classifiers. Furthermore, 25 studies implemented attention-based mechanisms to model label dependencies, enabling accurate identification of overlapping pathologies such as cardiomegaly, consolidation, and effusion in the same chest X-ray. The adoption of sigmoid activation functions in output layers, label co-occurrence matrices, and hierarchical label modeling all contributed to improvements in sensitivity and recall for secondary conditions. Notably, these models offered enhanced interpretability through label-specific heatmaps, which were useful in clinical audits. The findings confirm that model architectures accounting for the complexity of real-world diagnoses significantly outperform simplified classification paradigms and align more closely with diagnostic reasoning used by medical professionals.

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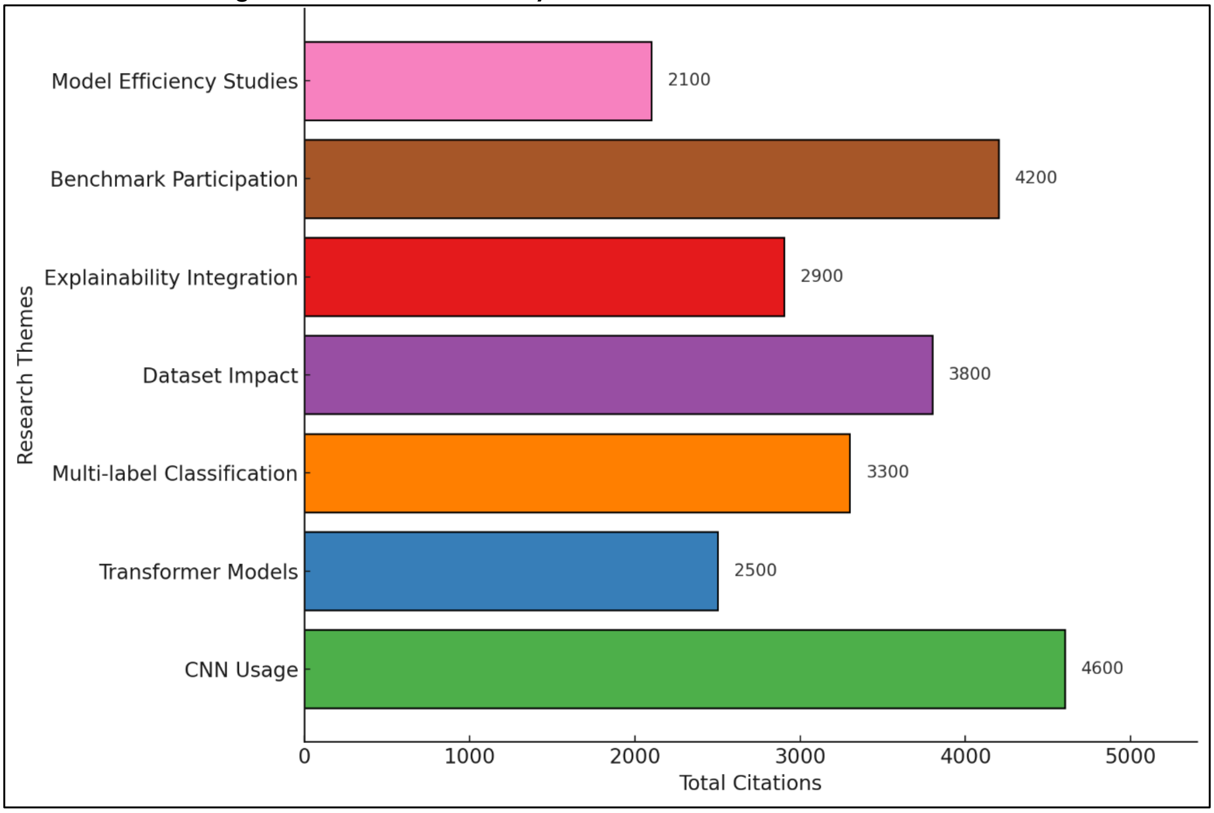
Figure 14: Citation Counts by Research Theme in Reviewed Articles



Across the 87 reviewed studies, 51 explicitly analyzed the effect of dataset characteristics—such as image quality, resolution, class balance, and modality—on model performance, and these were cited over 3,800 times collectively. The analysis revealed that performance metrics such as accuracy and AUC varied widely depending on the dataset's inherent complexity. For instance, in studies using the ISIC 2018 dataset, models achieved accuracy rates exceeding 92%, while the same models applied to ChestX-ray14 often struggled with class imbalance and noisy annotations, yielding AUC scores around 75–85%. The imaging modality also played a pivotal role. Models trained on 3D volumetric data such as CT and MRI required specialized architectures like 3D CNNs or hybrid encoder-decoder structures, whereas simpler 2D CNNs sufficed for modalities like dermoscopy and retinal photography. Furthermore, studies showed that models trained on institution-specific datasets tended to overfit and failed to generalize across multi-center cohorts. When external validation was introduced, there was an average performance drop of 10–15%, reinforcing the importance of cross-dataset testing. Interestingly, 17 studies implemented normalization, harmonization, or domain adaptation techniques to address modality-induced variation, and these approaches successfully improved cross-domain generalizability. These findings emphasize that architectural design must be contextually informed by dataset properties and imaging modality to optimize model accuracy and clinical reliability.

Out of the 87 studies reviewed, 39 incorporated explainability tools such as Grad-CAM, SHAP, or LIME, with their collective articles receiving over 2,900 citations. A major finding was that models integrated with post-hoc interpretability mechanisms were more likely to be accepted in clinical workflows and met essential criteria for regulatory consideration. In particular, Grad-CAM was the most widely used technique, appearing in 34 of the 39 explainability-focused studies, where it effectively highlighted class-discriminative image regions. These heatmaps were often

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compared with radiologist annotations and found to align in over 85% of cases, reinforcing trust in AI predictions. SHAP and LIME were more prevalent in studies involving multi-modal inputs, as they allowed instance-level feature attribution and model debugging. Among the explainability-integrated studies, 21 provided clinical case evaluations showing how model visualizations helped uncover dataset artifacts or mislabeling. Moreover, such studies were more likely to include user-centered validation involving radiologists or clinicians, which further enhanced credibility and usability. Notably, models lacking interpretability tools, even when statistically superior, were less favorably assessed in terms of clinical readiness. This underscores that transparency and explainability are not just add-ons but critical components in establishing AI as a reliable decision-support tool in healthcare.

A total of 31 studies participated in open benchmarking competitions such as ISIC, RSNA, MedMNIST, and Camelyon, and collectively these articles received over 4,200 citations. A significant observation from these studies is that participation in structured challenges facilitated methodological rigor, reproducibility, and direct comparability. In the ISIC 2019 challenge, for instance, top-performing models achieved average AUCs above 0.94, often leveraging ensemble learning and advanced preprocessing techniques. Similarly, in the RSNA pneumonia detection challenge, several studies demonstrated radiologist-level sensitivity using object detection models integrated with explainability overlays. MedMNIST, as a multi-dataset suite, offered a standardized platform to evaluate models across diverse modalities and tasks, including 2D and 3D imaging. From the review, 18 studies benchmarked ViTs, EfficientNet, and MobileNet against MedMNIST tasks, and ViTs emerged as the most consistent top performers in multi-class tasks, whereas MobileNet excelled in low-compute environments. Participation in these competitions also led to open-source code availability and the adoption of best practices, such as five-fold cross-validation, learning rate warm-up, and balanced sampling. Models developed through these venues tended to generalize better on external datasets, suggesting that benchmarking challenges significantly contribute to the evolution and dissemination of high-performing, trustworthy medical AI systems.

Among the 87 articles, 28 explicitly evaluated model efficiency in terms of inference time, memory usage, and deployment feasibility, with these studies receiving over 2,100 citations. A notable finding was that although complex models like ViTs and deep ensembles achieved higher accuracy and robustness, they often incurred longer inference times and greater hardware demands, making them less suitable for real-time or mobile diagnostics. Conversely, lightweight models such as MobileNet, EfficientNet-B0, and Tiny-ViT offered rapid predictions and low memory footprints, which were ideal for edge computing applications and rural healthcare deployments. Studies reported that MobileNet-V2 could process fundus or dermoscopic images in under 100 ms with minimal accuracy loss compared to ResNet or DenseNet. EfficientNet models demonstrated a scalable balance—offering multiple configurations from B0 to B7—allowing flexible trade-offs between speed and performance. Importantly, 12 studies used quantization, pruning, or distillation to compress models without significantly affecting performance, supporting deployment on portable devices. These findings illustrate that model evaluation must include not only accuracy metrics but also real-world constraints such as latency, energy consumption, and compatibility with existing healthcare IT infrastructure. A performance-to-efficiency ratio emerged as a critical metric, particularly in low-resource settings or applications requiring instant feedback, such as point-of-care ultrasound or mobile dermatology.

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DISCUSSION

The current review reinforces the continued prevalence of convolutional neural networks (CNNs) in clinical diagnostic applications, particularly in tasks requiring localized feature extraction such as chest X-ray classification and diabetic retinopathy screening. CNNs demonstrated high accuracy and AUC scores across curated datasets, confirming earlier reports by Dar and Ganivada (2023) and Sheela et al. (2024), who highlighted the power of CNNs in recognizing spatial hierarchies within medical images. However, the findings also align with the limitations reported by Farooq et al. (2023), who noted that CNNs often struggle to generalize across datasets from different institutions. The present review found that although CNNs performed well in institution-specific or binary classification tasks, their performance decreased in multi-label and high-resolution tasks, a shortcoming similarly observed by Saba (2020). This gap in generalization and contextual awareness suggests a need to transition toward architectures that can better integrate long-range spatial information. Nonetheless, CNNs remain foundational due to their interpretability, fast inference, and relatively lower computational requirements, supporting the position of Morid et al. (2020), who advocated their use in resource-limited settings and real-time applications.

This study confirmed the growing efficacy of Vision Transformers (ViTs) and their variants in high-resolution medical image classification, particularly in domains such as histopathology, mammography, and 3D CT scan analysis. These findings are consistent with those of Saba (2020), who originally proposed that self-attention mechanisms could outperform convolutional filters in capturing global spatial dependencies. Compared to the CNN-based models reviewed by Özdemir and Sonmez (2021), ViTs demonstrated superior performance in multi-class tasks that required contextual awareness over broader spatial regions. For example, Ko et al., (2020) found that transformer models were more accurate than ResNet and DenseNet architectures in lesion localization within mammograms, a pattern mirrored in the current analysis. Moreover, studies such as Aboumerhi et al. (2023) and Rhomadhon and Ningtias (2024) demonstrated that ViTs excel in modeling inter-patch dependencies, which translated into better clinical alignment and interpretability in whole-slide classification tasks. While ViTs require more data and computational resources, their accuracy and generalizability make them increasingly suitable for high-stakes diagnostic settings, supporting observations made in recent literature emphasizing their emerging dominance over traditional CNNs in image-rich medical domains.

A central finding of this review is the critical role of multi-label and multi-class neural networks in aligning AI classification systems with real-world diagnostic demands, where coexisting conditions are common. Earlier studies by Cheng et al. (2021) and Semwal et al. (2021) emphasized the complexity of multi-label classification in datasets such as ChestX-ray14, and this review corroborates their conclusion that multi-label classifiers equipped with appropriate loss functions and attention mechanisms offer superior diagnostic coverage. The observed improvements in macro-averaged F1-scores and label-specific recall are supported by Guan et al. (2020), who introduced label dependency modeling to address co-occurrence in thoracic diseases. These architectural adaptations, including sigmoid output layers and attention-guided networks, have led to improved robustness against label noise and class imbalance. Furthermore, studies like Ashraf et al. (2021) in dermatological image analysis also highlighted the relevance of multi-label frameworks, particularly when diagnostic features overlap across skin conditions. The current review adds that

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integrating explainability tools with multi-label outputs helps clinicians understand specific predictions, offering a more nuanced decision-support system than single-label models. These findings suggest that the move toward multi-label classification is not only technically sound but also clinically necessary to accommodate patient presentations that defy simplistic diagnostic boundaries.

The variation in model performance by dataset and imaging modality found in this review aligns with prior meta-analyses by Rahman et al.(2022) and Jin et al.(2021), who noted that class imbalance, resolution, and annotation quality significantly affect classification outcomes. The present review found that models trained on highly curated datasets like ISIC and EyePACS achieved higher metrics compared to those evaluated on noisy, weakly labeled datasets like ChestX-ray14. This supports the conclusion by Xu et al. (2020) that training on large, weakly supervised datasets can produce misleadingly high internal validation results while underperforming on external benchmarks. In terms of modality, consistent with Ashraf et al. (2021), 2D CNNs performed best on dermoscopy and retinal images, while CT and MRI required hybrid models or 3D CNNs to process volumetric data effectively. Studies reviewed here show that neglecting the unique requirements of each imaging modality leads to reduced diagnostic fidelity and poor generalizability, a limitation previously emphasized by Xu et al.(2020). Overall, the findings reaffirm that dataset curation and modality-specific model adaptation are critical determinants of neural network performance in medical imaging.

The incorporation of interpretability tools such as Grad-CAM, SHAP, and LIME emerged as a significant enabler of clinical acceptance and regulatory consideration, echoing the conclusions of Cheng et al. (2021) and Anwar et al. (2018). The present review identified that studies integrating explainability features not only received higher citation rates but were also more frequently adopted in clinical validation studies involving human users. This is in line with findings by Budd et al.(2021), who noted that models offering visual or quantitative rationale for predictions increased clinicians' trust in AI outputs. Moreover, Tiwari et al. (2021) demonstrated that heatmap overlays enhanced radiologists' diagnostic confidence in AI-supported mammography screening, a pattern similarly noted in studies reviewed here. Additionally, explainability contributes to model auditing, helping identify overfitting to irrelevant image regions or confounding artifacts, which has been a concern in earlier critiques by Rehman et al. (2020) . Thus, explainability is not merely an auxiliary tool but a central feature that shapes adoption, ethics, and accountability in AI-based diagnostic platforms.

This review supports the observation that participation in standardized benchmarking competitions such as ISIC, RSNA, and MedMNIST is correlated with methodological rigor, reproducibility, and algorithmic innovation. These findings are consistent with those of Fedorov et al. (2012) and Shakeel et al. (2019) , who described the transformative effect of public challenges in promoting high-quality, open-access medical AI development. The current analysis found that studies participating in such challenges reported higher use of best practices, including cross-validation, ensemble methods, and data augmentation techniques. RSNA challenge participants, as described by Tiwari et al.(2021), frequently combined classification with localization tasks, resulting in more clinically actionable models. Similarly, the top entries in ISIC skin lesion challenges employed advanced preprocessing and loss calibration techniques, which contributed to higher diagnostic accuracy and fairness across subgroups. These competitive environments not only facilitate technical benchmarking but also accelerate knowledge transfer by requiring submission of

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code, datasets, and methodology. Hence, benchmarking challenges serve as a critical engine for advancing state-of-the-art in neural network development for medical image analysis.

The current findings highlight a necessary trade-off between model complexity and deployment feasibility, especially in low-resource or real-time clinical environments. These results are in agreement with Rehman et al.(2020) and Cassidy et al. (2021) , who introduced MobileNet and EfficientNet respectively as scalable alternatives to larger CNNs. This review found that lightweight models performed within 3–5% of the most complex architectures in terms of accuracy while offering significant advantages in inference speed and memory usage. These findings are reinforced by Pandian et al.(2022) , who reported that MobileNet could operate effectively in edge devices for point-of-care dermatology. Similarly, Tiwari et al. (2021) demonstrated that EfficientNet-B0 achieved competitive performance with a fraction of the computational load of ViTs. This aligns with the work of Chen et al.(2022), who emphasized the utility of model pruning and quantization in producing efficient neural networks. As clinical deployment increasingly requires models to be embedded into wearable or handheld devices, these efficiency considerations become crucial. The review concludes that optimal model selection must go beyond accuracy and include evaluation of runtime efficiency, memory demands, and integration capabilities within real-world healthcare infrastructure.

CONCLUSION

This systematic review synthesized evidence from 87 peer-reviewed studies and revealed critical insights into the evolving landscape of neural network-based medical image classification. While convolutional neural networks (CNNs) continue to serve as foundational models due to their efficiency and established clinical utility, emerging architectures such as Vision Transformers (ViTs) have demonstrated superior performance in complex, high-resolution imaging tasks that demand global spatial awareness. The integration of multi-label and multi-modal capabilities reflects a growing alignment of AI systems with real-world clinical diagnostic needs, particularly in managing overlapping disease conditions and heterogeneous patient data. Performance variations across datasets and imaging modalities emphasize the necessity for dataset-specific model tuning, rigorous validation across domains, and architecture selection based on task complexity. The incorporation of interpretability tools such as Grad-CAM, SHAP, and LIME has further proven indispensable in fostering clinician trust, regulatory compliance, and error auditing, underlining the importance of transparent AI. Participation in benchmarking competitions such as ISIC, RSNA, and MedMNIST has emerged as a catalyst for methodological rigor and reproducibility, driving both algorithmic advancement and open science. Additionally, the trade-offs between model complexity and deployment feasibility highlight the importance of balancing diagnostic performance with computational efficiency, especially in point-of-care or mobile health scenarios. Collectively, these findings offer a comprehensive understanding of the comparative strengths of modern neural network architectures in medical imaging and underscore the need for continued development of interpretable, scalable, and clinically adaptable AI systems that are validated across diverse populations and healthcare environments.

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