The Role of Artificial Intelligence in Revolutionizing Cancer Detection and Diagnosis: A Focus on Convolutional Neural Networks

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Abstract— The integration of Artificial Intelligence (AI), particularly Convolutional Neural Networks (CNNs), has revolutionized cancer diagnostics by offering precise, efficient, and scalable solutions. CNNs excel at analysing complex patterns in medical imaging, enabling the detection of subtle anomalies critical for early-stage diagnosis. This paper provides a comprehensive review of CNN applications across imaging modalities such as mammograms, CT scans, MRIs, and histopathology slides, highlighting their adaptability and accuracy. Key topics include advancements in CNN architectures like ResNet, DenseNet, and InceptionNet, along with performance metrics such as sensitivity and specificity. Challenges such as limited annotated datasets, computational demands, and the "black-box" nature of CNNs are addressed, emphasizing the need for data augmentation, transfer learning, and explainable AI to foster clinical acceptance. Pre-processing techniques and transfer learning are explored as vital tools to enhance model performance despite resource constraints. Finally, the paper identifies emerging trends and proposes strategies, including multimodal data integration and enhanced interpretability, to address current limitations. These advancements aim to improve the scalability and real-world application of CNNs in cancer diagnostics, driving progress in early detection, treatment planning, and overall patient outcomes.

Keywords— Artificial Intelligence (AI), Convolutional Neural Networks (CNNs), Cancer Detection, Medical Imaging, Deep Learning, Early Diagnosis, Radiology, Histopathology, Image Processing, AI in Healthcare, Tumor Identification, Diagnostic Innovation, Healthcare Technology, Transfer Learning, Explainable AI, Multimodal Data Integration, Data Augmentation, Clinical AI Applications, Computational Diagnostics, Cancer Diagnostics Tools

I. INTRODUCTION

Cancer remains one of the most burdensome health problems worldwide. It causes millions of fatalities annually and places an inordinate strain on healthcare systems. The key to successful treatment and improved survival lies in early detection. Traditional diagnostic cancer methods, such as imaging and tissue analysis, although successful, are slow and susceptible to variability due to human interpretation. This raises an urgent need for speedier, more consistent, and scalable solutions.

Artificial Intelligence (AI), particularly Convolutional Neural Networks (CNNs), is revolutionizing cancer detection. CNNs are designed to work in a way that resembles how the human brain processes visual information; they excel at recognizing patterns within medical images. They classify images, locate abnormalities, and detect tumors with greater precision and speed than has been possible before, thereby not only easing the workload but also minimizing the possibility of errors by doctors.

Imaging types to which CNNs are being applied include mammograms, CT scans, MRIs, and histopathology slides. For example, they can identify tiny calcium deposits in mammograms or spot irregular cell patterns in tissue samples, often catching signs of cancer that might be missed by human eyes. Their ability to process volumes of big data with consistency makes them very useful to augment conventional techniques.

Despite the promise, challenges remain. High-quality, labeled datasets required for CNN training are scarce and expensive to prepare. Additionally, the "black-box" nature of these models—where their decision-making is difficult to understand—can make clinicians hesitant to trust them. Addressing these issues requires improvements in AI transparency and collaboration to ensure models are reliable and understandable. This discussion explores how CNNs are shaping cancer detection, their performance across imaging types, and the hurdles to integrating them into clinical practice. By tackling these challenges, AI can help revolutionize cancer care, improving early detection and patient outcomes worldwide.

II. PROVOCATION AND PURPOSE

Cancer is among the topmost burdens to global health, wreaking annihilation on individual cases, their cousins, and healthcare systems as a whole. Beforehand opinion can significantly ameliorate survival rates and enable less aggressive treatments. Traditional individual styles, similar as imaging ways or towel analysis, frequently warrant effectiveness, trustability, and vacuity in under- resourced settings. These approaches heavily calculate on mortal moxie and can produce variable results with slow processing in high- demand scripts.

In discrepancy, Artificial Intelligence(AI), particularly Convolutional Neural Networks(CNNs), is arising as a game-changer in prostrating these limitations. CNN ways, inspired by how the mortal brain processes visual data, can dissect medical images with remarkable delicacy and speed. They identify subtle patterns, descry abnormalities, and regularize individual workflows while minimizing mortal error and reducing the workload on healthcare professionals. This is especially pivotal in low- resource settings where professed medical staff may be in short force.

With cancer rates rising encyclopedically, the need to ameliorate individual capabilities has noway been more critical. CNNs can reuse vast quantities of data, descry subtle anomalies with high perceptivity, and give real- time perceptivity, making them an necessary asset in ultramodern healthcare.. They've shown great promise in analysing mammograms, CT scans, MRIs, and histopathology slides, often catching details that may be overlooked by human reviewers.

This study explores the growing role of CNNs in cancer detection, detailing their methodologies, performance, and applications. It also addresses challenges like the lack of large annotated datasets, concerns over how these "black-box" models make decisions, and the high computational demands of AI. Solutions such as transfer learning, data augmentation, and explainable AI are examined as ways to overcome these obstacles.

By focusing on emerging trends and potential solutions, this research highlights how AI can bridge the gap between advanced technology and practical healthcare needs. It aims to inspire further innovation in AI-powered diagnostics, paving the way for more accessible, efficient, and accurate cancer detection systems that can improve patient outcomes worldwide.

III. OVERVIEW OF CNNS

Introduction to Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a type of deep learning model specialized in analyzing structured grid-like data, such as images. Inspired by the human visual cortex, CNNs are particularly adept at recognizing spatial patterns, making them ideal for image-related tasks like classification, object detection, and segmentation.
One of CNNs' standout features is their ability to automatically learn features from raw data, eliminating the need for manual feature extraction. This capability is especially useful in fields like medical imaging, where subtle details, such as a tumor's edge or texture irregularities, are critical for diagnosis.

Key Components of CNNs
Convolutional Layers
The convolutional layer is the core of CNNs, using filters (kernels) to detect features like edges, textures, and patterns.
Filters/Kernels: Small matrices (e.g., 3x3 or 5x5) that slide over the input data to extract features.
Stride: Determines how much the filter moves with each step; larger strides reduce output size.
Padding: Adds borders to the input data to control the size of the output feature maps.
Convolutional layers progressively extract simple to complex features, enabling deeper layers to focus on more abstract patterns.
Pooling Layers
These layers reduce the dimensions of feature maps for computational efficiency and to prevent overfitting.
Max Pooling
The maximum value in a window of pooling is kept, giving emphasis on main features.
Average Pooling
The mean value in the window, for a smooth representation, is computed.
Global Pooling
This reduces an entire feature map into one single value per channel.
Pooling contributes to making CNNs less sensitive to slight changes in the input; for example, shifting or distorting an image does not greatly affect the output of the system.
Activation Functions
These introduce non-linearity that enables the CNN to learn complex patterns.
ReLU (Rectified Linear Unit): Outputs positive values and sets negatives to zero, promoting efficient training.
Sigmoid: Outputs values between 0 and 1, suitable for probabilistic tasks.
Tanh: Outputs values between -1 and 1, centered around zero.
Softmax: Converts outputs into probabilities for multi-class classification tasks.
Fully Connected Layers: These layers take the flattened output of previous layers and connect every neuron to the next, performing the final classification.
Dropout Layers: Randomly deactivate neurons during training to prevent overfitting and improve generalization.

Key CNN Architectures Used in Cancer Detection

AlexNet

AlexNet, introduced in 2012, was a game-changer in deep learning, becoming the first CNN to achieve major success in image recognition by winning the prestigious ImageNet competition. Its design features 5 convolutional layers and 3 fully connected layers, using ReLU activation to speed up training compared to older methods like sigmoid functions. To prevent overfitting, it introduced dropout layers, which made the model more robust. AlexNet's straightforward yet powerful architecture made it a practical starting point for cancer detection, especially in analyzing smaller datasets like histopathological images, paving the way for CNNs in medical imaging.

ResNet (Residual Network)

ResNet, introduced in 2015, addressed the challenge of vanishing gradients in deep networks by using residual connections, which create shortcuts to pass information efficiently through layers. This innovative design, featuring residual blocks that add the input directly to the output, enables ResNet to scale to hundreds of layers without losing performance. In cancer detection, ResNet's ability to extract deep and detailed features makes it especially effective for analyzing high-resolution imaging data, such as CT and MRI scans, where capturing intricate patterns is essential.

DenseNet (Dense Convolutional Network)

DenseNet, introduced in 2017, enhances efficiency by connecting each layer to every subsequent layer, enabling seamless information flow and feature sharing. Its dense blocks concatenate the output of one layer with the inputs of all following layers, reducing parameters and improving memory efficiency. This design is particularly useful for cancer detection in small datasets, as it maximizes feature reuse. DenseNet is especially effective in histopathological image analysis, where capturing detailed cellular structures is crucial.

IV. APPLICATIONS OF CNNS IN CANCER DETECTION

Convolutional Neural Networks have been successfully applied to the detection of cancers through their astounding performance in various imaging modalities on different types of cancers by providing high levels of accuracy and efficiency. Capable of examining complicated data and detecting minute patterns, they are now viewed as a highly valued device for the diagnosis and detection of various kinds of cancer. This section covers its application in different varieties of cancer-imaging methods.

Imaging Modalities

Mammography

CNN in the Classification and Detection of Breast Cancer

Mammography represents one of the current techniques in studies for the screening of breast cancers, which is very important with regard to early detection and timely treatment of the disease. CNN-based mammographic image analysis forms the basis of this process—mitigating manual interpretation ridden with the propensity and potential for human error, or at best, reducing human error, thereby upgrading the accuracy and efficiency quotient.

Feature Extraction and Classification
CNNs are very good at the detection of early signs of cancer in mammograms, such as microcalcifications and masses. Advanced models, including ResNet and DenseNet, have been very successful in classifying mammograms into benign, malignant, or normal with high accuracy.

Detection and Segmentation
CNNs, especially models like U-Net, are very effective in segmenting breast lesions and help to differentiate cancerous areas from healthy tissue, thus enabling clinicians to locate tumors accurately.

Clinical Impact: Research shows that CNN models, especially when used with computer-aided detection (CAD) systems, can match or surpass radiologists in diagnostic accuracy. This has made them useful in screening programs, especially in areas where specialists are scarce.

CT Scans and MRI
Application of CNNs in Lung, Brain, and Other Internal Cancers
CT and MRI are essential in the diagnosis of internal cancers because they provide clear images of the internal structures. CNNs have been widely applied with these imaging techniques to enhance the accuracy of diagnosis.

Lung Cancer in CT Scans
CNNs do an excellent job in the detection of pulmonary nodules and their malignant rating. Advanced models include the very best at recognizing small-sized nodules that may go undetected, including Faster R-CNN and YOLO. A pre-trained model based on transfer learning is generally utilized where a lesser amount of data may become available.

Brain Cancer in MRI
Similarly, in MRI-based analysis of the brain, CNN has also demonstrated excellence in brain tumor detection and classification through multi-spectral image processing of the input data. Models like 3D CNN perform well in volumetric scan analyses and detect tumors like gliomas and meningiomas with high precision.

Challenges and Advances
Variability in image quality, patient anatomy, and noise pose some challenges for CNNs. Such techniques as data augmentation and the integration of several types of imaging data are used in order to increase model robustness.

Automation of Tissue Analysis and Classification through Histopathology

Histopathology is the study of tissues, which forms the basis for cancer diagnosis. However, it can be very time-consuming and inconsistent. CNNs, therefore, have revolutionized the process into the automation of analysis of tissues, hence quick and accurate results.

Applications of CNN in Tissue Segmentation
CNN is applied to segmenting histopathological images by identifying regions such as tumor cells, stroma, and lymphocytes. The SegNet and U-Net models give outstanding performance in pixel-level segmentation tasks.

Grading of Cancer, Classification
CNNs inspect cell shape, nuclear irregularities, and the general structure of tissues as a way of classifying histopathology slides, helping to assess the grade of tumors and subsequently the seriousness or advancement in the stage of cancer.

Emerging Trends
Stain normalization and GANs continue to push the frontier of performance of CNNs on histopathology tasks by regularizing the preparation of slides and creating artificial additional data for training.

Cancer Types
Breast Cancer
CNN has well advanced in finding cancers of the breast, providing better results in terms of false positives in the analysis of mammograms.

Detection of Microcalcifications and Masses
CNNs thus detect and classify the signs of breast cancer with accuracy, while multi-scale models ensure that lesions of variable sizes are picked up.

Segmentation of Tumors
Precise tumor segmentation forms the very basis of any treatment plan. The CNN models have been successfully used in delineating tumor boundaries in imaging studies, such as Mask R-CNN.

Integration with 3D Imaging
Nowadays, application of CNNs also encompasses 3D mammography, namely digital breast tomosynthesis, with the intent of providing detailed insight into and enhancing the detection capability of small lesions.
Lung Cancer:
Applications of CNN's in CT Scans and X-rays Detecting lung cancer is challenging due to subtle early-stage signs, but CNNs have shown great potential in improving accuracy.

Pulmonary Nodule Detection: Researchers have used CNNs to develop models that detect nodules and assess malignancy, aiding early intervention..

Survival Prediction and Staging: CNNs analyze nodule size, shape, and texture to assess tumor stage and predict patient survival.

X-ray Analysis:

For resource-constrained settings, CNNs are applied to chest X-rays to detect lung cancer indicators, providing an affordable and accessible diagnostic tool.

Skin cancer: CNN-Based Analysis of Dermoscopic Images

CNNs have revolutionized skin cancer diagnosis by automating dermoscopic analysis. They classify skin lesions as benign or malignant with high accuracy using models like InceptionNet and precisely segment lesions to identify asymmetry and irregular borders—key signs of malignancy. Additionally, CNNs are being incorporated into mobile apps, making preliminary skin cancer screening accessible in remote areas.

Brain Cancer: MRI-based tumor segmentation and classification

CNNs are highly effective in diagnosing brain cancer through MRI analysis. They excel at detecting and segmenting tumors, with 3D CNNs providing detailed insights by analyzing spatial relationships across MRI slices. These models are particularly useful in identifying glioblastomas, offering critical information on tumor size, location, and growth. Despite challenges like noise and variability in brain MRIs, CNNs overcome these issues with advanced pre-processing and robust architectures.

V. METHODOLOGIES IN CNN-BASED CANCER DETECTION

The successful application of Convolutional Neural Networks (CNNs) in cancer detection relies not only on their architectures but also on the implementation of various supporting methodologies. These methodologies address challenges such as data scarcity, variability in medical imaging, and the need for multi-faceted insights. This section delves into four key methodologies: data preprocessing and augmentation, transfer learning, segmentation and classification techniques, and multimodal learning.

Data Preprocessing and Augmentation

Preprocessing and augmentation are essential for preparing medical images for CNN training, addressing issues like noise, inconsistent quality, and limited sample sizes. Techniques like normalization standardize image intensity across datasets, while cropping focuses on relevant areas, such as tumors. Flipping, rotation, scaling, and zooming increase data diversity and improve robustness to spatial variations. Noise injection simulates real-world imperfections, enhancing the model's ability to handle noisy inputs, while histogram equalization improves image contrast to highlight critical features. Transfer learning leverages pre-trained models, adapting them to medical imaging tasks by reusing general features like edges and textures and fine-tuning task-specific layers, overcoming the challenge of limited labeled datasets.

Pre-Trained Models Commonly Used

ResNet, with its deep architecture and residual connections, excels in tasks like lung nodule detection in CT scans, while **InceptionNet's** multi-scale processing makes it effective for melanoma classification in dermoscopic images. **DenseNe**t is particularly efficient for small datasets, making it ideal for histopathological analysis by reusing features across layers. In medical imaging, transfer learning saves time and resources by leveraging pre-trained models, reducing the risk of overfitting on small datasets. Fine-tuning these models on specific medical data helps them adapt to domain-specific patterns while retaining valuable pre-learned features.

Segmentation and Classification Techniques

Segmentation and classification are key in cancer detection, helping localize tumors and distinguish between benign and malignant conditions. Segmentation divides images into regions of interest, with models like U-Net and Mask R-CNN excelling at identifying tumor boundaries and performing pixel-wise classification to differentiate tumor cells from healthy tissue. Classification focuses on determining if a region contains cancerous tissue, with CNNs handling binary tasks like identifying malignant versus benign cases or multi-class tasks such as distinguishing tumor types in brain MRIs. Often, models combine both tasks, first segmenting tumors and then classifying them to assess malignancy.

Multimodal Learning

Multimodal learning combines data from imaging techniques like CT, MRI, PET, and histopathology to provide a more comprehensive cancer diagnosis. Each modality offers unique insights—CT shows structural details, MRI highlights soft tissue contrasts, and PET reveals metabolic activity. By integrating this information, CNNs gain a deeper understanding of cancer characteristics. Fusion techniques enhance this process: early fusion combines raw data before feature extraction, late fusion merges outputs from separate networks, and hybrid fusion integrates both low- and high-level features for improved performance.

Applications in Cancer Detection

Combining imaging data enhances cancer diagnosis, such as using CT and PET for better lung nodule classification or integrating MRI and fMRI to understand brain tumor structure and its effects on brain activity. However, challenges include aligning images from different modalities, which requires advanced preprocessing, and managing the higher computational demands of processing complex, multimodal data.

VI. PERFORMANCE EVALUATION METRICS

Performance metrics are essential for evaluating CNN models in cancer detection, ensuring accuracy and clinical reliability. Metrics like accuracy measure overall correctness but can be misleading with imbalanced datasets. Precision focuses on reducing false positives, while recall (sensitivity) ensures all actual positive cases are identified, minimizing false negatives. The F1 score balances precision and recall, making it useful for imbalanced datasets. The AUC (Area Under the ROC Curve) assesses the model's ability to distinguish between classes by analyzing the trade-off between sensitivity and specificity, with higher AUC values indicating better performance, especially in challenging datasets.

Specificity and Sensitivity Specificity measures the proportion of correctly identified negative cases, helping reduce false positives and unnecessary treatments, while sensitivity (recall) focuses on detecting true positives to ensure no cancer cases are missed. A confusion matrix is a vital tool for performance evaluation, outlining true positives, true negatives, false positives, and false negatives. It forms the basis for calculating key metrics like precision, recall, and specificity, offering a clear picture of the model's strengths and areas needing improvement.

VII. CHALLENGES IN ADOPTING CNNS FOR CANCER DETECTION

CNNs in medical imaging face challenges like data scarcity, computational constraints, interpretability issues, and limited generalization. Annotated datasets require significant expertise and resources, and small datasets risk overfitting, but solutions like data augmentation, synthetic data generation, and federated learning help address this. High computational demands and infrastructure limitations can be mitigated with transfer learning and optimizing models for edge devices. The "black-box" nature of CNNs raises trust concerns among clinicians, which can be improved using explainable AI tools like saliency maps and Grad-CAM. To enhance generalization across populations and modalities, training on diverse datasets and adopting multimodal approaches are effective strategies.

VIII. EMERGING TRENDS AND FUTURE DIRECTIONS

The future of CNN-based cancer detection is shaped by advancements that address current limitations while enhancing model reliability, accessibility, and scalability.

Key emerging trends and directions include:

Explainable AI
Model Transparency: Techniques like Grad-CAM (Gradient-weighted Class Activation Mapping) and LIME (Local Interpretable Model-Agnostic Explanations) provide visual or textual explanations for CNN predictions.

Clinical Trust: By highlighting regions or features influencing decisions, explainable AI builds trust and facilitates acceptance among healthcare professionals.
Federated Learning
Privacy Preservation: Federated learning enables training models on decentralized datasets without sharing sensitive patient data, addressing privacy concerns.

Collaborative Advantage: Hospitals and research centers can pool knowledge without compromising data security, improving model performance on diverse populations.

Lightweight Architectures
Low-Resource Models: Development of efficient CNN architectures like MobileNet and SqueezeNet allows deployment on devices with limited computational power.

Application in Underserved Areas: Lightweight models are critical for extending advanced diagnostic tools to resource-constrained settings, enabling global accessibility.

Wearables for Early Cancer Screening
AI-powered wearable devices, with sensors or imaging capability, can monitor biomarkers or detect abnormalities to enable early diagnosis.

Continuous Monitoring
Integration with smartphones and cloud systems increases the feasibility of these devices in daily health check-ups.

Multimodal Integration
Holistic Diagnostics
The integration of radiology, pathology, and clinical data offers a better understanding of cancer.

Improved Accuracy
Multimodal learning models synthesize diverse information to improve diagnostic accuracy with a reduced level of uncertainty.

IX. COMPARATIVE ANALYSIS OF CNN ARCHITECTURES

Convolutional Neural Networks have brought a revolution to cancer detection by analyzing intricately complex medical images and finding patterns from them. Models such as AlexNet, ResNet, DenseNet, and EfficientNet all have different powers they bring to cancer diagnostics.

AlexNet
AlexNet is a foundational model and works well on small-scale datasets but has limited usage regarding complex patterns. **ResNet's** deep residual connections excel at extracting detailed features, making it ideal for high-resolution tasks like lung and brain cancer detection, though it requires significant computational resources. **DenseNet's** feature-sharing design is highly efficient for small datasets, performing well in histopathology and skin cancer analysis, but its memory requirements can be demanding. **EfficientNet** optimizes network scaling to handle high-resolution images with fewer parameters, showing promise in multi-modal tasks integrating mammograms, CT scans, and pathology images. These architectures have significantly advanced diagnostic accuracy and accessibility in clinical applications.

X. CASE STUDIES AND REAL-WORLD IMPLEMENTATIONS

CNNs have been successfully implemented in cancer diagnostics, significantly improving accuracy and efficiency. For breast cancer, **Google Health's CNN** model reduced false positives and negatives in mammogram analysis, enhancing early detection. CNNs used by the National Cancer Institute improved sensitivity for the detection of early-stage nodules in computed tomography scans. Skin cancer classification tools, such as ISIC, have achieved dermatologist-level performance in analyzing dermoscopic images and provide scalable solutions for remote areas. Other platforms, such as PathAI, offer automation for histopathology tasks like tumor grading. These have improved diagnostic consistency and increased efficiency. Systems like IDx-DR and Qure.ai, which have been developed for other conditions, have been adapted to find cancer features in imaging. FDA-cleared platforms such as Arteries Oncology AI provide real-time tumor quantification to help doctors make more informed treatment decisions.

XI. Ethical and Regulatory Considerations

The use of CNN in cancer diagnostics carves out serious ethical and regulatory hurdles which, until these dates, needed to be sorted out with safety, equity, and transparency as an artificial intelligence, or AI, operationalized the clinic.

Protection of Personal Data Privacy and Consent
Personal details mined from the training and use of CNN with medical images required very high protection. Compliance with relevant privacy regulations such as GDPR and HIPAA, coupled with strong encryption practices for data security, will ensure that confidentiality for patients is guaranteed. Additionally, patients must provide informed consent, with clear explanations of how their data will be used, stored, and shared for AI development. Advanced techniques like federated learning further enhance privacy by allowing models to train on decentralized data, eliminating the need to transfer raw patient information and reducing the risk of data breaches.

Regulatory Challenges for Deployment: Deploying CNN models in healthcare requires approval from regulatory agencies like the FDA or EMA, demanding thorough validation of their accuracy, safety, and reliability. However, the absence of standardized evaluation criteria complicates the approval process. Once deployed, continuous post-market monitoring is vital to identify errors, biases, or performance issues in real-world applications. Imbalances in datasets, such as overrepresentation of certain populations, can result in biased models—for example, skin cancer detection tools trained predominantly on lighter skin tones may be less accurate for darker skin tones. Ensuring fairness requires diverse datasets, fairness-focused algorithms, and regular bias audits to address these disparities.

XII. CONCLUSION

Convolutional Neural Networks (CNNs) have transformed cancer detection by providing accurate, efficient, and scalable diagnostic tools, excelling in imaging modalities like mammography, CT, MRI, and histopathology. They enhance early diagnosis, treatment planning, and patient outcomes by automating complex tasks and detecting subtle anomalies. However, challenges like data scarcity, computational demands, interpretability, and generalization across diverse populations must be addressed for broader clinical adoption. Solutions such as explainable AI, privacy-preserving methods like federated learning, and lightweight architectures are key to overcoming these barriers. With interdisciplinary collaboration and advancements like multimodal data integration and wearable AI, CNNs have the potential to make cancer diagnostics more accessible, equitable, and personalized, ultimately improving global healthcare outcomes.

Architecture	Depth	Key Strength	Medical Imaging Applications	Limitations
AlexNet	Shallow	Simplicity, computational efficiency	Histopathology, small datasets	Limited depth, struggles with complex data
ResNet	Deep	Residual connections, scalability	CT scans, MRI, high-resolution datasets	Computationally intensive
DenseNet	Moderate	Feature reuse, parameter efficiency	Histopathology, breast cancer, small datasets	High memory requirements
Efficient Net	Scalable	Balanced scaling, high accuracy	Multi-modal imaging, resource-constrained environments	Requires careful tuning

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