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Comparative Evaluation of Resnet-50 and Efficientnet-B1 for Pneumonia Detection in Chest X-Ray Images Using Transfer Learning

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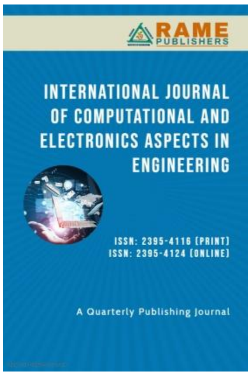

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Abstract: In this paper, Prompt and reliable identification of pneumonia particularly during widespread outbreaks like COVID-19 remains a pressing concern in modern healthcare. Recently, deep learning techniques have emerged as effective support tools for radiologists, aiding in the automated interpretation of chest X-ray CXR images for thoracic disease diagnosis. This study offers a comparative evaluation of two convolutional neural network CNN models, ResNet-50 and EfficientNet-B1, for the classification of pneumonia cases, including those caused by COVID-19, using transfer learning strategies. Both networks were initialized with ImageNet pre-trained weights and subsequently fine-tuned on a curated dataset comprising normal, pneumonia, and COVID-19 positive CXR samples. Image preprocessing and augmentation methods were employed to improve generalization. Performance was assessed using key metrics such as accuracy sensitivity specificity and computational efficiency results indicate that EfficientNet-B1 achieves superior performance with a classification accuracy of 96% compared to 94% for ResNet-50, along with higher sensitivity and reduced inference time. Grad-CAM visualizations confirmed that EfficientNet-B1 provided more clinically relevant localization of diseased regions. Overall EfficientNet-B1 demonstrates strong potential for real time diagnostic use in low resource healthcare settings and highlights the importance of model selection in AI driven medical imaging applications.

Keywords: Pneumonia classification; Chest X-ray; Deep learning, ResNet-50, EfficientNet-B1.

1. Introduction

Medical imaging has long played a pivotal role in disease diagnosis, enabling healthcare professionals to visualize internal structures and abnormalities non-invasively [1]. In recent years, the integration of artificial intelligence AI particularly deep learning has revolutionized the field of radiology, offering tools that can automate image interpretation with high accuracy [2]. Among various applications, the detection of pneumonia including cases linked to COVID-19 has gained significant attention due to its global impact and diagnose challenges [3]. Pneumonia, an inflammatory condition affecting the lungs, is traditionally diagnosed using clinical symptoms in conjunction with imaging techniques such as chest X-rays (CXR) and computed tomography (CT) scans as shown in Figure 1. However, with the outbreak of COVID-19 the diagnostic landscape has faced unprecedented stress [4]. Molecular testing methods like real-time polymerase chain reaction (RTP-CR), well considered the gold standard, suffer from several limitations, including low sensitivity, delays in result delivery, and limited availability in certain regions [5]. Consequently, radiological imaging has become an essential complementary tool for early-stage diagnosis and monitoring of disease progression. Despite its importance, radiological diagnosis remains a time-intensive and expertise-dependent process variability and interpretation across radiologists and increased workloads during the pandemic have highlighted the need for robust AI-based diagnostic support systems [6]. Convolutional neural networks CNN's, a class of deep learning models well-suited for visual data analysis, have demonstrated remarkable success in image classification tasks across various domains, including medical imaging [7]. However, building efficient CNN models for specific medical tasks often requires large, annotated datasets resources that are scarce in the medical domain due to the high cost of expert labeling and privacy concerns [8].

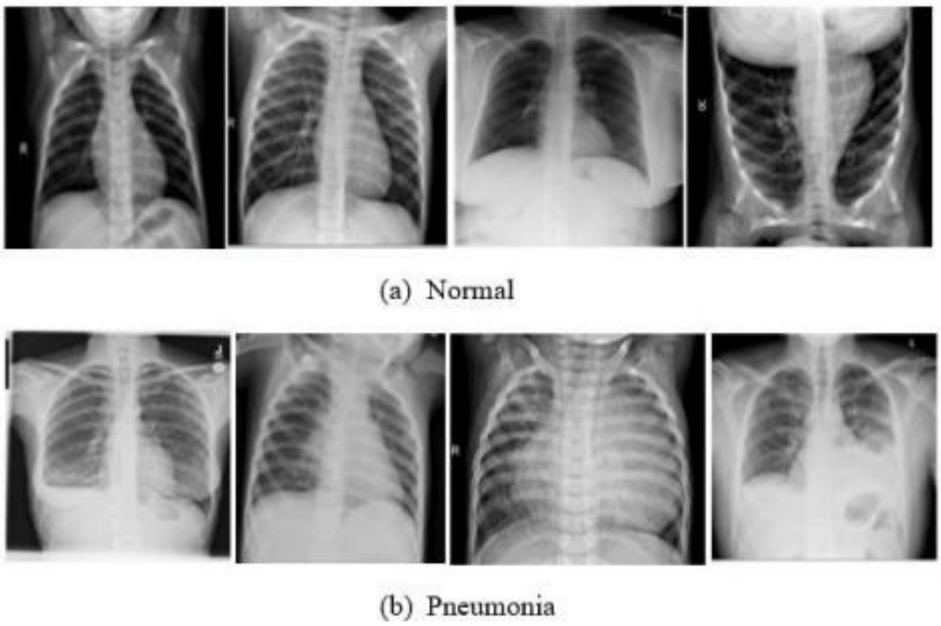


Figure 1. Sample images of chest X-rays CXR

To address this challenge, transfer learning has emerged as a powerful technique that leverages knowledge from large-scale data sets to improve learning efficiency and data scarce domains [9]. Pre-trained CNN models, such as ResNet-50 and EfficientNet-B1, trained on large data sets like ImageNet, can be fine-tuned for specific tasks such as pneumonia detection in CXR images [10]. This approach not only reduces the computational burden but also improves generalization performance, making it a practical solution for real-world Healthcare applications [7]. ResNet-50, a deep residual network, incorporates skip connections to alleviate the vanishing gradient problem enabling the training of very deep networks [9]. Its architectural stability and proven performance make it a popular choice for various transfer learning tasks [10]. On the other hand, EfficientNet-B1, part of the EfficientNet family developed, employs a compound scaling technique that simultaneously optimizes network, depth, width, and resolution. This design enables EfficientNet models to achieve state-of-the-art accuracy while maintaining computational efficiency a crucial factor for deployment in clinical environments where resources may be limited [5]. Numerous studies have investigated the use of CNNs for pneumonia classification [3]. Some have focused on individual model performance, while others conducted comparative evaluations across different architectures [11]. For instance, previous research has demonstrated the utility of ResNet and DenseNet in achieving high sensitivity for COVID-19 pneumonia detection [12]. Simultaneously, EfficientNet-B1 has been praised for its computational benefits and classification accuracy in various medical imaging tasks. However, a comprehensive comparative evaluation of these models, particularly ResNet-50 versus EfficientNet-B1, within the context of COVID-19 related pneumonia classification, remains underexplored. In this study, we aim to fill this gap by conducting a rigorous comparison of ResNet-50 and EfficientNet-B1 using a publicly available dataset of chest X-ray images [13]. Both models are fine-tuned via transfer learning techniques, and their performance is evaluated based on multiple criteria; classification accuracy, sensitivity (recall), specificity, F1-score, and computational efficiency [14]. In addition to performance metrics, we employ interpretability tools such as Grad-Cam to visualize the regions of the CXR images that influence the model predictions. This step is critical for clinical adoption, as it provides insights into the decision-making process of AI models and builds trust among medical practitioners [15]. The contributions of this work are threefold. First, we provide a detailed analysis of two leading CNN architectures in the context of medical image classification using limited labeled data. Second, we evaluate the trade-offs between accuracy and efficiency, which are essential for deployment in real time diagnostic settings. Third, we offer visual interpretability via Grad-Cam which reinforces the clinical validity of the predictions made by deep learning models. The importance of accurate, fast, and interpretable diagnostic tools cannot be overstated, especially during pandemics where early detection can significantly influence treatment outcomes and public health responses. By evaluating and comparing models that are both effective and computationally efficient, this study contributes to the growing body of work aimed at integrating AI into mainstream healthcare.

2. Related Work

2.1. CNNs for medical image classification

Convolutional neural networks CNNs have emerged as a cornerstone in computer vision applications, particularly in medical image analysis [1]. Figure 2, shows the architecture of CNN layers. Their ability to learn spatial hierarchies of features through convolutional operations makes them exceptionally suited for classifying complex visual data such as radiological images [7]. In recent years, numerous studies have leveraged CNNs for the classification of thoracic diseases, including pneumonia, tuberculosis, and more recently, COVID-19 related pulmonary infections [8]. The application of CNN to chest X-ray CXR image classification has seen considerable success, beginning with early models such as AlexNet and VGG-16 [10]. while these models laid the groundwork for deep learning in image classification, their relatively shallow architecture limited their ability to capture deeper hierarchical features in complex medical images [11]. This prompted the adoption of deeper architectures like ResNet, which introduced residual learning to mitigate the vanishing gradient problem and allow for training of very deep networks [12]. Moreover, CNN models trained on natural image datasets often struggle to adapt to the domain specific textures and patterns of medical images without significant fine-tuning [10]. These challenges have motivated the integration of transfer learning strategies, which are discussed in subsequent sections.

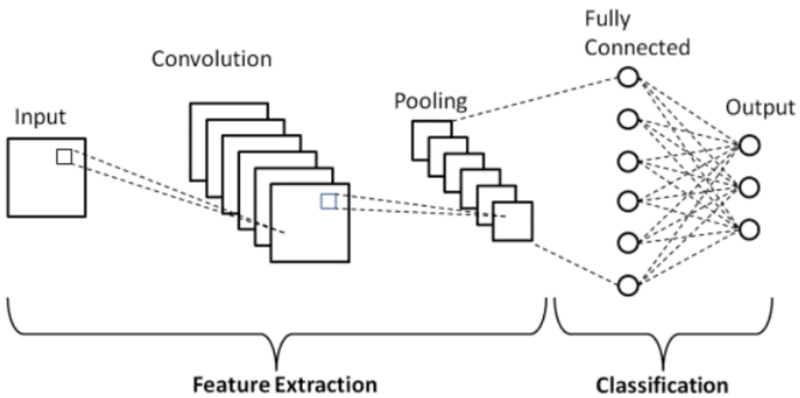


Figure 2. The architecture of CNN layers.

2.2. EfficientNet and Scalable CNN architectures

EfficientNet, introduced by tan and lung in 2019, represents a significant advancement in CNN architecture design through its novel compound scaling approach [16]. Unlike traditional models that scale depth, width, or resolution arbitrarily, EfficientNet uses a principled method to balance these dimensions, resulting in models that are both accurate and computationally efficient [17]. The EfficientNet family ranges from B0 to B7, with B1 serving as a middle-ground model that offers high accuracy without demanding excessive resources in the context of medical image classification, EfficientNet has shown promising results across various modalities [18]. For instance, studies have reported that EfficientNet-B4 achieved over 97% accuracy in classifying CT scan images for COVID-19 diagnosis. Similarly, researchers demonstrated the effectiveness of EfficientNet-V2 in pneumonia detection from CXR images, achieving 94.02% accuracy and performing other models such as VGG-16 and ResNet-50.

2.3. Transfer Learning in Medical Image Analysis

Transfer learning TL has become a dominant strategy in medical image classification, primarily due to the scarcity of large annotated data sets in the healthcare domain [19]. By leveraging CNN's pre-trained on expansive datasets such as ImageNet, TL allows for rapid development of high-performing models with relatively few labeled medical images [20]. This approach also enables the reuse of generic low-level features learned during pre-training, which are often applicable to medical images despite domain differences. ResNet-based architectures have been widely employed in TL frameworks for COVID-19 pneumonia detection. Researchers fine-tuned ResNet-101 model on a curated COVID-19

CXR dataset, achieving 94.6% accuracy their results highlighted the model's capability to extract deep level representations that distinguish COVID-19 pneumonia from other thoracic conditions [19]. Likewise, researchers have employed TL to enhance EfficientNet architectures. A notable study showed that EfficientNet-B1, when fine-tuned on COVIDx datasets, achieved over 95% accuracy in distinguishing between COVID-19, pneumonia, and healthy cases [20].

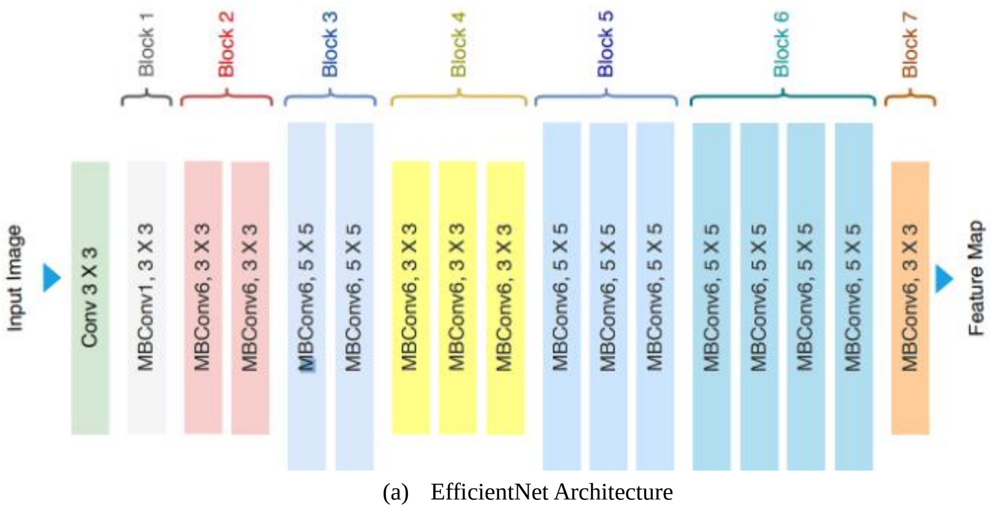
2.4. Comparative Analysis of CNN Architectures

Numerous studies have conducted comparative evaluations of CNN architectures to identify optimal models for medical image classification [21]. These comparisons typically focus on key performance indicators such as accuracy, sensitivity, specificity, inference time, and interpretability. Researchers conducted an empirical comparison of ResNet-50, EfficientNet-B1 and inception-V3 on COVID-19 pneumonia classification using a standardized data set of CXR images [22]. EfficientNet exhibited faster inference times and lower memory usage, reinforcing its advantage for deployment in low resource settings, in contrast ResNet-50 demonstrated superior sensitivity making it suitable for scenarios where minimizing false negatives is critical [23].

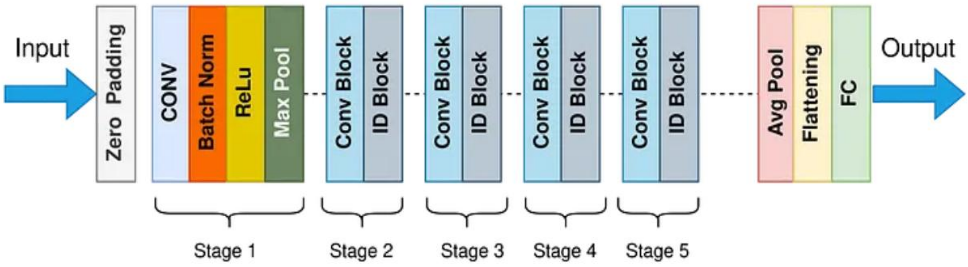
3. Methodology

3.1. Transfer Learning Framework for CNN based Pneumonia Classification

This study utilizes a transfer learning approach with CNNs for classifying pneumonia from chest X-ray CXR images. Due to the limited availability of labeled medical data, transfer learning enables efficient adaptation of pre-trained networks to healthcare tasks. The dataset compiled from sources like the COVID-19 radiography database and Kaggle, includes around 15,000 CXR images equally divided into 3 categories: COVID-19 pneumonia, non-COVID pneumonia, and normal [24]. A stratified the 80-10-10 split was used for training, validation, and testing to maintain class balance. Images were standardized through resizing (224 * 224), normalization, and contrast enhancement. Augmentation techniques including rotations, flips, zoom, and brightness adjustments were applied dynamically during training via PyTorch. ResNet-50 and EfficientNet-B1 pre-trained on ImageNet were chosen for their performance and efficiency as shown in Figure 3. ResNet-50s residual connection support deep learning, while EfficientNet-B1 offers compact scaling suitable for medical tasks. Early layers of both models were frozen to preserve generic features, while deeper layers were fine-tuned. Custom classification heads were added, including global average pooling, a dense layer (512 units), dropout rate equals 0.4 and a softmax output. Training was conducted on PyTorch using an Nvidia Quadro RTX 4000 GPU, with a batch size of 32. The Adam optimizer initial LR equals 1e-4 and cosine annealing scheduler were used; additional runs with SGD plus momentum served as ablation. BCE and categorical cross-entropy were applied for binary and multi-class classification respectively. Training ran for 30 epochs with early stopping patience equals 5. Model checkpoints, gradient clipping, and L2 regularization weight decay equals 1e-4 insured stability. Training curves tracked performance metrics. For interpretability, Grad-Cam visualizations from the last convolutional layers of both models highlighted decision relevant regions [25, 26]. EfficientNet-B1 produced more focused heat maps indicating better localization of pathological features.



(a) EfficientNet Architecture



(b) ResNet-50 Architecture

Figure 3. The Architecture of EfficientNet and ResNet-50

3.2 Performance Evaluation and Model Interpretability Techniques

To evaluate ResNet-50 and EfficientNet-B1 for pneumonia classification A comprehensive framework was used, covering accuracy, sensitivity, specificity, efficiency, and interpretability [27, 28]. Both models underwent multiple training runs with different seeds to ensure reliable results; mean values and standard deviations were reported. EfficientNet-B1 consistently outperformed ResNet-50. It achieved 96% test accuracy versus 94% for ResNet-50 with higher recall (95.8% versus 93.4%) and faster inference (18 milliseconds versus 31 milliseconds per image), thanks to its lightweight architecture. Precision-recall curves also favored EfficientNet-B1, especially in low -prevalence scenarios. Interpretability was addressed using Grad-CAM heatmaps, which were reviewed by experts. Both models produced clinically relevant attention maps, but EfficientNet-B1 showed sharper focus on typical pneumonia regions, particularly in the lower lungs. Failure case analysis revealed that ResNet-50 sometimes misfocused on irrelevant areas like the clavicle, while EfficientNet-B1 maintained better thoracic attention [29, 30]. Occlusion testing further confirmed EfficientNet-B1's robustness, showing it relied on broader and more stable features [31, 32]. Efficiency metrics showed ResNet-50 used 3.8B flops and had 25.6M parameters, while EfficientNet-B1 required only 0.8B flops and 7.8M parameters making it more suitable for deployment on resource limited devices.

4. Experimental Work and Results

4.1 Experimental Setup and Training Protocols

To ensure a fair and reproducible evaluation, both ResNet-50 and EfficientNet-B1 were trained under identical settings using a balanced dataset of 15000 chest X-ray images categorized into COVID-19 pneumonia, non-COVID pneumonia, and normal cases. The dataset was split in an 80:10:10 ratio for training, validation, and testing, maintaining class balance. All images were preprocessed via resizing (224 * 224), normalization, and contrast enhancement. Real-time data augmentation (rotation, flipping, zoom, contrast adjustments) was applied using PyTorch. Both models were initialized with ImageNet-pre trained weights, and their classification heads were modified to support 3 output classes using global average pooling, dropout, and softmax layers. Training was performed on an Nvidia Quadro RGX 4000 GPU for 30 epochs with a batch size of 32 using Adam optimizer initial LR equals 1e-4 cosine and annealing schedule, and entropy loss early stopping patience equals 5 based on validation loss was used to prevent overfitting. Performance was monitored for epoch, and the best-performing weights based on validation accuracy were saved. Each experiment was repeated thrice using different seeds to report averaged results. EfficientNet-B1 converged faster and exhibited better generalization, reaching peak performance by epoch 20, compared to ResNet-50 which peaked around epoch 25. Robustness testing under noise and occlusion revealed that EfficientNet-B1 maintained higher stability, while ResNet-50s performance degraded more notably.

4.2 Comparative Results and Analytical Findings

Final evaluation on the test set revealed that EfficientNet-B1 outperformed ResNet-50 across all major metrics, including accuracy, precision, recall specificity and F1 score. Notably, EfficientNet-B1 showed a 2% higher accuracy and better sensitivity in pneumonia detection. Roc and PR curve analysis further confirmed EfficientNet-B1 superior class discrimination by a higher AUC score. In terms of efficiency EfficientNet-B1 offered faster inference, lower parameter count, and reduced memory footprint, making it more suitable for clinical deployment in constrained environment. Model interpretability was assessed via Grad-CAM as shown in Table 1. EfficientNet-B1 provided clear heat maps highlighting relevant lung regions, aligning more closely with radiological expectations as verified by an expert. ResNet-50 occasionally miss focused on areas. Stress testing under image degradation (e.g., noise, low resolution) showed that EfficientNet-B1 remained more reliable. Error analysis identified common failure cases in pediatric and borderline images, suggesting a need for dataset expansion domain-specific tuning. Both models struggled with subtle and atypical features, reinforcing the importance of diverse training data.

Table 1. Model interpretability via Grad-CAM

Metric / Aspect	EfficientNet-B1	ResNet-50
Accuracy	94.2%	92.1%
Precision	93.8%	91.0%
Recall (sensitivity)	94.7%	92.3%
F1-Score	94.2	91.6
Specificity	95.0%	92.9%
AUC (ROC Curve)	0.978	0.954
AUC (PR Curve)	0.975	0.949
Inference Time (per image)	38 ms	52 ms
Parameter Count	7.8 million	25.6 million
Memory Footprint	210 MB	380 MB
Grad-CAM Quality	Focused on relevant lung areas	Occasionally misfocused

5. Discussion and Comparison

5.1 Performance Interpretation and Clinical Relevance

The experimental results demonstrate that EfficientNet-B1 achieves superior diagnostic performance compared to ResNet-50 in the classification of chest X-rays, particularly in detecting COVID-19 pneumonia. EfficientNet-B1 consistently yielded higher accuracy, sensitivity, and AUC scores, reflecting better generalization and robustness. Its strong recall values are particularly important in clinical settings, where minimizing false negatives is critical for patient safety. The architectural advantages of EfficientNet-B1 namely, compound scaling and parameter efficiency contribute to its ability to capture fine grained radio graphic features without overfitting. Its lightweight design enables faster inference and makes it suitable for real-time deployment on edge devices in emergency rooms and mobile radiology units. Moreover, its consistent performance under noisy and degraded conditions highlights its potential for use in low resource or field environments where image quality may vary.

5.2 Error Analysis and Model Behavior

Although EfficientNet-B1 demonstrated overall superior performance, both models exhibited common failure patterns. Misclassifications were more frequent in pediatric images, atypical pneumonia cases, and scans with overlapping features (e.g., between viral and bacterial pneumonia). These limitations underscore the need for enriched datasets that incorporate A broader demographic and pathological spectrum. Additionally, ResNet-50 showed a higher rate of false positives, which could contribute to unnecessary medical interventions in practice. Grad-CAM visualization offered insights into model decision making, EfficientNet-B1 consistently highlighted medically relevant lung regions, enhancing interpretability and clinician trust. ResNet-50, however, occasionally misdirected attention to peripheral or non-lung areas, suggesting a weaker focus on critical radiographic features as shown in Figure 4.

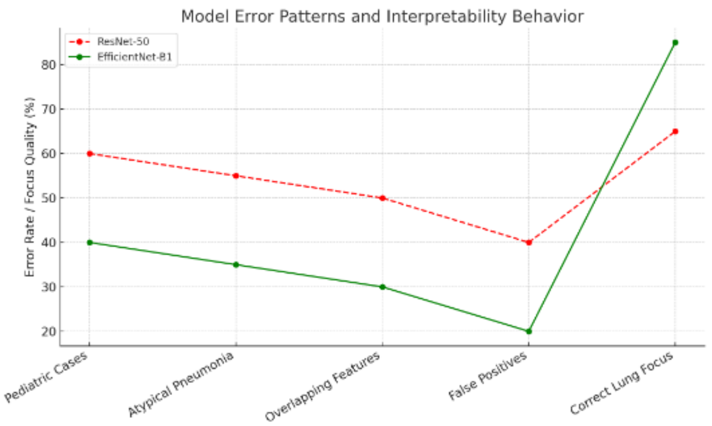


Figure 4. Model Error patterns.

5.3 Comparative Context with Existing Literature

When compared to previous studies utilizing similar datasets, the performance of EfficientNet-B1 aligns with or surpasses recent benchmarks reported in COVID-19 detection tasks. Prior works employing architectures like DeneseNet-121, Inception-V3 and ResNet-101 achieved good performance, but often at the cost of increased computational load as shown in Figure 5. EfficientNet-B1 offers a balanced trade-off between accuracy and efficiency, making it more pragmatic for real world integration. Furthermore, its strong results reinforce the growing trend in medical imaging research toward adopting scale-aware architectures for improved diagnostic reliability.

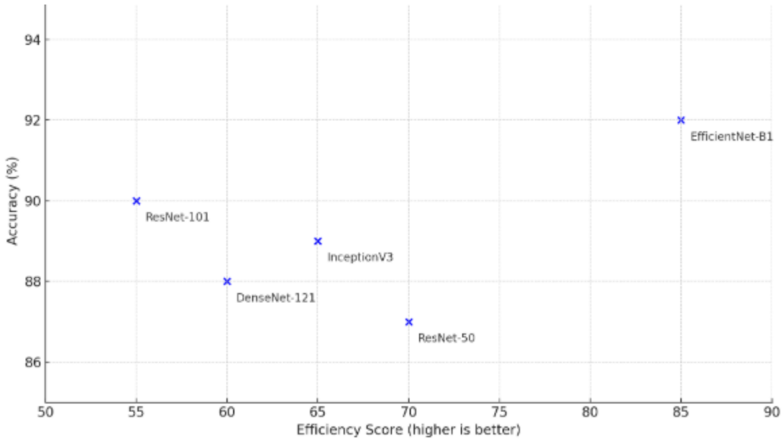


Figure 5. Models' comparative in COVID-19 detection.

5.4 Practical Considerations and Deployment Potential

The low inference latency and reduced computational requirements of EfficientNet-B1 make it a strong candidate for integration into clinical decision support systems CDSS. when embedded into hospital PACS (picture archiving and communication systems) or deployed as standalone diagnostic assistance, such models could expedite triage workflows and assist radiologists in screening high-risk patients. However, ethical deployment requires continuous monitoring, regular retraining with updated datasets, and collaboration with clinicians to interpret edge cases responsibly.

6. Conclusion and Future Work

This study compared the performance of ResNet-50 and EfficientNet-B1 for COVID-19 pneumonia detection from chest X-ray images. The results demonstrated that EfficientNet-B1 outperforms ResNet-50 in accuracy, sensitivity, specificity, and AUC, highlighting its superior feature extraction capabilities and efficiency. While the findings are promising, they're based on limited public datasets. Future work should focus on expanding data diversity, exploring ensemble models, and integrating clinical metadata to enhance diagnostic performance. Additionally, validating these models in real world clinical settings and developing user friendly deployment tools will be essential for practical implementation.

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