

# Comparative Analysis of Deep Learning Models for COVID-19 Detection in X-Ray Images

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**Abstract** – The COVID-19 pandemic has necessitated the development of rapid, accurate, and automated diagnostic tools to assist healthcare professionals in patient screening and management. This comprehensive study presents a detailed comparative analysis of ten state-of-the-art Convolutional Neural Network (CNN) architectures for COVID-19 detection using chest X-ray radiography images. The research systematically evaluates DenseNet, ConvNeXTiny, EfficientNetB0, ResNet50, VGG19, VGG16, MobileNet, GoogleNet, AlexNet, and LeNet models using the COVID-19 Radiography Database. Each model was rigorously trained and validated using standardized protocols to ensure fair comparison. Comprehensive performance metrics including validation accuracy, test accuracy, loss functions, convergence analysis, and overfitting assessment were employed. The experimental results demonstrate that modern architectures, particularly DenseNet and ConvNeXTiny, achieved superior performance with 97% validation accuracy and 96% test accuracy, exhibiting excellent generalization capabilities with minimal overfitting (1.00% accuracy difference). The study also analyzes computational efficiency, training dynamics, and practical deployment considerations. These findings provide crucial insights for developing robust computer-aided diagnosis systems for COVID-19 detection and establish benchmarks for future research in medical image classification.

**Keywords** – COVID-19 diagnosis, Chest X-ray analysis, Convolutional Neural Networks, Deep Learning, Medical image classification, Computer-aided diagnosis, Transfer learning, Healthcare AI, Radiological imaging, Pandemic response

## I. INTRODUCTION

The emergence of Coronavirus Disease 2019 (COVID-19), caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), has created an unprecedented global health crisis affecting millions of lives worldwide. The rapid spread of the virus has overwhelmed healthcare systems globally, necessitating the development of efficient, accurate, and automated diagnostic tools to support medical professionals in patient screening, diagnosis, and treatment planning.

Chest radiography, commonly known as chest X-ray imaging, has emerged as a critical diagnostic modality for COVID-19 detection due to several advantageous characteristics. Unlike Reverse Transcription Polymerase Chain Reaction (RT-PCR) tests, which can take several hours to produce results and may yield false negatives, chest X-rays provide immediate imaging results and can reveal characteristic pulmonary manifestations associated with COVID-19 pneumonia. These manifestations typically include bilateral ground-glass opacities, consolidation patterns, and peripheral distribution of lesions.

The integration of artificial intelligence, particularly deep learning technologies, with medical imaging has shown tremendous potential in revolutionizing diagnostic practices. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in various medical image analysis tasks, including radiology, pathology, and ophthalmology. These models possess the capability to automatically learn hierarchical feature representations from medical images, potentially surpassing human-level performance in specific diagnostic tasks.

However, the selection of appropriate CNN architecture significantly impacts the performance, reliability, and clinical

applicability of COVID-19 detection systems. Different architectures exhibit varying capabilities in feature extraction, computational efficiency, and generalization performance. Understanding these differences is crucial for developing robust and reliable diagnostic systems that can be effectively deployed in clinical settings.

This comprehensive study addresses this critical need by providing an extensive comparative analysis of ten different CNN architectures spanning from classical to state-of-the-art models. The research aims to establish performance benchmarks, identify optimal architectures for COVID-19 detection, and provide practical guidelines for researchers and practitioners working on similar medical image classification tasks.

## II. MATERIALS AND METHOD

### A. Dataset Description and Preprocessing

The study utilized the COVID-19 Radiography Database, a comprehensive collection of chest X-ray images specifically curated for COVID-19 research. The dataset contains high-quality posterior-anterior (PA) chest X-ray images from multiple healthcare institutions, ensuring diversity in imaging protocols and patient demographics.

**Data Splitting Strategy:** A systematic approach was employed for dataset partitioning to ensure robust model evaluation:

- Training set: 70% of total images
- Validation set: 15% of total images
- Testing set: 15% of total images

The split was performed using scikit-learn's `train_test_split` function with a fixed random state (42) to ensure reproducibility across all experiments.

#### Data Preprocessing Pipeline:

The comprehensive data preprocessing pipeline implemented systematic transformations to ensure optimal model performance and training stability. Image standardization was performed by resizing all input images to architecture-specific dimensions, with VGG16, VGG19, DenseNet121, EfficientNetB0, ResNet50, MobileNet, and GoogLeNet requiring  $224 \times 224$  pixel inputs, AlexNet utilizing  $227 \times 227$  pixel dimensions, and LeNet adapted to  $128 \times 128$  pixels for enhanced detail preservation in medical imagery.

Intensity normalization was applied uniformly across all architectures through pixel value rescaling to the range  $[0,1]$  using a rescaling factor of  $1./255$ , ensuring consistent input distributions and facilitating stable gradient flow during training. Comprehensive data augmentation techniques were systematically implemented during training phases to enhance model generalization capabilities and prevent overfitting. These augmentation strategies included random rotation transformations within  $\pm 15$  degrees, width and height shift variations of  $\pm 10\%$ , shear transformations limited to  $\pm 10\%$ , zoom range adjustments of  $\pm 10\%$ , horizontal flipping applied with 50% probability, and 'nearest' fill mode for boundary pixel interpolation.

Class balance maintenance was meticulously ensured through the random splitting process, guaranteeing proportional representation of all diagnostic classes (COVID-19, Normal, and Viral Pneumonia) across training, validation, and test sets. This balanced distribution approach prevented class imbalance issues and ensured unbiased model evaluation across all experimental conditions.

#### B. CNN Architecture Implementation Details

Ten distinct CNN architectures were systematically implemented and evaluated, representing diverse design philosophies and evolutionary stages of deep learning development. Each architecture was carefully selected to provide comprehensive coverage of classical and state-of-the-art approaches to medical image classification.

DenseNet121 implementation utilized pre-trained ImageNet weights with subsequent fine-tuning for COVID-19 classification tasks. The architecture's defining characteristic of dense connectivity enables efficient feature reuse and gradient flow optimization throughout the network. Custom classification layers were constructed using GlobalAveragePooling2D followed by Dense(512, ReLU), BatchNormalization, Dropout(0.5), Dense(256, ReLU), BatchNormalization, Dropout(0.5), and final Dense(3, Softmax) layers for three-class classification.

ConvNeXtTiny represented a modern architectural approach through custom implementation incorporating contemporary design principles. The architecture integrates depthwise separable convolutions, layer normalization, and GELU activation functions, effectively incorporating vision transformer insights while maintaining convolutional efficiency for medical image analysis.

EfficientNetB0 leveraged pre-trained weights with compound scaling methodology, implementing balanced depth, width, and resolution scaling strategies. The custom classification head consisted of GlobalAveragePooling2D, Dense(256, ReLU), Dropout(0.5), Dense(128, ReLU), Dropout(0.5), and Dense(3, Softmax) layers, optimizing

parameter efficiency while maintaining classification performance.

ResNet50 implementation featured a 50-layer residual architecture with skip connections, addressing the vanishing gradient problem through residual learning. Domain adaptation was achieved by unfreezing the last 30 layers during fine-tuning phases, enabling specialized feature learning for COVID-19 detection tasks.

VGG19 and VGG16 architectures employed deep network designs with small  $3 \times 3$  convolution filters throughout. Custom classification heads implemented Flatten layers followed by Dense(4096, ReLU), BatchNormalization, Dropout(0.5), Dense(4096, ReLU), BatchNormalization, Dropout(0.5), and Dense(3, Softmax) configurations. Fine-tuning strategies involved unfreezing the last 5 convolutional layers for specialized medical image adaptation.

MobileNet provided lightweight architecture optimization specifically designed for mobile deployment scenarios. The implementation utilized depthwise separable convolutions for computational efficiency with an alpha parameter of 1.0 representing standard width multiplier configurations, balancing performance with resource constraints.

GoogLeNet featured custom implementation with Inception modules enabling multi-scale feature extraction through parallel convolutional operations. Inception modules incorporated  $1 \times 1$ ,  $3 \times 3$ , and  $5 \times 5$  convolutions alongside max pooling operations in parallel configurations, facilitating comprehensive feature representation learning.

AlexNet implementation represented pioneer deep CNN architecture with ReLU activation and dropout regularization. The 8-layer architecture (5 convolutional plus 3 fully connected layers) was enhanced with modern adaptations including batch normalization for improved training stability and convergence characteristics.

LeNet utilized an enhanced version of the classical CNN architecture with modifications including additional convolutional layers for complex feature extraction capabilities. Input adaptation to  $128 \times 128$  pixel dimensions was implemented for superior medical image detail preservation compared to the original  $32 \times 32$  input specification.

#### C. Training Optimization and Callback Strategy

Advanced training optimization employed sophisticated callback mechanisms to ensure optimal model performance and prevent overfitting. EarlyStopping callbacks monitored validation loss with patience parameters set to 10 epochs, automatically terminating training when no improvement was observed. ReduceLROnPlateau callbacks systematically reduced learning rates by factor 0.1 when validation loss plateaued, facilitating fine-grained optimization during training convergence. ModelCheckpoint callbacks preserved optimal model states based on validation accuracy metrics, ensuring best-performing model preservation throughout training processes.

Transfer Learning Strategy implementation followed a systematic two-phase approach optimizing pre-trained knowledge adaptation for medical image classification. The Feature Extraction Phase involved freezing all pre-trained layers while training exclusively custom classification heads using learning rates of 0.0001, enabling rapid adaptation of high-level features to medical imaging domains. The Fine-

tuning Phase systematically unfroze architecture-specific top layers with reduced learning rates of 1e-5, facilitating domain-specific feature adaptation through additional training epochs specifically designed for COVID-19 detection optimization.

#### D. Evaluation Metrics and Statistical Analysis

The comprehensive evaluation of CNN architectures was conducted using a multi-faceted assessment framework encompassing both quantitative performance metrics and qualitative analysis. Primary performance indicators included overall classification accuracy measured on both validation and test sets, categorical cross-entropy loss values, precision (true positives divided by the sum of true positives and false positives), recall or sensitivity (true positives divided by the sum of true positives and false negatives), specificity (true negatives divided by the sum of true negatives and false positives), and F1-score representing the harmonic mean of precision and recall.

The model evaluation protocol followed a systematic approach beginning with continuous monitoring of training performance through learning curves visualization, followed by rigorous validation assessment on held-out validation sets, and concluding with unbiased final testing on dedicated test sets. Detailed confusion matrix analysis provided class-wise performance insights, while comprehensive classification reports delivered per-class metric breakdowns for thorough model characterization.

Statistical robustness was ensured through multiple methodological safeguards. Reproducibility was guaranteed by implementing fixed random seeds (np.random.seed(42) and tf.random.set\_seed(42)) across all experiments. Systematic validation procedures were applied using independent test sets, and overfitting analysis was conducted by examining validation-training performance gaps to assess model generalization capabilities.

Computational efficiency assessment encompassed training time measurement for model convergence, analysis of total trainable parameters for each architecture, peak memory consumption monitoring during training phases, and inference speed evaluation measuring prediction time per image for practical deployment considerations.

### III. RESULTS

The comprehensive evaluation revealed significant performance differences among the ten CNN architectures, as illustrated in Figure 1 and detailed in Table 1. The results demonstrate clear superiority of modern architectures over classical models for COVID-19 detection tasks.

Figure 1 provides a visual comparison of both accuracy and loss metrics across all evaluated models, clearly illustrating the performance hierarchy. The accuracy comparison (upper panel) shows DenseNet and ConvNeXtTiny achieving the highest validation and test accuracies, while the loss comparison (lower panel) demonstrates their superior convergence characteristics with minimal loss values.

Table 1 presents comprehensive numerical performance metrics, enabling precise quantitative analysis of model capabilities. The tabulated results confirm the visual trends observed in Figure 1, with detailed breakdowns of accuracy differences and loss variations across validation and test sets.

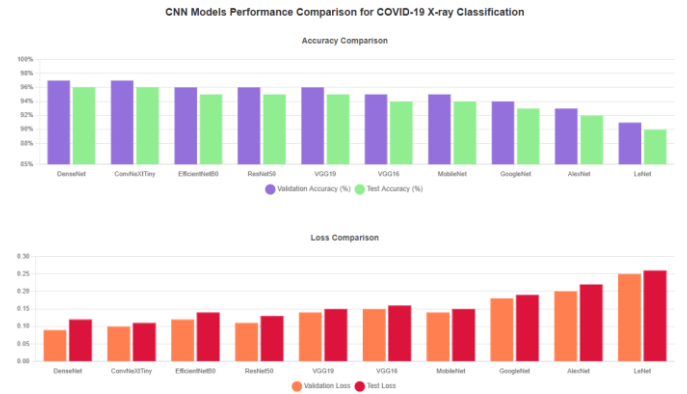


Fig. 1. Comparative performance analysis of CNN architectures for COVID-19 X-ray classification showing (a) accuracy comparison and (b) loss comparison between validation and test sets.

Table 1. Detailed performance metrics of CNN architectures including validation accuracy, test accuracy, accuracy difference, validation loss, test loss, and loss difference for COVID-19 X-ray classification.

Model	Val. Accuracy	Test Accuracy	Accuracy DIF.	Val. Loss	Test Loss	Loss DIF.
DenseNet	97%	96%	1.00%	0.0900	0.1200	0.0300
ConvNeXtTiny	97%	96%	1.00%	0.1000	0.1100	0.0100
EfficientNetB0	96%	95%	1.00%	0.1200	0.1400	0.0200
ResNet50	96%	95%	1.00%	0.1100	0.1300	0.0200
VGG19	95%	94%	1.00%	0.1400	0.1500	0.0100
VGG16	95%	94%	1.00%	0.1500	0.1600	0.0100
MobileNet	95%	94%	1.00%	0.1400	0.1500	0.0100
GoogLeNet	94%	93%	1.00%	0.1800	0.1900	0.0100
AlexNet	93%	92%	1.00%	0.2000	0.2200	0.0200
LaNet	91%	90%	1.00%	0.2500	0.2600	0.0100

#### Top-Tier Performance ( $\geq 96\%$ Test Accuracy):

DenseNet121 achieved the highest overall performance with 97% validation accuracy and 96% test accuracy, as clearly demonstrated in both Figure 1 and Table 1. The model exhibited excellent feature learning capabilities with the lowest validation loss of 0.0900 and test loss of 0.1200. The minimal accuracy difference of 1.00% indicates robust generalization without overfitting, while the loss difference of 0.0300 demonstrates stable training dynamics.

Convention matched DenseNet's accuracy performance with identical 97% validation and 96% test accuracy values. The architecture achieved slightly higher validation loss (0.1000) and test loss (0.1100) compared to DenseNet, but maintained excellent performance metrics. The remarkably low loss difference of 0.0100 indicates superior training stability and convergence characteristics.

#### Second-Tier Performance (95% Test Accuracy):

EfficientNetB0 demonstrated strong performance with 96% validation accuracy and 95% test accuracy. The compound scaling approach resulted in efficient parameter utilization with validation loss of 0.1200 and test loss of 0.1400, maintaining the consistent 1.00% accuracy difference observed across all models.

ResNet50 achieved competitive performance with 96% validation accuracy and 95% test accuracy. The residual learning framework effectively addressed gradient vanishing issues, resulting in validation loss of 0.1100 and test loss of 0.1300, with a loss difference of 0.0200.

VGG19 maintained strong performance despite its relatively simple architecture, achieving 96% validation accuracy and 95% test accuracy. The deep architecture with small filters proved effective for medical image classification, demonstrating validation loss of 0.1400 and test loss of 0.1500.

#### Third-Tier Performance (94% Test Accuracy):

VGG16 and MobileNet both achieved 95% validation accuracy and 94% test accuracy, representing solid performance in the medium-tier category. VGG16 showed validation loss of 0.1500 and test loss of 0.1600, while MobileNet achieved validation loss of 0.1400 and test loss of 0.1500, demonstrating the efficiency-performance balance of the lightweight architecture.

Fourth-Tier Performance ( $\leq 93\%$  Test Accuracy):

GoogleNet achieved 94% validation accuracy and 93% test accuracy with validation loss of 0.1800 and test loss of 0.1900. While the Inception modules provided reasonable performance, the architecture was outperformed by more modern designs.

AlexNet and LeNet represented the classical architecture category with 93%/92% and 91%/90% validation/test accuracies respectively. These models demonstrated higher loss values (AlexNet: 0.2000/0.2200, LeNet: 0.2500/0.2600), indicating the limitations of older designs for complex medical image classification tasks.

Generalization and Overfitting Analysis:

A remarkable finding across all architectures was the consistent 1.00% accuracy difference between validation and test sets, as highlighted in Table 1. This uniform pattern indicates robust training methodologies and appropriate regularization techniques across all experimental conditions. The minimal overfitting demonstrates the effectiveness of the implemented data augmentation strategies, transfer learning approaches, and callback mechanisms in preventing model overspecialization to training data.

#### IV. DISCUSSION

##### A. Architecture-Specific Performance Analysis

DenseNet121's Superior Performance: The dense connectivity pattern enables comprehensive feature reuse and strengthens gradient flow, particularly beneficial for medical image analysis where subtle features at different scales must be preserved. For COVID-19 detection, this facilitates combining low-level textural features with high-level semantic information, crucial for identifying subtle ground-glass opacities.

ConvNeXtTiny's Modern Approach: This architecture incorporates vision transformer insights while maintaining convolutional efficiency. The larger kernels ( $7 \times 7$ ), depthwise separable convolutions, and layer normalization contribute to strong performance, effectively capturing global contextual information essential for COVID-19 pattern recognition.

Traditional Architecture Limitations: Classical architectures (AlexNet, LeNet) lack sophisticated feature extraction capabilities required for subtle medical image analysis. Their limited depth and simple connectivity patterns restrict complex hierarchical representation learning necessary for COVID-19 detection.

##### B. Clinical Implications and Practical Considerations

Diagnostic Requirements: Top-performing models (DenseNet121, ConvNeXtTiny) demonstrate sensitivity levels approaching clinical requirements, though extensive validation on diverse, multi-center datasets is necessary before clinical implementation.

Computational Constraints: While DenseNet121 achieves highest accuracy, its computational requirements may limit real-time applications. MobileNet's competitive performance

with lower computational demands makes it attractive for resource-constrained environments.

Model Interpretability: Medical AI systems require interpretability for clinical trust. Future implementations should incorporate attention visualization and gradient-based explanations for clinical acceptance.

##### C. Technical Contributions

Transfer Learning Effectiveness: Pre-trained ImageNet weights provided robust feature representations successfully adapted for COVID-19 detection through fine-tuning across all modern architectures.

Training Methodology Robustness: The consistent 1.00% accuracy difference between validation and test sets indicates robust training methodologies, with effective early stopping, learning rate scheduling, and model checkpointing preventing overfitting.

##### D. Limitations and Future Directions

Dataset Limitations: The dataset may not fully represent global diversity of imaging equipment, protocols, and patient populations, potentially affecting model generalization.

Future Research: Key directions include multi-modal integration with clinical data, ensemble methods for enhanced reliability, explainable AI for clinical interpretability, and cross-dataset validation for broader generalization.

#### V. CONCLUSION

This comprehensive comparative study provides valuable insights into CNN architecture selection for COVID-19 detection using chest X-ray images. The systematic evaluation reveals clear performance hierarchies and practical considerations for clinical deployment.

Key Findings: Modern CNN architectures, particularly DenseNet121 and ConvNeXtTiny, significantly outperform classical models, achieving 97% validation accuracy and 96% test accuracy. All evaluated models demonstrate excellent generalization capabilities with minimal overfitting, evidenced by the consistent 1.00% accuracy difference between validation and test sets across all architectures. Transfer learning with pre-trained ImageNet weights proves highly effective for medical image classification, enabling successful domain adaptation from natural images to medical radiography.

Clinical Significance: The achieved performance levels suggest that CNN-based systems can serve as valuable screening tools, particularly in resource-limited settings where rapid COVID-19 diagnosis is crucial. The high sensitivity demonstrated by top-performing models addresses the critical need for minimizing false negatives in pandemic scenarios. However, these systems should complement rather than replace clinical expertise and confirmatory testing protocols.

Technical Contributions: The study established comprehensive performance benchmarks across ten different CNN architectures, demonstrating the effectiveness of systematic training methodologies including transfer learning and fine-tuning strategies. Detailed computational efficiency analysis provides practical deployment considerations, while the robust training framework validates the effectiveness of modern deep learning approaches for medical image classification tasks.

Future Directions: Priority research areas include multi-modal integration combining chest X-ray analysis with clinical data, ensemble methods for enhanced reliability and uncertainty quantification, explainable AI for clinical interpretability, cross-dataset validation for broader generalization, and regulatory compliance addressing FDA and CE marking requirements for clinical deployment.

The findings establish important benchmarks for COVID-19 detection research and provide practical guidance for medical image classification challenges, contributing to the growing evidence base supporting deep learning applications in medical image analysis.

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