



DEEP LEARNING-BASED COMPARISON OF CHEST X-RAY AND CT SCAN MODALITIES IN COVID-19 DIAGNOSIS

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ABSTRACT

The COVID-19 pandemic has propelled the development of rapid and accurate diagnostic tools, among which medical imaging plays a vital role. Chest X-ray (CXR) and computed tomography (CT) imaging have emerged as essential methods for assessing pulmonary involvement in COVID-19 cases. This research presents a comparative study of these two imaging modalities using image processing and deep learning models. By employing datasets from public repositories and using convolutional neural networks (CNNs) and transfer learning techniques, we analyze their diagnostic efficiency in terms of sensitivity, specificity, and accuracy. Our findings indicate that CT scans provide higher diagnostic precision, whereas CXRs offer greater accessibility, speed, and cost-efficiency. This study supports the need for a complementary imaging approach and highlights the potential of AI to improve diagnostic workflows.

1. Introduction

The emergence of Coronavirus Disease 2019 (COVID-19), caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has posed an unprecedented challenge to global healthcare systems. Early and accurate detection of the disease is crucial for effective isolation, treatment, and mitigation of its spread. While the reverse transcription polymerase chain reaction (RT-PCR) test is considered the diagnostic gold standard, it has several limitations, including low sensitivity in early stages, limited availability in resource-constrained areas, and delayed turnaround times. These limitations have necessitated the exploration of alternative diagnostic tools, particularly imaging-based approaches, which are rapid, widely available, and capable of visualizing the pulmonary manifestations of the disease.

Medical imaging techniques such as chest X-ray (CXR) and computed tomography (CT) have become vital in diagnosing and monitoring COVID-19. Chest X-rays are cost-effective, fast, and easy to perform, making them ideal for initial triage and widespread screening, especially in developing countries. However, their limited resolution and overlapping anatomical structures can make it difficult to identify early or subtle lung pathologies. In contrast, CT scans offer high-resolution, three-dimensional images that allow for more precise visualization of lung parenchymal abnormalities, including ground-glass opacities (GGOs), consolidation, and interstitial markings—hallmarks of COVID-19 pneumonia. Yet, CT scans are expensive, involve higher radiation exposure,



and are not always available in rural or overburdened healthcare facilities.

In recent years, artificial intelligence (AI) and deep learning (DL)—especially convolutional neural networks (CNNs)—have revolutionized medical image analysis. These algorithms can automatically extract relevant features from imaging data, classify pathological findings, and assist radiologists in achieving faster and more accurate diagnoses. In the context of COVID-19, numerous deep learning models have been developed for both CXR and CT scan images, showing promising results in terms of accuracy, sensitivity, and specificity.

However, there remains a gap in comprehensive, comparative studies that evaluate the relative performance, advantages, and limitations of using chest X-ray and CT scan images for COVID-19 detection using deep learning techniques. Most existing research tends to focus exclusively on one modality or uses disparate datasets and evaluation protocols, making it difficult to draw objective conclusions.

This study addresses that gap by conducting a systematic and data-driven comparative analysis of chest X-ray and CT scan modalities in the context of COVID-19 detection using deep learning. We investigate and contrast their diagnostic performance, clinical usability, computational complexity, and suitability in real-world healthcare environments. Our goal is to provide clear, evidence-based guidance for clinicians, researchers, and policymakers on the optimal use of these imaging modalities in conjunction with AI for pandemic response.

Specifically, this research aims to:

- Evaluate and compare deep learning models trained on both CXR and CT datasets.
- Analyze the impact of image modality on model accuracy, sensitivity, and specificity.
- Identify the practical advantages and disadvantages of each imaging technique.
- Highlight the role of image preprocessing and transfer learning in improving diagnostic performance.
- Discuss challenges such as dataset imbalance, noise, and the need for explainable AI in clinical practice.

By integrating findings from both experimental evaluation and literature review, this paper contributes to the growing body of knowledge on AI-assisted medical diagnosis and offers actionable insights into the deployment of imaging technologies for COVID-19 and other respiratory diseases.

This paper explores the comparative performance of CXR and CT scan images for COVID-19 detection using image processing and deep learning. We examine their respective roles in clinical settings and highlight how deep learning improves diagnostic reliability.

2. Related Work

Over the past few years, a surge in research has leveraged artificial intelligence and medical imaging for COVID-19 detection. This section highlights prominent works comparing chest X-ray and CT scan imaging modalities and employing deep learning techniques.

2.1 CT-Based Studies

- Sharma et al. (2022) [1] conducted a detailed analysis of CT imaging using DenseNet and VGGNet for COVID-19 detection. The study reported an accuracy of over 96% on CT images from the COVID-CT dataset. The research emphasized the advantage of CT imaging in identifying ground-glass opacities (GGOs) and bilateral infiltrates, key indicators in early COVID-19 pneumonia.
- Harmon et al. (2020) [2] developed a deep learning model trained on over 2,500 CT scans from 10 countries.



Using ResNet50 and segmentation layers, their model achieved a sensitivity of 90.8% and demonstrated generalizability across diverse populations.

- Bai et al. (2020) [3] compared radiologists' interpretation of CT scans with a CNN model. Their study found that the AI system performed comparably to expert radiologists, improving diagnostic speed and inter-rater reliability. This supports CT's diagnostic strength in AI-assisted workflows.

2.2 X-ray-Based Studies

- Singh et al. (2023) [4] proposed a CNN-based classification model for chest X-ray images and achieved over 92% accuracy using a dataset derived from the BIMCV-COVID19+ and COVIDx repositories. The model's simplicity and real-time inference capability made it suitable for deployment in mobile or rural healthcare settings.
- Ozturk et al. (2020) [5] developed a DarkNet-based CNN architecture trained on a curated dataset of chest X-rays. They achieved 98.08% accuracy for binary classification (COVID-19 vs Normal) and 87.02% for multi-class classification (COVID-19, Pneumonia, Normal). This work highlighted the efficiency of lightweight models on X-ray images for quick triaging.
- Wang et al. (2020) [6] introduced COVID-Net, a tailored deep CNN for COVID-19 detection in chest radiographs. Trained on the COVIDx dataset, COVID-Net achieved promising accuracy while maintaining transparency using explainability tools (e.g., GSInquire). This allowed clinicians to understand which regions the model relied on, improving trust in AI systems.

2.3 Comparative Studies

- Varalakshmi et al. (2023) [7] conducted a side-by-side comparative study of chest X-rays and CT images using pre-trained models like InceptionV3 and MobileNet. Their findings showed that CT scans consistently yielded higher classification performance; however, the X-ray models achieved competitive accuracy with much less processing time.
- Alshazly et al. (2021) [8] focused on explainable deep learning models for both CT and X-ray images. They integrated Grad-CAM-based visualization to compare the interpretability of CNN outputs. The study suggested that CT images provided more localized and focused activation maps, which made clinical validation easier.
- Loey et al. (2021) [9] experimented with multiple deep learning architectures including GoogleNet and AlexNet on CT images. They concluded that CT-based models outperformed X-ray models in cases involving early-stage infection, which is often harder to detect with low-resolution X-ray imaging.
- Apostolopoulos et al. (2020) [10] explored transfer learning with VGG19 and MobileNetV2 on X-ray images. The study demonstrated that transfer learning enabled reliable classification even with a relatively small dataset, achieving 96.78% accuracy using VGG19.

Synthesis of Related Work

From the review, the following observations emerge:

- CT imaging provides richer, high-resolution data beneficial for early detection and accurate lesion segmentation. Most CT-based models achieve higher sensitivity and are ideal for hospitalized or critical care patients.



- Chest X-rays, though lower in anatomical detail, offer cost and speed advantages. When combined with CNN or transfer learning techniques, they yield strong classification performance, making them practical for population-level screening.
- Model architecture influences performance: Lightweight models (MobileNet, SqueezeNet) are ideal for real-time applications, while deeper models (ResNet, DenseNet) excel in classification precision but require more computational power.
- Explainable AI is increasingly emphasized to enhance clinician trust, particularly in high-stakes diagnostic environments like COVID-19 detection.

3. Methodology

The methodology for this research comprises five key stages: (1) dataset collection, (2) preprocessing, (3) model architecture and training, (4) performance evaluation, and (5) comparative analysis. The approach aims to systematically analyze and compare the effectiveness of chest X-ray and CT scan images in COVID-19 detection using deep learning and image processing techniques.

3.1 Dataset Collection

To ensure a fair and comprehensive comparison, publicly available and medically validated datasets were selected for both imaging modalities.

3.1.1 Chest X-ray Datasets

- COVIDx Dataset: A curated dataset combining samples from multiple sources such as Cohen's COVID-19 image data collection, RSNA Pneumonia Detection Challenge, and others. It includes thousands of labeled images under three main categories: COVID-19, Pneumonia, and Normal.
- BIMCV-COVID19+ Dataset: This dataset includes CXR images from patients confirmed with COVID-19 in Spain. It provides high-quality images and metadata.

3.1.2 CT Scan Datasets

- MosMedData: Contains over 1,100 chest CT scans from COVID-19 positive and negative patients, labeled according to severity levels.
- COVID-CT Dataset: Includes 349 COVID-19 CT images and 463 non-COVID CT images collected from Chinese hospitals.

All datasets were organized and annotated into binary classes: COVID-19 positive and negative (normal or other pneumonia), to maintain consistency in model training and evaluation.

3.2 Image Preprocessing

Preprocessing is a crucial step to ensure that input images are standardized, noise-free, and optimized for feature extraction by deep learning models.

3.2.1 Common Steps

- Resizing: All images were resized to 224×224 pixels to fit into the input layer of pre-trained CNNs.
- Normalization: Pixel values were normalized to the [0, 1] range to reduce computation and standardize the intensity scale.
- Noise Reduction: Median and Gaussian filters were applied to reduce salt-and-pepper noise and image



blurring.

- Contrast Enhancement: CLAHE (Contrast Limited Adaptive Histogram Equalization) was applied to enhance low-contrast areas common in CXR images.
- Data Augmentation: To address class imbalance and improve model generalization:
 - Horizontal/vertical flipping
 - Random rotation (± 15 degrees)
 - Zoom and shift
 - Brightness variation

3.2.2 CT-Specific Preprocessing

- Lung Segmentation: U-Net-based segmentation was used to isolate lung regions in CT images to eliminate non-relevant anatomical structures.
- 3D Slicing: Selected 2D axial slices were extracted from 3D CT volumes for model input, focusing on middle lung regions where infection is most visible.

3.3 Deep Learning Model Design

This study employed both custom CNNs and transfer learning models to classify COVID-19 positive and negative cases.

3.3.1 Custom CNN Architecture

A 5-layer convolutional neural network was designed as follows:

- Conv Layer 1: 32 filters, 3x3 kernel, ReLU activation
- Max Pooling: 2x2
- Conv Layer 2: 64 filters, 3x3, ReLU
- Dropout: 0.25
- Conv Layer 3: 128 filters, 3x3
- Flatten, followed by Dense Layer (128 neurons)
- Output Layer: Sigmoid for binary classification

3.3.2 Transfer Learning Models

To leverage pre-trained knowledge, the following architectures were fine-tuned:

- VGG16 & VGG19: Pre-trained on ImageNet; modified dense layers.
- ResNet50: Included identity mapping and batch normalization.
- DenseNet121: Fewer parameters with efficient feature reuse.
- MobileNetV2: Used for comparison on low-resource systems.

Fine-tuning was applied to the last few convolutional blocks, while earlier layers were frozen to retain learned weights from ImageNet.

3.4 Training Parameters

- Loss Function: Binary Cross-Entropy
- Optimizer: Adam optimizer with learning rate of $1e-4$
- Batch Size: 32
- Epochs: 25–50 depending on convergence

- Validation Strategy: 80/20 train-validation split, with stratified k-fold cross-validation (k=5) used to prevent overfitting.

3.5 Evaluation Metrics

To ensure a robust performance evaluation, the following metrics were used:

Metric	Description
Accuracy	Overall percentage of correctly classified images.
Precision	Proportion of true positives among all predicted positives.
Recall (Sensitivity)	Proportion of actual positives correctly identified.
Specificity	Proportion of actual negatives correctly identified.
F1 Score	Harmonic mean of precision and recall.

AUC (Area Under ROC Curve) Measures trade-off between sensitivity and specificity.

Confusion matrices and ROC curves were plotted for both modalities to visualize classification performance.

3.6 Comparative Analysis Procedure

The models trained on CXR and CT datasets were evaluated separately. Comparative analysis was conducted based on:

- Quantitative Metrics: Accuracy, sensitivity, specificity, etc.
- Qualitative Insights: Feature map visualization using Grad-CAM.
- Model Efficiency: Inference time, parameter count, and training duration.
- Practical Factors: Cost, accessibility, radiation dose, and clinical relevance.

Comparative Analysis of CXR vs CT

A final table was constructed to summarize the strengths and limitations of each modality when integrated with deep learning methods.

Aspect	Chest X-ray (CXR)	CT Scan
Diagnostic Accuracy	Moderate to High (85–92%)	High (92–98%)
Sensitivity	Lower; may miss early-stage infection	Higher; detects fine-grained patterns (e.g., GGOs)
Specificity	Moderate (risk of false positives in overlapping lung conditions)	High; better distinction of COVID-19 vs other pneumonia types
Image Resolution	2D projection, lower anatomical detail	3D slices, detailed anatomical structures
Speed of Acquisition	Very fast (1–2 minutes)	Slower due to reconstruction and segmentation (5–10 minutes)
Radiation Exposure	Low	Higher (especially in repeated scans)
Equipment Cost	Low	High
Accessibility	Widely available, portable	Limited to advanced facilities



Aspect	Chest X-ray (CXR)	CT Scan
Use in Low-Resource Settings	Highly suitable for rural and mobile applications	Less feasible due to cost and infrastructure requirements
Model Complexity	Works well with lightweight CNNs (e.g., MobileNet, COVID-Net)	Benefits from deeper models (e.g., DenseNet, ResNet, U-Net)
Preprocessing Needs	Basic (resizing, normalization, contrast enhancement)	Complex (lung segmentation, slice selection)
Explainability (AI)	Good with Grad-CAM, but harder to localize small lesions	Easier to interpret heatmaps and lesion boundaries
Ideal Use Case	Mass screening, triage, mobile diagnostics	Confirmatory diagnosis, monitoring severity and progression

Table 1: Comparative Summary of Chest X-ray and CT Scan in Deep Learning-Based COVID-19 Detection

Key Insights:

- Chest X-rays are best suited for large-scale screening in low-resource environments, especially when enhanced by lightweight AI models.
- CT scans are ideal for detailed evaluation, severity grading, and early detection, particularly in hospital or ICU settings.
- Deep learning significantly improves performance on both modalities, but CT benefits more due to richer data.

5. Advantages and Disadvantages**5.1 Chest X-Ray (CXR)**

Advantages:

- Widely available and portable
- Low radiation exposure
- Low cost
- Faster acquisition and processing
- Suitable for mass screening

Disadvantages:

- Lower sensitivity than CT
- Difficult to detect early or subtle lung involvement
- Overlapping anatomical structures can obscure lesions
- Requires experienced radiologists or AI support

5.2 CT Scan

Advantages:

- High-resolution imaging
- Greater sensitivity in detecting ground-glass opacities and consolidations
- More reliable for early diagnosis and severity assessment



- 3D view enables better lesion segmentation and tracking

Disadvantages:

- Expensive and less accessible
- Higher radiation dose
- Slower acquisition and processing
- Not ideal for frequent or large-scale screening

6. Discussion

The comparative analysis of chest X-ray (CXR) and CT scan modalities in this study reveals a nuanced understanding of how imaging, when combined with deep learning, can significantly enhance COVID-19 detection.

6.1 Performance Analysis

From the experimental results and literature synthesis, it is evident that CT scans outperform CXRs in terms of sensitivity, specificity, and overall diagnostic accuracy. CT-based models, especially those using architectures like DenseNet, ResNet, and U-Net, have demonstrated accuracy above 95%, particularly in identifying early-stage infections and subtle lesions like ground-glass opacities (GGOs).

In contrast, chest X-rays, although inherently limited in image resolution and detail, still yielded competitive results (accuracy ranging from 85–92%) when paired with deep learning models such as COVID-Net, MobileNet, and VGG variants. Notably, when augmented with preprocessing techniques like CLAHE and enhanced by transfer learning, X-rays proved effective in large-scale screening contexts.

6.2 Clinical Utility and Resource Considerations

While CT scans are diagnostically superior, they are resource-intensive, requiring sophisticated equipment, skilled technicians, and longer processing times. Their higher radiation dose also limits repeat usage, especially in pediatric and vulnerable populations. Consequently, their deployment is best reserved for hospital-based diagnostics, particularly in moderate to severe COVID-19 cases or in ambiguous RT-PCR results.

On the other hand, CXRs offer portability, low cost, and rapid throughput, making them indispensable in mass screening, triage, and resource-limited regions. When interpreted using AI, CXR can act as a preliminary diagnostic tool, flagging suspected COVID-19 cases for further CT or PCR testing.

6.3 Deep Learning Implications

This study also underscores the transformative role of deep learning in medical image analysis:

- Transfer learning enabled models to achieve high performance with limited medical datasets.
- Explainable AI techniques like Grad-CAM enhanced model interpretability, improving clinician trust.
- Segmentation models (e.g., U-Net) were particularly valuable in CT imaging for localizing infected lung areas, aiding in disease monitoring and progression analysis.

Despite these advances, challenges remain:

- Dataset imbalance, particularly the underrepresentation of mild and asymptomatic COVID-19 cases, can bias model training.
- Generalizability across imaging devices, demographic groups, and institutions is still a concern.



- There's a pressing need for cross-modality fusion and multi-modal AI systems that can integrate X-ray, CT, clinical history, and lab results to support holistic diagnosis.

7. Conclusion

This research presents a detailed comparative study of chest X-ray and CT scan modalities for COVID-19 detection using deep learning and image processing techniques. The findings confirm that:

- CT scans provide superior diagnostic precision, especially for early-stage COVID-19, at the cost of higher resource demands.
- Chest X-rays are highly scalable and practical, particularly in rural, mobile, or overloaded healthcare settings, and perform reliably when supported by AI.
- Deep learning models significantly enhance diagnostic capabilities for both modalities, and the choice of architecture and preprocessing directly affects performance.

Ultimately, this study recommends a tiered imaging approach: using chest X-rays as the first-line screening tool and CT scans as the confirmatory diagnostic method, particularly in complex or high-risk cases. Furthermore, AI-driven tools should be developed and deployed with an emphasis on interpretability, clinical integration, and ethical data usage.

Future research should explore the development of multi-modal data fusion techniques that combine information from chest X-rays, CT scans, and other clinical inputs to improve diagnostic accuracy. Efforts should also focus on the real-time deployment of lightweight AI models on mobile platforms, enabling fast and accessible screening in remote or resource-constrained settings. Additionally, federated learning frameworks should be investigated to facilitate privacy-preserving model training across multiple healthcare institutions without the need to share sensitive patient data. Lastly, there is a strong need to design unified diagnostic systems that seamlessly integrate CXR, CT imaging, and clinical data to support comprehensive and reliable COVID-19 diagnosis and monitoring. In conclusion, combining medical imaging with AI offers a powerful, scalable strategy to combat not only COVID-19 but also future respiratory pandemics.

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