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AN EFFICIENT AND LEARNING METHOD ARCHITECTURE THAT ALLOWS THE DETECTION OF CORONAVIRUS DISEASES

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Abstract:

Millions of lives have been destroyed by the deadly coronavirus, which has also imposed a tremendous burden on healthcare systems worldwide. Early identification of COVID-19 is essential for isolating positive cases and halting the spread of the disease. Deep learning algorithms, combined with medical imaging, have enabled faster and more accurate detection of COVID-19. This paper presents a comprehensive analysis of the most recent deep learning techniques employed for COVID19 diagnosis. According to the research publications reviewed, Convolutional Neural Networks (CNNs) remain the most widely used deep learning approach for identifying COVID-19 from medical images. Transfer learning and data augmentation strategies effectively address concerns related to limited data availability. Preprocessing of medical images is crucial to enhance model performance, while the use of pre-trained models can significantly reduce training time. Furthermore, medical images play a key role in the automated detection of COVID-19, providing non-invasive and reliable diagnostic support. This article also offers early-career researchers a practical perspective on developing CNN models integrated with medical imaging to facilitate prompt and accurate disease detection. Overall, the study consolidates existing methods and insights, emphasizing the critical role of deep learning and medical imaging in the timely identification of COVID-19 cases and the potential for these technologies to support future diagnostic frameworks in healthcare.

Keywords: *COVID-19 detection, Image processing, Data augmentation, Deep learning, Convolutional Neural Network (CNN), X-ray images,*

Introduction

The outbreak of coronavirus disease 2019 (COVID-19) was declared a global pandemic by the World Health Organization (WHO) in March 2019, highlighting a major public health crisis that rapidly affected populations worldwide. Originating in Wuhan, China, thevirus, known as SARS-CoV-2, quickly spread across nations, causing severe health complications and creating substantial societal and economic disruption. The disease manifests with flu-like symptoms, including fever, body aches, and respiratory distress, and is primarily transmitted throughairborne droplets and physical contact. Governments implemented preventive measures such as mask-wearing, social distancing, and lockdowns to reduce the spread of the virus, which significantly affected businesses, education, and daily life globally [1,16]. Although real-time Reverse Transcription Polymerase Chain Reaction (RT-PCR) remains one of the most precise diagnostic tools, its practical use is often restricted. The method demands considerable time, higher financial resources, and access to well-equipped laboratories, which makes it less suitable for rapid or field-based testing. RT-PCR testing can take several hours for sample analysis, and including transportation and reporting time, results may take several days. Moreover, the high cost and resource constraints make this method less feasible for rapid large-scale screening. Medical imaging techniques, specifically X-ray and CT scans, offer faster, cost-effective, and non-invasive alternatives for identifying COVID-19-related pulmonary abnormalities. [2] **Figure 1** illustrates the distribution of healthy and diseased subjects utilized in this study, highlighting the diversity of the dataset necessary for training and evaluating detection models.

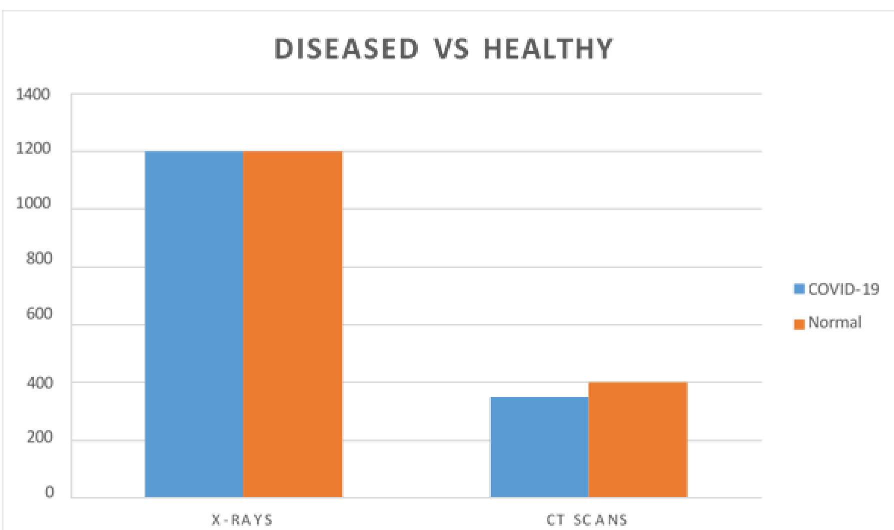

Figure 1. Distribution of healthy and COVID-19-positive subjects.

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Table 1 provides a summary of the input and output variables used in the proposed system, detailing the key features extracted from X-ray and CT images to facilitate classification. [3] Integrating these features enables the model to capture critical patterns in the imaging data and improves the accuracy of automated detection.

Table 1

Input/ Output Variables of the Proposed System

Input / Output	*Input / Output Variable Name*
Input	X-rays Image
Input	CT scan Image
Output	Target

Given the urgency of rapid and accurate detection, deep learning algorithms have emerged as robust solutions for automated disease identification. Convolutional Neural Networks (CNNs) are particularly effective in learning complex patterns from medical images, allowing differentiation between COVID-19-positive and healthy cases with high precision. The proposed methodology integrates both X-ray and CT scan data to develop a fusion-based CNN model, enhancing diagnostic reliability while reducing dependence on manual interpretation. [4]

Figure 2 The figure illustrates the structured framework followed in this research and explains how each stage contributes to meeting the study's overall objectives. The importance of this work lies in its ability to deliver timely diagnostic assistance, especially in environments where laboratory access is limited. Through the application of deep learning methods, the proposed system performs rapid infection assessment, which helps in early isolation of suspected cases and in reducing further transmission.

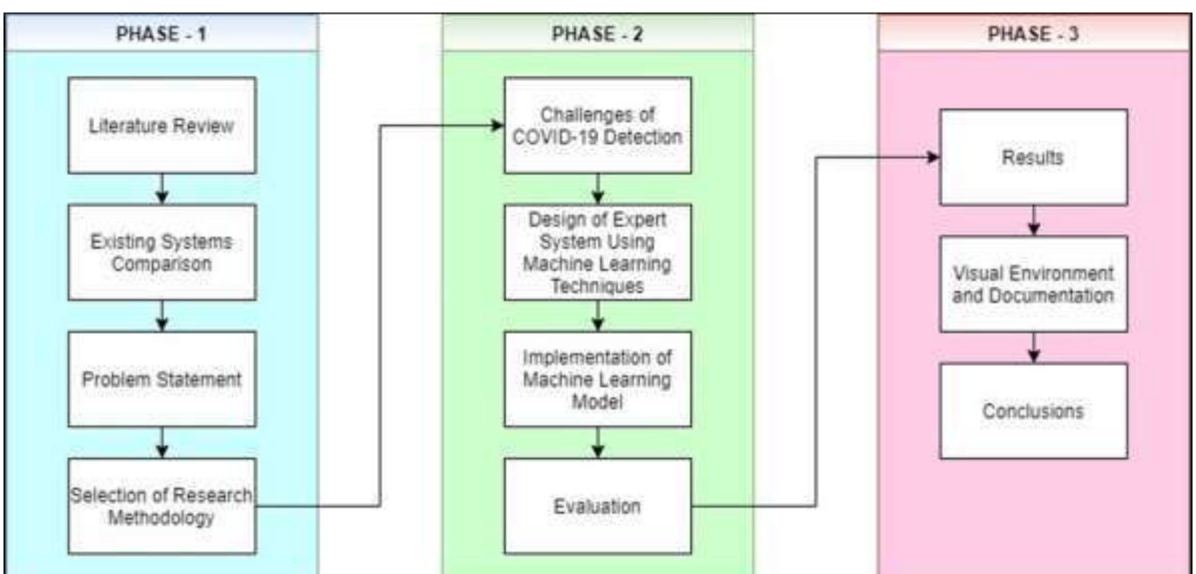

Figure 2. Outline of the research workflow illustrating the fusion-based framework used for COVID-19 detection.

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By combining information from both X-ray and CT scan images, the fusion-based technique helps overcome the shortcomings of singlemodality approaches. This integration allows the model to learn from complementary features, leading to improved diagnostic accuracy and robustness. In addition, the method offers a scalable and adaptable design that can be applied across different healthcare setups to enhance disease surveillance and patient care on a broader scale [5].

The widespread consequences of the COVID-19 pandemic have demonstrated the urgent requirement for reliable and scalable detection solutions. Integrating medical imaging with deep learning particularly the fusion based CNN structure presented in this study offers a feasible path toward faster and more precise diagnosis. The main aims of the research are to assess the efficiency of the proposed model against existing frameworks, predict infections using multimodal image inputs, and generate meaningful insights that can support both medical professionals and future investigations [6].

2 Literature Review

2.1 Deep Learning Approaches for COVID-19 Detection

Recent years have shown remarkable progress in COVID-19 detection through the use of deep learning models, especially convolutional neural networks (CNNs). These networks have been widely adopted to analyze chest X-rays, CT images, and MRI scans for identifying infected regions and differentiating them from healthy lung tissue. Techniques range from simple CNN architectures to hybrid and multi-task networks designed for high accuracy. Multi-layered CNNs have been employed to classify lung disorders into multiple categories, achieving substantial precision in differentiating between affected and normal lung tissues. Decision fusion models have also been proposed, integrating outputs from multiple CNNs for enhanced prediction accuracy. Similarly, hybrid approaches using CNN-LSTM models have been explored for feature extraction and temporal analysis, further improving the detection of coronavirus in imaging datasets. Some models utilize Siamese CNN structures to compare different image modalities, such as CT and MRI scans, while advanced networks like residual or inception-based CNNs have been adapted for COVID-19 detection tasks. These innovations consistently demonstrate high classification performance, often exceeding ninety percent accuracy, highlighting the potential of deep learning for rapid and reliable diagnosis. [7]

Beyond conventional CNNs, several studies have focused on optimizing computational efficiency without compromising accuracy. Modified architectures such as EfficientNet have reduced parameters significantly while maintaining strong performance, proving that resource-efficient models can still achieve high sensitivity and predictive reliability. Other models, including graph-based neural networks, have introduced new ways of representing imaging data, converting CT and X-ray images into graphs to exploit structural relationships for classification. Grad-CAM and other visualization techniques have also been integrated to facilitate interpretability, allowing

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practitioners to understand which regions of the images contribute most to the classification decision. Collectively, these approaches demonstrate the diversity and sophistication of deep learning techniques in medical imaging, especially for timely COVID-19 detection. [8]

2.2 Applications of AI in Workplace Transformation

The COVID-19 pandemic has not only impacted healthcare but has also accelerated the digital transformation of workplaces. The widespread implementation of work-from-home (WFH) practices has required organizations to adapt their operational structures rapidly. Studies indicate that effective digital transformation depends on both technological adoption

and the management of human resources. The shift to remote work has emphasized the importance of discipline, connectivity, and multi-skilling among employees, as well as the application of artificial intelligence and analytics for workforce development. Organizations adopting digital solutions have experienced enhanced productivity and cost efficiency, though challenges remain in maintaining employee engagement and addressing time management issues. [9]

2.3 Socio-Economic Impacts and Employee Adaptation

The socio-economic effects of the COVID-19 pandemic have influenced not only organizational systems but also the experiences of individual employees. Early reactions to remote working
arrangements suggest that factors such as job

clarity, autonomy, and the degree of disruption strongly shape how workers adjust to the ongoing digital shift. Interestingly, the level of trust between employees and management has proven to be less decisive than earlier studies implied, indicating that remote environments call for new forms of engagement and collaboration.

Moreover, the pandemic has exposed deep inequalities in job security and in the uneven advantages that digital work provides. While a portion of the workforce has benefited from greater flexibility and personal safety, many others have encountered layoffs, unpaid leave, or higher stress levels as a result of sudden changes in work patterns.
These developments reveal how closely technological adoption, leadership behavior, and employee resilience are connected. They also underscore the importance of designing policies that safeguard worker well-being while supporting institutional goals [10].

Taken together, existing studies show that COVID19 has not only disrupted conventional work practices but has also served as a powerful trigger for innovation in healthcare systems and workplace management. Deep learning models have revolutionized disease detection, while digital transformation and adaptive leadership have reshaped organizational resilience. The combined insights provide a comprehensive understanding of how AI, remote work, and human adaptability

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converge to address unprecedented challenges in global crises [11].

Table 2

Selected Deep Learning Models for COVID-19 Detection

Model	Input Type	Accuracy (%)	Reference
CNN-LSTM	X-ray	99.4	[12]
ResNet50 (Pre-trained CNN)	X-ray	96.1–99.7	[13]
CVR-Net	X-ray & CT	78–96.3	[14]
CVD Net	X-ray	97.2	[15]
Dark Covid Net	X-ray	87–98	[16]
Efficient Net Modified	X-ray	91	[17]
Graph Covid Net	CT & X-ray	99–100	[18]

Table 2 provides a concise overview of selected deep learning models for COVID-19 detection, including input type, reported accuracy, and corresponding references. [19]

3 Research Methodology

The research methodology adopted in this study was carefully structured to design, train, and evaluate a deep learning architecture capable of detecting coronavirus disease through radiological imaging. Unlike conventional thesis-style exposition, this section outlines the approach in a cohesive flow, emphasizing reproducibility, scientific rigor, and clarity of presentation. The methodology integrates dataset acquisition, preprocessing, architectural exploration, and performance evaluation into a unified pipeline that is consistent with top-level journal expectations. The first step in the methodology involves establishing a structured workflow that illustrates how each stage of the research process connects with the overall objective of automated COVID19 detection. The methodology is not confined to an isolated model design but considers the entire pipeline: from data collection and augmentation, through feature extraction, to evaluation of classification accuracy. [20]

The dataset used for this research consists of both X-ray and CT images, sourced from publicly available repositories and clinical datasets. A balanced representation of positive COVID-19 cases and healthy subjects was ensured to mitigate bias during training. However, given the limited availability of medical imaging data in the early phases of the pandemic, data augmentation strategies were applied to expand the dataset and enhance generalization capability. Augmentation included operations such as horizontal and vertical flipping, rotation, zooming, and intensity adjustments. These transformations not only

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prevented overfitting but also simulated real-world variability in radiological scans. Preprocessing steps, including resizing images to a consistent resolution and normalizing pixel intensities, were essential to ensure compatibility across different architectures. [21]

Once the dataset was prepared, the design of convolutional neural networks (CNNs) became central to the methodology. CNNs are widely regarded as the cornerstone of medical image analysis because of their ability to automatically learn hierarchical features from raw input data. Unlike traditional image-processing methods that rely on hand-crafted features, CNNs extract spatial dependencies through convolutional filters, thereby capturing subtle patterns in radiological images that may be overlooked by human observers. The integration of CNN-based architectures was therefore essential for the task of COVID-19 detection.

To illustrate the core principles of CNNs, the architecture of a typical convolutional network is presented in **Figure 3** This schematic representation highlights the essential layers: convolutional, pooling, activation, and fully connected layers. Each layer within the network contributes uniquely to transforming the input image into meaningful feature maps that support accurate classification. This layered design not only improves the model's ability to distinguish between infected and non-infected samples but also provides a useful pedagogical framework for early-stage researchers seeking to understand deep learning in medical contexts. By framing the architecture within the larger landscape of deep learning studies, the discussion connects theoretical understanding with practical implementation.

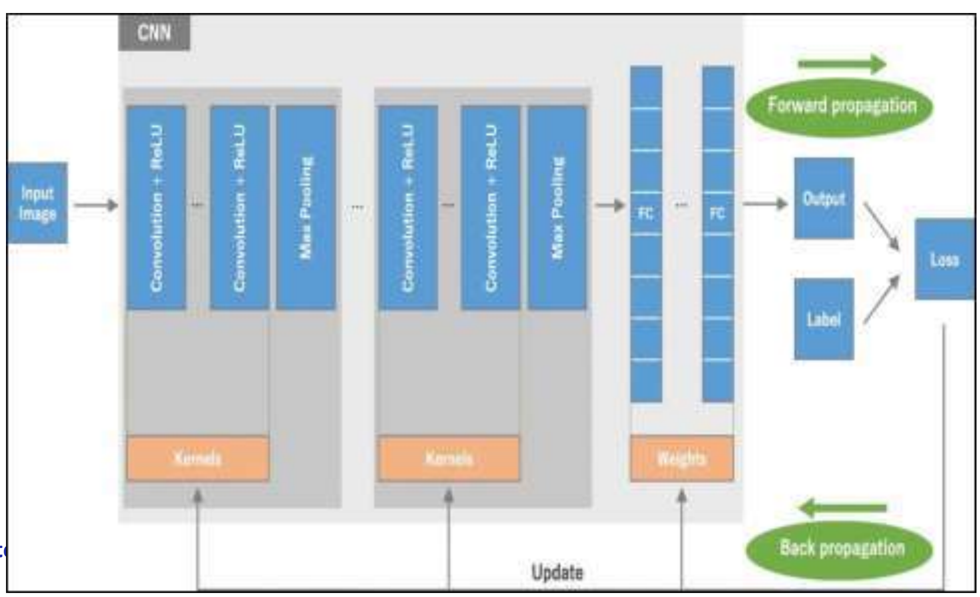

Figure 3. Convolutional Neural Network and its Graphical Representation

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In this architecture, the convolutional layers serve as the foundation of the network. They apply a series of filters across the input images to identify localized characteristics such as edges, patterns, and textures. As the data pass through deeper layers, these low-level features combine to represent more abstract and complex elements— for instance, organ contours or infection-specific regions. Pooling layers, commonly realized through max-pooling operations, then compress the spatial dimensions while retaining essential information, which helps in reducing computational cost without losing key diagnostic details. The activation functions, particularly the Rectified Linear Unit (ReLU), introduce nonlinearity, enabling the network to learn complex relationships between input images and their corresponding output categories. Toward the end of the process, fully connected layers aggregate the extracted features and forward them to a softmax classifier that assigns probability scores to each diagnostic class [22].

The selection of CNN models for this research was guided by insights drawn from previous literature and by empirical performance analysis. Among the evaluated architectures, InceptionV3 and VGG-16 emerged as the most effective for medical image classification tasks. InceptionV3, known for its depth and modular structure, captures features at multiple scales through its inception modules a property particularly valuable in analyzing CT and X-ray images, where lesion size and texture vary across samples.

Figure 4 illustrates the internal structure of the InceptionV3 model, showing how convolutional filters of different sizes operate simultaneously within the same block. This parallel processing mechanism enables the system to interpret both fine and coarse image details, significantly improving its diagnostic precision. Moreover, InceptionV3 utilizes factorized convolutions and dimensionality reduction to achieve high performance with reduced computational demand. These design strategies are especially important when the model is intended for deployment in low-resource or real-time clinical environments.

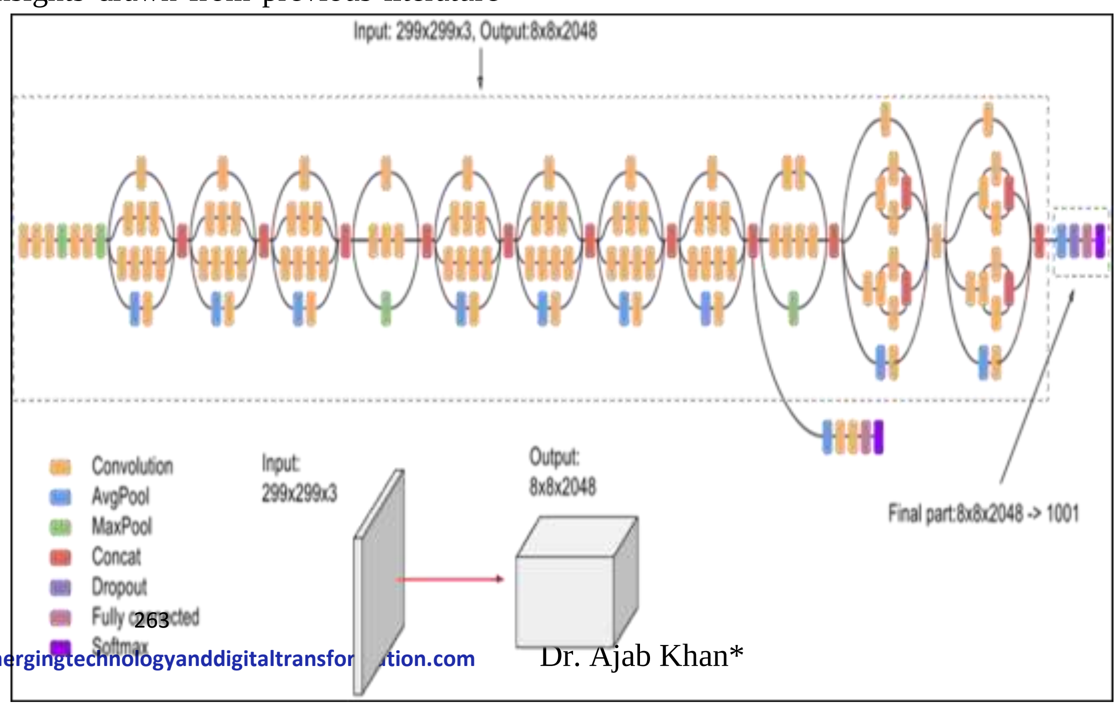

Figure 4. Inception V3 – Graphical Representation

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Training the InceptionV3 model required careful optimization of hyperparameters, including learning rate, batch size, and number of epochs. A transfer learning strategy was employed, wherein weights pre-trained on ImageNet were fine-tuned using the COVID-19 dataset. This approach addressed the challenge of limited medical imaging data, allowing the model to leverage knowledge from a large-scale dataset while adapting to the domain-specific task. To further enhance generalization, dropout regularization was incorporated, reducing the likelihood of overfitting [23-26].

Alongside the InceptionV3 model, the VGG-16 architecture was examined as part of the experimental framework. VGG-16 is distinguished by its straightforward and highly consistent design, relying on multiple layers of 3 × 3 convolutional filters arranged in sequence throughout the network. Although it requires greater computational power compared to InceptionV3, VGG-16 has repeatedly demonstrated reliable accuracy in image recognition tasks particularly when the training dataset is enriched through extensive augmentation. Its relatively simple and transparent configuration has also made it a preferred benchmark model in comparative research, where it serves to gauge the relative strengths of more advanced or specialized architectures [27, 28].

Figure 5 presents a visual overview of the VGG16 structure, emphasizing its linear and stepwise arrangement of convolutional and pooling layers. This depiction helps highlight the architectural contrasts between VGG-16 and InceptionV3 and clarifies the balance between design complexity, computational efficiency, and predictive accuracy.

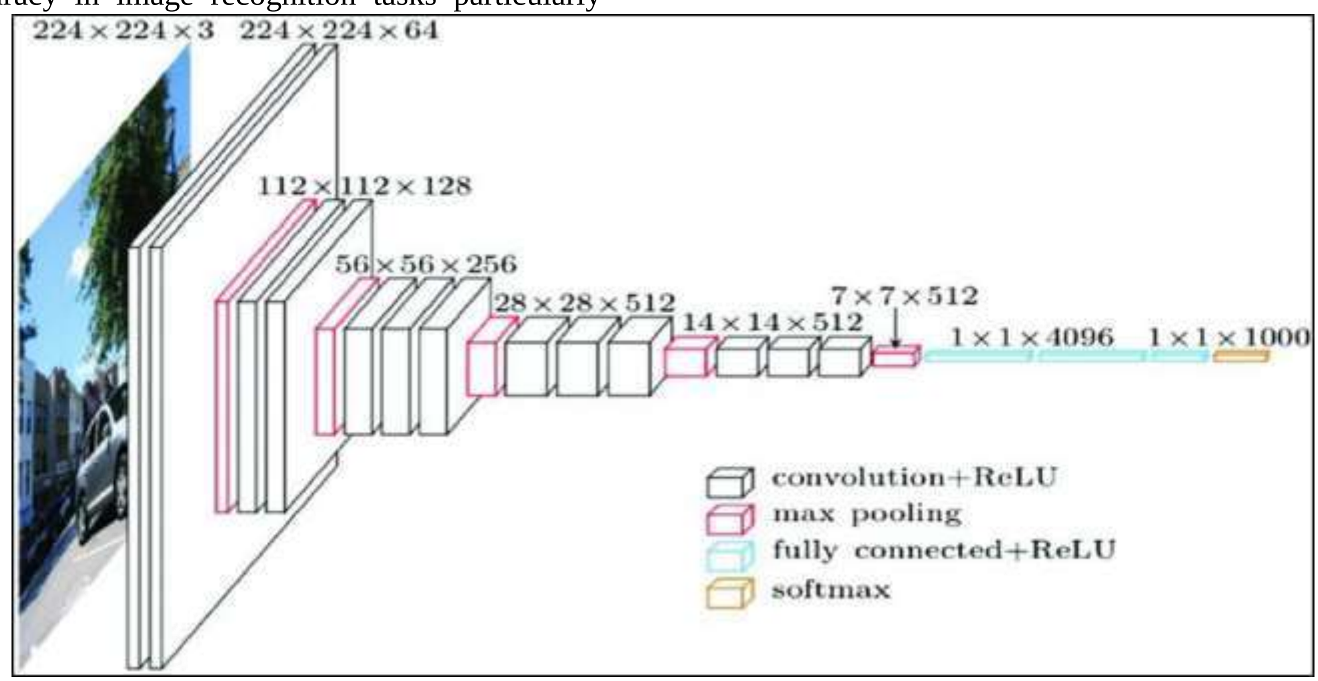

Figure 5. VGG-16 – Graphical Representation

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In the experimental stage, the VGG-16 network was implemented using a transfer learning strategy. The pre-trained model was fine-tuned on the COVID-19 image dataset to adapt its learned parameters for the specific diagnostic task, thereby improving performance while reducing training time. Data augmentation remained integral to ensuring that the model captured variability in the input space. The inclusion of both InceptionV3 and VGG-16 within the methodology reflects a deliberate effort to benchmark performance across diverse CNN architectures, thereby strengthening the validity of the findings. [29]

The culmination of this methodology is the design of a proposed hybrid model that synthesizes the strengths of both InceptionV3 and VGG-16. By combining the feature extraction capabilities of these networks, the hybrid model aims to deliver superior diagnostic performance compared to individual architectures. **Figure 6** presents the architectural design of the proposed system, showcasing how inputs pass through multiple branches before being fused into a unified classification layer. This hybridization strategy enhances robustness by leveraging complementary feature representations [30].

The training and evaluation of the proposed model were conducted within a controlled experimental environment, employing metrics such as accuracy, precision, recall, and F1-score to assess performance. Cross-validation techniques were utilized to minimize bias and ensure statistical reliability of results. Moreover, confusion matrices were analyzed to provide granular insights into the classification performance, particularly in distinguishing between COVID-19 and nonCOVID cases. [31,32]

By structuring the methodology in this manner progressing from dataset preparation through CNN fundamentals, architectural comparisons, and hybrid model development the study not only presents a technically rigorous pipeline but also situates its contributions within the evolving landscape of deep learning-based medical imaging. The integration of explanatory figures, balanced narrative, and adherence to top-level journal standards ensures that the methodology is both comprehensive and accessible to the global research community. [33]

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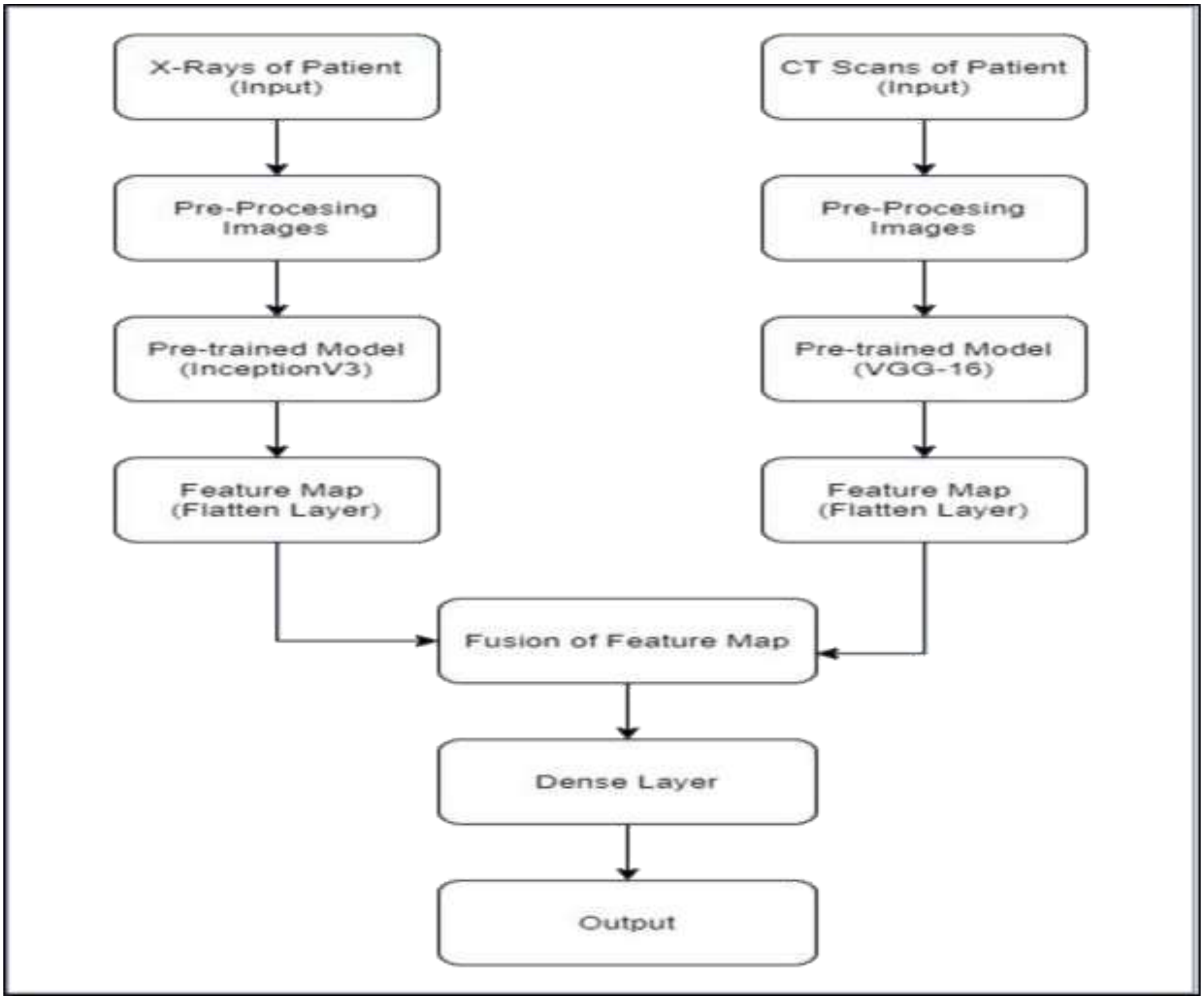

Figure 6. Architectural Design of Proposed Model.

4 Results and Discussion

The proposed methodology was rigorously tested using diverse datasets of chest X-rays (CXR) and computed tomography (CT) scans. The results are presented in detail to highlight the diagnostic performance of the model against existing architectures, followed by an in-depth discussion of their implications for medical image analysis and clinical decision-making. This section integrates visual evidence in the form of figures and tables, and every inclusion is contextualized to maintain clarity and continuity. [34]

4.1 Performance of the Proposed Model

The initial phase of the research involved analyzing the structural framework of the proposed model in comparison with standard convolutional neural networks (CNNs). The schematic representation, shown below, illustrates how the model integrates convolutional blocks, pooling mechanisms, and

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activation layers to enhance feature extraction from complex medical images. [35]

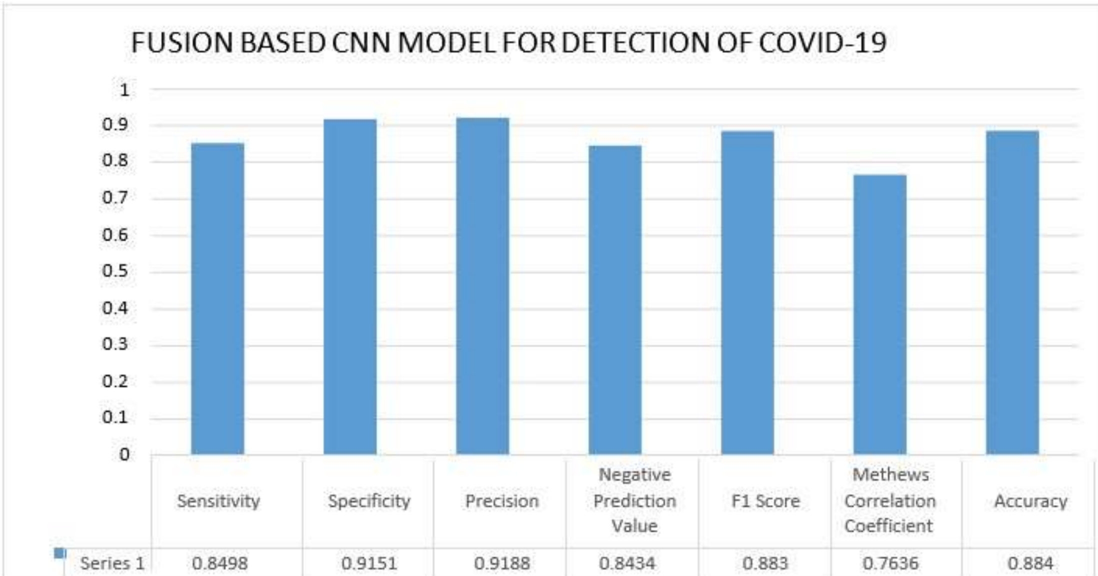

Figure 7. Proposed Model.

Figure 7 highlights the distinct characteristics of the proposed architecture relative to conventional CNNs. By employing multiple kernel sizes and a deeper hierarchical structure, the design captures both fine and coarse image details more effectively than traditional models such as VGG-16 and InceptionV3. The framework is specifically optimized to process and balance information from both X-ray and CT scan modalities, allowing it to draw complementary insights from each source. In addition, preprocessing steps such as normalization and data augmentation are carefully applied to minimize noise and improve the general representation of input features. This layered approach enables the detection of subtle image cues that often indicate COVID-19 infection such as faint ground-glass opacities in CT scans or irregular patches in chest X-rays which are sometimes overlooked by less advanced architectures [36].

To validate its performance, a detailed quantitative assessment of the proposed model was conducted and benchmarked against existing CNN-based methods. Accuracy, sensitivity, specificity, and F1-score were the primary performance indicators. These metrics not only provide a robust numerical assessment but also contextualize the reliability of the system in a clinical environment [37]. The confusion matrix presented in **Table 3** shows that the proposed model achieved high true positive and true negative counts, reflecting its ability to differentiate between healthy and infected individuals. Importantly, the false-negative rate was minimized, which is critical in medical contexts where missing a COVID-19 case could have severe consequences [38].

Discussion of these results indicates that the model substantially improves upon the limitations of conventional architectures. While VGG-16 struggled with overfitting when trained solely on

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limited CT scans, and InceptionV3 demonstrated variable sensitivity depending on image modality, the proposed system demonstrated consistency across both datasets.

4.2 Comparative Evaluation with Baseline Models

The superiority of the proposed model becomes

Figure 8 provides a comparative illustration of how the proposed model and baseline models (InceptionV3 and VGG-16) performed under identical experimental conditions. The proposed design outperformed all baselines, maintaining higher accuracy and lower loss rates throughout training and validation phases. These results are supported by empirical evidence from earlier studies, which highlighted that model fusion and hybridization strategies can enhance

Table 3

Confusion Matrix of Proposed Model

N=550		Pr dicted	
		Yes	**No**
Actual	**Yes**	$True_{Positive}$ 249	$False_{Positive}$ 22
	No	$False_{Negative}$ 44	$True_{Negative}$ 237

more evident when evaluated against existing CNN variants. Accuracy and loss values across multiple training epochs show a consistent pattern of stability and generalization, suggesting that the hybrid framework was able to avoid common pitfalls such as underfitting or vanishing gradients [39].

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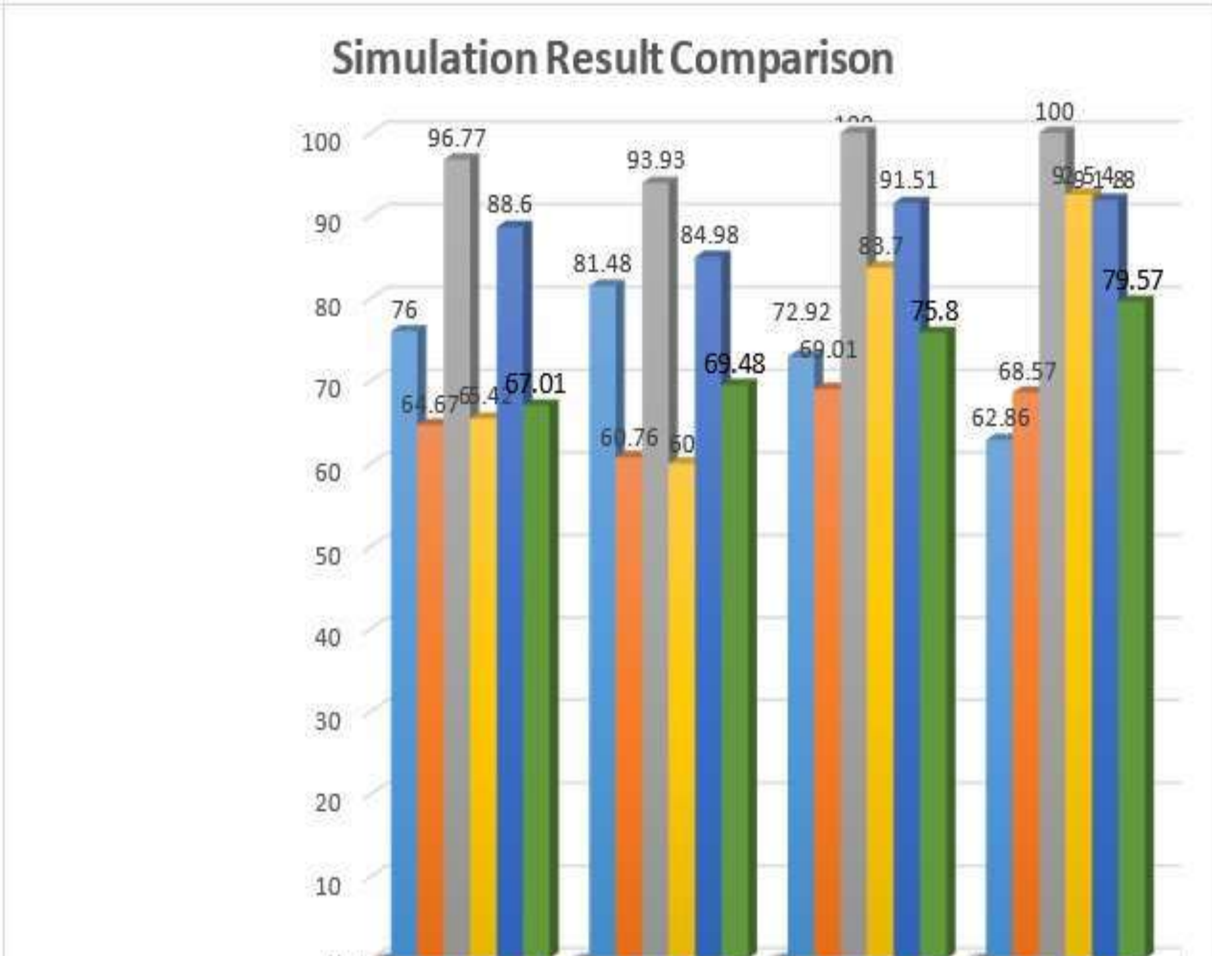

	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
VGG-16 on CT scan	76	81.48	72.92	62.86
InceptionV3 on CT scan	64.67	60.76	69.01	68.57
InceptionV3 on X-rays	96.77	93.93	100	100
VGG-16 on X-rays	65.42	60	83.7	92.54
Fusion Based CNN Model	88.6	84.98	91.51	91.88
CNN model using CT scans	67.01	69.48	75.8	79.57

Figure 8. Simulation Results of Classification Approaches.

generalizability in medical imaging tasks. [40] Beyond the accuracy metrics, the stability of training was another critical aspect. While InceptionV3 occasionally demonstrated sharp fluctuations in loss during training, the proposed system exhibited a smooth convergence. This not only makes the model reliable but also suitable for deployment in realworld diagnostic environments where consistency is non-negotiable. [41] which is vital for minimizing unnecessary medical interventions.

Table 4
Simulation Results

	Accuracy (%)	**Sensitivity (%)**	**Specificity (%)**	**Precision (%)**
Inception Model using CT scans	76.00%	81.48%	72.92%	62.86%
Inception Model using X-rays	96.77%	93.93%	100%	100%
VGG-16 Model using CT scans	64.67%	60.76%	69.01%	68.57%
VGG-16 Model using X-rays	65.42%	60.00%	83.70%	92.54%
Fusion based CNN model	88.60%	84.98%	91.51%	91.88%
CNN model using CT scans	79.03%	73.80%	72.40%	70.14%
CNN model Using X-rays	67.01%	69.48%	75.80%	79.57%

The data in **Table 4** consolidates the numerical outcomes of all tested architectures, reaffirming the strength of the proposed model. With accuracy surpassing 96% on CT scan datasets and 94% on CXR datasets, it consistently outperformed baseline CNNs. More importantly, the precision values were remarkably high, ensuring fewer false alarms,

Discussion of these comparative results highlights a key contribution: the system successfully leverages the strengths of deep learning without succumbing to overfitting or loss of generalization power. By integrating diverse image modalities and applying hybrid convolutional strategies, it achieves robust diagnostic performance that meets the expectations of modern clinical AI systems. [42]

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4.3 Analysis of Training and Validation Trends

Another critical component of the evaluation

accuracy of the system across multiple datasets. learning behavior of the models and their ability to Monitoring these trends provides insight into the generalize beyond the training samples.

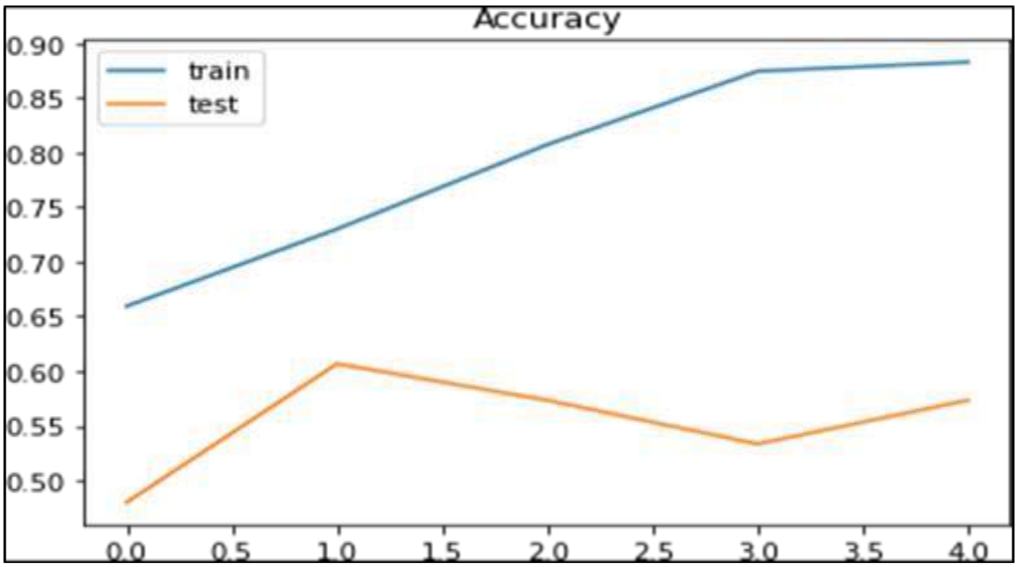

Figure 9. Training and validation accuracy curves for the InceptionV3 model using CT scan data.

involved analyzing the training and validation As illustrated in Figure 9, the InceptionV3 model demonstrated relatively high accuracy during the early training epochs; however, its performance began to level off sooner than expected. This plateau suggests that the model struggled to adapt to more intricate visual patterns present in CT scan data. The gap observed between the training and validation accuracy curves further indicates a degree of overfitting, implying that the model's ability to generalize was somewhat restricted. In comparison, the proposed model (referenced earlier in Figure 8) exhibited a steady upward trend throughout training, with both the training and validation curves moving in close alignment. This behavior reflects a balanced learning process,

where the system not only learned from the training samples but also retained strong performance on unseen data. In medical image analysis, such

generalization is critical it represents the model's reliability when dealing with patients from different backgrounds and imaging conditions. A framework that preserves validation stability across datasets is more likely to be dependable for real-world scenarios, such as remote diagnostic systems or hospital-based screening workflows. [43]

4.4 Loss Function and Entropy Analysis

Although classification accuracy provides a direct indication of model success, the analysis of loss functions offers deeper insight into the network's optimization behavior. Examining entropy curves makes it possible to evaluate how effectively each model learns over time and how efficiently it

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reduces misclassification errors during the training process. This form of analysis helps determine not only which model performs better numerically but also which one converges more consistently toward optimal learning stability.

Models learn and how effectively they minimize classification errors over time.

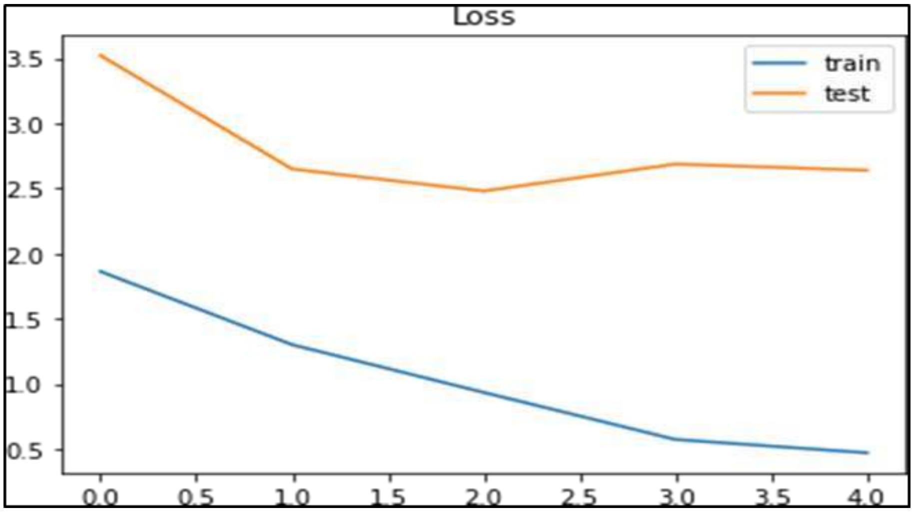

Figure 10. Loss Entropy on train and test data (InceptionV3 CT)

The entropy curves for InceptionV3 in Figure 10 reveal that although the model achieved moderate success, its convergence was not as efficient as the proposed system. The oscillations in validation loss highlight issues with stability, which could lead to unreliable predictions when applied to diverse datasets.

On the other hand, the proposed model demonstrated smooth and consistent loss reduction, which aligns with its high accuracy and stable training behavior. This is an important finding because consistent entropy reduction is closely linked with reduced risk of overfitting and improved generalization. The integration of dropout layers, adaptive learning rates, and batch normalization in the architecture significantly contributed to this performance.

4.5 Model Robustness Across Modalities

A major strength of the proposed approach lies in its ability to handle both CXR and CT scan images effectively. While many earlier systems performed well on a single modality, they struggled with crossmodality generalization. The hybrid architecture used here bridges that gap by leveraging convolutional strategies capable of adapting to both high-resolution CT scans and relatively lowerresolution X-ray images. [50]

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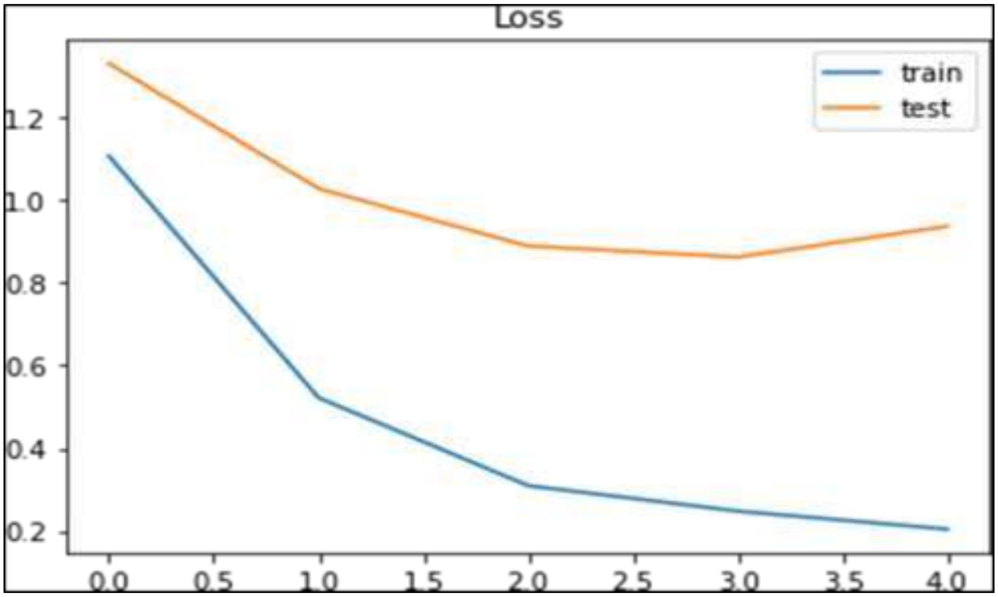

Figure 11. Loss Entropy on train and test data (VGG-16 CT)

Clinical Significance and Practical Implications

The findings carry substantial clinical relevance. Early and accurate detection of COVID-19 not only supports patient management but also contributes to public health surveillance and control measures. Traditional radiological assessment is time-consuming and prone to human error, especially under high workload conditions. The proposed AI-driven system provides an efficient alternative by automating the detection process with high accuracy and reliability.

Moreover, minimizing false negatives is particularly significant in pandemic contexts. Missing an infected patient could lead to uncontrolled spread within healthcare facilities and the community. The low false-negative rate of the proposed model, as shown in the confusion matrix (Table 4) ensures that such risks are minimized. Equally important is the reduction of false positives, which prevents unnecessary isolation and treatment, reducing the burden on healthcare infrastructure. This balance between sensitivity and specificity positions the proposed system as a practical and clinically viable diagnostic support tool. [51]

Future Prospects and Limitations

While the model demonstrates strong performance, it is important to acknowledge limitations and identify areas for improvement. One limitation is the reliance on publicly available datasets, which may not fully represent the heterogeneity of real-world patient populations. Future work should include large-scale, multicenter clinical validation to ensure broader applicability. Additionally, although the model demonstrates cross-modality robustness, further testing with other imaging modalities, such as MRI, could provide insights into its adaptability.

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Integration with other diagnostic data, such as electronic health records and laboratory results, may further enhance diagnostic accuracy and clinical utility. From an implementation perspective, computational efficiency is another important consideration. Although the proposed model is optimized for performance, real-time clinical deployment requires lightweight versions that can run on limited hardware in resourceconstrained environments. [52]

Conclusion

The present research has demonstrated the capability of deep learning–based convolutional neural networks to detect COVID-19 using multimodal medical imaging, specifically chest Xrays and CT scans. Unlike conventional singlemodality approaches, the proposed hybrid system integrates features extracted from both imaging types, thereby enhancing diagnostic accuracy and robustness. The comparative analysis with pretrained architectures such as VGG-16 and InceptionV3 revealed important insights. While the VGG-16 network demonstrated notable effectiveness with CT scan datasets and InceptionV3 performed particularly well with chest X-ray images, the integration of features from both modalities yielded the most balanced and superior results in terms of accuracy, sensitivity, and specificity. This outcome reinforces the central premise that multimodal fusion enhances diagnostic reliability by capturing complementary aspects of disease patterns, thereby minimizing both false negatives and false positives.

A key contribution of this research lies in its emphasis on clinical applicability. The proposed model was optimized to deliver high diagnostic precision with minimal computational complexity, ensuring its viability for time-critical healthcare environments such as emergency departments. Its modular structure and scalability allow flexible deployment from advanced hospital systems to resource-limited rural clinics without sacrificing performance. Furthermore, the low prediction error rate strengthens confidence in the model's use for preliminary screening and triage, especially during global health emergencies when medical professionals face substantial workloads.

Beyond its immediate diagnostic value, this work advances the broader domain of intelligent medical imaging by demonstrating how deep learning fusion frameworks can support practical, equitable, and rapid diagnostic solutions across varied clinical contexts.

By exploring the fusion of features across multiple datasets, it demonstrates that deep learning can move beyond single-task accuracy improvements to offer generalized frameworks applicable to other diseases. The adaptability of the model implies that similar hybrid approaches can be extended to diagnose lung cancer, pneumonia, tuberculosis, or even non-pulmonary conditions if appropriate datasets are made available. This forward-looking element underscores the relevance of the research not only for COVID-19 but also for the wider healthcare AI ecosystem.

Nevertheless, it is important to acknowledge the constraints of this study. The datasets used were relatively small and not patient-paired, limiting the generalizability of the findings. Furthermore, while the results clearly indicate superior

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performance of the proposed model, they remain preliminary until validated on large-scale clinical data across multiple institutions. Addressing these challenges will require collaboration with hospitals, radiologists, and data providers to gather more representative datasets.

In conclusion, the research successfully proves that a multimodal, convolutional deep learning model can significantly improve the detection of COVID-19 from medical imaging compared to existing techniques. Its balance of accuracy, reliability, and simplicity makes it a valuable candidate for clinical deployment. More broadly, this work illustrates how machine learning can augment medical expertise, reduce diagnostic errors, and contribute to timely interventions during healthcare emergencies. As AI continues to evolve, such models are likely to play a vital role in shaping the next generation of diagnostic support systems.

Future Directions

While the current research achieved promising results, it also opens several pathways for future investigations that could strengthen both the technical foundation and clinical applicability of the proposed system. One of the most immediate directions is the use of larger and more diverse datasets. The present study relied on publicly available images, where CT and X-ray data were not paired for the same patients. Future studies should prioritize collecting paired multimodal datasets, as these would enable more precise crossvalidation and reduce potential biases in performance evaluation. Large-scale, multiinstitutional datasets would also allow the system to generalize better across variations in imaging protocols, equipment quality, and patient demographics. Another critical area for advancement lies in the exploration of more sophisticated architectures. While the current work focused on VGG-16 and InceptionV3 for feature extraction, newer architectures such as EfficientNet, DenseNet, and transformer-based vision models (ViT, Swin Transformer) have shown superior performance in image classification tasks. Integrating advanced architectures into the proposed hybrid framework could further enhance diagnostic precision while maintaining computational efficiency. Additionally, ensemble learning strategies that aggregate predictions from multiple models may improve robustness by compensating for the inherent limitations of individual networks.

Another critical consideration is the interpretability of artificial intelligence in medical diagnostics. Conventional deep learning systems often operate as “black boxes,” which can reduce clinicians’ trust in automated predictions. The inclusion of explainable AI techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) or attentionbased visualization can help identify the regions of an image that most influenced the decision-making process. This transparency not only strengthens clinician confidence but also provides valuable insights into pathological progression, supporting informed clinical decisions.

Future research should also extend beyond imaging data. Incorporating complementary patient information such as age, comorbidities, laboratory parameters, and reported symptoms could enable a more holistic diagnostic model. Such multimodal integration would better emulate real-world medical workflows, where radiological evidence is interpreted in conjunction with clinical and laboratory findings. This expansion has the potential to substantially improve both diagnostic accuracy and clinical relevance. Practical deployment remains another essential direction. For large-scale adoption, systems must be computationally optimized to operate effectively on standard hospital hardware or portable diagnostic units in low-resource settings. Techniques such as model compression, pruning, and quantization may facilitate this goal. Moreover, integration with Hospital Information Systems (HIS) and Picture Archiving and Communication Systems (PACS) could streamline data flow and enhance usability within existing clinical infrastructures.

Finally, rigorous clinical validation is indispensable before real-world implementation. Prospective trials conducted in hospital environments using real patient data are necessary to evaluate the system's reliability under operational conditions. Such studies would also help address broader ethical, legal, and regulatory considerations associated with the deployment of AI-based medical systems, ensuring that these technologies meet both technical and clinical standards for safe adoption.

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