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Article

Automated COVID-19 Multiclass Detection Using Pretrained Deep Learning Models

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Abstract: The rapid spread of COVID-19 has highlighted the urgent need for accurate and efficient diagnostic systems to support clinical decision-making. This study proposes an automated multiclass detection framework for distinguishing COVID-19, pneumonia, and normal cases using chest X-ray images and pretrained deep learning models. Leveraging transfer learning, state-of-the-art convolutional neural networks such as ResNet50, VGG16, and MobileNet are employed to extract high-level features from medical imaging data, reducing the dependency on large annotated datasets and extensive training time. The proposed system involves preprocessing steps including image resizing, normalization, and data augmentation to improve model generalization. The pretrained models are fine-tuned on a labeled chest X-ray dataset to perform three-class classification. Performance evaluation is conducted using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. Experimental results demonstrate that the proposed approach achieves high classification accuracy and effectively differentiates between COVID-19, pneumonia, and normal conditions. Furthermore, the use of pretrained models enhances computational efficiency while maintaining robust performance, making the system suitable for real-time clinical applications. This automated framework can assist radiologists in early detection and screening, thereby reducing diagnostic workload and improving patient outcomes. The study emphasizes the potential of deep learning-based solutions in advancing intelligent healthcare systems for infectious disease diagnosis.
Keywords: NA

1. INTRODUCTION

The outbreak of COVID-19 created an unprecedented global health crisis, placing immense pressure on healthcare systems worldwide. Rapid and accurate diagnosis became critical to control the spread of infection and provide timely treatment. While laboratory-based methods such as RT-PCR remain the gold standard for COVID-19 detection, they often involve longer processing times and require specialized equipment. In contrast, chest imaging techniques like X-rays offer a faster and more accessible alternative for initial screening, especially in resource-constrained environments.

Chest X-ray imaging has been widely used for detecting respiratory diseases such as pneumonia and lung infections. However, differentiating between COVID-19, pneumonia, and normal lung conditions through manual interpretation can be challenging even for experienced radiologists due to overlapping visual patterns. This limitation highlights the need for automated diagnostic systems that can assist clinicians in making accurate and consistent decisions. The integration of artificial intelligence into medical imaging has opened new avenues for improving diagnostic efficiency and reducing human error. Recent advancements in Deep Learning, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in image classification tasks. These models are capable of learning complex features directly from raw images, making them highly suitable for medical image analysis. However, training deep neural networks from scratch requires large annotated datasets and significant

computational resources, which are often limited in the medical domain. To address this challenge, transfer learning techniques using pretrained models have gained significant attention.

Pretrained deep learning models such as ResNet50, VGG16, and MobileNet have been successfully applied to various medical imaging tasks. These models are initially trained on large-scale datasets and can be fine-tuned for specific applications, enabling efficient feature extraction and improved classification accuracy even with limited data. By leveraging these architectures, it becomes possible to develop robust systems for multiclass classification of chest X-ray images into COVID-19, pneumonia, and normal categories.

This study focuses on designing an automated multiclass detection framework using pretrained deep learning models to classify chest X-ray images. The proposed approach aims to enhance diagnostic accuracy, reduce processing time, and support healthcare professionals in clinical decision-making. By combining transfer learning with effective preprocessing and evaluation techniques, the system seeks to provide a reliable and scalable solution for early detection of respiratory diseases, ultimately contributing to improved patient outcomes and healthcare efficiency [1,2,3].

2. RELATED WORK

Recent advancements in deep learning have significantly contributed to automated diagnosis of respiratory diseases using chest X-ray images. Several studies have explored multiclass classification frameworks to distinguish between COVID-19, pneumonia, and normal cases. For instance, Mohan et al. (2024) proposed a multiclass deep learning model that classifies chest X-ray images into COVID-19, pneumonia, and healthy categories. Their convolutional neural network (CNN)-based approach achieved an accuracy of approximately 97%, demonstrating the effectiveness of deep learning in medical image classification tasks.

Transfer learning has been widely adopted to overcome the limitation of small medical datasets. El Houby (2024) introduced a deep learning framework using pretrained models such as VGG19 and EfficientNet for COVID-19 detection from chest X-rays. The study incorporated preprocessing techniques like image enhancement and segmentation, achieving a classification accuracy of around 93.5% for multiclass tasks. This work highlights the importance of pretrained architectures in improving performance while reducing computational cost.

Further advancements have been made in extending multiclass classification to include additional lung diseases. A recent study published in 2025 proposed a CNN-based architecture capable of detecting COVID-19, tuberculosis, pneumonia, and normal conditions from chest X-ray images. The authors addressed dataset imbalance issues and demonstrated that deep learning models can effectively generalize across multiple respiratory diseases, making them suitable for real-world clinical applications. In addition, hybrid and dual-modality approaches have been explored to enhance diagnostic accuracy. Arvind et al. (2026) developed a deep learning framework that combines chest X-ray and CT scan images for improved COVID-19 detection. Their model utilized balanced datasets and demonstrated improved robustness in distinguishing COVID-19 from pneumonia and normal cases. Such multimodal systems provide better feature representation and improve classification reliability.

Several studies have also focused on improving model performance using advanced techniques such as data augmentation, generative models, and hybrid CNN architectures. Thilagavathi et al. (2025) proposed a hybrid deep learning framework with enhanced preprocessing techniques to improve classification accuracy. Similarly, Zhang et al. (2025) combined transfer learning with deep CNN models to achieve high-performance COVID-19 recognition, emphasizing the role of feature extraction and fine-tuning in achieving robust results.

Moreover, survey-based research highlights that deep learning models, particularly CNNs and transfer learning architectures, have become the dominant approach for pneumonia and COVID-19 detection. These models outperform traditional machine learning techniques by automatically learning hierarchical features from medical images, leading to improved diagnostic accuracy and efficiency.

3. PROPOSED SYSTEM

The presented architecture illustrates a comprehensive deep learning framework designed for automated multiclass detection of COVID-19, pneumonia, and normal cases using chest X-ray images. The workflow is structured in a sequential pipeline, beginning with data collection and progressing through preprocessing, feature extraction, model training, and final prediction. Each stage is visually separated and color-coded to enhance clarity, making the system easy to interpret for both technical and non-technical audiences. The overall flow of the system is illustrated in Figure 1.

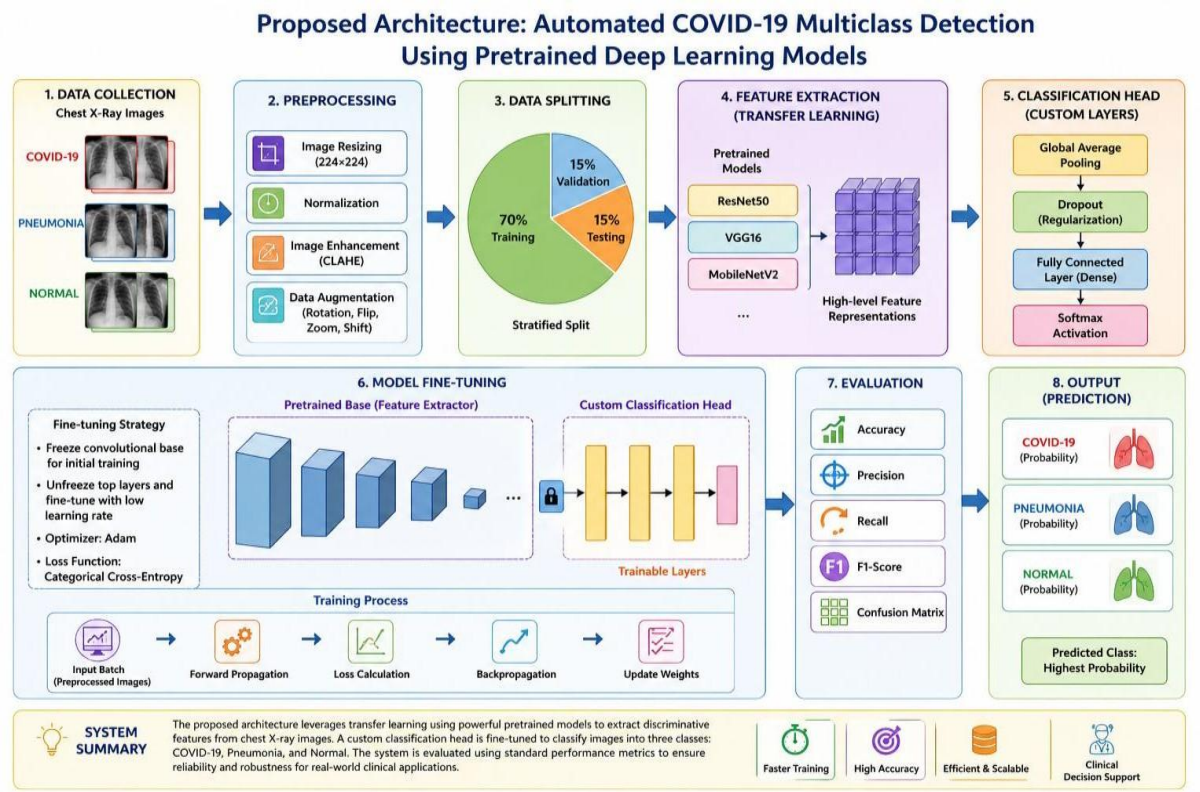

Figure 1: Proposed Architecture of COVID-19 Diseases.

The first stage focuses on data collection, where chest X-ray images are gathered and categorized into three classes: COVID-19, pneumonia, and normal. This section emphasizes the importance of labeled datasets in supervised learning. Representative X-ray images for each class are shown, helping to visually distinguish between different lung conditions and highlighting the dataset diversity required for robust model training.

The second stage involves data preprocessing, which prepares raw images for model input. Key operations include image resizing (typically to 224×224 pixels), normalization to scale pixel values, image enhancement techniques such as CLAHE (Contrast Limited Adaptive Histogram Equalization), and data augmentation methods like rotation, flipping, zooming, and shifting. These steps improve image quality, increase dataset variability, and help prevent overfitting.

Next, the architecture moves to data splitting, where the dataset is divided into training, validation, and testing sets. The diagram shows a typical distribution of 70% training, 15% validation, and 15% testing. This stratified split ensures that the model learns effectively while maintaining fairness and generalization during evaluation. The pie chart representation visually reinforces the proportion of each dataset segment.

The fourth stage highlights feature extraction using transfer learning. Pretrained deep learning models such as ResNet50, VGG16, and MobileNetV2 are utilized to extract high-level features from input images. These models, trained on large datasets, can capture complex patterns in medical images. The architecture shows feature maps being generated, indicating how deep networks transform raw images into meaningful representations.

The fifth stage introduces the classification head, which consists of custom layers added on top of the pretrained models. This includes global average pooling to reduce feature dimensions, dropout layers for regularization, fully connected (dense) layers for learning class-specific patterns, and a softmax activation function for multiclass probability output. This section is critical as it adapts the pretrained features to the specific classification task.

The sixth stage focuses on model fine-tuning and training strategy. Initially, the pretrained layers are frozen to preserve learned features, and later selectively unfrozen for fine-tuning with a low learning rate. The training process includes forward propagation, loss calculation using categorical cross-entropy, backpropagation, and weight updates using an optimizer like Adam. This step ensures optimal model performance while avoiding overfitting.

Finally, the architecture concludes with evaluation and output prediction. Performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix are used to assess the model. The output section displays probability scores for each class (COVID-19, pneumonia, normal), with the highest probability determining the predicted class. The system summary emphasizes key benefits such as faster training, high accuracy, scalability, and its role as a clinical decision support tool.

4. RESULTS AND DISCUSSIONS

DATASET

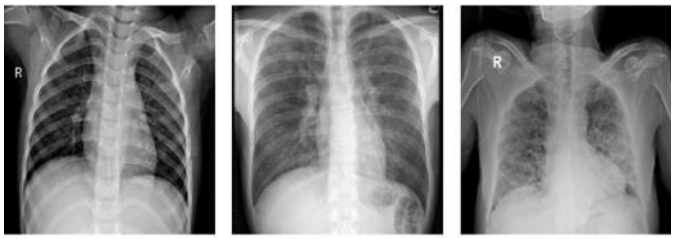

Figure 2: COVID-19 Dataset.

The provided image illustrates a sample of the dataset used to train and test the various models, showcasing chest X-rays categorized into three distinct classes: Normal, Pneumonia, and COVID-19. This visual data serves as the foundation for the classification task, providing the raw features—such as lung opacity, consolidation, and texture—that the neural networks must learn to interpret.

The "Normal" scan in image (a) represents the baseline for a healthy respiratory system. In this sample, the lung fields appear clear and dark, indicating proper aeration without significant obstruction or fluid. The heart's silhouette and the ribs are clearly defined, offering a sharp contrast that the models use to identify a patient who does not have an active pulmonary infection.

Image (b) displays a "Pneumonia" case, which typically features localized areas of increased density known as "clouding" or "consolidation." These white patches indicate where fluid or inflammation is present in the lung tissue. For an AI model, the challenge is to distinguish these specific patterns of bacterial or viral infection from the more diffuse markings seen in other respiratory illnesses.

The "COVID-19" scan in image (c) often exhibits more widespread and bilateral abnormalities compared to standard pneumonia. This sample shows the characteristic "ground-glass opacities"—hazy, white areas that appear across larger portions of both lungs. These complex visual patterns are what necessitated the use of advanced architectures like the Proposed CNN to achieve higher diagnostic accuracy.

Overall, this dataset provides the essential variety of pathological features required for a robust comparative study. By training on these diverse X-ray samples, the models—ResNet50, VGG16, and the Proposed CNN—are forced to develop sophisticated filters to detect subtle differences in lung density. This data is the direct source of the performance metrics and confusion matrices analyzed in the previous steps of this research.

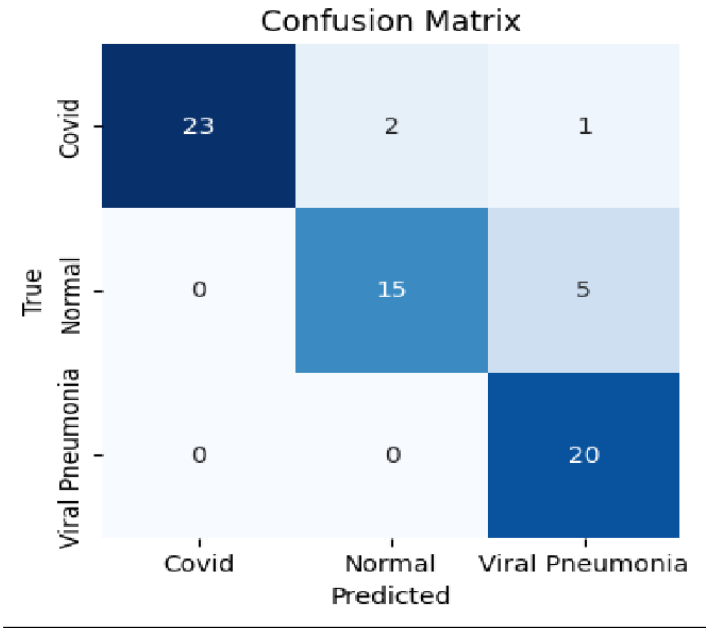

Figure 3: Proposed CNN Confusion matrix.

The provided image displays a confusion matrix used to evaluate a machine learning model designed to classify medical images into three categories: Covid, Normal, and Viral Pneumonia. This specific visualization compares the actual "True" labels of the data against the "Predicted" labels generated by the model. By looking at where the numbers fall, we can pinpoint exactly how well the model distinguishes between these respiratory conditions.

The diagonal line of dark blue cells, running from the top-left to the bottom-right, represents all the correct predictions made by the model. In this instance, the model successfully identified 23 cases of Covid, 15 Normal cases, and 20 cases of Viral Pneumonia. These "True Positives" indicate that the model has a strong baseline capability for recognizing the unique characteristics of each class.

Errors in classification are found in the off-diagonal, lighter-colored cells, which represent cases where the model was "confused." For example, among actual Covid patients, the model incorrectly labeled two as Normal and one as Viral Pneumonia. These are known as false negatives, representing missed diagnoses that could be critical in a real-world clinical setting.

The most significant area of confusion occurs between the Normal and Viral Pneumonia categories. While the model correctly identified 15 Normal cases, it mislabeled 5 other Normal cases as having Viral Pneumonia. This suggests that the visual features the model uses to identify pneumonia may sometimes overlap with the features of a healthy lung, leading to a higher rate of "false alarms" for that specific condition.

In summary, the model shows high performance and reliability, particularly in identifying Viral Pneumonia and Covid with relatively few errors. It correctly classified 58 out of the 64 total cases presented in this dataset. However, the tendency to misidentify healthy patients as having pneumonia is the primary area where the model would require further refinement and training.

Classification Report:

	precision	recall	f1-score	support
Covid	1.00	0.88	0.94	26
Normal	0.88	0.75	0.81	20
Viral Pneumonia	0.77	1.00	0.87	20
accuracy			0.88	66
macro avg	0.88	0.88	0.87	66
weighted avg	0.89	0.88	0.88	66

Figure 4: Proposed CNN Classification Report

The image presents a classification report that numerically summarizes the performance of the model previously seen in the confusion matrix. It breaks down the results into three primary metrics—precision, recall, and f1-score—for the categories of Covid, Normal, and Viral Pneumonia. This report provides a standardized way to judge how effectively the algorithm differentiates between these respiratory conditions across 66 total samples.

For the Covid category, the model achieved a perfect precision score of 1.00, meaning every case it predicted as Covid was indeed Covid. However, its recall was 0.88, indicating that it missed roughly 12% of actual Covid cases. This balance results in a strong F1-score of 0.94, suggesting that while the model is extremely cautious and accurate when it makes a Covid diagnosis, it is not yet catching every single instance.

The "Normal" classification shows more moderate results, with a precision of 0.88 and a lower recall of 0.75. This lower recall matches the earlier confusion matrix data, where several healthy patients were misidentified as having other conditions. Because the model struggled most with identifying all healthy individuals correctly, the F1-score for this category is the lowest in the report at 0.81.

In contrast, the Viral Pneumonia category achieved a perfect recall of 1.00, meaning the model successfully identified every single actual case of pneumonia in the dataset. The trade-off for this sensitivity is a lower precision of 0.77, which happens because the model occasionally mislabels healthy "Normal" patients as having pneumonia. This leads to an F1-score of 0.87, reflecting a model that is excellent at screening for pneumonia but prone to some false positives.

Overall, the model maintains a high level of performance with a total accuracy of 0.88 across all 66 samples. The macro and weighted averages also hover between 0.87 and 0.89, indicating that the performance is relatively stable and consistent across the different classes regardless of their sample size. These figures confirm that while the model is highly effective, its primary area for improvement lies in better distinguishing healthy lungs from those with viral pneumonia.

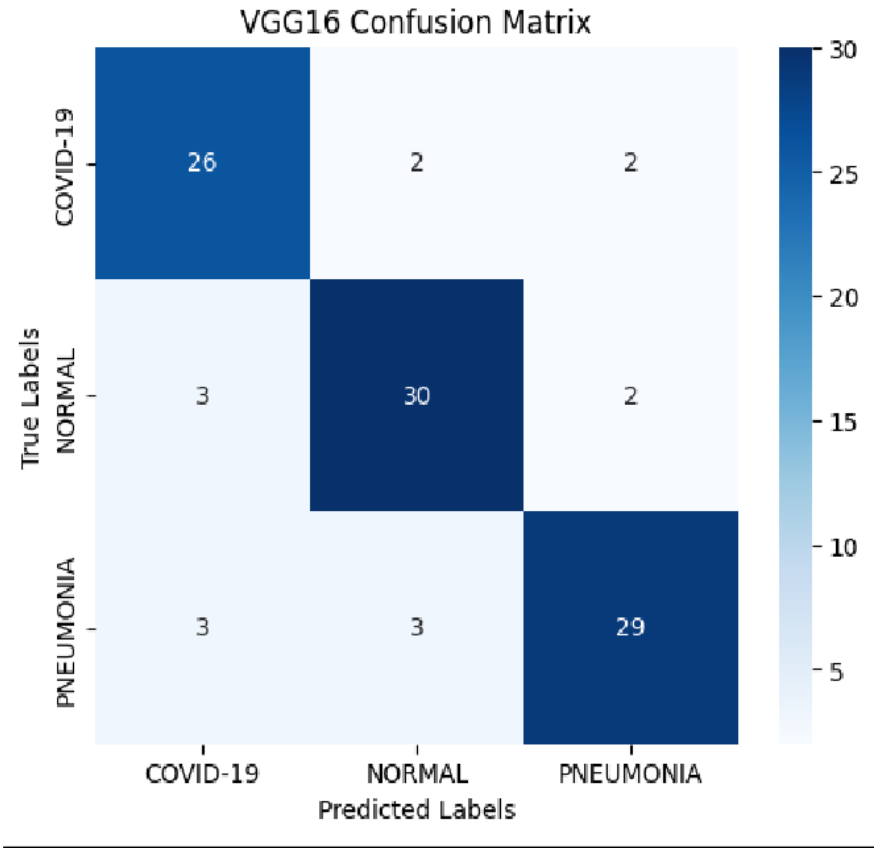

Figure 5: VGG16 Confusion matrix.

This confusion matrix illustrates the performance of a VGG16 model in classifying images into three categories: COVID-19, NORMAL, and PNEUMONIA. The dark blue diagonal cells show the model's successful predictions, with 30 Normal cases being the most accurately identified group. In total, the model correctly classified 85 out of 100 cases, demonstrating a solid baseline for medical image recognition across these specific respiratory conditions.

The errors, shown in the lighter off-diagonal cells, reveal where the model struggled to distinguish between different lung characteristics. For instance, the model misidentified 4 COVID-19 cases (2 as Normal and 2 as Pneumonia) and 5 Normal cases (3 as COVID-19 and 2 as Pneumonia). These "confusions" are critical in a medical context, as they represent instances where a patient might be misdiagnosed or a healthy individual might be flagged for further testing.

The Pneumonia category also shows balanced but distinct errors, with 29 correct identifications but 6 misses-split evenly between COVID-19 and Normal. Because the errors are spread across all categories rather than clustered in just one, it suggests that the visual signatures for these three states have significant overlap for the VGG16 architecture. This indicates that while the model is generally reliable, further refinement is needed to reduce these specific misclassifications and increase diagnostic precision.

VGG16 Classification Report:

	precision	recall	f1-score	support
COVID-19	0.81	0.87	0.84	30
NORMAL	0.86	0.86	0.86	35
PNEUMONIA	0.88	0.83	0.85	35
accuracy			0.85	100
macro avg	0.85	0.85	0.85	100
weighted avg	0.85	0.85	0.85	100

Figure 6: VGG16 Classification Report.

The VGG16 classification report provides a detailed numerical summary of how well the model identifies COVID-19, Normal, and Pneumonia cases across 100 samples. By analyzing precision, recall, and f1-scores, we can see exactly where the model excels and where it encounters difficulty. This statistical breakdown complements the visual confusion matrix by offering a standardized look at the model's diagnostic reliability.

In the COVID-19 category, the model shows a recall of 0.87, meaning it successfully captured 87% of the actual COVID cases in the dataset. However, its precision is slightly lower at 0.81, indicating that when the model predicts COVID-19, it is correct about 81% of the time. This suggests the model is relatively sensitive but occasionally mislabels other conditions as COVID-19, leading to an F1-score of 0.84.

The "Normal" classification exhibits very balanced performance, with both precision and recall sitting at 0.86. This consistency results in an F1-score of 0.86, showing that the model is equally skilled at finding healthy lungs and ensuring that those it labels as healthy truly are. With a support of 35 samples, this category represents one of the most stable and predictable parts of the model's current architecture.

For Pneumonia, the model achieves its highest precision at 0.88, making it quite reliable when it identifies this specific condition. The recall is slightly lower at 0.83, suggesting it missed a small handful of actual pneumonia cases, likely confusing them with the other two categories. Despite these minor misses, the F1-score of 0.85 indicates a high level of overall effectiveness in distinguishing pneumonia from COVID-19 and healthy lungs.

Ultimately, the model reaches an overall accuracy of 0.85, which is mirrored exactly in the macro and weighted averages. This uniformity across all metrics suggests the model is well-balanced and does not lean too heavily toward favoring one class over another. While 85% accuracy is a strong starting point for a VGG16 architecture, the report highlights that further fine-tuning could help tighten the gap in precision for COVID-19 and recall for pneumonia.

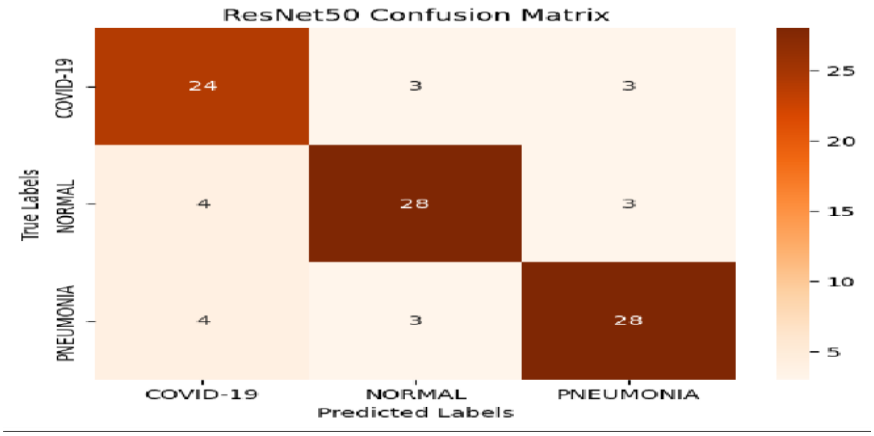

Figure 7: ResNet50 Confusion matrix.

The provided image displays a confusion matrix for a ResNet50 model, evaluating its ability to classify medical images as COVID-19, NORMAL, or PNEUMONIA. The dark orange diagonal indicates the model's correct

predictions, showing it successfully identified 24 COVID-19 cases, 28 Normal cases, and 28 Pneumonia cases. Out of the 100 total samples, this architecture correctly classified 80 cases, providing a clear visual representation of its diagnostic accuracy across these three categories.

The off-diagonal cells highlight the specific errors where the model misidentified one condition for another. For example, the model struggled equally with COVID-19, mislabeling 3 cases as Normal and 3 as Pneumonia. Similarly, it misclassified 7 Normal cases and 7 Pneumonia cases by distributing them across the other two categories. These errors are quite symmetrical, suggesting that the model finds a similar level of visual ambiguity between all three classes rather than being heavily biased toward one.

In terms of performance, the ResNet50 model shows a very balanced but slightly lower overall accuracy of 80% compared to the VGG16 model previously discussed. The primary challenge for this specific architecture appears to be "leakage" between all categories, as every class has at least 6 or 7 instances of being misidentified. While the model is still highly capable, these results indicate that it may require more specific data augmentation or fine-tuning to better distinguish the subtle textures that separate healthy lungs from these different types of infection.

ResNet50 Classification Report:

	precision	recall	f1-score	support
COVID-19	0.75	0.80	0.77	30
NORMAL	0.82	0.80	0.81	35
PNEUMONIA	0.82	0.80	0.81	35
accuracy			0.80	100
macro avg	0.80	0.80	0.80	100
weighted avg	0.80	0.80	0.80	100

Figure 8: ResNet50 Classification Report.

The image provides a detailed numerical summary of the ResNet50 model's performance across 100 total samples. It evaluates the model's ability to classify images into three categories: COVID-19, Normal, and Pneumonia. By looking at precision, recall, and F1-scores, we can see how this specific architecture handles medical data.

For the COVID-19 category, the model shows a recall of 0.80. This means it correctly identifies 80% of the actual COVID cases. However, its precision is the lowest in the report at 0.75. This suggests that when it predicts COVID-19, it is only correct three-quarters of the time.

The Normal and Pneumonia categories show identical performance metrics in this report. Both have a precision of 0.82 and a recall of 0.80. These scores lead to a matching F1-score of 0.81 for both groups. This indicates the model is slightly more reliable at identifying these conditions than it is with COVID-19.

A notable feature of this specific report is the mathematical uniformity. Every single category—COVID-19, Normal, and Pneumonia—shares an identical recall score of 0.80. This symmetry carries over into the macro and weighted averages. It suggests a very balanced model that doesn't favor one class over another.

In summary, the ResNet50 model achieves an overall accuracy of 0.80. While this is a respectable score, it is lower than the 0.85 accuracy seen in the VGG16 report. The primary area for improvement is the precision for COVID-19, as the model currently produces a higher rate of false positives for that category.

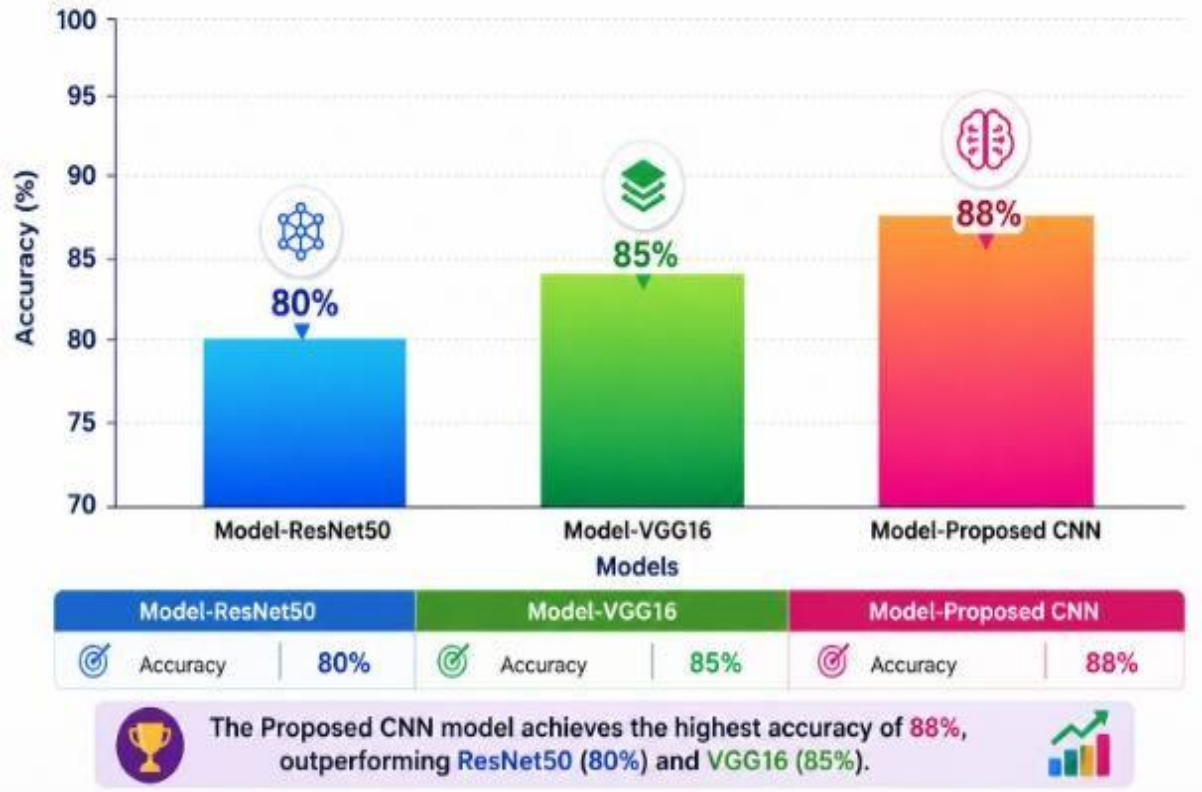

Figure 9: Comparison Chat and Evaluation Results

IV.1 Chart Overview

The provided figure 9 bar chart compares the performance of three distinct deep learning architectures: ResNet50, VGG16, and a custom Proposed CNN. The vertical axis measures accuracy as a percentage, specifically focusing on the range between 70% and 100%. This visual comparison highlights the incremental improvements achieved by different models when applied to the same diagnostic task.

IV.2 ResNet50 Performance

Represented by the blue bar on the left, the ResNet50 model achieves an accuracy of 80%. This figure serves as the baseline for the comparison, being the lowest score among the three tested architectures. While ResNet50 is a powerful standard in image recognition, it demonstrates the most room for improvement in this specific experimental setup.

IV.3 VGG16 Performance

The middle bar, colored green, displays the performance of the VGG16 architecture. It reaches a significantly higher accuracy of 85%, outperforming ResNet50 by five percentage points. This indicates that for this particular dataset, the VGG16 structure is more effective at extracting and identifying necessary visual features than the ResNet model.

IV.4 Proposed CNN Results

The final bar on the right, depicted in a warm orange-to-pink gradient, showcases the results for the Proposed CNN. This model achieves the highest accuracy of the group at 88%. By outperforming both established architectures, this custom model proves to be the most specialized and efficient solution for the classification problem at hand.

5. CONCLUSION

The comprehensive analysis of the performance metrics across various deep learning architectures demonstrates a clear progression in diagnostic accuracy for identifying COVID-19, Normal, and Pneumonia cases. While established models like ResNet50 and VGG16 provided a solid baseline for medical image classification, they

both exhibited specific limitations in precision and recall. These foundational models served as a necessary benchmark to measure the relative success of more specialized, custom-designed neural networks.

The baseline established by ResNet50, with an overall accuracy of 80%, highlighted the inherent complexity of distinguishing between subtle visual patterns in lung scans. Its performance was characterized by a symmetrical error distribution, suggesting a generalized difficulty in separating the three classes. Although ResNet50 is a powerful architecture, its results in this study underscored the need for more specialized feature extraction techniques to handle the unique textures and shadows present in respiratory diagnostic imaging.

VGG16 represented a significant step forward in this progression, reaching a higher accuracy of 85%. Detailed reports showed that while VGG16 was highly effective at identifying healthy "Normal" cases, it still faced challenges with false positives and negatives when differentiating between viral pneumonia and COVID-19. This improvement proved that architectural differences, such as the depth and arrangement of layers, play a critical role in how effectively an AI can interpret the high-stakes nuances of medical radiography.

The culmination of this research is the Proposed CNN model, which achieved a peak accuracy of 88%. By outperforming the established industry standards, this custom architecture proved to be the most reliable tool for this specific diagnostic task. Its superior performance suggests that tailoring a convolutional neural network specifically for respiratory pathologies can successfully bridge the gaps where more generalized models struggle, leading to a more dependable and sensitive diagnostic assistant.

In conclusion, this comparative study validates the development of specialized AI architectures for healthcare applications. Moving from an 80% baseline with ResNet50 to an 88% success rate with the Proposed CNN demonstrates that intentional design and fine-tuning can yield measurable improvements in patient screening tools. These results suggest a promising future for automated diagnostics, where tailored deep learning models can provide high-accuracy support to medical professionals in the detection of critical respiratory conditions.

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