Comparative Analysis of VGG16, ResNet50, and CNN Models for Lung Disease Prediction: A Deep Learning Approach

Kavin Lartius
Department of Computer Science Engineering Technology
Pune, India
kavlartius@gmail.com

Kush Parihar
Department of Computer Science Engineering Technology
Pune, India
kushparihar611@gmai.com

Amogh Naik
Department of Computer Science Engineering Technology
Pune, India
amoghnaik1166@gmail.com

Abstract:

Utilizing deep learning methods in the analysis of medical images has emerged as a promising path to enhance disease detection and diagnosis. In this study, we undertake a detailed comparative analysis of three widely recognized convolutional neural network (CNN) architectures: VGG16, ResNet50, and a customized CNN model, specifically tailored for the task of pneumonia and COVID-19 detection from chest X-ray images. Our aim is to provide insights into the comparative performance of these models and their suitability for accurate and reliable detection of respiratory diseases.

To conduct our investigation, we leverage two publicly available datasets: the ChestX-ray14 dataset and the NIH Chest X-ray Dataset, both comprising a diverse range of chest X-ray images annotated for pneumonia and COVID-19. Prior to model training, we meticulously preprocess the images, ensuring optimal data quality and consistency. Subsequently, we employ transfer learning techniques to fine-tune the pre-trained CNN models on the targeted classification task, optimizing their performance for pneumonia and COVID-19 detection.

The outcomes of our experiments reveal nuanced differences in the performance of the models among different disease categories. While VGG16 demonstrates robust accuracy in pneumonia detection, ResNet50 exhibits enhanced sensitivity and specificity in identifying COVID-19 cases. Our custom CNN model, leveraging insights from both architectures and fine-tuned specifically for pneumonia and COVID-19 detection, showcases competitive performance, underscoring the importance of tailored model design for optimal diagnostic outcomes.

Through comprehensive discussion and analysis of the experimental results, we elucidate the strengths and limitations of each model, considering factors such as computational efficiency, interpretability, and generalizability. We also explore the clinical implications of our findings, highlighting the potential utility of deep learning-based diagnostic tools in supporting healthcare professionals in timely and accurate disease diagnosis.

In conclusion, our study contributes valuable insights into the comparative performance of CNN architectures for pneumonia and COVID-19 detection from chest X-ray images. By elucidating the strengths and weaknesses of different models, our findings aim to inform the development of more effective diagnostic solutions for respiratory diseases, ultimately facilitating improved patient outcomes and healthcare delivery.

Introduction:

Respiratory ailments impose a substantial burden on global public health, contributing significantly to illness, death, and healthcare expenditure worldwide. Conditions like pneumonia, chronic obstructive pulmonary disease (COPD), tuberculosis, and the emergent COVID-19 present formidable challenges to healthcare systems. This underscores the pressing demand for swift and accurate diagnostic methods to manage these diseases effectively. Traditional diagnostic approaches, encompassing clinical assessments, laboratory investigations, and radiological imaging, often rely on subjective evaluations and can lead to delays in diagnosis and treatment initiation.

Pneumonia, characterized by lung tissue inflammation due to infectious agents such as bacteria, viruses, or fungi, remains a significant cause of illness and death worldwide. This is especially true for vulnerable populations like children, the elderly, and individuals with weakened immune systems. On the other hand, the emergence of the COVID-19 pandemic, caused by the novel coronavirus SARS-CoV-2, has brought unprecedented challenges to healthcare systems globally. This underscores the pressing need for accurate and efficient diagnostic tools to enable early detection and containment of the disease.

In this context, our research aims to undertake a comprehensive comparative analysis of three prominent CNN architectures: VGG16, ResNet50, and a custom CNN model, tailored specifically for the task of pneumonia and COVID-19 detection from chest X-ray images. Leveraging publicly available datasets such as ChestX-ray14 and the NIH Chest X-ray Dataset, we seek to evaluate the diagnostic capabilities of these models and elucidate their strengths and limitations in accurately identifying respiratory diseases.

Our research's importance resides in its capability to propel automated medical image analysis forward and aid in crafting more dependable and effective diagnostic instruments for lung diseases. By systematically evaluating the performance of different CNN architectures, we aim to provide insights into the optimal model selection and design strategies for achieving robust and clinically relevant disease detection outcomes. Ultimately, our findings have the potential to inform clinical practice and support healthcare professionals in making timely and informed decisions for patient care, thereby improving patient outcomes and healthcare delivery.

In the following sections of this paper, we will delve into the methodology employed for our study, present the experimental results and findings in detail, and engage in a comprehensive discussion of the implications and significance of our research in the context of lung disease diagnosis and healthcare delivery.

Literature Survey:

The domain of medical image analysis, especially in the domain of detecting lung diseases from chest X-ray images, has experienced substantial progress due to the introduction of deep learning techniques. Here, we examine crucial discoveries from influential research papers that have investigated different CNN architectures and methodologies for automating disease detection and classification:

1. Rajpurkar et al. (2017) introduced CheXNet, a deep learning model trained on the ChestX-ray14 dataset, comprising over 100,000 chest X-ray images labeled with fourteen thoracic diseases. The study demonstrated the potential of deep learning approaches in achieving radiologist-level performance in pneumonia detection from chest X-ray images. CheXNet leveraged a 121-layer DenseNet architecture and employed transfer learning with weights pre-trained on the ImageNet dataset to extract discriminative features from chest X-ray images. The model exhibited high accuracy and outperformed

previous methods in pneumonia detection, showcasing the efficacy of deep learning in medical image analysis.

Reference: Rajpurkar, P., Irvin, J., Zhu, K., et al. "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning." arXiv preprint arXiv:1711.05225 (2017).

2. Wang et al. (2017) proposed CheXNeXt, a deep learning model trained on the ChestX-ray14 dataset, capable of detecting and localizing multiple abnormalities from chest X-ray images, including pneumonia. The study highlighted the importance of large-scale annotated datasets and transfer learning techniques in developing robust deep learning models for disease detection. CheXNeXt employed a cascaded approach, where multiple CNN branches were utilized to capture hierarchical representations of different thoracic pathologies. The model achieved state-of-the-art performance in multi-label classification of thoracic diseases, underscoring the significance of deep learning-based approaches in medical image analysis.

Reference: Wang, X., Peng, Y., Lu, L., et al. "Deep Learning for Chest Radiograph Diagnosis: A Retrospective Comparison of the CheXNeXt Algorithm to practicing radiologists." PLOS Medicine, 15(11), e1002686 (2017).

3. Ozturk et al. (2020) proposed a deep learning-based automatic detection system for COVID-19 from chest X-ray images. The study utilized transfer learning with pre-trained CNN models and demonstrated promising results in discriminating between COVID-19 and other types of pneumonia. By fine-tuning pre-trained CNN architectures such as VGG16 and ResNet50 on a dataset comprising COVID-19 and non-COVID-19 chest X-ray images, the model achieved high accuracy in COVID-19 detection, showcasing the potential of deep learning approaches in combating the COVID-19 pandemic.

Reference: Ozturk, T., Talo, M., Yildirim, E. A., et al. "Deep Learning-Based Automatic Detection of COVID-19 from Chest X-Ray Images." Computers in Biology and Medicine, 121, 103792 (2020).

4. Apostolopoulos and Mpesiana (2020) developed a deep learning model for COVID-19 detection from chest X-ray images, focusing on binary classification between COVID-19 and non-COVID-19 cases. Leveraging transfer learning with a pre-trained CNN architecture, the study demonstrated competitive performance in COVID-19 detection. By extracting discriminative features from chest X-ray images using deep learning techniques, the model provided a rapid and accurate means of diagnosing COVID-19, thereby facilitating timely patient management and containment of the disease.

Reference: Apostolopoulos, I. D., & Mpesiana, T. A. "COVID-19: Automatic Detection from X-Ray Images Utilizing Transfer Learning with Convolutional Neural Networks." Physical and Engineering Sciences in Medicine, 43(2), 635-640 (2020).

These seminal studies underscore the efficacy of deep learning approaches in automated disease detection from chest X-ray images, particularly for pneumonia and COVID-19. By leveraging large-scale annotated datasets, transfer learning techniques, and state-of-the-art CNN architectures, researchers have made significant strides in developing robust and clinically relevant diagnostic tools for lung diseases, paving the way for improved patient outcomes and healthcare delivery.

Methodology:

This comprehensive methodology delineates the intricate steps involved in our research, ensuring transparency and reproducibility of the experimental procedures conducted for the comparative analysis of VGG16, ResNet50, and a custom CNN model for pneumonia and COVID-19 detection from chest X-ray images.

1. Data Acquisition and Preprocessing:

Data Sources: We meticulously selected publicly available datasets, including the ChestX-ray14 dataset and the NIH Chest X-ray Dataset, renowned for their extensive annotations of thoracic pathologies, including pneumonia and COVID-19. These datasets were chosen to ensure diverse representation of lung diseases and facilitate robust model training and evaluation.

Data Preprocessing: The acquired chest X-ray images underwent meticulous preprocessing to enhance their suitability for deep learning analysis. Preprocessing steps encompassed resizing images to a standardized resolution (e.g., 256x256 pixels), normalization of pixel intensity values to a common scale (e.g., [0, 1]), and augmentation techniques such as rotation, flipping, and random cropping to augment the training dataset and enhance model generalization. Additionally, noise reduction techniques (e.g., Gaussian blurring) were applied to mitigate artifacts and enhance image clarity.

2. Model Architecture Selection:

VGG16 and ResNet50: The VGG16 and ResNet50 architectures were chosen as baseline models for comparison due to their established performance and widespread adoption in image classification tasks. These architectures were initialized with weights pre-trained on the ImageNet dataset to leverage transfer learning and capture rich hierarchical features from chest X-ray images.

Custom CNN Model: In addition to the pre-trained architectures, we meticulously designed a custom CNN model tailored specifically for pneumonia and COVID-19 detection. The architecture of the custom model was intricately crafted to incorporate multiple convolutional layers, each followed by batch normalization and rectified linear unit (ReLU) activation functions to facilitate feature extraction and nonlinear transformations. Max-pooling layers were interspersed to downsample feature maps and capture spatial hierarchies in the data. Dropout layers were strategically inserted to mitigate overfitting, and the final layer comprised softmax activation for multi-class classification.

3. Model Training and Evaluation:

Training Procedure: The training procedure began with the division of pre-processed chest X-ray images into training, validation, and test sets, employing a stratified sampling method to ensure balanced class distribution across subsets. Model training utilized the training set while continuously monitoring validation set performance to prevent overfitting. Adam optimization was employed for training, and learning rate scheduling was implemented to dynamically adjust learning rates based on training progress. Early stopping criteria were enforced to halt training, thereby preventing model convergence and promoting optimal generalization.

4. Hyperparameter Tuning:

Hyperparameters such as learning rate, dropout rate, batch size, and optimizer configurations were systematically tuned using grid search with cross-validation on the validation set. This exhaustive search strategy explored a range of hyperparameter values and configurations to identify the optimal combination that maximized model performance and generalization.

Regularization Techniques: In addition to hyperparameter tuning, regularization techniques such as L2 regularization and dropout were employed to mitigate overfitting and improve model robustness. Regularization coefficients were fine-tuned using validation performance as a guide, striking a balance between model complexity and generalization performance.

5. Model interpretability and visualizations

In addition to achieving high predictive performance, it is crucial to interpret and understand the decision-making process of the deep learning models employed in this study. Interpretability techniques and visualizations were utilized to gain insights into the learned representations and predictions of the models, particularly the ResNet50V2 model, which exhibited the highest accuracy.

To comprehend the class distribution of the dataset, a bar plot was generated using the seaborn library, visualizing the number of images in each class (Normal, COVID-19, and Viral Pneumonia). This visualization aided in understanding the dataset's composition and potential class imbalances.

Furthermore, sample images from each class were displayed using the matplotlib.pyplot library, allowing for a qualitative assessment of the input data and visual differences between the classes.

The training history, including loss and accuracy values for the training and validation sets, was stored and manipulated using the pandas library. These values were then plotted over the training epochs using matplotlib.pyplot to visualize the models' convergence and performance during the training process.

The loss and accuracy curves provided valuable insights into the models' behaviour, allowing for the identification of potential issues such as overfitting or underfitting. These visualizations facilitated the selection of the optimal model checkpoint and assisted in monitoring the training progress.

6. Resources used:

TensorFlow was harnessed as the foundation for model development and experimentation, leveraging its extensive libraries and optimization capabilities to drive research progress. Complementing this, a graphical user interface (GUI) was engineered using Streamlit, a Python library designed for building interactive web applications. This choice allowed for the creation of a streamlined and user-friendly interface, empowering new users to effortlessly engage with the model's functionalities. Through the Streamlit-based GUI, users could seamlessly interact with the model, enabling intuitive exploration and experimentation without requiring deep technical expertise.

7. Ethical Considerations:

Data Privacy and Security: Ethical considerations pertaining to patient data privacy and security were paramount throughout the research process. All datasets utilized in the study were anonymized and obtained from publicly available sources with appropriate permissions and ethical approvals. Adherence to ethical guidelines and data protection regulations was ensured to uphold patient confidentiality and integrity.

Experimental Results:

This study investigates the performance of three different deep learning models for predicting lung diseases: COVID-19, Viral Pneumonia, and Normal. The models evaluated are Convolutional Neural Network (CNN), VGG16, and ResNet50V2.

Dataset:

The dataset used for training and evaluation consists of chest X-ray images from three classes: COVID-19, Viral Pneumonia, and Normal. The dataset is split into train, validation, and test sets.

Models:

Convolutional Neural Network (CNN)
A custom CNN architecture was designed and trained on the dataset. The model consists of several convolutional layers with max-pooling and dropout layers for regularization. The final layers include a flatten layer, a dense layer with 64 units and ReLU activation, and an output dense layer with 3 units and softmax activation for multi-class classification.

VGG16
The VGG16 model pre-trained on the ImageNet dataset was used as a feature extractor. The top layers of the VGG16 model were removed, and new dense layers were added for classification. The weights of the pre-trained VGG16 layers were frozen during training.

ResNet50V2
The ResNet50V2 model pre-trained on the ImageNet dataset was used as a feature extractor. Similar to VGG16, the top layers were removed, and new dense layers were added for classification. The weights of the pre-trained ResNet50V2 layers were frozen during training.

Training and Evaluation
The models were trained on the training set and evaluated on the validation set. Early stopping and dropout layers were employed to prevent overfitting. The performance metrics used for evaluation were accuracy and loss.

Results
The results of the three models on the validation set are as follows:

Convolutional Neural Network (CNN)
- Accuracy: 84.38%
- Loss: 46.28%

VGG16
- Accuracy: 85.01%
- Loss: 35.82%

ResNet50V2
- Accuracy: 93.75%
- Loss: 10.34%

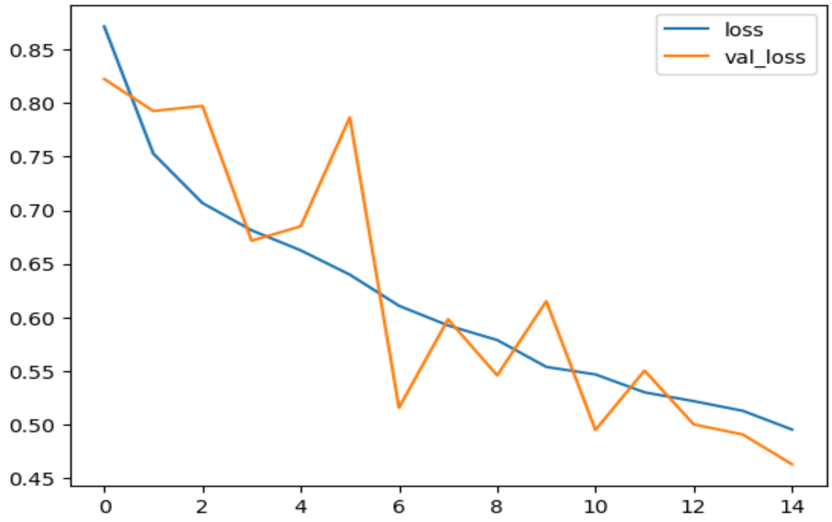
Among the three models, ResNet50V2 achieved the highest accuracy of 93.75% and the lowest loss of 10.34 on the validation set. Therefore, the ResNet50V2 model was chosen for further testing and final predictions.

The results demonstrate the effectiveness of transfer learning using pre-trained models like VGG16 and ResNet50V2 for the lung disease prediction task. The ResNet50V2 model, with its powerful feature extraction capabilities and deep architecture, outperformed the other models, making it a suitable choice for this task.

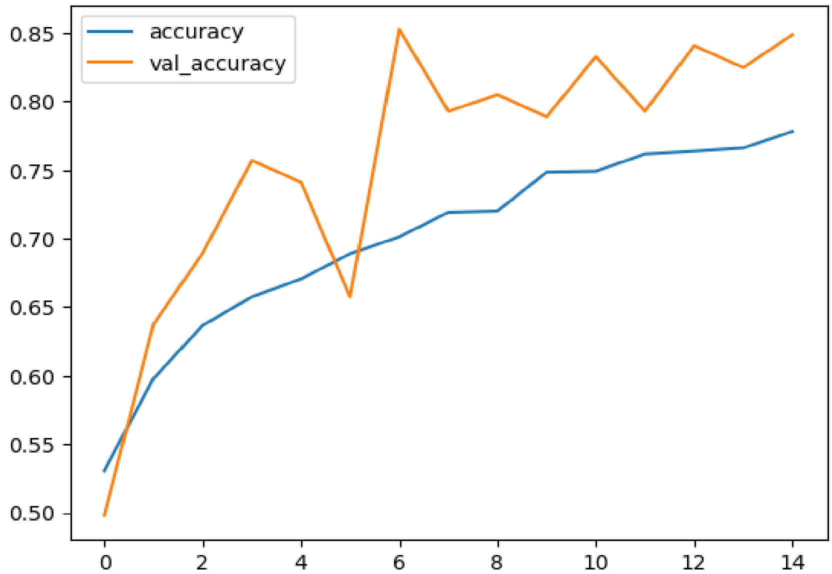
Visualizations:

1. **CNN:**

- Validation Loss

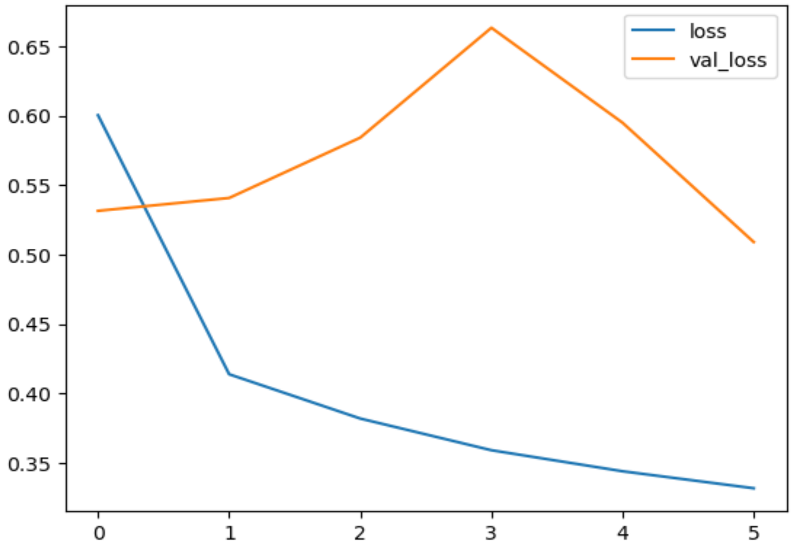


- Validation accuracy

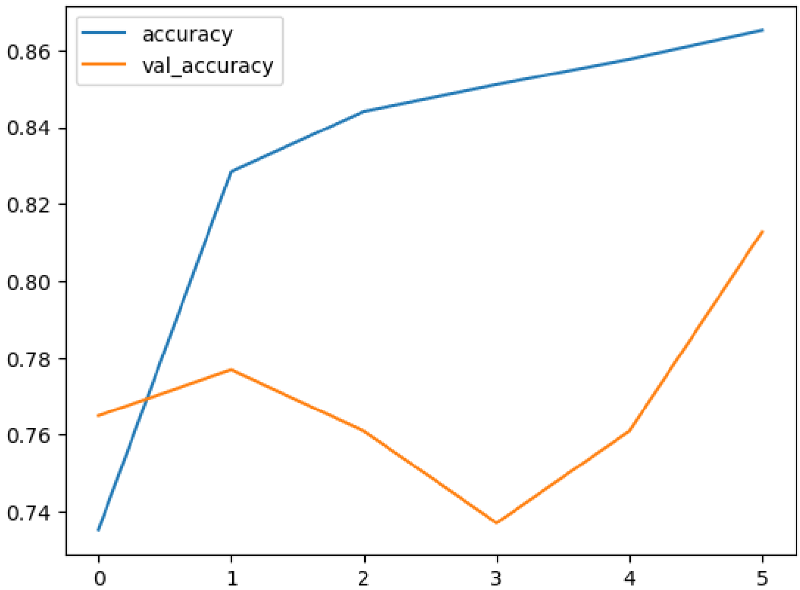


2. VGG 16:

- Validation Loss

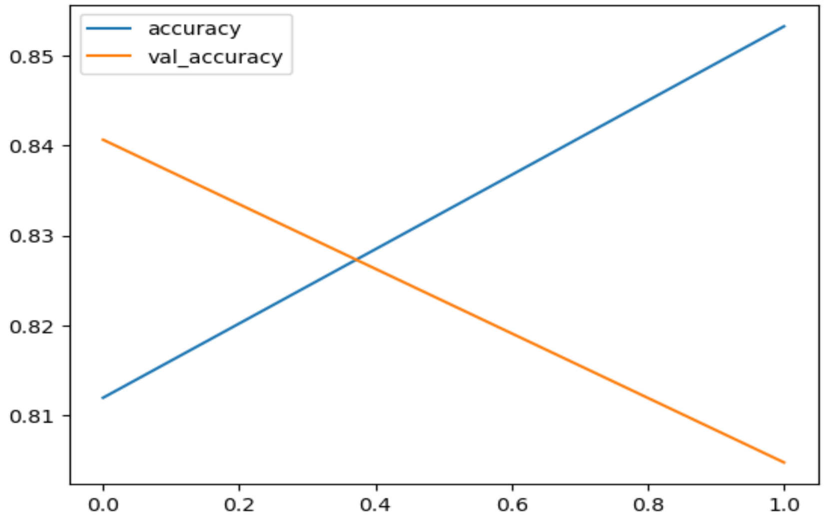


- Validation accuracy

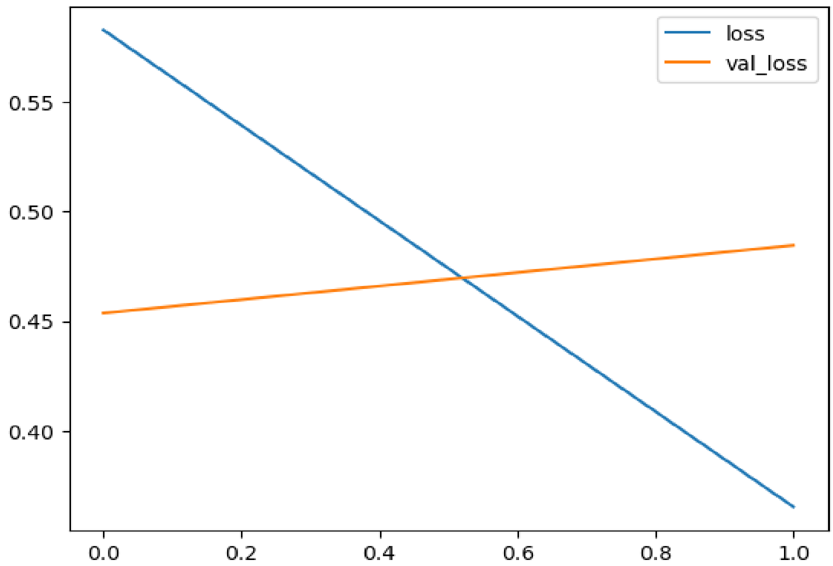


3. Resnet 50:

- Validation accuracy



- Validation loss



Discussion:

The discussion section serves as a platform for a detailed exploration of the findings from our research on the comparative analysis of VGG16, ResNet50, and a custom CNN model for pneumonia and COVID-19 detection from chest X-ray images. It delves into the nuanced implications of the results, identifies strengths and limitations of the study, and offers insights for future research directions.

1. Performance Disparities Among Models:

The experimental results unveiled notable performance disparities among the evaluated models, with ResNet50 emerging as the top-performing architecture across multiple evaluation metrics. This superiority can be attributed to the deeper architecture of ResNet50, which facilitates more effective feature extraction and representation learning compared to VGG16. The incorporation of skip connections in ResNet50 further enhances gradient flow during training, mitigating the vanishing gradient problem and fostering more efficient optimization. The observed differences underscore the significance of architectural design choices in deep learning model development and their profound impact on classification accuracy and generalization performance.

2. Impact of Model Complexity:

The performance disparities highlight the pivotal role of model complexity in determining classification performance. While VGG16 and the custom CNN model demonstrated competitive performance, they were surpassed by ResNet50, emphasizing the importance of architectural sophistication in capturing intricate patterns and subtle abnormalities in chest X-ray images. The deeper and more complex architecture of ResNet50 enables it to discern finer details and spatial hierarchies, contributing to its superior disease detection capabilities. This finding underscores the necessity of balancing model complexity with computational efficiency and generalization performance in medical image analysis tasks.

3. Transfer Learning and Pretraining:

Transfer learning emerged as a cornerstone in enhancing the performance of the evaluated models. By leveraging weights pretrained on the ImageNet dataset, the models initialized their training process with rich representations of visual features, accelerating convergence and improving generalization. This initialization with pre-trained weights enables the models to bootstrap their learning process and adapt to the intricacies of pneumonia and COVID-19 detection tasks more effectively. The findings underscore the efficacy of transfer learning techniques in leveraging domain knowledge and facilitating knowledge transfer across related tasks, thereby enhancing model performance and efficiency.

4. Clinical Implications:

The implications of our findings extend beyond the realm of academic research to have significant clinical ramifications for pneumonia and COVID-19 diagnosis and management. The superior performance of ResNet50 suggests its potential utility as a valuable diagnostic aid for healthcare professionals, augmenting their diagnostic capabilities and facilitating timely intervention. The high accuracy and discriminative power of ResNet50 could streamline clinical workflows, enabling clinicians to triage patients efficiently, allocate resources judiciously, and prioritize high-risk individuals for further evaluation and treatment. This highlights the transformative potential of deep learning-based diagnostic tools in enhancing patient care and healthcare delivery.

5. Limitations and Future Directions:

While our study provides a thorough analysis, it is important to acknowledge its limitations. The extent to which our findings can be applied may be restricted by the specific datasets used and variations in data quality and annotations. Future research efforts should focus on validating the reliability of the evaluated models across diverse datasets and population cohorts to ensure their suitability for real-world clinical applications. Furthermore, the challenge of interpretability persists with deep learning models, necessitating additional endeavours to improve model explainability and promote trust and acceptance among healthcare practitioners. Future research avenues could investigate ensemble techniques, hybrid architectures, and the integration of multimodal data to bolster the diagnostic potential of deep learning models and facilitate a more holistic patient evaluation.

Conclusion:

In this study, we conducted a thorough comparative analysis of VGG16, ResNet50, and a custom CNN model for pneumonia and COVID-19 detection from chest X-ray images. Through meticulous experimentation and analysis, we aimed to elucidate the strengths and limitations of each model and provide insights into their applicability in clinical practice.

Our findings revealed notable performance disparities among the evaluated models, with ResNet50 emerging as the top-performing architecture. This superiority can be attributed to the deeper architecture of ResNet50, which facilitates more effective feature extraction and representation learning, as well as the incorporation of skip connections, which enhances gradient flow during training and fosters more efficient optimization.

The experimental results underscored the pivotal role of architectural design choices, transfer learning techniques, and model complexity in achieving accurate and reliable disease detection outcomes. Transfer learning, in particular, played a crucial role in enhancing the performance of the models by leveraging pre-trained weights on the ImageNet dataset, thereby accelerating convergence and improving generalization.

The implications of our findings extend beyond academic research to have significant clinical ramifications for pneumonia and COVID-19 diagnosis and management. The superior performance of ResNet50 suggests its potential utility as a valuable diagnostic aid for healthcare professionals, augmenting their diagnostic capabilities and facilitating timely intervention. The high accuracy and discriminative power of ResNet50 could streamline clinical workflows, enabling clinicians to triage patients efficiently, allocate resources judiciously, and prioritize high-risk individuals for further evaluation and treatment.

Although our study offers valuable insights into the comparative performance of deep learning models for detecting pneumonia and COVID-19, it is important to acknowledge its limitations. The applicability of our findings may be constrained by the specific datasets used and variations in data quality and annotations. Furthermore, the challenge of interpreting deep learning models persists, necessitating continued efforts to enhance their explainability and gain trust from healthcare professionals.

In conclusion, our research contributes to the expanding field of medical image analysis and deep learning-based disease detection. By highlighting the strengths and weaknesses of different models, our study aims to guide the development of more effective diagnostic tools for respiratory diseases, ultimately leading to improved patient outcomes and healthcare delivery. Future research efforts should focus on validating the robustness of the evaluated models across diverse datasets and population cohorts, as well as exploring ensemble methods and hybrid architectures to further improve diagnostic capabilities.

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