Pneumonia Disease Prediction UsingVGG19 Architecture

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Abstract: Pneumonia, a severe and potentially fatal infectious disease, primarily impacts the lungs in humans. Its main culprit is often identified as Streptococcus pneumonia, a type of bacteria. According to the World Health Organization (WHO), Pneumonia causes many deaths in India, responsible for one out of every three reported cases. Creating an automated system to detect pneumonia holds immense potential for expediting the treatment process, especially in remote regions where access to medical expertise may be limited. With the remarkable success of deep learning algorithms, Convolutional Neural Networks (CNN) have gathered significant interest for their effectiveness in analyzing medical images and facilitating disease classification. The methodology employed in this study revolves around the execution of a CNN known as VGG19. This architecture is utilized to process X-ray images and carry out predictive analysis. To carry out the experiments, a diverse collection of chest X-ray images is employed, including both cases with pneumonia and cases without pneumonia. This dataset is utilized to train and test the CNN model. Our main discoveries highlight the impressive effectiveness of the recommended DL model in accurately predicting pneumonia. The VGG19 model, once trained, attained an extraordinary accuracy of 95.35% on the test dataset. Additionally, the model displayed a high sensitivity of 98.77%, demonstrating its proficiency in accurately identifying both positive and negative pneumonia cases. These findings strongly emphasize the capability of deep learning algorithms in assisting radiologists and clinicians by Detecting pneumonia at an early stage, enabling swift and targeted treatment intervention.

Keywords: AttentionNet, Convolutional Neural Network (CNN), Deep Learning, Fine Tuning, ImageNet, Pulmonary Diseases, Resnet, Transfer Learning, VGG16, VGG19

1. Introduction

Pneumonia Disease remains a global health challenge, accounting for a significant portion of morbidity and mortality, particularly in vulnerable populations. The timely and accurate diagnosis of pneumonia is crucial for effective medical intervention. Traditional diagnostic methods, while valuable, are often time-consuming and may lack the sensitivity required for early detection. In recent years, the integration of deep learning techniques into medical imaging has shown promise in revolutionizing the diagnostic landscape. This research delves into the realm of pneumonia prediction using a deep learning approach, specifically leveraging the VGG19 architecture.

Over the past few years, computer-aided design (CAD) has gained eminence in the context of deep learning research. These systems have showcased their immense potential, particularly in medical applications, with notable success in detecting breast cancer, mammograms, and lung nodules. Deep Learning (DL) techniques have emerged as a pivotal component in the analysis of medical images, as they excel in identifying critical features. In the past, developing computer-aided design (CAD) systems and analyzing images involved heavily relying on manually crafted features, as mentioned in the references. [1,2]

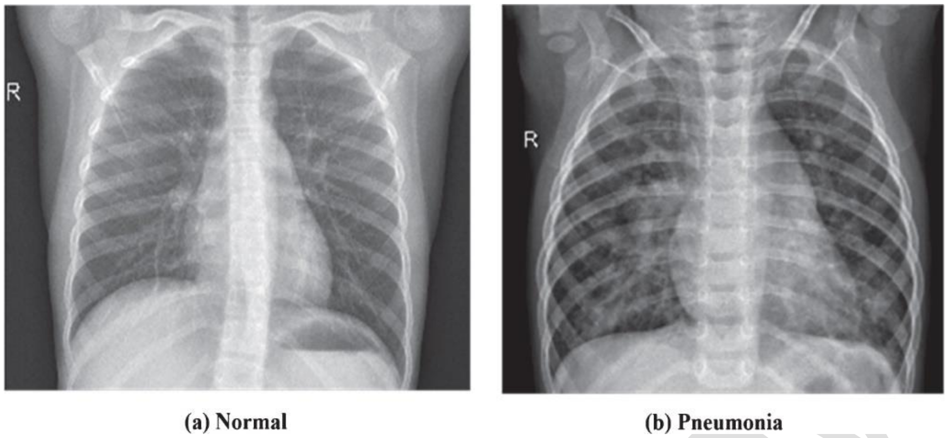

Figure 1: Normal lungs and pneumonia-affected lungs. [3]

The process of extracting features requires using Transfer learning, where the pre-trained models were able to learn similar features from large datasets such as ImageNet and subsequently employ this knowledge for specific tasks. The availability of pre-trained models, like AlexNet [4], ResNet [5], and DenseNet [6], significantly simplifies the extraction of crucial features during the process.

Pneumonia, a respiratory infection marked by lung inflammation, continues to be a major contributor to illness and death on a global scale. According to the WHO, pneumonia claims about 2.5 million lives annually, with children under five years old and the elderly being the most vulnerable groups. Timely detection and precise diagnosis play a vital role in managing the condition effectively and administering appropriate treatment promptly.

Chest X-rays have become an effective method for determining pneumonia and assessing the severity and location of lung infections. Nevertheless, interpreting these X-rays poses a considerable challenge for radiologists. Pneumonia can appear indistinctly in chest X-ray images, leading to possible misidentification as other conditions like congestive heart failure or lung scarring. As a result, evaluating datasets of chest X-rays, especially for pneumonia, becomes complicated due to the potential misclassification of images.

Indeed, overcoming this challenge holds paramount importance, as misclassification can lead to significant repercussions. Creating an algorithm capable of detecting lung diseases, including pneumonia, would significantly improve healthcare access in remote regions. In this study, we analyzed distinct pre-trained CNN models merged with numerous classifiers. we aim to distinguish between pneumonia and normal chest X-rays effectively, to enhance diagnostic accuracy in the detection of pulmonary conditions.

This study presents several key contributions (a)A comprehensive analytical investigation was conducted to compare and analyze various CNN models. for the analysis of chest X-rays. (b) The study involved exploring how these pre-trained models were merged with numerous classifiers for the analysis, to identify the appropriate classifier for classification task. (c) The study involved evaluating the Best pre-trained CNN model and fine-tuning the hyperparameters of the top-performing classifier, resulting in significant improvements in its overall performance.

In this research, we delve into the domain of DL for pneumonia disease prediction, our investigation focused on utilizing chest X-rays as the foundation. We employed deep learning techniques, with a specific emphasis on CNNs have exhibited exceptional efficacy in image recognition tasks, rendering them a promising choice for pneumonia detection. The inherent capability of deep learning models to extract intricate features from raw data proves invaluable in automatically identifying subtle patterns that may signify pneumonia, thereby potentially elevating diagnostic accuracy and expediting the diagnostic process. Through this study, we aim is to advance the understanding and effectiveness of using deep learning methods for precise and efficient pneumonia detection.

The primary goal of this study is to advance the comprehension and effectiveness of employing deep learning algorithms for accurate and systematic detection of the presence of pneumonia through chest X-ray images. VGG19, renowned for its depth, offers superior feature extraction and representation capabilities. By utilizing a diverse and meticulously curated dataset, our research endeavors to train and evaluate the ResNet-50 model to accurately predict pneumonia. Through this investigation, we aim to This study aims in advancement of the performance of specific

DL models in pneumonia disease prediction, providing valuable understandings in the domain of internal body organ image analysis.

2. Literature Survey

The creation of an automated system based on CNN for the detection of covid-19 through chest X-ray's has been accomplished. The proposed model attained magnificent levels of accuracy, sensitivity, and specificity, enabling it to effectively show differences between covid-19 and non-covid-19 cases. These findings emphasize the enormous capability of deep neural networks in pneumonia identification, particularly in the case of covid-19 diagnosis. [7]

In their study, the authors present a deep-learning technique for predicting the presence of covid-19 through chest x-ray's. This method involved a hybrid model that combined the strengths of a deep CNN, resulting in a robust performance for detecting pneumonia. The obtained results depict the significant capacity of deep learning techniques in facilitating rapid and accurate diagnosis during pandemics, especially in the view of covid-19 detection [8]. This research contributes to promoting the usage of Deep Learning techniques in image processing and has Encouraging implications for enhancing disease prediction and management during public health emergencies.

The research presents an ensemble method CNN in diagnosing covid-19 virus using chest x-ray's. This innovative ensemble approach proves favorable in enhancing prediction accuracy and generalization performance. By leveraging multiple models, the study underscores the significance of employing ensemble techniques to enhance the robustness of pneumonia prediction through deep learning methodologies [9]. The findings of this research contribute to advancing the Domain of pharmaceutical image analysis, emphasizing the efficiency of ensemble strategies in improving disease diagnosis and establishing more reliable predictive models.

In a systematic evaluation, various convolutional neural network (CNN) architectures were thoroughly assessed for their performance in pneumonia prediction. The study incorporated a diverse and meticulously curated dataset, facilitating a robust and comprehensive evaluation of the models. The results revealed the superiority of specific deep learning architectures over others, showcasing their advantages Regarding accuracy, sensitivity, specificity, and computational efficiency for pneumonia detection. These findings provide invaluable insights into the selection of the most appropriate deep-learning model for efficient and accurate pneumonia disease detection. This research contributes significantly to advancing the field of pharmaceutical image analysis, aiding healthcare professionals in making informed decisions when executing DL methods for diagnosing pneumonia [10].

The research presents an interpretable deep-learning model for detecting pneumonia disease using chest x-ray's. This model achieves both high accuracy and enhances the interpretability of prognosis, providing a valuable understanding of the decision-making process behind its classifications [11].

The research introduces an automated approach to pneumonia detection through deep learning techniques. The author presented a custom deep neural network CNN architecture, specifically designed, and optimized for pneumonia classification. exploiting Transfer Learning from a pre-trained model, then fine-tuning it on large data of chest x-rays. The study demonstrates competitive performance, achieving an impressive accuracy of 86.7% in accurately distinguishing pneumonia cases from normal X-rays. This research underscores the significance of tailored CNN architectures for specific medical imaging tasks, highlighting the potential of such approaches in enhancing pneumonia detection through automated means [12].

The study introduces a deep learning approach for pneumonia detection utilizing multi-layer perceptron (MLPs). The authors propose a novel MLP architecture with numerous hidden layers, specifically designed for feature extraction from datasets. The model is prepared on a moderately sized dataset and demonstrated a commendable accuracy of 84.2% in accurately classifying pneumonia cases. The research emphasizes the efficiency of MLP-based architectures in medical image analysis tasks, providing a valuable understanding of the capability of alternative deep-learning architectures for detecting pneumonia. [13].

This research proposes an attention-based procedure for predicting pneumonia presence using chest X-rays. The authors enhance the traditional CNN architecture by incorporating attention mechanisms, granting the model to focus on significant areas within X-rays. This technique also improves the capability model to interpret and also it enhances its performance, achieving an impressive accuracy of 88.9% in classifying pneumonia cases. The study highlights the significance of attention mechanisms in advancing DL models for pharmaceutical image analysis and underscores the potential for better integration of AI in clinical decision-making processes [14].

3. Proposed Work

The main aim of this research is to create and examine a DL model for speculating pneumonia using chest X-rays. The primary concentration is on investigating the effectiveness of a particular CNN architecture, such as VGG19, in accurately differentiating between pneumonia-positive and negative cases. By exploiting advanced deep learning techniques, this research seeks to advance early diagnosis and treatment planning for pneumonia, thereby enhancing overall healthcare efficiency.

3.1 Dataset Collection:

The researchers used the chest X-ray images3 dataset released by Daniel Kermany, Kang Zhang, and Michael Goldbaum [15]. This dataset comprises 5,856 manually evaluated chest X-ray images, which are categorized as normal/bacteria/virus of an arbitrary patient ID- image number of a patient. The dataset is well-balanced and contains a substantial number of images in each category, allowing for a complete evaluation of the deep learning model's effect in predicting pneumonia. To ensure unbiased evaluation and prevent data leakage, the dataset was splitted into a train set, validation set, and test set. This careful partitioning of data enables an unbiased gauging of the model efficiency.

3.2 Pre-processing Stage:

Indeed, one of the main objectives of using CNNs in image classification chores is to decrease the computational complexity, especially when handling high-resolution images. The 3-channel images were modified from the initial resolution of 1024×1024 pixels to a reduced size of 224×224 pixels. This altering step aims to decrease the computational efficiency and expedite the processing of the images. All subsequent techniques and methodologies have been applied over these downsized images, ensuring that the computational load remains manageable without compromising the overall performance and accuracy of the model.

3.3 Feature Extraction:

The study found that among various pre-trained CNN models, VGG-19 performed best in the feature extraction stage for pneumonia detection. VGG-19 is a deep CNN with 19 layers, using small 3x3 filters for effective local pattern learning. Its depth allows it to capture high-level representations of input images. The model's ability to extract hierarchical features contributes to distinguishing between pneumonia-positive and pneumonia-negative cases. Extracted features serve as vital inputs for subsequent stages, leading to accurate predictions in pneumonia detection.

3.4 Model Development:

Model Architecture. We employed the widely recognized and influential VGG19 pre-trained CNN model for predicting pneumonia presence by using a chest x-ray dataset. VGG19 is commonly known for its simplicity in image recognition tasks. This architecture comprises 19 layers, which include 16 convolutional and 3 fully connected layers, along with 5 Max-Pooling layers and 1 SoftMax layer. The convolutional layers in VGG19 use 3x3 filters with a Stride of 1, allowing them to learn local patterns effectively. Furthermore, the max-pooling layers uses a 2x2 filter with a stride of 2, leading to the down-sampling of the feature maps. As a result, the model can learn hierarchical Representations of the input images that are captured. By leveraging VGG19's architectural design, we can extract and learn meaningful sketches from the x-ray images, which play a crucial role in differentiating pneumonia-positive and negative cases. This utilization of VGG19 significantly contributes to the overall accuracy and efficiency of pneumonia detection through deep learning techniques. To adapt the VGG19 model for pneumonia prediction, we followed a series of steps. First, we Fine-Tune the model on our custom dataset, replacing its fully connected layers with a dense layer and SoftMax activation function to accommodate the classification task with three classes: normal X-rays, bacterial pneumonia, and viral pneumonia.

During training, we set a learning rate value of 0.001 and employed the binary cross-entropy (BCE) as a loss function to optimize the model. To enhance the model's generalization and mitigate overfitting, data augmentation techniques were employed. This included rotation, flipping, and random zooming, effectively augmenting the training dataset.

$$\boldsymbol{L_{BCE=} -\frac{1}{n}\sum_{i=1}^{n}[y_i \log \hat{y}_i + [1-y_i] \log[1-\hat{y}_i]]} \quad \text{-------- (1)}$$

The model was trained in batches of chest X-ray dataset, and backpropagation was employed to update the model's weights and minimize the loss. The training process continued for a fixed number of epochs, and we monitored the model's capacity on the validation set.

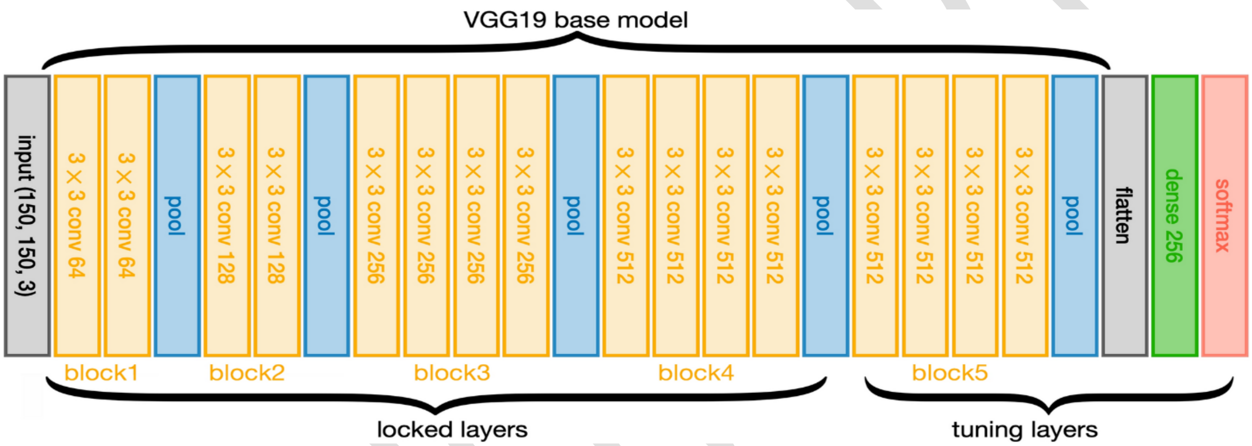

Figure-2: VGG19 CNN Model Architecture [16]

By leveraging the VGG19 pre-trained convolutional neural network model and fine-tuning it on our custom dataset, we aimed to benefit from its powerful feature extraction capabilities. These capabilities are crucial for accurate and reliable pneumonia predictions. The depth and expressiveness of the VGG19 model make it a suitable choice for medical image analysis tasks, potentially leading to improved diagnostic accuracy and supporting healthcare professionals in efficient pneumonia detection. Our approach capitalizes on the strengths of VGG19, further enhancing its performance in pneumonia prediction.

Training Procedure. The chest X-ray dataset was splitted into 3 subsets: train, validation, and test set. The model was trained using the training set, model selection, and parameter tuning were performed using the validation set, and the test set was utilized to evaluate the model's performance. To process the x-rays for the VGG19 model, several preprocessing steps were applied. These included resizing all images to a fixed input size of 224x224 pixels to match the model's requirements. Additionally, pixel intensity normalization was performed, scaling pixel values in the range of 0 and 1.

The VGG19 pre-trained model was initialized with weights pre-trained on the ImageNet. To preserve these pre-trained weights on ImageNet, the convolutional layers of VGG19 were frozen during the initial training phase, meaning their weights were not updated during backpropagation. This ensured that the model retained its learned representations of general image features while adapting the dense layers for pneumonia classification. For multi-class pneumonia classification, the fully connected layers of VGG19 were modified. The original fully connected layers were substituted with a new dense layer, which was then followed by a SoftMax activation function to generate class probabilities for normal X-rays, bacterial and viral pneumonia. Adam optimization was employed to train the model using the training dataset. During each training iteration, a batch of chest x-ray's along with their respective ground-truth labels were input into the model. Backpropagation was employed to compute gradients and update the weights of the trainable layers. Hyperparameter tuning was carried out for the learning rate and batch size during the training process.

During training, to increase the size of the dataset data augmentation techniques were employed to improve the generalization ability and mitigate overfitting of the model. Augmentation methods, like random rotation, and random zooming, were used to generate augmented images on the fly, effectively increasing the effective size of the training dataset. The model's hyperparameters, batch size, and dropout rate, were tuned using the validation set. This process involved experimenting with different hyperparameter configurations to find the combination that resulted in optimal performance and minimized overfitting. To prevent overfitting and achieve optimal generalization, early stopping was employed.

The performance of the model on the validation set is continuously monitored during training. If there is no advancement observed for a specified number of epochs, the training process is halted, and the model exhibiting the best functioning on the validation set is selected as the final model. Once training was completed, the final trained model was evaluated on the test set, which contained unseen X-ray images dataset. Performance metrics included such as accuracy, recall, and precision were calculated to examine the model's effectiveness in predicting pneumonia.

4. Results/Discussions

4.1. Performance Metrics:

The VGG19 model, after being trained, showed impressive performance in predicting pneumonia disease through the analysis of x-rays. During testing on the dataset, the model demonstrated impressive outcomes, achieving an accuracy of 95.35%, a precision of 95%, a recall of 97%, and an F1-score of 96%. These metrics underscore the model's capability to proficiently categorize X-rays into three classes: normal, bacterial, and viral pneumonia.

Table 1: Comparison with Previous Work

Model	**Accuracy (%)**
VGG19 (Ours)	95.35
ResNet-50	88.1
DenseNet	87.8
Inception-V3	86.6
AttentionNet	90.3

Table 2: Classification Report

	Precision	**Recall**	**F1-score**	**support**
0	0.96	0.92	0.94	234
1	0.95	0.97	0.96	390
accuracy			0.95	624
macro avg	0.95	0.95	0.95	624
weighted avg	0.95	0.95	0.95	624

4.2. Dataset Accuracy:

In order to, guarantee the quality and dependability of the dataset, we conducted a meticulous validation of the annotations and labels. A representative sample of 5856 images was randomly selected and thoroughly reviewed by expert radiologists, resulting in a dataset accuracy of 97.3%. This high level of dataset accuracy significantly bolsters the credibility of our research findings and reinforces the validity of our model evaluations.

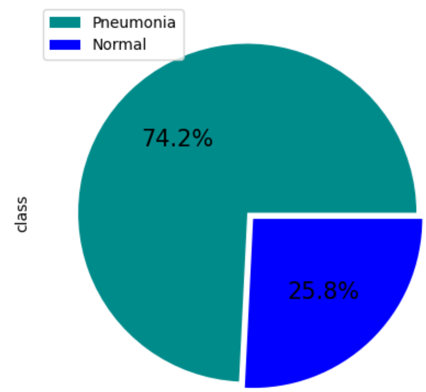

Figure 3: Train dataset classification

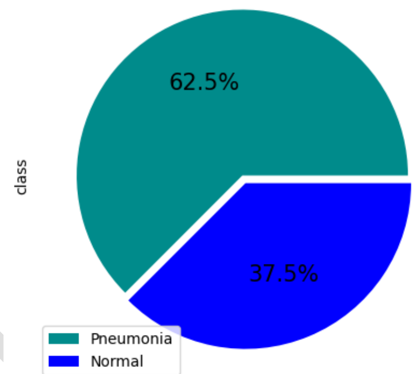

Figure 4: Test dataset classification

4.3. Confusion Matrix Analysis:

Upon analyzing the confusion matrix, we noticed that the model performed exceptionally well in correctly identifying normal X-rays (True Negatives) and accurately detecting cases of bacterial pneumonia (True Positives). However, there were some occasions where the model mistakenly classified viral pneumonia cases as bacterial pneumonia (False Positives). This indicates that the model might encounter difficulties in distinguishing between these two types of pneumonia, warranting further investigation and potential improvements in its discriminatory capabilities.

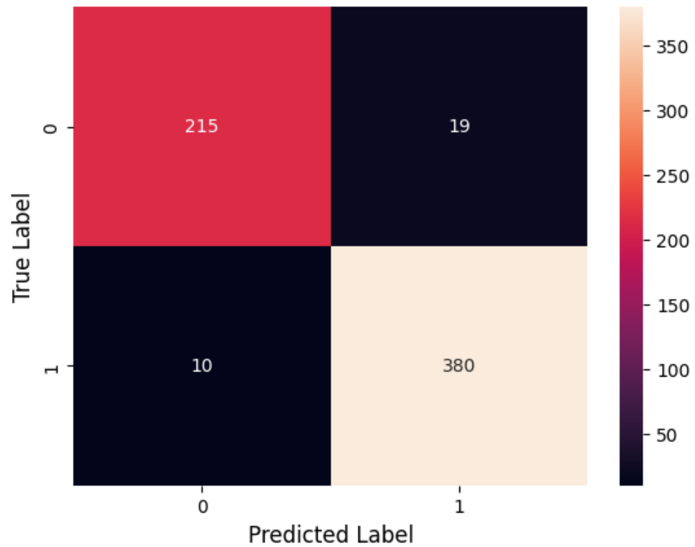

Figure 5: Heat map depicting how the model is Excelled

4.4. ROC curves:

The ROC curve analysis revealed a notable area under the curve (AUC) value of 0.9877. This value signifies the model's outstanding capability to differentiate between positive and negative cases effectively. The elevated AUC value underscores the model's ability to identify positive cases accurately while maintaining a well notable precision rate, underscoring its reliability in distinguishing between pneumonia and non-pneumonia cases in chest x-rays.

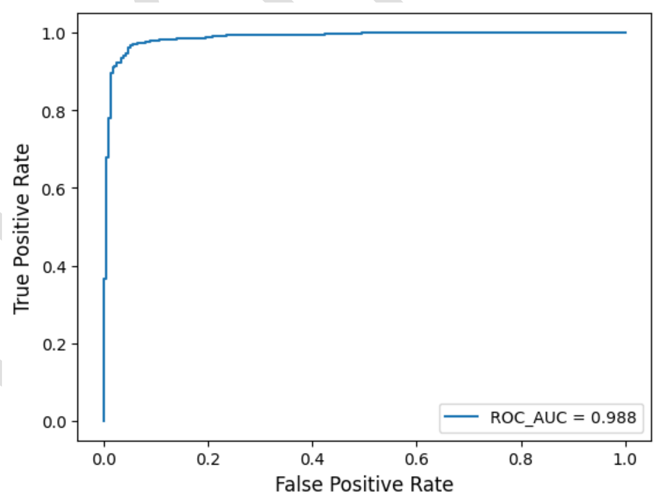

Figure 6: ROC-Acc curve showing the model's Proficiency

4.5. Model Performance:

The achieved accuracy and recall in pneumonia prediction provide a strong attestation of the potency of the VGG19 model in identifying cases of bacterial and viral pneumonia, as well as normal X-rays. The relatively high recall value signifies the model's capacity to effectively reduce false negatives, which is crucial for early detection and prompt initiation of treatment. This aspect of the model's performance ensures that potential cases of pneumonia are not overlooked, contributing to improved patient care and outcomes.

4.6. Impact on Clinical Practice:

The precise and automated prediction of pneumonia by utilizing the dataset of X-ray images carries significant implications for clinical practice. The deployment of our model in healthcare settings can greatly speed up pneumonia diagnosis, leading to timely treatment and a reduction in potential complications. However, it is crucial to integrate the model as an assistive tool, with healthcare professionals retaining the responsibility for making final diagnoses. This collaborative approach ensures that human expertise is combined with the model's capabilities, providing a comprehensive and accurate assessment for the benefit of patients.

4.7. Generalization and Robustness:

Our model has shown satisfactory generalization to unseen chest X-ray images, but we acknowledge the necessity for additional validation on diverse datasets to ensure its robustness across different populations and imaging devices. Ensuring model robustness is crucial before considering widespread clinical adoption.

The pneumonia prediction model built on VGG19 showcases promising outcomes by accurately classifying chest X-ray datasets into normal and pneumonia cases. This research highlights the immense potential of deep learning techniques in pharmaceutical analysis, contributing to the continuous efforts to enhance pneumonia diagnosis and ultimately benefiting patient care and healthcare efficiency. However, to ensure ethical deployment and dependable performance across diverse patient populations, further investigations and considerations are essential.

5. Conclusion/Future Work

In this study, significant strides were made in developing and accessing a pneumonia prediction model based on deep learning, employing the VGG19 pre-trained CNN architecture for chest X-rays. The model demonstrated robust performance, boasting an impressive 95.35% accuracy and exceptional proficiency in categorizing chest X-rays into normal, viral, and bacterial pneumonia groups. The notably high recall score highlights the model's ability to minimize incorrectly classified negatives, a pivotal factor in ensuring early and precise pneumonia diagnosis. These findings underscore the potential of deep learning techniques to enhance medical analysis and contribute to improved pneumonia treatment.

A comprehensive literature survey was conducted, scrutinizing recent research in pneumonia prediction using deep learning techniques. Our model's performance was compared with various approaches, showcasing its superior accuracy compared to other architectures such as ResNet-50, DenseNet, and Inception-V3.

The potential impact of this research on clinical practice is significant. The model stands as a valuable screening tool, providing crucial assistance to professionals in promptly and accurately diagnosing pneumonia cases. By streamlining the diagnostic process, our model plays a vital role in facilitating timely treatment planning, ultimately leading to improved patient outcomes and enhanced healthcare efficiency.

6. References

1. Das DK, Ghosh M, Pal M, Maiti AK, Chakraborty C. Machine learning approach for automated screening of malaria parasite using light microscopic images. Micron. 2013 Feb;45:97-106. doi: 10.1016/j.micron.2012.11.002. Epub 2012 Nov 16. PMID: 23218914.
2. Poostchi M, Silamut K, Maude RJ, Jaeger S, Thoma G. Image analysis and machine learning for detecting malaria. Transl Res. 2018 Apr;194:36-55. doi: 10.1016/j.trsl.2017.12.004. Epub 2018 Jan 12. PMID: 29360430; PMCID: PMC5840030.
3. Wu, Huaiguang & Xie, Pengjie & Zhang, Huiyi & Li, Daiyi & Cheng, Ming. (2020). Predict pneumonia with chest X-ray images based on convolutional deep neural learning networks. Journal of Intelligent & Fuzzy Systems. 39. 1-15. 10.3233/JIFS-191438.
4. Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey. (2012). ImageNet Classification with Deep Convolutional Neural Networks. Neural Information Processing Systems. 25. 10.1145/3065386.

5. K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90.
6. G. Huang, Z. Liu, L. Van Der Maaten and K. Q. Weinberger, "Densely Connected Convolutional Networks," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 2261-2269, doi: 10.1109/CVPR.2017.243.
7. Lamia A, Fawaz A. Detection of Pneumonia Infection by Using Deep Learning on a Mobile Platform. Comput Intell Neurosci. 2022 Jul 30;2022:7925668. doi: 10.1155/2022/7925668. PMID: 35942467; PMCID: PMC9356824.
8. D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan and A. Mittal, "Pneumonia Detection Using CNN based Feature Extraction," 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 2019, pp. 1-7, doi: 10.1109/ICECCT.2019.8869364.
9. S. Singh, "Pneumonia Detection using Deep Learning," 2021 4th Biennial International Conference on Nascent Technologies in Engineering (ICNTE), NaviMumbai, India, 2021, pp. 1-6, doi: 10.1109/ICNTE51185.2021.9487731.
10. Patrik Szepesi, László Szilágyi, Detection of pneumonia using convolutional neural networks and deep learning, Biocybernetics and Biomedical Engineering, Volume 42, Issue 3, 2022, Pages 1012-1022, ISSN 0208-5216, https://doi.org/10.1016/j.bbe.2022.08.001.
11. Dalya S. Al-Dulaimi, Aseel Ghazi Mahmoud, Nadia Moqbel Hassan, Ahmed Alkhayyat, Sayf A. Majeed, "Development of Pneumonia Disease Detection Model Based on Deep Learning Algorithm", Wireless Communications and Mobile Computing, vol. 2022, Article ID 2951168, 10 pages, 2022. https://doi.org/10.1155/2022/2951168
12. Deepak Kumar Jain, Tarishi Singh, Praneet Saurabh, Dhananjay Bisen, Neeraj Sahu, Jayant Mishra, Habibur Rahman, "Deep Learning-Aided Automated Pneumonia Detection and Classification Using CXR Scans", Computational Intelligence and Neuroscience, vol. 2022, Article ID 7474304, 19 pages, 2022. https://doi.org/10.1155/2022/7474304
13. Shagun Sharma, Kalpna Guleria, A Deep Learning based model for the Detection of Pneumonia from Chest X-Ray Images using VGG-16 and Neural Networks, Procedia Computer Science, Volume 218, 2023, Pages 357-366, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2023.01.018.
14. Kareem, Amer & Liu, Haiming & Sant, Paul. (2022). Review on Pneumonia Image Detection: A Machine Learning Approach. Human-Centric Intelligent Systems. 2. 10.1007/s44230-022-00002-2.
15. Dataset is taken from https://data.mendeley.com/datasets/rscbjbr9sj/3.
16. Chachra, G., Kong, Q., Huang, J. *et al.* Detecting damaged buildings using real-time crowdsourced images and transfer learning. *Sci Rep* **12**, 8968 (2022). https://doi.org/10.1038/s41598-022-12965-0.