# Pneumonia Detection in Chest X-Ray Images Using DenseNet121 with Dual Attention Networks

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***Abstract*— Pneumonia is a serious respiratory disease that requires fast and correct diagnosis in order to minimize consequences and aid efficient clinical decision making . X-ray imaging is a widely used imaging technique and the assessment of chest X-rays is still a time-consuming and relatively variable process particularly when a patient is in need of urgent care. In order to overcome these drawbacks, an automated DL framework based on DenseNet121 with dual attention techniques for pneumonia identification from chest X-ray images is designed. The workflow makes use of a structured image analysis pipeline which includes dataset exploration, image dimension analysis, contrast enhancement using CLAHE and texture characterization using GLCM features for image analysis. To boost the robustness of the training, data augmentation techniques such as rescaling, rotation, zooming and horizontal flipping are used. The classification architecture was followed by channel attention module and spatial attention module to enhance the discriminative feature representation, which was powered by DenseNet121 backbone pre-trained on ImageNet. Training is done utilizing class weighting and adaptive optimization algorithms. Experimental evaluation on chest X-ray datasets accuracy of 89.26%, precision of 88.36%, recall of 95.38%, F1-score of 91.74% and an AUC of 95.50%. The proposed method demonstrates reliable recognition performance for pneumonia and the efficiency of attention enhanced transfer learning for automated chest radiograph analysis.**

***"Keywords*— *Pneumonia Detection, Chest X-Ray Imaging, DenseNet121, Dual Attention Network, Deep Learning, Transfer Learning, Medical Image Classification, Computer-Aided Diagnosis."***

## I. Introduction

Pneumonia is a serious infection and inflammatory condition of the lungs, which is a main cause of morbidity and mortality not only in children, elderly and vulnerable groups, but also globally [1]. According to the global health surveys pneumonia and lower respiratory disorders are a significant public health problem, placing a tremendous burden on healthcare systems around the world, both in developed and developing countries [2]. Early and precise diagnosis is crucial for enhancing treatment outcomes and slowing down disease development.

The chest X-ray imaging is an extensively used diagnostic tool for the identification of pneumonia due to its availability, low cost, and clinical effectiveness. The interpretation of chest radiographs is, however, very dependent on the expert medical evaluation, and may be confounded by complexity of the images, inter-observer variability, and increasing diagnostic workload. Such problems lead to the need to develop intelligent diagnostic assistance systems that will help healthcare professionals in the provision of automated and reliable picture analysis.

With recent improvement of DL, there has been a paradigm shift in medical image analysis, enabling automated reconstruction of meaningful visual information straight from image data [3] [9]. The development of large-scale data resources and benchmark datasets of chest images has contributed to the rapid progress of computer-aided diagnostic systems for the diagnosis of thoracic diseases [4, 5]. CNNs and transfer learning algorithms demonstrated the great ability in medical image category tasks, which involve the knowledge of pre-trained visual information and fine-tuning it to domain-specific tasks [7]. In the current designs, densely connected convolutional networks have received many interests for their efficient information flow and powerful representation learning potential [6]. Furthermore, previous advances in chest x-ray analysis have shown that DL techniques can achieve very competitive performance to detect pneumonia and support clinical decision making [8].

Yet, existing approaches still face the challenge of ensuring strong performance when the radiographic appearance of an image varies, and of registering important image properties. As mentioned in recent reviews, better feature representation and model emphasis are still significant directions to improve automated pneumonia detection systems [10].

This objective is driven by the challenges such issues pose, and focuses on the study of an automatic DL based system for pneumonia recognition from chest X-ray images. The purpose of this is to allow the simultaneous, rapid and accurate screening with a minimum of human interpretation. It is limited to binary categorization of chest radiographs, and is part of a larger project to develop intelligent computer-aided diagnosis systems for medical imaging applications.

## II. Related Work

With the rapid growth of DL techniques and their potential to aid computer-aided diagnosis, automatic pneumonia detection using chest X-ray images has gained significant interest. Recent advances have mostly been in the realms of transfer learning, CNN, ensemble architectures and attention mechanisms to increase diagnostic performance and to lessen reliance on manual interpretation.

Transfer learning is one of the most widely-used techniques for medical picture classification due to the ability of pretrained networks to use visual representations learned on large-scale datasets. Chouhan et al. [11] introduced a transfer learning based approach to pneumonia diagnosis by fusing multiple pre-trained DL architectures and demonstrated that pre-trained feature extraction can be a significant boost to the classification capability. Likewise, Rahman et al. [12] investigated deep CNN with transfer learning for chest X-ray interpretation and demonstrated that transferring learned representation is useful and efficient in identifying pneumonia even in the absence of large medical data sets. In addition, Iparraguirre-Villanueva et al. [20] also confirmed the efficacy of transfer learning methods by showing that the performance of the classification was increased with adapted convolutional neural network models for pneumonia screening.

In addition to single transfer learning models, a few research works have been conducted on the ensemble-based designs to enhance the resilience and prediction accuracy. Kundu et al. [13] proposed pneumonia diagnosis using an ensemble of deep learning models and demonstrated that the accuracy of the diagnosis was higher than the accuracy using the single models. Gabruseva et al. [14] proposed an automatic pneumonia detection system with DL and highlighted the need of obtaining discriminative radiographic information for correct diagnosis. Jain et al. [15] also used CNN with Transfer Learning to categorize chest X-rays and demonstrated that the CNN could be used in real-world to build automated diagnostic systems.

Recent explorations have also been made towards increasing feature representation by architectural alterations. Mujahid et al. [16] presented an inception-V3 based model and convolutional based techniques for pneumonia classification and stated that the model was effective in feature extraction of chest X-rays. These architectures showed promising performance, but multiple research have shown that ordinary convolutional networks may not always focus on diagnostically relevant areas of medical pictures, which may restrict their applicability to other radiography situations.

Selective feature learning is important and it has gained increasing attention in order to improve the attention process. Brauwers and Frasincar [17] gave a comprehensive study of attention mechanisms and illustrated their ability in enabling neural networks to attend informative spatial and semantic representations. Cha et al. [18] proposed such an idea and demonstrated that the attention mechanism of the network to guide the focus on the region related to the disease can enhance the identification efficiency of pneumonia. Likewise, Wang et al. [19] introduced an attention-based DenseNet network for pneumonia diagnosis and demonstrated the benefits of attention-guided feature refinement for the development of more powerful discriminative learning and improved diagnostic performance.

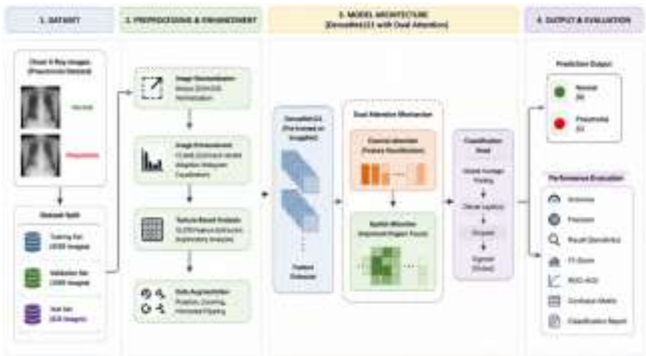
Although significant advances have been reported in the literature with the use of chest X-ray imaging for pneumonia diagnosis, there are numerous limitations. Ensemble models tend to be more computer intensive, and commonly used transfer learning algorithms might not focus on clinically relevant features of pictures sufficiently. Moreover, most of the existing methods rely on either pre-trained feature extraction or single attention mechanism without a unified framework for efficient feature reusing and better feature prioritizing.

Such findings require a method that makes use of the representation power provided by dense linked networks and enhances feature selection with complementary attention mechanisms. In this study, we address this gap by investigating an attention-enhanced DenseNet model to automatically identify pneumonia from chest X-ray images with the goal of achieving powerful and efficient classification performance.

## III. Methodology

### A. Overall Framework

Proposed platform is to provide automated pneumonia detection from chest X-ray pictures. The approach employs a carefully designed DL pipeline to map from X-ray inputs to diagnostic outputs. The first step in the process is the acquisition of X-ray images of the chest, followed by organization of the dataset and pre-processing of the images to standardize the quality and presentation of the images involved. These are called image enhancement and image pre-processing processes together to improve the visual qualities and to enable the successful extraction of features. These generated images are then passed on to a transfer learning based classification architecture with hierarchical feature learning, which locates patterns associated with pneumonia. To enhance the representation ability, we propose to use attention-driven feature refinement to emphasize the informative features and boost the discrimination between normal and pneumonia classes. Lastly, learnt representations are fed into a binary classifier and tested using standard measures. The whole framework is tailored to yield a computer-aided efficient and reliable approach to automated analysis of chest radiographs.



“Fig.1 System Architecture”

The general system architecture of pneumonia diagnosis system for chest X-ray image analysis for proposed framework is shown in Fig. 1. This workflow begins with the acquisition of chest X-rays, dataset preparation, image preprocessing, and image enhancement for standard input data. Then processed images are passed through a transfer learning approach DenseNet121 feature extraction stage to enhance the feature representation, using dual attention techniques. Finally, the framework conducts binary classification and assesses the prediction performance by common diagnostic assessment criteria.

### B. Dataset Description

The experimental evaluation was conducted using a publically available dataset of Chest X-Ray Images (Pneumonia) consisting of X-ray images which belong to two classes: Normal and Pneumonia. The data set was divided into training, validation, and testing sets to facilitate the model building and testing without any influence. There were 4192 training images, 1040 validation images and 624 test images. The parameters of the model were obtained from the training set and the validation set was employed to track the

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training process and to select the model. The independent test set was only employed for the final evaluation to obtain an objective measure of the level of generalization. Figure 2 demonstrates the distribution of the dataset by classes and subgroups and Figure 3 shows samples of chest X-rays for each class and subgroup.

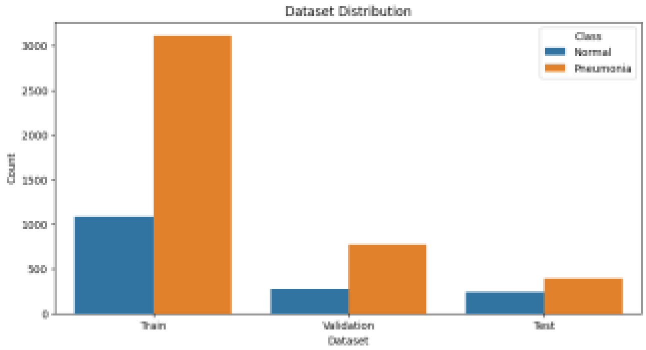


Fig.2 Dataset Distribution

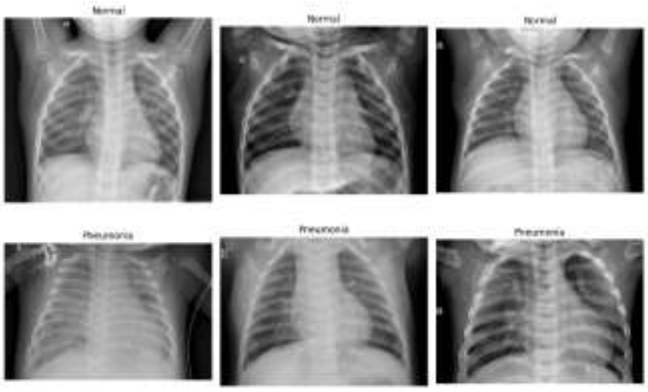


Fig.3 Dataset Images from both Classes

*C. Data Preparation and Image Processing*

Various data preparation and data picture processing steps were performed before the model training to ensure the consistency of model input and enhance the learning efficiency. The standardisation of dimensions, enhancement of visual quality, exploration of texture characterisation, and augmenting the dataset were all the goals of the preparation technique. These techniques were carried out prior to classification to be more robust and to effectively extract features from chest X-ray pictures.

*Image Standardization:* All chest X-ray images were normalized to a common input representation for all samples prior to input to the learning system. The images were then resized to a fixed spatial resolution of 224 × 224 pixels to be compatible with the selected transfer learning architecture and for consistency in computation. The pixel intensity values were also standardized by re-scaling so that they did not have too much variation in numerical values among the samples in order to be optimized at a constant level during model training.

*Image Enhancement:* These types of variations in illumination and contrast are very common in chest radiographs and are likely to affect the process of visual interpretation and automatic feature extraction. To address this issue, image enhancement technique known as CLAHE was employed to enhance local contrast of the images without losing the structural information. This improvement helps to clarify the visualization of radiographical patterns and to differentiate the anatomical properties in the areas of the lungs. The results of initial chest X-ray and the image after using CLAHE is shown in the figure 4.


Fig.4 Original vs CLAHE Enhanced Images

*Texture-Based Analysis:* And the texture was described by studying the spatial correlations of intensities in the chest X-ray images using Gray Level Co-occurrence Matrix (GLCM). The statistical descriptors of the texture variations of the radiogram were studied, including contrast, correlation, energy and homogeneity. This stage was part of an exploratory image analysis procedure to provide information on image features and was not included as one of the direct image analysis features to be incorporated into the final classification model.

*Data Augmentation:* To enhance the generalization of the model and reduce sensitivity to image orientation and appearance variations, data augmentation was used. Training images were augmented by adding carefully controlled transformations such as rotation, zooming and horizontal flipping. These processes yielded new variants, while preserving the underlying diagnostic content, which enabled the model to build more powerful visual representations and improve its ability to generalize beyond the images it had seen.

*D. Proposed DenseNet121 with Dual Attention Network*

The proposed architecture is a hybrid of transfer learning using DenseNet121 and dual attention mechanism for enhancing feature representation in the automated identification of pneumonia from chest X-ray images. The dense feature extraction and attention-based refinement are coupled to enhance the ability of classification. The overall structure is presented in Fig. 1.

*DenseNet121 Backbone:* The backbone network is DenseNet121, which is able to propagate features effectively and has powerful representation learning capability. The network was initialized using transfer learning technique with pretrained weights found in ImageNet. Dense connection enables every layer to have access to information from all of the preceding layers, leading to feature reuse and better flow of gradient. The pretrained backbone layers are fixed during the training to reduce training complexity and retain the visual knowledge learned.

Dense connectivity:

$$x_l = H_l([x_0, x_1, \ldots, x_{l-1}])$$

$H_l$ is the layer transformation and $x_l$ are the output features.

*Channel Attention Module:* To enhance the informative answer, an importance was added to the various feature channels using a channel attention mechanism. The gathered features were re-calibrated using the global context information aggregated from all over the world and converted into attention weights.

Channel attention:

$$M_c(F) = \sigma(W_2(ReLU(W_1(GAP(F)))))$$
$$F_c = M_c(F) \times F$$

where GAP is the Global Average Pooling and $\sigma$ is Sigmoid function.

*Spatial Attention Module:* In the feature maps, after channel refining, the important regions were emphasized using spatial attention. This process helps the network to go to the spatial locations that are most informative for categorization.

Spatial attention:

$$M_s(F) = \sigma(Conv_{7\times7}(F))$$
$$F_s = M_s(F) \times F$$

where Conv is the convolution based spatial attention generation.

*Classification Head:* This was implemented by transferring the refined features to a classification head comprising of Global Average Pooling and a fully connected dense layer. To prevent overfitting, dropout was used, and a sigmoid output layer was used to give the final probability score for binary classification of normal and pneumonia classes.

### E. Model Training Strategy

The recommended network has been trained as a binary classification task with the binary cross-entropy as an optimization objective, aiming to separate the normal and pneumonia classes. Model optimization was done with Adam optimizer with starting learning rate of 0.0001 . The training was done with a batch size of 16 and for a maximum of 10 epochs. To lessen the effect of class imbalance, class weights were used during training. Moreover, Early Stopping was used to remove the unnecessary training process and to reacquire the best model parameters, and Reduce Learning Rate on Plateau was used to change the learning rate adaptively in the training process during convergence. Model Checkpoint was used to keep the best performing model configuration.

### F. Performance Evaluation Metrics

To assess the effectiveness of the suggested framework for pneumonia identification, the effectiveness of the classification, the accuracy of the prediction, and the discriminative power were evaluated using several assessment metrics. These metrics are complementary to each other as they give information about the overall behavior and diagnostic ability of the model.

*Accuracy:* Accuracy will be the ratio of correctly classified samples to the total number of samples and represent the overall effectiveness of the classification.

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \quad (1)$$

TP, TN, FP and FN are TP, TN, FP and FN.

*Precision:* Precision is a measure of how right the forecast is , it is the percentage of positive predictions that are truly positive .

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \quad (2)$$

The more accurate the classification, the fewer false positive classifications .

*Recall:* Model correctly identifies positive cases of pneumonia out of all positive cases.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad (3)$$

The more sensitive that the detection of sickness, the higher is the recall.

*F1-score:* The F1-score is a balanced measure that combines precision and recall into a single measure of performance.

$$F1\ Score = 2 * \frac{Precision \text{ X } Recall}{Precision + Recall} \quad (4)$$

This measure is helpful if the distributions of the classes are not equal.

*ROC–AUC:* The Receiver Operating Characteristic — Area Under Curve (ROC–AUC) determines the ability of the model to make the distinction between the classes for different decision thresholds.

$$AUC = \int TPR(FPR)d(FPR) \quad (5)$$

The larger the AUC, the more accurately the classification is separated.

The model performance was further evaluated with a confusion matrix which was used to understand the class wise prediction behavior and a classification report which provides a detailed distribution of the metrics down the classes.

## IV. Results And Discussion

### A. Experimental Setup

Experimental evaluation was carried out by using a DL environment which is programmed in Python language, using the image processing, model creation, visualization and performance analysis libraries. We implement the proposed DenseNet121 with Dual Attention Network, which is trained by transfer learning for binary classification of chest X-ray images. The model was trained for a max of 10 epochs with Adam optimizer, learning rate of 0.0001 and binary cross-entropy loss function, using 16 samples per batch. To solve class imbalance the class weighting approach was used. For improved stability of training and to keep the best model configuration, Early Stopping, learning-rate reduction, and model checkpointing were used.

### B. Training Performance

The learning progression and convergence properties of the proposed model were examined by the combined accuracy and loss curves over the training epochs to assess the training behavior. Unified representation of training and validation accuracy and training and validation loss: Figure 5 Accuracy curves indicate the consistent improvement in prediction performance over time, with consistently good accuracy across the validation tests, while loss curves indicate the consistent decline in the optimization over time. The learning patterns observed are found to be converging well with controlled overfitting, suggesting that the learning configuration and regularization techniques used are suitable for good model generalization.

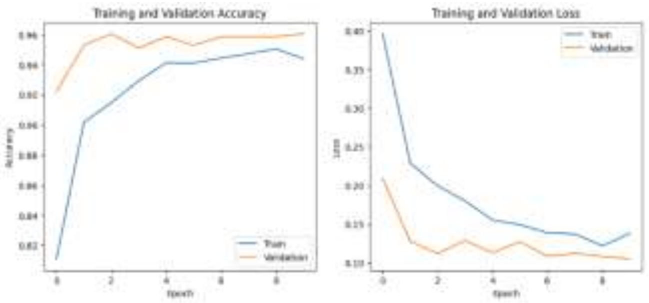


Fig.5 Model Training Performance

*C. Classification Performance*

The effectiveness of the proposed model for classification was explored through confusion matrix visualization and Class-Wise assessment measures, which were used to assess the effectiveness of predictions for both normal and pneumonia classes. The distribution of correct and incorrect classifications is depicted in the confusion matrix of figure 7, which also provides an insightful look into the prediction behaviour at the class level. Moreover, precision, recall and F1-score were assessed by the classification report, which provided a more detailed assessment than overall accuracy. Precision is a measure of reliability of prediction, recall a measure of sensitivity for the detection of pneumonia and F1-score is a balance measure of both. The acquired results gave good performance in detecting the diseases with dependable classification ability.

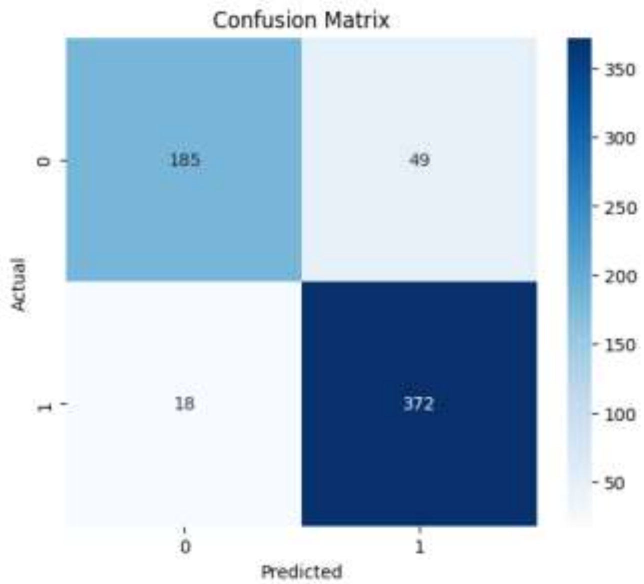


Fig.6 Confusion Matrix

*D. ROC Analysis*

Moreover, the discriminative ability of the proposed model was evaluated with ROC curve, which is presented in Fig. 7. ROC curve illustrates the relationship of TPR and FPR with various classification level and provides an intuition of the model's ability to classify between normal and pneumonia class. The performance metric that was not threshold dependent was the equivalent AUC. Good class separation and good prediction performance for different choice boundaries is indicated by the ROC characteristics obtained.

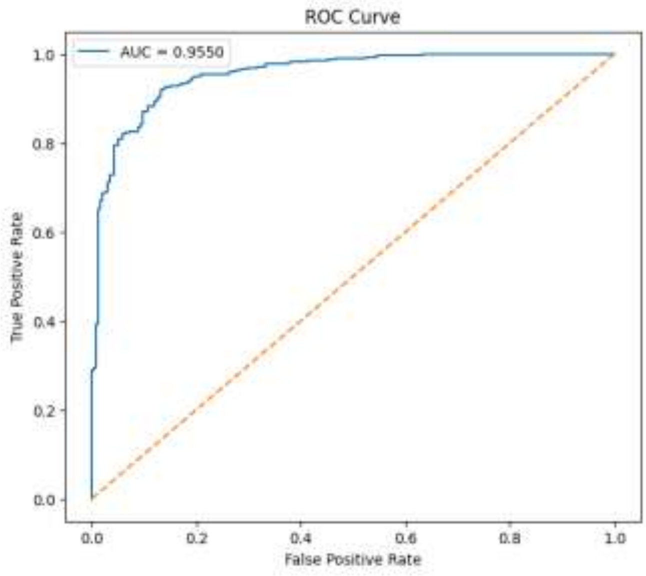


Fig.7 ROC Curve

*E. Comparative Performance Summary*

Conventional classification and ranking measures were used to report the overall effectiveness of the pneumonia detection framework proposed. Table I shows the quantitative evaluation results in terms of Accuracy, Precision, Recall, F1-score and AUC. These parameters provide a comprehensive assessment of the accuracy of prediction, the ability to detect the disease, class balance and discriminative ability. The summary results reflect that the proposed attention-based framework is able to achieve good classification accuracy on the assessment dataset.

Table 1. Performance Evaluation

| Metric | Value (%) |
|---|---|
| Accuracy | 89.26 |
| Precision | 88.36 |
| Recall | 95.38 |
| F1-Score | 91.74 |
| AUC | 95.50 |

## V. Conclusion

This work proposed a DL based automated framework for chest X-ray image categorization for pneumonia identification which will aid in a reliable and efficient diagnostic analysis. The primary objective was to develop a computer-aided diagnosis system to detect pneumonia from normal chest X-rays which faced the difficulties of manual image diagnosis and great variations of the chest X-ray image appearance. To this end, a transfer learning-based DenseNet121 and attention-guided feature refinement architecture is developed to boost the representation learning and classification performance.

The model constructed demonstrated good performance in recognizing visual patterns related to diseases and consistent classification accuracy in the test set. The obtained performance demonstrates the efficiency of the pre-trained DL models and attention-driven learning for medical image analysis tasks. The implementation also further illustrates the clinical utility of the automated chest radiograph assessment, by offering a standardized approach for clinical screening and reducing the need to review a full set of chest radiographs manually. Finally, the developed system demonstrates the potential of the intelligent image-based diagnostic system for improvement in automatic diagnosis of pneumonia and health care decision-making support.

Robustness, interpretability and clinical usefulness of automated pneumonia detection systems can be tackled in further research. This approach can be further refined by merging multiple clinical chest X-ray databases that are larger and more heterogeneous to boost generalization across population and imaging context. Future studies could explore more sophisticated attention mechanism and adaptive feature learning for improving localization of disease related patterns. The use of explainable approaches of AI can increase transparency and help to understand predictions in a clinical context. The framework for multi-class thoracic disease categorization could be extended and combined with the real-time computer aided diagnostic systems, thereby increasing the practical value of the framework for healthcare.

## References

[1] World Health Organization, "Pneumonia," 2021. [Online]. Available: https://www.who.int/health-topics/pneumonia

[2] Our World in Data, "Pneumonia and lower respiratory diseases statistics," 2021. [Online]. Available: https://ourworldindata.org

[3] D. S. Kermany *et al.*, "Identifying medical diagnoses and treatable diseases by image-based deep learning," *Cell*, vol. 172, no. 5, pp. 1122–1131, 2018. https://www.cell.com/fulltext/S0092-8674(18)30154-5

[4] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers, "ChestX-Ray8: Hospital-scale chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2017, pp. 3462–3471. https://openaccess.thecvf.com/content_cvpr_2017/html/Wang_Chest X-ray8_Hospital-Scale_Chest_CVPR_2017_paper.html

[5] Dataset from Kaggle, "Chest X-Ray Images (Pneumonia)," 2018. [Online]. Available: https://data.mendeley.com/datasets/rscbjbr9sj/2

[6] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2017, pp. 4700–4708. https://openaccess.thecvf.com/content_cvpr_2017/html/Huang_Densely_Connected_Convolutional_CVPR_2017_paper.html

[7] A. S. Razavian, H. Azizpour, J. Sullivan, and S. Carlsson, "CNN features off-the-shelf: An astounding baseline for recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. Workshops*, 2014, pp. 806–813. https://www.cv-foundation.org/openaccess/content_cvpr_workshops_2014/W15/html/Razavian_CNN_Features_Off-the-Shelf_2014_CVPR_paper.html

[8] P. Rajpurkar *et al.*, "CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning," *arXiv preprint* arXiv:1711.05225, 2017. https://arxiv.org/abs/1711.05225

[9] J. Wang, H. Zhu, S. H. Wang, and Y. D. Zhang, "A review of deep learning on medical image analysis," *Mobile Networks and Applications*, vol. 26, pp. 351–380, 2021. https://link.springer.com/article/10.1007/S11036-020-01672-7

[10] S. Sharma and K. Guleria, "A systematic literature review on deep learning approaches for pneumonia detection using chest X-ray images," *Multimedia Tools and Applications*, 2023. https://link.springer.com/article/10.1007/s11042-023-16419-1

[11] V. Chouhan *et al.*, "A novel transfer learning based approach for pneumonia detection in chest X-ray images," *Applied Sciences*, vol. 10, no. 2, p. 559, 2020. https://www.mdpi.com/2076-3417/10/2/559

[12] T. Rahman *et al.*, "Transfer learning with deep convolutional neural network (CNN) for pneumonia detection using chest X-ray," *Applied Sciences*, vol. 10, no. 9, p. 3233, 2020. https://www.mdpi.com/2076-3417/10/9/3233

[13] R. Kundu, R. Das, Z. W. Geem, G. T. Han, and R. Sarkar, "Pneumonia detection in chest X-ray images using an ensemble of deep learning models," *PLoS ONE*, vol. 16, no. 8, e0256630, 2021. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0256630

[14] T. Gabruseva, D. Poplavskiy, and A. Kalinin, "Deep learning for automatic pneumonia detection," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops*, 2020, pp. 350–351. https://openaccess.thecvf.com/content_CVPRW_2020/html/w22/Gabruseva_Deep_Learning_for_Automatic_Pneumonia_Detection_CVPRW_2020_paper.html

[15] R. Jain, P. Nagrath, G. Kataria, V. S. Kaushik, and D. J. Hemanth, "Pneumonia detection in chest X-ray images using convolutional neural networks and transfer learning," *Measurement*, vol. 165, p. 108046, 2020. https://www.sciencedirect.com/science/article/pii/S0263224120305844

[16] M. Mujahid *et al.*, "Pneumonia classification from X-ray images with Inception-V3 and convolutional neural network," *Diagnostics*, vol. 12, no. 5, p. 1280, 2022. https://www.mdpi.com/2075-4418/12/5/1280

[17] G. Brauwers and F. Frasincar, "A general survey on attention mechanisms in deep learning," *IEEE Transactions on Knowledge and Data Engineering*, vol. 35, pp. 3279–3298, 2021. https://ieeexplore.ieee.org/abstract/document/9609539/

[18] S. M. Cha, S. S. Lee, and B. Ko, "Attention-based transfer learning for efficient pneumonia detection in chest X-ray images," *Applied Sciences*, vol. 11, p. 1242, 2021. https://www.mdpi.com/2076-3417/11/3/1242

[19] K. Wang, P. Jiang, J. Meng, and X. Jiang, "Attention-based DenseNet for pneumonia classification," *IRBM*, vol. 43, pp. 479–485, 2022. https://www.sciencedirect.com/science/article/pii/S195903182100141X

[20] O. Iparraguirre-Villanueva, V. Guevara-Ponce, O. Roque Paredes, F. Sierra-Liñan, J. Zapata-Paulini, and M. Cabanillas-Carbonell, "Convolutional neural networks with transfer learning for pneumonia detection," 2022. https://repositorio.uwiener.edu.pe/entities/publication/190e3cc7-fbe4-4ad6-b624-10b38944588e