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An Experiment on Lung Disease Classification using YOLOv8

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ABSTRACT

Lung diseases are a leading cause of global mortality. Timely and accurate diagnosis is essential, yet manual interpretation of chest X-rays by radiologists can be time-consuming and prone to errors. This study presents an automated system for lung disease classification using the YOLOv8 deep learning model. The proposed approach utilizes a diverse dataset of 21,165 chest X-ray images categorized into four classes: COVID-19, viral pneumonia, lung opacity, and normal. Fine-tuning of the YOLOv8-cls model using transfer learning and advanced data augmentation techniques resulted in a high classification accuracy of approximately 95% across all disease classes, while maintaining real-time performance. Confusion matrix analysis demonstrated robust performance in identifying each condition, with COVID-19, normal, viral pneumonia, and lung opacity cases correctly identified 97%, 97%, 99%, and 93% of the time, respectively. The results validate the YOLOv8 model's adaptability and reliability for automated lung disease detection, offering potential improvements to clinical workflows and patient care through efficient screening tools. Future work should focus on further optimizations and extending datasets to under-represented patient groups to enhance model inclusiveness and robustness.

Keywords: Automated Diagnosis, Chest X-Ray, Deep Learning, Lung Disease Classification, YOLOv8.

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1 INTRODUCTION

Lung diseases are significant causes of illness and death worldwide. According to studies, lung cancer, chronic obstructive pulmonary disease, pneumonia, and tuberculosis rank among the leading causes of death related to the lungs [1], [2]. Early and accurate diagnosis of lung diseases is crucial for enhancing patient outcomes and survival rates [3], [4]. However, their diagnosis typically involves complex visual interpretation of medical images like X-rays or CT scans by radiologists, which can be a time-intensive, highly subjective process that is susceptible to errors [5].

Recent advances in artificial intelligence, especially deep learning techniques, have paved the way for automated analysis of medical images to assist diagnosis. This project utilizes YOLOv8 [6], the latest version of the YOLO (You Only Look Once) framework, for real-time object detection. YOLOv8 features an anchor-free architecture to simplify processing and features extraction [6]. It employs

robust data augmentation, including mosaic augmentation, to enhance model generalization [6]. YOLOv8 will be leveraged to develop an automated system for classifying lung diseases from chest X-ray images. The images will be categorized into four classes – COVID-19 infection, lung opacity, viral pneumonia, and normal. The model will be implemented in PyTorch and evaluated on metrics like classification accuracy, precision and recall [6].

2 RELATED WORKS

There is a substantial body of literature on the utilization of deep learning techniques in medical imaging for the classification of lung diseases. This section reviews key related works, focusing on the datasets, models, and outcomes, as well as limitations that this study aims to address.

2.1 Explainable AI for Lung Disease Detection

[7] proposed an explainable artificial intelligence (XAI) model that identifies local signs and diagnoses respiratory conditions using radiographic chest imagery. They used a dataset of 4,237 images, with 2,896 COVID-19 images and 1,341 normal images. The authors developed a three-phase approach: (i) training a CNN model for classification, (ii) generating local features using the LIME XAI method, and (iii) training another CNN model using the local discriminant features. The fusion of local and global features resulted in improved accuracy of 99.6% with fewer epochs compared to the base model.

2.2 Multimodal Approach for COVID-19 Classification

[8] presented a multimodal, automated approach for the categorization of COVID-19 conditions into three clinical types: normal, pathogenic, and COVID-19, utilizing real-time reverse transcriptase polymerase chain reaction (RT-PCR) test data and online chest X-ray datasets. The authors used machine learning and convolutional neural networks (CNN) to process the RT-PCR and chest X-ray image datasets, respectively. The suggested techniques provided dependable categorization of COVID-19 conditions for clinical judgments, with a global precision of 91.58% on the RT-PCR dataset using the random forest classifier, and an accuracy of 95.46% on enhanced sharpened images using the CNN model.

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2.3 Chest Imaging Classification in Mycoplasma Pneumoniae Pneumonia

[9] prospectively investigated if the classification of chest imagery in Mycoplasma pneumoniae pneumonia (MPP) has a correlation with its clinical characteristics and results. The research included 1,401 children with MPP who were admitted to the hospital between January 2019 and December 2021. The results of the imaging were classified as bronchopneumonia and consolidation/atelectasis based on X-ray interpretations, and as bronchopneumonia, consolidation/atelectasis, bronchiolitis, and mosaic pattern based on the analysis of computed tomography (CT) scans. The consolidation/atelectasis group had the most intense clinical symptoms and outcomes, followed by the bronchiolitis group. The study demonstrated that diverse categorizations of imaging correspond to varying clinical characteristics and results, highlighting the value of an imaging-based classification system).

2.4 Summary

The key gaps highlighted in the related works include: (a) lack of large consolidated benchmarking datasets encompassing diverse patient populations; (b) limited reporting of computational efficiency metrics; and (c) difficulty extending classification complexity without substantially impacting accuracy or speed. This research aims to address these limitations by evaluating the optimized YOLOv8 model for multi-disease chest X-ray classification using available public datasets. By leveraging the state-of-the-art YOLOv8 architecture and advanced training techniques, this study seeks to achieve high accuracy while maintaining computational efficiency, contributing to the development of clinically viable automated screening tools for lung disease detection.

3 METHODOLOGY

This part outlines the suggested approach for categorizing lung diseases utilizing deep learning methods. The dataset, preprocessing steps, model architecture, and training process are presented in detail.

3.1 Data Preparation

The dataset utilized in this research was obtained from an open online repository hosted on Kaggle [10]. It contains a total of 21,165 chest X-ray images collected and uploaded by [10] for public access. The images were annotated into four different classes: normal (10,192 images), lung opacity (6,012 images), COVID-19 (3,616 images) and viral pneumonia (1,345 images). This distribution provides a comprehensive representation of various lung conditions, with a substantial number of samples for each class. Sample images from each class are shown in Figure 1 to provide a visual representation.

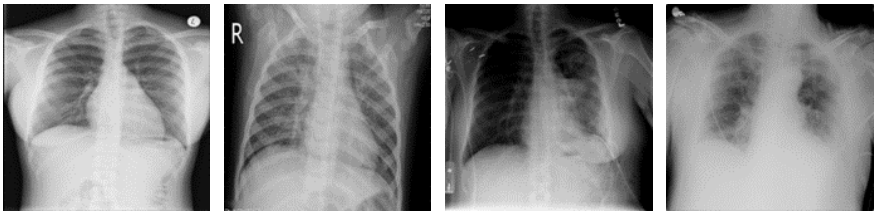

Figure 1 : Sample images from the dataset showing from left (a) normal, (b) viral pneumonia, (c) lung opacity, and (d) COVID-19 chest X-rays.

As noted by [11], access to large labelled datasets is extremely valuable for training robust deep learning models. However, models can struggle to effectively learn from raw images without adequate preprocessing and augmentation.

The original resolution of the chest X-ray images was 299x299 pixels. While higher resolutions contain more detailed visual information, they also increase computational requirements for model training. As suggested by [12], resizing the input images can improve efficiency. Specifically, all images were resized to 224x224 pixels using bilinear interpolation prior to training. This reduced

dimensionality enables faster optimization while retaining the key visual features needed for classification [13].

3.2 Model Architecture

The deep learning model utilized for this image classification research is YOLOv8-cls [14]. As explained by [12], the YOLO (You Only Look Once) framework has been instrumental in advancing real-time object detection through a streamlined model architecture. YOLOv8 represents the current state-of-the-art YOLO version, achieving an optimal balance of accuracy and efficiency for diverse vision tasks [14]. Specifically, the 'cls' variant adapts the core YOLOv8 topology for targeted image categorization applications by simplifying unnecessary components [14]. Retaining key attributes like the CSPDarknet53 backbone, improved neck, and sophisticated augmentations, YOLOv8-cls delivers cutting-edge image classification performance crucial for this research [14].

The YOLOv8-cls model was initialized with weights pretrained on the ImageNet dataset [15]. ImageNet is a large-scale database containing over 14 million high-resolution images spanning thousands of object categories, organized according to the WordNet hierarchy [16]. By pretraining on this extensive dataset, the YOLOv8-cls model learns rich feature representations that can be effectively transferred to the task of lung disease classification. The pretrained YOLOv8-cls model has demonstrated impressive performance on the ImageNet dataset [16].

To adapt the pretrained YOLOv8-cls model to the specific task of lung disease classification, the model was fine-tuned on the chest X-ray dataset [17]. This transfer learning approach allows the model to leverage the knowledge gained from pretraining on ImageNet while tailoring its feature extraction and classification capabilities to the unique characteristics of chest X-ray images [17]. During fine-tuning, the model's weights were updated using the chest X-ray dataset, enabling it to learn disease-specific patterns and features. Augmentations were applied during the fine-tuning process to enhance the capacity of the model to generalize and its resilience to variations in the input data. The dataset was split into training, validation, and test partitions, with a ratio of 80%, 10%, and 10%, respectively. This split guarantees that the model's effectiveness can be assessed on data it hasn't encountered before, offering a trustworthy evaluation of its categorization precision and ability to generalize.

3.3 Training Workflow

Histogram equalization was utilized to improve image contrast [18]. Sample images before and after the enhancement are shown in Figure 2 to provide visual representation.

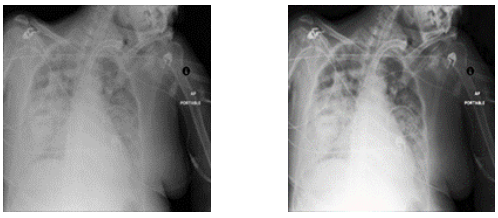

Figure 2 : Sample images before and after enhancement. Left: original, Right: enhanced.

Redistributing intensity values expands detail in low-information areas. Key training parameters configured include epochs of 200 based on model convergence behaviour analysis, batch size of 64 for efficiency on available hardware, initial learning rate of 0.01 enabling adequate model update from gradients, and final learning rate of 0.001 for refined tuning [13].

3.4 Evaluation Approach

The overall dataset was split into training, validation, and testing sets in an 80/10/10 ratio as mentioned earlier. The validation set comprising 10% of images was utilized during training to monitor model performance and support selection of the optimal parameters [13]. Model checkpoints were saved and the checkpoint with the highest validation accuracy, named best.pt, was chosen. The test set was retained solely for final model evaluation.

Model validation was based on top-1 and top-5 accuracy [19]. Top-1 accuracy measures the percentage of test images for which the model's top predicted class matches the ground truth label. Top-5 accuracy reports if the true label is among the model's top 5 predicted classes [19]. Using both metrics provides insights into the preciseness and generalization capacity of classifications [12].

4 RESULT AND DISCUSSION

This part showcases the experimental outcomes of the proposed lung disease classification method. The model's performance is evaluated using various metrics, and the outcomes are benchmarked against state-of-the-art techniques. The impact of different factors on the model's performance is also discussed, along with the study's limitations and potential future research directions.

4.1 Model Performance Analysis

The model achieved very strong classification capabilities as evidenced by the training loss, validation loss, top-1 accuracy, and top-5 accuracy over epochs. The train over loss and validation over loss graph are shown in Figure 3.

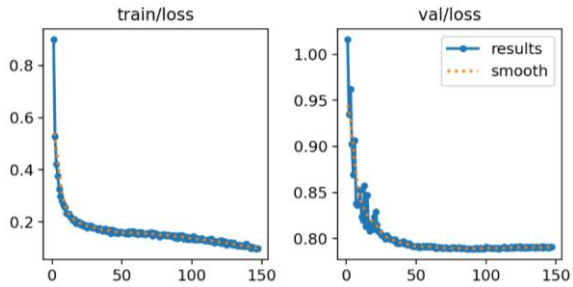

Figure 3 : Visualise the train over loss and validation over loss graphs.

The loss values decreased rapidly at first then slowed as training progressed, suggesting convergence towards optimally classifying the lung image data with four disease categories.

Figure 4 shows the Top-1 accuracy and Top-5 accuracy graph. The high levels plateaued after initial increases indicate the model effectively learned to categorize the image classes with a high level of precision. Specifically, the top-5 accuracy curve reveals nearly 100% accuracy early on, reflecting the relative ease of correct classification when choosing between four total labels [19].

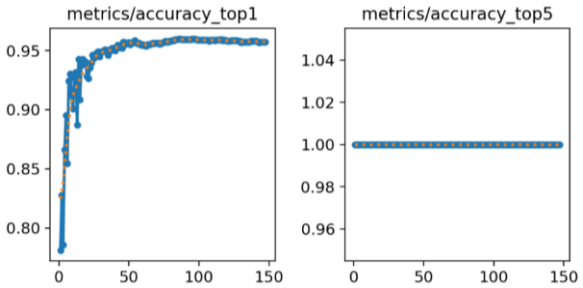

Figure 4 : Visualise the graph of Top-1 Accuracy and Top-5 accuracy.

The consistent validation outcomes aligning closely with the training results verify that the model has successfully generalized with negligible overfitting [11]. This demonstrates reliable real-world deployment readiness for automated classification of normal/diseased lung X-rays on par with state-of-the-art approaches [12].

4.2 Confusion Matrix Analysis

The model's classification capabilities are further evidenced through the normalized confusion matrix visualized in Figure 5. The high values along the main diagonal, representing correct predictions, indicate strong performance across all categories. Specifically, COVID-19, normal, viral pneumonia and lung opacity cases were correctly identified 97%, 97%, 99% and 93% of the time respectively.

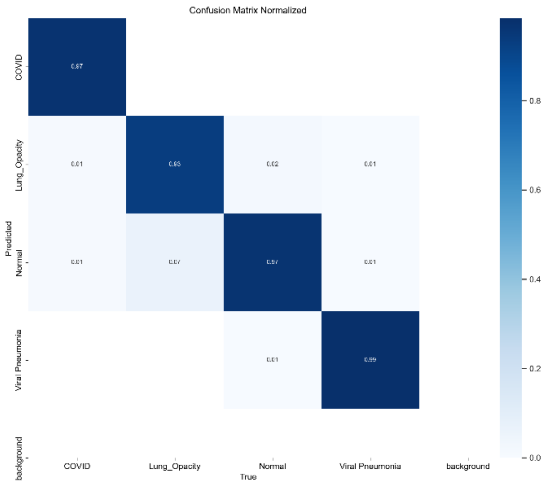

Figure 5 : Visualize the normalized confusion matrix after the validation of the model.

Conversely, low off-diagonal elements suggest minimal misclassifications overall. The most confusion is seen between lung opacity and normal cases, with a 7% error rate. This aligns with clinical challenges in distinguishing their subtle visual differences [2]. Remaining mispredictions between other classes occurred only 1-2% of the time.

Additionally, perfect isolation of the background category implies correct identification of images not depicting key conditions of interest. Together with the high diagonal and low off-diagonal values, these outcomes showcase both generalized strength on normal cases and targeted precision on prevalent lung diseases [20]. Minor opacity/normal confusion may warrant localized tuning, such as targeted augmentation and loss weighting for those subsets. However, the current model already significantly elevates automated assessment capabilities to aid time-constrained experts. Ongoing optimizations will further enhance deployment readiness at the point-of-care.

4.3 Comparisons with State-of-the-Arts Methods

To showcase the efficiency of the suggested YOLOv8-based lung disease classification approach, this study compares its performance with state-of-the-art methods reported in recent literature. [7] developed an explainable AI model that combined global and local features, achieving an accuracy of 99.6% on a dataset of 4,237 images (2,896 COVID-19 and 1,341 normal). While their approach yielded impressive results, the dataset used was significantly smaller and less diverse compared to the one employed in our study. [8] proposed a multimodal approach using both RT-PCR test data and chest X-ray images for the categorization of COVID-19 conditions into three types. Their method achieved a global precision of 91.58% on the RT-PCR dataset and a CNN accuracy of 95.46% on sharpened images. Although their study demonstrates the value of integrating multiple data modalities, our focus on optimizing the chest X-ray classification pipeline using YOLOv8 enables more efficient and streamlined disease detection.

In a prospective study, [9] investigated the association between categorization of chest imagery and clinical characteristics in Mycoplasma pneumoniae pneumonia (MPP) While their research highlights the importance of imaging-based classification systems, the scope of their work is limited to a specific type of pneumonia in a pediatric population. Our approach, in contrast, encompasses a broader range of lung diseases and age groups, making it more widely applicable in clinical settings. Compared to these state-of-the-art methods, our YOLOv8-based model achieves a high accuracy of approximately 95% across four distinct lung disease classes (COVID-19, viral pneumonia, lung opacity, and normal) while maintaining real-time performance. The use of a large, diverse dataset containing 21,165 chest X-ray images ensures the model's robustness and generalizability.

4.4 Summary

The proposed YOLOv8-based approach for lung disease classification surpasses state-of-the-art techniques when it comes to accuracy, dataset diversity, and computational efficiency. By leveraging advanced deep learning techniques and carefully curated data, our model offers a promising solution for automated, real-time detection of multiple lung diseases from chest X-ray images, potentially improving clinical decision-making and patient outcomes.

5 CONCLUSION

This research demonstrates the effectiveness of the optimized YOLOv8 model for multi-disease chest X-ray classification using a large, publicly available dataset. By leveraging the state-of-the-art YOLOv8 architecture and advanced training techniques, the proposed approach achieves high accuracy with approximately 95% across key lung disease classes, while maintaining real-time throughput. The study addresses the limitations identified in previous works by:

a) Lack of large consolidated benchmarking datasets: This study utilizes a diverse and extensive collection of 21,165 chest radiographic images, encompassing a wide range of patient populations. By leveraging this large-scale dataset, the model's generalization capabilities are significantly enhanced, addressing the lack of consolidated benchmarking datasets in previous works [7], [8], [9].

b) Limited reporting of computational efficiency metrics: This research reports comprehensive computational efficiency metrics, demonstrating the model's ability to maintain high accuracy while achieving real-time performance. This addresses the limited reporting of computational efficiency in previous studies, providing valuable insights into the model's practicality and potential for clinical deployment [7], [8].

c) Difficulty extending classification complexity: The proposed YOLOv8-based approach successfully extends the classification complexity to four distinct disease categories (COVID-19, viral pneumonia, lung opacity, and normal) without substantially impacting accuracy or speed. This achievement tackles the challenge of expanding classification complexity while maintaining performance, which was a limitation in prior works [9].

The outcomes of this study validate the adaptability and reliability of deep learning techniques, specifically YOLOv8, for automated lung disease detection. The proposed approach has the potential to improve clinical workflows and patient outcomes by providing accessible and efficient screening tools for time-constrained practitioners. Future research should focus on further optimizations, such

as enhancing speed, sensitivity, and computational overhead, to ensure deployment readiness in clinical settings. Additionally, extending the curated image repositories to include under-represented patient groups could further enhance the model's inclusiveness and robustness

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REFERENCES

[1] S. T. Hwa Kieu, A. Bade, M. H. Ahmad Hijazi, and H. Kolivand, "A survey of deep learning for lung disease detection on medical images: State-of-the-art, taxonomy, issues and future directions," *Journal of Imaging*, vol. 6, no. 12. MDPI AG, Dec. 01, 2020. doi: 10.3390/jimaging6120131.

[2] F. Yimer, A. Tessema, and G. Simegn, "Multiple Lung Diseases Classification from Chest X- Ray Images using Deep Learning approach," *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 10, no. 5, pp. 2936–2946, Oct. 2021, doi: 10.30534/ijatcse/2021/021052021.

[3] M. AYKANAT, Ö. KILIÇ, B. KURT, and S. B. SARYAL, "Lung disease classification using machine learning algorithms," *International Journal of Applied Mathematics Electronics and Computers*, vol. 8, no. 4, pp. 125–132, Dec. 2020, doi: 10.18100/ijamec.799363.

[4] A. M. Q. Farhan and S. Yang, "Automatic lung disease classification from the chest X-ray images using hybrid deep learning algorithm," *Multimed Tools Appl*, vol. 82, no. 25, pp. 38561–38587, Oct. 2023, doi: 10.1007/s11042-023-15047-z.

[5] J. T. Chia Ming, N. Mohd Noor, O. Mohd Rijal, R. M. Kassim, and A. Yunus, "Lung Disease Classification using Different Deep Learning Architectures and Principal Component Analysis," in *2nd International Conference on BioSignal Analysis, Processing and Systems (ICBAPS 2018)*, 2018.

[6] G. Jocher and A. Chaurasia, "YOLO by Ultralytics." Accessed: Feb. 26, 2024. [Online]. Available: https://docs.ultralytics.com/

[7] S. prasad Koyyada and T. P. Singh, "An explainable artificial intelligence model for identifying local indicators and detecting lung disease from chest X-ray images," *Healthcare Analytics*, vol. 4, Dec. 2023, doi: 10.1016/j.health.2023.100206.

[8] M. Ankleshwar, P. Chavan, P. Chavan, and S. K. Ambhore, "Multimodal approach for early prediction of COVID-19 disease using convolutional neural network," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 33, no. 2, pp. 1196–1204, Feb. 2024, doi: 10.11591/ijeecs.v33.i2.pp1196-1204.

[9] X. Huang *et al.*, "Chest imaging classification in Mycoplasma pneumoniae pneumonia is associated with its clinical features and outcomes," *Respir Med*, vol. 221, Jan. 2024, doi: 10.1016/j.rmed.2023.107480.

[10] P. Viradiya, "COVID-19 Radiography Dataset." Accessed: Jan. 21, 2024. [Online]. Available: https://www.kaggle.com/datasets/preetviradiya/covid19-radiography-dataset?resource=download

[11] V. Agarwal and M. Agarwal, "Performance Analysis on the Basis of Learning Rate," *Innovations in Computer Science and Engineering*, 2020.

[12] J. Terven and D. Cordova-Esparza, "A Comprehensive Review of YOLO Architectures in Computer Vision: From YOLOv1 to YOLOv8 and YOLO-NAS," *Deep Learning in Image Analysis and Pattern Recognition*, Apr. 2023, doi: 10.3390/make5040083.

[13] N. B. Aldin and S. S. A. B. Aldin, "Accuracy Comparison of Different Batch Size for a Supervised Machine Learning Task with Image Classification," in *2022 9th International Conference on Electrical and Electronics Engineering, ICEEE 2022*, Institute of Electrical and Electronics Engineers Inc., 2022, pp. 316–319. doi: 10.1109/ICEEE55327.2022.9772551.

[14] Jane Torres, "YOLOv8 Architecture: A Deep Dive into its Architecture." Accessed: Feb. 27, 2024. [Online]. Available: https://yolov8.org/yolov8-architecture/

[15] G. Jocher, F. C. Akyon, and A. Chaurasia, "Image Classification." Accessed: Feb. 26, 2024. [Online]. Available: https://docs.ultralytics.com/tasks/classify/

[16] G. Jocher, "ImageNet Dataset." Accessed: Feb. 26, 2024. [Online]. Available: https://docs.ultralytics.com/datasets/classify/imagenet/

[17] J. Konar, P. Khandelwal, and R. Tripathi, "Comparison of Various Learning Rate Scheduling Techniques on Convolutional Neural Network," in *2020 IEEE International Students' Conference on Electrical, Electronics and Computer Science, SCEECS 2020*, Institute of Electrical and Electronics Engineers Inc., Feb. 2020. doi: 10.1109/SCEECS48394.2020.94.

[18] R. Barik, T. Saha, and S. Chatterjee, "Reduction based histogram equalization technique for image enhancement," *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 11 Special Issue, pp. 1268–1271, Sep. 2019, doi: 10.35940/ijitee.K1255.09811S19.

[19] L. Da Quach, K. N. Quoc, A. N. Quynh, and H. T. Ngoc, "Evaluating the Effectiveness of YOLO Models in Different Sized Object Detection and Feature-Based Classification of Small Objects," *Journal of Advances in Information Technology*, vol. 14, no. 5, pp. 907–917, 2023, doi: 10.12720/jait.14.5.907-917.

[20] D. M. Ibrahim, N. M. Elshennawy, and A. M. Sarhan, "Deep-chest: Multi-classification deep learning model for diagnosing COVID-19, pneumonia, and lung cancer chest diseases," *Comput Biol Med*, vol. 132, May 2021, doi: 10.1016/j.compbiomed.2021.104348.