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Detection of Chest X-ray Abnormalities Using CNN Based on Hyperparameters Optimization †

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Abstract: The Chest X-ray (CXR) is a commonly used diagnostic imaging test that requires significant expertise and careful observation due to the complex nature of the pathology and fine texture of lung lesions. Despite the long-term clinical training and professional guidance provided to radiologists, there is still the possibility of errors in diagnosis. Therefore, we have developed a novel approach using a convolutional neural network (CNN) model to detect the abnormalities of CXR images. The model was optimized using algorithms such as Adam and RMSprop. Also, several hyperparameters were optimized, including the pooling layer, convolutional layer, dropout layer, target size, and epochs. Hyperparameter optimization aims to improve the model's accuracy by testing various combinations of hyperparameter values and optimization algorithms. To evaluate the model's performance, we used scenario modeling to create 32 models and tested them using a confusion matrix. The results indicated that the best accuracy achieved by the model was 97.94%. This accuracy was based on training and test data using 4538 CXR images. The findings suggest that hyperparameter optimization can improve the CNN model's accuracy in accurately identifying CXR abnormalities. Therefore, this study has important implications for improving the accuracy and reliability of CXR image interpretation, which could ultimately benefit patients by improving the detection and treatment of lung diseases. Acknowledging dataset constraints, we address future steps for model improvement.

Keywords: CNN; hyperparameters optimization; CXR diagnostic; lung diseases detection

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1. Introduction

Lung disease accounts for approximately 4 million annual global deaths, including a significant proportion among children under 5 [1,2]. Chest X-ray (CXR) images are pivotal in diagnosing heart and lung conditions [3,4], yet their interpretation demands specialized skills due to intricate pathology and subtle textural variations [5]. Even experts can face challenges, leading to potential misdiagnoses [6,7].

Convolutional Neural Networks (CNNs) excel in image analysis [8], particularly in medical applications like CXR abnormality detection [9,10]. However, CNN performance relies heavily on hyperparameters [11] like learning rate, batch size, optimizer, and epochs [12]. Hyperparameter optimization (HPO) seeks optimal configurations [13], enhancing CNN performance in diverse domains [14]. Although the impact of HPO on CXR abnormality detection CNNs is currently under research [15–17], this study proposes a CNN-based CXR abnormality detection model and evaluates the impact of HPO.

This study conducts 32 experiments using a publicly available dataset to assess CNN model performance with different hyperparameters and optimization algorithms. The results emphasize the significant improvement achieved through hyperparameter optimization (HPO) in CXR abnormality detection. Our approach focuses on optimizing hyperparameters such as learning rates, batch sizes, and architectural choices to enhance accuracy in lung disease detection from CXR images. We introduce innovative strategies for hyperparameter tuning, aiming to maximize CNN performance in CXR analysis.

This article unfolds in four sections. After this introductory overview, the subsequent section details materials and methods, focusing on CNN implementation and hyperparameter optimization. The third section presents implementation, results, and discussion, followed by conclusions in section four.

2. Materials and Methods

This section describes the process flow and methods used in this study based on the secondary dataset. To improve performance, this study uses the CNN method with hyperparameter optimizer and optimization algorithms. The process flow of this research is detailed in Figure 1.

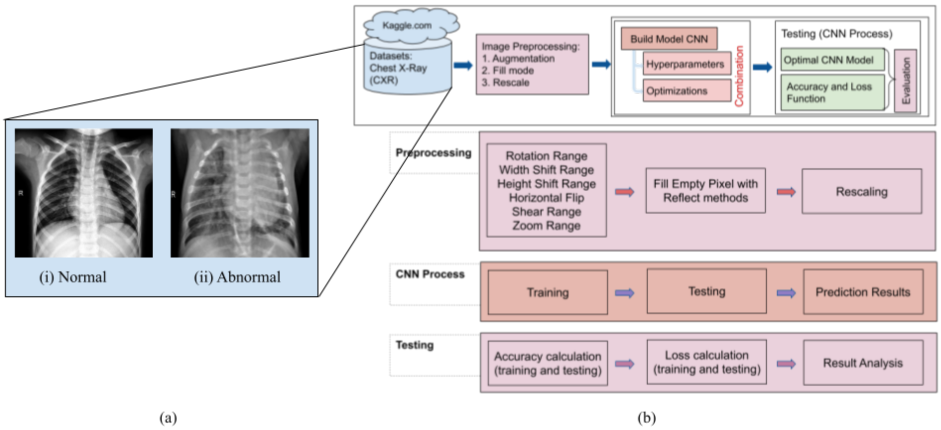


Figure 1. Flowchart of CXR image abnormality detection.

2.1. Dataset

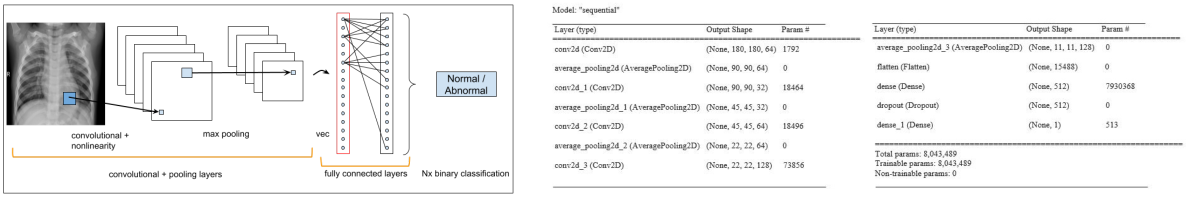
This study uses a secondary dataset from Kaggle.com as a benchmark dataset. The dataset contains 4578 CXR images divided into 2 classes, normal and abnormal (Figure 1a), both with the same amount of data. Pulmonologists and radiology specialists from Lubuksikaping Hospital, Pasaman Regency, West Sumatra, Indonesia, have validated the dataset. This validation aims to strengthen data quality in processing CXR image abnormality detection. The future will add datasets [10,18] for evaluation.

2.2. Identifying Lung Abnormalities

Lung abnormalities, from infections to structural issues, are detected using specialized imaging tests like chest X-rays and CT scans [19]. Our CNN approach uses annotated thorax images to identify conditions like pneumonia, tuberculosis, and lung cancer, adapting during training to improve accuracys [20]. However, final diagnoses are made by healthcare experts, with our study aimed at enhancing model performance through hyperparameter combinations, data augmentation, and CNN testing.

2.3. Convolutional Neural Networks (CNN)

CNNs, inspired by the visual cortex's functioning, excel in image recognition, classification, and segmentation [21]. Comprising multiple layers, CNNs automatically learn features, as depicted in Figure 2. The initial layer, convolutional, employs filters to detect features, followed by nonlinear activation, e.g., ReLU, and downsampling through pooling Figure 2a. Convolution and pooling cycles refine higher-level features. Fully connected final layers handle classification/regression. Backpropagation trains CNNs, with enhancements like residuals, normalization, and dropout elevating their performance.



Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 180, 180, 64)	1792
average_pooling2d (AveragePooling2D)	(None, 90, 90, 64)	0
conv2d_1 (Conv2D)	(None, 90, 90, 32)	18464
average_pooling2d_1 (AveragePooling2D)	(None, 45, 45, 32)	0
conv2d_2 (Conv2D)	(None, 45, 45, 64)	18496
average_pooling2d_2 (AveragePooling2D)	(None, 22, 22, 64)	0
conv2d_3 (Conv2D)	(None, 22, 22, 128)	73856
average_pooling2d_3 (AveragePooling2D)	(None, 11, 11, 128)	0
flatten (Flatten)	(None, 15488)	0
dense (Dense)	(None, 512)	7930368
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 1)	513

Total params: 8,043,489
Trainable params: 8,043,489
Non-trainable params: 0

(**a**) (**b**)

Figure 2. (**a**) CNN Architecture for CXR image classification and (**b**) the detailed model in Python.

Convolution, foundational in CNNs, extracts input data features through kernel sliding [22]. Dot product of kernel and input at each position yields an output value, forming the feature map, as seen in Figure 2b. Output size hinges on input, kernel, stride, and padding [23]. The output feature map size formula is expressed as Equation (1).

$$output\_size = (input\_size - kernel\_size + 2 * padding)/stride + 1 \tag{1}$$

Intensive convolution computation prompts hardware utilization like GPUs or TPUs. Pruning and quantization cut parameters, heightening network efficiency without hampering accuracy. Our research differs through hyperparameter optimization, enhancing model accuracy for precise CXR image interpretation, benefiting healthcare professionals and patients.

2.4. Hyperparameters Combination Scenario Design and Optimization Algorithms

This study focuses on refining the accuracy of identifying abnormal chest X-ray (CXR) images through strategic hyperparameter tuning and optimization. Max Pooling (MP) in the Pooling Layer (PL), a swift-converging CNN technique [24], enhances translation-invariance by capturing local maxima [25,26]. We apply Adam and RMSprop optimization algorithms. Adam integrates AdaGrad and RMSprop properties [27], This combination makes it particularly proficient at dynamically adjusting learning rates to suit intricate neural networks and large-scale datasets. RMSprop utilizes averaged gradients to adjust learning rates and mitigate gradient issues.

Both the Adam and RMSprop optimization algorithms play a pivotal role in training neural networks, with adjustable hyperparameters including the learning rate, momentum, and decay rate [28]. The learning rate guides training updates, while momentum aids in mitigating oscillations. Optimal configurations and algorithm choices have a significant impact on neural network performance [29], highlighting the importance of well-designed hyperparameters and appropriate algorithms for accurate and efficient machine learning.

3. Results

3.1. CXR Image Processing

In image processing, techniques such as augmentation, fill mode, and rescaling play a vital role in enhancing the quality and quantity of training data, thereby improving the accuracy of CNNs. Data augmentation encompasses operations like rotation (with a range of 5 degrees), width shifting (range of 10%), height shifting (range of 5%), horizontal flipping, shearing (range of 10%), and zooming (range of 15%). An 80:20 dataset split was employed for training and testing. The fill mode operation addresses missing pixel values by using the reflect method, replacing them with their nearest reflected counterparts. Furthermore, min-max normalization rescales pixel values by dividing them by 255, standardizing them within the range of 0 to 1. These preprocessing techniques ensure consistent image dimensions and pixel value ranges, contributing to heightened accuracy and efficiency of the model [18,30].

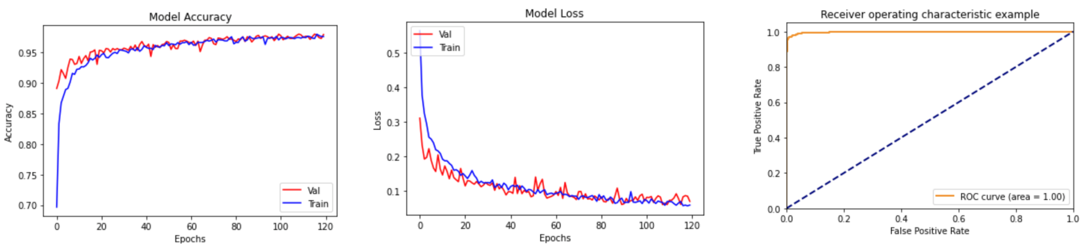
3.2. CXR Classification Based CNN

A comprehensive CNN model training and testing process was executed to optimize CXR image classification. This involved strategic hyperparameter tuning and optimization algorithms. The CNN model underwent 32 experiments, testing various hyperparameter combinations and optimization algorithms (Table 1).

Table 1. The results of testing the CNN model with hyperparameters optimization.

Hyperparameter		**4 Convolutional Layer**				**5 Convolutional Layer**			
Target Size (Pixel)		**64 × 64**		**180 × 180**		**64 × 64**		**180 × 180**	
Epoch		**50**	**120**	**50**	**120**	**50**	**120**	**50**	**120**
Maxpooling (Accuracy)	Adam	95.18%	93.69%	95.91%	93.70%	94.97%	96.81%	95.89%	97.09%
	RMSprop	91.99%	95.11%	88.17%	95.96%	93.96%	95.25%	96.10%	94.05%
Averagepooling (Accuracy)	Adam	96.52%	97.45%	96.38%	97.94%	95.75%	96.88%	96.10%	97.52%
	RMSprop	95.60%	95.04%	94.97%	95.11%	95.75%	96.17%	96.16%	95.96%

Table 1 highlights the superior performance of the **Adam** optimizer. It yielded an accuracy of 97.94%, reflecting optimal quality with the highest accuracy and lowest loss (Figure 3a,b. This model was employed for detecting CXR abnormalities. The visualization depicts stable curves indicating quality, free from overfitting or underfitting concerns.



(**a**) (**b**) (**c**)

Figure 3. Curves of (**a**) accuracy and (**b**) loss in the optimal trial training and validation process.

Findings indicate Adam's superiority over RMSprop in CXR abnormality detection, considering dataset specifics, architecture, and hyperparameters. Adam's adaptive learning rate accelerates convergence, particularly in intricate datasets. Its momentum-based updates aid in escaping local minima, crucial for sensitive tasks like chest X-ray abnormality detection. L2 regularization curbs overfitting and enhances generalization. However, achieving success relies on the selection of hyperparameters and optimization techniques.

Figure 3a,b, portray epoch-wise accuracy and loss. The blue accuracy curve signifies training, with higher values indicating better quality. The red curve reflects validation; proximity and stable value shifts denote optimal quality without overfitting.

An efficient CNN model exhibits low loss and high accuracy, evident in convergence with loss below 10% for training and validation. An accuracy of 97.94% with minimal divergence underscores model optimality.

4. Discussion

Selection of Hyperparameters and optimizers can get the optimal performance of machine learning models. In the case of CNNs, hyperparameters such as the number of convolutional layers, the size of the target image, the type of pooling, and the number of epochs can significantly impact the accuracy of the model. This study conducted 32 experiments with 5 parameters, each with 2 possible values, to find the optimal combination of hyperparameters and optimizers (32 combinations).

The results indicated that each hyperparameter and optimizer tested significantly impacted the quality of the model produced. The most optimal combination was found in the experiment, which used the Adam optimizer, average pooling, 4 convolutional layers, a target size of 180 × 180 pixels, and 120 epochs. This combination achieved the highest accuracy rate of 97.94%, a true positive rate of 97.03%, and a true negative rate of 98.87%. Therefore, if we aim to depict these results through an ROC curve based on this model, it is presented in Figure 3c. The lowest accuracy was achieved in the experiment, which used the RMSprop optimizer, max pooling, 4 convolutional layers, a target size of 180 × 180 pixels, and 50 epochs. Comparing our method to others (Table 2), our approach outperforms existing ones, achieving an accuracy of 97.94%, demonstrating its potential for more accurate chest X-ray classification.

Table 2. Comparison of proposed method with others for CXR classification.

Performance	**Proposed**	**QCNN** [31]	**CNN-b_0** [32]	**ConvNets** [33]	**CNN Dropout** [34]	**CNN-b_1** [35]	**CNN-SVM** [35]	**CNN-KNN** [35]
Accuracy	97.94%	93.75%	94.81%	93%	97.37%	94.55%	97.32%	96.55%

5. Conclusions

This paper presents a CNN-based approach for lung disease detection in CXR images, with a specific focus on hyperparameter optimization. While our core model architecture leverages existing CNN techniques, our novel strategies for hyperparameter tuning result in significantly improved accuracy. Our research contributes to the field by pushing the boundaries of CNN performance in CXR analysis. In future work, we plan to further evaluate the robustness of our model by incorporating additional data sources for evaluation.

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