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Pneumonia Disease Detection in X-Ray Images Using A Deep Learning Approach with CNN and Alexnet Architecture

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ABSTRACT

Effective treatment of pneumonia, a respiratory illness, depends on a prompt and precise diagnosis. However, using medical investigations to diagnose pneumonia can be laborious and rely on the skill of radiologists. To automatically identify pneumonia from chest X-ray pictures, this study intends to create an artificial intelligence model utilizing a Convolutional Neural Network (CNN) with the AlexNet architecture. 2,806 X-ray pictures that were classified as either normal or pneumonia were used. A variety of preprocessing methods were used to improve the quality of the data, and AlexNet, which had previously been trained on ImageNet, was used for transfer learning to increase the accuracy of detection. The model's accuracy, precision, and recall were 95.44%, 99%, and 94%, respectively. However, because Google Colab uses temporary sessions, speed varies a little when it is rerun. Despite this, the model continuously maintains an accuracy of over 90%. Furthermore, users can upload X-ray photos and get immediate results using a Gradio-based interface, which makes it accessible to those without technical knowledge. This study lays the groundwork for using AI in the diagnosis of pneumonia to increase the effectiveness and speed of medical imaging analysis.

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1. INTRODUCTION

Pneumonia is a respiratory tract infection marked by lung inflammation caused by bacteria, viruses, or fungi. This condition disrupts oxygen absorption and leads to breathing difficulties due to inflammation and fluid buildup in the alveoli, the air sacs responsible for gas exchange [1]. It poses a significant health risk, particularly to vulnerable groups such as elderly individuals and children under five years old [2].

If not treated promptly, pneumonia can be life-threatening and result in acute respiratory distress [3]. X-rays, especially chest radiographs, offer a non-invasive, cost-effective, and widely accessible method to identify pneumonia [4]. Shoar and Musher [5] emphasized that community-acquired pneumonia remains a critical cause of mortality, underscoring the need for fast and accurate diagnosis methods. Environmental pollutants also elevate the risk and severity of respiratory diseases like pneumonia [6].

In this context, deep learning techniques—specifically Convolutional Neural Networks (CNNs)—have been increasingly adopted in medical image analysis for automated disease detection [7]. CNNs have demonstrated remarkable performance in analysing chest X-ray images to detect pneumonia and COVID-19 [8]. These models can automatically learn and extract key image features, reducing the dependency on manual diagnosis [9].
Optimization techniques such as standard deviation calculation have also been applied to improve CNN classification performance in pneumonia detection tasks [10]. CNNs' success in broader computer vision fields, including social media analysis, validates their flexibility and robustness in image classification [11].

2. METHODS

2.1. Convolutional Neural Network (CNN)

CNN is a specialized deep learning model designed for processing grid-like data such as images. It consists of three main types of layers: convolutional layers, pooling layers, and fully connected layers. These layers operate in a sequence to learn spatial hierarchies of features from input images [12].

Several well-known CNN architectures include LeNet, ZFNet, VGGNet, GoogleNet, and ResNet. Each provides improvements in depth, computation, and feature extraction capabilities [13]. CNNs are particularly effective in medical image classification tasks, including pneumonia detection in chest radiographs, due to their ability to learn from raw pixel input without needing hand-crafted features [14].

The training process of CNN involves passing image data through multiple layers, applying filters, and using activation functions like ReLU to introduce non-linearity. Pooling operations help reduce the spatial dimensions of the data, and the final classification is performed using fully connected layers and softmax activation [15]. **Figure 1** shows the structure of a Convolutional Neural Network (CNN).

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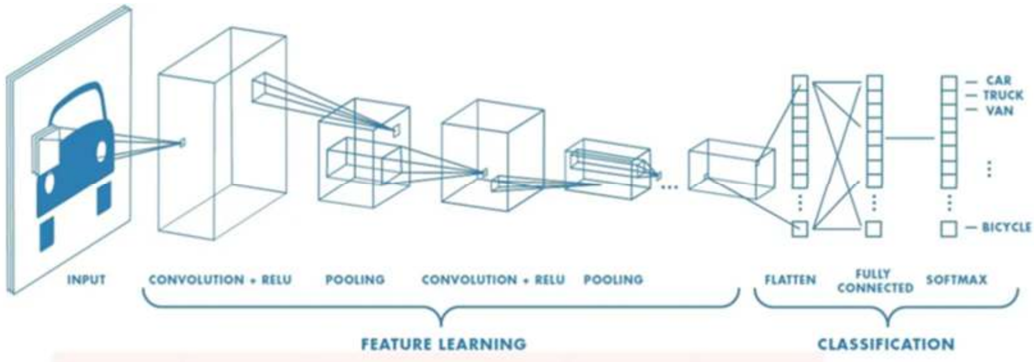

Figure 1. Convolutional Neural Network Layers

2.2. AlexNet Architecture

AlexNet is a deep CNN architecture that popularized deep learning by winning the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). It consists of five convolutional layers followed by three fully connected layers and incorporates techniques such as ReLU activation, dropout regularization, and max-pooling [16].

For pneumonia detection, AlexNet is used with transfer learning, where pre-trained weights (from ImageNet) are fine-tuned to classify chest X-ray images [17]. This technique significantly improves model accuracy and training efficiency, especially when working with limited datasets [18].

To optimize the training process, the Adam optimizer is commonly applied. Adam combines the advantages of two other extensions of stochastic gradient descent: AdaGrad and RMSProp. It computes individual adaptive learning rates for different parameters from estimates of first and second moments of the gradients [19].

In this study, Adam was used with a learning rate of 0.0001 and CrossEntropyLoss as the loss function, which helped improve convergence stability and classification performance [20]. **Figure 2** is a representation of the AlexNet architecture.

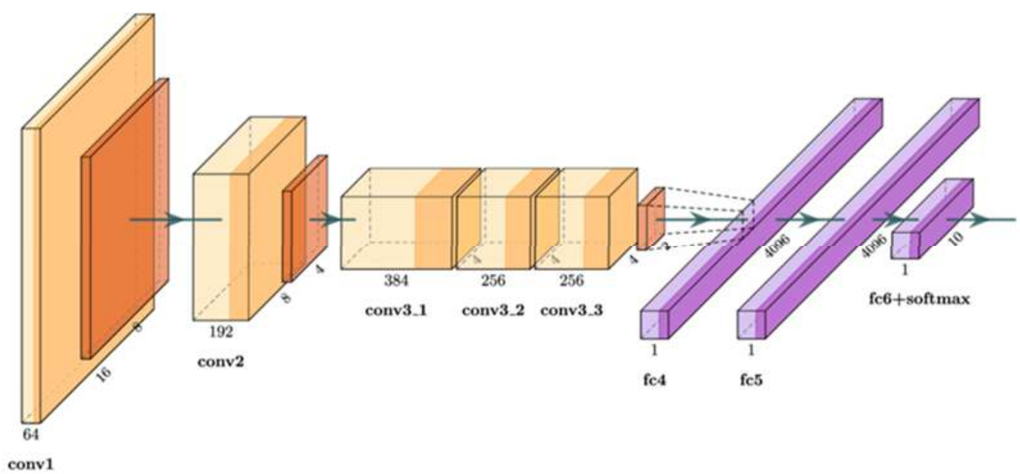

Figure 2. AlexNet Architecture

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2.3. Research Flow

The first step in this investigation is gathering a dataset of chest X-rays, which contains both normal radiographs and cases of pneumonia. Two kinds of patients—those with pneumonia and those in normal conditions—are represented in the dataset. Following the collection of the dataset, the photos are pre-processed before being entered into the model. Preprocessing includes dividing the dataset into training and testing sets, which are used to train and assess the model's performance, and normalizing pixel intensity to make sure values fall within a suitable range for the model. The AlexNet architecture will then be used to create a Convolutional Neural Network (CNN) model. **Figure 3** shows a summary of the research workflow.

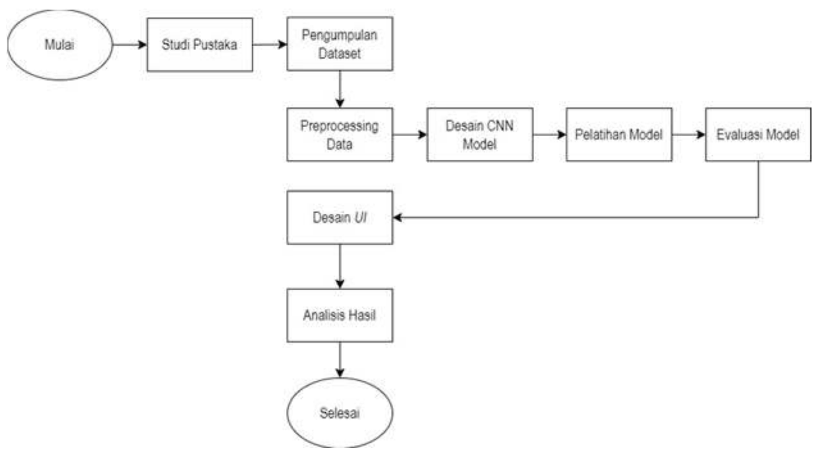

Figure 3. Research Flow

2.4. Research Object

The goal of this research is to use a Convolutional Neural Network (CNN) with the AlexNet architecture to detect pneumonia in chest X-ray pictures. A chest X-ray dataset from the Kaggle platform, comprising 2,804 X-ray images divided into two primary categories—normal and pneumonia—is used in this study. 25% of the dataset is used for testing, and the remaining 75% is used for training.

Based on earlier studies by Sedhy and associates in 2023, titled Deep Learning for the Detection of COVID-19, Pneumonia, and Tuberculosis in Chest X-ray Images, the dataset size was established. Employing CNN's AlexNet Architecture and 2,304 chest X-ray pictures. The study recommended expanding the dataset size for subsequent studies to attain better performance metrics and increased accuracy. By using a statistical method that adheres to the Central Limit Theorem (CLT), 500 more photos can improve the model's performance and reliability if the sample size is large enough.

2.5. Research Object

The UI design will include an input element where users can select and upload X-ray images from their devices. Once the image is uploaded, the system will automatically run the

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trained Convolutional Neural Network (CNN) model to detect pneumonia. The prediction results will be displayed as text, indicating whether the image represents a normal condition or pneumonia. The visual layout of the user interface will be straightforward to use, and it will include instructions to help users at every stage of the prediction process. The main objective of this user interface design is to guarantee pneumonia detection efficiency and convenience of use, making it available to researchers and medical professionals alike. **Figure 4** shows the user interface design.

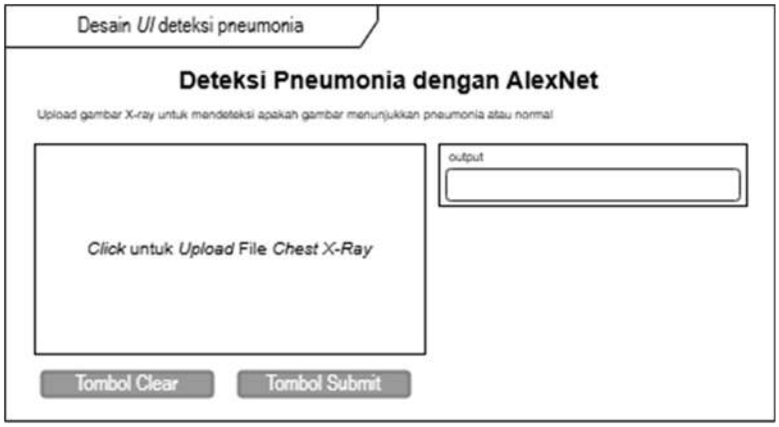

Figure 4. User Interface Design

3. RESULTS AND DISCUSSIONS

3.1. Dataset Description

Daniel S. Kermany's study, Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning, was the first to exploit this dataset. There are 1,403 JPEG images in each of the two classes of chest X-ray images in the dataset: pneumonias and normal images. **Figure 5** displays the images from the chest X-ray collection.

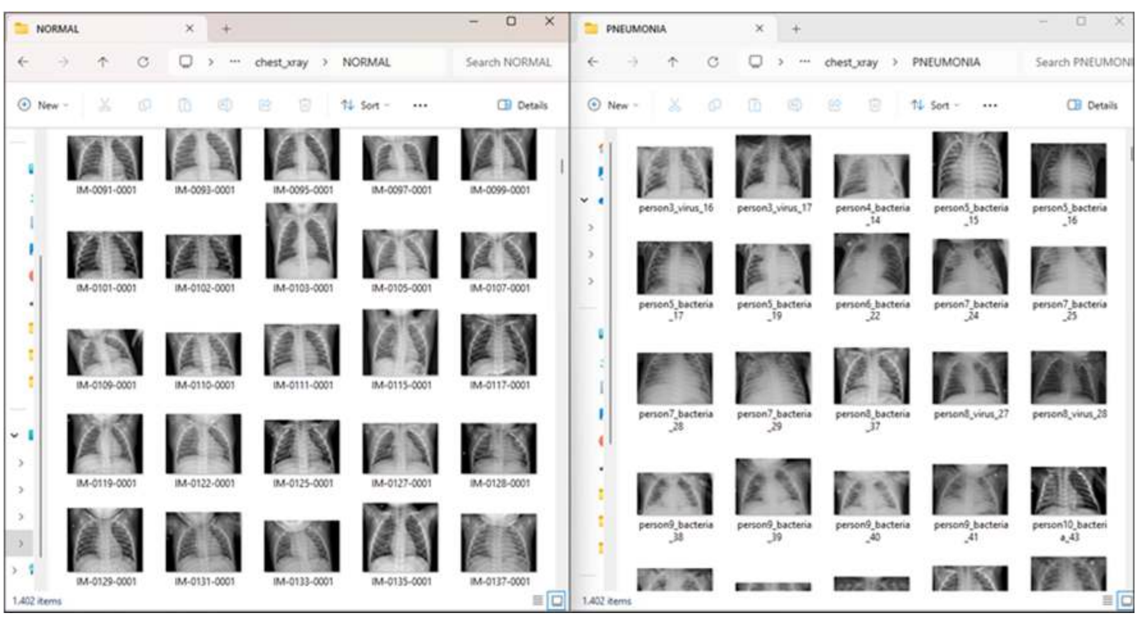

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Figure 5. Chest X-Ray Dataset

3.2. Preprocessing Data

The first step in preparing the X-ray dataset is to resize the images to 224x224 pixels to comply with the AlexNet model's input specifications. To enable the model to process the data numerically, the photos are resized and then transformed into tensor format using PyTorch's ToTensor function. To guarantee uniform pixel distribution, normalization is next applied using the mean and standard deviation values from the ImageNet dataset ([0.485, 0.456, 0.406] for the mean and [0.229, 0.224, 0.225] for the standard deviation). Data augmentation techniques like random rotations between -10 and 10 degrees and random horizontal flips are used to increase data diversity and avoid overfitting, which improves the model's capacity to identify various visual patterns.

Following the transformation, the dataset is divided into 75% training data and 25% testing data to make sure the model is tested on unseen images. PyTorch's DataLoader function is used to process data efficiently in batches, with the training set's images being shuffled in each epoch to expose the model to a variety of variations, and the testing set maintaining a fixed order for consistent evaluation. Each batch comprises 32 images, optimizing the training and testing process for better performance.

3.3. Design CNN Models

The model used to detect pneumonia from X-ray images is AlexNet, a Convolutional Neural Network (CNN) architecture. The model design process includes initialization and modification of the final layer for binary classification. PyTorch is used as the primary library for building the model, as it provides various functions for constructing fully connected layers and initializing weights. Additionally, Torchvision, a supporting PyTorch library, simplifies image data processing and provides pretrained models, including AlexNet.

Using the AlexNet_Weights class, which leverages previously trained weights to improve accuracy, the model is initialized with pretrained weights from the ImageNet dataset. AlexNet's classification layer is initialized and then adjusted to the binary classification task, allowing it to differentiate between images of pneumonia and normal X-rays. Two neurons, which stand in for the two categories, are used in place of the final layer in this study, even though AlexNet is by default built for 1000-class classification. After this adjustment, the Xavier initialization method is used to initialize the final layer weights, which speeds up training and preserves consistent learning performance. **Figure 6** shows the CNN AlexNet model's output.

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```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=(2, 2))
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (9): ReLU(inplace=True)
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(6, 6))
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=9216, out_features=4096, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in_features=4096, out_features=4096, bias=True)
    (5): ReLU(inplace=True)
    (6): Linear(in_features=4096, out_features=2, bias=True)
  )
```

Figure 6. CNN AlexNet Model Output

Several essential layers make up the model architecture, such as MaxPool to lower the dimensionality of the data, ReLU activation for non-linearity, and convolutional layers. Multiple fully connected layers, adaptive average pooling, and dropout to avoid overfitting are all incorporated into the final layers, which result in an output with two neurons that corresponds to the binary classification problem.

3.4. Model Training

Prediction errors in pneumonia classification are measured during the AlexNet model's training process using the CrossEntropyLoss function, and model weights are adaptively updated using the Adam optimizer, which has a learning rate of 0.0001. Multiple batches of chest X-ray pictures processed by the model make up each epoch throughout the training process. To provide predictions, the model does a forward pass. CrossEntropyLoss is then used to compare the predictions with the real labels. To improve prediction accuracy, the Adam optimizer uses the gradients of the loss function, which are then computed in a backward pass. The running loss value is recorded at each epoch as a measure of model performance.

To observe patterns in loss reduction, the CNN model's training using the AlexNet architecture was assessed over 20 and 30 epochs. The model's capacity to identify patterns in training data improved as the mean loss steadily dropped from 0.3434 to 0.0448 after 20 epochs. A continuous decrease in mean loss from 0.0417 to 0.0019 was also observed after 30 epochs of training, indicating a notable improvement in prediction accuracy. The overall loss decrease indicates that the model became more and more tuned for pneumonia classification from X-ray pictures, with gradually lower error rates, despite slight oscillations in certain epochs. **Figure 7** shows the outcome of the mean loss.

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```
Mulai pelatihan di cpu
Epoch 1/10 dimulai
Epoch [1/10], Rata-rata Loss: 0.3143
Epoch 2/10 dimulai
Epoch [2/10], Rata-rata Loss: 0.1610
Epoch 3/10 dimulai
Epoch [3/10], Rata-rata Loss: 0.1345
Epoch 4/10 dimulai
Epoch [4/10], Rata-rata Loss: 0.1123
Epoch 5/10 dimulai
Epoch [5/10], Rata-rata Loss: 0.1069
Epoch 6/10 dimulai
Epoch [6/10], Rata-rata Loss: 0.1134
Epoch 7/10 dimulai
Epoch [7/10], Rata-rata Loss: 0.0789
Epoch 8/10 dimulai
Epoch [8/10], Rata-rata Loss: 0.0886
Epoch 9/10 dimulai
Epoch [9/10], Rata-rata Loss: 0.0743
Epoch 10/10 dimulai
Epoch [10/10], Rata-rata Loss: 0.0842
Pelatihan selesai!
```

Figure 7. Output Mean Loss

3.5. Model Evaluation

Based on the test dataset, the AlexNet model's evaluation results show 95.44% accuracy, 99% precision, and 92% recall. The model's efficacy in classifying X-ray images for the detection of pneumonia is demonstrated by its accuracy, which is determined by dividing the number of correct predictions by the total test data. While the comparatively high recall shows the model's strong ability to detect the majority of pneumonia cases, the high precision suggests that the model rarely generates false positive predictions. The evaluation results of the AlexNet model can be seen in **Figure 8**.

```
Correct so far: 640/672
Processing batch 22/22
Predictions: tensor([1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1,
        1, 1, 0, 0, 1])
Correct so far: 669/701
Accuracy on test set: 95.44%
Precision: 0.99
Recall: 0.92
```

Figure 8. Evaluation Results of the AlexNet Model

Because the trainisng and test datasets are split randomly, the evaluation findings could change every time the model is run again. Furthermore, because Google Colab is used as a cloud computing platform in this study, the model must be run again for every new session, which may result in differences in recall, accuracy, and precision. However, the model's ability to identify pneumonia from X-ray pictures is consistently dependable.

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3.6. User Interface Display

The interactive interface built with Gradio is used to facilitate pneumonia detection using the AlexNet Using the AlexNet model, the interactive Gradio-built interface makes it easier to detect pneumonia by letting users upload X-ray images and get immediate prediction results. **Figure 9** shows the user interface display. There are three possible outputs for the detection results; **Figure 10** displays the Normal output. **Figure 11** displays the detection result for pneumonia. As seen in **Figure 12**, if the input is not a legitimate chest X-ray, the image cannot be processed.

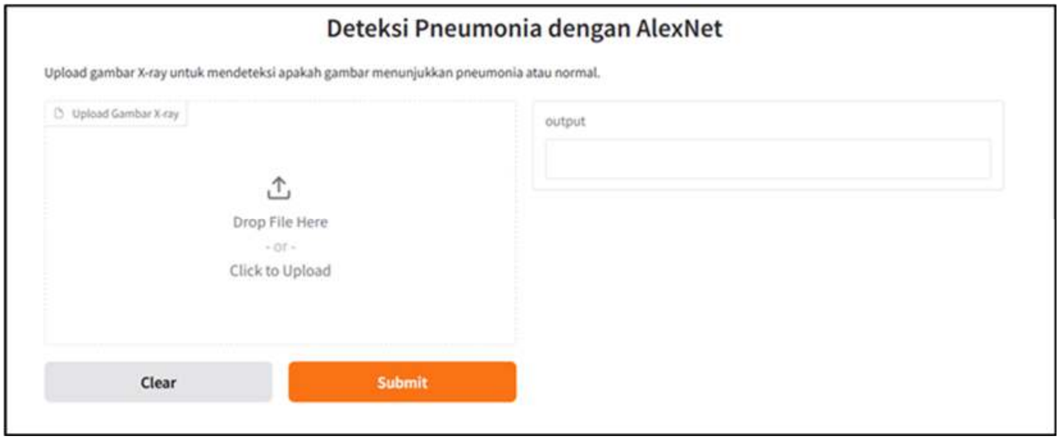

Figure 9. User Interface Display

Figure 10. UI Display for Detection Result as Normal

Figure 11. UI Display for Detection Result as Pneumonia

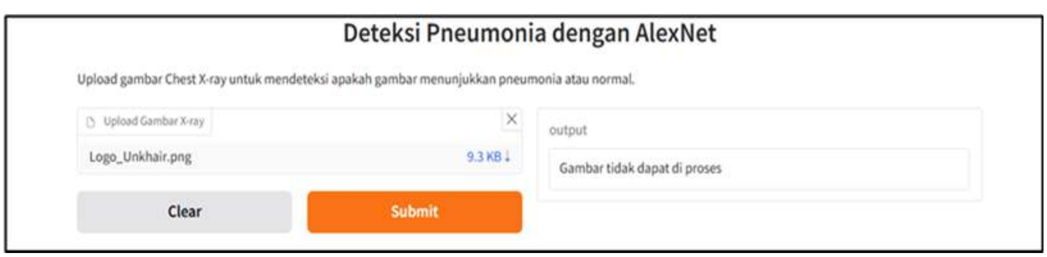

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Figure 12. UI Display of Detection Result for Invalid Input

X-ray data from the archives of RSUD Chasan Boesari Ternate were used to verify the model's ability to accurately identify pneumonia in medical photos. The testing X-ray pictures are shown in **Figure 13**.

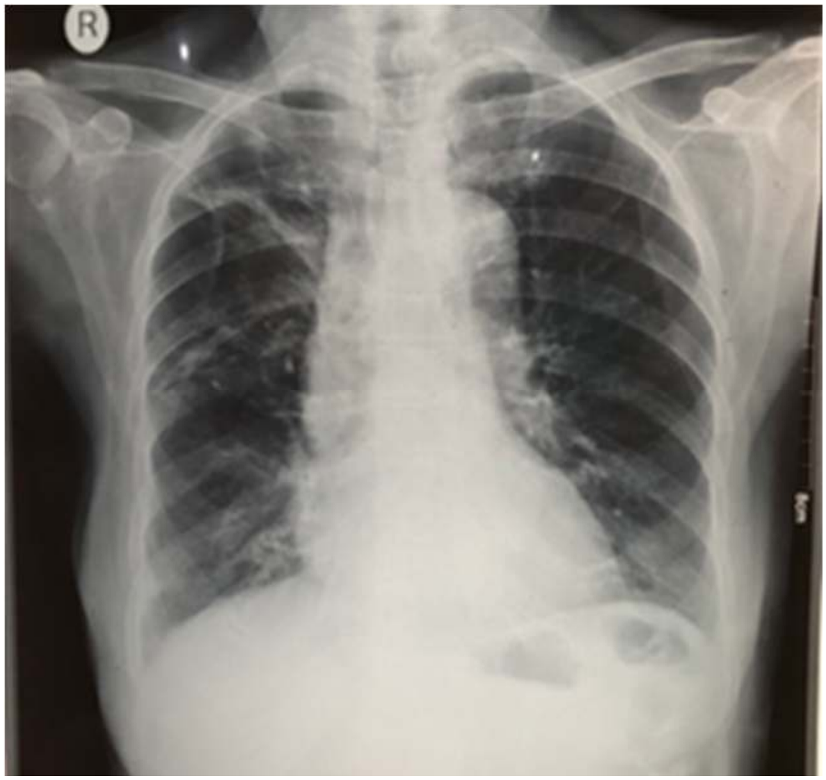

Figure 13. X-Ray Pneumonia District Hospital

4. CONCLUSION

This study evaluates the AlexNet CNN architecture for detecting pneumonia from chest X-ray images through several key stages. The process begins with the collection and preprocessing of 2,806 X-ray images, categorized as normal or pneumonia, using techniques such as resizing, normalization, and augmentation to enhance data quality. The AlexNet model was modified with pretrained weights from ImageNet to adapt it for binary classification. The model training was conducted using the Adam optimizer and CrossEntropyLoss, enabling the model to effectively recognize patterns in the data. Evaluation results showed an accuracy of 95.44%, precision of 99%, and recall of 94%, although slight variations may occur due to the nature of the Google Colab platform. All things considered, this study shows that AlexNet has great promise as a trustworthy tool for X-ray imaging-based pneumonia diagnosis.

5. AUTHORS' NOTE

For future research, it is recommended to use a GPU for the model training process. This study utilized a CPU, which resulted in a longer runtime. By using a GPU, the training process is expected to be faster and more efficient, allowing for experiments with more complex models or larger datasets.

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