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Comparison of Tuberculosis Detection using CNN Models (AlexNet and ResNet)

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Abstract: The bacterial infection caused by Mycobacterium tuberculosis, leading to tuberculosis is a prevalent contagious disease. This bacterium commonly targets the primary respiratory organs, particularly the lungs. Tuberculosis poses a significant global health challenge and necessitates early detection for effective management. In this context, to facilitate healthcare professionals in the early detection of patients, a technology capable of accurately identifying lung conditions is required. Therefore, CNN (Convolutional Neural Network) will be employed as the algorithm for detecting lung images. The research will utilize Convolutional Neural Network models, namely AlexNet and ResNet. The study aims to compare the performance of these two models in detecting TB through the analysis of chest X-ray images. The dataset comprises X-rays from both normal patients and TB patients, totaling 4.200 data points. The training process involves dividing the data into training and validation sets, with an 80% allocation for training and 20% for validation. The evaluation results indicate that the AlexNet model demonstrates higher detection accuracy, reaching 88.33% on the validation data, while ResNet achieves 83.10%. These findings suggest that the use of CNN models, especially AlexNet, can be an effective approach to enhancing early tuberculosis detection through the interpretation of chest X-ray images, with potential implications for improving global TB management and prevention efforts.

Keywords: AlexNet; ResNet; CNN; Early Detection; Tubercolosis

INTRODUCTION

The rapid development of technology in the modern era significantly aids human work, including in the field of medicine for disease detection (Malik et al., 2023). In society and social interactions, a healthy body serves as a bridge for humans to produce work and earn money, either through tangible creations or services offered via technology such as the Internet or other service platforms (Anwar et al., 2020). However, if a person suffers from health issues, it can hinder their activities and thereby impede the process of earning a livelihood.

As is known, the human body consists of five types of organs, including the heart, which functions as a pump to circulate blood, supplying oxygen and nutrients. Consuming food indiscriminately can affect heart performance. The heart works continuously without stopping and its performance declines with age. The human heart rate ranges between 60-100 beats per minute (Ayudhitama & Utomo Pujianto, 2020). Then there is the liver, which performs numerous functions, including detoxification, enzyme production, glycogen storage, and bile production, which aids digestion and maintains overall health (Sherbiny et al., 2023). The kidneys play a role in blood filtration, waste removal, and excess fluid elimination for urine formation. Shaped like beans, they are located in the middle of the human back on either side of the spine (Kuntiyellannagari et al., 2024). Next, the brain acts as the control center of the body, regulating various functions such as movement, perception, and other critical activities. The lungs are involved in the respiratory process, where oxygen is inhaled and carbon dioxide is expelled (Dendi Maysanjaya, 2020). The lungs are essential for gas exchange, ensuring the body receives oxygen and expels carbon dioxide, which is crucial for the proper functioning of all bodily organs (Dahmane et al., 2021). Some diseases to watch out for include pneumonia, COVID-19, and tuberculosis. Pneumonia is an inflammation of the lungs that can cause pain during breathing and limit oxygen intake. It is caused by bacteria, viruses, and fungi, such as the Respiratory Syncytial Virus (RSV), which primarily affects the upper respiratory tract (Adebiyi & Olugbara, 2021). COVID-19, caused by the coronavirus (COV), attacks the respiratory system, particularly the lungs. It was first identified in Wuhan Province, China, causing symptoms such as loss of appetite, fatigue, fever, shortness of breath, and cough. Its rapid spread led to severe infections and organ failure, making it the first major global health crisis (DR N. Paranietharan, 2024). Tuberculosis is a contagious disease caused by the TB bacteria

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(Mycobacterium tuberculosis), which is the second leading cause of death after COVID-19 (Astuti S, 2024). In the medical field, it is challenging to manage when an individual is infected through airborne transmission (droplets from a TB patient with positive sputum smears) (*Dinas Kesehatan Jawa Tengah. Profil Kesehatan Provinsi Jawa Tengah*, 2024). When the infected person coughs or sneezes, it can spread the disease, potentially leading to death if the medication is not taken regularly for six months (Juan et al., 2023). X-rays are used to capture lung images through radiography. Additionally, CT scans (Computerized Tomography Scans) can be used to get detailed images (Hijazi et al., 2019). The challenge arises when there are many patients with these diseases (Rani et al., 2024), leading to fatigue and long times needed to interpret the images (Songram et al., 2022).

Convolutional Neural Networks (CNNs) are a type of neural network used for processing image data, including medical images. CNNs mimic how the human brain detects and recognizes objects (Septhyan et al., 2022). CNNs help analyze and understand complex patterns (Wijaya Kusuma et al., 2023) using ALEXNET to detect early-stage infections through medical images, speeding up decision-making processes. ALEXNET has been used to identify brain tumors and classify diseases in corn leaves (Abbood et al., 2021). ALEXNET introduces a breakthrough by combining ConvNet with Dropout Regularization techniques (El Shenbary et al., 2023), using many layers to process image data, achieving 98% accuracy with tomato leaf images (Mahakud et al., 2022). RESNET, another image processing model, addresses the issue of deep training by introducing the concept of residuals and shortcut connections or skips, allowing signals to bypass certain layers. This helps prevent performance degradation often seen in very deep networks (Edderbali et al., 2024). RESNET has shown excellent results in previous studies involving pre-trained objects (Harahap et al., 2022). This forms the basis for the author to conduct a comparative study using ALEXNET and RESNET.

LITERATURE REVIEW

The research conducted (Falakhi et al., 2022) by applying the AlexNet and ResNet models in flower classification achieved accuracies of 87% and 96% for AlexNet and ResNet, respectively. The results indicate that the ResNet-based model is more effective compared to the AlexNet-based model. The subsequent research (Swasono et al., 2023) conducted disease classification on fruit images by implementing AlexNet as the architecture. The best results were achieved with a scenario of 90% training data and 10% validation data, obtaining an accuracy of 94.34%, precision of 93.0%, recall of 94.0%, and an F1 score of 95.0%. The best results were obtained with a combination of dropout scenarios, batch normalization, and fully connected layers. The subsequent study (Suprihanto et al., 2022) analyzed the performance of ResNet50 in classifying robusta coffee leaves. The research results showed that, in the binary class case, the accuracy reached 92.68%, and the F1-Score reached 92.88%. In the multiclass case, the accuracy reached only 88.98%, and the F1-Score reached 88.44%. Both cases were measured using testing data with a trained ResNet-50 model. The study conducted by (Sujatmiko et al., 2022) resulted in recorded accuracy in the classification process of three types of skin ranging from 92.60% to 92.90%, while for two types of skin, the accuracy ranged from 88.03% to 89.39%.

METHOD

The conducted study is of an experimental nature. In this experiment, the researcher aimed to assess the accuracy of the CNN algorithm by comparing AlexNet and ResNet in classifying lung image pictures in individuals with tuberculosis and healthy lungs.

The Model Used

In the conducted study, the models used were AlexNet and ResNet, serving as comparative models for classifying images of tuberculosis-infected lungs and healthy lungs.

Data Analysis

In the conducted research, Google Colab was utilized as the code editor to develop the application and Kaggle was employed as the dataset source for the study. Image test data was obtained from an online dataset collection listed on the data provider platform https://www.kaggle.com/datasets/tawsifurrahman/tuberculosis-tb-chest-xray-dataset. The image selection was based on the availability of relevant lung X-ray images for training the disease detection model. The dataset consists of a total of 4200 images, divided into two classes: 3500 images of normal lungs and 700 images of lungs infected with tuberculosis. This class distribution is crucial to ensure that the model can accurately recognize and distinguish between normal and tuberculosis-infected conditions.

Prep-processing

Before analyzing the images, several prep-processing steps were performed to prepare the data for model training. The steps include

1. Resizing: All images were resized to a uniform dimension of 244x244 pixels to ensure consistency during

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model training.

2. Normalization: Pixel values were normalized into a specific range, with 0 normal lung images and 1 for tuberculosis-infected lung images, to enhance model performance and reduce computational complexity.
3. Data Augmentation: The dataset will undergo several augmentation techniques, such as rotation, flipping,and zooming, to artificially expand the dataset. These techniques aim to increase data variation without adding new data. By applying augmentation, the model can better learn to recognize various image patterns, which helps improve its generalization ability. As a result, the model can achieve better accuracy during both training and testing.
4. Greyscal Conversion: The images in the dataset have already been converted to greyscale, so there is no need to convert them to grayscale again.
5.

Work Procedure

In this study, the process of handling images using the CNN algorithm can be accomplished through the subsequent procedures :

Dataset → Preprocessing Data → Model Implementation → Result

Fig. 1 Work Procedure

1. **Dataset:** Data for the study of tuberculosis and normal lungs was sourced from Kaggle, including diverse images of healthy and infected lungs. The meticulous data collection ensures dataset diversity and representatives, forming the basis for our analysis of disparities between tuberculosis-infected and normal lungs.
2. **Preprocessing Data:** The next step there is the data partitioning stage. In this stage, the data is divided into two categories: training data and validation data. The training data comprises 80%, while the validation data makes up 20%
3. **Model Implementation:** In the subsequent stage, constructing the AlexNet and ResNet models for utilization on the dataset will take place. In this phase, several necessary layers will be employed in the model, enabling it to train and test data optimally. After that training process, the training process involves 10 epochs and a batch size of 105. Data augmentation techniques applied include zoom_range, horizontal_flip, and rotation_range with a rotation value of 20 degrees. The previously partitioned data is processed into the model for testing and training purposes. Once the data has been trained by the model, training accuracy and testing accuracy will be improved.
4. **Result:** After the model is trained, it will be evaluated to assess how effectively it classifies normal and tuberculosis-infected lungs. Upon successful classification, a confusion matrix will be generated, displaying true positive and false positive classifications

RESULT

The results of the conducted research encompass data preparation, preprocessing, testing, and discussion regarding the comparison of models used for the classification of image patterns in tuberculosis and normal lung cases.

Data Preparing

The researcher prepared the data by downloading a dataset accessible online at https://www.kaggle.com/datasets/tawsifurrahman/tuberculosis-tb-chest-xray-dataset. The obtained dataset comprises 4.200 images with two lungs labels tuberculosis and normal. These images will be utilized to train and test the Convolutional Neural Network (CNN) model architecture. In this study, several limitations need to be acknowledged, including potential bias in the dataset, the impact of class imbalance, and the generalizability of the results to other populations or imaging modalities. The dataset used consists of 4,200 images, with 3,500 images of normal lungs and 700 images of tuberculosis lungs, which can lead to bias in model training. The imbalance in the number of images between the normal and tuberculosis categories may affect the model's accuracy, with the model likely performing better on the more prevalent class due to the larger sample size. Additionally, class imbalance can impact evaluation metrics such as precision, recall, and F1-score, making the model less accurate on the less frequently represented class. The results obtained may not be fully generalizable to other populations or different imaging modalities, as variations in real patient data or different imaging techniques may not be fully captured in this dataset.

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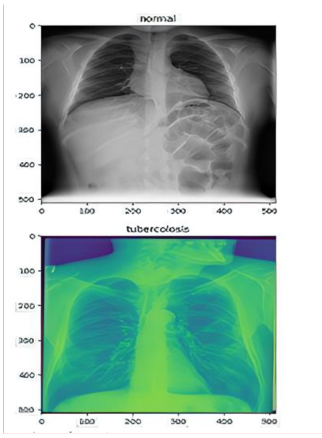

Fig. 2 DFU Dataset

Preprocessing

Before utilizing the data for training with the CNN model, a data preprocessing process is implemented. The data preprocessing stage is the initial step in images, involving resizing images to 224 x 224 pixels and image rotation to enhance focus sharpness in the data images to be tested. All models applied in this research are trained using the Adam Optimizer. In the development of deep learning models, the significance of data in training the model is strongly emphasized. Therefore, the data will be divided into two parts, namely training data for the model training process, and validation data to test the quality of the created model. The data division details include allocating 80% for training data and 20% for validation.

Testing

The next stage involves executing the training process using two models, namely ResNet and AlexNet. The dataset to be applied focuses on the detection of tuberculosis or normal conditions in individual lungs, which will be divided into two segments: training data and validation data [9]. Training data is generated through the partitioning of the original dataset, consisting of 4,200 data. The data is divided into 80% for training data and 20% for validation data. As a result, there are 3,360 data for training and 840 data for validation.

For each model, there are iterations (epochs) that determine how many times the model is trained to achieve an optimal level of accuracy. Detailed information on the number of iterations (epochs) can be found in the image below:

```
Epoch 1/10
105/105 [==============================] - ETA: 0s - loss: 0.4654 - accuracy: 0.8060WARNING:tensorflow:Learning rate reduction is conditioned on metric
105/105 [==============================] - 78s 684ms/step - loss: 0.4654 - accuracy: 0.8060 - val_loss: 0.4468 - val_accuracy: 0.8341 - lr: 0.0010
Epoch 2/10
105/105 [==============================] - ETA: 0s - loss: 0.3837 - accuracy: 0.8512WARNING:tensorflow:Learning rate reduction is conditioned on metric
105/105 [==============================] - 76s 726ms/step - loss: 0.3837 - accuracy: 0.8512 - val_loss: 0.4345 - val_accuracy: 0.8329 - lr: 0.0010
Epoch 3/10
105/105 [==============================] - ETA: 0s - loss: 0.3765 - accuracy: 0.8554WARNING:tensorflow:Learning rate reduction is conditioned on metric
105/105 [==============================] - 90s 858ms/step - loss: 0.3765 - accuracy: 0.8554 - val_loss: 0.4324 - val_accuracy: 0.8329 - lr: 0.0010
Epoch 4/10
105/105 [==============================] - ETA: 0s - loss: 0.3637 - accuracy: 0.8583WARNING:tensorflow:Learning rate reduction is conditioned on metric
105/105 [==============================] - 74s 703ms/step - loss: 0.3637 - accuracy: 0.8583 - val_loss: 0.3066 - val_accuracy: 0.8341 - lr: 0.0010
Epoch 5/10
105/105 [==============================] - ETA: 0s - loss: 0.3584 - accuracy: 0.8562WARNING:tensorflow:Learning rate reduction is conditioned on metric
105/105 [==============================] - 73s 694ms/step - loss: 0.3584 - accuracy: 0.8562 - val_loss: 0.3444 - val_accuracy: 0.8329 - lr: 0.0010
Epoch 6/10
105/105 [==============================] - ETA: 0s - loss: 0.3552 - accuracy: 0.8616WARNING:tensorflow:Learning rate reduction is conditioned on metric
105/105 [==============================] - 76s 724ms/step - loss: 0.3552 - accuracy: 0.8616 - val_loss: 0.3162 - val_accuracy: 0.8522 - lr: 0.0010
Epoch 7/10
105/105 [==============================] - ETA: 0s - loss: 0.3450 - accuracy: 0.8690WARNING:tensorflow:Learning rate reduction is conditioned on metric
105/105 [==============================] - 72s 690ms/step - loss: 0.3450 - accuracy: 0.8690 - val_loss: 0.2873 - val_accuracy: 0.8750 - lr: 0.0010
Epoch 8/10
105/105 [==============================] - ETA: 0s - loss: 0.3457 - accuracy: 0.8679WARNING:tensorflow:Learning rate reduction is conditioned on metric
105/105 [==============================] - 73s 700ms/step - loss: 0.3457 - accuracy: 0.8679 - val_loss: 0.2528 - val_accuracy: 0.8990 - lr: 0.0010
Epoch 9/10
105/105 [==============================] - ETA: 0s - loss: 0.3582 - accuracy: 0.8601WARNING:tensorflow:Learning rate reduction is conditioned on metric
105/105 [==============================] - 72s 691ms/step - loss: 0.3582 - accuracy: 0.8601 - val_loss: 0.2572 - val_accuracy: 0.9087 - lr: 0.0010
Epoch 10/10
105/105 [==============================] - ETA: 0s - loss: 0.3429 - accuracy: 0.8685WARNING:tensorflow:Learning rate reduction is conditioned on metric
105/105 [==============================] - 76s 724ms/step - loss: 0.3429 - accuracy: 0.8685 - val_loss: 0.2660 - val_accuracy: 0.8922 - lr: 0.0010
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Fig. 3 The training and validation results of the AlexNet model

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```
Epoch 1/10
105/105 [==============================] - 77s 734ms/step - loss: 0.4346 - accuracy: 0.8336 - val_loss: 0.4022 - val_accurac
y: 0.8341
Epoch 2/10
105/105 [==============================] - 77s 730ms/step - loss: 0.4196 - accuracy: 0.8384 - val_loss: 0.3929 - val_accurac
y: 0.8353
Epoch 3/10
105/105 [==============================] - 79s 750ms/step - loss: 0.4193 - accuracy: 0.8315 - val_loss: 0.4210 - val_accurac
y: 0.8353
Epoch 4/10
105/105 [==============================] - 78s 747ms/step - loss: 0.4127 - accuracy: 0.8354 - val_loss: 0.3970 - val_accurac
y: 0.8389
Epoch 5/10
105/105 [==============================] - 81s 769ms/step - loss: 0.4121 - accuracy: 0.8387 - val_loss: 0.3943 - val_accurac
y: 0.8365
Epoch 6/10
105/105 [==============================] - 78s 747ms/step - loss: 0.4156 - accuracy: 0.8408 - val_loss: 0.3877 - val_accurac
y: 0.8365
Epoch 7/10
105/105 [==============================] - 79s 756ms/step - loss: 0.4052 - accuracy: 0.8432 - val_loss: 0.3995 - val_accurac
y: 0.8377
Epoch 8/10
105/105 [==============================] - 77s 736ms/step - loss: 0.4053 - accuracy: 0.8402 - val_loss: 0.3831 - val_accurac
y: 0.8462
Epoch 9/10
105/105 [==============================] - 78s 740ms/step - loss: 0.3876 - accuracy: 0.8467 - val_loss: 0.3608 - val_accurac
y: 0.8450
Epoch 10/10
105/105 [==============================] - 82s 777ms/step - loss: 0.3972 - accuracy: 0.8506 - val_loss: 0.3912 - val_accurac
y: 0.8221
```

Fig. 4 The training and validation results of the ResNet model

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From the attached image, it can be observed that through the training of both training and validation data with a total of 10 iterations (epochs), accuracy and loss values are obtained. Accuracy is used as an indicator of how well the trained model can precisely detect test data, while the loss value reflects the extent of errors that arise when the model makes predictions on test data:

Table 1. Training and Testing Accuracy Results

Model	Training Data		Validation Data	
	Loss	Accuracy	Loss	Accuracy
AlexNet	30.38%	87.41%	26.50%	88.33%
ResNet	38.79%	84.58%	38.41%	83.10%

In the table above, you can observe the accuracy values and loss values for each model that has been presented, considering the same total amount of data. For the AlexNet model, the training and testing loss values are approximately 30.38% and 26.50%, respectively. A lower loss value indicates a more optimal model performance. However, despite achieving a maximum accuracy value of 87.41% for the training data and an accuracy value of approximately 88.33% for the testing data, it suggests that the AlexNet model has a high accuracy level without overfitting issues. In comparison, the ResNet model has a training loss of 38.79% and a testing loss of 38.41%, with training accuracy at 84.58% and testing accuracy at 83.10%. From the accuracy values between the two models, it can be observed that the model AlexNet yields higher accuracy results. Not only that, but the researcher also obtained visualizations of the graph depicting changes in accuracy and loss values in both training and validation data generated during each iteration (epoch), as shown in the following image.

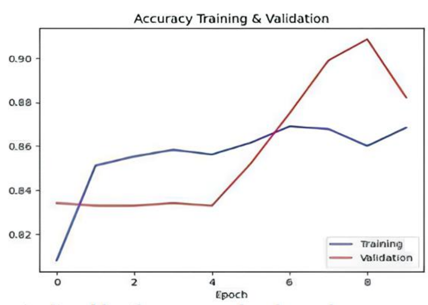

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Fig. 5 Accuracy Graph of Training and Testing for the AlexNet Model

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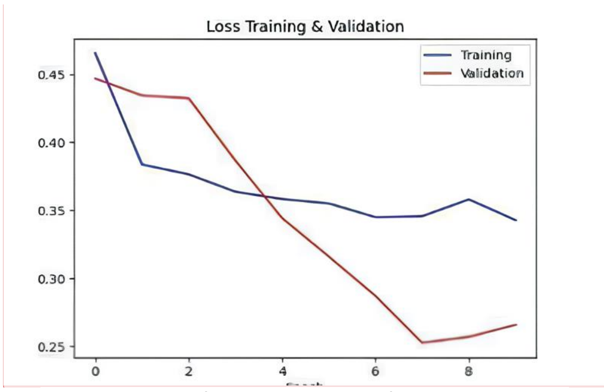

Fig. 6 Loss Graph of Training and Testing for the AlexNet Model

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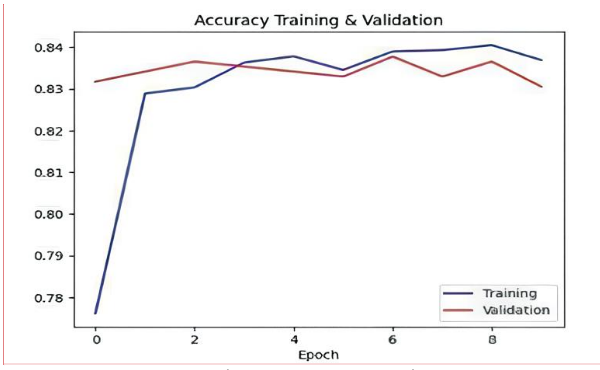

Fig. 7 Accuracy Graph of Training and Testing for the ResNet Model

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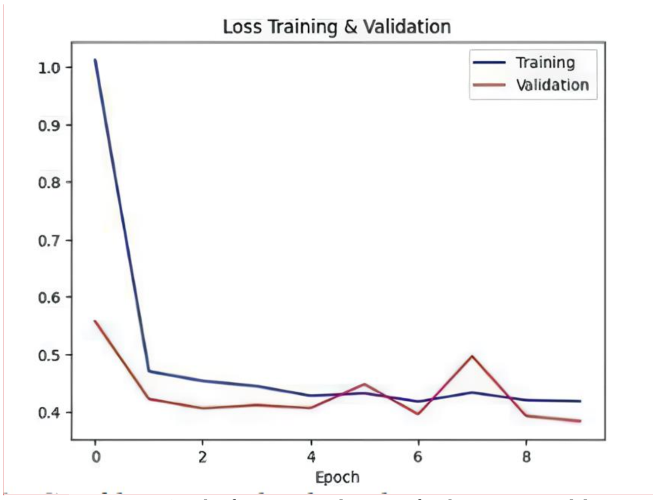

Fig. 8 Loss Graph of Training and Testing for the ResNet Model

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From the displayed graphs, it can be concluded that there is no occurrence of overfitting in both models. It is also evident from the above graph that the loss rate approaches zero or is low, while the accuracy rate continues to increase. This reflects positive results. Along with the increase in the number of iterations (epochs) used, the accuracy level in the training data also increases, while the loss level produced in the research data decreases. From the findings outlined earlier, it can be seen that both models demonstrate good performance without overfitting. Next, the researcher will present the image detection results from the AlexNet and ResNet models below. The researcher will only display 5 image detection results from both models.

Fig. 9 Results of normal image detection

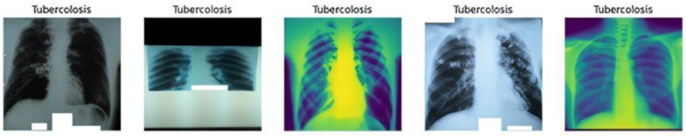

Fig. 10 Results of tubercolosis image detection

It can be observed that the model successfully detects normal and tuberculosis images. Subsequently, the researcher will present the confusion matrix results of the detection of normal and tuberculosis images below.

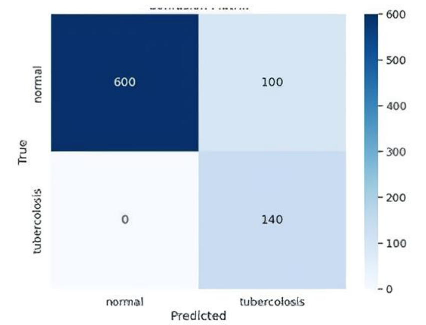

Fig. 11 Confusion Matrix AlexNet

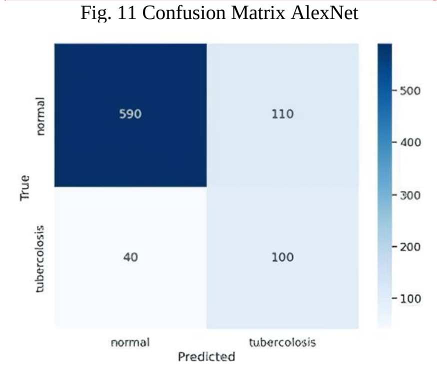

Fig. 12 Confusion Matrix ResNet

Based on the presented data, the results are derived from the Confusion Matrix of the AlexNet and ResNet models. The Confusion Matrix is a table in deep learning used to evaluate performance. This matrix provides information on how well the model can categorize instances of data into the correct categories. In the Confusion Matrix, it can

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indicate how accurately the model can detect tuberculosis and normal lungs. Based on the above explanation of the confusion matrix, it can be concluded that the AlexNet model outperforms the ResNet model in detecting normal and tuberculosis image results. AlexNet, designed with fewer layers compared to ResNet, has a simpler architecture with 8 main layers (5 convolutional layers and 3 fully connected layers). This allows it to perform feature extraction more efficiently on a relatively small dataset like this one. AlexNet also employs data augmentation techniques intensively, which helps improve accuracy and reduce overfitting. On the other hand, ResNet (Residual Network) has a deeper architecture with many residual layers that allow the model to handle higher complexity and learn more profound features. However, in this case, the advantages of ResNet may not be fully utilized or could lead to overfitting on the training data, resulting in less optimal performance on the validation data. Thus, although ResNet is designed to handle more complex datasets with greater depth, AlexNet shows better performance in detecting images of normal and tuberculosis lungs on this dataset, possibly due to its simpler architecture and the data augmentation techniques used.

CONCLUSION

Testing applied the deep learning method with Convolutional Neural Network models for the detection of individual lungs with normal and tuberculosis conditions using 4,200 data divided into two categories: training data and validation data. The training data consists of 3,360 samples, and the validation data consists of 840 samples. The Convolutional Neural Network models utilize the ResNet and AlexNet architectures. The results of the experiment prove that AlexNet outperforms in performance, achieving an accuracy of 88.33% on the validation data, while ResNet only achieves 83.10% on the validation data. To enhance the accuracy of both models, efforts are required to improve and balance the data in the dataset, as well as exploring alternative model architectures. To improve the accuracy of both models, it is recommended to explore advanced models or hybrid approaches that combine the strengths of AlexNet and ResNet, or to use other architectures such as DenseNet or EfficientNet, which may provide better results. Additionally, strategies for addressing class imbalance should be considered, such as performing oversampling on the minority class or using synthetic data generation techniques to enhance training and model performance. These approaches can help reduce model bias and improve detection accuracy for underrepresented classes. In this study, deep learning methods with Convolutional Neural Network (CNN) models were applied for the detection of normal and tuberculosis lungs using a dataset of 4,200 images. Experimental results showed that the AlexNet model outperforms in terms of accuracy, achieving 88.33% on validation data, compared to ResNet, which achieved 83.10%. This finding suggests that CNN models can be used to enhance automatic tuberculosis detection, potentially speeding up diagnosis and treatment for patients. For healthcare practitioners, it is recommended to integrate the AlexNet model into clinical diagnostic systems as a tool to assist in analyzing chest X-ray images. Training practitioners to use this system, as well as implementing software that integrates model prediction results with electronic medical records systems, can improve diagnostic efficiency. Additionally, expanding the dataset with more images and strategies to address class imbalance, such as oversampling or synthetic data generation, will improve model performance. Continuous evaluation and monitoring of the model are also necessary to ensure accuracy and relevance in tuberculosis detection, thereby enhancing diagnostic outcomes and patient care.

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