

Article

Classification of Tuberculosis Based on Chest X-Ray Images Using a Convolutional Neural Network (CNN)

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Abstract: Tuberculosis (TB) is an infectious disease caused by *Mycobacterium tuberculosis* and remains a significant global health burden, particularly in developing countries. Accurate early detection is essential to reducing transmission rates and mortality. This study aims to develop an automated TB detection system based on chest X-ray image classification using deep learning. The proposed model is built upon the EfficientNetB0 architecture with a transfer learning and fine-tuning strategy. The dataset used is the TB Chest Radiography Database sourced from Kaggle, consisting of 1,382 chest X-ray images divided into normal and tuberculosis classes with an 80:20 training-to-testing split, yielding 1,106 images for training and 276 images for testing. Data augmentation techniques — including rotation, zoom, shear, and horizontal flip — were applied to the training data to improve model generalization. Training was conducted in two phases: an initial phase with all base model layers frozen, followed by fine-tuning on the last 20 layers. The proposed model achieved an accuracy of 97% with a loss value of 0.093 on the testing data. The classification report demonstrates that EfficientNetB0 with transfer learning is highly effective for automated tuberculosis detection based on chest X-ray images. The trained model was then deployed as a web-based early detection system built with HTML, named TBDetect.

Keywords: Automatic Detection; Chest X-Ray Image Classification; Convolutional Neural Network; Deep Learning; EfficientNetB0; Tuberculosis

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1. Introduction

The lungs are a pair of primary respiratory organs located in the thoracic cavity, directly connected to the circulatory system to facilitate gas exchange. Each lung consists of bronchioles that channel air toward the alveoli—small, thin-walled sacs where gas exchange takes place. During respiration, oxygen is absorbed into the bloodstream through the alveoli, while carbon dioxide is expelled during expiration. In addition, the lungs are equipped with a defense system comprising fine hairs and mucus that filter particles and microorganisms from inhaled air, thereby protecting the respiratory organs [1-2].

Tuberculosis (TB) is a chronic infectious disease caused by *Mycobacterium Tuberculosis* [1]. Although it primarily attacks the lungs, the disease can also spread to other organs, including the bones, lymph nodes, meninges, and kidneys. Transmission occurs through the air, particularly when an infected individual coughs, sneezes, or speaks, releasing bacteria that can be inhaled by others. The high rate of transmission has kept Tuberculosis among the foremost public health concerns across many nations. According to the World Health Organization (WHO), Indonesia ranked as the second highest TB-burden country in the world in 2022, with estimated cases rising from 824,000 in 2021 to 1,060,000 in 2022, and a mortality toll reaching 134,000 deaths. Indonesia was

among eight countries collectively accounting for more than two-thirds of all global TB cases in 2022 [3].

Tuberculosis is curable, however, delayed treatment significantly increases the risk of mortality [4]. Diagnostic evaluation of pulmonary TB may involve assessment of clinical complaints and symptoms, microscopic examination, radiology, and the tuberculin skin test. Among these, chest X-ray examination remains one of the most widely employed diagnostic methods [1]. Each disease, including Tuberculosis, presents distinct patterns and characteristics. To date, diagnosis has largely depended on individual clinical judgment, rendering results inherently subjective. Consequently, there is a pressing need for technology capable of assisting healthcare professionals in analyzing X-ray findings rapidly and accurately through the application of computer- and data-based information technology [4].

The advancement of Artificial Intelligence (AI) technology has exerted a profound influence across numerous aspects of human life [5]. AI is a broad scientific field encompassing multiple subfields, one of which is Machine Learning (ML). Machine Learning refers to the application of computer systems and mathematical algorithms that are capable of learning patterns from data in order to generate predictions or decisions [6]. This technology has been adopted across various industries, with healthcare being one of the most prominent. Within the medical domain, the application of Machine Learning has grown rapidly, owing to its capacity to support clinicians in diagnosis, disease classification, and clinical decision-making. One notable application is its use as a tool for the early detection of Tuberculosis. Several researchers have further extended Machine Learning into a specialized subfield known as Deep Learning (DL) [1]. Deep Learning is a subset of Neural Networks characterized by more complex architectures and a greater number of layers, enabling it to produce accurate predictions on large and intricate datasets [7].

Convolutional Neural Network (CNN) is one of the principal methods within deep learning algorithms, capable of autonomous learning processes for object recognition, feature extraction, and classification. This algorithm draws inspiration from the neuronal cells of the human brain, which possess the ability to recognize and retain information about surrounding stimuli [8]. The objective of this algorithm is to construct a neural network capable of extracting salient features from a target object. These features are stored and subsequently used to identify similar objects in the future.

The present study is conducted under the title "Classification of Tuberculosis Based on Chest X-Ray Images Using the Convolutional Neural Networks (CNN) Method." This research employs the EfficientNetB0 architecture as the base model, complemented by a classification head. The overarching goal is to develop an early detection system capable of classifying chest X-ray images into two categories: class 0 (normal) and class 1 (tuberculosis).

2. Materials and Methods

2.1 Research Design

This study employs an experimental research design, utilizing deep learning techniques to develop an automated tuberculosis (TB) detection system from chest X-ray images. The research workflow consists of several stages, as illustrated in Figure 1.

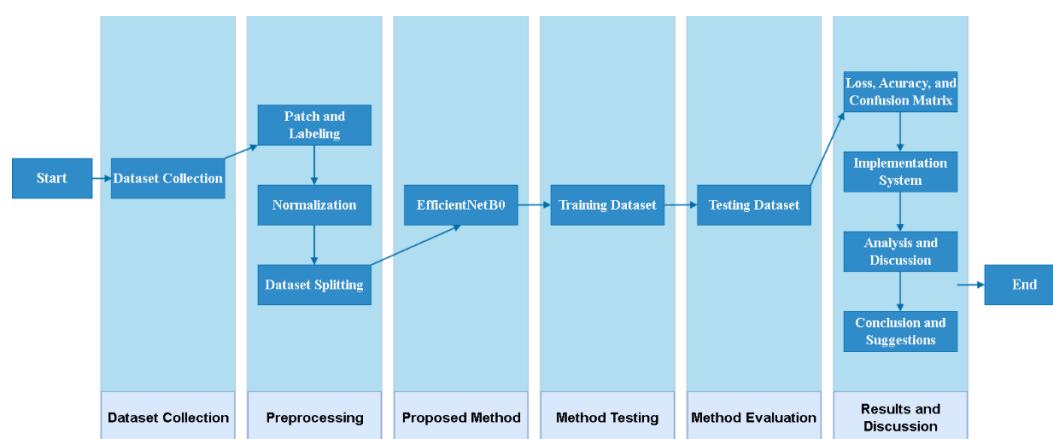


Figure 1. Research Stages

As shown in Figure 1, the research pipeline begins with dataset collection, followed by data preprocessing — which is divided into three stages: patching and labelling, normalization, and dataset splitting. The model is based on the EfficientNetB0 architecture with a transfer learning and fine-tuning strategy. Subsequently, method testing and method evaluation are conducted, and the model is deployed into a web-based early detection system.

2.2 Dataset

The dataset used in this study is the Tuberculosis (TB) Chest X-ray Database developed by Rahman et al. and publicly available through Kaggle [9]. This dataset consists of chest X-ray images categorized into two classes: Normal and Tuberculosis. In this study, a total of 1,382 images were used, comprising 700 Normal images and 682 Tuberculosis images. The training set consists of 1,106 images and the testing set consists of 276 images, as presented in Table 1.

Table 1. Amount of Training Data and Testing Data

Dataset	Data Training	Data Testing	Amount
Normal	560	140	700
Tuberculosis	545	137	682
Total	1105	277	1382

2.3 Data Preprocessing and Augmentation

All input images were resized to 224×224 pixels to meet the input requirements of the EfficientNetB0 architecture. Pixel values were normalized using the preprocess_input function from TensorFlow/Keras. To improve model generalization and reduce overfitting, data augmentation was applied exclusively to the training data, including random rotation up to 20°, width and height shifting, zoom, shear transformation of 20%, and horizontal flip. Validation data was processed without augmentation to ensure objective evaluation. A batch size of 16 was used. Class weights were computed using the compute_class_weight function from Scikit-learn to handle class imbalance.

2.4 Model Architecture

The proposed model architecture in this study consists of two main components: the EfficientNetB0 base model and the classification head. The model architecture is illustrated in Figure 2.

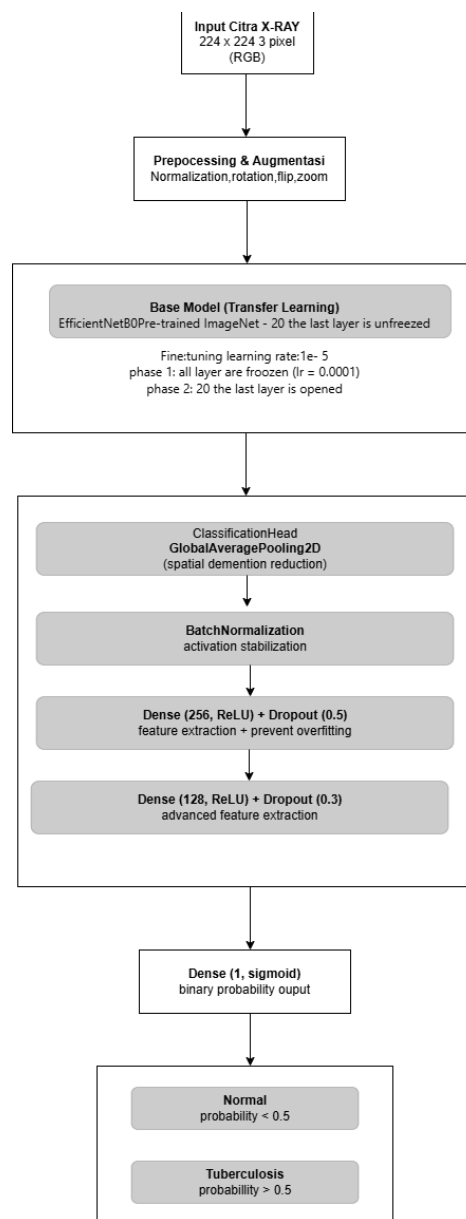


Figure 2. Model Architecture.

The model is built upon a pre-trained EfficientNetB0 using the ImageNet dataset. The classification layers added on top of the base model consist of a GlobalAveragePooling2D layer to reduce spatial dimensions, BatchNormalization to stabilize activations, Dense (256 units, ReLU) + Dropout (0.5), Dense (128 units, ReLU) + Dropout (0.3), and an output Dense layer (1 unit, Sigmoid) for binary classification.

2.5 Model Training

Model training was conducted in two phases. In Phase 1, all layers of the EfficientNetB0 base model were frozen so that their weights were not updated, and the model was trained for up to 20 epochs using the Adam optimizer with a learning rate of 0.0001 and binary cross-entropy as the loss function. One epoch represents a complete cycle in which the entire training data is processed by the model. With 1,106 training samples and a batch size of 16, each epoch consists of approximately 69 iterations. In Phase 2 (fine-tuning), the last 20 layers of EfficientNetB0 were unfrozen and trained for up to 10 additional epochs with a reduced learning rate of 1e-5. The use of a smaller learning rate ensures that weight updates occur gradually, preventing the disruption of features learned in the

previous phase. The total maximum training duration is 30 epochs, although training may terminate earlier if callback conditions are met. Three callbacks were applied during training: EarlyStopping (patience = 5, monitoring val_loss), ReduceLROnPlateau (factor = 0.2, patience = 2), and ModelCheckpoint (saving the best model based on val_accuracy).

2.6 System Implementation

The trained model was deployed as a web-based TB detection system using the Flask framework (Python) on the backend and HTML/CSS/JavaScript on the frontend, running on a localhost environment with an Apache XAMPP server.

2.7 Development Environment and Tools

All experiments were conducted using Google Colaboratory with CPU acceleration. The deep learning framework used was TensorFlow 2.x with the Keras API. Additional libraries utilized include NumPy, Matplotlib, Seaborn, and Scikit-learn. The dataset was stored and accessed via Google Drive.

3. Results and Discussion

3.1. Data Preprocessing Results

The data preprocessing stage was conducted to enhance the quality of X-ray images prior to the model training process. The results of data preprocessing are presented in Figure 3.

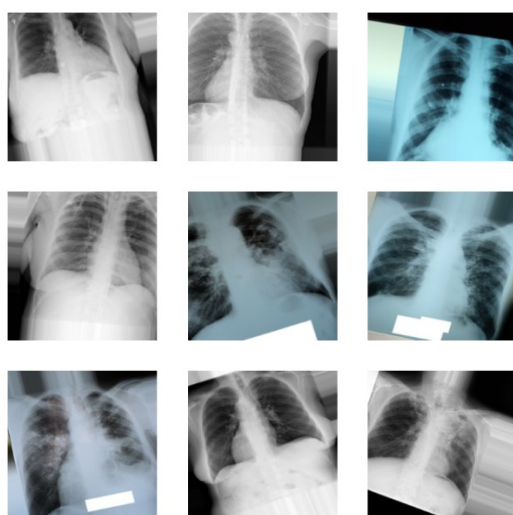


Figure 3. Data Preprocessing Results

The preprocessing results are illustrated in the X-ray images above. Based on these findings, several variations were identified within the dataset. In terms of color tone, some images appeared with a teal hue while others were in grayscale, indicating differences in the source acquisition devices. Variations in brightness and contrast were also observed across samples, with some images exhibiting high exposure while others appeared relatively dark. Furthermore, inconsistencies in cropping were noted, and several samples contained artifacts in the form of white boxes obscuring portions of the lung field. Clinically, certain images exhibited infiltrates and consolidation in the lung fields, suggesting the possibility of tuberculosis.

3.2. CNN Model Training Results

Based on the CNN model training results, performance graphs were obtained depicting changes in accuracy and loss values throughout the training process across each

epoch. These graphs were used to assess the model's capacity to learn patterns from chest X-ray image data during both the training and validation phases.

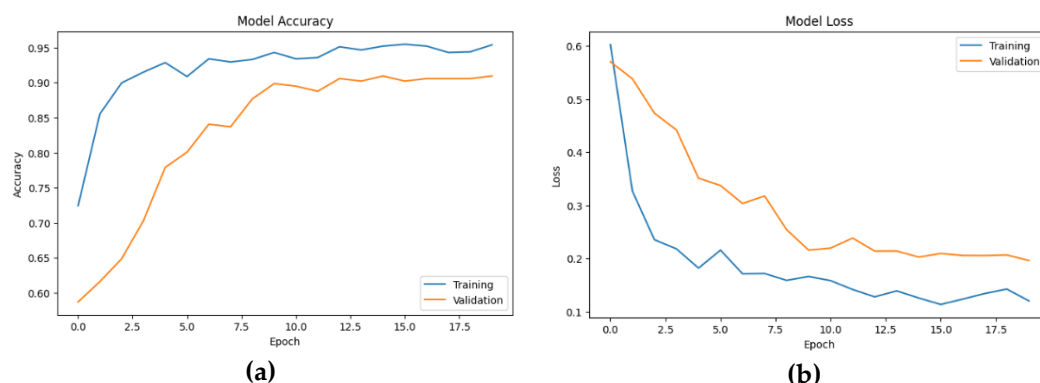


Figure 4. Accuracy graph of model accuracy and loss over 20 epochs. **(a)** Training accuracy reached 95% and validation accuracy 91%. **(b)** Training and validation loss decreased consistently.

The model accuracy graph measures the percentage of correct predictions generated by the model. The training accuracy increased rapidly from approximately 72% in the early epochs to approximately 95% by the end of training. Validation accuracy likewise improved from 58% to 91%. The consistently stable rise of both curves indicates that the model possesses strong learning and generalization capabilities. The relatively narrow gap between the training and validation curves suggests a low risk of overfitting. The model began to stabilize around epoch 10, after which accuracy improvements were no longer significant.

The model loss graph measures the degree of prediction error produced by the model. The training loss decreased drastically from approximately 0.60 to approximately 0.10. The validation loss also declined steadily from 0.57 in the early epochs to approximately 0.20 by the final epoch. This indicates that the model's prediction error diminished progressively as training proceeded. The absence of a sharp upward trend in the validation loss curve confirms that the model retained a satisfactory generalization capability with respect to unseen data.

3.3. Results of the CNN Model Training

3.3.1 Confusion Matrix

To assess the model's classification performance on chest X-ray images, an evaluation was conducted using a confusion matrix.

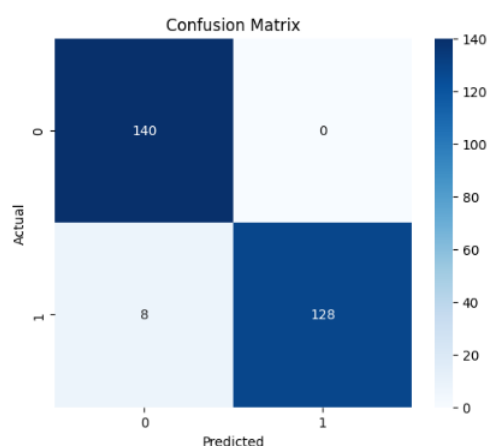


Figure 5. Confusion Matrix.

Based on Figure 5, the model demonstrated excellent classification performance across a total of 276 test samples. The model predicted the normal class perfectly, correctly classifying 140 samples as True Negative, with no normal samples misclassified as tuberculosis (zero False Positives). For the tuberculosis class, the model also performed well, correctly identifying 128 samples as True Positive; however, 8 samples were misclassified as normal (False Negatives). These results indicate that the model achieves a high level of accuracy and generalization, as the vast majority of samples were classified correctly.

3.3.2 Classification Report

Based on the confusion matrix results above, a further evaluation was conducted using a classification report to examine the detailed performance of the model in terms of precision, recall, F1-score, and support.

Table 2. Classification report

	Precision	Recall	F1-score	Support
0	0.95	1.00	0.97	140
1	1.00	0,94	0,97	136
accuracy			0,97	276
macro avg	0,97	0,97	0,97	276
weighted avg	0,97	0,97	0,97	276

As shown in Table 2, the model demonstrated excellent overall performance with an accuracy of 97% on 276 test samples. The normal class achieved a perfect recall, meaning all normal samples were correctly detected; however, precision was slightly lower, as a small number of tuberculosis samples were misclassified as normal. Conversely, the tuberculosis class achieved perfect precision, while its recall was slightly lower, as a small proportion of tuberculosis samples went undetected. Both classes yielded an equal F1-score of 0.97, indicating that the model performs consistently and in a balanced manner across both classes.

3.4. System Implementation

The resulting system is a web-based application named TBDetect, designed to detect findings from chest X-ray examinations. The system interface is presented in Figures 6–8.

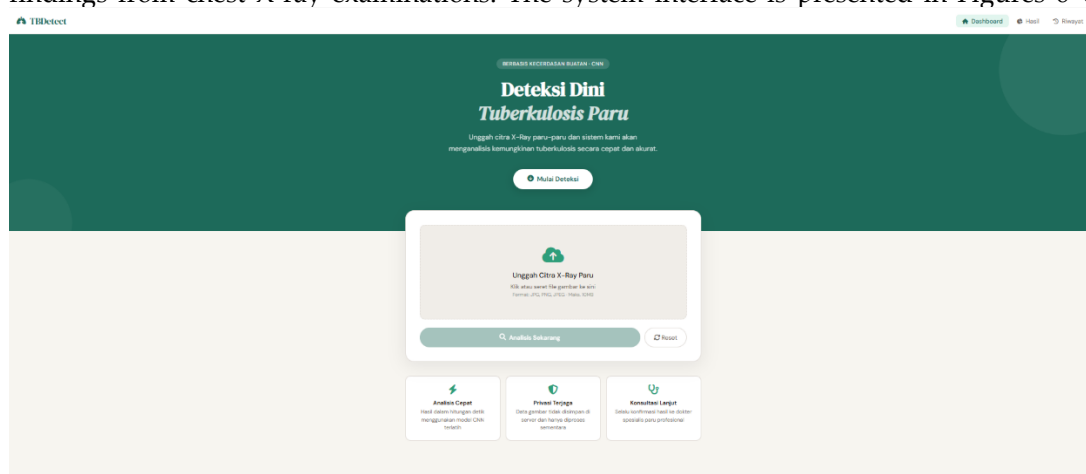


Figure 6. TBDetect System Dashboard View.

As shown in Figure 6, the dashboard page features a chest X-ray image upload function, which allows users to submit images prior to analysis by the system. Users can upload X-ray images in JPG, PNG, and JPEG formats with a maximum file size of 10 MB. Additionally, a reset button is available to remove the uploaded image and restart the data

input process in the event of an error. The system also displays several supplementary information sections, including quick analysis, data privacy, and further consultation.

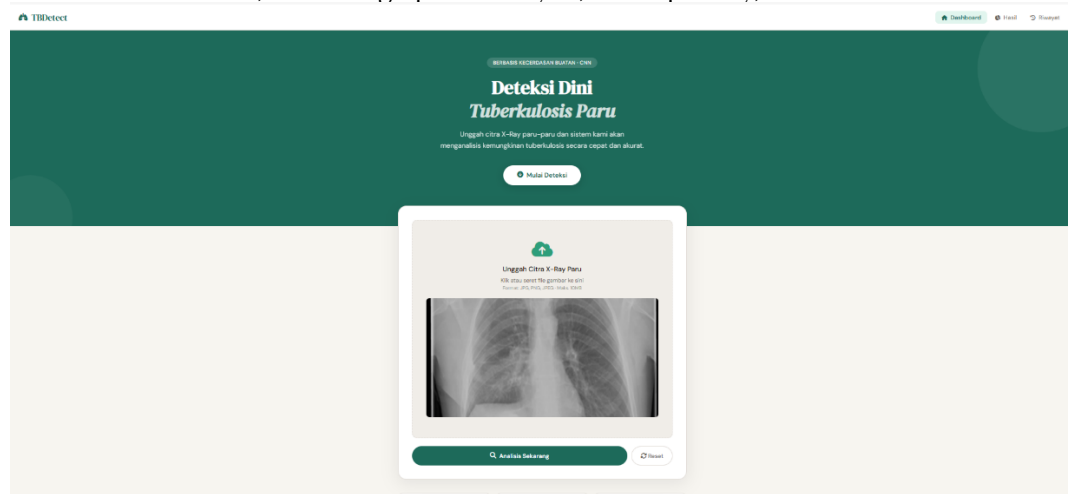


Figure 7. Screen Display During the Analysis Proses

As shown in Figure 7, the dashboard is equipped with an "Analisis Sekarang" button, which initiates the X-ray image classification process, categorizing the input as either tuberculosis or normal based on the previously trained CNN model.

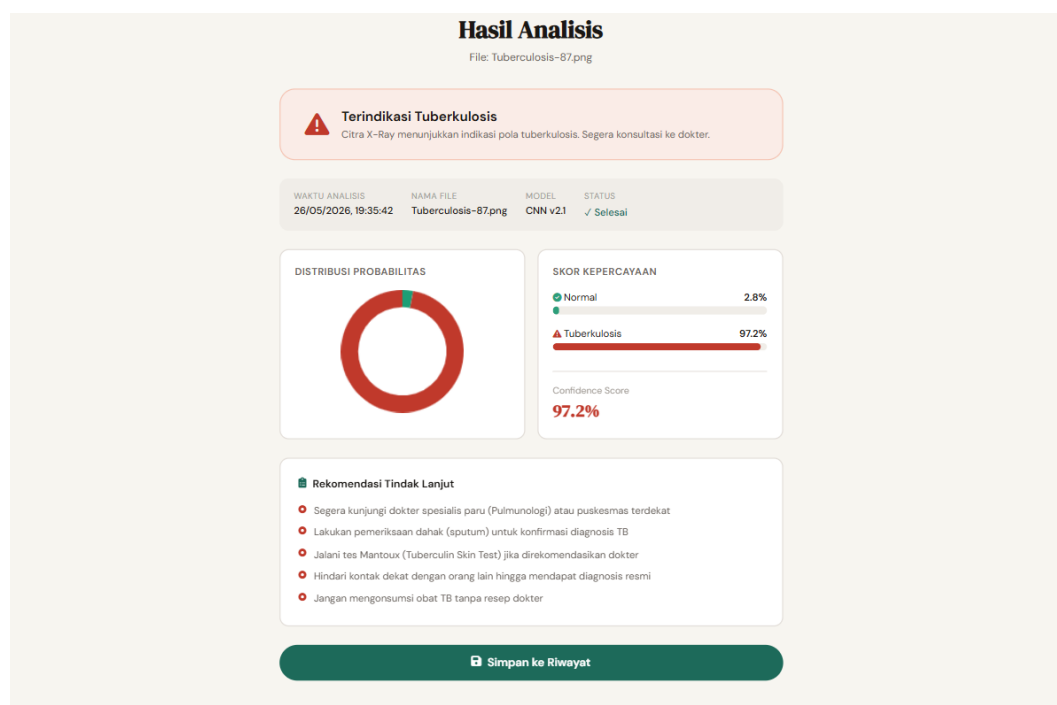


Figure 8. Analysis Results.

As shown in Figure 8, the classification result indicates that the image was detected as tuberculosis with a confidence score of 97.2%, while the probability for the normal class was only 2.8%. The probability distribution is visualized using a donut chart dominated by red, indicating that the prediction falls under the tuberculosis category. Furthermore, the system also displays follow-up recommendations in the form of medical advice, such as consulting a pulmonologist, conducting sputum examination, performing a Mantoux test, and a reminder to avoid consuming tuberculosis medication without a doctor's prescription. The detection history can be saved as documentation or as a reference for further monitoring.

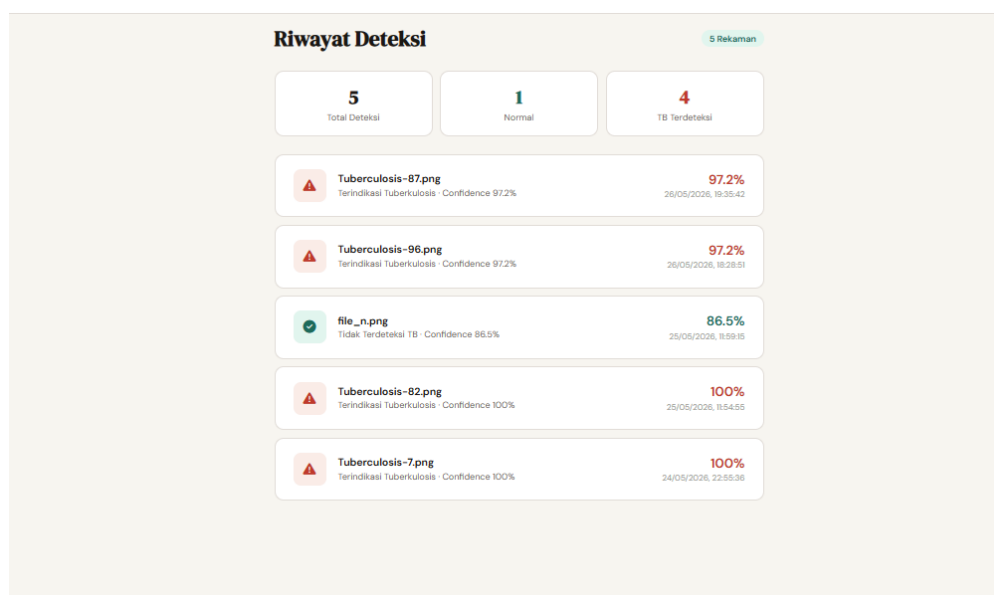


Figure 9. History View.

As shown in Figure 9, the page displays the detection history of all previously performed classifications, with a total of 5 records consisting of 1 normal and 4 TB cases correctly detected.

The results indicate that the use of EfficientNetB0 with a two-stage transfer learning strategy achieved an overall accuracy of 97% on the validation data. The accuracy and loss curves demonstrated consistent convergence with no signs of overfitting, and the model exhibited satisfactory generalization capability on chest X-ray image data. Based on the confusion matrix, the model successfully classified all 140 Normal images with a specificity of 100%, while 128 out of 136 Tuberculosis images were correctly detected, yielding a true positive sensitivity of 94.12%. However, 8 Tuberculosis images were misclassified as false negatives. The TBDetect early detection system successfully processed all 5 records with correct results.

These findings are consistent with several prior studies in the field of deep learning-based tuberculosis detection, as follows:

1. Goswami et al. reported an accuracy of 94.00% with a sensitivity of 96.85% and specificity of 91.49% using a custom CNN [10]. The model in this study outperforms in terms of accuracy (97%) and specificity (100%), although its sensitivity (94.12%) is slightly lower, reflecting a trade-off between the two metrics.
2. Oliveira and Pereira achieved an accuracy of 97.44% through an ensemble of five EfficientNet variants. The single EfficientNetB0 model in this study produced a nearly comparable accuracy (97%), demonstrating that a two-stage fine-tuning strategy is capable of maximizing the potential of a lighter architecture without requiring an ensemble approach [11].
3. Nafisah and Muhammad compared several CNN models for TB detection from chest X-rays and found that EfficientNetB3 achieved the highest accuracy of 99.1% with an ROC of 99.9%, further confirming that the use of segmented lung images consistently yields better performance compared to raw images [12].
4. Acharya et al. proposed NFNet with an accuracy of 96.91% [13], while Maheswari et al. achieved 95% accuracy using a shallow CNN with Bayesian optimization [14]. The model in this study surpasses both in overall accuracy, with the added advantage of EfficientNetB0's computationally lighter architecture.

Overall, the EfficientNetB0 model in this study achieved an accuracy of 97%, which is comparable to prior studies such as Oliveira & Pereira (97.44%) [11]. The key advantage of this model lies in its 100% specificity — a result not observed in any of the comparison studies — indicating that the model produces zero false positives. Nevertheless, the model's sensitivity of 94.12% remains below that of Goswami et al., who achieved 96.85% [10], suggesting that improving the detection capability for actual tuberculosis cases should remain a focus for future development. Overall, the EfficientNetB0-based transfer learning approach proves to be a competitive method for tuberculosis detection in chest X-ray images, albeit without fully surpassing all metrics achieved by previous studies.

4. Conclusions

This study successfully developed an automated tuberculosis (TB) detection system based on chest X-ray image classification using the EfficientNetB0 deep learning model with a transfer learning and fine-tuning strategy. The dataset used consisted of 1,382 images comprising Normal and Tuberculosis classes, split at an 80:20 ratio for training and validation. The developed model achieved an accuracy of 97% with a loss value of 0.093 on the validation data. The classification report yielded precision, recall, and F1-score values of 0.97 for both classes, indicating that the model is capable of detecting TB accurately with a very low error rate.

The model was subsequently deployed as a web-based application using HTML, enabling easy access for users through a browser. The findings of this study demonstrate that the EfficientNetB0 architecture with a transfer learning approach represents an effective and efficient solution for TB detection from chest X-ray images. For future research, it is recommended to utilize a larger and more diverse dataset, as well as to explore other deep learning architectures such as EfficientNetB3 or EfficientNetV2 to further improve model performance.

5. Patents

Author Contributions: Conceptualization, R.G.A.; methodology, R.G.A.; software, R.G.A.; validation, D.A.M.; formal analysis, S.D.O.R.; investigation, R.G.A.; resources, R.G.A.; data curation, R.G.A.; writing—original draft preparation, R.G.A.; writing—review and editing, D.A.M.; visualization, S.D.O.R.; supervision, M.Y.; project administration, R.G.A. All authors have read and agreed to the published version of the manuscript.

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References

- [1] A. Rasyid and L. Heryawan, "Klasifikasi penyakit tuberculosis (TB) organ paru manusia berdasarkan citra rontgen thorax menggunakan metode convolutional neural network (CNN)," *Jurnal Manajemen Informasi Kesehatan Indonesia*, vol. 11, no. 1, 2023.
- [2] D. Kusuma and D. B. Rarasati, "Klasifikasi penyakit paru-paru dengan citra X-Ray menggunakan metode convolutional neural network," *Jurnal Ilmiah Sains dan Teknologi*, vol. 9, no. 2, pp. 152–165, 2025.
- [3] World Health Organization, *Global Tuberculosis Report 2023*. Geneva: WHO, 2023. [Online]. Available: <https://www.who.int/teams/global-tuberculosis-programme/tb-reports>
- [4] D. R. Aldiansyah and M. Soleh, "Analisa performa arsitektur model convolutional neural network dengan variasi jumlah hidden layer untuk klasifikasi tuberculosis pada citra X-Ray," *Jurnal FASILKOM*, vol. 14, no. 3, pp. 729–734, 2024.

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- [5] A. J. E. Oktavianus, L. Naibaho, and D. A. Rantung, "Pemanfaatan artificial intelligence pada pembelajaran dan asesmen di era digitalisasi," *Jurnal Kridatama Sains dan Teknologi*, vol. 5, no. 02, pp. 473–486, 2023.
- [6] G. P. Andini, D. Rahmi, S. Yuniarti, and A. Kurniati, "Analisis real sebagai dasar matematika untuk pengembangan kecerdasan buatan dan machine learning," *AT-TAKLIM: Jurnal Pendidikan Multidisiplin*, vol. 2, no. 12, pp. 550–558, 2025.
- [7] S. Siswanto, M. U. Dewi, S. Kholifah, G. Widhiati, and W. Aryani, "Penggunaan model deep learning untuk meningkatkan efisiensi dalam aplikasi machine learning," *Jurnal Penelitian Sistem Informasi (JPSI)*, vol. 1, no. 4, pp. 215–238, 2023.
- [8] R. A. Tilasefana and R. E. Putra, "Penerapan metode deep learning menggunakan algoritma CNN dengan arsitektur VGG NET untuk pengenalan cuaca," *Journal of Informatics and Computer Science (JINACS)*, vol. 5, no. 01, pp. 48–57, 2023.
- [9] T. Rahman, A. Khandakar, M. A. Kadir, K. R. Islam, K. F. Islam, Z. B. Mahbub, M. A. Ayari, and M. E. H. Chowdhury, "Reliable tuberculosis detection using chest X-Ray with deep learning, segmentation and visualization," *IEEE Access*, vol. 8, pp. 191586–191601, 2020.
- [10] B. Goswami et al., "Tuberculosis detection using deep learning," *Cureus*, vol. 15, no. 7, p. e41583, Jul. 2023.
- [11] M. Oliveira and J. Pereira, "Ensemble of EfficientNets for the diagnosis of tuberculosis," *Applied Sciences*, vol. 11, 2021.
- [12] S. I. Nafisah and G. Muhammad, "Tuberculosis detection in chest radiograph using convolutional neural network architecture and explainable artificial intelligence," *Neural Computing and Applications*, vol. 36, pp. 111–131, Apr. 2022.
- [13] U. R. Acharya et al., "Automated tuberculosis detection using deep learning," *Computers, Materials & Continua*, vol. 2022, p. 2399428, 2022.
- [14] B. Maheswari et al., "Tuberculosis detection using shallow CNN with Bayesian optimization," *BMC Medical Imaging*, vol. 24, p. 32, 2024.