IJCCS (Indonesian Journal of Computing and Cybernetics Systems)
Vol.19, No.1, January 2024, pp. 49~60
ISSN (print): 1978-1520, ISSN (online): 2460-7258
DOI: https://doi.org/10.22146/ijccs.102601

Comparison of Artificial Intelligence Methods for Tuberculosis Detection Using X-Ray Images

I Putu Agus Eka Darma Udayana *[1], I Made Karang Satria Prawira[2], I Gede Bagus Arya Merta Tika[3]
[1,2,3]Departement of Informatic, Faculty of Technology and Informatics, Indonesian Institute of Business and Technology, Denpasar, Indonesia
e-mail: ***[1]agus.ekadarma@gmail.com**, [2]satriaprawira02@gmail.com, [3]arya.mertatika16@gmail.com

Abstrak

Penyakit tuberkulosis (TB), yang disebabkan oleh bakteri Mycobacterium tuberculosis, merupakan penyakit menular yang sangat berbahaya. Di Indonesia, TB adalah penyakit menular paling mematikan setelah COVID-19 dan menempati urutan ke-13 sebagai penyebab kematian global. Deteksi dini TB sangat penting untuk meningkatkan peluang kesembuhan, namun keterbatasan jumlah ahli radiologi menjadi tantangan utama. Teknologi deep learning, khususnya Convolutional Neural Network (CNN), mejadi solusi efektif untuk masalah ini. Oleh karena itu, pada penelitian ini akan membandingkan dua arsitektur CNN, yaitu AlexNet dan VGG-19, dalam mendeteksi TB pada citra rontgen paru-paru, dengan penerapan metode perbaikan kualitas citra, seperti Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), dan Gamma Correction. Dataset yang digunakan diperoleh dari Kaggle dan mencakup citra rontgen paru-paru normal serta TB. Evaluasi performa dilakukan berdasarkan akurasi, presisi, recall, dan F1-score. Hasil penelitian menunjukkan bahwa VGG-19 dengan CLAHE memberikan performa terbaik dengan akurasi 93.5%, presisi 98.88%, recall 88%, dan F1-score 93.12%. VGG-19 dengan Gamma Correction juga menunjukkan hasil yang sangat baik dengan akurasi 91%, presisi 97.67%, recall 84%, dan F1-score 90.32%. Temuan ini menggarisbawahi efektivitas kombinasi CNN dan metode pemrosesan citra dalam meningkatkan deteksi TB.

Kata kunci— *Pengolahan Citra, Kecerdasan Buatan, Deep Learning, Tuberkolosis, CNN, VGG-19*

Abstract

Tuberculosis (TB), caused by the bacterium Mycobacterium tuberculosis, is a highly dangerous infectious disease. In Indonesia, TB is the deadliest infectious disease after COVID-19 and ranks as the 13th leading cause of death globally. Early detection of TB is crucial for improving the chances of recovery, yet the limited number of radiologists poses a significant challenge. Deep learning, particularly Convolutional Neural Networks (CNNs), offers an effective solution to this issue. This study compares two CNN architectures, AlexNet and VGG-19, for detecting TB in chest X-ray images, employing image enhancement techniques such as Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), Contrast Limited Adaptive Histogram Equalization (CLAHE), and Gamma Correction. The dataset used is sourced from Kaggle and includes images of both normal lungs and TB. Performance evaluation is conducted based on accuracy, precision, recall, and F1-score. The results demonstrate that VGG-19 with CLAHE provides the best performance, achieving an accuracy of 93.5%, precision of 98.88%, recall of 88%, and F1-score of 93.12%. VGG-19 with Gamma Correction also shows excellent results with an accuracy of 91%, precision of 97.67%, recall of 84%, and F1-score of 90.32%. These findings underscore the effectiveness of combining CNNs with image processing techniques to enhance TB detection.

Received December 14th,2024; Revised January 20th, 2025; Accepted January 26th, 2025

Keywords— *Image Processing, Artificial Intelligence, Deep Learning, Tuberculosis, CNN, VGG-19*

1. INTRODUCTION

Chronic diseases are the leading cause of death worldwide. These conditions accounted for 73% of total deaths in 2020, with 60% of them caused by cancer, stroke, HIV/AIDS, and heart disease. One of these chronic diseases is Tuberculosis (TB), caused by Mycobacterium tuberculosis, which primarily attacks the lungs [1]. According to the Global TB Report 2022, TB is the second deadliest infectious disease after COVID-19 and ranks 13th as the leading cause of death worldwide. Indonesia ranks second after India, with 969,000 cases and 144,000 deaths. TB significantly affects countries with a high burden due to a lack of radiologists and medical equipment. Although TB is treatable, early diagnosis through chest X-rays is crucial. However, the limited number of radiologists poses a major challenge, making it necessary to develop semi-automated detection systems to support medical diagnosis [2]. Using CNNs, a deep learning technology, various types of diseases can be diagnosed quickly and effectively [3]. There are three main layers that make up a neural network (CNN): the convolutional layer, the pooling layer, and the fully connected layer. The convolutional layer, which serves as the backbone of CNN architecture, extracts image features by applying filters through a convolution operation [4]. VGG-19 is a well-known CNN architecture comprising 19 layers, which include 16 convolutional layers, 4 max pooling layers, 2 fully connected layers, and a single softmax layer. VGG-19 uses 224x224 input images and a 3x3 kernel, featuring 5 blocks of convolutional layers [5]. Chest radiology imaging, such as CT and X-ray, is crucial for the early diagnosis of TB. However, X-ray images have limitations in distinguishing soft tissues, necessitating image quality enhancement. Methods used include HE (Histogram Equalization), AHE (Adaptive Histogram Equalization), CLAHE (Contrast Limited Adaptive Histogram Equalization), and Gamma Correction [6]. This study will compare deep learning methods, AlexNet and VGG-19, with image quality enhancement using HE, AHE, CLAHE, and Gamma Correction in detecting TB. The evaluation will be conducted by comparing four indicator that is accuracy, precision, recall, and F1-score, utilizing chest X-ray images sourced from Kaggle. The aim of this study is to compare different deep learning methods for detecting tuberculosis using chest X-rays. The ultimate goal is to identify the most effective method for diagnosing the disease.

2. METHODS

This study involves five core steps as its main stages. The first stage involves data collection, followed by image quality enhancement using the CLAHE method, then data preprocessing, and the application of the AlexNet and VGG-19 methods. The second stage involves data collection, image quality enhancement using the AHE method, data preprocessing, and the application of the AlexNet and VGG-19 methods. In the third stage, data collection, image quality enhancement using the HE method, data preprocessing, and the application of the AlexNet and VGG-19 methods are carried out. The fourth stage includes data collection, data preprocessing, and the application of the AlexNet and VGG-19 methods without image quality enhancement. The final stage involves testing the results and accuracy, as well as comparing methods that use image enhancement with those that do not. Figure 1 below illustrates these research stages.

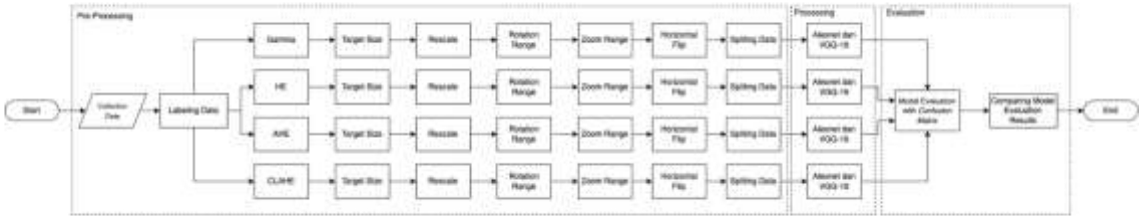

Figure 1 Research Flow

2.1 Datasets

The initial step involves gathering the dataset. For this research, a publicly accessible dataset obtained from the Kaggle platform. This dataset was developed by Rahman [7]. It contains chest X-ray images of normal lungs, with 3,500 images, and lungs affected by tuberculosis, with 1,500 images. Table 1 shows the data distribution.

Table 1 Dataset Distribution

Condition	Amount of data
Normal Lungs	3.500
Tuberculosis-Affected Lungs	1.500

2. 2 Preprocessing

The pre-processing stage in this research involves several techniques to enhance image data quality before it is used for model training. First, Histogram Equalization (HE) is applied to improve image contrast by redistributing pixel intensities more evenly. Second, Adaptive Histogram Equalization (AHE) enhances local contrast by applying equalization to small regions of the image, which helps in improving details in areas with varying lighting conditions. Third, Contrast Limited Adaptive Histogram Equalization (CLAHE) addresses the issue of excessive amplification found in AHE by limiting the contrast, thus preserving details while reducing excessive noise. Fourth, Gamma Correction is used to adjust the image brightness, where a gamma value greater than 1 darkens the image, and a value less than 1 brightens it, helping to normalize intensity variations in the image. Lastly, Target Size specifies a uniform standard size for all images, facilitating model training by ensuring all images have consistent resolution and proportions, thereby improving the model's efficiency and accuracy.

2. 2.1 Histogram Equalization

A histogram is a graph that represents the distribution of pixel intensity values, helping to determine whether an image is dark or bright [8]. Histogram equalization involves adjusting pixel intensity values to make their distribution uniform. This equalization is achieved by transforming the original pixel intensity values (r) to new values (s) using a transformation function TTT, such that s=T(r)s = T(r)s=T(r). This means that rrr can be retrieved from sss using the inverse transformation r=T−1(s)r = T^{-1}(s)r=T−1(s), where 0≤s≤10 \leq s \leq 10≤s≤1 and 0≤r≤10 \leq r \leq 10≤r≤1. To ensure consistent mapping within the allowed value range, the goal of histogram equalization is to achieve a comprehensive histogram spread so that each gray level has an approximately equal number of pixels [9]. Since the histogram indicates the probability of pixels having a specific gray level, the formula used for histogram equalization is:

$$P_r(r_k) = \frac{n_k}{n} \textit{ in this case } r_k = \frac{k}{t_{t-1}}, 0 \leq k \leq L - 1 \tag{1}$$

In histogram equalization, gray levels (k) are normalized with respect to the maximum gray level L−1L - 1L−1. Here, rk=0rk = 0rk=0 represents black, and rk=1rk = 1rk=1 represents white in the specified grayscale [9]. Another formula used to compute histogram equalization for an image with a grayscale of kkk bits is given by the following equation.

$$K_o = \text{round}\left(\frac{C_{i\left(2^{k}-1\right)}}{wh}\right) \quad (2)$$

2. 2.2 Adaptive Histogram Equalization

Adaptive Histogram Equalization (AHE) works by dividing an image into several regions and then performing histogram equalization (HE) on each region. Consequently, AHE processes multiple histograms, each representing a different region of the image. This technique enhances local contrast, allowing for more detailed observations [10]. Unlike standard histogram equalization, AHE uses an adaptive method that calculates multiple histograms for various parts of the image and applies them to adjust the distribution of pixel values. This makes AHE particularly effective to enhance local contrast and define edges definition in different areas of the image [11]. AHE is also known as Local Histogram Processing [12]. By applying HE to different regions, AHE enhances local contrast and edge definition, providing an effective solution for improving image quality.

2. 2.3 Contrast Limited Adaptive Histogram Equalization

This is a popular method to enhancing contrast images, especially useful for improving medical images like X-rays and enhancing details in standard photographs [13]. CLAHE is a modification of AHE and is known for its simplicity and efficiency in implementation. It can separate the background from the foreground in images, reduce noise, and enhance contrast [14]. The CLAHE algorithm operates by first segmenting the base image to smaller M x N sections. Then, a histogram is computed for every segmented region. Finally, the histogram of each sub-image is subjected to a clipping process to limit its intensity values. The pixel count within the the segmented region is allocated across each grayscale level. The mean quantity of pixels at every level of grayscale is calculated using equation (3).

$$N_{\text{avg}} = \frac{N_{CR-Xp} \times N_{CR-Yp}}{N_{\text{aray}}} \quad (3)$$

N_avg represents the mean pixel value, N_gray indicates the total grayscale levels within the sub-image, N_(CR-Xp) denotes the pixel count along the X-axis of the sub-image, and N_(CR-Yp) refers to the pixel count along its Y-axis. Then, calculate the clip limit of the histogram using equation (4).

$$N_{CL} = N_{CLIP} X N_{\text{avg}} \quad (4)$$

N_CL represents the clip limit, while N_CLIP is the maximum allowed average pixel value for each grayscale level within the sub-image. In the original histogram, pixel values are clipped if their count exceeds N_CLIP. The clipped pixels are then uniformly redistributed across each grayscale level (N_d), with N_TC indicating the overall count of clipped pixels, calculated using equation (5).

$$N_d = \frac{N_{TC}}{N_{\text{gray}}} \quad (5)$$

The variable M signifies the size of the area, N refers to the grayscale intensity value, and α represents the clip factor, which determines the level of histogram enhancement within a range of 0 to 100 [15].

2. 2.4 Gamma Correction

Gamma correction is a shading factor that affects the relationship within the input image intensity (grayscale level) and the resulting image, making the mapping potentially non-linear [16]. Gamma has a value greater than 0. When gamma is set to one, the mapping becomes linear. However, if gamma is less than one, the mapping generally produces higher output values, resulting in a brighter image. When gamma exceeds one, the mapping typically produces lower output values, leading to a darker image [17]. The pixel intensity of the image, γ, is a positive constant that introduces the gamma value. If γ is greater than 1, the output will be darker. Conversely, if γ is less than 1, the output will be brighter. In this context, gamma adjustment can be considered a contrast adjustment operation [18], [19].

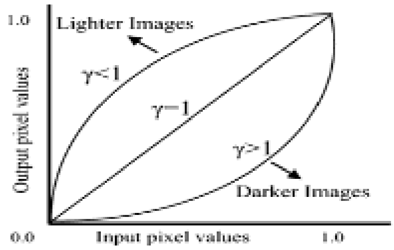

Figure 2 Gamma correction

2. 4 Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a specialized form of Multi-Layer Perceptron (MLP) designed for identifying images in two dimensions. CNN mimics the way the human brain recognizes objects, enabling computers to 'see' and 'distinguish' between various objects, a process known as image recognition [20]. CNN is a classification method in deep learning that uses convolutional layers to convolve input with filters. Generally, CNN shares similarities with regular neural networks, consisting of neurons with weights, biases, and activation functions. CNN employs two main methods: backpropagation for learning (training) and forward propagation for classification [21]. A standard A CNN consists of three main layer types: convolutional layers, pooling layers, and fully connected layers. The Convolutional Layer, which forms the backbone of the CNN structure, applies convolution using matrix filters (commonly 3x3) to identify essential features within the image. These features preserve specific relationships between pixels. Convolution with different filters can produce effects such as edge detection, blurring, and image sharpening. In addition to filters, there is also stride, which is the number of pixel shifts on the input. If the stride is 1, the filter moves by 1 pixel at a time. Padding is used if the filter does not fully fit the input [4]. The formula used in the Convolutional Layer can be seen in equation (6).

$$n_{(w,h)} = \left[\frac{n_{in} + 2p - k}{s}\right] + 1 \tag{6}$$

Activation functions are the stages that follow the convolution process. The output of the convolution is subjected to an The Rectified Linear Unit (ReLU) is among the most frequently utilized functions for activation in CNNs, aimed at minimizing error and saturation. This activation function is often chosen by researchers because it performs better and It is applied in every hidden layer of the neural network, with the mathematical expression for the ReLU activation function provided in the equation (7) [22].

$$f(\mathrm{x}) = \begin{cases} \mathrm{x}, & \mathrm{x} > 0 \\ 0, & \mathrm{x} \leq 0 \end{cases} \tag{7}$$

The ReLU function is an activation function that outputs 0 when the input is negative, and passes the input value unchanged when it is positive [23]. The pooling layer reduces the image dimensions following the convolutional layer. Pooling layers come in two types: Max pooling and average pooling are widely used techniques in convolutional neural networks. In max pooling, the pooling layer segments the output of the convolutional network into smaller grids to process the maximum value within each grid, and select full value from each grid to create the reduced image matrix [14]. The formula used in Max Pooling can be seen in equation (8).

$$n_{(w,h)} = \frac{(n_{(w,h)-1} - f)}{s} + 1 \tag{8}$$

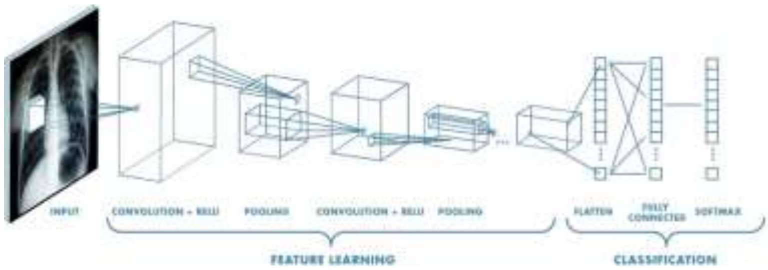

Figure 4 *Convolutional Neural Network process*

2. 5 Alexnet

In the method design phase, AlexNet is one of the methods used in this research. The data that has undergone preprocessing will be processed using the functions present in the layers of AlexNet [24]. AlexNet uses several important parameters. In this study, the AlexNet is build of five convolutional layers and three fully connected layers, along with 5 dropout layers implemented following some convolutional and fully connected layers to reduce overfitting by randomly ignoring some units. AlexNet also uses pooling layers after several convolutional layers to reduce data dimensions and extract important features. Finally, the dense layer functions as the output layer to produce the required predictions or outputs. This configuration make AlexNet model to learn important features in the image, also improve model generalization through dropout, resulting in better predictions.

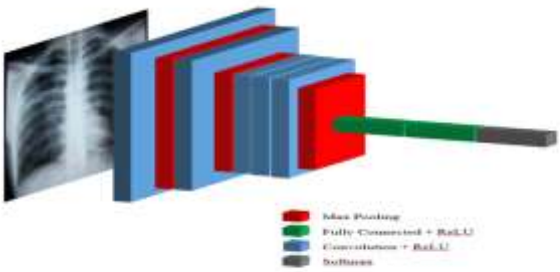

Figure 5 Architecture Alexnet

2. 6 VGG-19

In the method design phase, VGG-19 is one of the methods used in this research. The data that has undergone preprocessing will be processed using the functions present in the layers of VGG-19. VGG-19 uses several important parameters. In this study, VGG-19 comprises 16 convolutional layers and 3 fully connected layers, with 5 dropout layers strategically inserted after specific convolutional and fully connected layers. These dropout layers help reduce overfitting by randomly deactivating certain units. [25]. VGG-19 employs convolutional layers with small kernels (3x3) and a stride of 1 to capture intricate features from the image. It also uses pooling layers after several convolutional layers to reduce the data's dimensions and emphasize key features. Finally, The dense layer serves as the output layer to generate the desired predictions or outputs. This configuration allows the VGG-19 model to learn important features in the image data and improve model generalization through dropout, leading to better predictions [26].

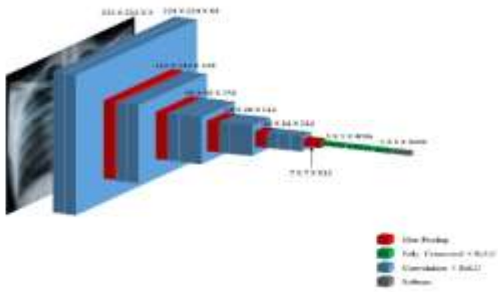

Figure 6 Architecture VGG-19

2. 7 Image Quality Assessment

IQA utilizes MSE and PSNR to assess the efficiency of contrast enhancement techniques for improving image quality. MSE evaluates the mean squared difference between the original image and the improved version, calculated by comparing the pixel values at corresponding positions in both images. Equation (9) is used to calculate the MSE value [10].

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N=1}(I(i-j)-E(i-j))^2 \quad (9)$$

In equation (9), I and E represent the input image and the enhanced image, i and j are the pixel positions in the image, and MN represents the size of the image. PSNR is the ratio between the image's pixel intensity dynamic range and the noise present in the image. It is used to assess the quality of an image after enhancement, with higher PSNR values indicating better image quality. PSNR can be calculated using equation (10) [27].

$$PSNR = 10\ log_{10}(\frac{(L-1)^2}{MSE}) \quad (10)$$

In equation (9), L represents the dynamic range of grayscale levels in the image.

2. 8 Evaluasi model

System performance is evaluated using A confusion matrix is a categorization evaluation tool by providing information on correct and incorrect predictions [28]. The matrix provides details on the accuracy of predictions in classification. The confusion matrix consists of four cells that represent the count of accurate and inaccurate predictions. The confusion matrix enables the derivation of various evaluation metrics for classification models, including accuracy, precision, recall, F1-score, and more [29]. The calculations for accuracy, precision, and recall are shown in equations (10), (11), and (12) below.

1. *Accuracy*

   Accuracy measures how well a system can classify overall correctness. Accuracy can be calculated using equation (11).

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (11)$$

2. Precision

   Precision can be calculated as the ratio of true positives to the total of true positives and false positives, with the accuracy of positive predictions indicated by a high precision value. Precision can be calculated using equation (12).

$$Precision = \frac{TP}{TP+FP} \tag{12}$$

3. Recall

Recall can be calculated as the ratio of true positives to the total of true positives and false negatives, with a high recall value indicating successful identification of the class. Recall can be calculated using equation (13).

$$Recall = \frac{TP}{TP+FN} \tag{13}$$

In addition to accuracy, precision, and recall, the F-Score—which combines precision and recall—can also be computed using the confusion matrix. The harmonic mean of precision and recall is used to get the F-Score. The F-Score can be calculated using equation (14).

$$F1score = 2 \cdot \frac{Recall \cdot Precision}{Recall+Precision} \tag{14}$$

In equations (11), (12), and (13), When the model accurately identifies a positive class as positive, it is called True Positive (TP). When the model correctly classifies a negative class as negative, it is referred to as True Negative (TN). When the model incorrectly labels a negative class as positive, it is considered False Positive (FP), while when the model wrongly classifies a positive class as negative, it is called False Negative (FN) [30].

3. RESULTS AND DISCUSSION

3.1 Image Enhancement Evaluation

Use IQA (Image Quality Assessment) with MSE and PSNR to evaluate the methods HE, AHE, CLAHE, and Gamma Correction in enhancing chest X-ray images. It will help to improve image.

Table 2 Results of the image enhancement model testing

Image Improvement Methods	MSE	PSNR
HE	1004.435	20.339
AHE	550.525	21.019
CLAHE	11.113	38.132
Gamma Correction	47.468	31.442

In this study, image enhancement performance is assessed through the Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) metrics to assess the quality of the enhanced image compared to the original image. The Histogram Equalization (HE) method shows a high MSE value of 1004.43 and a low PSNR of 20.33, indicating a notable disparity between the original and enhanced images. In contrast, the Adaptive Histogram Equalization (AHE) method results in an MSE of 550.53 and a PSNR of 21.02, showing an improvement in quality compared to HE. The CLAHE (Contrast Limited Adaptive Histogram Equalization) method provides the best results with a very low MSE of 11.11 and a high PSNR of 38.13, indicating excellent image quality. Gamma Correction yields an MSE of 47.47 and a PSNR of 31.44, which is better than HE but still less optimal compared to AHE and CLAHE. These findings suggest that CLAHE is the most effective method for enhancing image quality, which is crucial for medical applications such as tuberculosis detection in chest X-ray images.

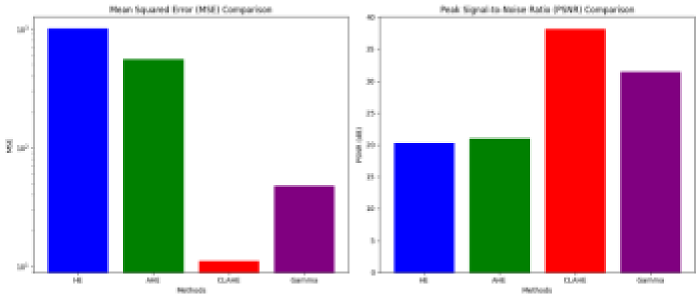

Figure 7 Image enhancement diagram

The graph above compares several methods based on Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR). The HE and AHE methods have high MSE values and low PSNR, indicating high error rates and poor image quality. CLAHE stands out as the best method with the lowest MSE and highest PSNR, indicating high accuracy and the best image quality. The Gamma method performs fairly well, with moderate MSE and high PSNR, though slightly below CLAHE.

3.1 Model Evaluation

The evaluation results using the confusion matrix for the AlexNet and VGG-19 methods in detecting tuberculosis from X-rays are presented below.

Table 3 Model testing results

Image improvement	Model	Accuracy	Precision	Recall	F1- Score
HE		72.5%	97.87%	46%	62.59%
AHE		77.5%	95.08%	58%	72.05%
CLAHE	Alexnet	84%	98.57%	69%	81.18%
Gamma Correction		85.5%	97.33%	73%	83.43%
HE		72.00%	97.83%	45%	61.64%
AHE		73%	96%	48%	64%
CLAHE	VGG-19	93.50%	98.88%	88%	93.12%
Gamma Correction		91%	97.67%	84%	90.32%

This study assesses detecting tuberculosis in chest X-ray images using employing different image processing techniques and two artificial neural network architectures, namely AlexNet and VGG-19, with data comprising 3500 normal images and 1500 TB images. The evaluation methods include accuracy, precision, recall, and F1-score. The results in the table above show that AlexNet with Histogram Equalization (HE) achieved an accuracy of 72.5%, precision of 97.87%, recall of 46%, and an F1-score of 62.59%. The Adaptive Histogram Equalization (AHE) method on AlexNet improved accuracy to 77.5% with precision of 95.08% and recall of 58%, while Contrast Limited Adaptive Histogram Equalization (CLAHE) provided an accuracy of 84% and recall of 69%. Gamma Correction showed the best performance with an accuracy of 85.5%, precision of 97.33%, and recall of 73%. On the other hand, VGG-19 performed better than AlexNet with HE, achieving an accuracy of 72% and recall of 45%. AHE on VGG-19 provided an accuracy of 73% and recall of 48%, while CLAHE on VGG-19 gave the best results with an accuracy of 93.5% and recall of 88%. Gamma Correction on VGG-19 also showed excellent performance with an accuracy of 91% and recall of 84%. Applying K-Fold

Cross Validation (K-Fold CV) to AlexNet led to an improvement in accuracy, even though the model was trained for only 10 epochs, because K-Fold CV reduces bias and variance. Conversely, VGG-19 without K-Fold CV showed less stable results with 10 epochs, but still performed well with CLAHE and Gamma Correction methods. In conclusion, the combination of VGG-19 with CLAHE is the best for tuberculosis detection, with precise image processing and efficient training techniques significantly improving detection performance.

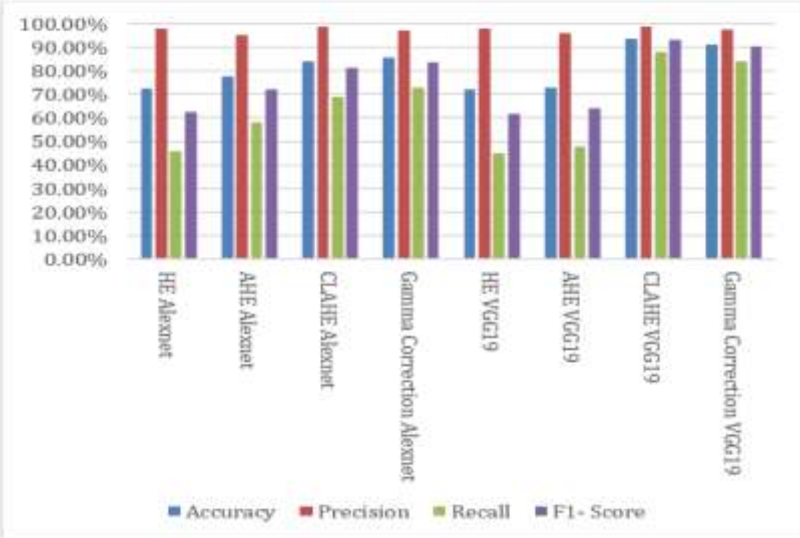

Figure 8 Model evaluation diagram

This graph shows the performance comparison of several approaches relying on four metrics: Accuracy, Precision, Recall, and F1-Score, tested on two different datasets, AlexNet and VGG-19. In both datasets, the CLAHE and Gamma Correction methods demonstrate the most balanced performance, with high values across all metrics. The HE and AHE methods tend to have very high precision but lower recall and F1-Score values, indicating an imbalance in output. Overall, CLAHE and Gamma Correction emerge as the top-performing methods, excelling in both accuracy and balance among precision, recall, and F1-Score.

4.CONCLUSIONS

The findings of this study indicate that the VGG-19 model, combined with the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique, delivers superior performance in detecting tuberculosis from chest X-ray images. So this method resulted in an accuracy of 93.5%, precision of 98.88%, recall of 88%, and F1-score of 93.12%. Overall, the combination of the VGG-19 model architecture and the CLAHE image processing method significantly improves performance in detecting TB compared to other tested methods and models, including AlexNet.

REFERENCES

[1] L. Khattrine Noviyanti, K. Dwi Nugroho, and S. Asmara Dewa, "'PAK DEDE' (PROGRAM AKTUALISASI KADER DETEKSI DINI DEPRESI) LANSIA DENGAN PENYAKIT TBC," *J. Indones. Mengabdi*, vol. 2, no. 1, pp. 24–33, Mar. 2023, doi: 10.55080/jim.v2i1.136.

[2] W. H. Achmad, N. Saurina, N. Chamidah, and R. Rulaningtyas, "Pemodelan Klasifikasi Tuberkulosis dengan Convolutional Neural Network," *Pros. Semin. Implementasi Teknol. Inf. dan Komun.*, vol. 2, no. 1, 2023, doi: 10.31284/p.semtik.2023-1.3989.

[3] Y. F. Riti and S. S. Tandjung, "Klasifikasi Covid-19 Pada Citra CT Scans Paru-Paru Menggunakan Metode Convolution Neural Network," *Progresif J. Ilm. Komput.*, vol. 18,

no. 1, p. 91, 2022, doi: 10.35889/progresif.v18i1.784.

[4] I. Hartono, A. Noertjahyana, and L. W. Santoso, “Deteksi Masker Wajah dengan Metode Convolutional Neural Network,” *J. Infra*, 2022.

[5] D. Marcella, Y. Yohannes, and S. Devella, “Klasifikasi Penyakit Mata Menggunakan Convolutional Neural Network Dengan Arsitektur VGG-19,” *J. Algoritm.*, vol. 3, no. 1, pp. 60–70, 2022, doi: 10.35957/algoritme.v3i1.3331.

[6] N. Hilmi, D. Wahyu, and A. Saputra, “Edu Komputika Journal Implementasi HE, AHE, dan CLAHE Pada Metode Convolutional Neural Network untuk Identifikasi Citra X-Ray Paru-Paru Normal atau Terinfeksi Covid19,” *Edu Komputika*, vol. 10, no. 1, pp. 1–9, 2023.

[7] T. Rahman *et al.*, “Reliable tuberculosis detection using chest X-ray with deep learning, segmentation and visualization,” *IEEE Access*, vol. 8, pp. 191586–191601, 2020, doi: 10.1109/ACCESS.2020.3031384.

[8] W. P. Putra and S. Handayaningsih, “Analisis Perbandingan Histogram Equalization dan Model Logarithmic Image Processing (LIP) Untuk Image Enhancement,” *J. Inform.*, vol. 2, no. 2, pp. 200–208, 2012.

[9] R. E. Manalu, “Analisis Metode Histogram Equalization Dalam Proses Perbaikan Gambar Closed Circuit Television (CCTV),” *TIN Terap. Inform. Nusant.*, vol. 2, no. 1, pp. 1–5, 2021.

[10] D. Setyawan, A. Wuryandari, and R. Ari Wibowo, “Peningkatan Kualitas Citra Malaria Menggunakan Metode Contrast Enhancement Berbasis Histogram,” *JIKO (Jurnal Inform. dan Komputer)*, vol. 5, no. 3, pp. 194–200, 2022, doi: 10.33387/jiko.v5i3.5237.

[11] B. Hartono, “Analisa Teknik Adaptive Histogram Equalization dan Contrast Stretching untuk Perbaikan Kualitas Citra,” *J. Teknol. Inf.*, vol. 19, no. 1, pp. 1–10, 2014.

[12] I. W. A. Wijaya Kusuma and A. Kusumadewi, “Penerapan Metode Contrast Stretching, Histogram Equalization Dan Adaptive Histogram Equalization Untuk Meningkatkan Kualitas Citra Medis Mri,” *Simetris J. Tek. Mesin, Elektro dan Ilmu Komput.*, vol. 11, no. 1, pp. 1–10, 2020, doi: 10.24176/simet.v11i1.3153.

[13] N. K. N. Nilasari, Y. Divayana, and R. S. Hartati, “Perbandingan Metode Median Filtering dengan CLAHE dalam Mengidentifikasi Koloni Bakteri,” *Maj. Ilm. Teknol. Elektro*, vol. 21, no. 1, p. 71, Jul. 2022, doi: 10.24843/mite.2022.v21i01.p10.

[14] T. Tinaliah and T. Elizabeth, “Peningkatan Kualitas Citra X-Ray Paru-Paru Pasien Covid-19 Menggunakan Metode Contrast Limited Adaptive Histogram Equalization,” *J. Teknol. Inf.*, vol. 4, no. 2, pp. 345–349, 2020, doi: 10.36294/jurti.v4i2.1709.

[15] K. Saputra, I. Taufik, D. F. Dharma, and M. Hidayat, “Analisis Perbaikan Kualitas Citra Menggunakan CLAHE dan HE Pada Citra X-Ray Covid-19 dan Pneumonia,” vol. 6, no. 2, pp. 97–104, 2021.

[16] Y. Wang, Z. Liu, J. Liu, S. Xu, and S. Liu, “Low-Light Image Enhancement with Illumination-Aware Gamma Correction and Complete Image Modelling Network,” *Proc. IEEE Int. Conf. Comput. Vis.*, pp. 13082–13091, 2023, doi: 10.1109/ICCV51070.2023.01207.

[17] D. Ibrahim, A. Hidayatno, and R. Isnanto, “Pengaturan Kecerahan dan Kontras Citra Secara Automatis dengan Teknik Pemodelan Histogram,” pp. 1–7, 2011.

[18] R. Hansyana, Yassir, and Rachmawati, “Penggunaan Koreksi Gamma Dengan Metode Robert, Prewitt, Dan Sobel Untuk Penyempurnaan Gambar Pada Citra Dalam Air,” *Tektro*, vol. 7, no. 1, pp. 66–71, 2023.

[19] K. Alomar, H. I. Aysel, and X. Cai, “Data Augmentation in Classification and Segmentation : A Survey and New Strategies,” 2023, doi: https://doi.org/10.3390/jimaging9020046.

[20] T. B. Waskito, S. Sumaryo, and Casi Setianingsih, “Kendali Robot Beroda Dengan Gerak Isyarat Tangan Berbasis Image Processing,” *eProceedings ...*, vol. 6, no. 3, pp. 10052–10059, 2019.

[21] I. Nihayatul Husna, M. Ulum, A. Kurniawan Saputro, D. Tri Laksono, and D. Neipa Purnamasari, “Rancang Bangun Sistem Deteksi Dan Perhitungan Jumlah Orang

Menggunakan Metode Convolutional Neural Network (CNN)," *Semin. Nas. Fortei Reg.*, vol. 7.

[22] R. Magdalena, S. Saidah, N. K. C. Pratiwi, and A. T. Putra, "Klasifikasi Tutupan Lahan Melalui Citra Satelit SPOT-6 dengan Metode Convolutional Neural Network (CNN)," *J. Edukasi dan Penelit. Inform.*, vol. 7, no. 3, p. 335, 2021, doi: 10.26418/jp.v7i3.48195.

[23] A. Kholik, "Klasifikasi Menggunakan Convolutional Neural Network (Cnn) Pada Tangkapan Layar Halaman Instagram," *J. Data Min. dan Sist. Inf.*, vol. 2, no. 2, p. 10, 2021, doi: 10.33365/jdmsi.v2i2.1345.

[24] I. D. Irawati, G. Budiman, S. Saidah, S. Rahmadiani, and R. Latip, "Block-based compressive sensing in deep learning using AlexNet for vegetable classification," *PeerJ Comput. Sci.*, vol. 9, pp. 1–15, 2023, doi: 10.7717/peerj-cs.1551.

[25] D. Rastogi, P. Johri, and V. Tiwari, "Augmentation based detection model for brain tumor using VGG 19," *Int. J. Comput. Digit. Syst.*, vol. 13, no. 1, pp. 1227–1237, 2023, doi: 10.12785/ijcds/1301100.

[26] S. Kumar and H. Kumar, "Classification of COVID-19 X-ray images using transfer learning with visual geometrical groups and novel sequential convolutional neural networks," *MethodsX*, vol. 11, no. December 2022, p. 102295, 2023, doi: 10.1016/j.mex.2023.102295.

[27] M. Fitra Hanafiah and Y. Fitri Annisa Lubis, "Prosiding SNASTIKOM: Seminar Nasional Teknologi Informasi & Komunikasi Paper Analisis Pengaruh Citra Gelap Terhadap Kinerja Metode High Boost Filtering Dan Adaptive Histogram Equalization."

[28] A. O. C. Pratiwi, "Klasifikasi Jenis Anggur Berdasarkan Bentuk Daun Menggunakan Convolutional Neural Network Dan K-Nearest Neighbor," *J. Ilm. Tek. Inform. dan Komun.*, vol. 3, no. 2, pp. 201–224, 2023, [Online]. Available: http://journal.sinov.id/index.php/juitik/article/view/535

[29] N. M. Setiohardjo and A. Harjoko, "Analisis Tekstur untuk Klasifikasi Motif Kain (Studi Kasus Kain Tenun Nusa Tenggara Timur)," *IJCCS (Indonesian J. Comput. Cybern. Syst.*, vol. 10, no. 1, p. 177, 2014, doi: 10.22146/ijccs.6545.

[30] Y. N. FUADAH, I. D. UBAIDULLAH, N. IBRAHIM, F. F. TALININGSING, N. K. SY, and M. A. PRAMUDITHO, "Optimasi Convolutional Neural Network dan K-Fold Cross Validation pada Sistem Klasifikasi Glaukoma," *ELKOMIKA J. Tek. Energi Elektr. Tek. Telekomun. Tek. Elektron.*, vol. 10, no. 3, p. 728, Jul. 2022, doi: 10.26760/elkomika.v10i3.728.