Comparison of Deep Learning Methods for Detecting Tuberculosis Through Chest X-Rays

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ABSTRACT

Chronic diseases are the leading cause of death worldwide, accounting for 73% of deaths in 2020. Tuberculosis (TB), caused by the bacterium Mycobacterium tuberculosis, is one of these diseases and has a significant impact on countries with a high TB burden due to a lack of radiologists and medical equipment. Early diagnosis of TB is crucial but challenging because of its similarity to lung cancer and the shortage of radiologists. A semi-automatic TB detection system is needed to support medical diagnosis and improve public health services. Deep learning technology, such as Convolutional Neural Networks (CNN), offers an effective solution for disease diagnosis with high accuracy. This study compares deep learning methods using an 8-layer CNN and VGG-19, both enhanced with Histogram Equalization (HE) for improved image quality. The study utilizes chest X-ray images of normal lungs and TB-affected lungs from Kaggle. Model performance is evaluated using accuracy, precision, recall, and F1-score metrics. Results indicate that the VGG-19 model outperforms the 8-layer CNN across all evaluation metrics, achieving an accuracy of 72.00% compared to 65.00% for the 8-layer CNN. VGG-19 also demonstrates better precision, recall, and F1-score, making it a more suitable choice for TB detection with enhanced image quality.

Keywords: Tuberculosis; Deep Learning; CNN; VGG-19; Histogram Equalization

1. INTRODUCTION

Chronic diseases are the leading cause of death worldwide, accounting for 73% of total global deaths in 2020. Among these, 60% are due to chronic diseases such as heart disease, cancer, COPD, stroke, and HIV/AIDS. One such chronic disease is Tuberculosis (TB), caused by the bacterium Mycobacterium tuberculosis, which primarily attacks the lungs (Noviyanti et al., 2023)According to the Global TB Report 2022, TB in Indonesia is the second deadliest infectious disease after Covid-19 and ranks 13th as the leading cause of death globally. Indonesia ranks second after India with 969,000 cases and 144,000 deaths annually.

The shortage of radiologists and medical equipment affects the management of TB in countries with a high TB burden. TB can be treated and detected through chest X-rays. Early diagnosis is crucial to improving the chances of recovery, but the lack of radiologists is a significant challenge. Semi-automatic TB detection systems are essential for providing better healthcare services (Achmad et al., 2023). Technological advancements, such as deep learning, offer solutions to these problems. Deep learning is a fast and efficient technique for diagnosing diseases with high accuracy (Riti & Tandjung, 2022). One of the widely used deep learning methods is Convolutional Neural Network (CNN). CNNs typically have three main layers: convolutional layers, pooling layers, and fully connected layers. Convolutional layers extract prominent features from images, while pooling layers and fully connected layers assist in classification (Hartono et al., 2022).

A common CNN architecture used is VGG-19, consisting of 19 layers with an input image size of 224x224 and a 3x3 kernel. This architecture has been trained using over 1 million images from the ImageNet database (Marcella et al., 2022). Chest radiology, such as CT and X-ray, plays a crucial role in the early diagnosis and treatment of TB (Saputra et al., 2021). Image quality enhancement techniques, such as Histogram Equalization (HE), are important for improving the quality of X-ray images for more accurate diagnosis. HE modifies the distribution of pixel intensity values in an image to be more uniform, enhancing the contrast and quality of the image (Hilmi et al., 2023).

This study will compare deep learning methods, specifically CNN with 8 layers and VGG-19, using Histogram Equalization (HE) for image quality improvement. The goal of this research is to compare the accuracy, precision,

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recall, and f1-score of both methods in detecting TB using chest X-ray images of normal lungs and TB-affected lungs from Kaggle. The expected outcome is to determine the best method for TB diagnosis with high accuracy.

2. LITERATURE REVIEW

This study builds on previous research that has been conducted as references and comparisons related to solving existing problems. The aim is to expand and delve into various theories relevant to the current research being designed by the researchers, and to avoid any assumptions of similarity with previous studies. Here are five related studies with topics and theories relevant to this research:

1. Study by Rasywir et al. (2020) on "Analysis and Implementation of Palm Disease Diagnosis Using Convolutional Neural Network (CNN)". This study uses CNN to diagnose diseases in oil palm based on images from the Jambi Provincial Plantation Service. The results show a fairly high classification accuracy for various oil palm diseases.
2. Study by Achmad et al. (2023) on "Tuberculosis Classification Modeling Using Convolutional Neural Network". This research uses CNN to classify positive and negative TB images with an accuracy rate of 88%.
3. Study by Riti & Tandjung (2022) on "Covid-19 Classification Using Convolutional Neural Network Method on Lung CT Scans". This study shows that CNN can distinguish between Covid-19 and normal CT scan images with very high accuracy.
4. Study by Marcella et al. (2022) on "Eye Disease Classification Using CNN and VGG-19 Architecture". This research uses VGG-19 to classify eye diseases, achieving significant results in accuracy, precision, recall, and F1-score.
5. Study by Setiawan (2020) on "Comparison of Convolutional Neural Network Architectures for Fundus Classification". This study compares several CNN architectures for fundus classification and finds that VGG19 and VGG16 provide optimal results in terms of sensitivity, specificity, and accuracy.

By referring to these studies, researchers are expected to develop better methods and provide valuable contributions to their field of study.

3. METHOD

TUBERCULOSIS

Tuberculosis (TB), caused by Mycobacterium tuberculosis, remains a significant health challenge in Indonesia (Manurung, 2021). The disease spreads through the air when an infected individual coughs, sneezes, or even talks, allowing the bacteria to infect others and affect various organs such as the lungs, brain, kidneys, and spine (Bahri et al., 2021). TB poses an increased risk when left untreated, potentially leading to fatal outcomes for the affected individuals. Mycobacterium tuberculosis bacteria can remain airborne for several hours, facilitating inhalation and subsequent latent infection. Latent TB infection may not show active clinical symptoms initially but can progress to active disease if not treated promptly (Making et al., 2023). Transmission of TB often occurs among individuals in close and prolonged contact with infected persons, such as family members or colleagues (Achmad et al., 2023). Hence, effective preventive measures are crucial, including the use of masks or protective gear during interactions with TB-infected individuals, especially during activities like coughing, sneezing, or talking that increase the risk of transmission. Populations vulnerable to TB include those regularly in contact with infected individuals, underscoring the importance of understanding transmission pathways and prevention strategies to control the disease's spread. Awareness of symptoms, early diagnosis, and access to quality medical care are critical steps in reducing the burden of TB in Indonesia and globally.

Dataset

This study utilizes a dataset of images related to Tuberculosis (TB) cases, sourced from Kaggle as per the research by (Rahman et al., 2020). The dataset comprises 3,500 chest X-ray images classified as normal and 700 chest X-ray images identified as indicative of Tuberculosis. To collect this data, we used specific keywords such as "Chest X-ray Tuberculosis" and "Tuberculosis Symptoms" to obtain relevant images. Each image in the dataset represents an example of either a normal chest X-ray or a TB case, which can be used for further analysis. Examples of these images can be seen in Figures 1 and 2. The dataset is credited to the work of Rahman et al. (2020).
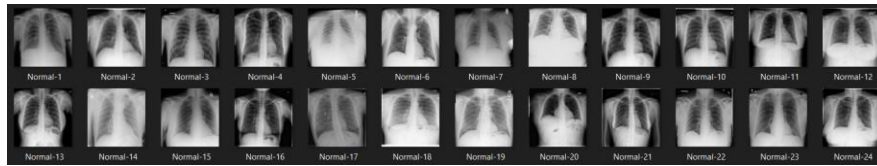
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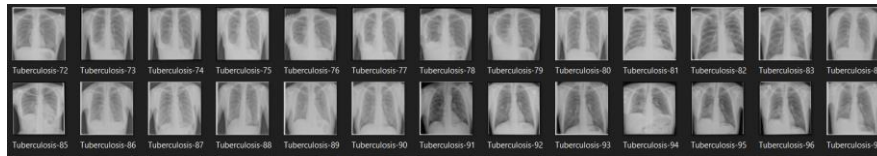Fig. 1 Dataset Normal Lugs X-Ray

Fig. 2 Dataset Tuberculosis Lugs X-Ray

Histogram Equalization

Histogram Equalization (HE) is a histogram processing technique often used to make the pixel intensity distribution of an image more uniform or equalized. This method can be applied globally to the entire image or locally to specific blocks of the image. The goal is to enhance contrast and expand the histogram range, which improves visual details in the image (Hidayat et al., 2019). HE is an effective image processing technique for enhancing contrast within the grayscale range by equalizing the pixel intensity distribution. This process results in an image with a more uniform pixel intensity distribution, displayed as a histogram graph showing the probability and frequency of gray levels in the image (Winarno et al., 2022). Histogram Equalization (HE) works by adjusting the pixel intensities to create a more uniform intensity distribution. This can be done globally across the entire image or locally within specific image blocks. The histogram reflects the probability and frequency of gray levels in the image, showing significant changes after applying HE. Equation 4 is used to implement the Histogram Equalization (HE) process.

$$h(v) = \text{round}\left(\frac{cdf(v) - cdf_{min}}{(MxN) - cdf_{min}} \times (l - 1)\right) \qquad (1)$$

In Histogram Equalization (HE), VVV represents the pixel value for which we seek the replacement, $Cdf(v)Cdf(v)Cdf(v)$ denotes the cumulative distribution function (CDF) for the pixel value vvv, and $Cdf_{min}Cdf_{min}Cdf_{min}$ is the minimum value of the cumulative distribution. $M \times NM \times NM \times N$ signifies the dimensions of the image, where MMM is the number of columns and NNN is the number of rows. LLL stands for the number of gray levels available; for an 8-bit grayscale image, $L=256, L = 256, L=256$ (Hidayat et al., 2019).

CONVOLUTION NEURAL NETWORK (CNN)

A Convolutional Neural Network (CNN) is a type of Multi-Layer Perceptron (MLP) specifically designed for identifying two-dimensional images. CNNs mimic the human brain's way of recognizing objects it sees. With the help of CNNs, computers can "see" and distinguish between various objects, a feature known as image recognition. CNN is a classification method in deep learning that utilizes convolutional layers to convolve inputs with filters. Broadly speaking, CNNs are similar to regular neural networks, consisting of neurons with weights, biases, and activation functions. The CNN method involves two main processes: training using backpropagation and classification using forward propagation (Nihayatul Husna et al., 2022).

Generally, CNNs consist of three layers: the convolutional layer, pooling layer, and fully connected layer. The Convolutional Layer is the core of the CNN architecture. In this layer, convolution operations are performed using filter matrices typically sized MXN (commonly 3x3) to extract prominent features from images. These extracted features contain specific relationships at each pixel. Convoluting images with different convolution filters can perform tasks such as edge detection, blurring, and image sharpening. In addition to selecting filters, the Convolutional Layer includes a concept called stride. Stride refers to the number of pixels the filter moves across the input matrix. When the stride is set to 1, the filter moves one pixel at a time. Padding is another concept used in the Convolutional Layer.

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Sometimes, filters applied to inputs may not perfectly fit, and padding helps address this issue (Hartono et al., 2022). An example of a Convolutional Layer is depicted in Figure 3.
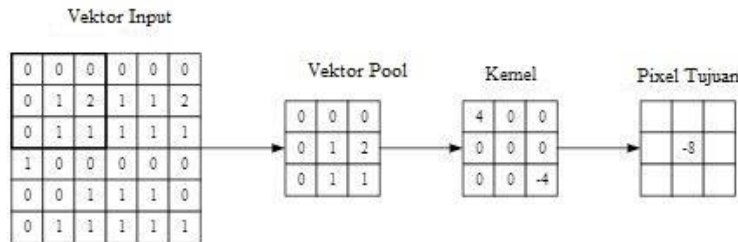

Fig. 3 Convolutional Layer

The following is the formula used in the Convolutional Layer, as shown in Equation 2.

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

Explanation:

$n_{(w,h)}$ = Result of input image size
k = Size of the kernel used
s = Size of the stride
p = Size of the padding
n_{in} = Value of the input image size

Activation function is a stage after the convolution process. The output of the convolution is passed through an activation function. Rectified Linear Unit (ReLU) is the most commonly used activation function in CNNs, aimed at minimizing errors and preventing saturation. Researchers often choose this activation function because it performs well and is used in every hidden layer of the neural network. The equation for the ReLU activation function is shown in Equation 3 (Magdalena et al., 2021).

$$f(x) = \begin{cases} x, & x > 0 \\ 0, & x \leq 0 \end{cases} \tag{3}$$

The ReLU function is an activation function where the output value of a neuron is expressed as 0 if the input value is negative. If the input value is positive, then the output of the neuron is the same as the input activation value itself (Kholik, 2021). The ReLU layer can be observed in Figure 4.
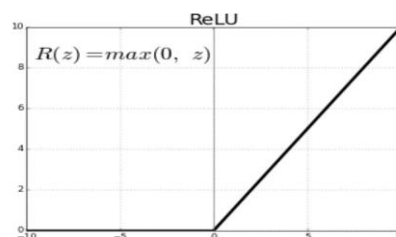

Fig.4 ReLU Layer

The pooling layer is a layer where the process of reducing the size of the image occurs after convolutional layers. There are two types of pooling layers: maximum pooling and average pooling. In max pooling layers, the output of the convolutional network is divided into smaller grids, where the maximum value of each grid is selected and included

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in the reduced matrix of the image produced by the pooling layer (Nihayatul Husna et al., 2022). An example of a pooling layer can be seen in Figure 5.
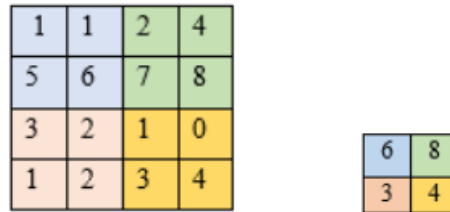

Fig. 5 Max pooling Layer

Here is the formula used in Max Pooling, as shown in Equation 5.

$$n_{(w,h)} = \frac{(n_{(w,h)-1}-f)}{s} + 1 \tag{4}$$

Explanation:

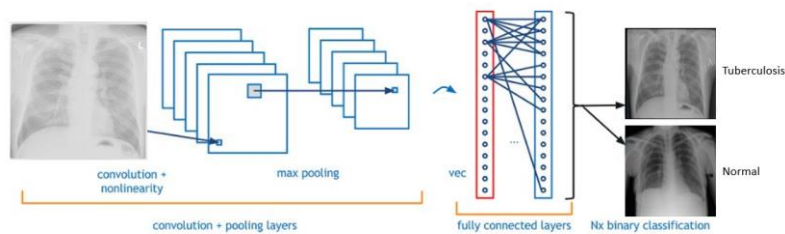|	
$n_{(w,h)}$	= Resulting height and width size
$n_{(w,h)}$	= Previous width and height size
s	= Stride size
f	= Kernel size

Fig. 6 *Convolutional Neural Network Process*

Figure 5 shows the architecture of a Convolutional Neural Network (CNN), which is used in image processing for classification. It goes through several stages, including: image input, feature extraction using convolutional layers, dimensionality reduction of the feature maps with pooling layers, flattening the feature maps into a one-dimensional vector, combining features with fully connected layers, and finally, producing probabilities for each class through the softmax layer, thus enabling the final classification of objects in the image.

CNN 8 Layer Model

In this study, the Convolutional Neural Network (CNN) architecture consists of 8 layers. This architecture is designed to efficiently process and detect features within image data through a structured series of steps. Here is an explanation of each layer in the CNN architecture used:
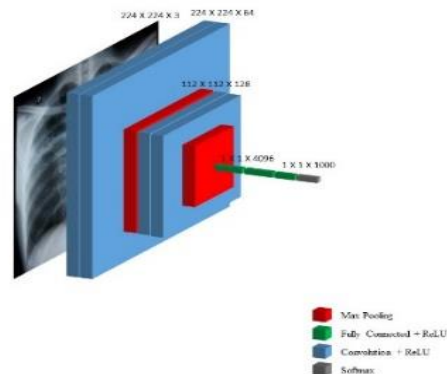
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Fig. 7 CNN 8 Layer Architecture

Here's the explanation of CNN architecture in this study. The research will utilize 8 layers. The first step is the input layer, which loads and inputs data to proceed to subsequent layers. Next is the Convolutional Layer, where filters are used to detect specific features within the image. These filters are convolved across the entire image to extract local features. Following convolution, an activation function like ReLU (Rectified Linear Unit) is applied to deactivate negative values and produce a more nonlinear representation of the data. Next, the process moves to the pooling layer, where matrix reduction occurs—sometimes referred to as dimensionality reduction. From each feature produced by the convolutional layers, the maximum value is taken from each window to reduce the matrix dimensions, known as Max pooling. After a series of convolutional and pooling layers, the image representation is flattened into a one-dimensional vector through the flattening layer. This prepares the data for input into the fully connected layers. The last layer is the Fully Connected Layer, where the matrix is transformed into a vector through flattening. This layer performs input classification by applying activation functions such as softmax or sigmoid. In this stage, classification is determined based on the category value with the highest probability.

VGG-19 Model

In this study, the utilized VGG-19 architecture consists of 19 layers. This architecture is designed to efficiently process and detect features within image data through a structured series of steps. While the steps in this method are similar to CNNs, VGG-19 has several key differences. Here is an explanation of each layer within the VGG-19 architecture used:
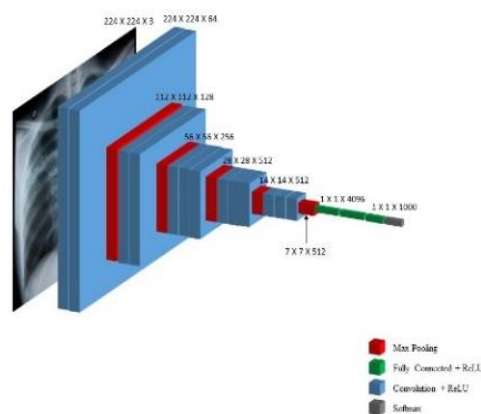

Fig. 8 VGG-19 Architecture

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The VGG-19 architecture utilizes 19 layers in its research. The process begins with the Input Layer, which first loads and takes in data to pass on to subsequent layers. The next layer is the Convolutional Layer, where filters are employed to detect specific features within an image. These filters convolve across the entire image to extract local features. Following convolution, activation functions such as ReLU (Rectified Linear Unit) are applied to deactivate negative values, producing a more non-linear representation of the data.

The next step is the Pooling Layer, which reduces matrix dimensions by taking the maximum value from each window (Max pooling). After a series of convolutional and pooling layers, the image representation is flattened into a one-dimensional vector. This prepares the data to enter the Fully Connected Layer, which is the final layer. Here, the flattened vector is reshaped into a matrix and used for input classification by applying activation functions like softmax or sigmoid. At this stage, classification is determined based on the highest probability category from the output values. Thus, the VGG-19 architecture follows a similar process to standard CNN methods, starting from data intake through the input layer to classification outcomes via the fully connected output layer.

Evaluation Model

Confusion matrix is a matrix used to evaluate classification performance by showing correct and incorrect predictions. It provides detailed information about the accuracy of predictions in classification tasks (Kholik, 2021). The matrix consists of four cells representing the counts of true positives, true negatives, false positives, and false negatives. Through the confusion matrix, various evaluation metrics of classification models such as accuracy, precision, recall, F1-score, and others can be computed (Anissa Ollivia Cahya Pratiwi, 2023). The calculation of accuracy, precision, and recall is shown in Equations (5), (6), and (7) as follows.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{5}$$

$$Precision = TP/(TP + FP) \tag{6}$$

$$Recall = TP/(TP + FN) \tag{7}$$

Here are the definitions in English:

True Positive (TP)   : The number of positive samples correctly predicted by the model.
False Positive (FP)   : The number of negative samples incorrectly predicted as positive by the model.
False Negative (FN)   : The number of positive samples incorrectly predicted as negative by the F1-score, which harmonizes precision and recall, can be calculated using the following formula:

$$F1\ score = \frac{Recall\ x\ Precision}{Recall+Precision} \tag{8}$$

Cross-validation ensures that model evaluation is not solely reliant on a single split of training and test data. Instead, it involves multiple iterations to produce more consistent and reliable evaluations.

RESULTS

Menggunakan dataset pelatihan yang terdiri dari 3.840 sampel, dataset validasi yang terdiri dari 960 sampel, dan dataset pengujian yang terdiri dari 200 sampel, hasil evaluasi yang diperoleh ditampilkan dalam Tabel 1. Dataset pelatihan digunakan untuk melatih Jaringan Saraf Konvolusi (Convolutional Neural Network atau CNN) dengan memungkinkan model belajar dari data yang diberi label. Dataset validasi digunakan untuk menyetel hiperparameter dan mencegah overfitting dengan menyediakan dataset independen untuk mengevaluasi kinerja model selama pelatihan. Terakhir, dataset pengujian digunakan untuk menilai kemampuan generalisasi model yang telah dilatih pada data yang belum pernah dilihat sebelumnya, memberikan evaluasi akhir terhadap kinerjanya. Hasil dalam Tabel 1 mencerminkan akurasi, presisi, recall, dan metrik relevan lainnya dari model tersebut di seluruh dataset ini.

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Table 1. Confusion Matrix Result

Image Enhancement	Model	Accuracy	Precision	Recall	F1- Score
HE	CNN 8 LAYER	65.00%	96.87%	31%	46.97%
HE	VGG-19	72.00%	97.83%	45%	61.64%

The table above presents the evaluation results of two convolutional neural network models used for image enhancement. The two models compared are an 8-layer CNN and VGG-19. The evaluation results include several performance metrics: accuracy, precision, recall, and F1-Score.

For the 8-layer CNN using Histogram Equalization (HE), the accuracy is 65.00%, indicating the percentage of all correct predictions out of the total predictions made by the model. The precision is 96.87%, which shows the percentage of true positive predictions out of all positive predictions made by the model. The recall is 31%, indicating the percentage of all actual positive cases that were correctly detected by the model. The F1-Score is 46.97%, representing the harmonic mean of precision and recall, providing a balance between the two.

For the VGG-19 model using Histogram Equalization (HE), the accuracy is 72.00%, indicating a higher percentage of correct predictions compared to the 8-layer CNN. The precision is 97.83%, showing a slightly higher percentage of true positive predictions. The recall is 45%, which is significantly better than the 8-layer CNN, indicating more actual positive cases were correctly detected. The F1-Score is 61.64%, reflecting a better balance between precision and recall.

In summary, the 8-layer CNN demonstrates very high precision (96.87%) but low recall (31%), suggesting that while the model is excellent at correctly predicting positive cases, it misses many actual positive cases. Consequently, its accuracy and F1-Score are relatively low. On the other hand, VGG-19 performs better overall, with an accuracy of 72%, precision of 97.83%, recall of 45%, and F1-Score of 61.64%. This indicates that VGG-19 is more effective at detecting positive cases than the 8-layer CNN, though there is still room for improvement in recall. Overall, VGG-19 shows superior performance in the task of image enhancement based on the provided metrics.
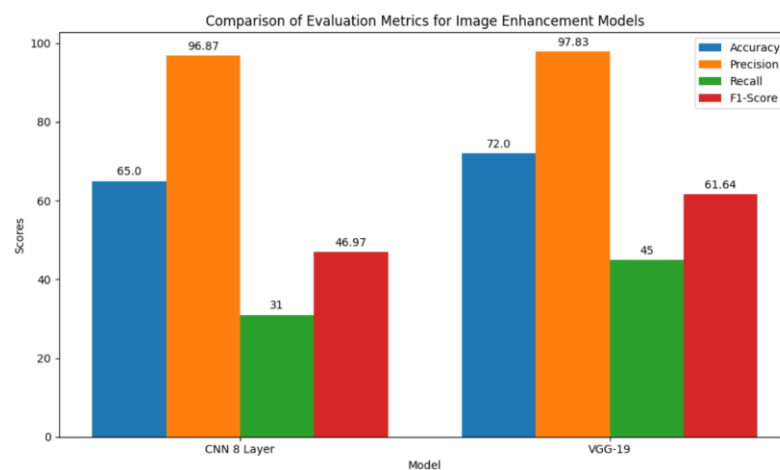

Fig.9 Evaluation Result

Based on the performance evaluation results presented in the diagram, it can be conclusively determined that the VGG-19 architecture significantly outperforms the 8-layer CNN model in terms of effectiveness. The VGG-19 model not only achieves a higher accuracy compared to the 8-layer CNN but also demonstrates superior performance across various evaluation criteria. Specifically, VGG-19 exhibits better precision, recall, and F1-score, all of which are crucial indicators for assessing the quality and reliability of classification outcomes.

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The substantial improvement in accuracy indicates that VGG-19 is more proficient at correctly identifying and classifying images, which is vital for tasks requiring high levels of precision. Additionally, the enhanced precision suggests that VGG-19 generates fewer false positive predictions, while the higher recall highlights its ability to capture a larger proportion of true positives. The higher F1-score reflects a balanced performance, considering both precision and recall, making VGG-19 a more effective model overall.

Given these significant advantages, the VGG-19 architecture is highly recommended for tasks involving image classification and enhancement. The demonstrated superiority in performance metrics makes it a more reliable and accurate choice compared to the 8-layer CNN model, offering substantial benefits for achieving higher-quality classification results and more optimal image enhancement.

DISCUSSIONS

This study compares the performance of an 8-layer Convolutional Neural Network (CNN) with the VGG-19 architecture in detecting Tuberculosis (TB) from chest X-ray images after enhancing their quality using Histogram Equalization (HE). Evaluation results indicate that VGG-19 significantly outperforms the CNN 8-layer model across all metrics. VGG-19 achieves an accuracy of 72.00%, which is higher than the 65.00% achieved by the CNN 8-layer model. The precision of VGG-19 reaches 97.83% compared to 96.87% for the CNN 8-layer model, while recall also improves from 31% (CNN 8-layer) to 45% (VGG-19). The F1-score, which combines precision and recall, shows an improvement from 46.97% (CNN 8-layer) to 61.64% (VGG-19). The enhanced performance of VGG-19 can be attributed to its deeper architecture and ability to extract more complex features from images, which is crucial in tackling diagnostic challenges such as distinguishing TB from other conditions. Despite requiring more computational resources, the use of VGG-19 provides better results in TB detection from chest X-ray images.

This research underscores the benefits of employing deep learning technologies in medical diagnosis, with the potential for broader applications to enhance public healthcare services.

4. CONCLUSION

This study demonstrates that the VGG-19 architecture significantly outperforms the 8-layer CNN in all evaluation metrics used to detect Tuberculosis from chest X-ray images enhanced with Histogram Equalization (HE). VGG-19 achieves an accuracy of 72.00% (compared to 65.00% for the CNN 8-layer), precision of 97.83% (compared to 96.87%), recall of 45% (compared to 31%), and F1-score of 61.64% (compared to 46.97%). This improvement is attributed to VGG-19's ability to extract complex features from images, demonstrating the potential of deep learning applications to enhance medical diagnosis on a broader scale.

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