Journal of Electronics, Electromedical Engineering, and Medical Informatics
Multidisciplinary: Rapid Review: Open Access Journal Vol. 6, No. 4, October 2024, pp: 332-342; eISSN: 2656-8632

RESEARCH ARTICLE OPEN ACCESS

Manuscript received May 2, 2024; revised May 23, 2024; accepted May 27, 2024; date of publication August 2, 2024
Digital Object Identifier (**DOI**): https://doi.org/10.35882/jeeemi.v6i4.457

How to cite: Ica Nurcahyati , Triando Hamonangan Saragih , Andi Farmadi , Dwi Kartini, and Muliadi, "Classification of Lung Disease in X-Ray Images Using Gray Level Co-Occurrence Matrix Method and Convolutional Neural Network", Journal of Electronics, Electromedical Engineering, and Medical Informatics, vol. 6, no. 4, pp. 332-342, October 2024.

Classification of Lung Disease in X-Ray Images Using Gray Level Co-Occurrence Matrix Method and Convolutional Neural Network

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ABSTRACT The lungs are an essential part of the human body, as they serve as a place for oxygen exchange. They have a very complex task and are susceptible to damage from the polluted air we breathe every day, which can lead to various diseases. Lung disease is a very common health problem that can be found in everyone, but there are still many people who do not pay attention to their lung health, making them vulnerable to lung disease. One of the methods used to detect lung disorders is by examining images obtained from X-rays. Image processing is one of the techniques that can also be used for lung disease identification and is most commonly used in medical images. Therefore, the purpose of this research is to implement image processing to determine the accuracy of lung disease identification using deep learning algorithms and the application of feature extraction. In this research, there are two experiments conducted consisting of the application of the classification method, namely Convolutional Neural Network and Gray Level Co-Occurrence Matrix feature extraction with CNN. The results show that the CNN model with AlexNet architecture using SGD optimizer gets precision 0.92, recall 0.92, f1-score 0.92, and average accuracy 0.92. Combining the GLCM method with CNN with AlexNet architecture using SGD optimizer produces precision 0.87, recall 0.87, f1-score 0.87, and average accuracy 0.87. The results of this study indicate that the use of CNN in the lung disease classification model based on X-ray images is superior to the GLCM-CNN method.

INDEX TERMS Lung Disease, Convolutional Neural Network, Gray Level Co-Occurrence Matrix

I. INTRODUCTION

The lungs are one of the vital organs in the human body and have an important role as a place of respiration. The lungs function to enter oxygen and remove carbon dioxide when inhaling air so, this organ deserves to be called a very important organ for humans[1]. The lungs are located in the chest cavity (thorax) covered by two walls separated by a layer of air called the pleural cavity and have a very heavy task. The lungs can experience disorders or abnormalities and infections, for example, due to a disease caused by certain factors such as smoking or exposure to harmful substances that make the lungs abnormal. This can be fatal because it can cause sufferers to have difficulty breathing, difficulty doing activities, and lack of oxygen.

One type of abnormality or disease that can occur in the lungs is lung opacity, which refers to areas in radiologic images of the lungs that appear darker or lighter than the surrounding environment[2]. This opacity can be seen in the results of radiological examinations such as chest X-rays or CT scans of the lungs. Then, other diseases that can attack the lungs include Tuberculosis, Pneumonia, Asthma, pneumothorax, infiltration, nodules, and lung cancer. In addition, the latest is Coronavirus Disease (COVID-19) caused by the SARS-CoV-2 virus [3], and first appeared in December 2019 in Wuhan, China. If these abnormalities in the lungs are not treated quickly, they can cause death.

In the medical world, one way to identify abnormalities in the lungs is by looking at images of the lungs obtained from X-rays.[4]. Image processing has become the most commonly used processing technique in medical images, remote sensing, and natural images. Image processing has the aim of improving image quality in order to obtain the beauty of the image, the importance of image analysis, and correcting the image from any disturbances that occur during data recording [5]. Image processing leads to the processing of two-dimensional images using computers.

Convolutional Neural Network (CNN) is a method that can extract features from images and reduce the number of parameters without a significant decrease in the quality of the model[6]. CNN can share weights (weight sharing) to save computing time and memory. CNN can perform classification activities [7], segmentation, recognition, image repair, and transfer learning. Research conducted by [6], using CNN to classify Covid and non-Covid x-ray images showed good results. Based on the test results, it was obtained to achieve 95% training accuracy and 98% validation accuracy. Analytical testing results show that the CNN method is capable enough to perform image classification.

In Research [8], it was suggested that the use of the Convolutional Neural Network method proved to be the most superior in the classification system. However, because the data to be used is an X-ray image, good feature extraction is needed to improve the performance of the model or system. Feature extraction is one of the important initial processes for image classification in image processing. One of the feature extraction techniques that can be used in X-ray image processing is the Gray Level Co-occurrence Matrix (GLCM).

Gray Level Co-occurrence Matrix (GLCM) is a feature extraction method to determine the color or texture of an object [9]. GLCM is a method used as a digital image analysis approach in various applications, especially in medical image analysis, and is a popular texture-based feature extraction method[10]. GLCM is most often used in research on pattern recognition, image segmentation, and others. Research conducted by [11], used a combination of deep learning and GLCM methods by utilizing Entropy, Contrast, Energy, Dissimilarity, Homogeneity, and Correlation features to improve the model in skin disease classification. From the study, results were obtained that achieved 96.69% accuracy, 96.2% recall, 96.2% precision, and 96.2% F1 score in terms of performance evaluation measures. This proves that the GLCM method provides a good model for accurately diagnosing skin disorders.

In this study, to distinguish it from previous studies [2], [12], CNN architecture with different optimizers is used, as well as the application of GLCM feature extraction with different features, distances, and angles for the Covid-19 Radiography dataset. Research conducted[10], in the case of polyp diagnosis using a combined GLCM-CNN method resulted in quite good accuracy. The addition of the GLCM method to CNN can improve the quality of the dataset, reduce the size of the dataset that is too large and can overcome the problem of overfitting in the classification system.

Therefore, this study aims to compare the CNN method and the combined GLCM-CNN feature extraction to find out how accurate both are. This is expected to provide knowledge about the performance of which method is superior in terms of lung disease classification on X-ray images. This comparison is also expected to explain the advantages and disadvantages of each method so that it can help develop an effective classification model. The results of this research are expected to contribute such as:

a. Provide knowledge about the comparison of performance results generated from the application of feature extraction and classification techniques on x-ray images.
b. Information on how well the accuracy was achieved using the GLCM-CNN and CNN feature extraction methods.
c. The results of this study are expected to add insight and existing knowledge about image classification.

II. MATERIALS AND METHODS

In this research, the Python programming language version 3.8 was used. Python was chosen because of its extensive support for various libraries and frameworks used in machine learning and image processing. In addition, Python has a large community and good documentation, which is very helpful in development and troubleshooting. The machine learning frameworks used are TensorFlow and Keras. TensorFlow (version 2.4) is an open-source platform for numerical computing and machine learning that is highly efficient and flexible. Keras is a high-level API for building and training deep learning models, which runs on top of TensorFlow. The choice of TensorFlow and Keras is based on their ease of use, the ability to run models on both CPUs and GPUs and broad support for various types of artificial neural network architectures.

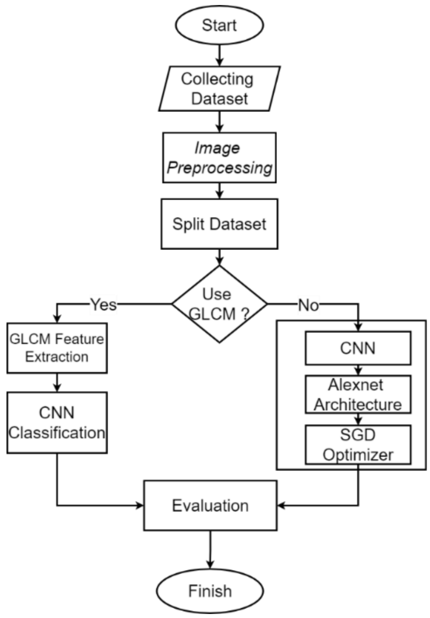

FIGURE 1. Research Flowchart

Then, for feature extraction from X-ray images used the Gray Level Co-occurrence Matrix (GLCM) method implemented using the scikit-image library version 0.18.1. Scikit-image is an open-source library for image processing that provides various functions for image analysis, including co-occurrence matrix generation. This research involves the comparison of two methods GLCM-CNN and CNN. The CNN architecture used to be different from previous research, namely the AlexNet architecture with the SGD optimizer. This research is organized using five sequential stages: data collection, image preprocessing, data sharing, model training, and analysis of evaluation results. The research flow carried out in this study can be seen in FIGURE 1.

A. DATA COLLECTION

The dataset used in this research is the Covid-19 Radiography Dataset taken from the Kaggle website and can be accessed via https://www.kaggle.com/datasets/preetviradiya/covid19-radiography-dataset/. This dataset consists of four classes namely Covid-19, Lung Opacity, Normal, and Viral Pneumonia with a size of 299 x 299 pixels. The total of the entire dataset is 21,173 images. However, this study only took 4000 image data with each class totaling 1000 images. For the sampling method used, the dataset was taken randomly. This reduction in dataset size is done to maintain computational efficiency, as using a dataset that is too large can require very high computational resource time, both in terms of processing time and memory. In addition, this was done to maintain a balanced number of images per class and ensure sufficient representation of each image. The dataset used can be seen in FIGURE 2 below.

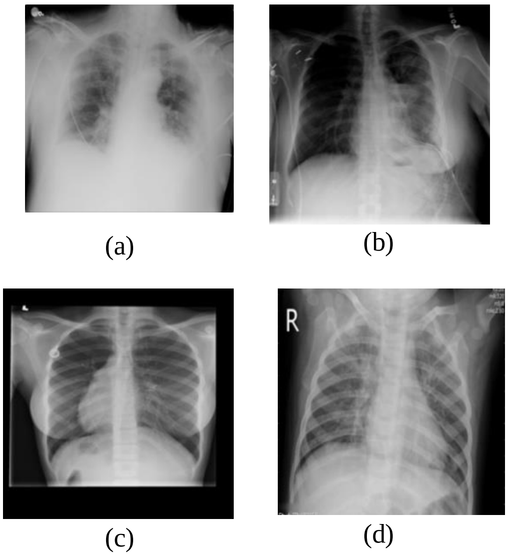

FIGURE 2. Sample image dataset used (a) Covid-1, (b) Lung Opacity, (c) Normal, (d) Viral Pneumonia

B. IMAGE PREPROCESSING

Preprocessing is the process of improving the quality of raw data before use [13] and removing noise to simplify subsequent processing steps and improve accuracy [17][14]. The steps used are resizing and labeling. Resizing is done by changing the size to equalize all image sizes according to the size used, namely 227x227 pixels to adjust the AlexNet architecture modeling,[15][16], to improve computational processing. In the labeling step, each class is grouped or collected and aligned according to the type of lung disease, thus helping in identification.

C. DATA SHARING

In this research, the dataset is divided into training data, testing data, and validation data. Training data is a collection of data that will be used to train the model. Testing data is used to test the performance and success of the model obtained from training data. The purpose of this test is to evaluate the performance of the model on data that has never been seen before and to measure the extent to which the model can generalize and make accurate predictions on new data. Data validation is used to be able to evaluate the model during model training. Data validation helps the data training stage using training data. The training process uses training data to validate the authenticity and similarity of the data read by the architecture model from the training data and the process will continue to repeat until the training and test accuracy results are obtained.

D. GLCM FEATUR EXTRACTION

Gray Level Co-occurrence Matrix (GLCM) is a technique for extracting texture and features from an image[17]. This matrix shows how often two pairs of pixels with the same intensity appear in the image at different distances and directions[18]. GLCM is one of the methods developed for texture analysis and stores intensity distribution and distance information from the original image. Coordinates with pixels have a distance of angular orientation θ, the distance is represented in pixels and the angle is formed based on angular directions such as 0°, 45°, 90°, or 135° and the distance between pixels is (d = 1,2,3,...) pixels[19]. The stages performed in the GLCM calculation are as follows:

1. Create an initial GLCM matrix consisting of pixel pairs aligned at angles of 0°, 45°, 90°, or 135°.
2. Create a symmetric matrix by adding the initial GLCM matrix to its transpose.
3. Normalize the GLCM matrix by dividing each element by the total number of pixel pairs.
4. Feature Extraction: Feature extraction defined in this research are energy, homogeneity, contrast, correlation, entropy, and dissimilarity.

Energy is a measure of image homogeneity shown in Eq. (1). Energy shows a high value when the image pixels are homogeneous [20]. $P(x,y)$ is the element of the GLCM at position (x,y). x , y are the row and column indices in the GLCM. While $\sum x \sum y$ indicates that the calculation is done by summing all the elements in the GLCM matrix after the elements are squared.

$$\boldsymbol{Energy} = \sum_x \sum_y \boldsymbol{P(x,y)^2} \tag{1}$$

Contrast is a measure of the presence of variations in the gray level of one pixel with adjacent pixels throughout the image[20], this is shown in Eq. (2).

$$\boldsymbol{Contrast} = \sum_x \sum_y \boldsymbol{(x-y)^2 P(x,y)} \tag{2}$$

Correlation shows a measure of the linear relationship of the gray level of one pixel relative to another pixel at a certain position[20]. This is shown in Eq. (3), where μ_x is the average of the x value in the GLCM. μ_y is the average of the y values in the GLCM, and $\sigma_x\sigma_y$ is standard deviation of the x, y values in the GLCM.

$$Cor = \sum_x \sum_y \frac{(x-\mu_x)(y-\mu_y)p(x,y)}{\sigma_x\sigma_y} \quad (3)$$

Homogeneity measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal[20]. This is shown by Eq. (4).

$$\boldsymbol{Hom} = \sum_x \sum_y \frac{p(x,y)}{1+|x-y|} \quad (4)$$

Entropy is a measure of the irregularity of gray levels in the image[20]. It is shown by Eq. (5). Where $logp(x,y)$ is the logarithm of probability value $p(x,y)$. This logarithm is used to calculate the uncertainty contribution of each pixel pair.

$$\boldsymbol{Entropy} = \sum_x \sum_y \boldsymbol{p}[\boldsymbol{x},\boldsymbol{y}]\boldsymbol{logp}[\boldsymbol{x},\boldsymbol{y}] \quad (5)$$

Dissimilarity is a measure that defines the variation in intensity levels of pixel pairs in an image[20]. This is shown by Eq. (6).

$$Diss = \sum_x \sum_y |x-y| P(x,y) \quad (6)$$

E. CLASSIFICATION

1. CNN

Convolutional Neural Network (CNN) is a deep learning algorithm used in image machines. Deep learning itself is a sub-section of machine learning that applies the concept of human neural systems so that computers can determine decisions based on the data provided. CNN algorithm is an algorithm that can extract features from images and reduce the number of parameters without any significant decrease in the quality of the model[6]. The more parameters, the heavier the computational weight of the model [21]. Parameter reduction is done in the convolutional layer and pooling layer. The CNN algorithm will also pay attention to small details in an image so that object classification can be carried out properly. There have been many publications on the use of CNN algorithms, especially in object detection, object classification, image segmentation, and even natural language processing. CNN consists of three layers namely the convolutional layer, pooling layer, and fully-connected layer which is illustrated in FIGURE 3.

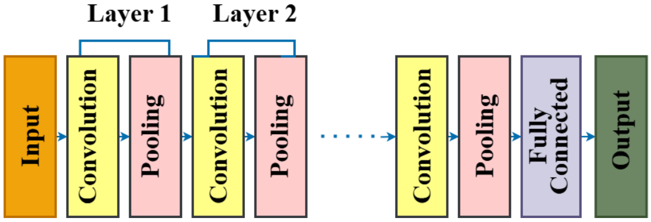

FIGURE 3. **Building Blocks of CNN Algorithm**

CONVOLUTIONAL LAYER. The convolutional Layer is the first layer in the CNN algorithm. Large input images will be divided into small image parts. In this layer, the input image will be filtered by multiplying the input image with a filter[22]. The output of this layer is a feature map that will be used in the activation [23].

POOLING LAYER. The pooling layer or sub-sampling layer is a layer that will reduce the dimension of the feature map generated by the convolutional layer [24]. This layer will take part of the feature map and produce one output depending on the type of pooling used [25]. The purpose of the pooling layer is to reduce the computed parameters.

FULLY CONNECTED LAYER. This layer is the last in the CNN algorithm. In this layer, all neurons from the previous layer will be taken. Then these neurons will be operated with neurons in the current layer to produce an output[22].

2. ALEXNET

AlexNet is an architecture of CNN (Convolutional Neural Network) that was born through research conducted by Alex Krizhevsky et al, from the University of Toronto at the ILSVRC (ImageNet Large Scale Visual Recognition Competition) competition held by ImageNet in 2012[26]. According to Krizhevsky, the Alexnet network architecture is deeper than the standard CNN which consists of 8 layers, and this layer is divided into two layer sections. The first five layers are convolution operation layers followed by three fully-connected layers in the second layer. In the fully connected layer, a soft-max operation is used to perform image classification on existing labels. In ILSVRC, the case study is the output of the last fully-connected layer which produces 1000 class labels using 1000 kinds of soft-max operations. An overview of the AlexNet architecture can be seen in FIGURE 4.

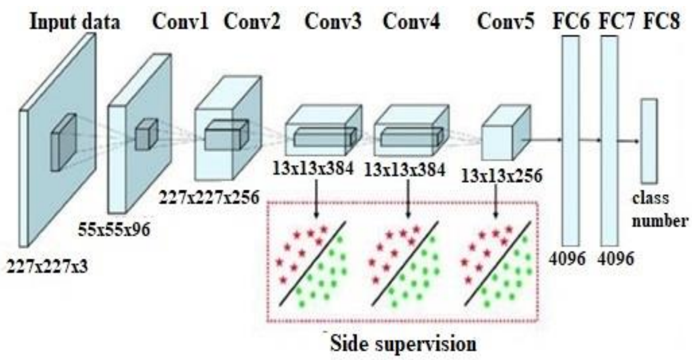

FIGURE 4. **AlexNet Architecture**

3. SGD OPTIMIZER

Stochastic Gradient Descent (SGD) is an efficient and straightforward method for linear classification using discriminative learning. It is an iterative optimization algorithm designed to find the minimum point of a function. Initially, the algorithm makes a guess and then corrects this guess in subsequent iterations using the gradient (derivative) of the function to be minimized. SGD can accelerate the learning process for classification tasks and is not constrained by the size of the training dataset in terms of execution time. The SGD algorithm aims to find the value of θ that minimizes the function J(θ)[27]. To determine the initial value of θ, a search algorithm is used, and then at each iteration, the value of θ is continuously updated until it finds the minimum point or the minimum J value. The process of updating the value of θ at each iteration uses Eq. (7). Updating is done simultaneously for all values of j = 0, ..., n. Variable α is a learning rate that regulates how much the value is updated. The equation for the value of J(θ) can be seen in Eq. (8), where L is a loss function used on the training data $(x_i y_1), \ldots (x_n y_x)$, and R is a regularization or penalty for model complexity.

$$\boldsymbol{\theta j = \theta j - \alpha \frac{\partial y}{\partial x} J(\theta)} \tag{7}$$

$$\boldsymbol{\theta j = \frac{1}{n} \sum_{i=1}^{n} L\big(yi, f(x)\big) + \alpha R(W)} \tag{8}$$

F. EVALUATION

In this study, the evaluation of classification algorithms' accuracy and performance, whether for classifying or predicting attributes, is conducted using the confusion matrix. This matrix serves as a crucial evaluation tool for machine learning algorithms employed in tackling classification problems. It comprises data that contrasts the system's classification outcomes with the anticipated results [28]. In the Confusion Matrix, there are False Negative (FN), False Positive (FP), True Negative (TN), and True Positive (TP) which are defined in the table, the matrix table can be seen in TABLE 1 [29].

TABLE 1
Confusion Matrix

Actual Class	**Predicted Class**	
	Class = Yes	**Class = No**
Class = Yes	True Positive (TP)	False Negative (FN)
Class = No	False Positive (FP)	True Negative (TN)

By using a confusion matrix, it can calculate various evaluation matrices such as accuracy, precision, and recall. The following is the calculation formula[30][31].

1. Accuracy
   Accuracy is the number of correct data comparisons to the total number of data. Accuracy can be calculated in Eq. (9) as follows.

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{9}$$

2. Recall
   Recall is used to show the percentage of positive data classes that are successfully predicted correctly from all positive class data, which is calculated using in Eq. (10) as follows.

$$Recall = \frac{TP}{TP + FN} \tag{10}$$

3. Precision
   Precision is used to measure how large the proportion of positive classes that are successfully predicted correctly from all positive classes, which is calculated using the Eq. (11) as follows.

$$Precision = \frac{TP}{FP + TP} \tag{11}$$

4. F1- Score
   F1-Score is an evaluation metric that reflects the balance between Precision and Recall. F1-Score can be calculated in Eq. (12) as follows.

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{12}$$

III. RESULTS

This research will present the results of evaluating the performance of the model in the classification of lung diseases based on x-ray images using the CNN model, and GLCM Feature Extraction with CNN. The CNN model used is the AlexNet architecture with SGD optimizer.

A. THE RESULTS OF THE CNN METHOD

In this research, the results of experiments using CNN classification models using AlexNet architecture and SGD Optimizer will be presented. For the distribution of datasets, a ratio of 70:10:20 is used, where training data is 70% then 10% for validation data, and 20% for testing data. Model training will be carried out using several parameters to support the success of the model in training. The parameters used can be seen in TABLE 2.

TABLE 2
Model Training Parameters

Hyperparameter	Value
Activation Function	Relu, SoftMax
Learning Rate	0,001
Optimizer	SGD
Epochs	10,30,50,100
Batch Size	16
Dropout Rate	0,5

Then, the details of the AlexNet architecture used can be seen in TABLE 3.

TABLE 3
AlexNet Architecture Detail

Layer	Feature Map	Size	Kernel Size	Stride	Act.
Input	1	227x227x3	-	-	-
Convolutional 1	96	55x55x96	11x11	4	Relu
Pooling	96	27x27x96	3x3	2	Relu
Convolutional 2	256	27x27x256	5x5	1	Relu
Pooling 2	256	13x13x256	3x3	2	Relu
Convolutional 3	384	13x13x384	3x3	1	Relu
Convolutional 4	384	13x13x384	3x3	1	Relu
Convolutional 5	256	13x13x256	3x3	1	Relu
Pooling 3	256	6x6x256	3x3	2	Relu
Fully connected 1	-	9216	-	-	Relu
Fully connected 2	-	4096	-	-	Relu
Fully connected 3	-	4096	-	-	Relu
Output	-	1000	-	-	Soft Max

The performance of the CNN model using AlexNet architecture with SGD optimizer can be seen in TABLE 4, TABLE 5, TABLE 6, TABLE 7.

TABLE 4
CNN epoch 10

Class	CNN		
	Precision	Recall	F1-Score
Covid-19	0.76	0.82	0.79
Lung Opacity	0.96	0.89	0.92
Normal	0.80	0.81	0.80
Viral Pneumonia	0.96	0.89	0.91
Average	0.86	0.85	0.86

The average accuracy value generated from the CNN method at 10 epochs is 0.85.

TABLE 5
CNN epoch 30

Class	CNN		
	Precision	Recall	F1-Score
Covid-19	0.89	0.88	0.88
Lung Opacity	0.91	0.94	0.92
Normal	0.86	0.91	0.88
Viral Pneumonia	0.93	0.86	0.90
Average	**0.90**	**0.90**	**0.90**

The average accuracy value generated from the CNN method at 30 epochs is 0.90.

TABLE 6
CNN epoch 50

Class	CNN		
	Precision	Recall	F1-Score
Covid-19	0.89	0.88	0.88
Lung Opacity	0.93	0.93	0.93
Normal	0.88	0.84	0.86
Viral Pneumonia	0.88	0.94	0.91
Average	**0.90**	**0.90**	**0.89**

The average accuracy value generated from the CNN method at 50 epochs is 0.90.

TABLE 7
CNN epoch 100

Class	CNN		
	Precision	Recall	F1-Score
Covid-19	0.89	0.88	0.89
Lung Opacity	0.96	0.96	0.96
Normal	0.88	0.89	0.89
Viral Pneumonia	0.93	0.93	0.93
Average	**0.92**	**0.92**	**0.92**

The average accuracy value generated from the CNN method at 100 epochs is 0.92.

In the CNN model using AlexNet Architecture and SGD Optimizer, the best results can be seen in TABLE 7, with an average accuracy of 0.92, precision of 0.92, recall of 0.92, and f1-score of 0.92. Then, to find out the amount of data that was successfully detected correctly or incorrectly by the system can be seen from the confusion matrix results. The confusion matrix obtained on the CNN model can be seen in FIGURE 5, showing that of the 792 images used for validation data, 725 images were successfully detected correctly according to their respective classes, while 67 other images were detected incorrectly.

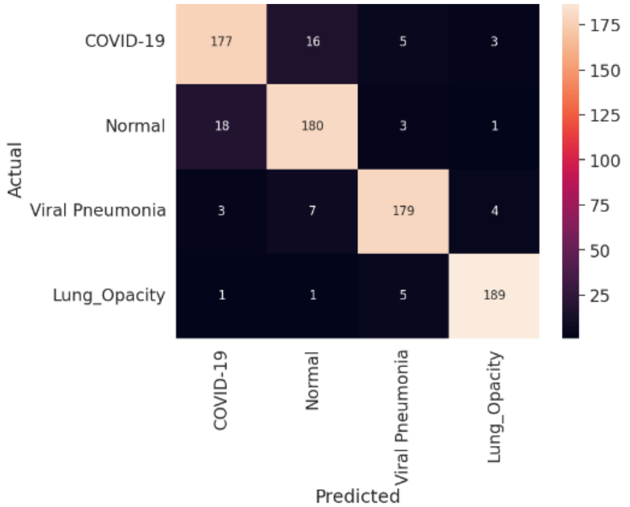

FIGURE 5. **Confusion Matrix**

In model training, the values of training accuracy, training loss, validation accuracy, and validation loss are obtained. For training and validation accuracy graphs can be seen in FIGURE 6.

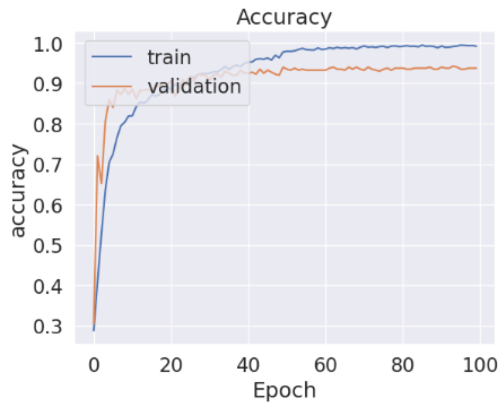

FIGURE 6. **Training and Validation Accuracy Graphs**

For training and validation loss graphs can be seen in FIGURE 7.

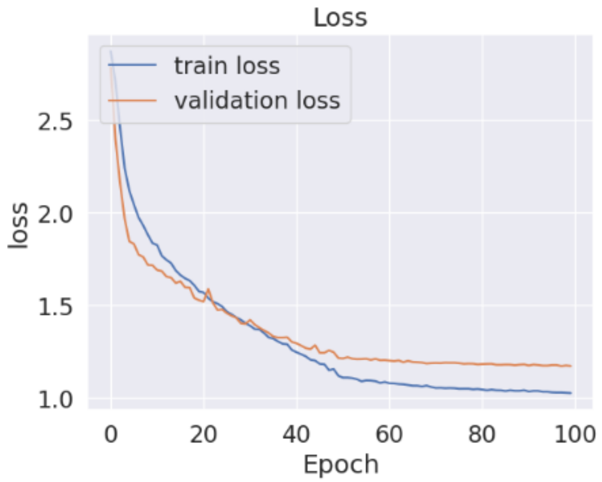

FIGURE 7. **Training and Validation Loss Graphs**

B. THE RESULTS OF THE CNN METHOD USING GLCM FEATURE EXTRACTION

In the results of this study, the results of experiments using the CNN classification model using GLCM extraction features will be presented. The GLCM features used in this research can be seen in TABLE 8.

TABLE 8
List of GLCM Used in the Feature Extraction

Hyperparameter	Description
energy	Image homogeneity measure
homogeneity	Measuring the closeness of the distribution of elements in the GLCM to the diagonal GLCM
contrast	A measure of the presence of variations in the gray level of one pixel with adjacent pixels
correlation	A measure of the linear connectedness of the gray level of one pixel relative to another pixel at a given position
entrophy	A measure of gray-level irregularity in the image
dissimilarity	A measure that defines the variation in intensity levels of pairs of pixels in the image

Then, for the angles used are 0°, 45°, 90°, and 135°, with a distance between pixels of d = 1, 3, 5. After obtaining the value of GLCM, then classified using the CNN method with the parameters used can be seen in TABLE 9.

TABLE 9
Hyperparameter Setup for CNN Method

Hyperparameter	Value
Activation Function	Relu, Softmax
Learning Rate	0,001
Optimizer	SGD
Epochs	100
Batch Size	16
Dropout	0.5

After getting the best combination value of the hyperparameters, then classified using CNN. The CNN architecture uses the AlexNet architecture with a combination of SGD optimizers. The performance of the CNN model using GLCM feature extraction can be seen in TABLE 10.

TABLE 10
CNN with GLCM Results

Class	GLCM+CNN		
	Precision	**Recall**	**F1-Score**
Covid-19	0.85	0.85	0.85
Lung Opacity	0.84	0.85	0.85
Normal	0.92	0.84	0.88
Viral Pneumonia	0.87	0.94	0.90
Average	**0.87**	**0.87**	**0.87**

For training and validation accuracy graphs can be seen in FIGURE 8.

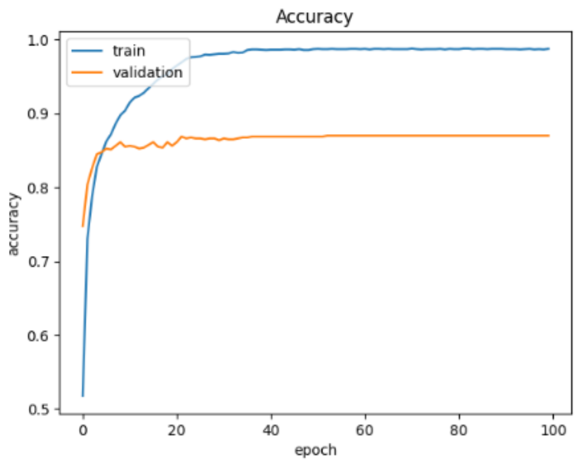

FIGURE 8. **Training and Validation Accuracy Graphs**

For training and validation loss graphs can be seen in FIGURE 7.

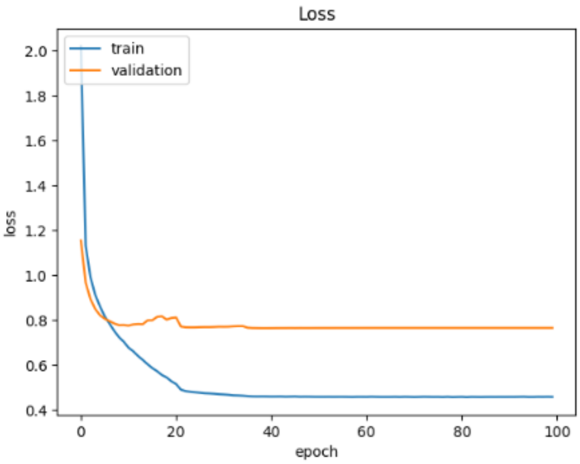

FIGURE 9. **Training and Validation Loss Graphs**

In the CNN model using GLCM feature extraction, the results can be seen in TABLE 10 obtained accuracy of 0.87, precision of 0.87, recall of 0.87, and f1-score of 0.87.

IV. DISCUSSION

From the research results previously described, there are two experiments conducted in this study. The experiments include the application of classification methods, namely Convolutional Neural Network and GLCM-CNN, the first using CNN for classification using AlexNet architecture and SGD optimizer. Then GLCM feature extraction with energy, homogeneity, contrast, correlation, entropy, and dissimilarity features and classified using the CNN method to compare the results of the model prediction performance.

In the CNN method, the number of epochs used in this study starts from epochs 10, 30, 50, and 100. This is done to find the best number of epochs that can produce balanced accuracy between training and testing with graphical results. FIGURE 6 and FIGURE 7 show the comparison of accuracy and loss values obtained during the training and testing stages. From the graph in FIGURE 6, it can be seen that up to epoch 25 the CNN model used is quite good. However, at the next epoch, the test value decreased but slowly increased again. This result is supported by the loss condition in FIGURE 7.

It can be seen in TABLE 4, TABLE 5, TABLE 6, and TABLE 7 that the CNN method shows the best results after epoch 100, where these hyperparameters can still be improved by changing or adding epoch variations. Thus, these values can still be searched again and explored for the optimal combination using the SGD optimizer.

For visualization comparison of CNN method evaluation results at each different epoch can be seen in FIGURE 10.

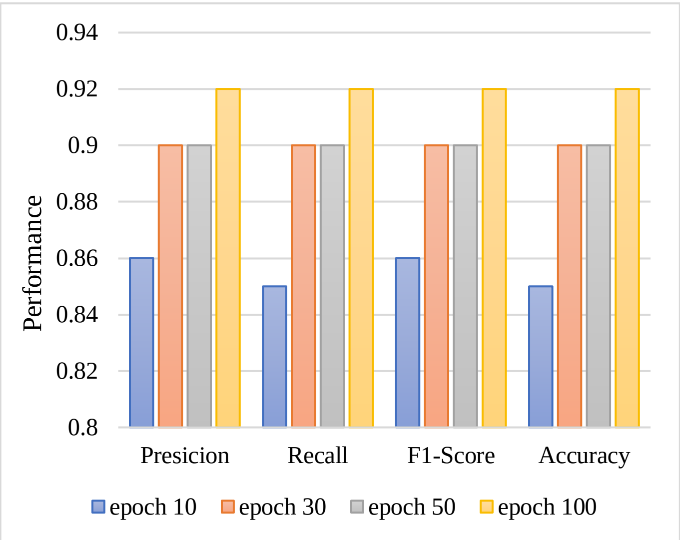

FIGURE 10. Comparison CNN Results

FIGURE 10 shows that there is an improvement in the performance of several evaluation metrics such as accuracy, precision, recall, and f1-score when the CNN model uses different epochs for parameter tuning. These results illustrate that the addition of more epochs has a real positive impact in improving the performance of the model in this CNN method. For visualization of CNN performance results for each class at epoch 100 can be seen in FIGURE 11.

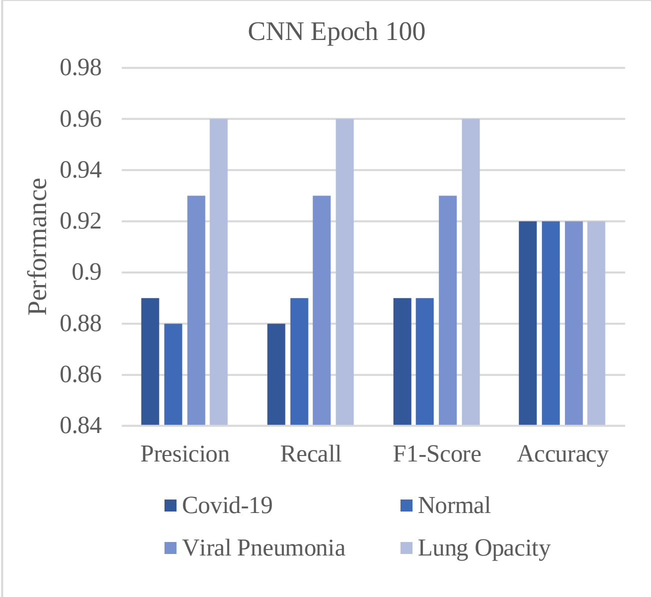

FIGURE 11. CNN Result Epoch 100

For visualization of CNN evaluation results using GLCM feature extraction can be seen in FIGURE 12. Furthermore, the method that uses a combination of GLCM feature extraction with CNN AlexNet architecture can be seen in TABLE 10. After adding the GLCM method to the AlexNet architecture, it decreased from 0.92 to 0.87 at epoch 100. This decrease can be interpreted as the addition of GLCM feature extraction affects the performance of the AlexNet architecture in the classification of lung diseases based on X-ray images

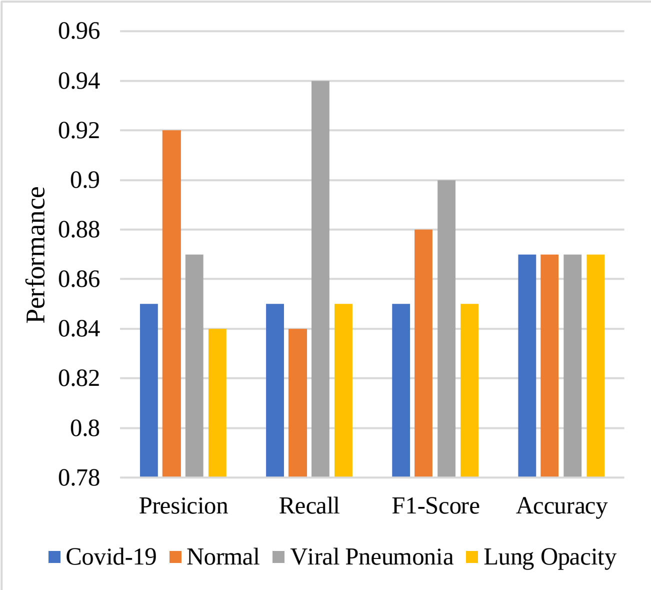

FIGURE 12. GLCM-CNN Result

For visualization comparison of evaluation results between CNN and CNN using GLCM feature extraction can be seen in FIGURE 13.

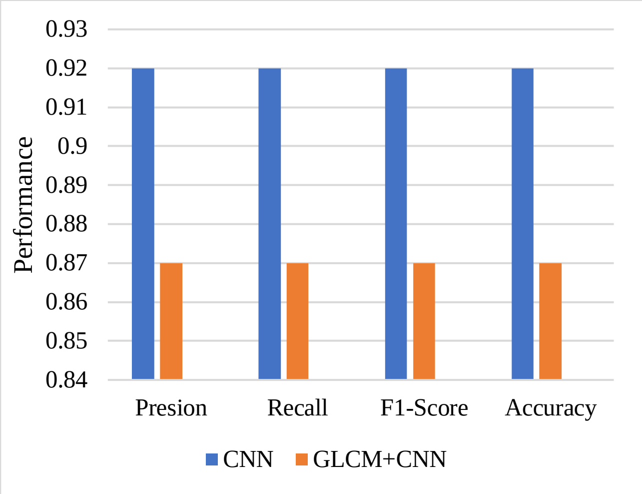

FIGURE 13. Comparison CNN and GLCM-CNN Result

As seen in FIGURE 13, it shows that the CNN model using Alexnet architecture with SGD optimizer provides superior performance compared to GLCM-CNN in the case of lung disease classification on X-ray images. Additional testing was conducted through a comparative analysis of the evaluation results obtained in this study with other studies that used a four-class dataset. This comparison aims to assess the performance achieved in this study with previous studies. The results of the comparison are presented in TABLE 11.

TABLE 11
Comparison of accuracy result with previous research

Research	Technique	Number of Class	Accuracy (%)
[2]	MobileNetV2 + VGG19 + ResNet	4 classes	87.12
[12]	ResNet-50	4 classes	95
[32]	RetinaNet+Mask R-CNN	3 classes	83.8
Proposed model	AlexNet + SGD	4 classes	92
Proposed model	GLCM+ CNN AlexNet	4 classes	87

Compared with research [2], the findings of this study show that the use of the CNN method with AlexNet architecture combined with SGD optimizer is more effective in classifying lung disease data on four-class COVID-19 radiography X-ray images. Then, when compared to research [32], the combined method between CNN + GLCM achieved similar results. Although the CNN method with AlexNet architecture and SGD optimizer does produce quite a good accuracy, it cannot outperform the research [12] that uses ResNet-50 architecture. Therefore, it is important to acknowledge the limitations and shortcomings of this study. In particular, the performance of the resulting model is quite good but has not been able to outperform research using other CNN architectures. The suboptimal performance of lung disease detection based on this could be because the use of AlexNet architecture is not suitable for classification on X-ray images. In addition, the extraction of GLCM features in combination with the CNN method using the AlexNet architecture is also considered less suitable so it still produces less than optimal performance. Although the method model proposed in this study has not achieved better performance compared to some previous studies, this study has significant implications for the field of medical image analysis in the diagnosis of lung diseases. The findings can enrich the existing literature and theories on the use of hybrid methods in medical image processing.

V. CONCLUSION

In this study, deep learning and feature extraction algorithms are used to identify and classify lung diseases. The approach involves five different steps, including data collection, image pre-processing, dividing the data into training, testing, and validation data, training the model, and comparing the results. The results describe two experiments that include the application of the CNN classification method using the AlexNet architecture and SGD optimizer, as well as the application of GLCM feature extraction combined with the CNN method. Data analysis shows the best hyperparameters of each method after increasing epochs. However, these values can still be improved by exploring optimal combinations such as learning rate, activation function, and different batch sizes.

Evaluation of the results was done by considering various performance parameters such as accuracy, recall, precision, and f1-score. After completing the training of all models, it was found that the CNN model using AlexNet architecture and SGD optimizer at epoch 100 produced higher accuracy with an average accuracy of 0.92, precision of 0.92, recall of 0.92, f1-score of 0.92 for covid-19 radiography dataset. Thus, this research can help in improving the clinical prediction of lung diseases based on x-ray images.

However, to enhance the performance of lung disease classification methods, future research should focus on several critical areas. One important aspect is the need for larger and more diverse datasets, encompassing a broader range of image classes. This expansion will enable the model to discern intricate patterns more effectively and deliver more precise predictions. Additionally, researchers can explore different convolutional neural network (CNN) architectures and experiment with alternative optimizers. Incorporating Gray-Level Co-occurrence Matrix (GLCM) features with various distances and angles could also enrich the analysis. Lastly, there is a need for further investigation into optimal hyperparameter combinations specific to CNNs for enhancing classification methodologies. By addressing these aspects, future studies aim to achieve significantly improved accuracy in classifying lung disease image data.

REFERENCES

[1] J. E. Cotes, D. J. Chin, and M. R. Miller, *Lung Function : Physiology, Measurement and Application in Medicine*, 6th editio. Blackwell Publishing, 2006.
[2] F. Türk and Y. Kökver, “Detection of Lung Opacity and Treatment Planning with Three-Channel Fusion CNN Model,” *Arabian Journal*

for Science and Engineering, pp. 9–11, 2023, doi: 10.1007/s13369-023-07843-4.

[3] L. Kong and J. Cheng, "Classification and detection of COVID-19 X-Ray images based on DenseNet and VGG16 feature fusion," *Biomedical Signal Processing and Control*, vol. 77, no. January, p. 103772, 2022, doi: 10.1016/j.bspc.2022.103772.

[4] R. M. Diar, R. Y. N. Fu'adah, and K. Usman, "Classification Of The Lung Diseases Based On X Ray Image Processing Using Convolutional Neural Network," *e-Proceeding of Engineering*, vol. 9, no. 2, pp. 476–484, 2022.

[5] L. Jiao and J. Zhao, "A Survey on the New Generation of Deep Learning in Image Processing," *IEEE Access*, vol. 7, pp. 172231–172263, 2019, doi: 10.1109/ACCESS.2019.2956508.

[6] P. Mahesh, Y. G. Prathyusha, B. Sahithi, and S. Nagendram, "Covid-19 Detection from Chest X-Ray using Convolution Neural Networks," *Journal of Physics: Conference Series*, vol. 1804, no. 1, 2021, doi: 10.1088/1742-6596/1804/1/012197.

[7] C. Lam, C. Yu, L. Huang, and D. Rubin, "Retinal Lesion Detection With Deep Learning Using Image Patches," *Invest Ophthalmol Vis Sci*, vol. 59, pp. 590– 596, 2018, [Online]. Available: https://doi.org/10.1167/ iovs.17-22721

[8] P. Purnawansyah *et al.*, "Comparative Study of Herbal Leaves Classification using Hybrid of GLCM-SVM and GLCM-CNN," *ILKOM Jurnal Ilmiah*, vol. 15, no. 2, pp. 382–389, 2023, [Online]. Available: https://jurnal.fikom.umi.ac.id/index.php/ILKOM/article/view/1759

[9] G. Preethi and V. Sornagopal, "MRI image classification using GLCM texture features," *Proceeding of the IEEE International Conference on Green Computing, Communication and Electrical Engineering, ICGCCEE 2014*, 2014, doi: 10.1109/ICGCCEE.2014.6922461.

[10] J. Tan *et al.*, "Glcm-cnn: Gray level co-occurrence matrix based cnn model for polyp diagnosis," *2019 IEEE EMBS International Conference on Biomedical and Health Informatics, BHI 2019 - Proceedings*, pp. 1–4, 2019, doi: 10.1109/BHI.2019.8834585.

[11] Z. J. Hussein, A. M. Hussein, G. I. Maki, and H. Q. Gheni, "Improved Model for Skin Illnesses Classification Utilizing Gray-Level Co-occurrence Matrix and Convolution Neural Network," *Journal of Advances in Information Technology*, vol. 14, no. 6, pp. 1273–1279, 2023, doi: 10.12720/jait.14.6.1273-1279.

[12] E. M. Senan, A. Alzahrani, M. Y. Alzahrani, N. Alsharif, and T. H. H. Aldhyani, "Automated Diagnosis of Chest X-Ray for Early Detection of COVID-19 Disease," *Computational and Mathematical Methods in Medicine*, vol. 2021, 2021, doi: 10.1155/2021/6919483.

[13] M. R. Faisal *et al.*, "LSTM and Bi-LSTM Models For Identifying Natural Disasters Reports From Social Media," *Journal of Electronics, Electromedical Engineering, and Medical Informatics*, vol. 5, no. 4, pp. 241–249, 2023.

[14] P. A. Riadi, M. R. Faisal, D. Kartini, R. A. Nugroho, D. T. Nugrahadi, and D. B. Magfira, "A Comparative Study of Machine Learning Methods for Baby Cry Detection Using MFCC Features," *Journal of Electronics, Electromedical Engineering, and Medical Informatics*, vol. 6, no. 1, pp. 73–83, 2024, doi: 10.35882/jeeemi.v6i1.350.

[15] M. Irfan *et al.*, "Role of hybrid deep neural networks (Hdnns), computed tomography, and chest x-rays for the detection of covid-19," *International Journal of Environmental Research and Public Health*, vol. 18, no. 6, pp. 1–14, 2021, doi: 10.3390/ijerph18063056.

[16] Y. E. Almalki *et al.*, "A novel method for COVID-19 diagnosis using artificial intelligence in chest x-ray images," *Healthcare (Switzerland)*, vol. 9, no. 5, pp. 1–23, 2021, doi: 10.3390/healthcare9050522.

[17] Ş. Öztürk and B. Akdemir, "Application of Feature Extraction and Classification Methods for Histopathological Image using GLCM, LBP, LBGLCM, GLRLM and SFTA," *Procedia Computer Science*, vol. 132, no. Iccids, pp. 40–46, 2018, doi: 10.1016/j.procs.2018.05.057.

[18] S. S. Sastry, T. V. Kumari, C. N. Rao, K. Mallika, S. Lakshminarayana, and H. S. Tiong, "Transition Temperatures of Thermotropic Liquid Crystals from the Local Binary Gray Level Cooccurrence Matrix," *Advances in Condensed Matter Physics*, vol. 2012, 2012, doi: 10.1155/2012/527065.

[19] E. A. Abbood and T. A. Al-Assadi, "GLCMs Based multi-inputs 1D CNN Deep Learning Neural Network for COVID-19 Texture Feature Extraction and Classification," *Karbala International Journal of Modern Science*, vol. 8, no. 1, pp. 28–39, 2022, doi: 10.33640/2405-609X.3201.

[20] Z. Abbas, M. U. Rehman, S. Najam, and S. M. Danish Rizvi, "An Efficient Gray-Level Co-Occurrence Matrix (GLCM) based Approach Towards Classification of Skin Lesion," *Proceedings - 2019 Amity International Conference on Artificial Intelligence, AICAI 2019*, pp. 317–320, 2019, doi: 10.1109/AICAI.2019.8701374.

[21] C. W. Wu, "ProdSumNet: reducing model parameters in deep neural networks via product-of-sums matrix decompositions," no. 1, pp. 1–10, 2018, [Online]. Available: http://arxiv.org/abs/1809.02209

[22] F. Sultana, A. Sufian, and P. Dutta, "Advancements in image classification using convolutional neural network," *Proceedings - 2018 4th IEEE International Conference on Research in Computational Intelligence and Communication Networks, ICRCICN 2018*, no. 1, pp. 122–129, 2018, doi: 10.1109/ICRCICN.2018.8718718.

[23] A. Saxena, "An Introduction to Convolutional Neural Networks," *International Journal for Research in Applied Science and Engineering Technology*, vol. 10, no. 12, pp. 943–947, 2022, doi: 10.22214/ijraset.2022.47789.

[24] M. Ahmadi, S. Vakili, J. M. P. Langlois, and W. Gross, "Power Reduction in CNN Pooling Layers with a Preliminary Partial Computation Strategy," *2018 16th IEEE International New Circuits and Systems Conference, NEWCAS 2018*, no. 1, pp. 125–129, 2018, doi: 10.1109/NEWCAS.2018.8585433.

[25] H. Gholamalinezhad and H. Khosravi, "Pooling Methods in Deep Neural Networks, a Review," 2020, [Online]. Available: http://arxiv.org/abs/2009.07485

[26] S. Liu and W. Deng, "Very deep convolutional neural network based image classification using small training sample size," *Proceedings - 3rd IAPR Asian Conference on Pattern Recognition, ACPR 2015*, pp. 730–734, 2016, doi: 10.1109/ACPR.2015.7486599.

[27] E. Yazan and M. F. Talu, "Comparison of the Stochastic Gradient Descent Based Optimization Techniques," *IEEE*, 2017.

[28] S. B. Knight, P. A. Crosbie, H. Balata, J. Chudziak, T. Hussell, and C. Dive, "Progress and prospects of early detection in lung cancer," *Open Biology*, vol. 7, no. 9, 2017, doi: 10.1098/rsob.170070.

[29] Y. F. Zamzam, T. H. Saragih, R. Herteno, and D. Turianto, "Comparison of CatBoost and Random Forest Methods for Lung Cancer Classification using Hyperparameter Tuning Bayesian Optimization- based," vol. 6, no. 2, pp. 125–136, 2024.

[30] M. Yildirim and A. Cinar, "Classification of Alzheimer's disease MRI images with CNN based hybrid method," *Ingenierie des Systemes d'Information*, vol. 25, no. 4, pp. 413–418, 2020, doi: 10.18280/isi.250402.

[31] Ahmad Badruzzaman and Aniati Murni Arymurhty, "A Comparative Study of Convolutional Neural Network in Detecting Blast Cells for Diagnose Acute Myeloid Leukemia," *Journal of Electronics, Electromedical Engineering, and Medical Informatics*, vol. 6, no. 1, pp. 84–91, 2024, doi: 10.35882/jeeemi.v6i1.354.

[32] I. Sirazitdinov, M. Kholiavchenko, T. Mustafaev, Y. Yixuan, R. Kuleev, and B. Ibragimov, "Deep neural network ensemble for pneumonia localization from a large-scale chest x-ray database," *Computers and Electrical Engineering*, vol. 78, pp. 388–399, 2019, doi: 10.1016/j.compeleceng.2019.08.004.

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