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BACTERIAL AND VIRUS PNEUMONIA INFECTION DETECTION ON CHEST X-RAY IMAGES USING MACHINE LEARNING

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ABSTRACT

Pneumonia is a lung inflammation caused by viruses or bacteria, resulting in millions of deaths each year. Pneumonia can be diagnosed by analyzing chest x-ray images by radiologists. This research aims to help, accelerate, and simplify pneumonia detection processes. In this research, we proposed a deep learning framework for pneumonia detection using machine learning. Features from chest x-ray images are extracted using convolutional neural network models pre-trained on ImageNet. The extracted features were then fed into a classifier to predict virus pneumonia, bacterial pneumonia, and normal images. This research used four neural network architectures as features extractors, specifically MobileNetV2, MobileNetV3, ResNet50, DenseNet169. For prediction, we used CNN default classifier Artificial Neural Network (ANN), Support Vector Machines (SVM), Random Forest (RF), and Linear Discriminant Analysis (LDA). This research is using dataset from Guangzhou Women and Children's Medical Center, Guangzhou. The final classification result achieves 96.5% accuracy on normal, bacterial, dan virus pneumonia classification using ResNet50 combined with SVM, continued by achieving 97.6% accuracy using ResNet50 combined with Random Forest on bacterial and virus classification. This result outperformed previous research using only DenseNet169. Hence, this approach can be used by radiologists or novices in pneumonia detection processes.

Keywords: *Pneumonia Detection, Machine Learning, Convolutional Neural Network, Support Vector Machine, Random Forest*

1. INTRODUCTION

Pneumonia is a form of acute respiratory infection that affects the lungs and is the single largest infectious cause of death in children worldwide [1]. Pneumonia is the single largest infectious cause of death in children worldwide and is most prevalent in South Asia and Africa. The main cause of pneumonia is bacterial or viruses. Fungi can also cause pneumonia, but it is less common [2]. The first main causes of pneumonia, bacterial pneumonia can be infected by another person when someone infected sneezes or coughs. People with a weakened immune system have a higher risk for bacterial pneumonia. This type of pneumonia usually treated using antibiotics. On the other hand, virus pneumonia or viral pneumonia is caused by viruses invading lungs and causes them to swell, blocking oxygen flow. Virus pneumonia has a similar symptom to bacterial pneumonia, but virus pneumonia patients may have additional symptoms such as headaches, muscle pain, worsening cough, and shortness of breath. Virus pneumonia can be infected to everyone since it is airborne and contagious. This type of pneumonia cannot be treated using antibiotics, and it depends on the virus pneumonia symptoms.

Radiologists or experts can diagnose pneumonia by analyzing chest x-ray images. However, not all experts can analyze chest x-ray images easily, because the features are often confused with other diseases. Besides, the limited number of radiologists and experts is one of the biggest problems compared with the number of pneumonia cases. The improvement in machine learning can solve many problems such as infection detection with a good result or even better than the experts [3]. Using machine learning in the medical field must be able to have a good result with high accuracy to avoid misdiagnosis.

Convolutional Neural Network (CNN), an advancement of Computer Vision with Deep Learning, is one of the popular machine learning models used in image processing or image classification. CNN has been widely used to help image classification, including in a lot of research for medical images classification or disease detection. Many kinds of CNN architectures have been developed to achieve better result. By general, CNN is divided into feature extractors and classifiers. The input image of CNN will be extracted by the feature extractor using the convolutional layer and pooling layer. The features that have been extracted will be classified by the classifier, which by default is a fully connected (FC) layer of an artificial neural network (ANN). There are many types of CNN architecture created by researchers to improve the performance results, such as VGG [4], MobileNet [5], ResNet [6], and DenseNet [7]. In the struggle of improving machine learning performance and accuracy, a lot of researchers combine CNN features extractor with another classifier besides ANN such as Support Vector Machines (SVM), K-nearest Neighbors (KNN), Naïve Bayes, Decision Trees, etc.

Research and studies in pneumonia detection using chest x-ray images have achieved a good result. A research in pneumonia detection using three classes of chest x-ray image i.e., normal, bacterial pneumonia, and virus pneumonia has achieved 95.72% accuracy using DenseNet169 architecture [8]. Accuracy on medical images classification is very important. A Misclassification problem can lead to misdiagnoses, resulting to mishandling of patients. The result of 3 classes classification on normal, bacterial, and virus pneumonia can be improved by using other classification method, as done on research using CNN with LDA [9].

Motivated in improving classification accuracy in three classes chest x-ray image classification i.e., normal, bacterial pneumonia, and virus pneumonia, this research aimed to combine CNN feature extractor with a machine learning classifier with the best accuracy result on the dataset from Guangzhou Women and Children's Medical Center, Guangzhou [10]. Furthermore, this research will use feature extractors of MobileNetV2 [11], MobileNetV3 [5], ResNet [6], and DenseNet [7] along with neural network, LDA [12], Random Forest [13], and SVM [14] as the classifier.

The rest of the paper is structured as follows. Section 2 presents an overview of related works in the field of pneumonia detection. Section 3 presents the theory and methods used in the research. Section 4 presents the proposed methods of this research. The summary of experiments and results obtained is discussed in Section 5. Finally, the conclusion and future works is discussed in Section 6.

2. RELATED WORKS

A lot of research in pneumonia detection results in several techniques and methods aiming to create a classification model with good accuracy results. Research in pneumonia infection detection with image processing using Otsu Thresholding resulting in a two-class classification of normal and pneumonia chest x-ray image [15]. With the success of machine learning in solving various types of classification problems, another research in pneumonia detection used a machine learning model to classify normal and pneumonia chest x-ray images using multilayer perceptron (MLP) and logistic regression resulting in 95.39% and 95.63% accuracy [16].

CNN, a sub-branch of deep learning has proven very effective in image recognition and classification. Research by Asnaoui et al. [17] in pneumonia detection and classification using ResNet 50, MobileNetV2, and Inception ResNet V2 can achieve high accuracy of 96% in normal and pneumonia classification. A research by Stephen et al. [18] on pneumonia and normal classification using deep learning obtained 95.31% training accuracy and 93.73% validation accuracy. A classification using VGG16 model by Moujahid et al. [19] achieved 96.81% training accuracy using RMSProp optimizer and Categorical cross entropy loss function. Another research by Elshennawy et al. [20] using the ResNet152V2 model can achieve 99.22% accuracy. Furthermore, there are also research using the CNN model with transfer learning i.e., a classification model with ImageNet pre-trained weight and Stochastic Gradient Descent (SGD) optimizer with 98.43% accuracy [21], and another transfer learning using 49 convolutional layers with 2 dense layers resulting in 90.5% accuracy [22].

Two types of pneumonia, bacterial and virus pneumonia, can also be recognized and classified using machine learning. Gu et al. [23] using Deep Convolutional Neural Network (DCNN) features with SVM for binary classifier results in 80,48% accuracy. A classification using multi-view ensemble CNN proposed by Ferreira et al. [24] results on 97.9% accuracy on normal and pneumonia classification, and 92.1% accuracy on bacterial and virus pneumonia classification.

Besides solving two classes classification problem of normal and pneumonia, several researchers solved three classes classification problem of normal, bacterial pneumonia, and virus pneumonia. Research by Hammoudi et al. [8] using DenseNet169 resulting 95.72% in normal, bacterial, and virus classification. This research also achieved 97.97%, 96.62%, and 92.57% accuracy on the bacterial, virus, and normal class. Research by Rahman et al. [25] using the DenseNet201 model can achieve 98%, 95%, and 93.3% on normal and pneumonia classification, bacterial and virus pneumonia classification, and bacterial, virus, and normal classification. Another research by Chouhan et al. [26] also applied transfer learning on the ensemble model of AlexNet, DenseNet121, InceptionV3, ResNet18, and GoogleNet. This ensemble model resulting in an accuracy of 95.39% on the bacterial, virus, and normal classification. A proposed CNN model by Polat et al. [27] achieved 92% accuracy on bacterial and virus pneumonia classification, and 90% accuracy on normal, bacterial, and virus classification.

Several studies have demonstrated the combination of CNN with another classifier besides neural network classifiers such as SVM, Naïve Bayes, KNN, and Random Forest can result in a good classification model. Varshni et al. [28] using Xception, ResNet50, VGG16, VGG19, and DenseNet169 as feature extractor and SVM, Naïve Bayes, KNN, and Random Forest as classifier. The best result achieved an AUC number of 0.8002 on the DenseNet169 feature classified using SVM. Another research using AlexNet, VGG16, and VGG19 as feature extractors and combined with the decision tree, KNN, LDA, linear regression, and SVM resulted in 99.41% accuracy of normal and pneumonia classification [9]. The best accuracy was achieved by using 300 features of each CNN model and classified using LDA.

3. THEORY AND METHODS

CNN is a machine learning model widely used as image classifier. CNN generally divided into two main parts, feature extractors which includes convolutional and pooling layer, and classifiers which contains dense layers of fully connected layer (FC Layer). The output of CNN is determined from the last layer of FC Layer.

3.1. Feature Extractor

In this step, each CNN model MobileNetV2 [11], MobileNetV3 [5], ResNet [6], and DenseNet [7] will be trained using a training dataset. The images will be extracted on a feature extractor which includes convolutional layers and pooling layers for extracting images. The extracted features from each model will be classified using a neural network (FC Layer). Each model will be trained using transfer learning from ImageNet pre-trained model.

3.1.1. MobileNetV2

MobileNetV2 [11] is a CNN model architecture dedicated to mobile use that improves state-of-the-art performances on multiple tasks. This CNN model is a lightweight model based on depth-wise separable convolution, linear bottleneck, and inverted residual. The architecture of MobileNetV2 can be seen in Table 1.

Table 1. MobileNetV2 Architecture. Where t: expansion factor, c: number of output channels, n: repeating number, s: stride.

Input	Operator	t	c	n	s
224x224	Convolution 2D	-	32	1	2
112x112	Bottleneck	1	16	1	1
112x112	Bottleneck	6	24	2	2
56x56	Bottleneck	6	32	3	2
28x8	Bottleneck	6	64	4	2
14x14	Bottleneck	6	96	3	1
14x14	Bottleneck	6	160	3	2
7x7	Bottleneck	6	320	1	1
7x7	Convolution 2D	-	1280	1	1
7x7	Average Pooling	-	-	1	-
1x1	Dense Layer	-	k	-	-

3.1.2. MobileNetV3

MobileNetV3 [5] is a development of MobileNetV2. This model is a combination of network architecture search (NAS) complemented by the NetAdapt algorithm and then subsequently improved through novel architecture advances. There are two models of MobileNetV3, MobileNetV3-Small, and MobileNetV3-Large. MobileNetV3 is more accurate and reduces latency compared to MobileNetV2. This research will be conducted using MobileNetV3-Small, which architecture can be seen in Table 2.

Table 2. MobileNetV3-Small Architecture.

Input	Operator	t	c	s
224x224	Convolution 2D	-	16	2
112x112	Bottleneck	16	16	2
56x56	Bottleneck	72	24	2
28x28	Bottleneck	88	24	1
28x28	Bottleneck	96	40	2
14x14	Bottleneck	240	40	1

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14x14	Bottleneck	240	40	1
14x14	Bottleneck	120	48	1
14x14	Bottleneck	144	48	1
14x14	Bottleneck	288	96	2
7x7	Bottleneck	576	96	1
7x7	Convolution 2D	-	576	1
7x7	Average Pooling	-	-	1
1x1	Dense Layer	-	1024	1
1x1	Dense Layer	-	k	-

3.1.3. ResNet

ResNet [7] a residual learning framework which was made to overcome the problem of exploding and vanishing gradients by applying the skip connection concept. The core idea of ResNet is the use of identity shortcut connection that skips one or more layers. This model typically implemented with double or triple layer skips that contain nonlinearities using ReLU and batch normalization between layers. The ResNet50 architecture that will be used in this research can be seen in Table 3.

Table 3. ResNet50 Architecture.

Operator	Output	Shape	c	s
Conv 2D	112x112	7 x 7	64	2
Max Pool	56x56	3 x 3	-	2
Conv 2D	56x56	1 x 1 3 x 3 1 x 1	64 64 256	1
Conv 2D	28x28	1 x 1 3 x 3 1 x 1	128 128 512	1
Conv 2D	14x14	1 x 1 3 x 3 1 x 1	256 256 1024	1
Conv 2D	7x7	1 x 1 3 x 3 1 x 1	512 512 2048	1
Average Pooling	7x7	7 x 7	-	7
Dense Layer	1000d fully connected	-	-	-

3.1.4. DenseNet

DenseNet [6] using concatenation, where each layer will get information from all the layers that existed previously in each Dense Block. This will also have the impact of reducing the number of channels used to minimize computational and memory costs. Each DenseNet architecture will have 4 Dense Block layers consisting of 1 x 1 and 3 x 3 convolution layers, to be able to produce more diverse features compared to other CNN models. Apart from the Dense block, DenseNet also has a transition layer consisting of a 1 x 1 convolution layer and an average pool layer. This research will be conducted using DenseNet169, which architecture can be seen in Table 4.

Table 4. DenseNet169 Architecture.

Operator	Output	Shape	s
Convolution 2D	112 x 112	7 x 7	2
Max Pool	56 x 56	3 x 3	2
Dense Block	56 x 56	1 x 1 3 x 3	1
Convolution 2D Average Pool	56 x 56 28 x 28	1 x 1 2 x 2	1 2
Dense Block	28 x 28	1 x 1 3 x 3	1
Convolution 2D Average Pool	28 x 28 14 x 14	1 x 1 2 x 2	1 2
Dense Block	14 x 14	1 x 1 3 x 3	1
Convolution 2D Average Pool	14 x 14 7 x 7	1 x 1 2 x 2	1 2
Dense Block	7 x 7	1 x 1 3 x 3	1
Average Pool	1 x 1	-	-
Dense Layer	1000d fully connected	-	-

3.2. Classifier

As a default, CNN uses a neural network classifier or fully connected layer to classify output. The classifier process in a neural network includes global average pooling layers and dense layers. However, in this research, after images have been extracted on feature extractor, the features will be classified not only with neural network classifier but also with other machine learning classifiers such as SVM, Random Forest, and LDA.

3.2.1. Neural Network

The neural network is a computational model inspired by the human neural network. Each layer on the ANN model consists of a collection of nodes linked by weight with biases to the next layer until it reached the last output layer. Neural networks do recognition or classification by doing forward propagation to analyze the pattern and doing backward propagation to adjust weight and bias.

3.2.2. SVM

SVM [14] is a supervised machine learning algorithm by separating two classes with a linear classifier using a hyperplane. SVM use linear model as decision boundary in the form of:

$$y(x) = w\,\emptyset(x) + b \quad (1)$$

where x is input vector, w is weight parameter, $\emptyset(x)$ is a basis function, and b is bias. By default, SVM can only do binary classification, however, to solve multiclass classification or non-linearly separable problems SVM used kernel to transform data to a higher dimension. Kernelized SVM performs well in high or low dimension data. Several kernel functions on SVM are Gaussian Kernel, Radial Basis Function Kernel (RBF), Sigmoid Kernel, and Polynomial Kernel.

3.2.3. Random Forest

Random forest or random decision forest [13] is an ensemble learning method, which us several algorithms for classification. The output results from the random forest will be determined through the average prediction (regression) or the most class (classification) from each decision tree. The algorithm works by selecting N data from the dataset and making a decision tree based on those data. This step will be repeated, and each decision tree will predict the result. The output of random forest will be determined from most classes predicted by the decision tree.

3.2.4. LDA

LDA [12] is a statistical method to find a linear combination of features that separates two or more classes. LDA is often used in pre-processing stage of machine learning as a feature reduction by removing redundant and dependent features of data. To find a lower-dimensional projection with maximum class variance and minimum class variance, LDA performs separability calculations, namely the distance between different classes or what is called the variance between classes. To perform these calculations will be done using the formula:

$$S_b = \sum_{i=1}^{g} N_i\,(x_i - x)(x_i - x)^T \quad (2)$$

The last step to construct a lower-dimensional space is to find a projection space P in a lower dimension, which is also called Fisher's Criterion:

$$P_{lda} = \frac{P^T S_b P}{P^T S_w P} \quad (3)$$

The classification result of LDA will use the Bayes theorem to calculate the probabilities of each class.

3.3. Hyperparameter tuning

The process of choosing a set of optimal hyperparameters for the model. Choosing optimal hyperparameters can help classifier to perform better prediction results. This process is needed for CNN model on optimizer, loss function, and learning rate.

Besides CNN model, hyperparameter tuning also needed for another machine learning classifier. SVM need can be hyperparameter-tuned on kernel, gamma, class weight, etc. Same as SVM, each machine learning classifier that have parameter can be tuned to perform better prediction result.

4. PROPOSED METHODS

Each CNN Model will be fine-tuned, trained, validated, and evaluated using identical divided dataset. The best accuracy result from tested CNN model will be classified using different machine learning classifiers. The feature extraction process on CNN model without including the classifier layer (top layer) which consists of 7 x7 global average pooling and dense layer. Each CNN models feature extractor can be seen in Table 5 – Table 8.

Table 5. MobileNetV2 Architecture without classifier

Input	Operator	t	c	n	s
224x224	Convolution 2D	-	32	1	2
112x112	Bottleneck	1	16	1	1
112x112	Bottleneck	6	24	2	2
56x56	Bottleneck	6	32	3	2
28x8	Bottleneck	6	64	4	2
14x14	Bottleneck	6	96	3	1
14x14	Bottleneck	6	160	3	2
7x7	Bottleneck	6	320	1	1
7x7	Convolution 2D	-	1280	1	1

Table 6. MobileNetV3 Architecture without classifier

Input	Operator	t	c	s
224x224	Convolution 2D	-	16	2
112x112	Bottleneck	16	16	2
56x56	Bottleneck	72	24	2
28x28	Bottleneck	88	24	1
28x28	Bottleneck	96	40	2
14x14	Bottleneck	240	40	1
14x14	Bottleneck	240	40	1

14x14	Bottleneck	120	48	1
14x14	Bottleneck	144	48	1
14x14	Bottleneck	288	96	2
7x7	Bottleneck	576	96	1
7x7	Convolution 2D	-	576	1

Table 7. ResNet50 Architecture without classifier

Operator	Output	Shape	c	s
Conv 2D	112x112	7 x 7	64	2
Max Pool	56x56	3 x 3	-	2
Conv 2D	56x56	1 x 1 3 x 3 1 x 1	64 64 256	1
Conv 2D	28x28	1 x 1 3 x 3 1 x 1	128 128 512	1
Conv 2D	14x14	1 x 1 3 x 3 1 x 1	256 256 1024	1
Conv 2D	7x7	1 x 1 3 x 3 1 x 1	512 512 2048	1

Table 8. DenseNet169 Architecture without classifier

Operator	Output	Shape	s
Convolution 2D	112 x 112	7 x 7	2
Max Pool	56 x 56	3 x 3	2
Dense Block	56 x 56	1 x 1 3 x 3	1
Convolution 2D Average Pool	56 x 56 28 x 28	1 x 1 2 x 2	1 2
Dense Block	28 x 28	1 x 1 3 x 3	1
Convolution 2D Average Pool	28 x 28 14 x 14	1 x 1 2 x 2	1 2
Dense Block	14 x 14	1 x 1 3 x 3	1
Convolution 2D Average Pool	14 x 14 7 x 7	1 x 1 2 x 2	1 2

Features from selected architecture is obtained from the output of last feature extractor layer. The features will be fed into machine learning classifier for the classification result. The best classification result will be selected.

This research proposed method can be seen on Figure 1. First step of the research will split the dataset into 3 parts, training dataset, validation dataset, and testing dataset. The divided dataset will be trained, validated, and tested on MobileNetV2, MobileNetV3, ResNet50, and DenseNet169. The hyperparameter-tuning process will be implemented on the optimizer, that will be selected out of:

- Adam Optimizer
- Stochastic Gradient Design (SGD) Optimizer
- RMSprop Optimizer.

Besides optimizer, the loss function of each CNN model will also be tuned out of:

- Categorical Cross-entropy
- Huber
- Mean Absolute Error (MAE).

The highest testing accuracy result of tuned CNN model will be selected and trained with another machine learning classifier e.g., SVM, LDA, and Random Forest (RF). Hyperparameter-tuning will also be done on SVM parameters e.g.:

- Regularization C
- Gamma
- Kernel.

LDA classifier will be tuned on solver between:

- Singular value decomposition
- Least squares solution
- Eigenvalue decomposition.

Random Forest classifier will be tuned on these parameters:

- Maximum depth
- Number of estimators
- Maximum features
- Bootstrap.

Finally, the best result and accuracy of CNN model with machine learning classifier will be proposed as pneumonia detection model.

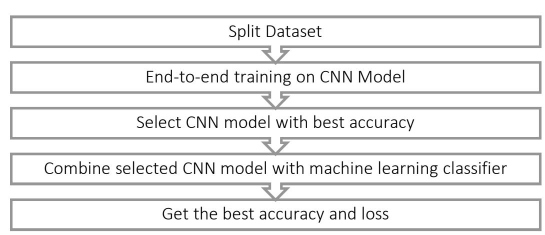

Figure 1. Experiment Process

5. EXPERIMENTS

A comprehensive experiments detail will be discussed in this section.

5.1. Dataset

In this research, we conducted a series of experiments using the dataset from Guangzhou

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Women and Children's Medical Center, Guangzhou [10]. The dataset consists of 5856 images of 3564 images of bacterial pneumonia, 709 images of virus pneumonia, and 1583 of normal chest x-ray. Chest x-ray images were selected from retrospective cohorts of pediatric patients of one to five years old and performed as part of patient's routine clinical care. The dataset will be divided into 3 sections: training dataset, validation dataset, and testing dataset.

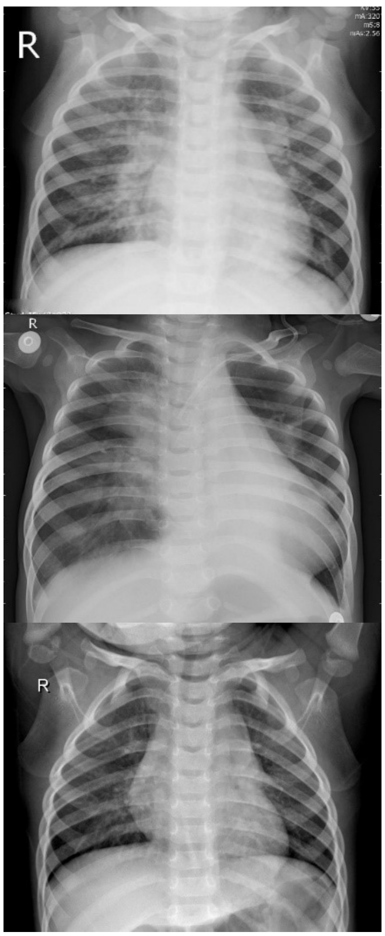

Figure 2: Chest X-Ray images: Virus Pneumonia, Bacterial Pneumonia, and Normal.

5.2. Experimental Design

The research will be conducted in the training, validation, and testing step. During training phase, the chest x-ray images were extracted using CNN feature extractors, and then the features were fed into neural network classifiers. The best result from the CNN model will be trained with another machine learning classifier i.e., SVM, Random Forest, and LDA.

This research will start on the end-to-end training phase using training dataset of 80% of the whole dataset, followed by validation phase using 10% dataset, and testing phase using 10% dataset on each CNN model. The performance of each CNN model will be evaluated using confusion matrix as seen in Table 9.

Table 9. Confusion Matrix

		Predicted			Total
		Bacterial	Virus	Normal	
Actual	Bacterial	TP_B	FN_V	FN_N	B
	Virus	FN_B	TP_V	FN_N	V
	Normal	FN_B	FN_B	TP_N	N
Total		B'	V'	N'	

The CNN Model will be selected by the best training, validation, and testing result. After selecting the CNN model, the CNN model will be trained using another machine learning classifier. This method will be evaluated using accuracy, precision, recall, and f1-score. The accuracy will be calculated with formula:

$$Accuracy = \frac{TP_N + TP_V + TP_B}{N+V+B} \quad (4)$$

Precision will be calculated using the formula below:

$$Precision\ (normal) = \frac{TP_N}{N'} \quad (5)$$

$$Precision\ (virus) = \frac{TP_V}{V'} \quad (6)$$

$$Precision\ (bacterial) = \frac{TP_B}{B'} \quad (7)$$

Recall will be calculated using the formula below:

$$Recall\ (normal) = \frac{TP_N}{N} \quad (8)$$

$$Recall\ (virus) = \frac{TP_V}{V} \quad (9)$$

$$Recall\ (bacteria) = \frac{TP_B}{B} \quad (10)$$

For the F1 score, will be calculated using the formula below:

$$F1\ Score = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recal} \quad (11)$$

The result of this experiments will be compared with previous research on pneumonia detection and classification methods.

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5.3. Experimental Results

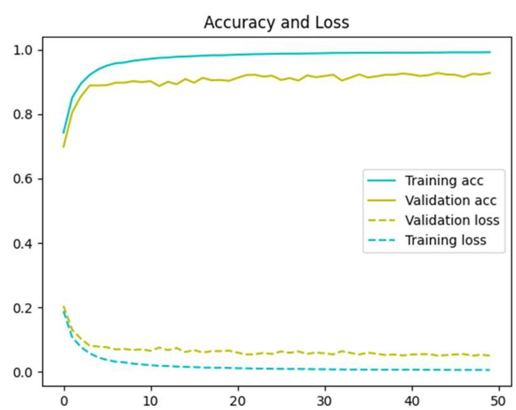
The research conducted in the training, validation, and testing step on divided dataset. The hyperparameter tuning process on each CNN model optimizer and loss function result can be seen on figure below. The training and validation process using Early Stopping function evaluation the validation loss.

Table 10. CNN Model Hyperparameter-Tuning

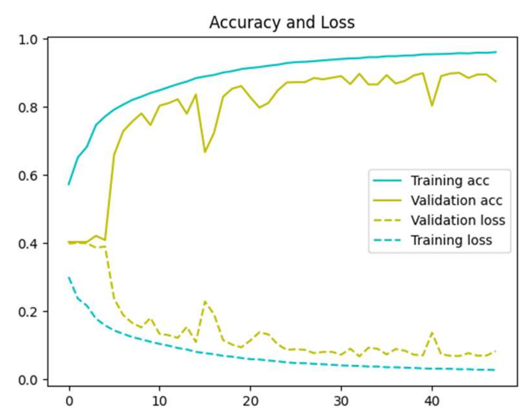
CNN Model	Optimizer	Loss Function
MobileNetV2	SGD	MAE
MobileNetV3	SGD	MAE
ResNet50	SGD	Categorical Cross-entropy
DenseNet169	SGD	MAE

Each fine-tuned CNN model with feature extractor and classifier accuracy result can be seen in Table 11. The best accuracy was achieved by ResNet50 and MobileNetV2, which achieved above 93% accuracy on 3 class classification. The graph of training accuracy, training loss, validation accuracy, and validation loss can be seen on Figure 3. The confusion matrix from CNN models can be seen in Table 12.

Figure 3. Plots of Training and Validation Accuracy and Loss

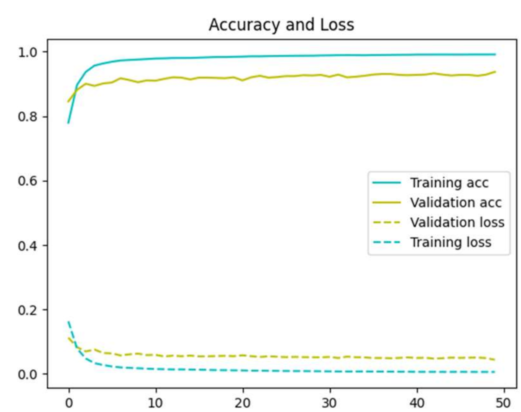


(a) MobileNetV2



(b) MobileNetV3

(c) ResNet50



(d) DenseNet169

Table 11. Training, Validation, and Test Result

CNN Model	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy	Test Loss	Test Accuracy
MobileNetV2	0.005	0.992	0.050	0.928	0.052	0.923
MobileNetV3	0.027	0.961	0.083	0.876	0.072	0.893
ResNet50	**0.003**	**0.999**	**0.357**	**0.941**	**0.410**	**0.934**
DenseNet169	**0.006**	**0.991**	**0.044**	**0.938**	**0.042**	**0.940**

Table 12. CNN Model Confusion Matrix Result

		Actual		
		Bacteria	Virus	Normal
Predicted	Bacteria	241	3	52
	Virus	3	344	1
	Normal	19	3	390

(a) MobileNetV2

		Actual		
		Bacteria	Virus	Normal
Predicted	Bacteria	226	4	66
	Virus	0	340	8
	Normal	26	9	377

(b) MobileNetV3

		Actual		
		Bacteria	Virus	Normal
Predicted	Bacteria	256	2	38
	Virus	4	343	1
	Normal	22	2	388

(c) ResNet50

		Actual		
		Bacteria	Virus	Normal
Predicted	Bacteria	268	1	27
	Virus	5	341	2
	Normal	26	2	384

(d) DenseNet169

Table 13. Training Result on 3 class classification (normal, bacterial, and virus pneumonia)

Model	accuracy	precision	recall	f1-score
Densenet169 + SVM	**100%**	**100%**	**100%**	**100%**
Densenet169 + LDA	81,8%	81,7%	81,8%	81,7%
Densenet169 + RF	**100%**	**100%**	**100%**	**100%**
ResNet50 + SVM	**100%**	**100%**	**100%**	**100%**
ResNet50 + LDA	83,2%	83,2%	83,2%	83,2%
ResNet50 + RF	**100%**	**100%**	**100%**	**100%**

Table 14. Testing Result on 3 class classification (normal, bacterial, and virus pneumonia)

Model	accuracy	precision	recall	f1-score
Densenet169 + SVM	**95,6%**	**95.8%**	**95.2%**	**95.6%**
Densenet169 + LDA	81,7%	81,7%	81,4%	81,6%
Densenet169 + RF	94,8%	94,6%	94,6%	94,6%
ResNet50 + SVM	**96,5%**	**96,6%**	**96,4%**	**96,4%**
ResNet50 + LDA	80,4%	80.3%	80,4%	80,4%
ResNet50 + RF	95,9%	95,9%	95.7%	95.7%

Table 15. Testing Result on 2 class classification (bacterial and virus pneumonia)

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Model	accuracy	precision	recall	f1-score
Densenet169 + SVM	94,2%	95,1%	93,2%	93,9%
Densenet169 + LDA	78,1%	77,7%	76,6%	76,9%
Densenet169 + RF	**97,0%**	**97,0%**	**97,0%**	**97,0%**
ResNet50 + SVM	94,1%	94.2%	94,1%	94,1%
ResNet50 + LDA	77,7%	77,6%	77,6%	77,6%
ResNet50 + RF	**97,6%**	**97,6%**	**97,6%**	**97,6%**

The best result from CNN Model with dense layer are ResNet50 and MobileNetV2. Therefore, the CNN feature extractor result will be trained with another classifier i.e., SVM, Random Forest, and LDA with identical dataset. The hyperparameter tuning result from each machine learning classifier can be seen on Table 16.

Table 16. Machine Learning Classifier Hyperparameter-tuning

Classifier	Hyperparameter-tuning
SVM	C: 1000, gamma: 0.0025
LDA	Solver: svd
RF	N_estimators: 300, max_Features: auto, max_depth: 50, bootstrap: True

We trained selected CNN model with machine learning classifier on both 3-class classification (bacterial, virus, and normal) and 2 class classification (bacterial and virus). The training result of 3-class classification can be seen in Table 13. Both DenseNet169 and ResNet50 combination with SVM and Random Forest achieve the highest accuracy of 100%. The testing result of 3-class classification (bacterial, virus, and normal) can be seen in Table 14. The best result is achieved by using ResNet50 with SVM classifier, which achieved 96.5% accuracy. The result of 2-class classification (bacterial and virus) can be seen in Table 15. The best result on 2 class classification was achieved by using ResNet50 with Random Forest, which achieved 97.6% accuracy.

This result and method outperformed previous research on pneumonia detection both in 3 class classification (bacterial, virus, and normal) and 2 class classification (bacterial and virus classification). The comparison of 3 class classification (bacterial, virus, and normal) with previous research can be seen on Table 17, while the comparison of 2 class classification (bacterial and virus classification) can be seen on Table 18.

Table 17. Result Comparison of 3 Class Classification (bacterial, virus, and normal)

Method	Accuracy
CNN Model [27]	90%
DenseNet201 [25]	93.3%
DenseNet169 [8]	95.7%
ResNet50 & SVM	**96.5%**

Table 18. Result Comparison of 2 Class Classification (bacterial and virus classification)

Method	Accuracy
CNN Model [27]	92%
DenseNet201 [25]	95.0%
ResNet50 & Random Forest	**97.6%**

6. CONCLUSION AND FUTURE WORKS

Pneumonia is a lung inflammation with the single largest infectious cause of death in children worldwide. Pneumonia can be detected by using chest x-ray images by radiologists. To help pneumonia diagnosing process, we proposed a high accuracy model of pneumonia classification. A model used in pneumonia detection must be accurate, to prevent misdiagnosis problem. In this research we showed that CNN model combined with machine learning classifier e.g., SVM, Random Forest, can achieve higher accuracy than general CNN model using dense layer or FC Layer as the classifier. The final proposed model reached an accuracy of 99% on bacteria and virus classification using CNN Model with SVM classifier; 97% on bacteria, virus, and normal classification using CNN model with both SVM and Random Forest classifier, outperforming previous research on the unseen dataset from Guangzhou Women and Children's Medical Center, Guangzhou. Hence, this approach can be used by radiologists or novices in pneumonia detection processes. In addition, this model can be used on another chest x-ray-based infection or disease detection e.g., COVID-19 pneumonia, emphysema, cancer, etc.

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