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COMPARATIVE ANALYSIS OF LUNG DISEASES FROM CHEST X-RAY IMAGES USING CONVOLUTIONAL NEURAL NETWORK AND SUPPORT VECTOR MACHINE

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ABSTRACT

The lungs are important in the human respiratory system, regulating body temperature, and protecting against harmful substances. Although the nose is the primary organ for smelling, the lungs can experience disorders. Chest X-ray images are used to diagnose lung diseases, although interpreting them poses significant challenges. This study compares lung diseases using Convolutional Neural Network (CNN) and Support Vector Machine (SVM). CNN is renowned for object recognition, while SVM promises good generalization performance. The research involves preprocessing and comparative analysis of three types of diseases: Covid-19, Tuberculosis, Pneumonia, and Normal. Additionally, the study compares the classification of CNN and SVM using chest X-ray image datasets, aiming to develop an effective algorithm for classifying lung diseases. The results indicate that CNN outperforms SVM with an accuracy of 0.95 compared to SVM's 0.65.

Keywords: Lung Disease, CNN, SVM

ABSTRAK

Paru-paru penting dalam sistem pernapasan manusia, menjaga suhu tubuh, dan melindungi dari zat berbahaya. Meskipun hidung fokus utama penciuman, paru-paru bisa mengalami gangguan. Gambar sinar-X dada digunakan untuk mendiagnosis penyakit paru-paru, meski menafsirkannya tantangan besar. Penelitian ini membandingkan penyakit paru-paru menggunakan Convolutional Neural Network (CNN) dan Support Vector Machine (SVM). CNN terkenal dalam pengenalan objek, sedangkan SVM menjanjikan kinerja generalisasi yang baik. Penelitian ini melibatkan pra-pemrosesan dan analisis perbandingan tiga jenis penyakit: Covid-19, Tuberkulosis, Pneumonia, dan Normal. Selain itu, penelitian membandingkan klasifikasi CNN dan SVM menggunakan dataset gambar sinar-X dada, bertujuan mengembangkan algoritma efektif untuk mengklasifikasikan penyakit paru-paru. Hasilnya menunjukkan CNN lebih unggul dengan akurasi 0.95 dibandingkan SVM yang mencapai 0.65.

Kata kunci: Penyakit Paru, CNN, SVM

INTRODUCTION

The lungs are an important human organ in the human body, especially in the respiratory system (Dwiningrum et al., 2021). Another function of the lungs is to maintain stable body temperature to protect the body from dangerous substances, the nose is the sense of smell, but sometimes the lungs will experience conditions where they do not function normally (Mujahid et al., 2022). Illnesses affecting human organs, particularly the lungs, typically result from factors such as smoking, air pollution, or bacterial infections, which can impair the respiratory system and lead to severe complications (Sembiring et al., 2021). Lung diseases were documented globally in 2019, totaling 212.3 million reported cases, with fatalities reaching 74.4 million (Safiri et al., 2022). A respiratory system weakened by lung disease necessitates careful attention from the patient to alleviate the issue (Hussein et al., 2022). Chest x-ray images are recognized for their potential in monitoring and examining lung diseases like pneumonia, tuberculosis, and COVID-19 (Ismael & Şengür, 2021).

COVID-19, also known as Coronavirus Disease 2019, is an infectious ailment caused by an unprecedented virus (Alom et al., 2020). COVID-19, a disease that emerged in December 2019 in Wuhan, China, is the latest in a series of highly contagious respiratory viral (Astuti et al., 2022) infections that have sparked past epidemics. Its initial appearance raised widespread concern globally, particularly within the healthcare sector (Giri et al., 2021; Phan, 2020). Pneumonia, an infectious ailment triggered by viruses, microbes, fungi, and bacteria, affects the lungs, posing a significant danger that can be life-threatening if not detected early (Tan et al., 2021). In 2010, pneumonia resulted in over 1.1 million hospital admissions and claimed the lives of 50,000 individuals. The majority of pneumonia-related deaths were recorded in patients aged 65 and older (Djoar & Anggarani, 2019). Tuberculosis, an infectious bacterial illness, spreads through direct contact or airborne transmission (Fati et al., 2022). Tuberculosis primarily affects the lungs but can also target other organs in the body such as the kidneys, bones, spine, and brain. It is estimated that nearly 4.3 million individuals will contract tuberculosis in 2020, resulting in approximately 700,000 deaths (Demir et al., 2020).

Chest x-ray images are widely recognized as the primary clinical tool for diagnosing lung diseases (Zulkifli et al., 2022). Nevertheless, interpreting lung conditions from these images presents a formidable challenge, even for experienced radiologists (Bintoro, 2023). The x-ray findings of individuals with COVID-19, pneumonia, and tuberculosis are frequently ambiguous, leading to numerous subjective judgments among radiologists regarding lung ailments (Ayan & Ünver, 2019). Hence, there is a requirement for a supportive system to aid radiologists in diagnosing lung diseases from chest X-ray images (Sapada & Asmalinda, 2023). Within the domain of deep learning image processing, CNN, a pivotal technology, has garnered significant interest. Building upon the considerable success of AlexNet, enhancement models like VGG, ResNet, and InceptionNet persistently evolve, with ongoing research endeavors aiming to achieve the State-of-the-Art status (Hong et al., 2021).

A comprehensive investigation conducted by (Lee et al., 2020) underscores the criticality of addressing lung ailments, particularly COVID-19 and pneumonia. Besides tackling lung-related issues, CNN offers solutions to various medical challenges such as breast cancer detection (Masud et al., 2022; Ragab et al., 2019), brain tumor segmentation (Kumar et al., 2018; Xie et al., 2022), diagnosis of Alzheimer's disease and classification of skin lesions (Ahmad et al., 2020; Aldhyani et al., 2022) among others. Although deep learning in lung disease studies remains scarce. (Sharma et al., 2020) proposed a CNN with a distinct architecture to extract features from chest x-ray images, successfully discerning pneumonia presence. In (Fati et al., 2022) lucidated the application of CNN and ANN for tuberculosis diagnosis, achieving promising results. Meanwhile, (Waheed et al., 2020) expanded the dataset with synthetic data augmentation using CovidGAN, enhancing classification performance to 95% accuracy with ACGAN and CNN. In introduced an end-to-end system employing Inception Recurrent Residual Neural Network (IRRCNN) for COVID-19 detection and region localization from various medical modality images, yielding commendable accuracy. Additionally, (Irfan et al., 2020) xplored deep transfer learning's efficacy in classifying pneumonia from chest x-ray images, demonstrating enhanced performance with slight fine-tuning and achieving notable improvements in area under the curve (AUC).

METHOD

This chapter will provide a general overview of research methods in developing a lung disease classification system from chest x-ray images using the convolutional neural network method which consists of tools and materials, system design, and system testing.

Research Stages

The stages in conducting research start from data collection, initial data processing, model training using CNN and SVM, and conducting model testing. In data collection, the activities carried out were collecting data from the Kaggle website and acquiring chest x-ray image data. The initial data processing stage or preprocessing is to prepare image data into images to enter into CNN and SVM. The model training stage is for the learning process and getting the best model by looking for CNN and SVM parameters that can produce the best accuracy. The final stage is the testing stage to evaluate the best model produced from the research stage.

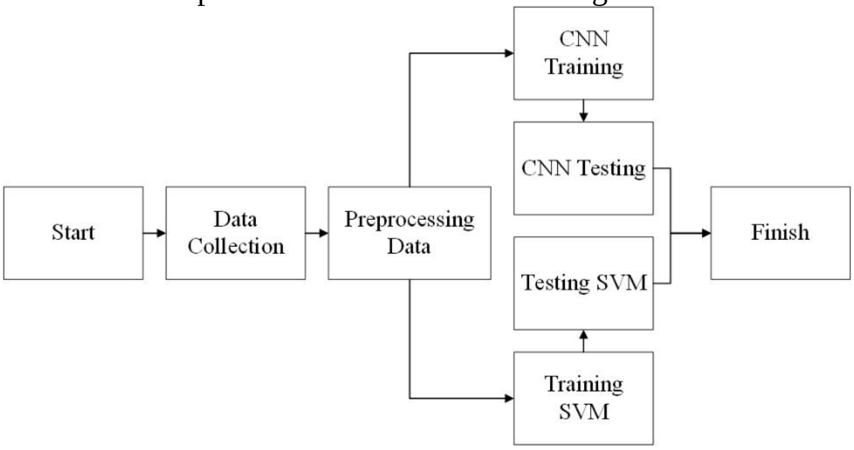


Figure 1. Research Stages.

Data Collection

The chest x-ray image dataset was acquired by downloading it from the website: https://www.kaggle.com/datasets/tawsifurrahman/tuberculosis-tb-chest-xray-dataset. Retrieving the chest x-ray images involves downloading the dataset from the website. Figure 2 shows an example of a chest x-ray image dataset.

Figure 2. Example of a Chest X-Ray Image Dataset.

Then each chest x-ray image is labeled according to the disease. After each image is labeled the data is divided into 4 types, namely COVID-19, Pneumonia, Tuberculosis, and Normal. The flow of labeling chest x-ray image data is shown in Figure 3 and the results of labeling chest x-ray image data are shown in Figure 4.

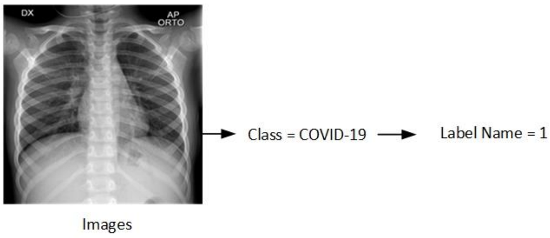


Figure 3. Chest X-ray Image Data Labeling.

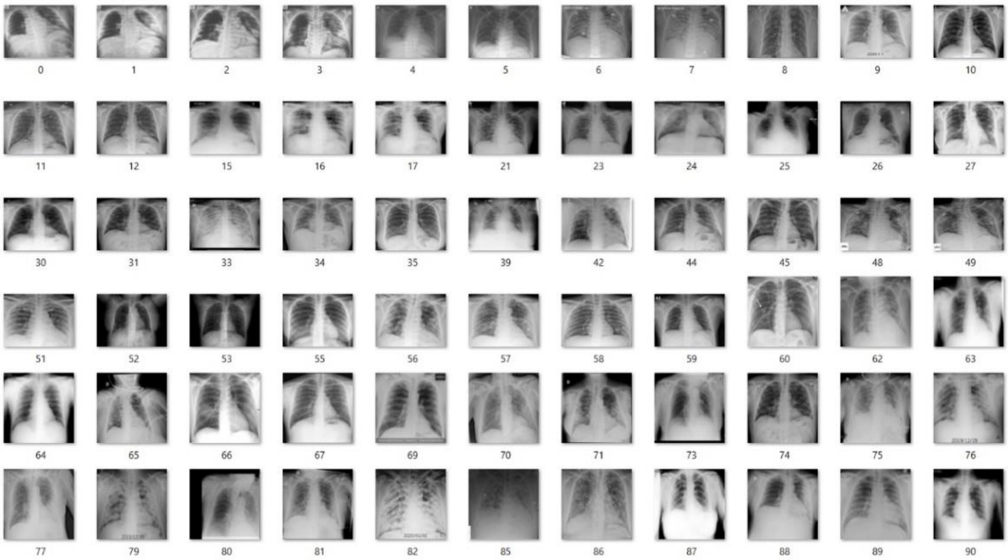


Figure 4. Results of labeling x-ray image data.

From the labeling results, the total data used in this research is presented in Table 1.

Table 1

Total X-ray Image Data

No	Data	Total Data
1	Covid-19	3616
2	Normal	9573
3	Tuberculosis	700
4	Pneumonia	1995

Data Preprocessing

Preprocessing refers to a data manipulation process aimed at preparing the data for use as input in the training phase. In both the training and testing phases, preprocessing occurs in two stages: resizing and data augmentation. In the current research stage, the planned preprocessing steps are as follows:

1. *Resize*

   Resizing is a stage to equalize the image of each data you have, because the data you have still varies in size. In this research the image data will be resized to 256x256 pixels, this size was chosen because it was considered small enough to minimize memory usage but not eliminate the information or features contained in the image. An example of resizing is shown in Figure 5.

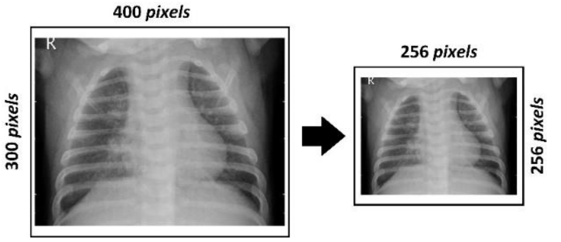
   

   Figure 5. Resize Chest X-ray Data.

2. *Data Augmentation*

   The subsequent preprocessing step, referred to as data augmentation, is implemented due to the limited amount of data obtained during the data collection phase for each class. To achieve satisfactory classification results, a substantial volume of data is required. The data augmentation process includes rescale, shear range, zoom range, rotation range, horizontal flip, and fill mode. An example of data augmentation is shown in Figure 6.

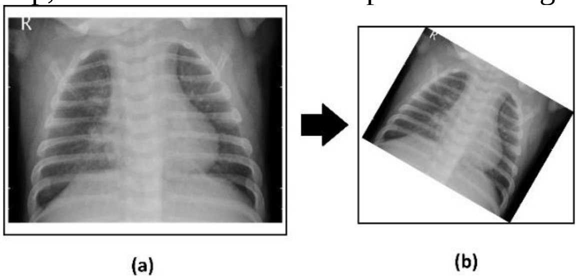
   

   Figure 6. Chest X-Ray Data Augmentation.

Convolutional Neural Networks

In the CNN model, there are many architectures that can be created, each architecture with certain data must go through tuning to get the optimal model. The CNN architecture in this research uses the AlexNet architectural extraction layer (Alex Krizhevsky, Ilya Sutskever, 2007). The architectural design of the CNN model is shown in Figure 7.

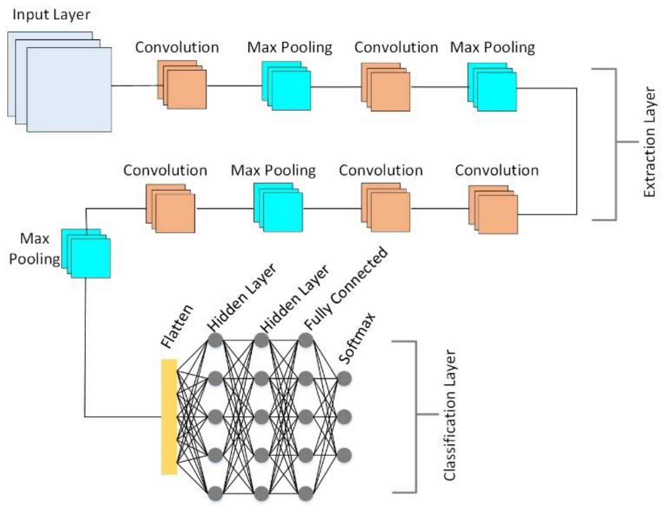


Figure 7. CNN Architectural Design.

In the CNN architecture, there are 2 parts, namely the extraction layer and the classification layer. In the extraction layer there is an input layer, 5 convolution layers, 4 max pooling layers. In the classification layer there is a flatten layer, 2 hidden layers, and a fully connected layer with softmax activation. Table 2 is a detailed design of the CNN architectural model used in this research.

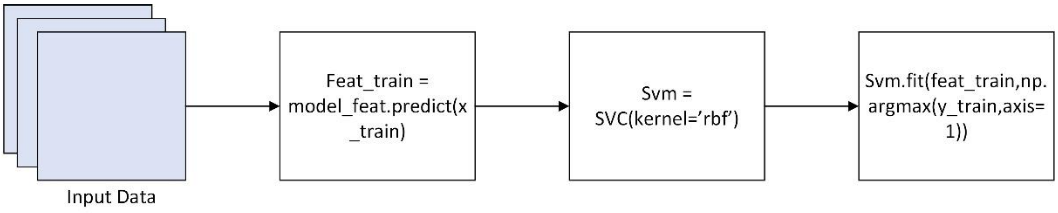
Table 2

CNN architecture model design

Layers	CNN	Output
Input Layer	256x256x3	256x256x3
Convolution Layer	11x11x128	123x123x128
Pooling Layer	3x3 *max pooling*	61x61x128
Convolution Layer	5x5x128	61x61x128
Pooling Layer	3x3 *max pooling*	30x30x128
Convolution Layer	3x3x256	30x30x256
Convolution Layer	3x3x384	30x30x384
Pooling Layer	3x3 *max pooling*	14x141x384
Convolution Layer	3x3x256	14x14x256
Pooling Layer	3x3 *max pooling*	6x6x256
Flatten Layer	-	9216
Hidden Layer	1024, ReLU	1024
Hidden Layer	512, ReLU	512
Output Layer	*num class, softmax*	5

Support Vector Machine

The method after CNN is the use of SVM for classification of chest x-ray image data. The SVM design is shown in Figure 8.



```
Feat_train = model_feat.predict(x_train)
Svm = SVC(kernel='rbf')
Svm.fit(feat_train,np.argmax(y_train,axis=1))
```

Figure 8. SVM Architectural Design.

Figure 8 shows the design of the SVM that will be used. Input data for the SVM program comes from chest x-ray image data. The next step is to make predictions on the x_train data. Initialize the SVM kernel which will be used for character recognition, and then fit the SVM model that has been created.

Evaluation Metrics

The final process is evaluation to determine the performance of the model that has been created. At this stage, it is carried out by classifying all testing data, namely having 4 classes. Then the accuracy, precision, recall and f1-score calculation process will be carried out using the confusion matrix.

1. Accuracy

$$\frac{\sum_{i=1}^{l} \frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i}}{l} * 100\% \tag{1}$$

2. Precision

$$\frac{TP_{class}}{TP_{class} + FP_{class}} * 100\% \tag{2}$$

3. Recall

$$\frac{TP_{class}}{TP_{class} + FN_{class}} * 100\% \tag{3}$$

4. F1-score

$$2 * \frac{Recall_{class} * Presisi_{class}}{Recall_{class} + Presisi_{class}} \tag{4}$$

RESULTS AND DISCUSSION

Model Training Methodology

In a CNN model, each layer for increasing depth is trained using Stochastic Gradient Descent optimization with standard performance parameters (learning_rate=0.001, momentum=0.9, and nesterov=True) employing a batch size of 16, conducted through 5-fold cross-validation with 10 epochs across the complete dataset. Additionally, an effective learning rate scheduling technique called "ReduceLROnPlateau" is incorporated to regulate the relevance of loss. It begins with a learning rate of 0.0001 as required.

PCA feature extraction reduces image dimensions to n_components=153, resulting in a variation ratio of 0.920. The n_components outcome was utilized as training data for SVM. In the SVM model, various parameters including kernel='rbf', C=5, class_weight='balanced', and gamma='scale' were employed, selected based on GridSearch's optimal estimation.

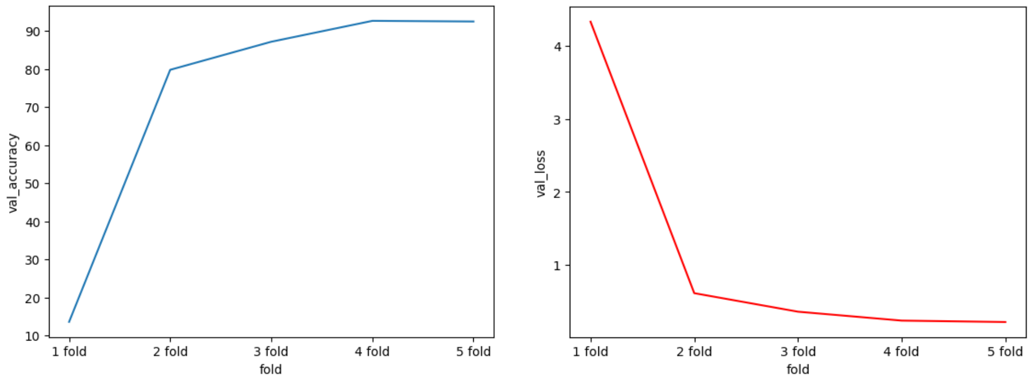
Result of Model CNN and SVM

Research experiments use CNN and SVM models. Table 3 and Figure 9 show the results of the trained and tested models.

Table 3

Training and Testing Accuracy of Model CNN

Model	Training Accuracy	Testing Accuracy
CNN	0.92	0.23



(a) (b)

Figure 9. General Performance of The CNN Classifier.

Table 4 illustrates that the CNN model achieves the highest accuracy scores of 0.92 and 0.23 for training and testing, respectively. The learning curve for the CNN model is depicted in Figure 9. This outcome was anticipated, considering the considerable variability in the X-ray image dataset. The subsequent experiment involves a combination of PCA classification with SVM, as indicated in Table 4.

Table 4

General Performance of The SVM Classifier

Model	Parameter	Accuracy
PCA-SVM	(rbf; C=1; balanced; scale)	0.68

Table 4 displays the outcomes of the PCA-SVM method. The optimal outcomes were achieved using the rbf kernel, C=1, class_weight='balanced', and gamma='scale', yielding an accuracy score of 0.68. Consequently, a confusion matrix and classification report can be provided.

Result of Evaluation Metrics

The proposed model undergoes evaluation through confusion matrices, encompassing metrics such as accuracy, precision, recall, and F1 score. The CNN architecture model was assessed using chest X-ray (CXR) images, totaling 583 in number. Among these, the test dataset comprises 295 COVID-19 cases, 120 Normal cases, 64 Tuberculosis cases, and 104 Viral Pneumonia cases. Table 5 depicts the evaluation outcomes of the CNN model, while the confusion matrix is illustrated in Figure 10.

Table 5

The Performance Evaluation Results of The CNN Model

Model	Accuracy	Precision	Recall	F1-score
CNN	0.95	0.95	0.92	0.93

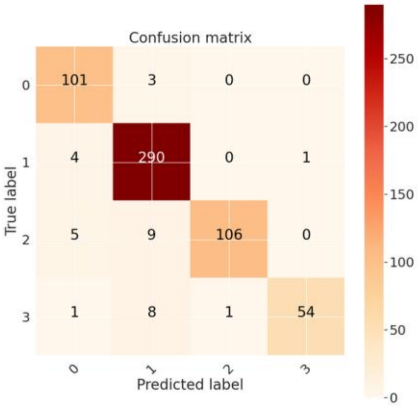


Figure 10. The Performance Confusion Matrix Results of The CNN Model.

Table 6 shows the evaluation results of the combination of PCA and SVM classification, while the confusion matrix for the PCA-SVM model is presented in Figure 11.

Table 6

The Performance Evaluation Results of The SVM Model

Model	Accuracy	Precision	Recall	F1-score
SVM	0.68	0.51	0.48	0.48

Figure 11. The Performance Confusion Matrix Results of The SVM Model.

CONCLUSIONS AND SUGGESTIONS

This study introduces a system designed for comparative analysis of lung diseases using Convolutional Neural Network (CNN) and Support Vector Machine (SVM) methodologies. CNN, a technique renowned in object recognition, incorporates specialized layers—convolution and pooling layers—that facilitate effective feature learning. SVM, on the other hand, is a comparative analysis method rooted in statistical learning theory, ensuring robust generalization performance. The research encompasses two primary processes: preprocessing and comparative analysis. Four disease classes—COVID-19, Tuberculosis, Pneumonia, and Normal—are considered for comparative analysis. Additionally, a comparison between CNN and SVM classification methods is conducted. The research dataset comprises chest X-ray images. The study culminates in the development of an optimized algorithm for classifying lung diseases from chest X-ray images. Results indicate that the CNN model outperforms the SVM model, achieving an accuracy of 0.95 compared to SVM's 0.65.

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