JOIV : Int. J. Inform. Visualization, 8(1) - March 2024 183-189

INTERNATIONAL JOURNAL ON INFORMATICS VISUALIZATION

journal homepage : www.joiv.org/index.php/joiv

Analysis of Pneumonia on Chest X-Ray Images Using Convolutional Neural Network Model ResNet-RS

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***Abstract*—Pneumonia, a prevalent inflammatory condition affecting lung tissue, poses a significant health threat across all age groups and remains a leading cause of infectious mortality among children worldwide. Early diagnosis is critical in preventing severe complications and potential fatality. Chest X-rays are a valuable diagnostic tool for pneumonia; however, their interpretation can be challenging due to unclear images, overlapping diagnoses, and various abnormalities. Consequently, expedient, and accurate analysis of medical images using computer-aided methods has become crucial. This research proposes a Convolutional Neural Network (CNN) model, specifically the ResNet-RS Model, to automate pneumonia identification. The Contrast Limited Adaptive Histogram Equalization (CLAHE) technique enhances image contrast and highlights abnormalities in pneumonia images. Additionally, data augmentation techniques are applied to expand the image dataset while preserving the intrinsic characteristics of the original images. The proposed methodology is evaluated through three testing scenarios, employing chest X-ray images and pneumonia dataset. The third testing scenario, which incorporates the ResNet-RS model, CLAHE preprocessing, and data augmentation, achieves superior performance among these scenarios. The results show an accuracy of 92% and a training loss of 0.0526. Moreover, this approach effectively mitigates overfitting, a common challenge in deep learning models. By leveraging the power of the ResNet-RS model, along with CLAHE preprocessing and data augmentation techniques, this research demonstrates a promising methodology for accurately detecting pneumonia in chest X-ray images. Such advancements contribute to the early diagnosis and timely treatment of pneumonia, ultimately improving patient outcomes and reducing mortality rates.**

***Keywords*—Pneumonia; CNN; ResNet-RS; CLAHE; analysis; augmentation.**

Manuscript received 15 Oct. 2020; revised 29 Jan. 2021; accepted 2 Feb. 2021. Date of publication 31 Mar. 2024.

I. Introduction

Pneumonia, namely lung tissue that is inflamed or swollen, causes mild illness to death at any age and is a significant factor in child mortality. There is a case that a child died as a result of pneumonia within 39 seconds; even though this disease attacks children around the world, the impact and risk are greater in low and middle-income countries where cases and deaths occur in most countries, and currently someone as a patient with pneumonia, the alveoli in the lungs are filled with pineapple and fluid and cause shortness of breath and block oxygen from entering. This disease is commonly caused by bacterial or viral infections such as the popular coronavirus (COVID-19). Pneumonia accounts for 14% of all child deaths under five years of age and killed 740,180 children in 2019[1].

Pneumonia can be treated with antibiotics or antiviral and antifungal medications, but early diagnosis is necessary to prevent complications that can lead to death[2]. One of the supporting diagnostic methods used to diagnose pneumonia is chest X-ray, namely chest radiography, used in diagnosing situations that affect the chest wall structure and internal bones of the chest cavity. Where this radiography uses ionizing radiation in the form of X-rays to depict the shape of a predator, this detection tool can be an obstacle for radiologists because the images are often unclear or overlap with other diagnoses or disorders. Therefore, rapid and accurate medical image analysis with the help of computers is essential in this case. A computer system is needed to assist experts in diagnosing pneumonia from chest X-ray images [3].

Deep learning, a sub-branch of artificial intelligence, is widely used in medical data analysis[4]. In deep learning architecture, automatic disease detection and classification are performed on radiographic images using a Convolutional Neural Network (CNN). In 2020, Pant et al. [5]. researched pneumonia classification [5] using deep learning. The dataset used in their study consisted of 5856 images obtained from

Kaggle. The research proposed a deep learning convolutional neural network method by comparing two models. Model 1 was a U-Net based on ResNet, which achieved accuracy worth 0.82 and recall of 0.99, proving where there is a false negative value, meaning the model has a low degree of predictive errors for negative class values. Thus, this model tends to lead to a picture of pneumonia, and model 2, the U-Net, according to EfficientNet-B4, won a valued accuracy of 0.94 and a recall of 0.93. The high accuracy and recall indicate fewer false positive and false pessimistic predictions. Then, the benefits of both models were combined by taking an ensemble, so that the model could obtain better results than both models individually.

The research conducted in 2020 by Shah et al.[6], used a dataset of 6000 images sourced from Kaggle. This study proposed a method of Deep Learning Convolutional Neural Network (CNN) to classify individuals who are affected by Pneumonia or not. During the data augmentation and preprocessing stage, it was ensured that the performance of the convolutional neural networks and deep neural networks did not suffer from overfitting, so that the results obtained are always logical.

The next study was conducted in 2021 by Nafi'iyah et al. [7], using a dataset sourced from the Guangzhou Women and Children's Medical Center in China. In this study, a Convolutional Neural Network (CNN) method was proposed. Chest X-ray images improved by CLAHE were trained with 8 CNN architecture models. The training results of the eight CNN architecture models each had a loss function value of 0.0057, 0.028, 0.0964, 0.0446, 0.0473, 0.0573, 0.0979, and 0.1407. The highest accuracy result during testing of the eight architecture models was 82.53% using the CNN 35 Layers architecture model, with grayscale input image description with a size of 224x224.

In the next study in 2020 by Khoiriyah et al. [8], a dataset of 5856 images sourced from Kaggle was used. In this study data, the conventional CNN method applies the augmentation technique explained in classifying pneumonia where there are three interconnected layers applied together with changes in the size of the flip and rotation of the augmentation strategy in preventing overfitting. The results of the study show that the argumentation strategy manifests an accuracy value of 83.25% while without augmentation the value was 80.25%. In addition, a study conducted by Nair et al.[9] stated that the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique can help reduce loss and improve model performance. In the study, the Resnet-RS model achieved a training speed 4.7x higher on TPU (5.5x on GPU) compared to the EfficientNet-B5 model when trained together on ImageNet and an additional 130 million semi-labeled images[10].

Based on the previous study, this research proposes a classification of Pneumonia using a CNN architecture using the Resnet-RS model. The Resnet-RS architecture is recommended because it has optimization in terms of performance than other architectures [11]. In the data preprocessing phase, CLAHE technique is used by applying the concept of contrast adjustment. By implementing the CLAHE technique in this study, it is expected to provide the best performance for the Resnet-RS model used in classifying Pneumonia image. Image augmentation techniques are also applied in the preprocessing stage to avoid overfitting during the training process, resulting in a more optimal model[8].

II. Materials and Method

In this phase there is a presentation of the research phase in classifying pneumonia chest X-ray. Below is an overview of the stages of the research. This section consists of work and techniques that aim to apply solutions to categorize research data carried out through various scenarios in examining the influence of different stages of prepositions on the application of augmentation methods that can be implemented through pneumonia disease datasets. The research stage diagram of this research can be seen in Figure 1.

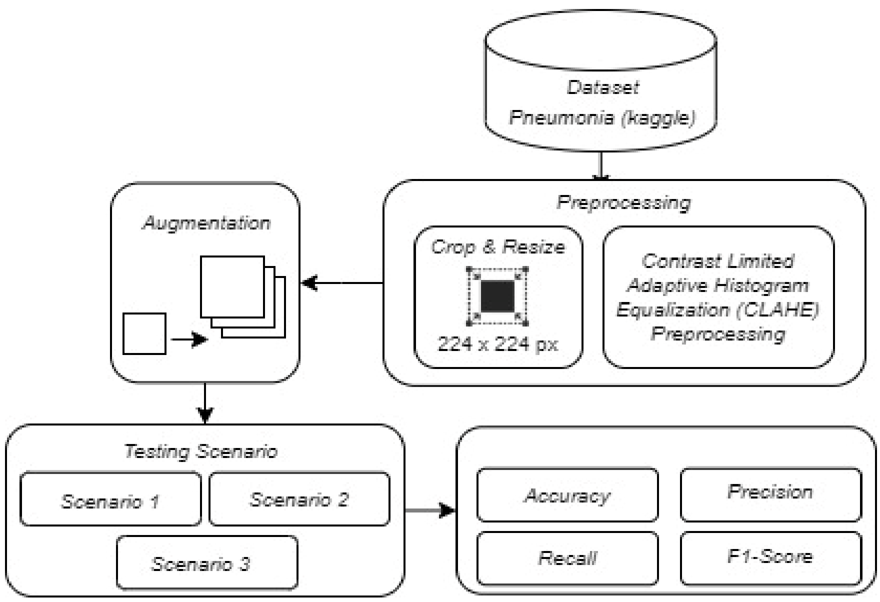

Fig. 1 Research Stage Diagram

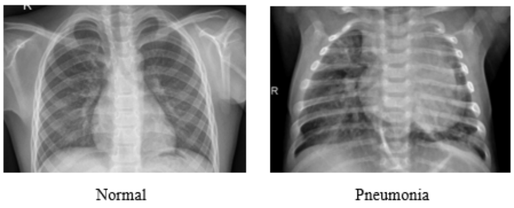

Fig. 2 Sample data from Pneumonia and Normal Disease Classes

A. Dataset

The dataset is integrated through the Kaggle website with the title “Chest X-Ray Images (Pneumonia)”[12]. The cohort was determined through a retrospective cohort of pediatric patients aged 1-5 years through the China Guangzhou Women's and Children's Medical Center. the data set classification contains 3 parts, namely training, validation, and testing datasets and has 5,856 images and in this study has two classes, namely pneumonia and normal.

Chest x-ray datasets total 5856 images. The dataset has been divided into three, namely training data of 89.07%, data test value of 10.65% and data validation of 0.27%, the use of data train in conducting model training so that it is able to recognize the data that has been presented then text data is applied in validating and testing data through the model which is already below is sample data from every class of disease through Figure 2.

B. Preprocessing Dataset

In this study, a preprocessing stage was carried out on the Pneumonia disease dataset by changing the image size to 224 x 224 pixels, which refers to the previous study[7]. The size is adjusted to the input size of the ResNet-RS model. In the next stage, the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique was implemented. The CLAHE technique can provide clearer images in X-Ray Pneumonia images. The preprocessing stage was also carried out by performing data augmentation.

C. Preprocessing CLAHE

CLAHE is a method that aims to reduce noise and improve image features and contrast by making the aberrations clearer between groups of flattened histograms, CLAHE is more natural in appearance and is useful for minimizing noise amplification [13]. Unlike the normal histogram equalizer in the adaptive method there are some histograms that are calculated on different parts of the image. and these histograms are used to redistribute the brightness values of the image[14]. Before applying the CLAHE process, the crop and unsharp masking techniques will be implemented [15]. Subsequently, when the CLAHE technique is utilized on a negative image, it enhances the visual attributes and generates an enriched version with heightened details [16]. Unsharp masking is a technique for sharpening images by reducing the original image with an image that has undergone Gaussian blur (unsharp)[17]. The image resulting from the unsharp masking technique is applied to the CLAHE technique by taking information channels as well as showing the differentiation of clinical symptoms and the green background through RGB images colors. Figure 3 is the sample before CLAHE technique and after CLAHE technique.

D. Data Augmentation

In this stage, a data augmentation process is performed on the Pneumonia disease images aimed at manipulating the number of images using augmentation techniques to be recognizable with different images but still maintaining the core of the image [18]. Several types of augmentation processes are implemented on the preprocessed dataset. The augmentation process is intended to reduce or avoid overfitting in the dataset [19]. Table 1 contains details of the types to be used in the augmentation process.

TABLE I
DATA AUGMENTATION

No	Augmentation	Description	Score
1	Rotation Range	Rotating images within the range of 0º - 360º	90 º
2	Zoom Range	Enlarging within the range of [0 - 1]	0.2
3	Shift Range	Shifting for width and height within the range of [0-1]	0.2
4	Flipping	Performing horizontal and vertical flipping with a Boolean value of True or False	True

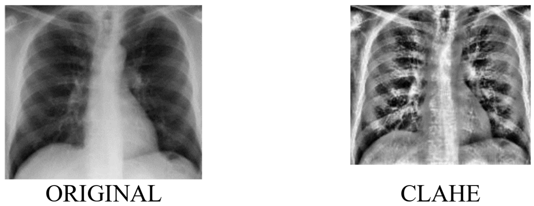

Fig. 3 Sample Data from Normal Disease Classes after CLAHE

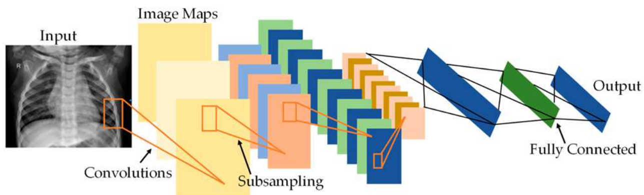

Fig. 4 Illustration of Convolutional Neural Network Architecture [21]

E. Convolutional Neural Network

The Convolutional Neural Network (CNN) is an artificial neural network architecture that aims to classify an image. As per the computer vision concept based on pattern recognition of images, it requires a feature extraction stage to extract the pattern features. The feature extraction stage aims to present image patterns that must be recognized in the features obtained from that stage. One of the advantages of the Convolutional Neural Network is that it can eliminate the pattern extraction stage. In the feature extraction stage, the Convolutional Neural Network uses a Convolutional layer that is used to automatically extract pattern features so that it can execute a generated feature until the classification process [20]. The illustration of CNN can be seen on Figure 4 and the procedural steps involved in utilizing CNN for this research are expounded upon in the following section.

1) Convolutional Layer: The Convolutional Layer is the main and most important layer in CNN modeling, as the convolution operation output occurs in the underlying layer of the main process in CNN. This layer can automatically extract image features. The working principle of the Convolutional Layer is by sliding window and weight sharing.

2) Pooling Layer: Pooling layer is a layer that is placed after the Convolutional layer to reduce the number of parameters and computation time in a neural network. The purpose of the pooling layer is to summarize the information generated by Convolution [22]. The pooling layer works by reducing the feature map of the convolutional layer by extracting important pixels and eliminating noise in the image. There are two types of pooling layers, max pooling, and average pooling. Max pooling is intended to take the maximum value in the matrix when the layer shift process is applied to the activation map and feature map. Average pooling is intended to take the average value in the matrix when the layer shift process is applied to the activation map or feature map[23].

3) Dense Layer: Dense layer is also known as a fully connected layer because each neuron in this layer receives input from every neuron in the previous layer. The main purpose of the Dense layer is to perform a non-linear transformation on the input received from the previous layer and output it to the next layer. This layer is usually added at the end of the convolutional layers, after the feature extraction process has been completed, to classify the image based on the features extracted by the previous layers[24].

4) Dropout Layer: Dropout Layer is a layer that is a regularization technique used to remove or stop input to the next layer. Dropout Layer functions to handle parameters generated from each stacked layer or called overfitting. Dropout is implemented to avoid overfitting by randomly removing some neurons in the fully connected layer[25].

5) Fully Connected Layer: Fully Connected Layer is actually a single layer that consists of nodes that are fully connected to the previous layer[26]. It is also known as a dense layer or a fully connected neural network. The purpose of this layer is to process data in a way that produces the desired output. Hidden layers, which are made up of dense and dropout layers, are added to this layer to reduce overfitting[27]. The activation functions commonly used in this layer are ReLU and Sigmoid. The sigmoid function is used to transform a value into a new value within a specific range[28].

F. Model Architecture Design

The proposed model design is a representation of a program that will be created for the classification of images between Pneumonia and normal cases. At this stage, the proposed model architecture is the ResNet model, specifically the ResNet-RS model. In the implementation stage, the initial layer is the input layer with a size of 224x224 that has been adjusted to the ResNet-RS152 model. This is followed by a fully connected layer with two dense layers, two dropout layers, and an output layer with ReLu activation. The ReLu algorithm has the advantage of being faster during the training and testing process[9]. The next layer then implements Global Average Pooling, which aims to overcome overfitting [29]. Figure 5 shows the proposed ResNet-RS152 architecture model.

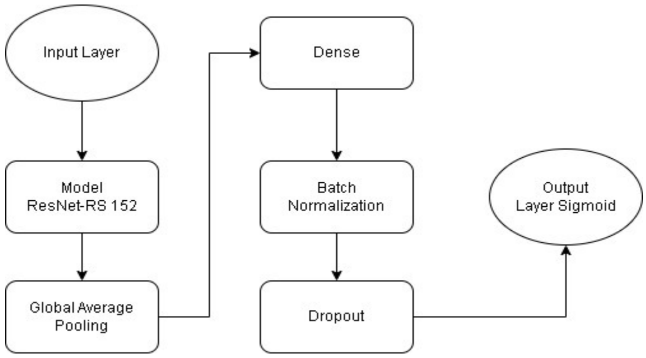

Fig. 5 Model Architecture Design Details

G. ResNet-RS

The architecture model named Residual Network or ResNet namely Artificial Neural Networks introduced by Kaiming He et al [30], in a paper entitled Deep Residual Learning for Image RecognitionResNet-RS is one of the models in the ResNet series. In a study conducted by Irwan Bello et al. in 2021 [10], it was mentioned that ResNet-RS is a family of ResNet architectures that use less memory during training and are 1.7x-2.7x faster on TPU (2.1x-3.3x faster on GPU) than efficientNets on the accuracy-speed pareto curve. The state of the art of ResNet-RS has been shown on Figure 6.

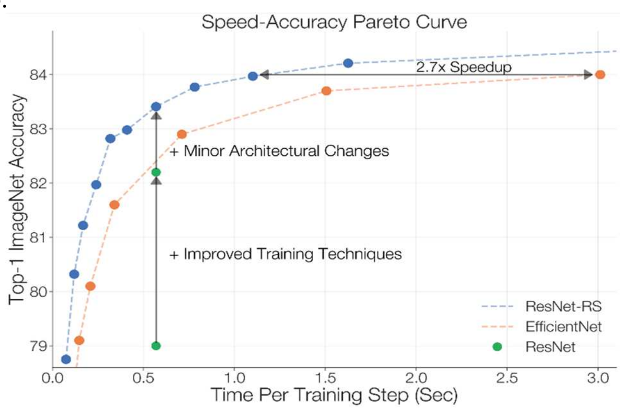

Fig. 6 State of The Art

III. Results and Discussion

This phase tested 3 types of scenarios in examining the impact of the preprocessing technique and the augmentation of the proposed model, namely ResNet-RS. The test applies "Chest X-Ray Images (Pneumonia)", with a focus on momonia and optimal Adam 100 training periods with a beach size of 32 and 0.000003 of learning degrees as well as a "Binary Crossentropy" loss function where gains over all scenarios are compared through aspects of accuracy, precision, loss, recall, and f1-score.

A. Results

The testing scenario consists of three stages. All scenarios are trained using 100 epochs, size 32 and level 0.000003 and applied to the proposed model of scenario. The first scenario trains the original dataset using the ResNet-RS model, second scenario trains the dataset using the ResNet-RS model and implementation of the CLAHE preprocessing technique and the third scenario trains the dataset using the ResNet-RS model, implements CLAHE preprocessing technique, and is further data augmentation. The results of this research can be seen below:

1) Scenario 1: ResNet-RS with Preprocessing. In this first scenario, testing could be conducted using the proposed ResNet-RS model. Testing is performed apply the model that has been proposed in the process viz preprocessed without the CLAHE technique and without augmentation as described before and result can be seen in Figure 7.

2) Scenario 2: ResNet-RS with Preprocessing CLAHE: For the second scenario, testing is performed using the ResNet-RS model added with the CLAHE preprocessing technique without augmentation data to determine the effect of the CLAHE process in ResNet-RS model as describe before and result can be seen in Figure 8.

3) Scenario 3: ResNet-RS with Preprocessing CLAHE and Data Augmentation. For the third scenario, testing is performed using the ResNet-RS model added with the CLAHE preprocessing technique and augmentation process to determine the effect of the CLAHE and augmentation process as describe, and result can be seen in the Figure 9.

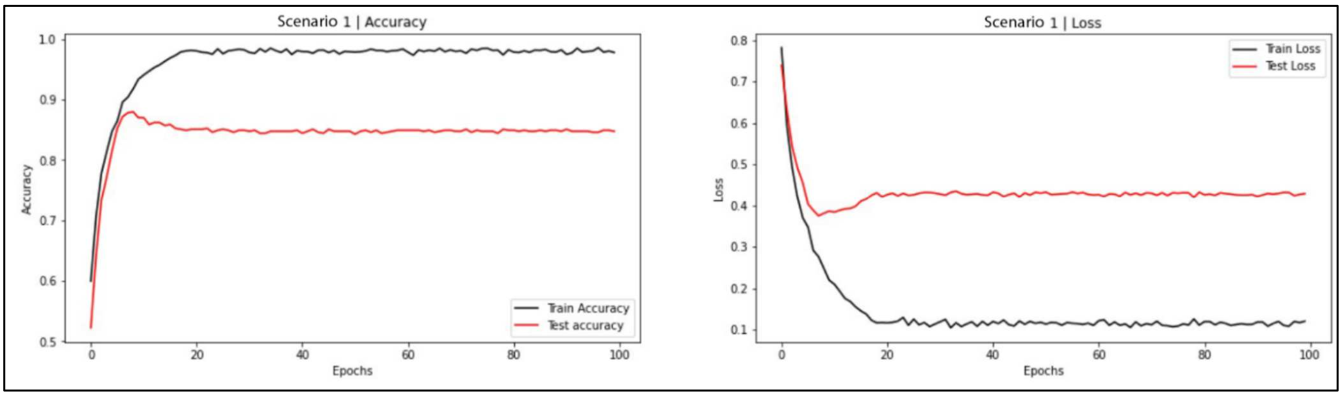

Fig. 7 Result of 1st Scenario Graph of 1st Scenario Accuracy and Scenario Loss

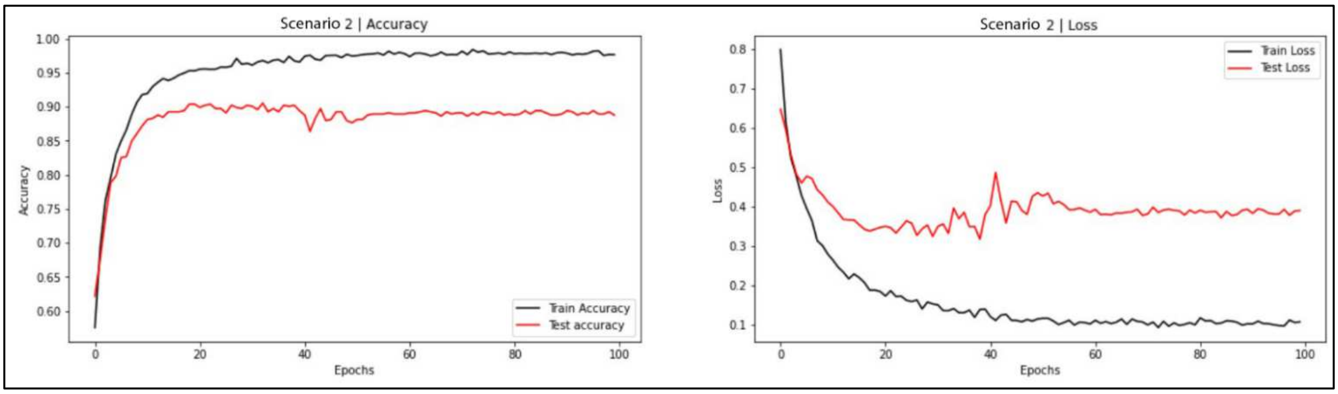

Fig. 8 Result of 2nd Scenerio Graph of 2nd Scenario Accuracy and Scenario Loss

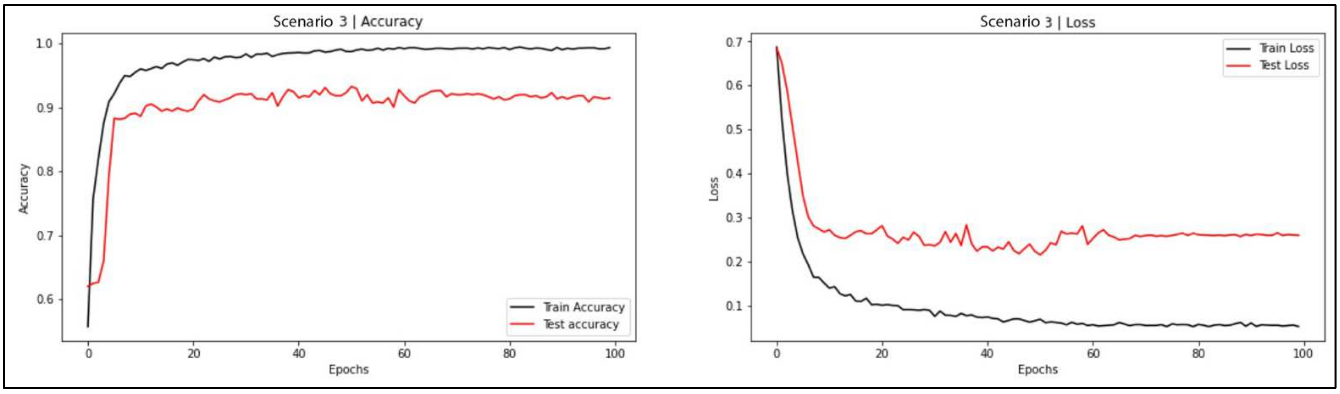

Fig. 9 Result of 3rd Scenario Graph of 3rd Scenario Accuracy and Scenario Loss

B. Discussion

At this stage, a discussion is being held regarding the comparison of the results of the model training that has been conducted in the three scenarios with previous research. This comparison is aimed at identifying the differences produced by each testing scenario influencing the model's performance during the training process. The following is Table 2 regarding the comparison of the results of previous research with the research conducted on the Chest X-Ray Pneumonia dataset.

TABLE II
SUMMARY OF RESEARCH COMPARISON ON PNEUMONIA DATASET

Method	Train		Test		WeightedAvg		
	Acc	**Loss**	**Acc**	**Loss**	**Precision**	**Recall**	**F1-Score**
CNN with CLAHE (Nur Nafi'iyah)			82.53%	0.047			
CNN with Augmentation (Septy Aminatul Khoiriyah)			83.38%	0.6602			
Scenario 1 (ResNet-RS 152 + Original Dataset)	97%	0.1206	84%	0.4273	0.8647	0.8477	0.8392
Scenario 2 (ResNet-RS 152 + CLAHE)	97%	0.1074	88%	0.3890	0.8949	0.8878	0.8890
Scenario 3 (ResNet-RS 152 + CLAHE + Augmentation)	99%	0.0526	91%	0.2598	0.9163	0.9150	0.9154

Based on the testing results using the ResNet-RS model with different scenario methods, Table 2 shows that scenario 3 performed the best in terms of accuracy at 92%, loss at 0.26, precision at 92%, recall at 91%, and f1-score at 91%, compared to scenarios 1 and 2. This scenario proves that the CLAHE preprocessing technique and data augmentation can improve performance. Although scenarios 1 and 2 have a slight difference compared to scenario 3, testing with higher epochs did not yield better results than scenario 3. In scenario 1, there was significant overfitting, as evidenced by the gap between the accuracy on the test data and the training data, which was 13% compared to scenario 3, which used data augmentation, where the gap between the test data and training data was reduced to 7%. This suggests that data augmentation can reduce the level of overfitting in the model.

Previous research using the Chest X-Ray Pneumonia dataset was conducted by Nafi'iyah [7] using a CNN model. In the research conducted by Nafi'iyah [7], 8 CNN model architectures were used, and the CLAHE preprocessing technique was applied. The highest accuracy obtained in the study was 82.53%, with grayscale input image descriptions with a size of 224x224.

In this current study, the same dataset as the previous research conducted by Nafi'iyah [7] was used. Several testing scenarios were proposed to determine the effect of preprocessing using the proposed ResNet-RS152 model. Additionally, this study aimed to investigate the effect of data augmentation on the proposed model. In scenario 2, the same preprocessing technique used by Nafi'iyah [7] was applied, but with a different model architecture, ResNet-RS152. The accuracy obtained in this scenario exceeded that of the previous study, with 97% accuracy on the training data and 88% on the test data.

In scenario 3, the CLAHE technique was applied, along with data augmentation, resulting in 99% accuracy on the training data and 92% accuracy on the test data. This shows that augmentation has an impact and is effective in reducing the level of overfitting in the built model.

IV. CONCLUSION

In this research, the ResNet-RS model was employed to analyze the effects of preprocessing and data augmentation techniques on the classification of Chest X-Ray pneumonia datasets. Several testing scenarios were conducted to investigate the impact of CLAHE preprocessing and augmentation techniques on the model's performance. The results revealed that not all preprocessing techniques had a significant influence on the proposed model. In the first scenario, the presence of overfitting was observed, indicated by a noticeable gap of 13% between the training and testing graphs. However, in scenario 2, the implementation of the CLAHE preprocessing technique demonstrated its effectiveness in reducing overfitting during testing. Furthermore, scenario 3, which incorporated augmentation processes, led to improved image quality inputs, and yielded a remarkable accuracy of 92%. This finding indicates that the inclusion of data augmentation techniques enhanced the model's ability to accurately classify pneumonia cases in Chest X-Ray images. The utilization of the ResNet-RS model, in conjunction with the CLAHE preprocessing technique and data augmentation, proved to be a successful approach for pneumonia detection. This research contributes to the advancement of automated diagnosis and timely treatment of pneumonia based on Chest X-Ray images, thereby improving patient outcomes, and potentially reducing mortality rates.

ACKNOWLEDGMENT

The authors thank the Department of Informatics of Muhammadiyah Malang University for supporting research on "Pneumonia Classification".

REFERENCES

[1] World Health Organization, "No Title," 2021. https://www.who.int/news-room/fact-sheets/detail/pneumonia

[2] and B. I. National Heart, Lung, "No Title," 2022. https://www.nhlbi.nih.gov/health/pneumonia

[3] A. K. Acharya and R. Satapathy, "A Deep Learning Based Approach towards the Automatic Diagnosis of Pneumonia from Chest Radio-Graphs," vol. 13, no. March, pp. 449–455, 2020.

[4] P. Rajpurkar *et al.*, "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning," pp. 3–9, 2017, [Online]. Available: http://arxiv.org/abs/1711.05225

[5] A. Pant, A. Jain, K. C. Nayak, D. Gandhi, and B. G. Prasad, "Pneumonia Detection: An Efficient Approach Using Deep Learning," 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Jul. 2020, doi:10.1109/icccnt49239.2020.9225543.

[6] S. Shah, H. Mehta, and P. Sonawane, "Pneumonia Detection Using Convolutional Neural Networks," 2020 Third International Conference on Smart Systems and Inventive Technology (ICSSIT), Aug. 2020, doi: 10.1109/icssit48917.2020.9214289.

[7] I. Departement, U. I. Lamongan, and I. Technology, "Lung X-Ray Image Enhancement to Identify Pneumonia with CNN 1st N ur N afi'iyah," pp. 421–426, 2021.

[8] S. A. Khoiriyah, A. Basofi, and A. Fariza, "Convolutional Neural Network for Automatic Pneumonia Detection in Chest Radiography," 2020 International Electronics Symposium (IES), Sep. 2020, doi:10.1109/ies50839.2020.9231540.

[9] V. Nair, S. Suranglikar, S. Deshmukh, and Y. Gavhane, "Multi-labelled Ocular Disease Diagnosis Enforcing Transfer Learning," 2021 55th Annual Conference on Information Sciences and Systems (CISS), Mar. 2021, doi: 10.1109/ciss50987.2021.9400227.

[10] I. Bello *et al.*, "Revisiting ResNets: Improved Training and Scaling Strategies," *Adv. Neural Inf. Process. Syst.*, vol. 27, no. NeurIPS, pp. 22614–22627, 2021.

[11] S. Showkat and S. Qureshi, "Efficacy of Transfer Learning-based

ResNet models in Chest X-ray image classification for detecting COVID-19 Pneumonia," Chemometrics and Intelligent Laboratory Systems, vol. 224, p. 104534, May 2022, doi:10.1016/j.chemolab.2022.104534.

[12] Kaggle, "No Title." https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

[13] G. U. Nneji, J. Cai, J. Deng, H. N. Monday, E. C. James, and C. C. Ukwuoma, "Multi-Channel Based Image Processing Scheme for Pneumonia Identification," Diagnostics, vol. 12, no. 2, p. 325, Jan. 2022, doi: 10.3390/diagnostics12020325.

[14] U. Dubey and R. K. Chaurasiya, "Efficient Traffic Sign Recognition Using CLAHE-Based Image Enhancement and ResNet CNN Architectures," International Journal of Cognitive Informatics and Natural Intelligence, vol. 15, no. 4, pp. 1–19, Jan. 2022, doi:10.4018/ijcini.295811.

[15] B. Ramasubramanian and S. Selvaperumal, "A comprehensive review on various preprocessing methods in detecting diabetic retinopathy," 2016 International Conference on Communication and Signal Processing (ICCSP), Apr. 2016, doi: 10.1109/iccsp.2016.7754220.

[16] P. A C, L. S, and M. T. Somashekara, "An Improved Method for Reconstruction and Enhancing Dark Images based on CLAHE," International Research Journal on Advanced Science Hub, vol. 5, no. 02, pp. 40–46, Feb. 2023, doi: 10.47392/irjash.2023.011.

[17] M. Siddhartha and A. Santra, "COVIDLite: A depth-wise separable deep neural network with white balance and CLAHE for detection of COVID-19," pp. 1–25, 2020, [Online]. Available: http://arxiv.org/abs/2006.13873

[18] Z. Mushtaq, S.-F. Su, and Q.-V. Tran, "Spectral images based environmental sound classification using CNN with meaningful data augmentation," Applied Acoustics, vol. 172, p. 107581, Jan. 2021, doi:10.1016/j.apacoust.2020.107581.

[19] P. Naveen and B. Diwan, "Pre-trained VGG-16 with CNN Architecture to classify X-Rays images into Normal or Pneumonia," 2021 International Conference on Emerging Smart Computing and Informatics (ESCI), Mar. 2021, doi:10.1109/esci50559.2021.9396997.

[20] H. T. Thanh, P. H. Yen, and T. B. Ngoc, "Pneumonia Classification in X-ray Images Using Artificial Intelligence Technology," 2020 Applying New Technology in Green Buildings (ATiGB), Mar. 2021, doi: 10.1109/atigb50996.2021.9423017.

[21] T. Rahman et al., "Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X-ray," Applied Sciences, vol. 10, no. 9, p. 3233, May 2020, doi:10.3390/app10093233.

[22] X. Li, F. Chen, H. Hao, and M. Li, "A Pneumonia Detection Method Based on Improved Convolutional Neural Network," 2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), Jun. 2020, doi:10.1109/itnec48623.2020.9084734.

[23] B. D. Satoto, M. I. Utoyo, R. Rulaningtyas, and E. B. Koendhori, "Custom convolutional neural network with data augmentation to predict Pneumonia COVID19," 2020 3rd International Conference on Biomedical Engineering (IBIOMED), Oct. 2020, doi:10.1109/ibiomed50285.2020.9487567.

[24] M. Aledhari, S. Joji, M. Hefeida, and F. Saeed, "Optimized CNN-based Diagnosis System to Detect the Pneumonia from Chest Radiographs," 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Nov. 2019, doi:10.1109/bibm47256.2019.8983114.

[25] H. Sharma, J. S. Jain, P. Bansal, and S. Gupta, "Feature Extraction and Classification of Chest X-Ray Images Using CNN to Detect Pneumonia," 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Jan. 2020, doi: 10.1109/confluence47617.2020.9057809.

[26] İstanbul AREL Üniversitesi, IEEE Engineering in Medicine and Biology Society, Institute of Electrical and Electronics Engineers. Turkey Section, and Institute of Electrical and Electronics Engineers, "Scientific Meeting on Electrical-Electronics, Computer and Biomedical Engineering : 24-26 April 2019 : Istanbul AREL University, Kemal Gözükara Campus - Prof. Dr. Aziz Sancar Conference Hall = Uluslararası Katılımlı Elektrik-Elektronik, Bilgisayar, Biyo," pp. 0–4, 2019.

[27] X. Liu, Z. Wang, L. Zheng, and J. Gao, "Pneumonia Recognition Based on Convolutional Neural Network Feature Map Fusion," Journal of Physics: Conference Series, vol. 1757, no. 1, p. 012047, Jan. 2021, doi: 10.1088/1742-6596/1757/1/012047.

[28] Z. Rustam, R. P. Yuda, H. Alatas, and C. Aroef, "Pulmonary rontgen classification to detect pneumonia disease using convolutional neural networks," Telkomnika (Telecommunication Computing Electronics and Control), vol. 18, no. 3, p. 1522, Jun. 2020, doi:10.12928/telkomnika.v18i3.14839.

[29] A. H. Ahnafi, A. Arifianto, and K. N. Ramadhani, "Pneumonia Classification from X-ray Images using Residual Neural Network," *Ind. J. Comput.*, vol. 5, no. September, pp. 43–54, 2020, doi:10.21108/indojc.2020.5.2.454.

[30] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition", IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770-778, 2016.