Image Enhancement Techniques on Chest X-Ray Images to Improve COVID-19 Detection

Tengku Muaz Abdussalam
Department of Electrical and Information Engineering
Universitas Gadjah Mada
Yogyakarta, Indonesia
tengkumuaz.abs@students.ugm.ac.id

Hanung Adi Nugroho
Department of Electrical and Information Engineering
Universitas Gadjah Mada
Yogyakarta, Indonesia
adinugroho@ugm.ac.id

Indah Soesanti
Department of Electrical and Information Engineering
Universitas Gadjah Mada
Yogyakarta, Indonesia
indah@ugm.ac.id

2022 4th International Conference on Biomedical Engineering (IBIOMED) | 978-1-6654-6079-8/22/$31.00 ©2022 IEEE | DOI: 10.1109/IBIOMED56408.2022.9987990

***Abstract*—The COVID-19 pandemic has claimed many lives. The diagnosis is made to prevent the spread of COVID-19. One of the diagnostic methods that have now become the gold standard is RT-PCR, but this method still has shortcomings in terms of accuracy so it is at risk of causing inaccurate decision-making. The use of medical imaging techniques such as CXR and chest CT scans in the diagnosis of COVID-19 is considered to be able to increase the accuracy of COVID-19 detection so that the risk of making inappropriate decisions can be minimized. Compared to a chest CT scan, CXR is considered superior in terms of price and availability so with these advantages the use of CXR is more effective in diagnosing COVID-19. However, it should be noted that in terms of performance, the chest CT scan far outperformed CXR. For CXR to be better utilized, image enhancement techniques are applied and combined with several classification algorithms. The experiments on two datasets showed that applying BCET (Balance Contrast Enhancement Technique) prior to classifying consistently outperforms other classification methods without enhancement techniques on other compared methods. Moreover, the SVM algorithm achieved the best classification results for all image types in both datasets by scoring the highest AUC compared to other algorithms.**

Keywords*—*COVID-19, CXR, image enhancement

I. Introduction

Coronavirus disease 2019 or commonly referred to as COVID-19 is caused by the SARS-CoV-2 virus and has been declared a pandemic by the World Health Organization (WHO) [1]. According to WHO as of June 2022, the total number of deaths caused by COVID-19 worldwide has exceeded 6.3 million people [2]. Many things are being done to prevent the transmission of COVID-19 such as border restrictions, flight restrictions, social distancing, and keeping stay clean and hygiene. But after all, the virus still spreads rapidly [3].

The role of screening, testing, and contact tracing is very much needed in the diagnosis and control of COVID-19 [4]. Screening is an examination action by giving several questions to the patient being examined while testing is the process of checking whether COVID-19 is in a person's body or not. One of the testing methods that has been considered a gold standard is Real-Time Polymerase Chain Reaction (RT-PCR) [5]. However, RT-PCR provides a low sensitivity value ranging from 42% to only 71% when used to diagnose COVID-19 [6].

The weakness of RT-PCR is in its high false-negative results which sometimes indicate people who should be indicated with COVID-19 as normal or healthy people. Another weakness of RT-PCR is that it is a time and resources consuming process [7]. The weaknesses of RT-PCR are certainly very worrying because they can increase the risk of transmission which lead to more positive cases or even deaths.

Narin [1] showed that the process of diagnosing COVID-19 not only relied on RT-PCR, but also involved a medical imaging approach. Medical imaging techniques Chest X-ray (CXR) and chest Computed Tomography (CT) images or chest CT scans are two approaches that have been widely used in the diagnosis of COVID-19 [8].

The CXR and chest CT scan techniques have their advantages and disadvantages. Chest X-ray (CXR) is a low-cost medical imaging technique. It is a common procedure for the identification of many respiratory diseases compared to MRI, CT, and PET scans [9]. CXR is faster, more common, and more diffuse than chest CT scans [10]. Elmahalawy et al. [11] also stated that the cost involved in the chest CT scan process was more expensive and its application was impractical. By looking at the current state of COVID-19, the existence of CXR with cheaper prices and more available certainly makes CXR more needed and more practical than a chest CT scan. However, Benmalek et al. [7] revealed that the performance of chest CT scans in terms of accuracy was better than CXR. The use of CXR images with poor quality is feared to have an impact on inaccurate classification results.

The objective of this study is to improve the performance of CXR by applying image enhancement techniques combined with an optimal classification algorithm. The main goal of image enhancement is to create an image that is subjectively better than the original image by changing the pixels of the input image.

II. Literature Review

One of the implementations of image enhancement techniques is applied on CXR images. According to Rahman et al. [12], image enhancement is an important image capture technique because this process can improve the quality of the process compared to stunning images. They used different kinds of image enhancement techniques which were then applied to a CXR dataset. The results showed that the gamma

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correction technique outperformed the other image enhancement techniques with an accuracy value of 96.29%.

The selection of the most optimal classification algorithm for COVID-19 is based on and motivated by the large number of algorithms that have been developed and have been implemented at the current time so it becomes a big challenge for medical organizations and health care providers to choose which algorithm is the most optimal in the case of COVID-19. To overcome this problem, Mohammed et al. [13] has carried out benchmarking and testing on 12 different classification algorithms and applied them to a CXR dataset. The purpose of this benchmarking study is to assist health care providers in selecting the optimal classification algorithm for COVID-19 cases. To determine the most optimal COVID-19 classification algorithm, the entropy and TOPSIS approaches were used. The results of this study indicate that among 12 tested algorithms, the SVM algorithm with a linear kernel occupies the top rank with an accuracy of 98.3%. Other studies also reported that SVM performed better classification compared to other algorithms as mentioned in [14][15].

III. Proposed Methodology

This study aimed to apply different image enhancement techniques to CXR images and classify them with different classification algorithms to find out which algorithms perform better and hence become the optimal ones. Figure 1 shows the proposed methodology started from gathering dataset to classification performance evaluation.

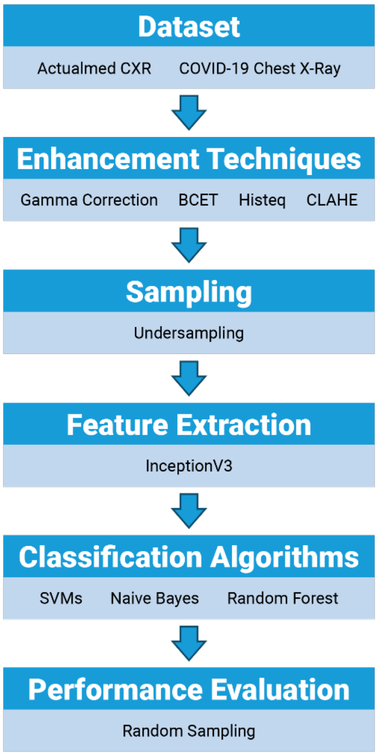

Fig. 1 Proposed methodology

Datasets used for this study were Actualmed CXR Dataset and COVID-19 Chest X-Ray Database, both were collected from GitHub [15] and Kaggle [16], respectively. Actualmed CXR dataset contains 238 images (58 COVID-19 and 180 No Finding) while COVID-19 Chest X-Ray Database contains 13,808 images (3,616 COVID-19 and 10,192 Normal). Two classes are determined, namely COVID-19 and Normal/No Finding. Both datasets had already been reviewed in [18]. Figure 2 and Figure 3 show CXR images from each class.

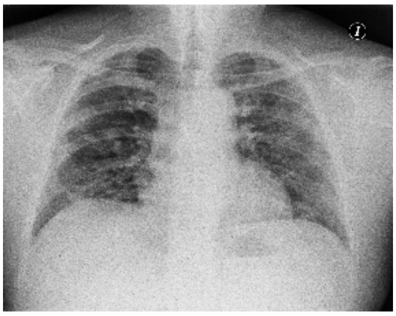

Fig. 2 Example of CXR COVID-19 image

Fig. 3 Example of CXR Normal/No Finding image

In this study, images were enhanced by using four enhancement techniques consisting gamma correction [12], balance contrast enhancement technique (BCET) [12], histogram equalization (HE) [19], and contrast limited adaptive histogram equalization (CLAHE) [20]. Figure 4 shows the result of a CXR image after being applied with different techniques.

Sampling is used to balance the data count for each class. Some sampling methods that are generally used are oversampling, undersampling, and hybrid sampling [21]. In this study, the undersampling method was used to balance the datasets. Undersampling works by reducing the number of majority samples [22]. This step resulted in 58 COVID-19 + 58 No Finding images for Actualmed CXR Dataset and 1000 COVID-19 + 1000 Normal images for COVID-19 Chest X-Ray Database.

Features from the sampled CXR images were extracted using the InceptionV3 model. InceptionV3 is a Google-made CNN model and is already trained to the ImageNet database.

Three classification algorithms were used, namely Support Vector Machine (SVM), Naïve Bayes, and Random Forest. For the SVM algorithm, four kernels are selected; Linear, Polynomial, Radial Basis Function (RBF), and Sigmoid.

Performance evaluations were done by using random sampling method. Each dataset is divided using ratio of 70% for training and 30% for testing, this ratio was also used in [23][24]. For performance metric, Area Under Curve (AUC) is used since these experiments contain binary classification only [25]. Oher performance metric is also used which is consisted of Classification Accuracy (CA), F1-Score, Precision (P), and Recall (R) [26].

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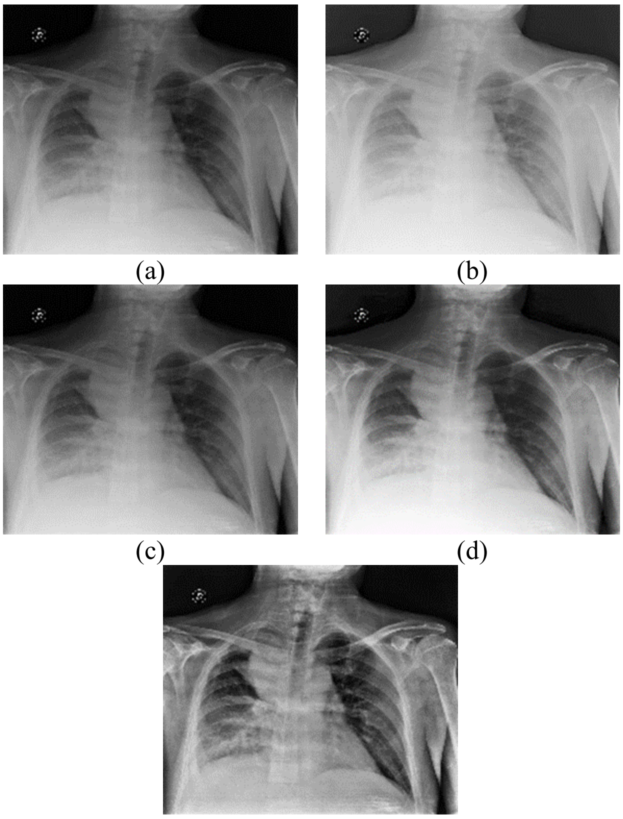

Fig. 4 Example of (a) original CXR images undergoing several image enhancement techniques (b) gamma correction, (c) BCET, (d) HE, and (e) CLAHE

IV. Result and Discussion

Sampled datasets were extracted and classified successfully using three different classification algorithms. The most optimal algorithm was selected by evaluating the AUC score since AUC has been widely used as a performance measure for classification algorithms [27].

Table I provide the classification result of the three algorithms from the Actualmed CXR dataset. The result shows that CXR with BCET enhanced technique SVM with polynomial kernel scored the highest AUC with 85.4% while the original only scored 84.0%.

TABLE I Comparison of the best algorithms using different enhancement techniques from Actualmed CXR Dataset

Enhancement Techniques	Best Algorithms	AUC (%)	CA (%)	F1 (%)	P (%)	R (%)
Original	SVM (Polynomial)	**84.0**	78.9	78.8	79.3	78.9
Gamma correction	SVM (Polynomial)	**83.2**	77.7	77.7	77.8	77.7
BCET	**SVM (Polynomial)**	**85.4**	**79.7**	**79.7**	**80.1**	**79.7**
HE	SVM (Sigmoid)	**83.0**	78.6	78.6	78.6	78.6
CLAHE	SVM (Sigmoid)	**81.7**	76.0	76.0	76.3	76.0

Meanwhile, Table II shows the result of the second experiment using the COVID-19 Chest X-Ray Database which reveals that CXR with HE and CLAHE scored the same highest AUC with 91.8% while the original only scored 91.2%.

TABLE II Comparison of the best algorithms using different enhancement techniques from the COVID-19 Chest X-Ray Database

Enhancement Techniques	Best Algorithms	AUC (%)	CA (%)	F1 (%)	P (%)	R (%)
Original	SVM (RBF)	**91.2**	82.9	82.8	82.9	82.9
Gamma Correction	SVM (RBF)	**91.6**	83.6	83.6	83.8	83.6
BCET	SVM (RBF)	**91.7**	83.5	83.5	83.8	83.5
HE	SVM (Polynomial)	**91.8**	83.8	83.8	84.0	83.8
CLAHE	**SVM (Polynomial)**	91.8	**83.9**	**83.9**	**84.0**	**83.9**

It is interesting to note only the BCET technique that is consistently being ahead by always scoring higher AUC than the original (85.4% and 91.7%) on both datasets. Therefore, this work proves that BCET is the most optimal image enhancement technique on CXR images. Meanwhile, gamma correction, HE and CLAHE work better only to the second dataset.

Furthermore, this work also considers that SVM is the most optimal classification algorithm on CXR since it always scores the highest AUC for every classification using every kind of images (original and enhanced images) from both datasets compared to other algorithms (Naïve Bayes and Random Forest) as shown in Figure 5 and Figure 6.

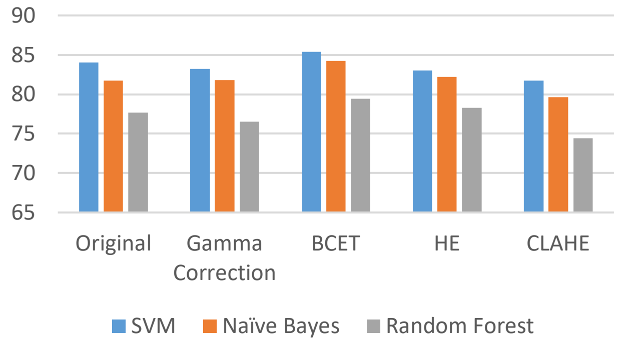

Fig. 5 Comparison of Algorithms AUCs from experiment using Actualmed CXR Dataset

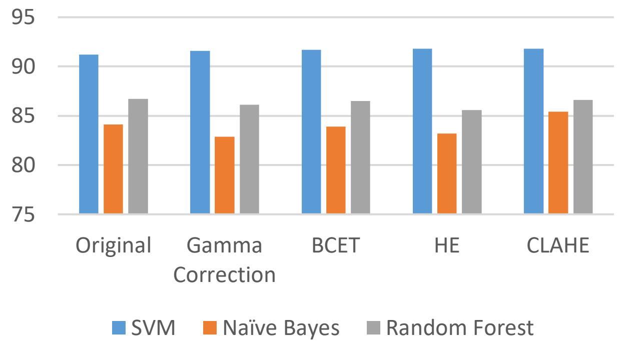

Fig. 6 Comparison of Algorithms AUCs from experiment using COVID-19 Chest X-Ray Database

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V. Conclusion

The application of medical imaging techniques such as CXR and chest CT scans is considered to be able to increase the accuracy of COVID-19 and detection performance. CXR is recommended over chest CT scans because it is cheaper and more available. To improve the performance of CXR, image enhancement techniques have been employed to increase the image quality and combined with several classification algorithms. In general, this study proves that BCET is considered as the most optimal image enhancement technique for CXR images. It is indicated by higher AUC on classification compared to that one without enhancement for two datasets. For the classification algorithm, SVM is selected as the best classification algorithm by scoring the highest AUC for all kinds of classification for both datasets (85.4% and 91.7%).

References

[1] A. Narin, "Accurate detection of COVID-19 using deep features based on X-Ray images and feature selection methods," *Comput. Biol. Med.*, vol. 137, no. March, p. 104771, 2021, doi: 10.1016/j.compbiomed.2021.104771.

[2] World Health Organization (WHO), "WHO Coronavirus (COVID-19) Dashboard," *World Health Organization (WHO)*, 20201. https://covid19.who.int/table

[3] M. E. H. Chowdhury *et al.*, "Can AI Help in Screening Viral and COVID-19 Pneumonia?," *IEEE Access*, vol. 8, pp. 132665–132676, 2020, doi: 10.1109/ACCESS.2020.3010287.

[4] M. Peña *et al.*, "Performance of SARS-CoV-2 rapid antigen test compared with real-time RT-PCR in asymptomatic individuals," *Int. J. Infect. Dis.*, vol. 107, pp. 201–204, 2021, doi: 10.1016/j.ijid.2021.04.087.

[5] S. Soedarsono, A. Febriani, H. Hasan, and A. Widyoningroem, "Management of severe COVID-19 patient with negative RT-PCR for SARS-CoV-2: Role of clinical, radiological, and serological diagnosis," *Radiol. Case Reports*, vol. 16, no. 6, pp. 1405–1409, 2021, doi: 10.1016/j.radcr.2021.03.049.

[6] B. Brogna *et al.*, "Typical CT findings of COVID-19 pneumonia in patients presenting with repetitive negative RT-PCR," *Radiography*, vol. 27, no. 2, pp. 743–747, 2021, doi: 10.1016/j.radi.2020.09.012.

[7] E. Benmalek, J. Elmhamdi, and A. Jilbab, "Comparing CT scan and chest X-ray imaging for COVID-19 diagnosis," *Biomed. Eng. Adv.*, vol. 1, no. March, p. 100003, 2021, doi: 10.1016/j.bea.2021.100003.

[8] G. Jia, H. K. Lam, and Y. Xu, "Classification of COVID-19 chest X-Ray and CT images using a type of dynamic CNN modification method," *Comput. Biol. Med.*, vol. 134, no. April, p. 104425, 2021, doi: 10.1016/j.compbiomed.2021.104425.

[9] F. Munawar, S. Azmat, T. Iqbal, C. Gronlund, and H. Ali, "Segmentation of Lungs in Chest X-Ray Image Using Generative Adversarial Networks," *IEEE Access*, vol. 8, pp. 153535–153545, 2020, doi: 10.1109/ACCESS.2020.3017915.

[10] R. M. Pereira, D. Bertolini, L. O. Teixeira, C. N. Silla, and Y. M. G. Costa, "COVID-19 identification in chest X-ray images on flat and hierarchical classification scenarios," *Comput. Methods Programs Biomed.*, vol. 194, 2020, doi: 10.1016/j.cmpb.2020.105532.

[11] I. I. Elmahalawy, N. M. Doha, O. M. Ebeid, M. A. Abdel-Hady, and O. Saied, "Role of thoracic ultrasound in diagnosis of pulmonary and pleural diseases in critically ill patients," *Egypt. J. Chest Dis. Tuberc.*, vol. 66, no. 2, pp. 261–266, Apr. 2017, doi: 10.1016/j.ejcdt.2016.10.005.

[12] T. Rahman *et al.*, "Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images," *Comput. Biol. Med.*, vol. 132, no. March, p. 104319, 2021, doi: 10.1016/j.compbiomed.2021.104319.

[13] M. A. Mohammed *et al.*, "Benchmarking Methodology for Selection of Optimal COVID-19 Diagnostic Model Based on Entropy and TOPSIS Methods," *IEEE Access*, vol. 8, pp. 99115–99131, 2020, doi: 10.1109/ACCESS.2020.2995597.

[14] E. F. Ohata *et al.*, "Automatic detection of COVID-19 infection using chest X-ray images through transfer learning," *IEEE/CAA J. Autom. Sin.*, vol. 8, no. 1, pp. 239–248, 2021, doi: 10.1109/JAS.2020.1003393.

[15] C. Fernandez-Grandon, I. Soto, D. Zabala-Blanco, W. Alavia, and V. Garcia, "SVM and ANN classification using GLCM and HOG features for COVID-19 and Pneumonia detection from Chest X-rays," in *SACVLC 2021 - Proceedings: 2021 3rd South American Colloquium on Visible Light Communications*, Nov. 2021, pp. 01–06. doi: 10.1109/SACVLC53127.2021.9652248.

[16] Agchung, "Actualmed-COVID-chestxray-dataset," *GitHub*, 2020. https://github.com/agchung/Actualmed-COVID-chestxray-dataset

[17] T. Rahman, "COVID-19 Radiography Database," *Kaggle*, 2021. COVID-19 Radiography Database

[18] B. Garcia Santa Cruz, M. N. Bossa, J. Sölter, and A. D. Husch, "Public Covid-19 X-ray datasets and their impact on model bias – A systematic review of a significant problem," *Med. Image Anal.*, vol. 74, p. 102225, 2021, doi: 10.1016/j.media.2021.102225.

[19] M. Veluchamy and B. Subramani, "Image contrast and color enhancement using adaptive gamma correction and histogram equalization," *Optik (Stuttg).*, vol. 183, pp. 329–337, Apr. 2019, doi: 10.1016/j.ijleo.2019.02.054.

[20] J. B. Zimmerman, S. M. Pizer, E. V. Staab, J. R. Perry, W. McCartney, and B. C. Brenton, "An evaluation of the effectiveness of adaptive histogram equalization for contrast enhancement," *IEEE Trans. Med. Imaging*, vol. 7, no. 4, pp. 304–312, Dec. 1988, doi: 10.1109/42.14513.

[21] M. Zheng *et al.*, "An automatic sampling ratio detection method based on genetic algorithm for imbalanced data classification," *Knowledge-Based Syst.*, vol. 216, p. 106800, Mar. 2021, doi: 10.1016/j.knosys.2021.106800.

[22] Z. Xu, D. Shen, T. Nie, and Y. Kou, "A hybrid sampling algorithm combining M-SMOTE and ENN based on Random forest for medical imbalanced data," *J. Biomed. Inform.*, vol. 107, no. May 2019, p. 103465, 2020, doi: 10.1016/j.jbi.2020.103465.

[23] N. Absar *et al.*, "Development of a computer-aided tool for detection of COVID-19 pneumonia from CXR images using machine learning algorithm," *J. Radiat. Res. Appl. Sci.*, vol. 15, no. 1, pp. 32–43, Mar. 2022, doi: 10.1016/j.jrras.2022.02.002.

[24] A. P. Adedigba, S. A. Adeshina, O. E. Aina, and A. M. Aibinu, "Optimal hyperparameter selection of deep learning models for COVID-19 chest X-ray classification," *Intell. Med.*, vol. 5, p. 100034, 2021, doi: 10.1016/j.ibmed.2021.100034.

[25] R. Hussein and R. Ward, "Energy-efficient EEG monitoring systems for wireless epileptic seizure detection," in *Energy Efficiency of Medical Devices and Healthcare Applications*, Elsevier, 2020, pp. 69–85. doi: 10.1016/B978-0-12-819045-6.00004-2.

[26] A. Kulkarni, D. Chong, and F. A. Batarseh, "Foundations of data imbalance and solutions for a data democracy," in *Data Democracy*, Elsevier, 2020, pp. 83–106. doi: 10.1016/B978-0-12-818366-3.00005-8.

[27] W. Ma and M. A. Lejeune, "A distributionally robust area under curve maximization model," *Oper. Res. Lett.*, vol. 48, no. 4, pp. 460–466, 2020, doi: 10.1016/j.orl.2020.05.012.

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