



Image classification system for COVID-19 patient X-Ray results using median filter with deep learning method

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Abstract - An image is a representation of an object that is rewritten on a medium with specific values (intensity) and has x and y coordinates. X-ray images are one type of medical image that can be used to detect and study a disease. However, X-ray images can sometimes appear blurry, making interpretation a bit challenging. Furthermore, there is variation in X-ray attenuation between normal tissue and tissue affected by a disease. By using the median filter and implementing deep learning as a method for classifying images based on feature extraction and weights in artificial neural networks. The stages carried out include preprocessing, with training and testing, feature extraction using layers of artificial neural networks that have undergone the filtering process. Then, a custom classifier layer is created to train the classification of COVID and normal classes using data from bottleneck.npy. The results of training and testing yielded an average accuracy of 95%, while the F1 Score evaluation result was 0.9.

Keywords: classification, deep learning, F1 score method, image processing, lung X-ray

1 Introduction

Medical imaging is the technique and process of creating a visual representation of the internal body for analysis and medical intervention of organ or tissue function (physiology). Medical imaging can also be defined as a series of non-invasive techniques that produce images of the body's internal aspects. Medical imaging employs X-ray radiographic technology, magnetic resonance imaging, medical ultrasonography, endoscopy, and nuclear medicine functional imaging techniques such as PET (Positron Emission Tomography) and SPECT (Single Photon Emission Tomography). Digital images with noise can lead to issues such as unclear interpretations, thereby reducing the information contained within the image and potentially leading to misdiagnoses.

The risk associated with digital images containing noise can be minimized through image processing. Digital image processing, in general, serves the purpose of visualization and analysis. For visualization purposes, this can involve image enhancement to sharpen and image restoration to repair. Image enhancement aims to improve image quality and highlight specific features. Meanwhile, for analysis purposes, the computer is expected to recognize desired objects, including document analysis, texture analysis, biometric analysis, and object recognition.

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Numerous studies have been conducted to filter images using various methods. For instance, the median filter can eliminate noise in lung images, such as white spots around the lungs, resulting in clearer images. However, some studies suffer from the limitation of using a single type of filter. Research on filtering processes was also undertaken by Hamida in 2017, employing a Gaussian low-pass filter to remove noise with a normal distribution. This is often found in images resulting from the digitization process using a camera, albeit at the cost of using two filter types. The study employs X-ray lung images with diverse image conditions.

According to Listyalina's 2017 research titled 'Improving the Quality of X-Ray Images as a Medium for Lung Cancer Detection,' the software design to enhance X-ray image quality involves stages like pre-processing, median filtering, and adaptive histogram equalization, which were then analyzed. In implementing the Gaussian Filter Method for Noise Elimination in Images Using GPU, it was recommended to use median filters, mean filters, Gaussian filters, alpha-trimmed filters, adaptive median filters, and minimum filters to improve image quality. Non-Kernel filters, such as the median filter and Wiener filter, are employed.

In edge detection analysis, changes in the image of the fetus are detected to form an image object's edge, which aids in detection. The technique is used to discern intensity differences, utilizing filters such as mean and median filters. The mean filter is a linear filter that refines and eliminates noise by replacing pixel values with the average of neighboring pixel values. Image processing, particularly powered by deep learning, can solve these issues. Deep learning's capacity to extract clinical features and laboratory results can enable earlier Covid-19 detection.

Deep learning's implementation with image classification enables the sorting of images based on feature extraction and weights using artificial neural networks. This technique is not limited to sorting but can also predict an image's group based on training. Image processing with deep learning includes Convolutional Neural Networks, Residual Neural Networks, Dense Neural Networks, etc. This research utilizes deep learning through the bottleneck method and the CNN algorithm as a feature extractor. The bottleneck method is efficient, extracting features only once but yielding satisfactory results. According to a Keras blog tutorial titled 'Building Powerful Image Classification Models Using Very Little Data' by Chollet in 2016, this method can achieve accuracy rates of over 90%. Keras, an open-source framework supported by PlaidML, is chosen for this purpose due to its flexibility and GPU support, which accelerates computation compared to CPU."

1.1 Theoretical basis

The digitization process through computed radiography (CR) involves converting an analog system in conventional radiography into digital radiography by using photostimulable imaging plates to acquire data and display parameters from images that can be manipulated by a computer. The components of Computed Radiography include:

- 1 Imaging Plates: These are film plates capable of storing X-ray energy, which can be released through a scanning process using a laser.
- 2 Cassette: The cassette used in computer radiography is made of carbon fiber with an aluminum back, serving as protection for the Imaging Plate.
- 3 Image Reader: The image reader serves to process images obtained from the imaging plate, utilizing a laser scanner for reading.
- 4 Image Console: This component processes images using a computer with specialized software for medical imaging. Images can be processed to enhance their quality and improve their display.
- 5 Imager (Printer): If printing of the image is desired, it can be sent to the imager section to be printed as required. The imager functions as an image printer. Unlike traditional methods, this

printing process doesn't require a darkroom and can be performed directly using a dry imager, eliminating the need for darkroom facilities and chemicals like fixer and developer, resulting in a cleaner workplace.

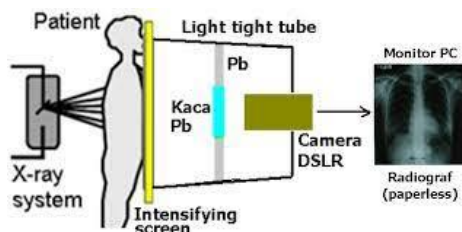


Fig. 1. Image Acquisition Process in Computed Radiography

Figure 1 illustrates the image acquisition process in Computed Radiography technology. X-ray beams that pass through the patient are captured by the imaging plate. The imaging plate, a crucial component of computed radiography, replaces the function of the film screen in conventional radiography. On the imaging plate, X-rays are stored as photo-stimulable phosphor (PSP) and then converted into digital data. Mechanically, the imaging plate is then transferred to the image reader, which functions as both a reader and image processor. Within the image reader, data from the imaging plate is scanned using a laser, releasing visible light from the plate. The resulting image is then displayed on a monitor screen. Meanwhile, the imaging plate proceeds to the data erasure section for cleaning, allowing for reuse. The image reader is accompanied by an image console, which is a monitor used to display images read by the image reader. The image console is a specialized computer for medical imaging, equipped with menus to support image processing tasks, including adjusting density, sharpness, and contrast of radiographic images. The final step in the process involves distributing processed images from the image console to the image recorder. This step includes storing and outputting images onto compact disc media.

An image is a two-dimensional signal perceivable by the human visual system. From a mathematical perspective, an image represents a continuous function of light intensity on a 2D plane. The object reflects light after being illuminated by a light source. This light reflection is captured by optical devices like the human eye, cameras, scanners, resulting in the formation of the image, which is essentially the shadow of the object. Digital images are formed through a process called quantization. Just as with 1-dimensional signals, this involves sampling analog signals. In the case of images, spatial domain sampling is performed, converting the analog image into discrete dots of information. Each dot, the smallest unit of a digital image, is referred to as a pixel. This digitization can be done using digital cameras or scanners.

2 Materials and methods

Digital image representation is formed by a collection of dots known as pixels (picture elements). Each pixel is represented as a small square and possesses a positional coordinate. The coordinate system assigns coordinates represented as 'x' for row position and 'y' for column position to each pixel. A digital image is expressed as a function $f(x, y)$, where 'x' and 'y' are spatial coordinates, and 'f' represents the gray or color information from the image at those coordinates. For grayscale images, 'f' values range from 0 to 255, given an 8-bit depth. Image size is indicated by limited 'x' and 'y' values. Quantization, a procedure to convert continuous signals into discrete forms, is used to create digital signals. In images, this quantization process involves making the image intensity values discrete by quantizing them into integer values. Binary images have two intensity values, 0 (black) and 1 (white).

In color images, similar principles apply, but black is represented by three basic color elements: red (R), green (G), and blue (B). The research described in this paper is quantitative in nature and employs secondary data in the form of lung CT scan images. The proposed algorithm undergoes various stages, including training and testing deep learning architectures. The algorithm's performance is evaluated after subjecting the data to an automatic detection process facilitated by deep learning. The algorithm's performance is measured in terms of automatic detection accuracy, comparing algorithmic outputs with actual diagnostic results.

The study uses secondary data, specifically lung CT scan image data. The input consists of thorax/lung X-ray image files with dimensions of 2048x2048 pixels. The dataset includes three classes: normal lung images, lung cancer images, and lung effusion images, each containing three examples. These chest X-ray images were obtained digitally from Dharmais Hospital in Jakarta.

The research tool used was a laptop equipped with a Core-i5 processor and 4GB of RAM, running Matlab software. Matlab supports data processing tasks such as pre-processing, resizing, cropping, and filtering. The image data processing plan involves transforming image data into deep learning input during the training stage and assessing performance during the testing stage, utilizing the 10-Fold cross-validation method. Performance assessment involves using the accuracy parameter.

The research progressed through several stages, as depicted in Figure 2. These stages include data collection, selection of lung image results, and filtering using Median, Maximum, Minimum, and Average filters. The research results are analyzed in stages to determine the best filtering outcomes. The research method involves preprocessing, image data filtering, feature extraction, and classification. Preprocessing rescales intensity values to a range of -1 to 1. Filtering aims to eliminate noise from X-ray images using the median filter. Feature extraction involves employing the ANN VGG16 (Visual Geometry Group Artificial Neural Network with 16 weighted layers) to extract features. These extracted features are then used as input for the classifier layer, enabling the deep learning model to differentiate between classes. The method is designed for both training and testing stages, and the 10-Fold cross-validation method is used for performance assessment, measuring accuracy.

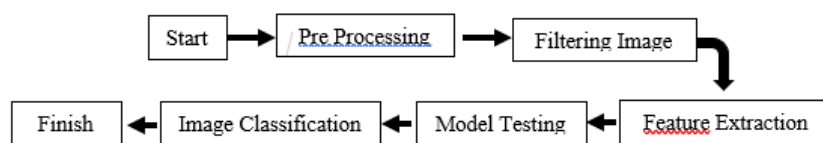


Fig. 2. Flowchart Design System

3 Result and discussion

The testing of the data is carried out using a feature extractor with a variable containing the VGG16 model (model2), to which the predict_generator() function is added. The predict_generator() function is populated with the dataset variables. For testing the classes, a variable containing the trained model, known as the model variable, is utilized. The model variable is integrated into the predict_classes() function. The predict_classes() function incorporates the feature extractor variables. Subsequently, the array containing class predictions is transformed into a one-dimensional matrix using the flatten() function. Data processing is conducted after the completion of the prediction process.

The subsequent step involves storing the raw prediction data into a comma-separated value (.csv) file. In this raw data, predictions and labels are represented using numerical values: 0 for COVID and

1 for Normal. The data is further processed to replace the numerical values with COVID and Normal labels, utilizing the DataFrame functionality from the pandas module.

After the labels are converted to COVID and Normal, the prediction results are visualized. This is accomplished by displaying the prediction outcomes using the crosstab function of the pandas module, which presents the results in a tabular format. Additionally, the prediction results are transformed into a graphical representation using the heatmap function from the Seaborn module. This heatmap simplifies the calculation of result accuracy, as illustrated in Figure 3.

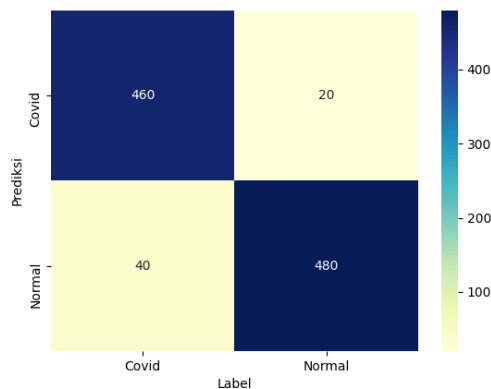


Fig. 3. Prediction Results

The pre-processing of the dataset used as input for the VGG16 deep learning model's system requires three channels. However, grayscale images consist of only one channel. Consequently, the default model handles this by replicating the first channel to create three identical channels, each with the same intensity values. This process is depicted in Figure 4.

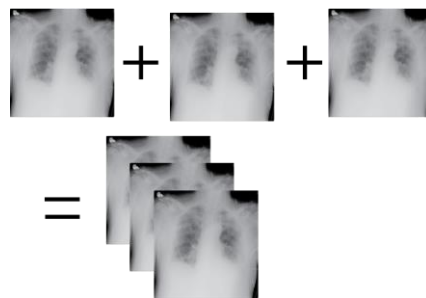


Fig. 4. Illustration of Three Grayscale Channels

Training for COVID-19 image detection involves entering data into the layer intended for training, in the form of a feature map resulting from the feature extraction of the VGG16 deep learning model without its top layer, as illustrated in Figure 5.

The outcomes of the training in this study manifest as a trained model, indicated by its weight and stored with the '.h5' extension. Files bearing the '.h5' extension are recognized as HDF5 files, denoting Hierarchical Data Format version 5—a format utilized for data storage and management. Beyond the model, the results encompass a comprehensive training history spanning from the initial epoch (0th) to the final epoch (100th). The progression of training is visually represented in Figure 6.

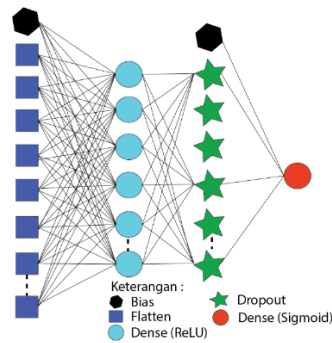
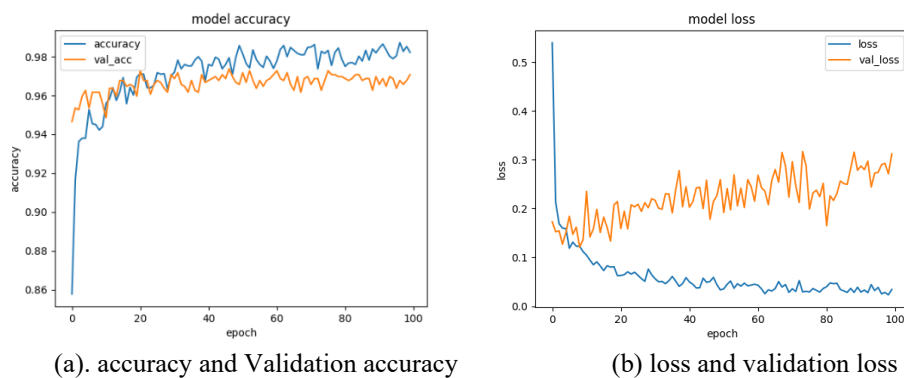


Fig. 5. Visualization of Top-Layer JST Nodes



(a). accuracy and Validation accuracy

(b) loss and validation loss

Fig. 6. Training Progression

The study's test results are presented through a display of the confusion matrix generated by the crosstab module. This presentation is further enhanced by heatmaps from the Seaborn module and Microsoft Excel files. The crosstab module facilitates the depiction of both label and prediction data within a comprehensive table, enabling straightforward computation of test accuracy and error rates. The outcomes of the crosstab analysis are encapsulated in a table format, as illustrated in Figure 7.

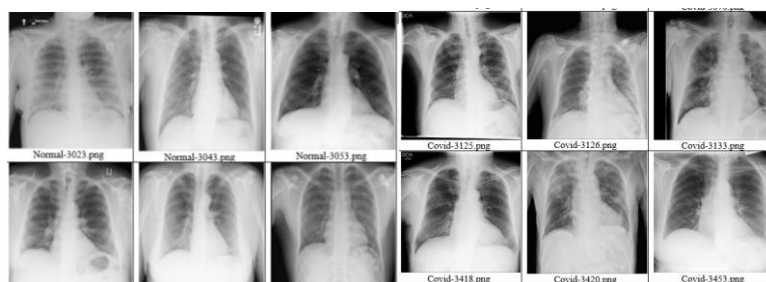


Fig. 7. Sample Covid Image Data with Predictions and File Names

After knowing the test results, then calculate the accuracy and F1 Score to see the level of accuracy and success of the model that has been trained.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} \quad (1)$$

$$\text{Accuracy} = \frac{460 + 480}{460 + 40 + 20 + 480} = \frac{940}{1000} = 94\%$$

Calculate precision using the following equation:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (2)$$

$$\text{Precision} = \frac{460}{460 + 40} = \frac{460}{500} = 0,92$$

And to calculate recall with the following formula:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

$$\text{Recall} = \frac{460}{460 + 20} = \frac{460}{480} = 0,958$$

Then calculate the F1 Score using the following formula:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

$$\text{F1 Score} = 2 \times \frac{0,92 \times 0,958}{0,92 + 0,958} = 2 \times \frac{0,88136}{1,878} = \frac{1,76272}{1,878} = 0,9$$

The trained model achieved an accuracy value of 94% and an F1 score of 0.9. Additionally, the accuracy attained during data validation in training reached 97%, and the accuracy rate for testing data was 94%. These figures collectively attest to the model's strong performance. Notably, the proximity between the accuracy achieved in data validation during training and the accuracy of the testing phase underscores the model's robustness.

4 Conclusion

The classification of hard-based X-ray images is conducted using PlaidML as the backend, employing the bottleneck method. This process is facilitated through the Anaconda application, supplemented by requisite modules, datasets, and Artificial Neural Network (ANN) models for training and testing. PlaidML provides hardware support for this endeavor.

The training and testing phases encompass pre-processing and feature extraction, leveraging the VGG16 architecture's JST layer with convolution and pooling excluded. This produces 'bottleneck.npy' data, which is subsequently used to construct a dedicated classifier layer. This classifier is trained to classify COVID-19 and normal classes. The achieved accuracy levels are noteworthy: during training, validation, and testing stages, accuracy rates of 99%, 97%, and 94% are

attained respectively. The F1 Score for testing stands at 0.939. The proximity between accuracy values in data validation and test accuracy underscores the model's consistency. This collective evidence affirms the competence of the trained model."

References

- [1] Acharya, Tinku dan Ray, Ajoy K.. "Image Processing: Principle and Applications". New Jersey: John Wiley & Sons, Inc., Hoboken, Canada: simultaneously, ISBN-13 978-0-471-71998-4 (cloth: alk. paper) ISBN-10 0-471-71998-6 (cloth: alk. paper) Tahun 2005
- [2] Petrou, Maria dan Bosdogianni, Panagiota.. "Image Processing: The Fundamentals". Singapore: JOHN WILEY & SONS, LTD, ISBN 0-471-99883-4 Tahun 1999
- [3] Chollet, Francois.. "Deep Learning with Python". Shelter Island: Manning. ISBN 9781617294433 Tahun 2017
- [4] Clara, Serafim, dkk.. "Implementasi Seleksi Fitur Pada Algoritma Klasifikasi Machine Learning Untuk Prediksi Penghasilan Pada Adult Income Dataset". Seminar Nasional Mahasiswa Ilmu Komputer dan Aplikasinya (SENAMIKA) Hal. 741-747. e-ISBN 978-623-93343-3-8 Tahun 2023
- [5] Dewi, Ni Luh Gede M.U., "Analisis Perbandingan Filter Median, Filter Maksimum-Minimum dan Filter Rerata menggunakan Citra Rontgen Paru". Skripsi. Universitas Respati Yogyakarta. Tahun 2022
- [6] Rahman, Tawisfur et al. "Exploring the Effect of Image Enhancement Techniques
- [7] Arfian.. "Implementasi Convolutional Neural Network terhadap Transportasi Tradisional Menggunakan Keras". Tugas Akhir. UII Tahun 2018
- [8] Gao Bolin and Pavel Lacra, "On the Properties of the Softmax Function with Application in Game Theory and Reinforcement Learning". arXiv:1704.00805v4 [math.OC]. 21 Agustus Tahun 2018
- [9] Dartamasia,. "Deteksi Penggunaan Masker menggunakan Xception Transfer Learning". Jurnal INSTEK (Informatika Sains dan Teknologi) Volume 5 Nomor. 2, Oktober 2020 P –ISSN: 2541-1179, E-ISSN : 2581-1711 Tahun 2020
- [10] Pereira, Rodolfo M. et al. "COVID-19 identification in chest X-ray images on flat and hierarchical classification scenarios". *Computer Methods and Programs in Biomedicine* 194 (2020) 105532. <https://doi.org/10.1016/j.cmpb.2020.105532>. Tahun . 2020
- [11] Wulandri, Putri. "Klasifikasi Tingkat Keganasan Kanker Serviks Menggunakan Metode Deep Residual Network (ResNet)". Skripsi. UIN Sunan Ampel Surabaya Tahun 2019..
- [12] S. -m. Yoo et al., "Structure of Deep Learning Inference Engines for Embedded Systems," *International Conference on Information and Communication Technology Convergence (ICTC)*, Jeju, Korea (South), 2019, pp. 920-922, doi: 10.1109/ICTC46691.2019.8939843. Tahun 2019
- [13] Rahmadewi, Reni, dkk.. "Klasifikasi Penyakit Paru Berdasarkan Citra Rontgen dengan Metode Segmentasi Sobel". *Jurnal Teknik Elektro* Vol. 5 No. 1 Maret 2016. ISSN: 2302 – 2949. DOI: 10.20449/jnte.v5i1.174 Tahun 2016

- [14] Yudistira, Novanto, dkk.. “Deteksi Covid-19 Citra Sinar-X Dada Menggunakan Deep Learning yang Efisien”. *Jurnal Teknologi Informasi dan Ilmu Komputer (JTIIK)* Vol. 7 No. 6 hlm. 1289-1296. e-ISSN: 2528-6579. DOI: 10.25126/jtiik.202073651 Tahun 2020
- [15] Gulli, Antonio dan Sujit pal. “Deep Learning with Keras”. Birmingham: Published by Packt Publishing Ltd. ISBN 978-1-78712-842-2 Tahun 2017.
- [16] Wani, M. Arif, et al.. “Advances in Deep Learning”. *Studies in big data* vol. 57. Singapura: MetaPress dan Springerlink. ISBN 978-981-13-6794-6 Tahun 2020
- [17] Shafira, Tiara. “Implementasi Convolutional Neural Networks untuk Klasifikasi Citra Tomat Menggunakan Keras”. Tugas Akhir. UII Tahun 2018.
- [18] on COVID-19 Detection using Chest X-rays Images”. Preprint to submitted to Elsevier. 25 November Tahun 2020.
- [19] Susilo, Supriyadi, Sutikno, Sunarno, & Setiawan, R. (2014). RANCANG BANGUN SISTEM PENANGKAP GAMBAR RADIOGRAF DIGITAL BERBASIS KAMERA DSLR. *Jurnal Pendidikan Fisika Indonesia*, 10, 66–74. <https://doi.org/10.15294/jpfi.v10i1.3052>