Detection of Covid Chest X-Ray using Wavelet and Support Vector Machines

Ni Wayan Sumartini Saraswati[1*], Ni Wayan Wardani[2], and I Gusti Ayu Agung Diatri Indradewi[3]

[1]Informatics Engineering, STMIK STIKOM Indonesia, Denpasar, Bali, Indonesia
[*]sumartini.saraswati@stiki-indonesia.ac.id
[2]Informatics Engineering, STMIK STIKOM Indonesia, Denpasar, Bali, Indonesia
niwayan.wardani@stiki-indonesia.ac.id
[3]Informatics Engineering, STMIK STIKOM Indonesia, Denpasar, Bali, Indonesia
diatri.indradewi@stiki-indonesia.ac.id

Abstract The study of digital image processing is still a hot topic in the realm of research, especially in medical research. The presence of various digital image processing methods and machine learning also contributes to the progress of research in this field. Detecting Covid Chest X-Ray is a prediction problem solving with a supervised classification method. In this study, the SVM method was chosen because it is proven to function as a good classifier as has been done in previous studies. Where previously the chest x-ray image feature extraction was carried out using wavelet transform. Feature extraction using wavelets has given the distinctive features of normal lung X-rays and distinguishes them from the distinctive features of Covid lung X-rays. The measurement results of the average classification model for the approximate, vertical, horizontal and diagonal dataset are 93.91% accuracy, 6.09% error rate, 98.75% recall, 89.06% specificity, and 91.26% precision. The vertical dataset is the best dataset to get a classification model because it has the best value in the accuracy and recall variables, but still provides good performance in measuring precision.

***Index Terms*— Chest X-Ray, Covid detection, Support Vector Machines, Wavelet.**

I. Introduction

Medical field is one of the most interesting field in digital image processing study. X-Ray data often use as input in digital image processing to diagnose a disease. There are a number of studies that use image processing on chest X-Ray data as describes below. A novel approach for detecting presence of pneumonia clouds in chest X-Ray is conducted in [1]. Indigenous algorithms have been developed for cropping and for extraction of the lung region from the images. Otsu thresholding was used to segregate the healthy part of lung from the pneumonia infected cloudy regions. The automatic method employed image multiscale intensity texture analysis and segmentation were using to detect pneumothorax in chest X-Ray images [2]. In this paper, features are extracted from lung images with the LBP (local binary pattern). The background and noises in chest images were removed for segmenting abnormal lung regions. The segmentation of abnormal regions is used for texture transformed from computing multiple overlapping blocks. The rib boundaries are identified with Sobel edge detection. Finally, in obtaining a complete disease region, the rib boundary is filled up and located between the abnormal regions. Principal Component (PCA) and kernel Principal Component Analysis (kPCA) techniques were used to extract features from chest X-Ray images [3]. Filter and wrapper feature selection method using linear regression model were applied on these techniques. The performance of PCA and kPCA are analyzed and found that the accuracy of PCA using wrapper approach is better than kPCA with 96.07% of accuracy. InceptionV3 CNN was used to perform feature extraction from chest X-ray images [4]. The extracted feature was used to train three classification algorithm models to predict the cases of pneumonia from a Kaggle dataset with K-Nearest Neighbor, Neural Network, and Support Vector Machines. Among all the classification models, Support vector machines model achieved the highest AUC (rate of successful classification) of 93.1%. Deep Neural Network with DarkNet model was used as classifier for the you only look once (YOLO) real time object detection system [5]. This study implemented 17 convolutional layers and introduced different filtering on each layer. Automated approach for lung boundary detection and chest X-Ray classification in conventional poster anterior chest radiographs [6]. The lung regions, sizes of regions, and shape irregularities were extracted using the gray level co-occurrence matrix (GLCM). The probabilistic neural network (PNN) was usetd to classify chest X-Ray images.

In addition to the feature extraction methods that have been used in previous studies, feature extraction can also be performed using wavelet transforms. The texture features extracted by wavelet transforms could be used to classify the images with classifier algorithm. Comparative study of transform-based image texture analysis for the evaluation of banana quality had showed that the Wavelet transform exhibited the most reliable results for all of the reference parameters followed by Tamura and the Gabor transform [7]. Haar wavelet decomposition approach was used in a novel iris recognition for feature extraction [8]. It was chosen because it can reduce the noise level of the iris texture effectively. Furthermore, it accelerates the extraction process of the iris pattern and it simplifies the computing process. The advantages of haar wavelet which can reduce the level of noises effectively, accelerates the extraction process, and simplifies computing process in iris recognition system are interesting facts. Therefore, in this study, the image processing method used is only haar wavelet transform to determine whether this method alone could obtain appropriate feature for classification.

Detecting Covid Chest X-Ray is a prediction problem that is solved by a supervised classification method. In this study, the SVM method was chosen because it has been proven to be able to function as a good classifier as has been done by the following previous studies. In the research conducted by Rizal, SVM was able to classify faces with an accuracy rate of 90% and an error rate of 10% for 200 data [9]. Different studies to classify images whether the object is a car or motorbike at the toll gate shows that the proposed SVM method has an average accuracy of 82.22% for the 1000 image dataset with class category with two-wheeled and four-wheeled objects[10]. The SVM also provides 93.8% accuracy for recognizing Russian characters [11]. SVM has a high generalization capability without any requirement of additional knowledge, even with the high dimension of the input space[12]. So that SVM as a classifier is not only used to classify images as in the study above but is also used for text classification [13] as well as the classification of datasets in relational databases [14][15] by producing excellent accuracy.

Based on the literature review that has been conducted, no one has examined the prediction of covid chest X-Ray with wavelet feature analysis and classification using SVM, so this is the aim of this study. Based on what has been done by previous researchers, it is presumed that in this study the wavelet is able to extract the image feature from Covid X-Ray and SVM is able to classify Chest X-Ray images with good results.

II. METHODS

Lung x-ray data with covid diagnosis is obtained from the internet at the following link *https://github.com/ieee8023/covid-chestxray-dataset/tree/master/images*. The data selection process is carried out by paying attention to metadata, where metadata with covid identification is selected for the experiment. Healthy lung x-ray data were obtained from the medical record installation of Ganesha General Hospital in Gianyar Bali. All data that has been collected is then verified and validated by experts. Image data selected and used in this study amounted to a balance between normal lung x-ray and covid lung x-ray with 82 data each. So that the total data for each experiment is 164 data records.

The lung x-ray image data used have image quality in accordance with the research needs in average, so that the pre-processing stage is carried out only in terms of uniform dimensions and image types. All image data used have different dimensions, so that to standardize the image processing process, the image dimensions are uniformed to a size of 160 × 160 pixels. The image size is converted to a smaller size to reduce the computation time required for image processing. Before changing the image dimensions, some x-ray images had to be cropped because the lung position was not ideal in the image. An example of an x-ray image input data for normal lungs is shown in Figure 1. The initial dimensions of this image are 1511 × 1589 pixels with a 24-bit RGB image type. An example of an x-ray image input data for covid lungs is shown in Figure 2. The initial dimensions of this image are 1175 × 1332 pixels with a 24-bit RGB image type.

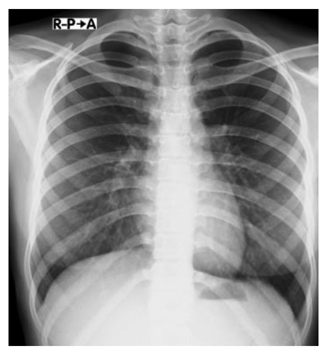

Fig. 1. Normal Lung X-Ray Image Data

Fig. 2. Covid Lung X-Ray Image Data

An x-ray image of the lungs that has been converted into dimensions measuring 160 × 160 pixels and converted to an 8-bit grayscale image is then transformed using haar wavelets. This transformation is used to extract the features that exist in the image. This feature feature will be used to classify an x-ray image of the lungs into normal or covid classes. The full flowchart for the experiment is shown by figure 3. Wavelet transformation is a method commonly used to present data or functions or operators into different frequency components, then study each component with a resolution that matches the scale. This transformation is able to bring out the special characteristics of the image under study [1]. Generally, discrete wavelet transform is an image decomposition at the image subband frequency, where the components are generated by decreasing the decomposition level. The implementation of discrete wavelet transforms can be done by passing high-frequency and low-frequency (low-pass) signals.[2].

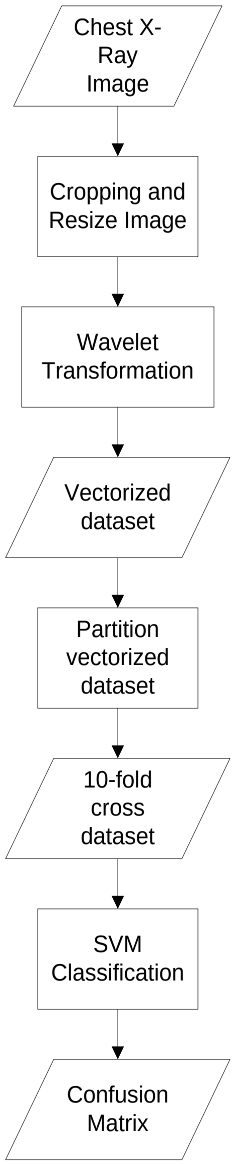

Fig. 3. Flowchart of the experiment

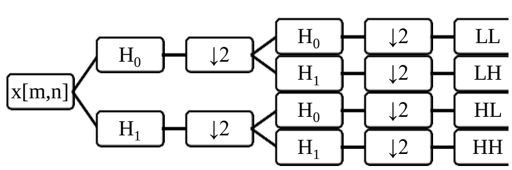

Fig. 4. Illustration of 1-level 2D Wavelet Transformation (Image Source : [3])

The transformation results consist of a sub-image that has been passed through a high pass filter in the horizontal and vertical direction (HH), a sub-image that has been passed through a high pass filter in the horizontal direction and a low pass filter in the vertical direction (HL), a sub-image that has been passed through the low pass filter in the horizontal direction and the high pass filter in the vertical direction (LH), and the sub-image that has been passed by the low pass filter in the horizontal and vertical direction (LL). The LL section is often called the approximation component. Meanwhile, the HL, LH, and HH sections are also called the detail components [3].

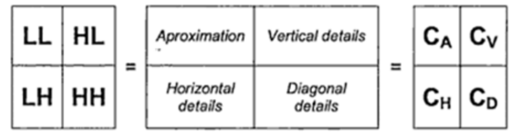

Figure 5. Schematic of 1 level 2D Wavelet Transformation Results (Image Source : [3])

One type of wavelet transform is Haar. Haar is the oldest and simplest wavelet, introduced by Alfred Haar in 1909. The concept of Haar wavelet transformation in an image is to divide (decompose) an image into four sub-images. The first time a horizontal decomposition of the line was carried out. Then performed a vertical decomposition of the column. At each level, the decomposition process is only carried out on the result of the leveling process and the result of the decomposition process is a combination of the leveling process with all the results of the reduction process. The smoothing and subtraction process is carried out using the following formula[3]:

$$p = \frac{x + y}{2} \tag{1}$$

$$p = \frac{x - y}{2} \tag{2}$$

In wavelet transform, there are paired transformation coefficients, namely h_0 and h_1. This pair of coefficients is called the lowpass filter and the highpass filter. The coefficient h_0 is related to the smoothing process. Whereas h_1 is related to the reduction process. The coefficients h_0 and h_1 in the Haar wavelet transform are as follows [3]:

$$h_0 = \left(h_0(0), h_0(1)\right) = \left({}^{1}/_{2}, {}^{1}/_{2}\right) \tag{3}$$

$$h_1 = \left(h_1(0), h_1(1)\right) = \left({}^{1}/_{2}, -{}^{1}/_{2}\right) \tag{4}$$

Haar level 1 wavelet transformation produces an image measuring ½ times the original size, so that for the input image measuring 160 × 160 pixels it produces an output image measuring 80 × 80 pixels. An example of the result of haar level 1 wavelet decomposition for x-ray images of normal lungs is shown in Figure 5. There are 4 (four) coefficients produced, namely the approximate coefficient, horizontal detail coefficient, vertical detail coefficient, and diagonal detail coefficient.

Figure 6 is the result of level 1 haar wavelet decomposition in the image of the covid lungs. As in Figure 5, the results of wavelet decomposition on the covid lung image also produce 4 (four) coefficients.

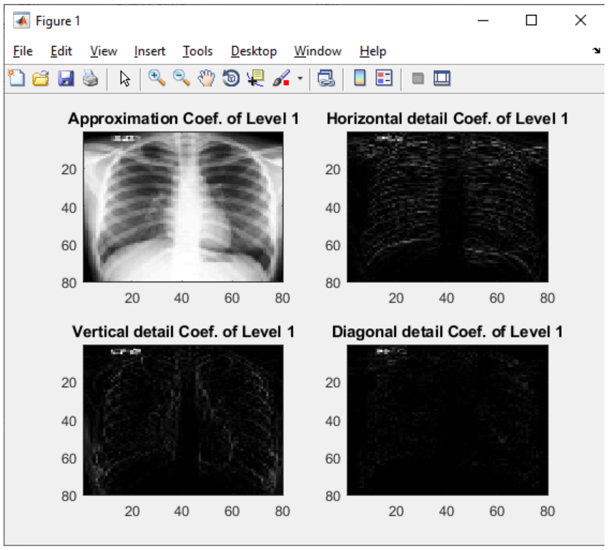

Fig. 6. Results of Level 1 Wavelet Haar Decomposition in Normal Lung Image

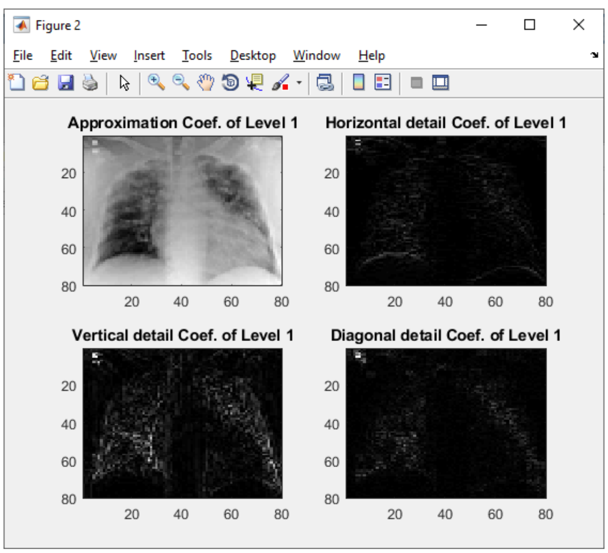

Fig. 7. Results of Level 1 Wavelet Haar Decomposition of Covid Lung Images

The four coefficients resulting from the haar level 1 wavelet decomposition are transformed into a vector form using the reshape function. The result of the reshape function is a vector of 6,400 elements each dataset.

Experiments were carried out respectively for approximate, vertical, horizontal and diagonal images. In each image group, a 10-fold cross validation method is carried out as a testing technique to maintain the accuracy of the classification results. The data mentioned above will be divided into test data for the first 8 datasets, the second 8 datasets and so on to the 10th 8 dataset. Other data that is not used as test data will be used as training data to build the model.

The SVM classification model in this study was built using the Matlab programming language, where the kernel type used is linear. The process is carried out in two stages, first the stage of forming a classification model with training data input where a support vector and hyperplane will be formed. The second stage is testing where the classification results are tested based on the test data and models that have been previously formed.

The classification results are present in confusion matrix. Confusion matrices are very useful for analyzing the quality of the classifier in recognizing the tuples of an existing class. TP and TN state that classifer recognizes tuples correctly, meaning that positive tuples are recognized as positive and negative tuples are recognized as negative. On the other hand, FP and FN stated that classifer mistakenly recognized tuples, negative tuples were recognized as positive and positive tuples were recognized as negative. In this study, positive tuple was represented by normal lung x-rays and negative tuple represented by covid lung x-rays.

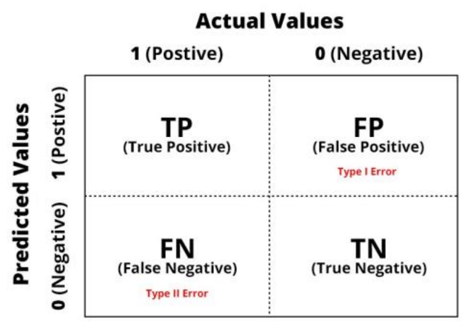

Fig. 8. Confusion Matriks

There are a number of measures that can be used to assess or evaluate classification models, including: accuracy or recognition rate, error rate, recall or sensitivity, specificity, precision, F-measure or F-score. In this study, the classification model measurement tool was used as shown in Table 1.

TABLE I

EVALUATION MEASURES OF THE CLASSIFICATION MODEL

No	Measures	Formulas
1	Accuracy	$\frac{TP+TN}{P+N}$
2	Error rate	$\frac{FP+FN}{P+N}$
3	Recall	$\frac{TP}{P}$
4	Specivicity	$\frac{TN}{N}$
5	Precision	$\frac{TP}{TP+FP}$

Where :
P = number of positive test data / normal lung x-rays
N = number of negative test data / covid lung x-rays

III. RESULT AND DISCUSSION

The SVM classification model in this study provides good performance by measuring model evaluation in the form of accuracy, error rate, recall, specificity and precision values as shown in Table 2. The measurement results are the average of the measurement results of each experiment using 10-fold cross validation method. It can be said that the Wavelet and SVM methods can classify the Covid Chest X-Ray very well, as indicated by the average accuracy of 93.91% for all datasets. The recognition rate of normal Chest X-Ray also showed very good results with an average value of 98.75% for all datasets represented by recall while the recognition rate for Covid Chest X-Ray also gave good results with an average value of 89 , 06% for all datasets.

TABLE II
MEASUREMENT RESULT OF THE CLASSIFICATION MODEL EVALUATION

	Accuracy	Error Rate	Recall	Specificity	Precisio
pproximate	94,38%	5,63%	97,50%	91,25%	93,27%
ertical	95,00%	5,00%	100,00%	90,00%	91,72%
orizontal	94,38%	5,63%	97,50%	91,25%	92,35%
iagonal	91,88%	8,13%	100,00%	83,75%	87,72%
verage	**93,91%**	**6,09%**	**98,75%**	**89,06%**	**91,26%**

Accuracy was used as a general measure to describe the quality of the classification model. As a comparison of each dataset, in this study the highest accuracy is shown by the vertical dataset and the lowest accuracy is shown by the diagonal dataset as shown in Figure 9.

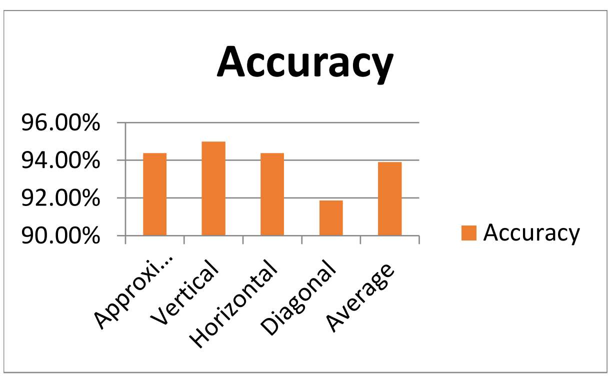

Fig. 9. Comparison of the accuracy value of each dataset

The error rate is inversely proportional to accuracy, as shown in Figure 10 where the vertical dataset provides the best performance to get the lowest error rate while the diagonal dataset provides the lowest performance by giving the highest error rate.

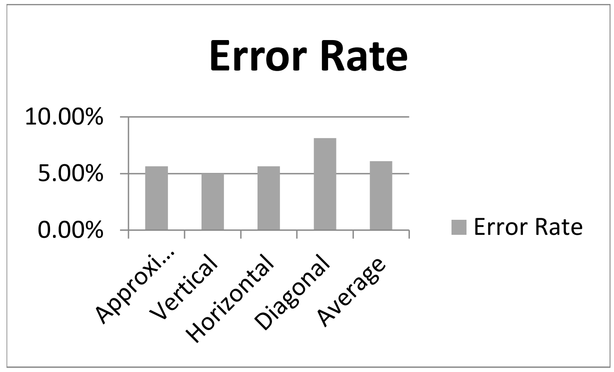

Fig.10. Comparison of the error rate for each dataset

Recall is often referred to a measure of completeness, in this study the percentage of positive tuples that are labeled as positive which means the model is able to recognize normal Chest X-Ray images. Thus recall is the same as sensitivity or true positive rate. This classification model has good sensitivity where the highest measurement value is obtained by the vertical dataset and the diagonal dataset as shown in Figure 11.

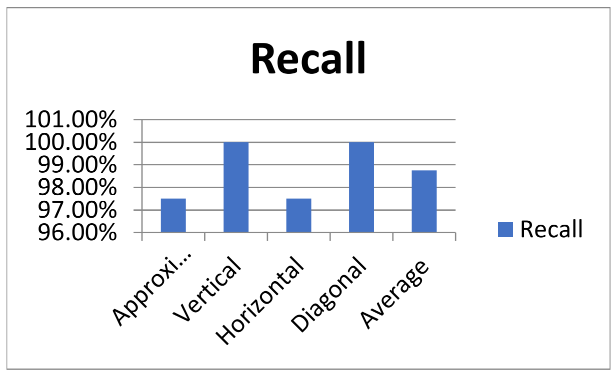

Fig. 11. Comparison of recall / sensitivity values for each dataset

In this study, specificity is the true negative rate which gives the value of how the classification model recognizes negative tuples (test image = "covid"). The model provides a good specifity value with an average of 89.06%. Where the best specificity value is given by the approximate and horizontal dataset while the lowest value is given by the diagonal dataset as shown in Figure 12.

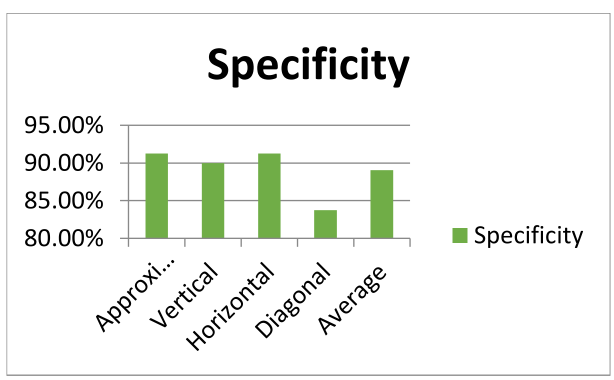

Fig. 12. Comparison of the specificity value of each dataset

Precision is a measure of certainty, i.e. what percentage of tuples labeled positive are true in reality. The precision values in this classification model are good with the highest precision shown by the approximate dataset and the lowest shown by the diagonal dataset. Precision and recall tend to have an inverse relationship. This means that if we try to increase the precision, the recall tends to decrease. This can be seen from the relationship between the graph above. The diagonal dataset that has the highest recall but has the lowest precision in this experiment.

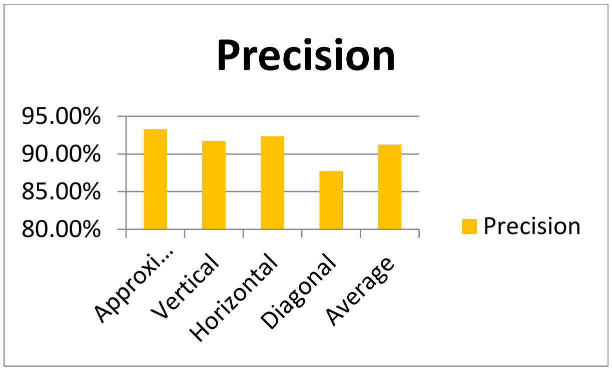

Fig. 13. Comparison of the precision values for each dataset

In declaring a classifier as a high quality classifier, it cannot only based on the accuracy value but simultaneously based on the following minimum three values, sensitivity, specificity and accuracy. Based on the results of the measurement evaluation of the classification model above, the vertical dataset has the highest both values in the measurement variables above, accuracy and recall and still has good values in variable specificity. Therefore, it can be said that in this study the wavelet transformation with vertical dataset gives the best performance in classification using SVM.

IV. CONCLUSION

Based on the experimental results, image processing using the Haar Wavelet transform with a chest X-Ray image grayscale 160 x 160 is sufficient to produce an image that can be classified using SVM. Feature extraction using wavelets has given the distinctive features of normal lung X-rays and distinguishes them from the distinctive features of Covid lung X-rays. The measurement results of the average classification model for approximate, vertical, horizontal and diagonal datasets are 93.91% for accuracy, 6.09% for error rate, 98.75% for recall, 89.06% for specificity, and 91.26% for precision. SVM with linear kernel is able to classify Chest X-Ray as normal lung class and covid lung class well which is shown by the best accuracy of 95%. The vertical dataset is the best dataset to get a classification model because it has the best value for measuring accuracy and recall variables, on the other hand, it is still good value for the specificity measurement variable.

V. ACKNOWLEDGMENT

The author would like to thank Ganesha General Hospital for providing research data in the form of x-ray images of the lungs. The author also thanks STMIK STIKOM Indonesia, especially LPPM, which has supported the implementation of this research so that we can produce this article.

REFERENCES

[1] IEEE Staff, *2017 Nirma University International Conference on Engineering (NUiCONE).* IEEE, 2017.

[2] Y. Chan, Y. Zeng, H. Wu, M. Wu, and H. Sun, 'Effective Pneumothorax Detection for Chest X-Ray Images Using Local Binary Pattern and Support Vector Machine', *J. Healthc. Eng.*, vol. 2018, 2018.

[3] H. Roopa and T. Asha, 'Feature Extraction of Chest X-ray Images and Analysis Using PCA and kPCA', *Int. J. Electr. Comput. Eng.*, vol. 8, no. 5, pp. 3392–3398, 2018.

[4] S. L. K. Yee and W. J. K. Raymond, 'Pneumonia Diagnosis Using Chest X-ray Images and Machine Learning', in *ACM International Conference Proceeding Series*, 2020, pp. 101–105.

[5] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. Rajendra Acharya, 'Automated detection of COVID-19 cases using deep neural networks with X-ray images', *Comput. Biol. Med.*, vol. 121, 2020.

[6] A. Zotin, Y. Hamad, K. Simonov, and M. Kurako, 'Lung boundary detection for chest X-ray images classification based on GLCM and probabilistic neural networks', *Procedia Comput. Sci.*, vol. 159, pp. 1439–1448, 2019.

[7] N. Hashim, S. E. Adebayo, K. Abdan, and M. Hanafi, 'Comparative study of transform-based image texture analysis for the evaluation of banana quality using an optical backscattering system', *Postharvest Biol. Technol.*, vol. 135, pp. 38–50, 2018.

[8] N. Ahmadi and M. Nilashi, 'Iris Texture Recognition based on Multilevel 2-D Haar Wavelet Decomposition and Hamming Distance Approach', *J. Soft Comput. Decis. Support Syst.*, vol. 5, no. 3, 2018.

[9] R. A. Rizal, I. S. Girsang, and S. A. Prasetiyo, 'Klasifikasi Wajah Menggunakan Support Vector Machine (SVM)', *Ris. dan E-Jurnal Manaj. Inform. Komput.*, vol. 3, no. September, pp. 1–5, 2019.

[10] M. Athoillah, M. I. Irawan, and M. Imah, 'Support Vector Machine Untuk Image Retrieval', in *Seminar Nasional Matematika dan Pendidikan Matematika*, 2015, no. 978, pp. 279–287.

[11] D. F. Azid, B. Irawan, and C. Setianingsih, 'PENERJEMAHAN HURUF CYRILLIC RUSIA KE HURUF LATIN MENGGUNAKAN ALGORITMA SVM (SUPPORT VECTOR MACHINE)', in *e-Proceeding of Engineering*, 2017, vol. 4, no. 3, pp. 4007–4014.

[12] Neneng, K. Adi, and R. R. Isnanto, 'Support Vector Machine Untuk Klasifikasi Citra Jenis Daging Berdasarkan Tekstur Menggunakan Ekstraksi Ciri Gray Level Co-Occurrence Matrices (GLCM)', *J. Sist. Inf. Bisnis*, vol. 01, pp. 1–10, 2016.

[13] N. W. S. Saraswati, *Text mining dengan metode naïve bayes classifier dan support vector machines untuk sentiment analysis*. Universitas Udayana, 2011.

[14] A. A. Kasim and M. Sudarsono, 'Algoritma Support Vector Machine (SVM) untuk Klasifikasi Ekonomi Penduduk Penerima Bantuan Pemerintah di Kecamatan Simpang Raya Sulawesi Tengah', in *Seminar Nasional APTIKOM (SEMNASTIK)*, 2019, pp. 568–573.

[15] N. W. S. Saraswati, K. K. Widiartha, and L. P. A. Prapitasari, 'Vector machine to predict student retention: A computerized approach', in *Journal of Physics: Conference Series*, 2020.

[16] R. A. Gitasari, B. Hidayat, and S. Aulia, 'Klasifikasi Penyakit Diabetes Retinopati Berdasarkan Citra Digital Dengan Menggunakan Metode Wavelet Dan Support Vector Machine', *E-Proceeding Eng.*, vol. 2, no. 1, pp. 510–514, 2015.

[17] N. W. S. Saraswati, 'Transformasi Wavelet Dan Thresholding Pada Citra Menggunakan Matlab', *J. TSI*, vol. 1, no. 2, 2010.

[18] D. Putra, *Pengolahan Citra Digital*. Yogyakarta: Andi Offset, 2010.