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# Combination of gray level co-occurrence matrix and artificial neural networks for classification of COVID-19 based on chest X-ray images

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**ABSTRACT**

This research uses the gray level co-occurrence matrix (GLCM) and artificial neural networks to classify COVID-19 images based on chest X-ray images. According to previous studies, there has never been a researcher who has integrated GLCM with artificial neural networks. Epochs 10, 30, 50, 70, 100, and 120 were used in this research. The total number of data points used in this investigation was 600, divided into 300 normal chests and 300 COVID-19 data points. Epoch 10 had 91% accuracy, epoch 30 had 91% accuracy, epoch 50 had 92% accuracy, epoch 70 had 91% accuracy, epoch 100 had 92% accuracy, and epoch 120 had 90% accuracy in categorization. As indicated by the results of the classification tests, combining GLCM and artificial neural networks can produce good results; a combination of these methods can yield a classification for COVID-19.



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## 1. INTRODUCTION

In March 2020, World Health Organization (WHO) declared the coronavirus or COVID-19 as a pandemic outbreak [1]–[3]. In December 2019, the first start of this coronavirus was found in the Wuhan area of Hubei Province, China. This outbreak spread so quickly from one person to another and has spread rapidly to all countries worldwide [4]. The emerging COVID-19 virus pandemic puts significant pressure on limited health resources; several ways have been done to quickly reduce the number of COVID-19 sufferers [5], including independently reducing transmission [2]. Most of the symptoms that arise are high temperature, persistent cough, and loss of smell or taste [5]–[8]. Transmission can occur as a result of hand contact with contaminated surfaces. Therefore, it is necessary to quickly and accurately prevent infection and potential diagnosis [9].

Several previous studies regarding the prediction and classification of COVID-19 have been carried out using various methods with different results, such as in Alamsyah *et al.* [1] implements recurrent neural network (RNN) on the Elman network and uses a dataset obtained from Kaggle. The dataset used consists of 70% training data and 30% test data. Furthermore, Aminu *et al.* [4] proposes the CovidNet architecture, which requires fewer parameters than the others. This research shows that CovidNet outperforms other deep learning models in detecting COVID-19. Shorfuzzaman *et al.* [2] proposes learning based on convolution neural network (CNN) by utilizing transfer learning using parameters (weights) from different models, then combining them into one model by extracting features from each image, Maksum *et al.* [10] concluded that using the computer-aided diagnosis system can be used to classify chest X-ray images using the machine learning method. The initial stage is to do the preprocessing step using gray-level co-occurrence matrix (GLCM). Li *et al.* [11] proposes a combination of deep learning methods with stacked generalization ensembles with VGG16 to form a data classification.

The results obtained from this combination are sensitivity 93.57%, specificity 94.21%, precision 89.40%, and F1-Score 91.74%. Hasan *et al.* [12] proposes a variety of deep learning with feature extraction from Q-deformed to classify COVID-19 and pneumonia by utilizing the results of a computed tomography (CT) scan of the lungs. The classification results obtained were 99.68% of the total 321 patients. Santana *et al.* [13] proposed classification model is to implement and rely on preprocessed data sets by applying several models from machine learning. The research results are the methods used to help detect COVID-19 in Brazil. Pham [14] uses the COVID-19 dataset obtained from a shared database of CT scan results. Classification of COVID-19 by proposing an investigative method from CNN, previously trained to get good results. Jaiswal *et al.* [15] utilizes chest CT scan images to diagnose COVID-19 using deep learning architecture. Training is carried out before the detection stage, and training is carried out on the deep learning architecture. Miroshnichenko and Mikhelev [16] uses the CNN method to approach the problem-solving classification of chest health. The data used in this study used X-ray images of COVID-19 and normal patients [17]. This study uses CNN to automatically classify the chest of patients with COVID-19 by utilizing the results of a chest CT scan. Researchers grouped the COVID-19 dataset into three classes. The results of this study can help the government and hospitals in dealing with the upcoming pandemic. Ibrahim *et al.* [18] applies a multi-classification model from deep learning to diagnose COVID-19 sufferers. Of the three proposed models, the VGG19+ model got better results. VGG19+ achieves an accuracy of 98.05%. Ozyurt *et al.* [19] proposes deep learning with a pyramid feature extraction and hybrid feature model for the automatic detection of COVID-19. The results obtained are by using the hybrid feature to get better results. Elmuogy *et al.* [20] proposes a worried deep neural network (WDNN) model from a deep neural network (DNN) for classification by utilizing transfer learning. The results of the analysis show that WDNN gets better performance results.

Many feature extraction methods are proposed to classify COVID-19 or other diseases, including using the feature extraction method. Most of these methods are combined with other classification methods to get different performance results. However, to improve the method's performance, the feature extraction method needs to be combined with other classification methods to get better performance results. Most previous studies have never had a combination of feature extraction and artificial neural network implementation in an application. Therefore, this study proposes a combination method of feature extraction and neural networks in one application. Many methods are used to obtain good and accurate feature extraction results, one of which is the GLCM method [21]. The extraction method used in this study is the GLCM. GLCM is a statistical analysis for feature extraction on an image [22]. Meanwhile, the classification method used is backpropagation neural network. The reason for choosing the backpropagation neural network classification method is that it can provide good and accurate classification results [23]. The proposed method is implemented in an application made using Matlab. In this study, the image of the lungs of patients with COVID-19 was extracted using GLCM texture analysis. Then the image was converted into grayscale and classified using an artificial neural network. Before the classification stage, lung images were first trained using 600 images, including 300 normal chest images and 300 COVID-19 images. The data used as testing data was 20% of the total of each normal chest data and COVID-19 data. A total of 120 data were used for the testing process, including 60 with a normal chest and 60 with a COVID-19 chest.

## 2. METHOD

### 2.1. Literature study

The literature study stage is carried out by looking for the latest and relevant references from previous studies related to the topics discussed and related articles such as the classification of COVID-19 in covid 19 patients, the theory of GLCM, artificial neural network theory. Then this literature study will be used as a reference in improving this research. Literature studies use the latest research taken from quality journals.

### 2.2. Data collection

This study uses datasets collected on dataset-sharing websites such as Kaggle. The dataset consists of chest X-ray images in patients with COVID-19, normal, and pneumonia [23], [24]. The total data used in this study amounted to 600 data, in Table 1 details the amount of data used in this study. After the data collection stage is carried out, the next step is to apply the GLCM method for lung image extraction. Image extraction is done to obtain image extraction values so that they are later used for the classification process. Figure 1 is an example of a chest image with a COVID-19 patient and Figure 2 is an example of a normal chest image.

### 2.3. GLCM implementation

The implementation of GLCM was carried out to obtain extraction values from chest images of patients with COVID-19 and normal chests. GLCM is a feature extraction often used to get the texture value of an image, whose value is stored in a matrix I x j x n, where n is the GLCM number with a different rotation direction [11], while the features used in this study are contrast, homogeneity, correlation, and energy [25]. Figure 3 is the rotation direction of the GLCM [26].

$$\text{Correlation: } \sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \; \frac{(i-m_r)\,(j-m_c)\,p_{ij}}{\vartheta_r\,\delta_c} \tag{1}$$

$$\text{Contrast: } \sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \; (i-j)^2\, P_{ij} \tag{2}$$

$$\text{Homogeneity: } \sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \; P_{ij}^2 \tag{3}$$

$$\text{Energy: } \sum_{i}^{k} = 1 \sum_{j}^{k} = 1 \; \frac{P_{ij}}{1+[i-j]} \tag{4}$$

Table 1. Research data

| Data used | Image format | Amount of data |
|---|---|---|
| COVID-19 | JPEG | 300 |
| Normal | JPEG | 300 |



Figure 1. COVID-19 chest Figure 2. Normal chest

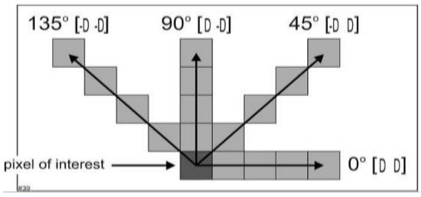


Figure 3. The direction of GLCM rotation

### 2.4. Application of artificial neural networks

The artificial neural network (ANN) classification method was chosen because ANN can think like a human and process information from an image [27]. This research applies backpropagation neural network with a multi-layer, two hidden layers, and one output. ANN is used to classify chest images of patients with COVID-19 and normal chests, previously extracted using GLCM. The number of images used for the training process is 600, consisting of 300 appearances for the chest of COVID-19 sufferers and 300 ideas for the average bin. At the same time, the images used for the testing process are 120 images, consisting of 60 shots for the chest of COVID-19 sufferers and 60 ideas for the average bin.

## 3. RESULTS AND DISCUSSION

In implementing the proposed combination method, the software used is MATLAB Version R2020a [28], and the hardware specifications used are Windows 10 operating system, Intel i7 Gen 11th Processor, and 8GB RAM. Before the testing phase, we first conduct training using 480 data, including 240 normal chest and 240 COVID-19 data. After data collection was carried out [29], the data was tested using a combination of the proposed methods. Several tests have been carried out using Epochs 10, 30, 50, 70, 100, and 120. The application's performance that we created can give good results using Epoch 30 and Epoch 100.

Training process using Epoch 10, learning rate 0.1 and getting an accuracy of 89.37% with 51 incorrect data and 429 correct data out of 480 data. Training process using Epoch 30, learning rate 0.1 and getting an accuracy result of 92.5% with 36 incorrect data and 444 correct data out of 480 data. And the training process using Epoch 50 learning rate of 0.1 and getting an accuracy of 93.12% with 33 incorrect data and 447 correct data out of a total of 480 data. Training process using Epoch 70, learning rate 0.1 and getting 93.54% accuracy results with 31 incorrect data and 449 correct data out of 480 data. Training process using Epoch 100, learning rate 0.1 and getting an accuracy result of 94.79% with 25 incorrect data and 455 correct data out of 480 data. Training process using Epoch 120, learning rate 0.1 and getting an accuracy result of 95.20% with 23 incorrect data and 457 correct data from 480 data. Table 2 is a detail of the overall results of the training.

In this study, we conducted a test to see how far the performance of the proposed method was. The progress of the test can be seen in Figure 4, and Table 3 is the result of the overall difficulty. The data used at the testing stage is 120 data, including 60 data from the normal chest and 60 from COVID-19.

Figure 4 is the result of a classification test carried out with several tests, and the classification stage is carried out in stages based on the epoch that has been determined. Before the classification, the stage is carried out. First, the network created during training needs to be loaded to get lessons from the training process. The overall results of the classification can be seen in Table 3.

Table 2. The overall result of the training process

| Epoch | Iteration | Time elapsed | Amount of incorrect data | Accuracy |
|---|---|---|---|---|
| 10 | 10 | 00.00.00 | 51 | 89.37% |
| 30 | 30 | 00.00.00 | 36 | 92.5% |
| 50 | 50 | 00.00.00 | 33 | 93.12% |
| 70 | 70 | 00.00.00 | 31 | 93.54% |
| 100 | 100 | 00.00.02 | 25 | 94.79% |
| 120 | 120 | 00.00.01 | 23 | 95.20% |

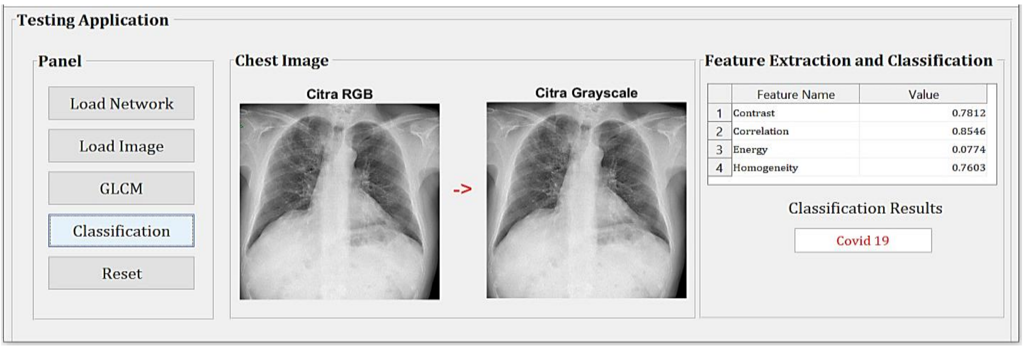


Figure 4. Classification of COVID-19

Table 3 shows the overall classification results, whereby using epoch 50 and epoch 100 with a learning rate of 0.1, the highest accuracy results from the other epochs are 92%. In this study, we tried to test by increasing the number of epochs and learning rate, but the accuracy results obtained were lower. This study uses epochs 10, 30, 50, 70, 100, and 120 and a learning rate of 0.1 in the training process because the epochs experienced a significant increase. We have tried to increase epochs and use various epochs, but the results obtained have decreased, and there are similarities in results, so it is concluded that the epochs used are 10, 30, 50, 70, 100, and 120 a learning rate of 0.1. Furthermore, comparing the results of the method used with relevant research using the GLCM method and different classification models by utilizing X-ray image data on normal lungs and COVID-19 lungs. The performance metrics used are the accuracy results obtained. The results comparison can be seen in Table 4. In this research, we propose a classification system to classify COVID-19 chest and normal chest, using a combination of GLCM feature extraction and backpropagation neural network. A total of 300 data for COVID-19 chest and 300 data for Normal chest, based on the classification results, show the system can classify COVID-19 chest and normal chest using Epoch 50 and 100 and learning rate 0.1 and achieve 92% accuracy.

Table 3. Overall results of the testing process

| Epoch | Classification result accuracy |
|---|---|
| 10 | 91% |
| 30 | 91% |
| 50 | 92% |
| 70 | 91% |
| 100 | 92% |
| 120 | 90% |

Table 4. Comparison of the proposed COVID-19 classification model with the COVID-19 classification with different methods

| Method | Number of X-ray datasets | Classifiers | Accuracy |
|---|---|---|---|
| GLCM [30] | COVID-19 (127)<br>Normal (127)<br>Pneumonia (127) | Support vector machine | 93.2% |
| GLCM [31] | COVID-19 (180)<br>Non-COVID-19 (180) | Logistic | 98.61% |
| GLCM [31] | COVID-19 (180)<br>Non-COVID-19 (180) | Ensemble of logistic, simple logistic, and randomforest | 99.17% |
| GLCM [32] | Test (+)<br>COVID-19 (453)<br>Non-COVID-19 (23)<br>Test (-)<br>COVID-19 (37)<br>Non-COVID-19 (467) | Latent-dynamic conditional random fields (LDCRFs) | 95.88% |
| GLCM [33] | COVID-19 (1252)<br>No COVID-19 (1230) | Deep learning neural network | 98% |
| Our method | COVID-19 (300)<br>Normal (300) | Neural network backropagation | Epoch 10: 91%, 30: 91%, 50: 92%, 70: 91%, 100: 92%, and 120: 90% |

## 4. CONCLUSION

Based on the results of the tests that have been carried out, the proposed system can get good accuracy results. The proposed method can give different results, including tests carried out using Epoch 10 and learning rate 0.1 getting 91% accuracy results, testing with Epoch 30 and learning rate 0.1 getting 91% results, testing with Epoch 50 and learning rate 0.1 getting 92% results, testing with Epoch 70 and learning rate 0.1 getting 91% results, testing with Epoch 100 and learning rate 0.1 getting 92% results while for testing with Epoch 120 and learning rate 0.1 getting 90% results. From various tests carried out, Epochs 50 and 100 with a learning rate of 0.1 get better accuracy results than the other epochs, with an accuracy of 92%. In this study, the larger the epoch used, the lower the accuracy. Therefore, it is necessary to improve the architecture of the proposed model so that it can achieve maximum accuracy results.

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