Covid-19 Detection on Chest CT-Scan Image Using GLCM-Based Feature Extraction with K-NN and Naïve Bayes Classification

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Abstract- Covid-19 is a virus that has spread and become a global pandemic. This virus infected the vital human organ, which is the lungs. Therefore, this research identified Covid-19 and non-covid-19 diseases based on chest CT-Scan images using K-NN and Naïve Bayes classification methods. The system is constructed through pre-processing, segmentation, GLCM-based feature extraction, and dividing the testing and training data with K-fold cross-validation with the value of 5 and 10, then evaluated using Confusion Matrix. The algorithm accuracy value from the K-NN classification model is obtained as 99,6% and Naïve Bayes got the value of 93,5%. In comparison, the K-NN method obtained the highest sensitivity level with a value of 100% and a specificity value of 98.4% for the two methods used. In this test, the K-NN classifier method is more appropriate than the Naïve Bayes method because some features of GLCM are more accommodating to the KNN classifier.

I. Introduction

By the end of February 2003 in China, residents of Guangdong were infected by the Severe Acute Respiratory Syndrome (SARS) virus. Then, a new virus emerged at the end of 2019 with the same subgroup; beta Coronavirus–which killed hundreds of lives and spread worldwide rapidly [1,2]. This pandemic was named Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) or Coronavirus 2019 (Covid-19) by the International Committee on Taxonomy of Viruses (ICTV) in 2020 [3,4]. Until now, statistical data from the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU) showed that the total of confirmed worldwide cases is about 388,048,849 and 5,712,849 deaths of February 4th, 2022. New cases continue to occur because Covid-19 can be transmitted from human to human through droplets about microns size from the nose and/or mouth. This virus affects the respiratory tract and causes a wound layer on the thorax. High severity can lead to pneumonia, acute respiratory syndrome, and death [5,6].

To effectively recognize that Covid-19 infects someone is a problem facing today. Antibody and antigen tests, such as Polymerase Chain Reaction (PCR) as a detection tool, require a long time to know the result, so they are not adequate for the number of patients [7]. Meanwhile, to identify the form of infection caused by Covid-19, it is necessary to do a scan or imaging using Computed Tomography (CT-Scan) [8,9]. Based on the literature review [10], CT-Scan thorax images of Covid-19 patients showed air bronchograms, consolidation, and ground-glass opacities (GGO) as indications of thorax damage. However, radiologists in observing thorax images in Covid-19 patients are still subjective, so the analysis results are still biased because they are affected by the observer's experience [11]. For this reason, an automatic identification model is needed when using CT-Scan imaging of Covid-19 patients, reducing manual involvement.

The CT-Scan image detection process can be identified based on color, texture, and other characteristics. Several papers have shown research with various methods. As done, Ahsan, Md Manjurul, et al. [12] detect patients infected from COVID-19 with CT scan using NasNetMobile have the highest accuracy 82.94%. Kadry, Seifedine, et al. [13] has proposed MLS (Machine Learning System) for detection of COVID-19 patients using CT scan Slices (CTS), in which the highest accuracy is found to be of SVM with Fused-Feature-Vector (FFV) of 89.80%. Sahinbas and Catak [14] has proposed Five deep learning CNN models such as DenseNet, ResNet, VGG16, VGG19 and InceptionV3 on COVID- 19 detection. VGG-16 has found to be the best model in terms of performance with an accuracy of 80%.

Furthermore, Abraham, Bejoy, and Madhu S. Nair [15] have used multi Convolutional Neural Network and Bayesian classifier for the detection of COVID-19. Multi CNN achieved an accuracy of 91.16% wit the first dataset and an accuracy of 97.44% of accuracy with the second dataset. Hemdan, Ezz El-Din, et al. [16] has proposed a model COVIDX-Net for the detection of SARS-COV-2 with the X- ray images and found to have the best performance with the accuracy of 90% whereas InceptionV3 is found to have worst accuracy of 50%. Ameer and Mohammed [17] detected Covid-19 using a CT-Scan based on GLCM and got an accuracy of 94%. Thepade, et al [18] also used GLCM feature extraction, combined it with wavelet transform, and used K-NN and SVM as classifiers to identify Covid-19 in lung X-Ray images. This study resulted in the highest accuracy value when using the K-NN Classifier, 92.6%.. Then, Bakheet san Al-Hamadi [19] used GLCM feature extraction and LDCRF classifier, resulting in the highest accuracy with an average of 95.88%.

From the previous research, it is clear that the chest CT-scan process required an additional process, namely digital image processing, so that information related to Covid-19 detection in exposed lungs is easier to be detected. Of course, selecting the right feature extraction will improve the performance of Covid-19 detection. Based on the explanation described above, the researchers classified CT-Scan chest image data to identify Covid-19 disease using GLCM feature extraction with the K-NN and Naïve Bayes classification methods. This study was conducted to identify Covid-19 based on chest CT-Scan data, so that the results from the classification can be useful and help medical personnel classify between patients infected by Covid-19 and non-Covid-19.

II. MATERIALS AND METHODS

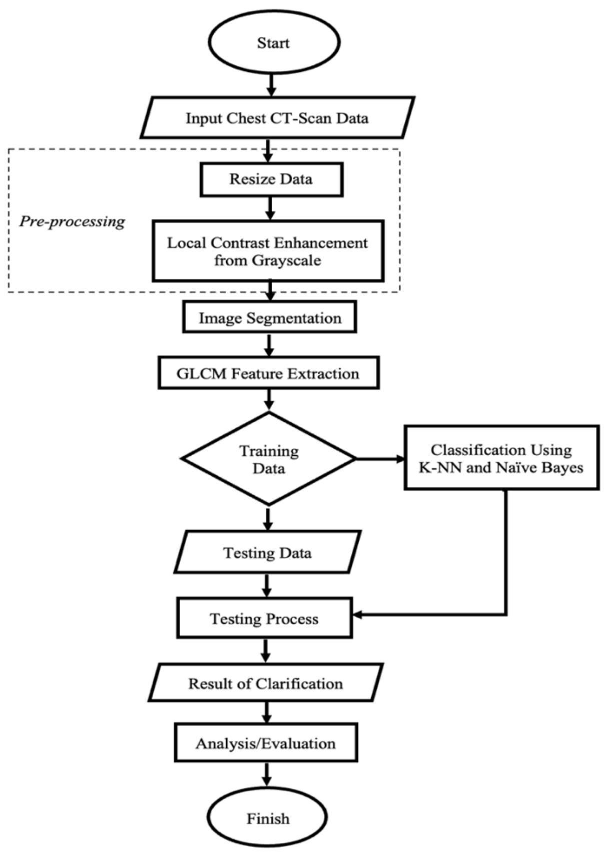
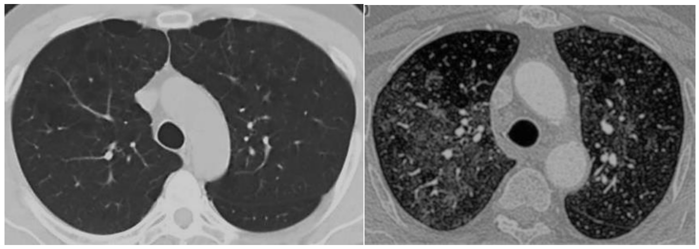


FIGURE 1. Research Flow

FIGURE 1 shows the stages of the research. Chest CT-Scan images are used as input in the classification system in this study. These stages are in the form of preprocessing with resize, RGB to grayscale, and edge-aware local contrast, followed by a segmentation process, image feature extraction using GLCM, classification by K-NN and Naive Bayes methods, and evaluation of the performance of the classifier, namely the level of accuracy, sensitivity, and specificity

Dataset

The dataset was obtained from the Radiology Installation of Hasanuddin University Hospital as many as 62 Covid-19 images and 198 non-Covid-19 images, which were used as input data for processing at the pre-processing, segmentation, and feature extraction stages as well as classification through the K-NN and Naïve Bayes methods. The results of the chest CT-scan image can be seen in Fig. 2.

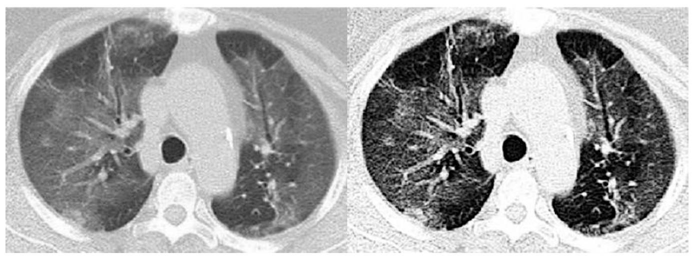


(a) (b)

FIGURE 2. (a) The image of chest CT-Scan non covid and (b) covid

Pre-Processing

To begin with, resizing needed to be done, which is changing the initial size of an image to 224 × 224. The next step is edge-aware local contrast to increase the local contrast of the grayscale or RGB image. The pre-processing process can be seen in Fig.3.



(a) (b)

FIGURE 3. (a) Original image and (b) image after the pre-processing process

From **FIGURE 3**, there are several stages:

3. In the first stage, image processing is carried out with the input data, which is a grayscale image generated from the chest CT-Scan process that has been resized.
4. The second stage, the grayscale image is given an edgeThreshold function which defines the minimum intensity amplitude from the edge to be left intact in the range 0-1, where if the value is close to 0 the image will approach the original image, while if it is close to the value 1 the image will increase the contrast intensity of the image.
5. The last stage, after the data is given the edgeThreshold function, then set the edgeThreshold value parameter to adjust the desired contrast level. At this stage, edgeThreshold 0.9 is used to improve the contrast quality of the image, whereas if the edgeThreshold is given a value of 1, the pre-processing process experiences an error which causes the image quality cannot be increased.

In this process, it is necessary to see more clearly which parts of the area have been exposed to Covid-19.

Image Segmentation

Using an active contour model of a closed curve that moves wide or narrow by minimizing the energy of the external image and is also influenced by lines or edges. The segmentation process can be seen in Fig.4 and 5. From Fig.4 and 5, it is known that there are several stages:

In the active contour image process, the initial stage takes the value of n, which is used to initialize the foreground lung section in the segmentation process and is a controlled point that is sequentially from one another. A value of n is used of 500 to select an intact foreground lung. Whereas if the value of n is below 500 lungs, not all of them are selected as foreground.

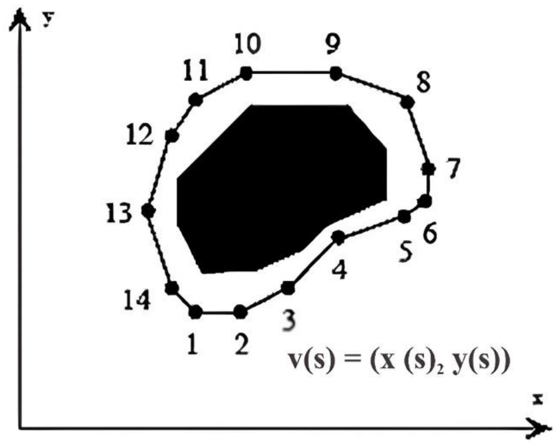
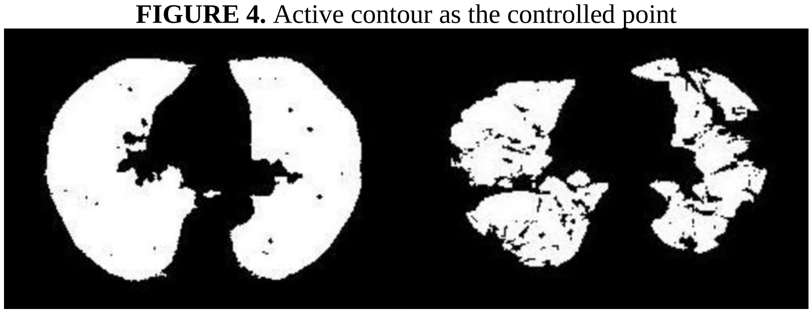


FIGURE 4. Active contour as the controlled point



(a) (b)

FIGURE 5. The result of active contour segmentation of non-covid (a) and covid (b)

The final stage separates the foreground and background on the lungs using the active contour method. With active contour, part of the lung is selected as the foreground whose image energy has been minimized with a closed curve model, while the part that is not selected is the background part of the lung. With this segmentation, the gray image will be converted into a binary image to know which areas are foreground and background objects.

Feature Extraction

The results of the segmentation image are processed using Gray Level Co-accuracy Matrix (GLCM) feature extraction with an orientation of 0◦ by looking for the feature values of contrast, dissimilarity, homogeneity, ASM, or energy, and correlation.

1. Energy

Energy or ASM is used to determine the intensity of gray with a measure of the concentration of a particular pair.

$$Energy\ = \sum i \sum j\ P(ij)^2 \quad (1)$$

2. Contrast

Contrast is a calculation related to the amount of intensity variation in the gray image.

$$Contrast\ = \sum i \sum j\ (i - j)^2\ (Pij) \quad (2)$$

3. Homogeneity

Homogeneity is used to determine the amount of higher grey levels.

$$Homogenity\ = \sum i \sum j\ \frac{P(i,j)}{1+|i-j|} \quad (3)$$

4. Correlation

Correlation is a calculation to indicate the linear structure in the image by showing a linear dependence of the gray’s degree.

$$Correlation = \sum i \sum j\ \frac{(i-\mu x)(j-\mu y)P(i,j)}{\sigma x \sigma y} \quad (4)$$

Classification

Classification is a process that provides conclusions to categorize classes. The k-nearest neighbor (K-NN) and Naïve Bayes algorithms are used in this test. K-NN is a simple classification algorithm that stores all conditions and classifies them into new conditions based on the shortest distance. This method is processed on the shortest distance from the query instance to the training data and takes the closest k data. Eucliden distance is one of the calculations to calculate the distance between new and old data.

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (5)$$

Naïve Bayes is a simple probabilistic classifier that calculates a set of probabilities by calculating certain frequencies and combinations of data. P(A|B) is the probability that event A occurs when event B occurs, P(A) is the probability that event A occurs, P(B|A) is the probability that event B occurs when event A occurs, P(B) is the probability that event B occurs.

$$P(A|B) = \frac{P(A)P(B|A)}{P(B)} \quad (6)$$

There are two classes used in the classification process: non-covid and covid. The classification process uses the Scilab application's help to make it easier to classify the features used. The first stage, Scilab data input, is excel data that contains feature extraction values that have been categorized as class 0 for non-covid and 1 for covid. In the second stage, the extraction value is normalized to change the scale of attribute values to fit within a certain range. This process uses proportion range normalization, where each attribute value is normalized as a proportion of the total number of each attribute, namely the attribute value divided by the total number of attribute values. In the third stage, the normalized data is then separated into testing and training data using a cross-validation operator to estimate the statistical performance of the data used. In the fourth stage, testing and training data are combined with being classified using the K-NN classifier and Naïve Bayes. In the last stage, the classifier obtained results to determine the performance of Covid-19 detection.

Evaluation Method

The results obtained are the results of feature values that have been classified against the training data and testing data that have been combined and classified using the K-NN and Naïve Bayes methods with the algorithm made on Scilab.

Cross-validation

Operators that perform cross-validation to estimate the statistical performance of learning operators are mainly used to estimate how accurate the model is using the K-fold value parameter. The principle of the K-fold is to divide each group of data used for training and testing data into a number of K, where the K-fold values used in this study are 5 and 10. This training and testing data will be input for classification by combining the two data as the structure of the actual and predicted diagnostic procedures.

Confusion Matrix

The confusion matrix is necessary as the general structure of the actual and predicted diagnosis procedure. The table Confusion is explained in Table 1.

TABLE 1. Confusion Matrix

	Actual True	**Actual False**
Predicted True	True Positive (TP)	False Negative (FN)
Predicted False	False Positive (FP)	True Negative (TN)

TP = *true positive* (the number of images of covid that have been detected as covid).
TN = *true negative* (the number of images of non-covid that have been detected as non-covid).
FP = *false positive* (the number of images of covid that have been detected as non-covid).
FN = *false negative* (the number of images of non-covid that have been detected as covid).

Performance on the system is calculated based on the following parameters:

1. *True Positif* (TP), *False Positif* (FP), *False Negatif* (FN) dan *True Negatif* (TN)
2. Accuracy

Accuracy is the exactness of a measurement result close to the true value. The accuracy value is calculated using equation (7).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}\ x\ 100\ \% \quad (7)$$

3. Sensitivity

The sensitivity indicates the possibility of testing being true by identifying subjects who are indeed detected as infected with COVID. The sensitivity value is calculated using equation (8).

$$Sensitivity = \frac{TP}{TP+FN}\ x\ 100\ \% \quad (8)$$

4. Specificity

Specificity indicates the possibility of testing being true by identifying people who are indeed detected as non-covid patients. The specificity value was calculated using equation (9).

$$Specifity = \frac{TN}{TN+FP}\ x\ 100\ \% \quad (9)$$

4. Results and Discussion

Feature Extraction

TABLE 2. GLCM Features

Image	**Contrast**	**Homogeneity**	**Energy/ASM**	**Correlation**	**Class**
1	6.52845747e+01	4.18816589e-01	6.04274327e-02	9.94101842e-01	0
2	6.40219455e+01	4.18814963e-01	5.97541640e-02	9.94035956e-01	0
3	6.13606652e+01	4.14571122e-01	5.84586378e-02	9.94244866e-01	0
4	2.99364954e+02	1.16831756e-01	1.94655938e-02	9.48990658e-01	1
5	2.63284027e+02	1.19009329e-01	1.96581008e-02	9.53609970e-01	1
6	2.41351379e+02	1.23131281e-01	1.99601671e-02	9.52971306e-01	1
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
255	6.58400806e+01	4.17843689e-01	5.42153085e-02	9.93507846e-01	0
256	6.63793422e+01	4.09748336e-01	5.41042559e-02	9.93352529e-01	0
257	6.36394970e+01	4.12465303e-01	4.79797383e-02	9.93772483e-01	0
258	2.85187466e+02	1.21735465e-01	1.97264972e-02	9.49374562e-01	1
259	3.12035659e+02	1.19327647e-01	2.00059155e-02	9.45969663e-01	1
260	2.83695274e+02	1.22746277e-01	1.96053999e-02	9.52102478e-01	1

Feature extraction is the process of finding information from an image. In this research, using GLCM feature extraction, The co-occurrence matrix is formed from four orientation directions, 0^o. **TABLE 2** is the result of the feature extraction of GLCM features. The value was obtained based on the calculation using the equation of (1)-(4) on "Feature Extraction" part. This feature value is used as input classification, giving the code 1 for covid and 0 for non-covid class.

From the value of the feature data, it can be seen in the contrast column, or inertia, which states the amount of variation in the gray intensity of the image. The contrast value will be higher if the degree of gray of each pair of pixels is farther away. In the table above, the inertia value for non-covid images is much lower than for covid images. There is a high difference in gray level in the covid image, while non-covid has a gray level almost the same as its neighboring pixels. These matches Figure 2(b), where there are white spots on the Covid chest CT-Scan image compared to Figure 2(a).

The homogeneity value shows the number of similar gray levels in the image. If the pixels are more uniform, the homogeneity value is higher. The table above clearly shows that the value in class 0 gets a higher value than class 1. The calculation results from the algorithm that have been executed are in match the existing theory, where the non-covid image appears clean with lungs full of air without any white spot.

The GLCM results table shows that the correlation has almost the same value in each case, that the non-covid value is > 0.99 and all corvids are 0.94 - 0.95. This result is in the match with correlation as a feature that performs calculations to show a dependence of the gray degree measurement to indicate the presence of a linear structure in the image.

Similar to the energy characteristic, called uniformity or ASM, expresses the concentration of pairs with gray intensity in the matrix. Class 0 produces energy extraction with a higher value than class 1, which matches the energy value requirements. Uniformity will get a high value when the image has good homogeneity, or pixel values are almost similar. Because no lesions or haze were seen on the chest CT-Scan image for non-covid cases, the lungs were clear, represented by the same gray color.

From the explanation above, it can be concluded that the value of the calculation results of the GLCM-based feature extraction algorithm on both Covid and non-covid chest CT-Scan images matches the applicable theory.

Classification and Performance Evaluation

After the image data has gone through pre-processing with resizing, RGB to grayscale, edge-aware local contrast or local contrast enhancement, segmentation, and extraction, then dividing the dataset. Classification is done using the k-nearest neighbor (K-NN) and Naïve Bayes algorithm. The evaluation of the classification results, whether the prediction does or does not match with the actual data received from the Universitas Hasanuddin Hospital.

In the research that has been done, Scilab is used to classify data from the results of feature extraction on images done in Python. Each feature has several characteristic values , which will be processed using the K-NN and Naïve Bayes classification methods. This classification method determines two classes: non-covid (0) and covid (1).

Classification is done by dividing the training and testing data using K-fold Cross-Validation with k-fold values of 5 and 7. This method aims to validate the accuracy by predicting models built based on certain datasets and testing the accuracy's stability when using different training and testing data.

From the experiments tested, the values of TP, TN, FP, and FN are the result of the combined value of the training and test data. A high TP value and a low FN value will increase the sensitivity value, while a high TN value and a low FP value will increase the specificity value. In the classification used, the performance at accuracy, sensitivity, and specificity levels obtained high scores. The performance results are presented in the Table 3 below.

TABLE 3. Performance of the GLCM Feature Classification

Method	*Number of Fold*	TP	TN	FP	FN	Accuracy	Sensitivity	Specificity
K-NN	**5**	198	61	1	0	99.6%	100%	98.4%
	10	198	61	1	0	99.6%	100%	98.4%
Naïve	**5**	182	61	1	16	93.5%	91.9%	98.4%
Bayes	**10**	183	60	1	16	93.5%	92.4%	98.4%

From **TABLE 3**, it can be seen that from the two methods used, K-NN has high accuracy and sensitivity values compared to Naïve Bayes. The highest level of accuracy with a value of 99.6% has the same value on the K-fold parameter used. While the highest level of sensitivity is also obtained in the K-NN method with a value of 100%. Followed by a specificity value of 98.4% for both methods used. With the K-NN classification, it is known that the GLCM feature with k-fold values of 5 and 10 can detect non-covid and covid with good performance. In this test, the K-NN classifier method is more suitable than the Naïve Bayes because some of the features of GLCM are more accommodating to the KNN classifier.

Extraction Method Performance Comparison

TABLE 4. Extraction Method Performance Comparison

No.	Literature	Data Source	Methodology Used	Dataset	Accuray
1	Ahsan, et al.	Kaggle	NasNet Mobile	400 CT-Scan	82.94%
2	Kadry et. al	LIDC-IDRI and RIDER-TCIA	SVM with FFV	500 images CT-Scan	89.80%
3	Sahinbas and Catak	Github	DenseNet & InceptionV3	140 images X-Ray	90.00%
4	Abraham, et.al.	Kaggle	Multi CNN	77 images X-Ray	80.00.%
5	Hemdan, et al.	Github	COVIDX-Net	50 images X-Ray	97.44%
6	Ameer and Mohammed	Github and Kaggle	GLCM, Gaussian Filter	244 images CT-Scan	94.00%
7	**Present Method**	**Radiology Installation of Hasanuddin University Hospital**	**GLCM, K-NN&Naïve Bayes**	**260 images CT-Scan**	**99.60%**

In **TABLE 4,** the results of the tests that have been carried out will be compared with studies from various researchers. Ahsan, Md Manjurul, et al. [12] aimed to detect patients infected from COVID-19 with X-ray or CT scan using NasNetMobile have the highest accuracy 82.94%. Local Interpretable Model-agnostic (LIME) is used in this paper to help in screening and differentiating healthy people from COVID-19 patients by identifying the characteristics or features that help in deep learning models.

Kadry, Seifedine, et al. [13] has proposed MLS (Machine Learning System) for detection of COVID-19 patients using CT scan Slices (CTS). MLS involves Image multi- Thresholding that involves Kapur's Entropy and Chaotic- Bat- Algorithm (CBA+KE). The image is separated into 2 parts with the chosen threshold. Then features are extracted from the image and to improve the accuracy feature fusion is employed. Using different feature vectors performances of different classifiers including Support Vector Machine using linear kernel (SVM), Random Forest (RF), Decision Tree (DT), Naive Bayes (NB) and k-Nearest Neighbors (KNN) are compared in which the highest accuracy is found to be of SVM with Fused-Feature-Vector (FFV) of 89.80%.

Sahinbas and Catak [14] has proposed a model on COVID- 19 detection.The dataset is obtained from GitHub and is divided into training data set that includes 100 images(50 images for patients who are suffering from COVID-19 and 50 images for healthy people) and testing data set consisting of 40 images (20 images for positive COVID-19 patients and 20 images for negative). The images are resized by scaling to 256x22. Five deep learning CNN models such as DenseNet, ResNet, VGG16, VGG19 and InceptionV3 are discussed. VGG-16 has found to be the best model in terms of performance with an accuracy of 80% whereas ResNet has shown the lowest performance with an accuracy of 50%. The accuracy can be increased in these models by enhancing the dataset by including more images in it.

Abraham, Bejoy, and Madhu S. Nair. [15] have used multi Convolutional Neural Network and Bayesian classifier for the detection of COVID-19. The enhanced performance of Multi CNN is discussed as compared to single CNN. Multi CNN includes many pre-trained CNN for extracting attributes from the X-ray. It is used with the combinaton of Bayesian classifier for detection.Two public datasets are used, one with the more number of images (453 COVID-19 positive images and 497 COVID negative images) and the other with the less number of images (71 COVID-19 images and 7 non-COVID images). Multi CNN achieved an accuracy of 91.16% wit the first dataset and an accuracy of 97.44% of accuracy with the second dataset.

Hemdan, Ezz El-Din, et al. [16] has proposed a model COVIDX-Net for the detection of SARS-COV-2 with the X- ray images. The public dataset is used which is divided into 2 classes including positive COVID-19 cases and negative normal cases and consist of 50 images. Dataset is divided into training and testing phase in which 80% i.e, 40 images are used in the training phase. For experimental setup, all images were scaled to 224 × 224 pixels in size. The COVIDX-Net framework includes seven models of deep learning that are compared including InceptionResNetV2, Xception, ResNetV2, MobilenetV2, VGG19, InceptionV3, and DenseNet121 are compared in which VGG19 and DenseNet201 models are found to have the best performance with the accuracy of 90% whereas InceptionV3 is found to have worst accuracy of 50%. Furthermore, Aseel Qasim and Raghad obtained an accuracy of 94% using GLCM as image extraction and Gaussian filter as a classifier [17].

By using the method tested in this research, it is known that the accuracy value is higher than previous studies, with a value of 99.6% for K-NN and 93.5 for Naïve Bayes. This is because the amount of data used is more, the stages of the method used are different, such as preprocessing the dataset first, such as resizing, RGB to grayscale, local contrast enhancement, and segmentation. Not only that, before classifying the feature data, it is normalized to change the scale of attribute values to fit within a certain range. From the studies that have been carried out, of course, it is possible that some suitable features can be used to accommodate the clasifer to produce good performance. So, the steps to produce the value of feature features must be with the right selection to improve the resulting performance.

III. Conclusion

Based on the results of the GLCM extraction with various features used, it shows that the extracted image produces good values and the classification of COVID-19 and non-COVID-19 using the K-NN and Naïve Bayes methods show very good performance results with an accuracy performance of 99.6 % and 93.5% in analyzing Covid-19 and non-Covid-19 images. The algorithms and approaches utilized in this system, particularly in the feature extraction stage, are simple and utilize less memory. It is easy to understand and involves no complicated mathematical formulas. The system's ability can be increased by using additional characteristics in the input dataset. Time-consuming for executing all steps in the proposed system is less than two seconds. Determine whether there is a COVID-19 or not, as well as in order facilitate the doctor's work in the diagnosis and alert if nothing is noticed in the picture. The filters were used to filter CT scan images, mostly snouted due to the patient's movement or the device picked up poorly.

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