

Original Article

Prediction of COVID-19 with Statistical Data on Chest Radiography using Artificial Intelligence

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Abstract

Introduction: COVID-19 is rapidly spreading around the world and has a high mortality rate. Artificial intelligence (AI) technology is a method that can be used to diagnose the presence of COVID-19 via chest radiographic apparatus. AI can be found to provide accurate results and increased diagnostic efficiency.

Objectives: To evaluate the efficacy of artificial intelligence for COVID-19 diagnosis using statistical data from radiographic chest images.

Methods: The research population sample consisted of 10,000 normal healthy individuals and 10,000 COVID-19 chest radiographs of patients were used for training (70.0%), validating (20.0%), and testing (10.0%). The images were segmented into the left and right lung regions by using the U-net architecture and then statistical data was calculated, including integrated density, mean, standard deviation, skewness, and kurtosis. Three artificial intelligence methods (support vector machine, K-mean clustering, and restricted Boltzmann machine) were compared the models' predictions. The performance of three methods were analyzed for accuracy, sensitivity, specificity, precision, and F1-score.

Results: The accuracy of the support vector machine, K-mean clustering, and restricted Boltzmann machine were 70.5%, 62.5%, and 63.2%, respectively. The trend of the sensitivity, specificity, precision, and F1-score were similar in terms of accuracy, sensitivity, specificity, precision, and F1-score of the support vector machine, which were 64.2%, 73.5%, 68.2%, and 68.5%, respectively.

Conclusions: The most successful technique for diagnosing COVID-19 from chest radiographs was the support vector machine. It outperformed the restricted Boltzmann machine, which was followed by K-mean clustering.

Keywords: Prediction, Artificial intelligence (AI), Chest radiography, COVID-19, Statistical data

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Introduction

The infectious Coronavirus disease 2019 known as COVID-19 has proven to be difficult to initially identify. COVID-19 has rapidly spread worldwide, resulting in hardship and economic turmoil. The virus triggers severe acute respiratory syndrome disorders that can lead to death. In April 2022, the World Health Organization (WHO) reported 6 million deaths due to the virus in addition to more than 500 million confirmed infected cases. In April 2022, the highest numbers of new weekly cases were reported from the Republic of Korea (972,082 new cases), France (827,350 new cases), Germany (769,466 new cases), Italy (421,707 new cases), and Japan (342,665 new cases). In the South-East Asia Region, since mid-January 2022 Thailand had reported both the highest number of new cases and new deaths (146,474 new cases and 799 new deaths).¹

A highly specific and sensitive method for diagnosis of the COVID-19 virus detects the presence of specific genetic material, real time-polymerase chain reaction (RT-PCR). The World Health Organization (WHO) recommends that COVID-19 self-testing procedures using Severe Acute Respiratory Syndrome Coronavirus 2 Antigen Rapid Diagnostic Tests (SARS-CoV-2 Ag-RDTs) can reliably and accurately be used to self-test for the COVID-19 virus.² In hospitals, computed tomography imagery and chest radiography can be utilized to confirm and detect the effects of COVID-19 in the lung region. An automatic detection program using artificial intelligence (AI) can be used to aid physicians to screen for COVID-19 lesions.

Deep learning and machine learning are commonly used forms of artificial intelligence used with medical imaging for the diagnosis of lesions. AI can automatically detect and identify COVID-19 on the image, but the AI model must learn from a large dataset.^{3,4} The deep learning model can automatically extract features of the image and learn the differences in the structure of the image. Several works have used the deep convolutional neural network (DCNN) model to detect COVID-19 on computed tomography and chest radiography.⁵⁻¹⁰ The Visual Geometry Group 16-layer model (VGG-16) and the Residual Network with 50 layers (ResNet-50) model can predict COVID-19 with more than 96.0% accuracy.¹¹ Machine learning is

an alternative method to learn information from image data. Medical images consist of many small pixels that fill the number of pixel values. Machine learning can analyze and classify image data from pixel values. Many studies have used machine learning models to detect COVID-19, such as K-nearest neighbor, support vector machine, decision tree, and K-means clustering.¹²⁻¹³ The objective of this research is to evaluate the efficacy of artificial intelligence to detect COVID-19 using statistical data from chest radiography.

Methods

The study approved by the ethics committee of Naresuan University, Thailand (IRB No. P10110/64). The chest radiography dataset is available on www.kaggle.com, which includes 10,000 normal and 10,000 COVID-19 chest radiography images, all image were labeled as normal and COVID-19.¹⁴ The image files are in the portable network graphics (PNG) format. All images were divided into three groups, with 70.0% in the training group, 20.0% in the validation group, and 10.0% in the test group. The images were uploaded to google drive and converted to 256 x 256 matrix size before processing by Google Colaboratory.¹⁵

Figure 1 shows how the chest radiography was segmented using the artificial intelligence called U-shaped Network (U-net) architecture¹⁶ to separate the lung regions. The area of the lung segmented in the initial image was separated to calculate statistical data. Pixel values of the lung segmented regions were calculated using statistical data, including integrated density, mean, standard deviation, skewness, and kurtosis. The integrated density shows the summation of the pixel value of the segmented lung region. The mean is the average pixel value of the lung region. The standard deviation is the variation of the pixel value. Skewness refers to the distortion or asymmetry of the probability of distribution of the pixel value. Kurtosis is the measure of the sharpness of the peak of a pixel value distribution.

The statistical data of normal and COVID-19 images were divided into five characteristic groups. First is a group of five types of statistical data (integrated density, mean, standard deviation, skewness, and kurtosis). Second, four of the statistical data were alternated. Third, three of

the statistical data were alternated. Fourth, two of the statistical data were alternated. Fifth, each of the statistical data without an alternative are presented in Table 1.

The statistical data alternative was chosen to reduce the number of types from five data in category (Cate) 1 to a single type in Cate 5. This involved swapping and changing the type of statistical data.

To evaluate the mean difference in five statistical data sets between normal and COVID-19 chest radiography, the Mann-Whitney U test was conducted with a significance level set at 0.05 (P -value = 0.05).

Statistical data was evaluated by three artificial intelligence methods (support vector machine, K-mean clustering, and restricted Boltzmann machine). The total statistical data, 14,000 training and 4,000 validation items, was processed using three method parameters, as shown in Table 2.

After training and validation examination, 2,000 items of test statistical data were tested by the same parameters.

Performance evaluation of three artificial intelligence methods

To assess the classification of COVID-19 using statistical data from chest radiography, the two-confusion matrix of this study describes the performance of a classifier in four terms:

True Positives (TP): AI detects COVID-19 on a COVID-19 image.

True Negatives (TN): AI cannot detect COVID-19 on a non-COVID-19 image.

False Positives (FP): AI detects COVID-19 on a non-COVID-19 image.

False Negatives (FN): AI cannot detect COVID-19 on a COVID-19 image.

Each normal and COVID-19 image was labeled by the database on each website¹⁴ to indicate the true result regarding whether the images were normal or COVID-19.

The equation of performance evaluation, accuracy, sensitivity (recall), specificity, precision, and F1-score can be evaluated by Equations (1) - (5).

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

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

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

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \quad (4)$$

$$\text{F1 score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (5)$$

Results

Table 3 presents the results of the statistical data of normal and COVID-19 chest radiography. The mean of the statistical data (integrated density, mean, standard deviation, skewness, and kurtosis) of normal and COVID-19 chest radiography images are compared, with the results indicating they are significantly different (P -value < 0.05).

Figure 2 (a) shows the best values of accuracy, precision, sensitivity, specificity, and F1-score for each group test of the support vector machine methods. The highest accuracy ratio (0.705) was attained with the Cate 1 group (integrated density, mean, standard deviation, skewness, and kurtosis). Next, the Cate 2 group (mean, standard deviation, skewness, and kurtosis) achieved an accuracy ratio of 0.704, followed by the Cate 3 group (integrated density, standard deviation, and kurtosis) with an accuracy ratio of 0.687. The Cate 4 group (skewness and kurtosis) obtained an accuracy ratio of 0.677, and finally, the Cate 5 group (kurtosis) achieved the lowest accuracy ratio at 0.665.

The performance of sensitivity, specificity, and F1-score of the support vector machine methods is similar to the accuracy tendency, except for the precision of the Cate 2 group (mean, standard deviation, skewness, and kurtosis: 0.646), which was expected to be higher than that of the Cate 1 group (integrated density, mean, standard deviation, skewness, and kurtosis: 0.642).

In addition, Figure 2 (b) shows the best value of accuracy, precision, sensitivity, specificity, and F1-score of each group test of the K-mean clustering methods. The result of the Cate 4 group (skewness, and kurtosis) was able to classify COVID-19 with the highest accuracy ratio (0.632), second was the Cate 3 group (standard deviation, skewness, and kurtosis: 0.628), third was Cate 5 group (kurtosis: 0.625), fourth was the Cate 1 group (0.615), and finally, the Cate 2 group (integrated density, mean, skewness, and kurtosis) achieved the lowest accuracy ratio at 0.560.

The Cate 3 group achieved the highest precision performance. The sensitivity of the Cate 4 group was highest. The specificity and F1-score of the Cate 1 group was the highest.

Moreover, the best values of accuracy, precision, sensitivity, specificity, and F1-score of each group test of the restricted Boltzmann machine methods are shown in Figure 3. The result of Cate 5 group (kurtosis) can classify COVID-19 with the highest accuracy ratio (0.644), second was the Cate 2 group (mean, standard deviation, skewness, and kurtosis: 0.632), third was the Cate 3 group (mean, skewness, and kurtosis: 0.631), fourth was the Cate 4 group (skewness, and kurtosis: 0.630), and fifth is a Cate 1 group (0.552).

Cate 5 group (kurtosis) had the highest tendency of precision, sensitivity, specificity, and F1-score.

Figure 4 presents the best performance comparison of three artificial intelligence methods. Accuracy, sensitivity, specificity, and F1-score of the support vector machine (SVM) were highest, followed by the restricted Boltzmann machine (RBM), and finally K-mean clustering. With the exception of precision, the restricted Boltzmann machine (RBM) performed the best.

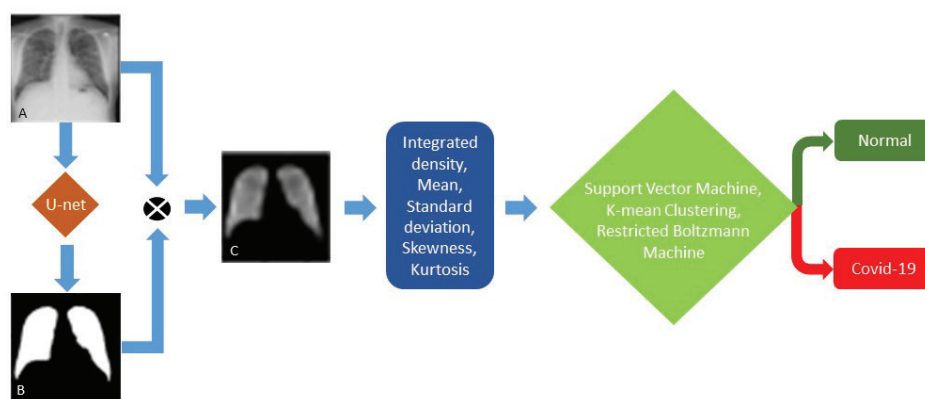


Figure 1 The workflow of this research shows the chest radiography was segmented by U-net architecture and statistical data was calculated from the image, and three methods (support vector machine, K-mean clustering, and restricted Boltzmann machine) were used to detect COVID-19.

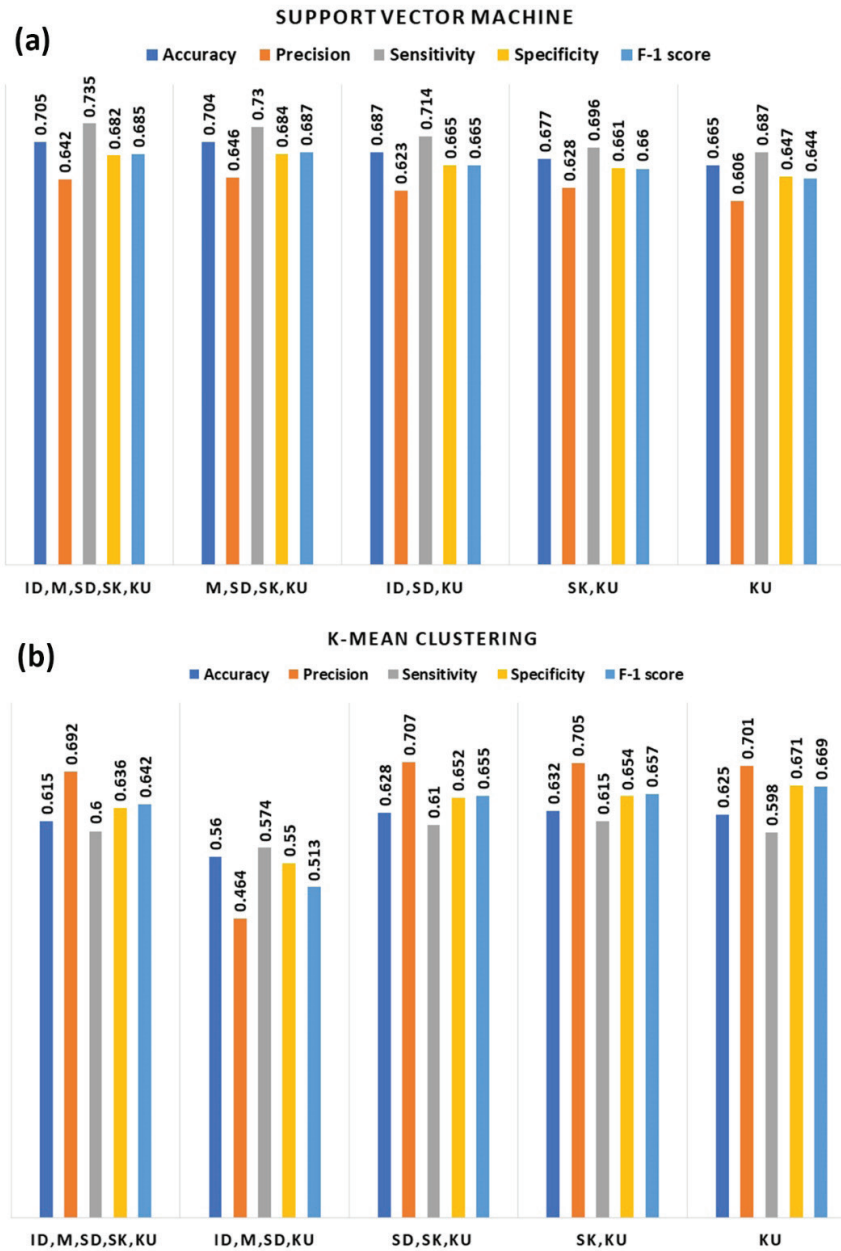


Figure 2 Accuracy, precision, sensitivity, specificity, and F1- score of (a) support vector machine and (b) of K-mean clustering. (ID is integrated density, M is mean, SD is standard deviation, SK is skewness, and KU is kurtosis).

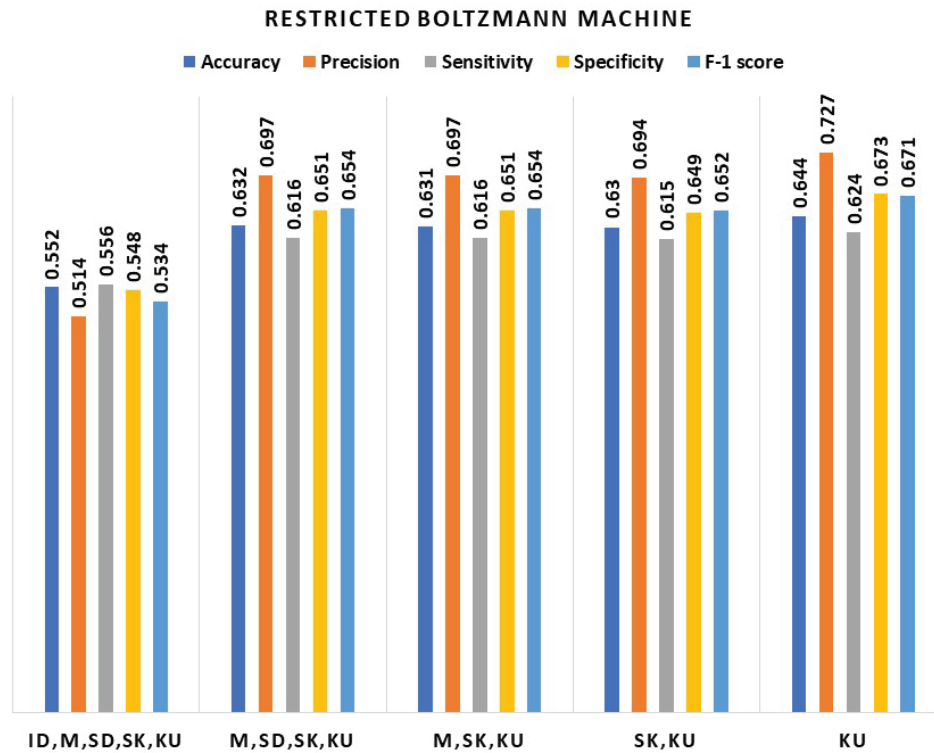


Figure 3 Accuracy, precision, sensitivity, specificity, and F1- score of restricted Boltzmann machine on the group of statistical data (ID is integrated density, M is mean, SD is standard deviation, SK is skewness, and KU is kurtosis).

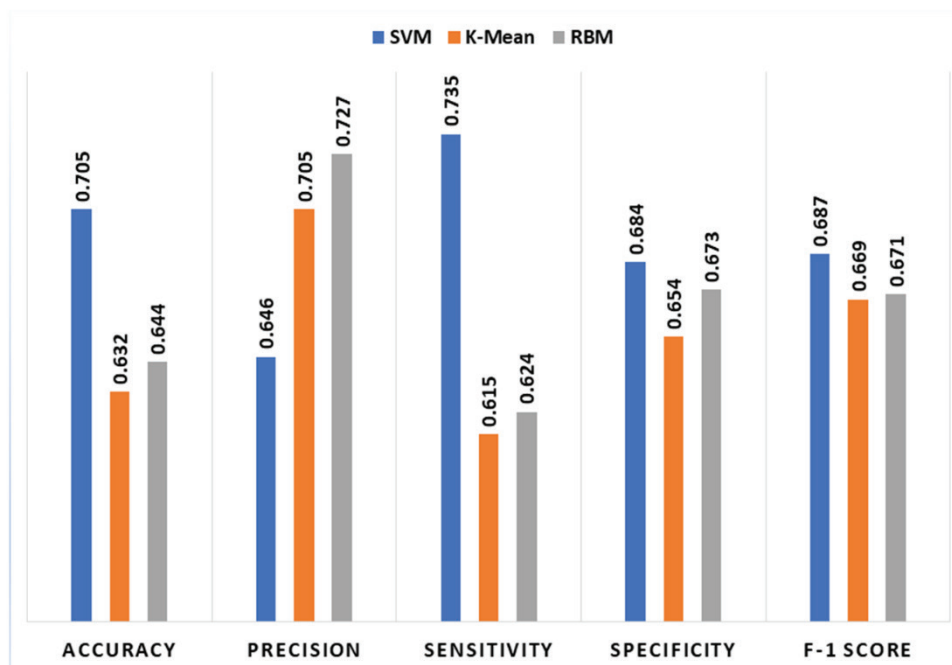


Figure 4 The best performance comparison of three artificial intelligence methods: support vector machine (SVM); K-mean clustering; and restricted Boltzmann machine (RBM).

Table 1 The five characteristic groups of the statistical data for analysis

A group of five statistical data (Cate 1)	Four statistical data were alternated (Cate 2)	Three statistical data were alternated (Cate 3)	Two statistical data were alternated (Cate 4)	Statistical data (Cate 5)
Integrated density, Mean, Standard deviation, Skewness, and Kurtosis.	1. Integrated density, Standard deviation, Kurtosis. 2. Integrated density, Standard deviation, Skewness. 3. Mean, Standard deviation, Kurtosis.	1. Integrated density, Standard deviation, Kurtosis. 2. Integrated density, Mean, Skewness. 3. Integrated density, Mean, Kurtosis. 4. Integrated density, Standard deviation, Skewness. 5. Integrated density, Standard deviation, Kurtosis. 6. Integrated density, Skewness, Kurtosis. 7. Mean, Standard deviation, Skewness. 8. Mean, Standard deviation, Kurtosis. 9. Mean, Skewness, Kurtosis. 10. Standard deviation, Skewness, Kurtosis	1. Integrated density, Mean deviation. 2. Integrated density, Standard deviation, Skewness. 3. Integrated density, Kurtosis. 4. Mean, Standard deviation. 5. Mean, Skewness. 6. Mean, Kurtosis. 7. Standard deviation, Skewness. 8. Standard deviation, Kurtosis. 9. Skewness, Kurtosis. 10. Standard deviation, Kurtosis	1. Integrated density 2. Mean 3. Standard deviation 4. Skewness 5. Kurtosis

Table 2 The parameter of three methods (support vector machine, K-mean clustering, and restricted Boltzmann machine)

Support vector machine (SVM)	K-mean clustering	Restricted Boltzmann machine
regularisation parameter (C) = 0.1, kernel = <i>rbf</i> , degree of the polynomial kernel function = 3, gamma = <i>scale</i> , the shrinking heuristic = <i>True</i> , probability estimates = <i>False</i> , tolerance for stopping criterion = <i>1e-3</i> , size of the kernel cache = 200, class weight = <i>None</i> , verbose = <i>False</i> , maximum iteration = -1, decision function shape = <i>ovr</i> , break ties = <i>False</i> , random state = <i>None</i> .	number of clusters = 2, number of times the k-means algorithm = 10, maximum number of iterations = 300, relative tolerance = <i>1e-4</i> , verbose = 0, random state = <i>None</i> , copy_x = <i>True</i> , the algorithm = <i>Auto</i> .	number of components = 2, learning rate = 0.1, batch size = 10, number of iterations = 50, verbosity level = <i>True</i> , random state = 0, logistic regression parameters; solver = <i>newton-cg</i> , tolerance for stopping criteria (tol) = 1, inverse of regularisation strength = 60.

Table 3 Example statistical data of 10,000 normal and 10,000 COVID-19 chest radiography images

Statistical data of normal chest radiography						Statistical data of COVID-19 chest radiography					
No	Integrated density	Mean	Standard deviation	Skewness	Kurtosis	No	Integrated density	Mean	Standard deviation	Skewness	Kurtosis
0	1379434	21.050	30.027	1.053	1.109	0	1923475	29.350	27.153	1.079	1.478
1	664312	10.140	26.703	1.057	0.679	1	701134	10.698	27.526	0.477	-0.124
2	1028326	15.690	32.736	1.01	0.958	2	826680	12.614	33.059	0.918	0.622
3	1142249	17.430	37.128	0.726	-0.127	3	2299892	35.094	40.997	0.334	-0.874
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9,999	1028977	15.700	41.125	0.9222	0.262	9,999	2036144	31.069	20.52	-0.114	-0.749
Mean	1678901	25.620	30.254	0.667	0.265	Mean	1623907	24.779	31.686	0.547	-0.026

The mean difference of all couple of statistical data between normal and COVID-19 were significantly different ($P = 0.000$)

Discussion

This research compared the performance of three artificial intelligence methods: support vector machine (SVM); K-mean clustering; and restricted Boltzmann machine (RBM). Statistical data was calculated to evaluate the three artificial intelligence methods. Statistical data (integrated density, mean, standard deviation, skewness, and kurtosis) of chest radiography was utilized to identify structure characteristics on the images. Five statistical data sets were extracted from the chest radiography, were trained and tested by three above artificial intelligence methods.

The statistical analysis comparing the mean differences between all pairs of statistical data in normal and COVID-19 images indicates that the means were significantly different.

The overall performance result for the support vector machine was the best, with an accuracy of 0.705 for Cate 1, sensitivity of 0.735 for Cate 1, specificity of 0.684 for Cate 2, F1-score of 0.687 for Cate 2, and precision of 0.646 for Cate 2.

For Cate 5, the accuracy of the restricted Boltzmann machine was 0.644, sensitivity was 0.624, specificity was 0.673, F1-score was 0.671, and precision was 0.727.

The accuracy of K-mean clustering was 0.632 for Cate 4, sensitivity was 0.615 for Cate 4, specificity was 0.671 for Cate 5, F1-score was 0.669 for Cate 5, and the precision was 0.707 for Cate 3.

The support vector machine indicates that the multi-parameters of statistical data for Cate 1 (integrated density, mean, standard deviation, skewness, and kurtosis) and Cate 2 (mean, standard deviation, skewness, and kurtosis) are suitable for classifying COVID-19 chest radiography. For the restricted Boltzmann machine, Cate 5 (kurtosis) achieved the highest score, while for K-mean clustering, Cate 4 (skewness and kurtosis) and Cate 5 (kurtosis) obtained the highest scores for classifying chest images.

The multi-parameters were not suitable for two artificial intelligences (restricted Boltzmann machine and K-mean clustering). Overfitting was the reason for the misclassification of COVID-19 images, possibly due to the differing size of integrated density data compared to other data, which may be the main cause of overfitting. To address this issue, normalizing the data will be

the solution in future work. The lower performance of the restricted Boltzmann machine and K-mean clustering highlights the effectiveness of using one or two parameters of statistical data.

The statistical data of this work were extracted using the first-order features technique.¹⁷ Other features extraction techniques¹⁷, such as gray level co-occurrence matrix (GLCM), gray level size zone matrix (GLRZM), or neighboring gray tone matrix (GLDM), may be alternative choices for extracting data from chest radiography.

Compared with the present study, Khan identified COVID-19 on chest radiography using K-mean clustering and support vector machine, with the support vector machine achieving an accuracy of 94.1%.¹⁴ Nour et al. studied COVID-19 classification by K-nearest neighbor, support vector machine, and decision tree.¹⁸ The support vector machine was found to be the best method to detect COVID-19 with an accuracy of 98.9%, sensitivity of 89.4%, specificity of 99.8%, and F1-score of 96.7%. In the present study, Figure 4 also illustrates that the support vector machine achieved the best performance. The limitation of this study is that the data closely resemble values in normal and COVID-19 images. Therefore, it is advisable to consider using different statistical data or employing artificial intelligence methods such as deep learning to enhance performance.

Conclusions

This study compared the COVID-19 prediction capabilities of three artificial intelligence methods. The support vector machine demonstrated the highest potential for detecting COVID-19 with chest radiography, achieving accuracy (70.5%), precision (64.2%), sensitivity (73.5%), specificity (68.2%), and F1-score (68.5%). In future work, researchers will analyze statistical data of chest radiography using other artificial intelligence methods.

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Compliance with Ethics Requirements This study approved by the ethics committee of Naresuan University, Thailand (IRB No. P10111/64).

Conflict of interest : None

References

1. World Health Organization. Weekly epidemiological update on COVID-19-20 April 2022. Geneva: WHO. <https://www.who.int/publications/m/item/weekly-epidemiological-update-on-COVID-19---20-april-2022>. Published 2022. Accessed April 28, 2022.
2. World Health Organization. Use of SARS-CoV-2 antigen-detection rapid diagnostic tests for COVID-19 self-testing (2022). Geneva: WHO. https://www.who.int/publications/i/item/WHO-2019-nCoV-Ag-RDTs-Self_testing-2022.1 Published 2022. Accessed April 28, 2022.
3. Hassantabar S, Ahmadi M, Sharifi A. Diagnosis and detection of infected tissue of covid-19 patients based on lung x-ray image using convolutional neural network approaches. *Chaos Solit Fractals*. 2020;140:110170.
4. Sethy PK, Behera SK. Detection of coronavirus disease (covid-19) based on deep features. *Prepr*. 2020:2020030300.
5. Lakhani P, Sundaram B. Deep Learning at Chest Radiography: Automated Classification of Pulmonary Tuberculosis by Using Convolutional Neural Networks. *Radiology*. 2017;284(2):574-582.
6. Ni Q, Sun Z Y, Qi L, Chen W, Yang Y, Wang L, et al. A deep learning approach to characterize 2019 coronavirus disease (COVID-19) pneumonia in chest CT images. *Eur Radiol*. 2020;30:6517-6527.
7. Kumar R, Arora R, Bansal V, Sahayasheela V J, Buckchash H, Imran J, et al. Accurate prediction of COVID-19 using chest x-ray images through deep feature learning model with SMOTE and machine learning classifiers. *medRxiv*. 2020;20063461.
8. Liu B, Gao X, He M, Lv F, Yin G. Online COVID-19 diagnosis with chest CT images: Lesion-attention deep neural networks. *medRxiv*. 2020;20097907.
9. Ibrahim D M, Elshennawy N M, Sarhan A M. Deep-chest: multi-classification deep learning model for diagnosing COVID-19, pneumonia, and lung cancer chest diseases. *Comput Biol Med*. 2021;132:1-13.
10. Yang D, Martinez C, Visuña L, Khandhar H, Bhatt C, Carretero J. Detection and analysis of COVID-19 in medical images using deep learning techniques. *Sci Rep*. 2021;11:1-13.
11. Das AK, Kalam S, Kumar C, Sinha D. TLCoV- An automated Covid-19 screening model using transfer learning from chest x-ray images. *Chaos Solit Fractals*. 2021;144:110713.
12. Joshi RC, Yadav S, Pathak VK, Malhotra HS, Khokhar HVS, Parihar A, et al. A deep learning-based COVID-19 automatic diagnostic framework using chest X-ray images. *Biocybern Biomed Eng*. 2021;41(1):239-254.
13. Khan MA. An automated and fast system to identify COVID-19 from X-ray radiograph of the chest using image processing and machine learning. *Int j Imaging Syst Technol*. 2021;31(2):499-508.
14. COVID-19 Radiography Database. Kaggle Inc. <https://www.kaggle.com/datasets/tawsifurrahman/covid19-radiography-database>. Published 2022. Accessed April 28, 2022.
15. Google colab. Google Research. colab.research.google.com Published 2022. Accessed April 28, 2022.
16. Pandey N. Lung segmentation from Chest X-Ray dataset. Kaggle Inc. <https://www.kaggle.com/code/nikhilpandey360/lung-segmentation-from-chest-x-ray-dataset/notebook>. Published 2022. Accessed April 28, 2022.
17. Pyradiomics. Radiomics features, <https://www.pyradiomics.readthedocs.io>. Published 2016. Accessed December 12, 2023.
18. Nour M, Cömert Z, Polat K. A novel medical diagnosis model for COVID-19 infection detection based on deep features and Bayesian optimization. *Applied Soft Computing*. 2020;97:106580.