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AN APPROACH FOR COVID-19 DETECTION USING DEEP CONVOLUTIONAL FEATURES ON CHEST X-RAY IMAGES

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ABSTRACT

First screening of COVID-19 becomes very crucial because of its fast spread. There are several ways to diagnose someone who has COVID-19, but chest X-ray is one of the efficient tools that can be used. Deep learning, especially Convolutional Neural Network (CNN), is commonly utilized in medical images due to its superiority in extracting high-level features of images. However, in order to train CNN, we need enormous data to avoid overfitting. Meanwhile, there is a limit of chest X-ray availability that can be access publicly. Considering this problem, we propose pre-trained CNN model as a feature extractor, and the feature vector obtained as the output of CNN that is used as the input of machine learning classifier, namely Support Vector Machines (SVM), Random Forest (RF), and k-Nearest Neighbors (kNN). Using the data from Kaggle COVID-19 Radiography Database, our proposed method with SVM as a classifier succeeded in delivering accuracy of 99.73% in the testing data. Moreover, the performance of CNN-SVM held on training data provides the average accuracy of 99.77%. Thus, our proposed approach can be used as an alternative on screening COVID-19.

Keywords: *Convolutional Neural Network, Feature Extraction, Hybrid Method, Medical Image*

1. INTRODUCTION

The coronavirus disease 19 (COVID-19) causes the pandemic situation all over the world. This respiratory disease appeared in Wuhan, China, for the first time and has rapidly spread to many countries. The cause of COVID-19 is severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) which belongs to the Coronaviridae family [1]. As of 27 December 2020, according to the World Health Organization (WHO), there are 79,232,555 confirmed cases and 1,754,493 confirmed deaths because of COVID-19. However, this number of cases can still increase while a fully effective vaccine has not been found yet (27 Dec 2020).

According to Lauer et al. [2], the median incubation period of COVID-19 was 5.1 days. Then, after 14 days, 101 out of every 10,000 cases will develop symptoms. In most cases, the COVID-19's suffering shows mild to moderate symptoms. The onsets of COVID-19 symptoms are cough, fever, fatigue, dyspneal, headache, sputum production, diarrhea, hemoptysis, and lymphopenia [3]. Furthermore, this disease can lead to severe pneumonia. Also, patients with COVID-19 have the possibility to have acute respiratory distress syndrome (ARDS) and multiple organ failure [4]. Therefore, early detection of COVID-19 might help patient to increase their survival rate.

The detection tool in the medical sector is chest radiological imaging including computed tomography scan (CT Scan) and X-ray that are used to detect COVID-19 [5]. To analyze the radiological imaging, a radiologist will be needed, but there is a limited number of them. Other concerns are the test costs, waiting time for the test results, and human error [5]. To help medical staffs classify COVID-19 to overcome those issues, advanced technology is required. It is important to detect COVID-19 precisely in the early stage because it can affect the patient's treatment and the patient's survival rates.

Deep learning, especially Convolutional Neural Network (CNN) method, has reached state-of-the-art to classify image [6]. CNN can learn to optimize the features during the training phase directly from the raw input because they combine the feature extraction and feature classification processes. Recently, CNN is widely used to detect COVID-19 from radiology images. From previous research, Apostolopoulos and Mpesiana [7] got 96.78% accuracy to detect COVID-19 using transfer learning with CNN. Also, Narin et al. [8] used ResNet50 as a pre-trained convolutional neural

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network that is reached 96.1% accuracy for classifying COVID-19 and normal x-ray images. Another research, Ozturk et al. [5] used DarkCovidNet which had 98.08% accuracy. However, CNN needs a lot of image data so that it will perform better in detecting unseen image. As we know, the availability of X-ray images of COVID-19 patients is limited even though the case of COVID-19 worldwide is high. Therefore, the researchers need to develop more models to get higher accuracy.

Machine learning method can be an alternative to build a model with small amount of data training. There are a lot of robust machine learning algorithms such as Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbor (kNN). SVM has a great capability especially with high-dimensional data because of the use of kernel function. In the other hand, RF utilizes a tree-based model while kNN uses the distance-based rule to classify the data. However, machine learning algorithm usually need a hand-crafted features built beforehand because it cannot extract features automatically as CNN does.

Therefore, in this research, to maximize the capability of CNN in extracting features while classifying unseen data as accurate as possible, the authors combined CNN with robust machine learning algorithm including Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbor (kNN). CNN is used to extract the features, and machine learning algorithm is used for the classification. After getting all the accuracy of the three methods, such as CNN-SVM, CNN-RF, and CNN-KNN, we compared them to find out which combination of CNN with classic machine learning that got the highest result. Data X-ray images of COVID-19 and normal were taken from Kaggle COVID-19 Radiography Database [9].

2. MATERIAL AND METHODS

This section discusses the dataset used, the theoretical bases of the Convolutional Neural Network, Support Vector Machines, Random Forest, and k-Nearest Neighbor.

2.1 Data

The image data of people with COVID-19 and normal obtained from Kaggle COVID-19 Radiography Database [9]. The chest X-ray data were used to be classified as COVID-19 or normal. There are a total of 1,143 chest X-rays from COVID-19 patients and 1,342 chest X-rays from healthy people. Figure 1 shows the example of image data used in this research.

(a)

(b)

Figure 1. The examples of chest X-ray image used in the study: (a) COVID-19; and (b) Normal.

2.2 Convolutional Neural Network

Convolutional Neural Networks (CNN) is a widely used machine learning method. This method used convolution as a dot product operation with filters between input matrices [10]. The CNN method has two stages [11]; first, the convolution layers as the feature extraction along with pooling layer. Then, the fully connected layer or Multi-Layer Perceptron as trainable classifier for classification.

In this research, VGG19 is chosen as the CNN architecture that will be used as a feature extractor. We will use a pretrained model that has been trained on ImageNet database, and shows that this model can be used as a feature extractor of medical image even though it was trained before with natural image. This model consists of 19 layers with 16 convolution layers, 5 max-pooling layers, 3 fully connected layers, and 1 SoftMax layer. However, as a feature extractor, we will take the feature extracted by the 'fc1' layer that is the second last of full connected layers.

2.3 Support Vector Machines

Support Vector Machine (SVM) is one of which machine learning methods frequently used for regression and classification. Initially, SVM was used for linear problems [12]. For non–linear problems, it works by applying a kernel function into a higher dimensional space where an optimal hyperplane is formed by separating the data into classes [13]. The idea is to build an optimal hyperplane by measuring the maximum distance between the closest vectors of either class or by maximizing the margin [14]. Figure 2 below is the ilustration of SVM [15].

Given a dataset $\{\boldsymbol{x}_i, y_i\}$for $i = 1, \ldots, N$ where $\boldsymbol{x}_i \in R^D$ and $y_i \in \{-1, 1\}$ is the labeled class for the classification of two classes, and N is the samples number. The hyperplane equation can be seen in Equation (1) where $\boldsymbol{w}$ is the weight and b is the bias value.

$$\boldsymbol{w} \cdot \boldsymbol{x} + b = 0 \qquad (1)$$

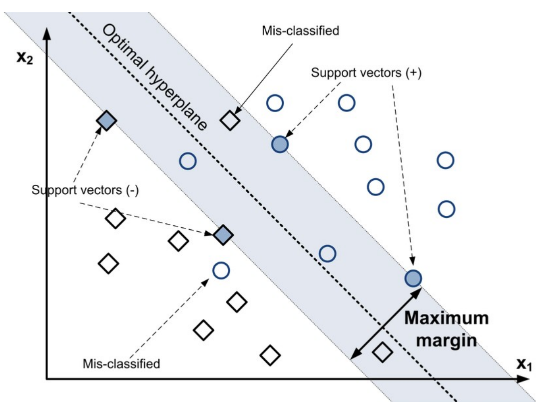

Figure 2. The illustration of SVM [15]

SVM uses Quadratic Programming (QP) as the basic formulation that is written in Equation (2), with the constraints in Equation (3). Quadratic Programming (QP) is a non-linear optimization problem where the objective function is quadratic, and the constraint is a linear function [16].

$$\min\left(\frac{1}{2}\,||\boldsymbol{w}||^2\right), \qquad (2)$$

$$y_i\,(\boldsymbol{w} \cdot \boldsymbol{x}_i + b) \geq 1, \forall i = 1, \ldots, N. \qquad (3)$$

Both QP equation in Equation (2) and constraints in Equation (3) will be solved using the Lagrange Multiplier that is shown in Equation (4). Lagrange multiplier is a technique that is often used in optimization problems with certain constraints [17].

$$L(\boldsymbol{w}, b, \alpha) = \frac{1}{2}\,||\boldsymbol{w}||^2 - \sum_{i=1}^{N} \alpha_i \left(y_i\left((\boldsymbol{w}.\boldsymbol{x}_i + b) - 1\right)\right) \quad \text{for } i = 1,2,\ldots,N \qquad (4)$$

After solving all the equations above, we will get the values of w and b which can be seen in Equations (5) and (6).

$$\boldsymbol{w} = \textstyle\sum_{i=1}^{N} \alpha_i y_i \boldsymbol{x}_i \qquad (5)$$

$$b = \frac{1}{N_s} \textstyle\sum_{i \in S} \left(y_i - \sum_{j \in S} \alpha_j y_j \boldsymbol{x}_j \cdot \boldsymbol{x}_j\right) \qquad (6)$$

Lastly, Equations (5) and (6) will be substituted for the function in Equation (7).

$$f(x) = \mathrm{sign}(\boldsymbol{w} \cdot \boldsymbol{x} + b) \qquad (7)$$

SVM also uses the concept of kernel function. Kernel function is used in problems where the classes are not separable linearly. This function works by mapping the vectors of the feature into a higher dimensional space where the classes or the data are separated linearly [18]. The formula of kernel function can be seen in Equation (8).

$$\mathrm{K}(\boldsymbol{x}, \boldsymbol{z}) = \varphi(\boldsymbol{x})^{\mathrm{T}} \cdot \varphi(\boldsymbol{z}) \qquad (8)$$

In this research, Gaussian RBF kernel will be used. The formula of this kernel function is given in Equation (9).

$$\mathrm{K}(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp(-\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2 / \sigma^2) \qquad (9)$$

2.4 Random Forest

Random Forest (RF) is an ensemble method of machine learning that is extensively used for classification and based on decision trees [20]. Each node is picked randomly from the subset of the features and used as candidates in order to obtain the best split of the node in the decision tree [21].

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The result of RF is obtained by the majority vote from the prediction result of each classification tree. Figure 3 below is the illustration of RF [22].

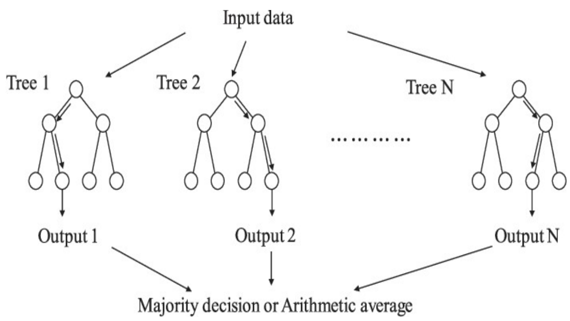

Figure 3. The illustration of Random Forest [22]

The illustration of RF algorithm in input training set, M features, and the number of trees in forest N [23]:

1) Select T trees from the dataset.
2) Construct a decision tree from the T trees.
3) Repeat step 1 and 2, N times.
4) At each node:
   Construct m as a tiny subset of M.
   Split on best feature in m.
5) New records are given to the category that has the most votes.

The RF is built by some decision trees where each tree is constructed from a bootstrap sample of the data [22]. There was an out-of-bag (OOB) sample which is not included in the bootstrap sample. OOB is used as a testing set for a decision tree where the tree is constructed on a bootstrap data [24].

2.5 K-Nearest Neighbors

The k-Nearest Neighbor (kNN) algorithm is one of the machine learning methods that is popularly used for classification because of its simplicity to implement and has good performance [25]. The idea of kNN is calculating the distances between testing ex-ample and training data to identify its nearest neighbors and creates the output of classification [26]. The distance function that is mostly used is Euclidean distance. Two points can be calculated by Euclidean distance with Equation (10) [25].

$$d(\boldsymbol{X_i}, \boldsymbol{Y_i}) = \sqrt{\sum_{j=1}^{N} \left(x_{ij} - y_{ij}\right)^2} \qquad (10)$$

where $\boldsymbol{X}_i = (x_{i1}, x_{i2}, \ldots., x_{iN})$ and $\boldsymbol{Y}_i = (y_{i1}, y_{i2}, \ldots., y_{iN})$ are the two points where $\boldsymbol{X}_i, \boldsymbol{Y}_i \in R^N$. The Euclidean distance can be defined as the similarity level between testing data and training data. If the distance is small, then the similarity level would be closer between testing and training. However, bigger distance means the level of similarity is farther [25].

For the classification problem, the illustration can be seen in Figure 4.

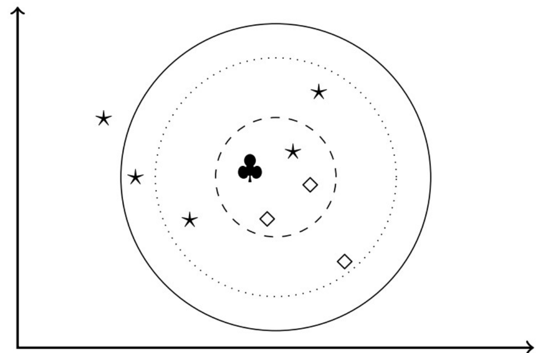

Figure 4. The Classification Problem with kNN [28]

In Figure 4, there is a star (⋆) and diamond (◇) class. This algorithm wants to deter-mine the class for club (♣) data. From Yang et. a [26l, there are three cases of k uses. In the first case, if we use the small, dashed circle (k = 3), club data should be classified as a diamond. In the second case, if we use the big solid circle (k = 7), club data should be classified as a star. Then, in the third case, if we use the dotted circle (k = 6), the club data class would not be easy to determine. Therefore, k is a sensitive parameter that affects the performance of the model. In this research, we used random search to find suitable k for detecting COVID-19.

2.6 Our Proposed Method

In this paper, CNN will be used as a feature extractor and machine learning algorithms namely SVM, RF, and kNN will be utilized as a classifier. CNN model used in this research is pre-trained model VGG19. The model has been trained in ImageNet which has millions images with 1000 categories.

The illustration of our proposed method is given in Figure 5. In this figure, we can see that transfer learning is utilized as we transfer the weight of CNN learned in ImageNet dataset to extract the features of COVID-19 X-ray images.

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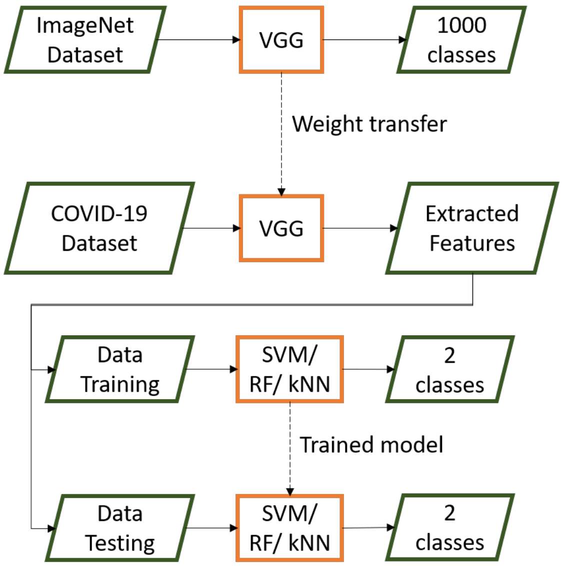

Figure 5. The Illustration of Our Proposed Method

2.7 Confusion Matrix

The evaluation of model performance is measured by using the confusion matrix. The high results measured from the model with a confusion matrix show the good performance of the classification model. The confusion matrix can be seen in Table 1 [28].

Table 1: Confusion Matrix.

Predicted Class	Actual Class	
	Positive	Negative
Positive	TP	FP
Negatif	FN	TN

- True Positive (TP) is the number of samples suffering from COVID-19 and is classified correctly.
- False Positive (FP) is the number of healthy individuals who are misclassified as COVID-19.
- False Negative (FN) is the number of samples of patients with COVID-19 is incorrectly classified as healthy person.
- True Negative (TN) is the number of healthy individuals correctly classified.

Furthermore, some calculations are measured from the confusion matrix, which include accuracy, recall, precision and F1–score. This research is focused on finding the accuracy of the classifier. The formula of this calculation accuracy is defined in Equation (11).

$$\text{accuracy} = \frac{T_p + T_N}{T_P + T_N + F_P + F_N}. \tag{11}$$

3. RESULTS

In this research, we used a dataset from Kaggle COVID-19 Radiography Database [9]. Dataset consists of 1,143 COVID-19 positive X-ray images and 1,341 normal X-ray images. Before the data were used in the proposed method, data will be pre-processed. X-ray im-ages on the dataset do not have the same shape so we applied zero paddings to make all the images have the same shape that is 1,024×1,024. After that, we resized the images into 224×224. Then, the data will be divided into 70% for training and 30% for testing. Then, the data are ready to become input for the methods.

The architecture convolutional neural network used in this research is VGG19. This model consists of 19 layers with 16 convolution layers, 5 max-pooling layers, 3 fully connected layers, and 1 SoftMax layer. The illustration of VGG19 architecture can be seen in Figure 6.

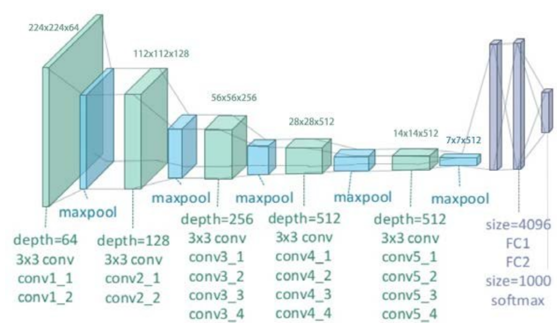

Figure 6. The Illustration of VGG19 Architecture [29]

After VGG19 is applied, the output data of CNN that are in form of feature vector be-come an input to the classic machine learning such as Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbor (kNN). Training process in machine learning is done using 5-fold cross validation in order to ensure the reliability of the results. The result of CNN-SVM, CNN-RF, and CNN-kNN can be explained as follow.

3.1 CNN-SVM

In the first step, we searched the best hyperparameter for SVM in range gamma = [2^0,

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2^{-15}] and C = [2^0, 2^{15}] with random search. Then, the best one to classify COVID-19 is gamma = 2^{-15} and C = 2^2. Using those values, CNN-SVM has reached 99.77% accuracy on data training and 99.73% accuracy on data testing. The confusion matrix of CNN-SVM can be seen in Table 2.

Table 2: The Confusion Matrix of CNN-SVM Performance

Predicted Class	Actual Class	
	Positive	Negative
Positive	341	0
Negatif	2	403

According to Table 2, we can see that there are 2 cases of positive COVID-19 but misclassified as normal.

3.2 CNN-RF

For Random Forest, we also searched the best hyperparameter with random search. The best hyperparameter is obtained when the number of trees is 100 and the criterion is entropy. The result is CNN-RF has reached 99.19% accuracy on data training and 98.66% accuracy on data testing. The confusion matrix of CNN-RF can be seen in Table 3.

Table 3: The Confusion Matrix of CNN-RF Performance

Predicted Class	Actual Class	
	Positive	Negative
Positive	337	4
Negatif	6	399

In Table 3, there are 6 cases of positive COVID-19 which are misclassified as normal and there are 4 cases of normal which are misclassified as COVID-19. The error caused by CNN-RF is not only on the COVID-19 images, but also in the normal images. Furthermore, the performance was worse than CNN-SVM.

3.3 CNN-kNN

To find the best hyperparameters of k-Nearest Neighbor, random search is utilized. The best hyperparameter is obtained when using the number of neighbors = 3 and weight is distance. Thus, CNN-KNN has reached 99.31% accuracy on data training and 99.59% accuracy on data testing. The confusion matrix of CNN-kNN performance can be seen in Table 4.

Based on Table 4, there are 2 of cases positive COVID-19 but misclassified as normal and there is 1 case of normal but misclassified as COVID-19.

Table 4: The Confusion Matrix of CNN-kNN Performance

Predicted Class	Actual Class	
	Positive	Negative
Positive	341	1
Negatif	2	402

4. DISCUSSIONS

Combining Convolutional Neural Network with classic machine learning can be a useful method to classify X-ray images of COVID-19 and normal. The convolutional neu-ral network can extract the features and the classic machine learning does a classification task. The results of the proposed method, such as CNN-SVM, CNN-RF, and CNN-KNN, can be seen in Table 5.

Table 5: The Accuracy Comparison of CNN-SVM, CNN-RF, and CNN-kNN method in Detecting COVID-19 through X-ray Images

Method	Accuracy on Data Training (%)	Accuracy on Data Testing (%)
CNN-SVM	**99.77**	**99.73**
CNN-RF	99.19	98.66
CNN-KNN	99.31	99.59

In Table 5, all the proposed method shows the good performance to classify COVID-19 and normal X-ray images with more than 98% accuracy. Compared between accuracy on data training and data testing, CNN-SVM and CNN-RF have higher accuracy on data training than accuracy on data testing while CNN-KNN reversely. However, CNN-SVM is the best method because it has reached the highest accuracy on data training and data testing with 99.77% and 99.73% respectively. The second best is CNN-KNN with 99.31% accuracy on data training and 99.59% accuracy on data testing. Then, the last one is CNN-RF.

The use of CNN as a feature extractor has also done by several researchers. Turkoglu [30] utilized pre-learned deep features ensemble extracted from AlexNet and SVM for classifying X-ray images obtained from many sources. The data consists of 219 COVID-19 and 1,583 normal images. These amount of COVID-19 image data is small compared to our dataset. However, it succeeds in providing 99.18% accuracy even though our proposed method that is CNN-SVM achieved better with 99.73% accuracy.

In another study, Islam, Islam, and Asraf [31] used combined CNN and LSTM where they obtained 97% accuracy. However, LSTM as a classification method requires a heavier computational load in training data compared to using conventional machine learning methods such as SVM utilized in our proposed method.

Problems related to the computational load required to train deep learning models are also found in the research of Nour, Cömert, and Polat [32] and Maia et al. [33]. Nour et al. (2020) conducted experiments on several classification methods such as kNN, SVM, and DT to classify COVID-19 based on feature extracted by CNN. Based on their experiment, they achieved 98.97% accuracy. Meanwhile Maia et al [33] also did similar experiment, but only utilized SVM and obtained 98.14% accuracy. However, the CNN model used by them was formed from scratch or did not use transfer learning techniques as we did in our proposed method.

The comparison between the performance of our proposed method and the other papers are summarized in Table 6.

Table 6: Comparison of our proposed method with related studies in terms of accuracy

Author	Architecture	Accuracy (%)
Turkoglu [30]	Pre-learned deep features ensemble and SVM	99.18
Islam, Islam, and Asraf [31]	CNN-LSTM	97.00
Nour, Cömert, and Polat [32]	CNN+SVM	98.97
Maia et al [33]	CNN + SVM	98.14
Our Proposed Method	**CNN + SVM**	**99.73**

5. CONCLUSION

COVID-19 has caused a pandemic situation in almost all countries in the world since its first appearance in Wuhan, China. Among the detection tools, chest X-ray can be an efficient and effective tool to use in screening COVID-19. However, to do so, there are test costs, waiting time for the results, and human error that can be the issues when the workload of radiologists increases. Therefore, Computer Aided Diagnosis (CAD) can be a help for the radiologists in assisting them detecting COVID-19 based on chest X-ray results.

Convolutional Neural Network is a well-known method that is frequently used in medical image. It can extract feature on low and high level of image. In this research, pretrained model VGG19 that has been trained in ImageNet database with 1,000 classes is used. Despite the weight of the model built upon the natural image, we used the 'fc1' layer of VGG19 model to extract the feature. The features then flatten and used as an input to machine learning classifier. In this study, three machine learning algorithm will be used which are Support Vector Machines (SVM), Random Forest (RF), and k-Nearest Neighbors (kNN). These classifiers are frequently used method because of their high performance.

In this research, Kaggle COVID-19 Radiography Database is used to examine the performance of our proposed approach. Using 70% of data as training set and 30% of data as testing set, the hybrid CNN-SVM gives the highest accuracy that is 99.77% in training set and 99.73% in testing set. After analyzing the performance in training and testing dataset, we can conclude that our proposed approach can handle the overfitting that probably happens if we train the CNN from scratch. CNN-SVM also gives better performance among three proposed classification methods. Furthermore, our proposed method succeeds in increasing the accuracy in detecting COVID-19 compared to related studies done by researchers before. Therefore, our proposed approach can be a solution to assist the radiologists in differentiating the chest X-ray of COVID-19 patient from the normal/healthy person.

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