International Journal on Advanced Science Engineering Information Technology

Vol.13 (2023) No. 4
ISSN: 2088-5334

An Analysis of Several Optimizers on CNNSVM and CNNRF for COVID–19 Chest X–ray Images

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***Abstract*—COVID–19 is a new type of ailment caused by the strenuous acute respiratory syndrome, namely SARS–CoV-2, also frequently well–known as the Coronavirus. An early tendency of COVID–19 for some sufferers can cause no symptoms at all as no experience is referred to as asymptomatic confirmation cases, yet these sufferers can still transmit COVID–19 to other people. Therefore, the authors developed a program using Machine Learning that sustains data to be analyzed based on the input served under the proposed methods of Convolutional Neural Network–Support Vector Machine (CNNSVM) and Convolutional Neural Network–Random Forest (CNNRF), along with several optimizers to be compared. Convolutional Neural Networks is a deep learning algorithm that can train large data sets with millions of parameters and has attracted attention in various fields that are commonly used for the classification and detection of Convolution in Neural Networks. In amalgamation with Support Vector Machines, a technique that uses two vectors to form a dividing line or side and fairly high accuracy,y random forests classification. In the manner of image data obtained from ChestX–ray images of people with COVID–19 from the Italian Society of Medical and Interventional Radiology (SIRM), a total of 1750 observations consisting of 1000 data for COVID–19 images and 750 data for non-COVID–19 images. This research aims to determine which optimizer is better for analyzing COVID–19 ChestX–ray images by evaluating both methods. Hopefully, both methods can provide higher accuracy for future studies with wider databases to provide better results for analyzing different ailments.**

***Keywords*—COVID–19; ChestX–ray; machine learning; convolutional neural networks; support vector machines; random forests.**

Manuscript received 20 Dec. 2022; revised 26 Apr. 2023; accepted 10 May 2023. Date of publication 31 Aug. 2023.

I. INTRODUCTION

COVID–19 is a new type of ailment caused by the strenuous acute respiratory syndrome, namely SARS–CoV-2, also frequently well–known as the Coronavirus [1]. COVID–19 can lead to respiratory system disorders, which range from mild tendencies such as flu to lung taints. At the end of December 2019, the ailment's first case occurred in Wuhan, China [2], then dispersed amongst people right away to dozens of countries, including Indonesia. Its prompt dispersion has aimed several countries to fulfill policies for asserting lockdowns towards avert the dispersion of the Coronavirus. In Indonesia, the government has fulfilled Large–Scale Social Restrictions tact to depress the dispersion of this virus.

According to the Task Force of the Republic of Indonesia's data, the Acceleration of Handling COVID–19 released the confirmed positive case numbers up to May 5th, 2021, out of 1,677,274 people, with 45,796 people of death toll [3]. From those numbers, it can be deduced that the case mortality rate in Indonesia is around 2.7%. Of all COVID–19 sufferers who passed away [4], 0.6% were aged 0–5 years old, followed by 6–18 years old with 0.7%, 19–30 years old with 2.8%, 31–45 years old with 11.4%, 46–59 years old with 35.9% and last above 60 years old with 48.7%. COVID–19 can contaminate whomever, but the aftermath could be more noxious if it assails the elderly, smokers, pregnant women, people with weak immune systems, and sufferers of certain ailments.

An early tendency of COVID–19 taint can take after flu tendencies, such as fever, headache, sore throat, dry cough, and runny nose [5]. The tendencies above emerge when the body responds contrary to the COVID–19 virus. The tendencies may dissolve and mend, but patients with strenuous tendencies might incident high fever, chest pain, shortness of breath, cough with phlegm, bleeding, or even get worse [6]. In some sufferers, COVID–19 can cause no symptoms as no experience is referred to as asymptomatic confirmation cases. These sufferers can still transmit COVID–19 to other people. To determine whether these symptoms are symptoms of the Coronavirus, a rapid test or PCR is needed [7].

Mistakes are often found throughout the diagnosis despite the conduction of a specific analysis. Therefore, the authors developed a program using Machine Learning that sustains data to be analyzed based on the input served. The proposed methods in this research are Convolutional Neural Network–Support Vector Machine and Convolutional Neural Network–Random Forest, along with several optimizers to be compared. Previous studies have shown that all methods individually are oftentimes used to analyze divers' ailments, including skin cancer [8], diarrhea [9], and cardiovascular [10]. This research aims to determine which optimizer is better for analyzing COVID–19 Chest X–ray images by evaluating both methods.

II. Material and Methods

This section discusses data and methodology used to analyze in this research, such as Chest X–ray, Convolutional Neural Networks, Support Vector Machines, Random Forests, and Confusion Matrix, along with several algorithm optimizers that were compared in this research, namely Adam, AdaGrad, and Stochastic Gradient Descent (SGD) optimizer that summarized and are explained further in the subsections below.

A. Data

The image data used to carry out this research are obtained from Chest X–ray images of people with COVID–19 from the Italian Society of Medical and Interventional Radiology (SIRM). Chest X–ray (CXR) is a radiographic projection of the thorax to diagnose conditions that affect the thorax, its contents, and nearby structures. Photo of the chest using ionized radiation in the form of X–rays dosing about 0.06 mSv. These results were used to diagnose COVID–19 patients to determine whether the virus has spread in the body. A total of 1750 observations consist of 1000 data for COVID–19 images and 750 data for non-COVID–19 images. Figures 1 and 2 are the image data used in this research.

Fig. 1 Sample Non COVID–19 Image Data (Source: Italian Society of Medical and Interventional Radiology)

Fig. 2 Sample COVID–19 Image Data (Source: Italian Society of Medical and Interventional Radiology)

B. Convolutional Neural Networks

The design of the Deep Learning algorithm is similar to the function of the human cerebral cortex, which represents a Deep Neural Network or neural network with many hidden layers [11]. Convolutional Neural Networks is a deep learning algorithms that can train large data sets with millions of parameters [12], take the form of 2D images as input, and combine them with filters to produce the desired output. Convolutional Neural Networks are a type of neural network that dominates many computer vision tasks and has attracted attention in various fields commonly used to classify and detect Convolution in Neural Networks [13]. Figure 3 is an illustration of MobileNetV2 of CNN architecture that was used in this research [14]. Convolutional Neural Networks aim to study the hierarchical spatial structure of elements automatically and adaptively by using backpropagation of multiple building blocks [15], [16].

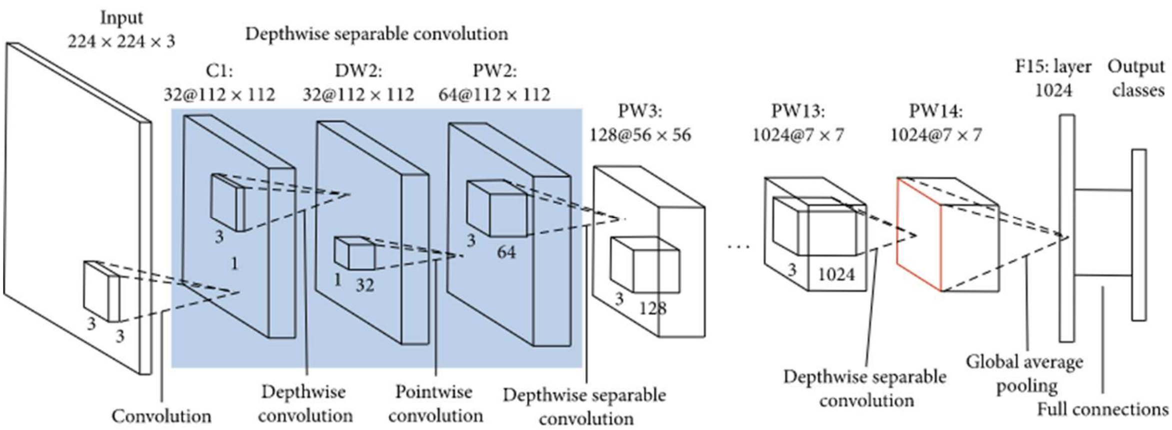

Fig. 3 Illustration of MobileNetV2 of CNN Architecture [14]

C. Convolutional Layer

It is necessary to perform initial processing before applying traditional neural networks to an image. The most important layer in this layer is the convolutional layer. This convolutional layer consists of basic building blocks called convolution applied to a small portion of the image, then sample the pixel values in that area, and finally convert them to one pixel.

D. Pooling Layer

Convolutional Neural Networks can include local or global connection layers to simplify basic calculations. The pooling layer reduces the data dimension by combining the output from the combined neurons into one neuron in the next layer. Convolutional layers do not reduce the image size significantly. Therefore, a general method for doing this involves maximal merging which the maximum pooling layer has a size and width. Unlike the convolutional layer, the pooling layer is applied to a two–dimensional image depth slice.

E. Fully Connected Layer

A fully connected neural network composed of a sequence of fully connected layers with each output size relies on every input size.

F. Support Vector Machines

Support Vector Machines is a technique that uses two vectors that could form a dividing line or side (if three dimensions and above). A hyperplane is the divider formed from these two vectors [17]. The way SVM works can be seen through a very simple illustration [see Figure 4].

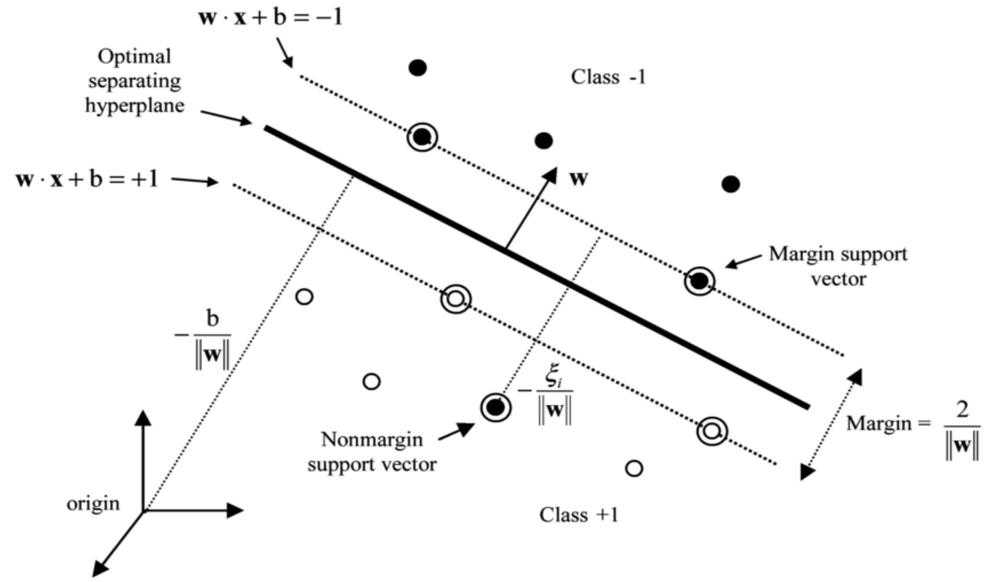

Fig. 4 Illustration of Support Vector Machines finds the optimal hyperplane [21]

First, we have a dividing line in which each line is formed by two points closest to the line [18]. As we have two data groups, the task is to divide these two groups as best as possible. The boundary line can separate two groups with the farthest distance between the outermost points in each group with the boundary line itself [19]. It should be noted that the two outermost points, namely support vectors, must be perpendicular to the hyperplane, which can provide the farthest distance between 2 different groups to determine the best hyperplane [20]. The naming of positive and negative hyperplanes is free. Figure 3 illustrates Support Vector Machines finding the optimal hyperplane [21].

First, we have the main formula of SVM [22] as written in Equation (1) that maximizes the margin using parameters w (weight) and b (biased).

$$f(x) = w \cdot x + b. \tag{1}$$

This leads further to the definition in Equation (2) which the general and smaller possible errors were produced, along with the margin developed in Equation (3).

$$\frac{|f(x)|}{w} \tag{2}$$

$$\max_{w,b\cdot} \frac{|f(x)|}{||w||} \tag{3}$$

Then Equation (4) was later constructed as the main optimization of SVM, followed by Equation (5).

$$min \frac{1}{2} ||w||^2 \tag{4}$$

$$s.t \quad y_i(w \cdot x_i + b) \geq 1\ ;\ i = 1,2, \dots, N. \tag{5}$$

In Equation (6), the parameters aim to maximize the hyperplane and minimize error classification using smaller margin values in Equation (7) and (8).

$$\min(\frac{1}{2} ||w||^2 + C \tag{6}$$

$$s.t. \quad y_i(w \cdot x_i + b) \geq 1 - \xi_i\ ;\ i = 1,2, \dots, N, \tag{7}$$

$$\xi_i \geq 0\ ;\ i = 1,2, \dots, N \tag{8}$$

This research uses kernel functions in SVM to solve algorithms expression and dimensional problems as presented in Table 1 [23].

TABLE I
KERNEL FUNCTION

Name	Kernel Function
Linear	$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \llbracket \boldsymbol{x}_i \rrbracket^T \boldsymbol{x}_j$
Polynomial	$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \llbracket (t + \llbracket \boldsymbol{x}_i \rrbracket^T \boldsymbol{x}_j) \rrbracket^d$
Gaussian Radial Basis Function (RBF)	$K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp\left(-\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2 / \sigma^2\right)$

G. Random Forests

This classification technique is a technique that has a fairly high accuracy, namely random forest classification [24]. The Discussion of this technique is similar to random forests regression, except that the goal is not to predict a value but classify the data. This technique generates many decision tree classifications and makes decisions based on several decision trees that have been made [25]. The real applications of this technique are numerous, as one futuristic application is for motion detection [26]. Figure 5 is an illustration of Random Forests architecture [27].

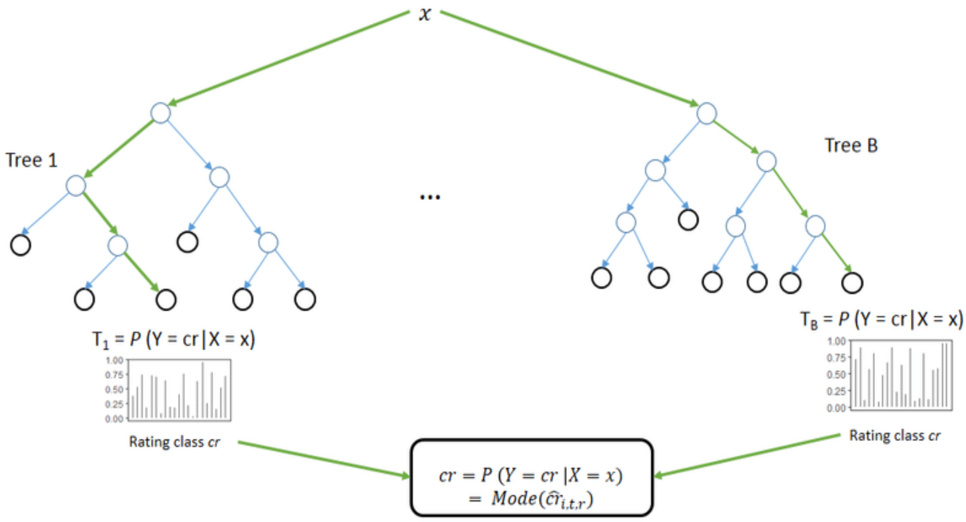

Fig. 5 Illustration of Random Forests Architecture [27]

The steps are as follows [28]:

- Foremost, select some data in training set as many as K, then create the Decision Tree from the K data that has been selected previously.
- Select the number of N–trees (a collection of trees) you want to create and repeat the two previous steps.
- Keep making as many decision trees as possible, generally above 200 times.
- For new datasets, make each N–tree predict groups from the new dataset and enter the group that has the highest probability of all N–tree combinations.

H. Optimizer

Optimizer is an algorithm for updating weights and biases in an artificial neural network's learning process to minimize the error or difference between the network output and the target [29]. The basic algorithm commonly used is gradient descent, which has a weakness that is sometimes very slow to reach a fairly small error value [29]. To overcome these weaknesses, various algorithms have been developed, some of which used in this research are follows [30]–[32]:

I. Adam Optimizer

Adam Optimizer is a combination of the RMSProp and momentum optimizer, which has several advantages, including being computationally efficient, memory efficient and suitable for a variety of non–convex optimization problems in machine learning. In the Adam algorithm, Adaptive Moment Estimation, the running average and the second moment of the gradient are the former.

J. AdaGrad Optimizer

AdaGrad Optimizer is a modified stochastic gradient descent algorithm that preserves a parameter learning rate that rectifies performance on problems with infrequent gradients. The increases in learning speed are for the less frequent parameters, as the decreases are for the less thin parameters. This strategy frequently rectifies convergence performance over descending standard stochastic gradients in settings where data are thin, and parameters are seldom more informative.

K. Stochastic Gradient Descent Optimizer

Stochastic Gradient Descent Optimizer is an iterative method of optimizing an objective purpose by fitting smoothness properties as it supplants the proper gradient with its estimate. The subsided computational load reaches prompt iterations in the trade of degraded convergence rates in advanced dimensional optimization problems. By preserving one learning rate of all weight updates and not shifting through training, it could be maintained towards every network weight and adjust aloof as learning unfolds.

L. Confusion Matrix

Accuracy is the primary parameter to inspect classification success with the confusion matrix used for accurate measures, as presented in Table 2 [33].

TABLE II
CONFUSION MATRIX

Actual	Prediction	
	Positive	Negative
Positive	T_P	F_N
Negative	F_P	T_N

- True Positive (T_P) is the number of samples suffering from the disease and is classified correctly.
- False Positive (F_P) is the amount of non–COVID–19 individuals misclassified.
- False Negative (F_N) is the number of samples of patients with COVID–19 and incorrectly classified as non–COVID–19.
- True Negative (T_N) is the number of non–COVID–19 individuals classified correctly.

The evaluation of model performance as the accuracy value is the greater is the better in classifying and predicting, which the formulation of accuracy [33] is shown in Equation (9).

$$accuracy = \frac{T_P+T_N}{T_P+T_N+F_P+F_N}. \quad (9)$$

III. RESULTS AND DISCUSSION

This section further discusses the Convolutional Neural Network–Support Vector Machine and Convolutional Neural Network–Random Forest, which is used to analyze the COVID–19 Chest X–ray image data with several optimizers. The result is analyzed by implementing the program using the model's prediction accuracy.

A. The Model Used

The Convolutional Neural Network–Support Vector Machine and Convolutional Neural Network–Random Forest modeling is applied with Tensorflow. In this research, the image data is classified into two classes under the performance results of the model accuracy value. First, the Binary Cross–Entropy was used as the loss function then three optimizers used be compared in both models. For CNN–SVM, the model used three kernel functions in the SVM section: Linear, Polynomial, and Gaussian RBF. This research used parameter C equals 5 for both linear and polynomial kernels and Gaussian RBF kernel with parameter gamma equals 5.

B. The Results Analysis

This research used testing data of 10% to 90% with 10 epochs and 16 batches for both methods of Convolutional Neural Network–Support Vector Machine and Convolutional Neural Network–Random Forest, then took the average of all test data accuracy applied. The results of the accuracy test for COVID–19 Chest X–ray images dataset of each optimizer are summarized in Table 3.

Table 3 shows that the Adam optimizer performs best compared to other optimizers. The highest accuracy results, with 94.70% were obtained from CNN–SVM linear kernel model. The second best performance applied is the Stochastic Gradient Descent optimizer, with the highest accuracy results of 98.82% from CNN–RF. Lastly, the Adagrad optimizer, the lowest performance applied amongst the three with the highest accuracy results, obtained 87.05% from CNN–SVM polynomial kernel and CNN–RF.

TABLE III
MODEL'S ACCURACY OF EACH OPTIMIZER

Model Used	Optimizer		
	Adam	**Adagrad**	**Stochastic Gradient Descent**
CNN–SVM Linear Kernel	94.70	81.17	77.64
CNN–SVM Polynomial Kernel	92.94	87.05	90.94
CNN–SVM Gaussian RBF Kernel	92.94	82.94	91.94
CNN–RF	92.94	87.05	98.82
Average	**93.38**	**84.55**	**89.83**

The authors also observed the accuracy generated from the Convolutional Neural Networks program for comparison in analyzing the COVID–19 Chest X–ray images dataset. The comparison of the performance of CNN's accuracy and the proposed method obtained is shown in Table 4.

TABLE IV
COMPARISON OF CNN AND PROPOSE MODEL'S ACCURACY OF EACH OPTIMIZER

Model Used	Optimizer		
	Adam	**Adagrad**	**Stochastic Gradient Descent**
CNN	92.58	90.94	82.94
CNN–SVM Linear Kernel	94.70	81.17	77.64
CNN–SVM Polynomial Kernel	92.94	87.05	90.94
CNN–SVM Gaussian RBF Kernel	92.94	82.94	91.94
CNN–RF	92.94	87.05	98.82
Average	**93.22**	**85.82**	**88.45**

The results further show that the Adam optimizer still had the best performance for analyzing the COVID–19 Chest X–ray images dataset with an average of 93.22%. Followed by the Stochastic Gradient Descent optimizer with an average of 88.45% and the Adagrad optimizer with an average of 85.82%. Therefore, the best optimizer for analyzing the COVID–19 ChestX–ray images dataset was found to be the Convolutional Neural Network–Support Vector Machine Linear Kernel with Adam Optimizer.

IV. CONCLUSION

The presence of the ailment was predicted by analyzing it with a machine learning method to aid medical staff in analyzing it. Significantly because an early analysis of ailment is essential, it allows the patient to get prompt and proper curing, thereby reducing health risks and increasing the survival rate. This research focuses on COVID–19 which was conducted using 1750 data collected and two classes observed. By using a combined methodology of Convolutional Neural Network–Support Vector Machine and Convolutional Neural Network–Random Forest, along with several optimizers used to be compared as Adam, AdaGrad, and SGD optimizer, experimental results exemplified that both methods were able to analyze the data fairly and precisely. Based on the findings, the combination methodology of Convolutional Neural Network–Support Vector Machine Linear Kernel with Adam Optimizer was the best model to analyze the COVID–19 Chest X–ray images dataset with an average of 94.70% accuracy. Therefore, this method is expected to generate higher accuracy so future studies with wider databases can provide better results for analyzing diverse ailments.

ACKNOWLEDGMENT

The University of Indonesia financially supported this research with a PUTI 2022 grant scheme.

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