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Research article

Optimization of the VGG Deep Learning Model Performance for Covid-19 Detection Using CT-Scan Images

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ABSTRACT

Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-Cov-2) causes a pneumonia-like disease known as Coronavirus Disease 2019 (COVID-19). The Reverse Transcription Polymerase Chain Reaction (RT-PCR) test is the current standard for detecting COVID-19. However, CT scans can be applied for radiological inspection to detect infections in their earliest lung stages. Machine learning, specifically deep learning, can potentially speed up the evaluation of CT scan diagnoses of COVID-19. To date, no studies have been discovered that employ SGD, Adamax, or AdaGrad optimization methods with deep learning VGG model variants for COVID-19 detection in CT scan images with datasets comprising 2,038 images. This study aims to assess and compare the performance of various optimization methods for detecting COVID-19 utilizing variations of the VGG-16 and VGG-19 models based on CT scan images. Results from performance optimization comparison tests employing two VGG deep learning models were obtained, demonstrating the influence of optimization methods on model performance. The Adamax optimization method applied to the VGG-16 model performance achieved an average accuracy of 94.11% in COVID-19 detection using CT scan images, while the Adamax optimization method applied to the VGG-19 model performance achieved an average accuracy of 93.77%.

1. Introduction

The Coronavirus Disease 2019 (COVID-19) is an emerging widespread pandemic. Before the epidemic in Wuhan, China, in December 2019, the virus and the disease produced by this newly identified Coronavirus were unknown. A growing number of people worldwide have been infected with COVID-19 because of its fast global dissemination. As of August 2020, 260 countries were affected by the COVID-19 pandemic, which was first declared on March 11, 2020, by the World Health Organization (WHO). In Indonesia, over 130,718 confirmed cases of COVID-19 were reported. As of August 2020, 34 provinces in Indonesia had reported 85,798 recovered cases and 5,903 fatalities due to this pandemic [1], [2].

Early diagnosis of COVID-19 significantly facilitates isolation, containment, and individual care. One of the most common procedures for identifying COVID-19 in respiratory samples is the Reverse Transcription Polymerase Chain Reaction (RT-PCR) test. Additionally, CT scan images from a radiological examination can be utilized to detect COVID-19 infection in its early stages, allowing for the identification of infections in the lungs [3]. A study in 2021 established a program to diagnose COVID-19 and non-COVID-19 using CT scan image data. It utilized the VGG-19 model compiled with the ADAM optimization with the default learning rate and binary cross-entropy loss function, and the VGG-16 and DensNet-169 models compiled with RMSPROP optimization. It also tested the CTnet-10, DensNet-169, VGG-16, ResNet-50, Inception-V3, and VGG-19 models. Among all the tested models, the VGG-19 model proved to be superior, achieving an accuracy of 94.52% [4].

Previous studies have combined VGG deep learning models with optimization methods, including ADAM and RMSPROP. However, this is the first work to employ the SGD, Adamax, and AdaGrad optimization methods on VGG deep learning model variants designed to identify COVID-19. This study utilized VGG deep learning model variants to evaluate the effectiveness of the SGD, Adamax, and AdaGrad optimization methods. This study aims to determine the optimal optimization method for accurately detecting COVID-19 from CT scan images.

2. Materials and methods

Pneumonia induced by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-Cov-2) is known as Coronavirus Disease 2019 (COVID-19). The Severe Acute Respiratory Syndrome Coronavirus (SARS-Cov) and the Middle East Respiratory Syndrome Coronavirus (MERS-Conv) are the other two extremely dangerous Coronaviruses identified in humans [5]. SARS-Cov-2 can spread faster than SARS-Cov and MERS-Conv. COVID-19 has a substantially lower mortality rate than either SARS-CoV (9.5%) or MERS-CoV (34.4%) [6]. Coronavirus belongs to the Coronaviridae family in the order Nidovirales. The virus was named for the crown-shaped spikes on its surface [7]. Coronavirus has a single-stranded, positive-sense Ribonucleic Acid (RNA) genome, whose length ranges from 26 to 32 kbs, making it the largest genome of all RNA viruses (Novel Coronavirus, 2020) [8].

2.1 Deep Learning

The Artificial Neural Network (ANN) is applied in deep learning, a subfield of machine learning, to solve complex problems with the help of extensive datasets. Supervised learning can benefit significantly from the architecture provided by deep learning. In machine learning, deep learning is one of several models based on ANN [9]. Deep learning is an artificial intelligence (AI) function that attempts to simulate how the human brain processes information using a network that can autonomously learn to process data [10].

The Convolutional Neural Network (CNN) is an algorithm used in deep learning for object detection and image recognition. Deep learning offers many advantages: it enhances the performance of unstructured data, eliminates the need for feature engineering, produces higher-quality output displays, and lowers the cost of development operations [11]. CNNs, a type of neural network, are commonly used with image data. They can identify and recognize objects in an image. CNNs are similar to ordinary neural networks in many respects. The neural component of a CNN includes a weight, a bias, and an activation function. The neurons in the convolutional layer are placed to provide a long and narrow filter (in terms of pixels). The two main components of a CNN's design are the feature Extraction Layer and Fully Connected Layer [12].

CNN is a machine learning method developed from Multi-Layer Perceptron (MLP), designed to manage two-dimensional data. Feed-forward processing is employed for image categorization, while backpropagation is utilized during the learning stage in CNN. CNN's operation is similar to that of MLP, but unlike MLP, each neuron in CNN is represented in two dimensions [13]. Simonyan and Zisserman from University of Oxford presented the Visual Geometry Group (VGG) as one of the CNN architectural models for the ILSRVRC-2014 competition. The VGG model architecture is a cutting-edge method for object detection and can have up to 19 distinct layers. As a deep CNN, VGG achieves better results than the baseline on various tasks and datasets. There are five distinct configurations of the VGG architecture, each corresponding to a different number of layer depths. In terms of sheer numbers, the VGG-16 and VGG-19 models emerge as clear frontrunners. The number of layers in each model is where VGG-16 and VGG-19 diverge. VGG-16 has 16 layers, while VGG-19 has 19 [14].

2.2 Optimization

Adjusting attributes like weights and learning rates, as well as optimizing, can help neural networks achieve better accuracy and lower loss [15]. Optimization determines the best outcome by maximizing or minimizing the objective function (loss). Learning and modifying the output of all process outcomes aim to minimize loss during training. The optimization algorithms included in the Keras library are SGD, RMSprop, Adam, Adadelta, Adagrad, Adamax, Nadam, and Ftrl [16]. This study employed three different optimization methods from the Keras library: the SGD, Adamax, and Adagrad optimization methods.

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In each iteration of the Stochastic Gradient Descent (SGD) method, the model parameters are updated and modified stochastically. If the dataset has 1,000 rows, SGD will update or adjust the model parameters 1,000 times over the dataset cycle, as opposed to just once during Gradient Descent (GD) [15]. Each training sample checks the loss function and adjusts the model to achieve a minimal coalescence in a shorter time without increasing the variance, which can cause the model to deviate from its target location. Since this SGD optimization does not keep track of prior loss function values, it employs much less memory than its predecessor. After computing the gradient from a randomly selected point, SGD adjusts the weights [17].

The same researcher who developed the Adam optimization algorithm also developed a variant of SGD adaptation called Maximum Adaptive Movement Estimation (Adamax). Adamax is an optimization method based on Adaptive Movement Estimation (Adam), which combines GD momentum and RMSprop. When applied to certain situations, Adamax generalizes the method to the infinite (max) norm (a function that translates some inputs to some outputs), leading to better improvements. Adamax is an optimization-acceleration gradient descent. The maximum of the previous gradient and the current gradient is the value used for the update when generalizing Adam to the infinity norm [18].

The Adaptive Gradient Algorithm (AdaGrad) is an optimization method that incorporates several weights with varying degrees of learning depending on the frequency with which values are updated. AdaGrad's benefits include its ability to adapt to varying training parameters and handle datasets with missing or sparse samples. However, AdaGrad has a relatively slow learning process due to division by larger numbers. AdaGrad's key advantage is that it eliminates the manual requirement to complete learning paces [19].

Three different optimization methods were applied in this research: SGD, Adamax, and Adagrad. Several previous studies have employed one of these three optimization methods to detect COVID-19. For instance, a study in 2021 classified COVID-19 X-ray images using the DenseNet model and various optimization methods, including Adamax, AdamW, and SGD. The Adamax optimization method achieved the highest accuracy, at 98.45% for the normal data class and 98.32% for the COVID-19 data class [20]. Using the VGG-16 model for image classification, X-ray and CT scan images were employed to diagnose COVID-19 in a study conducted in 2020. The research continued with only the VGG-16 model and incorporated the Adagrad optimization method, resulting in an overall accuracy of 97.8%. When applied to detecting COVID-19 in X-ray images, it generated a sensitivity of 99.3%, a specificity of 99.98%, and a positive predictive value of 99.6% [21].

SGD, Adamax, and Adagrad are among the optimization methods applied in the previously mentioned research to identify COVID-19. Although these methods have been utilized in other investigations, only the VGG-16 model and other models not used in this study have been reported. Previous studies have demonstrated that SGD, Adamax, and Adagrad optimization methods offer the most promise for identifying COVID-19 with the highest accuracy. This research compared the performance of three optimization methods for detecting COVID-19 in CT scan images, all while employing VGG deep learning model variants. This research consists of five research steps, i.e., dataset preparation, pre-processing, model training, model testing, and model performance analysis. Fig. 1 depicts the phases involved in diagnosing COVID-19 using CT scan images.

2.3. Dataset Preparation

This research employed publically available data from chest CT scan images [22]. This study utilized CT scans of both COVID-19-affected and unaffected lungs and chests, totaling 2038 images. Of these, 905 images were of COVID-19-affected lungs, and the remaining 1,133 were of unaffected lungs. This study utilized CT scan images as the data, with the CT_COVID and CT_NonCOVID datasets comprising 2,038 images. Only 20% of the total datasets were taken for testing, while 80% were employed for training. After that, 20% of the 80% of the training data were used to validate the trained models.

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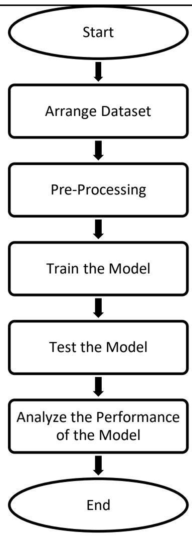

Fig. 1 Research Stages

2.4. Pre-Processing

To ensure optimal performance, CT scan image data underwent pre-processing. At this point, the CT scan image data were resized (their dimensions were altered) and shared. The image resizing stage aimed to simplify the data training and testing to evaluate variants of the VGG deep learning models. A resizing operation was performed because the VGG-16 and VGG-19 models being compared employed a standard image size of 224x224 pixels. Fig. 2 provides an example of the resized image achieved using this method.

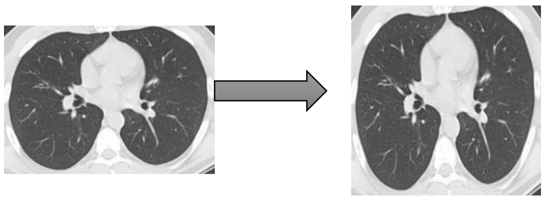

Fig. 2 Image Resizing Before and After

After the images were resized, their quality was enhanced by augmentation to strengthen the model performance. The augmentation stage played an essential role in data training. Image data were flipped horizontally and then enhanced. Fig. 3 exhibits an example of the enhanced image produced by image augmentation.

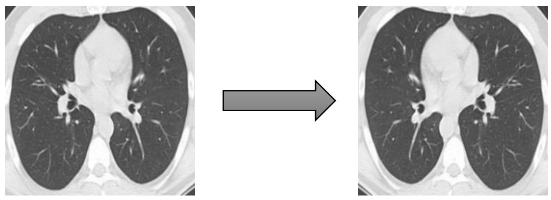

Fig. 3 Image Augmentation Before and After

To evaluate the performance of a machine learning model, cross-validation was employed. Models with sparse data can also be assessed with cross-validation, which involves repeatedly sampling the same dataset. Table 1 illustrates the breakdown of the training and testing data in this study. For each K-Fold, the data were randomly divided into K group. The testing data are shown in white, while the training data are shown in blue.

Table 1. K-Fold Cross Validation

K-Fold	Dataset-n				
I	Data 1	Data 2	Data 3	Data 4	Data 5
II	Data 1	Data 2	Data 3	Data 4	Data 5
III	Data 1	Data 2	Data 3	Data 4	Data 5
IV	Data 1	Data 2	Data 3	Data 4	Data 5
V	Data 1	Data 2	Data 3	Data 4	Data 5

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This research utilized randomly determined training and testing data, by the models, divided into five K-Folds to produce five different training datasets. The amount of validation data to train the models on K-Fold Cross-Validation was 20% of the total training data. In each folder, groups of data were applied as testing data, and the rest were deployed as training data.

2.5. Model Training

The training phase involved the utilization of the VGG-16 and VGG-19 model variants to classify two groups of CT scan images: CT-COVID and CT-NonCOVID. As a first step in deep learning training, the data were organized based on their categories. Several steps beyond data collection were required for optimal pre-processing results. Then, the K-Fold was divided into five folds, as displayed in Table 1, containing training and testing data. Finally, a fold of the testing data was employed as validation data during model training. Subsequently, the training was performed using two VGG deep learning model variants, with SGD, Adamax, and AdaGrad optimization methods. The training employed a batch size of 32 and a mass (epoch) of 50. When a K-Fold completed a training session, the collected data were saved to Google Drive.

2.6. Model Testing

Image data stored from the previous training results were employed for testing, utilizing 20% of the total data. The data testing was performed as much as the K-Fold added to the training. After the testing, the resulting data from image prediction or classification displayed several random sample image data with predictive marker labels using different colors: CT-COVID (CT-COVID) and CT-NonCOVID (CT-NonCOVID) for correct predictions were colored green, while CT-NonCOVID (CT-COVID) and CT-COVID (CT-NonCOVID) for incorrect predictions were colored red. In addition to sample images, the testing results were presented in a confusion matrix to analyze each model variation's performance.

A confusion matrix with three or more classes has been employed to measure performance in machine learning classification issues. According to the literature [23], a confusion matrix consists of a table with four distinct combinations of expected and actual values. Accuracy, precision, recall, specificity, and F-score are only a few of the matrix performance indicators used to evaluate the classification model's effectiveness in light of the confusion matrix.

Tabel 3 exhibits the formulas used to determine the performance matrix. The categorization outcomes can be described using the following terms. (a) True Positive (TP (A)), positive data predicted as true; (b) True Negative (TN (B)), negative data correctly predicted as negative; (c) False Positive (FP (C)), negative data incorrectly predicted as positive; and (d) False Negative (FN (D)), positive data incorrectly predicted as negative [24].

Table 2. Two-Class Confusion Matrix Formula

PREDICTED / ACTUAL	**TRUE**	**FALSE**
TRUE	TP (A)	FP (B)
FALSE	FN (C)	TN (D)

Table 3. Two-Class Confusion Matrix Formula

Matrix Performance	**Formula**
Accuracy	$\frac{(TP + TN)}{(TP + TN + FP + FN)}$
Precision	$\frac{TP}{(TP + FP)}$
Recall	$\frac{TP}{(TP + FN)}$
Specificity	$\frac{TN}{(TN + FP)}$
F-score	$\frac{2\ X\ (Recall\ x\ Precision)}{(Recall +\ Precision)}$

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Table 4. Class Confusion Matrix Formula

Matrix Performance	Class	Formula
Accuracy	Class 1	$\frac{(A + D)}{(A + D + B + C)}$
	Class 2	$\frac{(D + A)}{(D + A + C + B)}$
Precision	Class 1	$\frac{A}{(A + C)}$
	Class 2	$\frac{D}{(B + D)}$
Recall	Class 1	$\frac{A}{A + B}$
	Class 2	$\frac{C}{(C + D)}$
Specificity	Class 1	$\frac{D}{(C + D)}$
	Class 2	$\frac{A}{(A + B)}$
F-score	Class 1	$\frac{(2 X A)}{(2A + B + C)}$
	Class 2	$(2 \frac{X D)}{(2D+B+C)}$

2.7. Model Performance Analysis

The testing analysis aimed to measure the performance of the training models used for the confusion matrix. The confusion matrix had two classes: CT-COVID and CT-NonCOVID. The standard parameters for comparison were matrix performance, including accuracy, precision, recall, specificity, and F-score. For a clearer way of measuring model performance, the formulas for calculating two classes were described in Tabel 3, and for calculating each class, they were described in Table 4. The analysis utilized the results of all classes in each fold in the confusion matrix. The higher the results of calculating the performance matrix, the better and more efficient the model performance.

3. Results and Discussion

3.1. Comparison of Training Model Performance Optimization

Table 5 and Table **6** presents comparisons of training using different iterations of the VGG models and the three different optimization methods. These tables provide a comparison of the results of training the VGG deep learning models with the SGD, Adamax, and AdaGrad optimization methods. This study's analysis of CT scan images suggested that Adamax optimization offered the most beneficial results. Since Adamax optimization yielded an accuracy above 90%, its results could be considered the best **in this study.**

Table 5. Comparison of Optimization with Model Variations in the Training

K-Fold	VGG-16					
	SGD Optimization		Adamax Optimization		Adagrad Optimization	
	Accuracy (%)	Loss (%)	Accuracy (%)	Loss (%)	Accuracy (%)	Loss (%)
I	90.94%	21.24%	**95.63%**	**16.74%**	**94.06%**	**15.62%**
II	90.31%	24.99%	93.75%	21.56%	91.87%	21.39%
III	**92.19%**	20.85%	91.87%	33.92%	93.44%	19.46%
IV	91.87%	**19.86%**	94.38%	32.45%	91.25%	22.13%
V	89.38%	27.13%	94.38%	20.02%	89.69%	24.01%

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Table 6. Comparison of Optimization with Model Variations in the Training

K-Fold	VGG-19					
	SGD Optimization		Adamax Optimization		Adagrad Optimization	
	Accuracy (%)	Loss (%)	Accuracy (%)	Loss (%)	Accuracy (%)	Loss (%)
I	**92.19%**	**19.60%**	92.50%	23.11%	91.87%	20.04%
II	89.69%	25.53%	91.87%	33.36%	91.25%	23.02%
III	89.06%	25.87%	94.69%	20.00%	91.87%	19.26%
IV	90.94%	20.41%	**96.25%**	**11.55%**	**93.12%**	**17.78%**
V	87.50%	28.30%	91.87%	39.09%	87.19%	30.12%

3.2. VGG-16 Model Testing With SGD Optimization

Table 7 summarizes the testing results of the VGG-16 model and the SGD optimization method. It exhibits the results of data tested using the VGG-16 model and the SGD optimization method. The average accuracy obtained was impressive, reaching 91.07%. K-Fold II performed the best, with an overall performance accuracy matrix rating of 94.36%. It showed the highest values for precision (93.84%), recall (94.32%), specificity (94.39%), and F-score (94.08%).

Table 7. Matrix Performance of Each Fold of VGG-16 with SGD

K-Fold	Accuracy	Precision	Recall	Specificity	F-score
I	92.89%	91.62%	92.13%	93.47%	91.87%
II	94.36%	93.84%	94.32%	94.39%	94.08%
III	89.46%	83.72%	90.56%	88.75%	87.00%
IV	87.96%	79.44%	92.25%	85.31%	85.37%
V	90.66%	89.38%	89.38%	91.66%	89.38%
Average	**91.07%**	**87.60%**	**91.73%**	**90.72%**	**89.54%**

3.3. VGG-16 Model Testing with Adamax Optimization

The testing results of the VGG-16 model with the Adamax optimization method are displayed in Table 8. It illustrates the results of data testing performed using the VGG-16 model and the Adamax optimization method. It yielded the most favorable outcomes for the data testing. K-Fold II's performance on the accuracy matrix was the best as a whole, with 96.32%. K-Fold II also achieved the highest precision of 93.33%, recall of 98.91%, and F-score of 96.04%. Meanwhile, K-Fold I obtained the highest specificity of 94.65%.

Table 8. Matrix Performance of Each Fold of VGG-16 with Adamax

K-Fold	Accuracy	Precision	Recall	Specificity	F-score
I	94.61%	92.73%	94.85%	94.65%	93.78%
II	96.32%	93.33%	98.91%	94.19%	96.04%
III	93.14%	94.76%	89.56%	96.01%	92.09%
IV	92.87%	87.22%	96.31%	90.57%	91.54%
V	93.61%	87.15%	98.11%	90.72%	92.30%
Average	**94.11%**	**91.04%**	**95.55%**	**93.23%**	**93.15%**

3.4. VGG-16 Model Testing With Adagrad Optimization

Tabel 9 portrays the testing results of the VGG-16 model and the Adagrad optimization method. Following this table, the testing results unveiled a high level of accuracy, with an average of 92.34 %. Regarding the accuracy matrix, K-Fold II had the most outstanding overall performance, with 94.61%. K-Fold I obtained the highest precision of 91.62% and specificity of 93.50%. K-Fold II generated the greatest F-score of 94.17%, while K-Fold IV acquired the highest recall of 97.94%.

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Table 9. Matrix Performance of Each Fold of VGG-16 with Adagrad

K-Fold	Accuracy	Precision	Recall	Specificity	F-score
I	93.14%	91.62%	92.65%	93.50%	92.13%
II	94.61%	91.28%	97.26%	92.44%	94.17%
III	91.42%	85.46%	93.63%	90.03%	89.36%
IV	90.17%	79.44%	97.94%	85.82%	87.73%
V	92.38%	84.91%	97.43%	89.24%	90.74%
Average	**92.34%**	**86.54%**	**95.78%**	**90.21%**	**90.83%**

3.5. VGG-19 Model Testing with SGD Optimization

The testing results using the VGG-19 model and the SGD optimization method are depicted in Table 10. It demonstrates that the average yield was over 80%, indicating good overall performance. K-Fold II achieved the highest overall performance of any accuracy matrix, which was 92.89%, and produced the greatest F-score of 92.50%. K-Fold I obtained the highest recall of 95.03%. K-Fold III generated the highest precision of 93.79% and specificity of 94.49%.

Table 10. Matrix Performance of Each Fold of VGG-19 with SGD

K-Fold	Accuracy	Precision	Recall	Specificity	F-score
I	91.67%	85.47%	95.03%	89.47%	90.00%
II	92.89%	91.79%	93.22%	92.59%	92.50%
III	89.71%	93.02%	84.21%	94.49%	88.39%
IV	87.22%	85.55%	85.55%	88.54%	85.55%
V	91.40%	88.82%	88.82%	91.41%	90.08%
Average	**90.58%**	**88.89%**	**89.88%**	**91.30%**	**89.30%**

3.6. VGG-19 Model Testing With Adamax Optimization

The testing results of the VGG-19 model and the Adamax optimization method are presented in Table 11. These results show the highest accuracy among the three optimization methods in the VGG-19 model, suggesting that the outcomes were relatively excellent. The average percentage of correct predictions for images was 97.48%. According to the accuracy matrix, K-Fold II achieved the highest performance with a value of 95.83%. K-Fold I attained the greatest recall of 99.51%. K-Fold II accomplished the highest precision of 92.82% and the most prevalent F-score of 95.51%. K-Fold III achieved the highest specificity of 94.58%.

Table 11. Matrix Performance of Each Fold of VGG-19 with Adamax

K-Fold	Accuracy	Precision	Recall	Specificity	F-score
I	90.44%	78.77%	99.29%	85.71%	87.85%
II	95.83%	92.82%	98.36%	93.75%	95.51%
III	94.61%	92.44%	94.64%	94.58%	93.52%
IV	94.10%	89.44%	96.98%	92.11%	93.06%
V	93.86%	87.70%	98.12%	91.09%	92.62%
Average	**93.77%**	**88.23%**	**97.48%**	**91.45%**	**92.51%**

3.7. VGG-19 Model Testing with Adagrad Optimization

Tabel 12 displays the testing results of the VGG-19 model with the Adagrad optimization method. It signifies that the testing results were reasonably good, with an accuracy of over 90%. K-Fold II achieved the best overall performance of the accuracy matrix, with 94.85%. Precision attained the most outstanding result in K-Fold V, with 94.97%. Recall reached the most remarkable result of 95.78% in K-Fold I. Specificity obtained the finest result of 95.65% in K-Fold V. Finally, the F-score had the most significant result of 94.54% in K-Fold II.

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Table 12. Matrix Performance of Each Fold of VGG-19 with Adagrad

K-Fold	Accuracy	Precision	Recall	Specificity	F-score
I	93.38%	93.29%	91.75%	94.69%	92.52%
II	94.85%	93.33%	95.78%	94.03%	94.54%
III	90.93%	87.20%	90.90%	90.94%	89.02%
IV	88.70%	90.55%	84.89%	92.09%	87.63%
V	90.93%	94.97%	85.00%	95.65%	89.70%
Average	**91.76%**	**91.87%**	**89.67%**	**93.48%**	**90.68%**

3.8. Comparison of Testing Data for Each Class Using the Matrix Performance Standard

The testing results in a confusion matrix were employed to compare the three optimization methods using the VGG-16 and VGG-19 models. The acquired data were then re-evaluated using the matrix performance standards, encompassing accuracy, precision, recall, specificity, and F-score to compare the findings of this study based on the two classes.

Table 13. Comparison of Each Class Using the Matrix Performance Standard

Matrix Performance	**Class**	**VGG-16**			**VGG-19**		
		SGD Optimization	Adamax Optimization	Adagrad Optimization	SGD Optimization	Adamax Optimization	Adagrad Optimization
Accuracy	CT-COVID	91.06%	94.13%	92.34%	90.57%	93.76%	91.65%
	CT-NonCOVID	91.06%	94.13%	92.34%	90.57%	93.76%	91.65%
	Average	**91.06%**	**94.13%**	**92.34%**	**90.57**	**93.76%**	**91.65%**
Precision	CT-COVID	91.73%	95.55%	95.78%	89.88%	97.48%	89.67%
	CT-NonCOVID	88.80%	87.88%	85.39%	91.30%	91.45%	93.48%
	Average	**90.26%**	**91.72%**	**90.59%**	**90.59%**	**94.46%**	**91.57%**
Recall	CT-COVID	93.23%	93.23%	93.23%	88.93%	88.23%	91.87%
	CT-NonCOVID	91.81%	91.09%	91.81%	91.93%	98.16%	91.48%
	Average	**92.52%**	**92.16%**	**92.52%**	**90.43%**	**93.20%**	**91.67%**
Specificity	CT-COVID	91.81%	91.09%	91.81%	91.93%	98.16%	91.48%
	CT-NonCOVID	93.23%	93.23%	93.23%	88.93%	88.23%	91.87%
	Average	**92.52%**	**92.16%**	**92.52%**	**90.43%**	**93.20%**	**91.67%**
F-score	CT-COVID	89.54%	93.15%	90.83%	89.30%	92.51%	90.68%
	CT-NonCOVID	92.17%	94.86%	93.40%	91.56%	94.64%	92.41%
	Average	**90.85%**	**94.00%**	**92.11%**	**90.43%**	**93.58%**	**91.55%**

The results imply relatively excellent results when comparing the three optimization methods with the VGG-16 and VGG-19 models using the matrix performance standard. The Adamax optimization method on the VGG-16 model achieved the highest average accuracy of 94.13%, while on the VGG-19 model, it acquired a best-in-class average accuracy of 94.46%. Adamax optimization also yielded the highest overall results of 93.20% for recall and specificity with the VGG-19 model. Moreover, the Adamax optimization method using the VGG-16 model generated the highest F-score of 94.00%.

Adamax optimization proved to be superior to other methods in this comparison. It is a generalization optimization method based on an approach to an infinite norm (max), which can produce a more effective optimization in diagnosing COVID-19 CT scan images than the Adagrad optimization method, which has a learning speed that tends to decrease over time and a slow learning rate. When optimizing a model's performance, applying VGG deep learning variants significantly impacted accuracy, precision, recall, specificity, and F-score metrics.

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4. Conclusion

After extensive testing to determine the best method for identifying COVID-19 utilizing VGG-16 and VGG-19 model variants, the following findings were reached. COVID-19 CT scan image data could be classified using three optimization methods with VGG deep learning model variants. VGG-16, combined with Adamax optimization, achieved the best average accuracy of 94.11%, while VGG-19 combined with the same optimization method achieved 93.77%. The overall average results indicated that the Adamax optimization was the best method, and among the two deep-learning model variants, VGG-16 outperformed VGG-19. The Adamax optimization method, which generalizes from an approach to the infinite norm (max), proved more effective for optimizing the diagnosis of COVID-19 CT scan images.

Based on the testing methods, the following recommendations are proposed. It is advised that image data be of high quality and clarity to achieve the most outstanding classification results using VGG deep learning model variants. Additionally, testing with various types of deep learning model variants is recommended to enhance references and comparisons in the CNN model for categorizing COVID-19 CT scan image data.

Author Contributions

S. Riyadi: Conceptualization, funding acquisition, methodology, project administration, supervision, validation, visualization, and writing – review & editing. C. Damarjati: Conceptualization, data curation, formal analysis, investigation, methodology, analysis, funding acquisition, methodology, resources, software, supervision, validation, visualization, and writing – review & editing. S. Khotimah: Data curation, investigation, software, validation, visualization, and writing – original draft. A. J. Ishak: Conceptialization, methodology, validation, visualization, and writing – review & editing.

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Declaration of Competing Interest

We declare that we have no conflict of interest.

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