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Multi Deep Learning to Diagnose COVID-19 in Lung X-Ray Images with Majority Vote Technique

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Abstract: The COVID-19 pandemic has become the focus of world problems that need to be resolved. This is because the rate of spread is speedy and able to take down the world's health system. Therefore, many researchers are focusing their research on solving this problem by doing an initial screening on the X-Ray image of the subject's lungs. One of them is by using Deep Learning. Several articles that talk about implemented Deep Learning for classifying X-Ray images have been published. But most of them are comparing different architecture CNN (Convolutional Neural Network). In this study, the authors try to create a multi-classifier Deep Learning system that consists of nine different CNN architectures and combined with three different Majority Vote techniques. The target of this research is to maximize the performance of classification and to minimize errors because the final decision is a compilation of decisions contained in each CNN architecture. Several models of CNN are tested in this study, both the model which used Majority Vote and Conventional CNN. The results show that the proposed model achieves an accuracy value average F1-Score 0.992 and Accuracy 0.993, according to 5 K-Fold test. The best model is CNN, which used Soft Majority Vote.

Keywords: COVID-19, Deep learning, Ensemble, Majority vote, X-Ray.

1. Introduction

All Coronavirus Disease 2019 (COVID-19) is a virus outbreak that has infected more than 1.2 million people with more than 100 countries worldwide affected. Even though it has a low fatality rate (2%) when compared to other types of disease [1], COVID-19 also carries symptoms that can torture people who have been infected by it. Moreover, with its rapid spread, it will undoubtedly have an impact on the hospital's ability to serve patients. Therefore, several countries have issued policies to tackle the spread of this virus, one of which is the rapid test to immediately. One of the most commonly used test kits is Reverse Transcription Polymerase Chain Reaction (RT-PCR) [2]. However, RT-PCR takes 4-6 hours to find out the results [3]. This indeed can be said to take quite a long time when compared with the rapid spread of the Coronavirus. Also, RT-PCR has a limited number in each region through the need to use this tool is very large.

Given this fact, researchers around the world have brought the issue to a research trend focused on creating a test method that is faster, cheaper, always available, and has a level of accuracy that is the same as RT-PCR. One such way is to analyze the X-Ray of the subject's lungs [4]. By analyzing the subject's lungs, the presence of Coronavirus can be determined. This is related to the effects of the virus that does attack the human respiratory tract, especially the lungs [5, 6]. These symptoms are known as pneumonia [7, 8]. What's more, this correlation testing process has already been compared. The results show that testing using X-Ray has a higher sensitivity level (97%) compared to RT-PCR. This is contained in an article written by Strunk et al. [4]. Of course, the results of this study are promising.

With the progress of the development of the world of Artificial Intelligence (AI), the diagnosis can be made using a machine. This is intended so that the level of accuracy obtained is high, fast, and efficient because the task is carried out by the machine [9]–[11]. This is also supported by several contributions that have been given by the development of AI in the medical world [12]–[14]. One of them is the problem that we are facing now, namely digital image processing for classifying X-Ray images in the lungs [15-18].

If reviewed from the use of X-Ray to diagnose the lung of COVID-19 subject, especially by using deep learning, it will find several studies that have been widely published in various journals [19, 20]. Some of the research articles include the use of CT-Scan [3], [21-23], and X-Ray [16, 24-32] to detect Coronavirus infection in the lung's image. Both studies are conducted using separate data, namely the use of CT-Scan itself and X-Ray itself, or together - together to be combined [33]. Some of these studies include studies that have been conducted by Zhang et al. [25], who use X-Ray data in their research. In the study conducted, researchers used a Deep Learning network structure in the form of a Backbone Network with an accuracy rate of 96% with two classes. Likewise, with other studies that have been conducted by other researchers, such as research conducted by Wang et al. [26]. In this study, researchers not only used three classes as the label (normal, non-COVID19, COVID19) but also used a convolutional neural network (CNN) structure with the given name COVNet with an accuracy rate of 92.4%. Then in research that was conducted by Mangal et al. [34], the CovidAID architecture was used and gave an accuracy of 90%. In this study, the researcher using a 6014 X-Ray image that comes from any source and then classifying it into three classes (normal, non-COVID-19, COVID-19) and four classes (normal, bacteria, viral Pneumonia, COVID-19). Also, the study was conducted by Chowdhury et al. [28], which used three classes and four classes classification and got the best results using the SqueezeNet architecture with an accuracy of 98.3%. Another CNN architecture also has been used, which is the DarkNet model and produced 98.08% for binary classification (two classes) and 87.02% for multiclass classification. Besides that, for research related to CT-Scan, it can also be found in several studies in published studies [35]. As research conducted by Wang et al. [22] which uses deep learning structures such as DenseNet 121-FPN with an accuracy rate of 86%. And from the best results is a study conducted by Chen et al. [23], which uses the UNet ++ structure with an accuracy rate of 95.24%. Some of these journals are journals that conduct comparative research on several CNN architectures in solving these cases [24], [28], [36]–[40]. However, from the published articles, several CNN architectures are often used, such as VGG16, VGG19, Inception V3, DenseNet121, and ResNet50. And the other research is trying to increase the accuracy of classification using different techniques from the previous studies. In this study, Togacar et al.,[41] using a fuzzy color technique and image stacking technique with three labels as labels (normal, COVID-19, and Pneumonia). Using CNN as feature extraction, namely MobileNetV2 and SqueezeNet, then combined the output of this model as combined features, then classified it using SVM. The accuracy gained in this study was 99.27%.

However, several studies have been shown that CNN (Convolutional Neural Network) architecture is still used singly. That is, decisions are taken only through one architecture. The results obtained by researchers also vary in the level of accuracy of each architecture used. This has opened up opportunities for ideas to be able to classify X-Ray images by using many architectures, which are then drawn conclusions based on specific techniques. One of them is the majority vote technique [9], [42]. By using this technique, classification errors can be minimized. This is because the final decision will be decided by using a particular algorithm so that the classification performance increases [9], [43]. By seeing this opportunity, then in this paper, the researcher will propose a classification system for lung X-Ray images by combining several CNN architectures. Then the final decision was decided using the majority vote technique.

In this study, the system will be formed using nine CNN architectures combined with a majority vote. The architectures used in this research there are AlexNet, ResNet 50, Wide ResNet 50 – 2, ResNet 101, ResNet 152, VGG16, VGG16 Batch Normalization (BN), VGG19, and VGG19 Batch Normalization (BN). While the majority vote technique used is three techniques, namely Hard Majority Vote, Average-Majority Vote, and Soft Majority Vote. So the total model formed in this study is three according to the Majority Vote Technique used, which in each Majority Vote technique contains nine architectures of CNN.

For knowing the best performance of several systems that have been built, the three decision-making techniques (Majority Vote) will be compared to get maximum performance in the classification process of X-Ray images. All of the performance

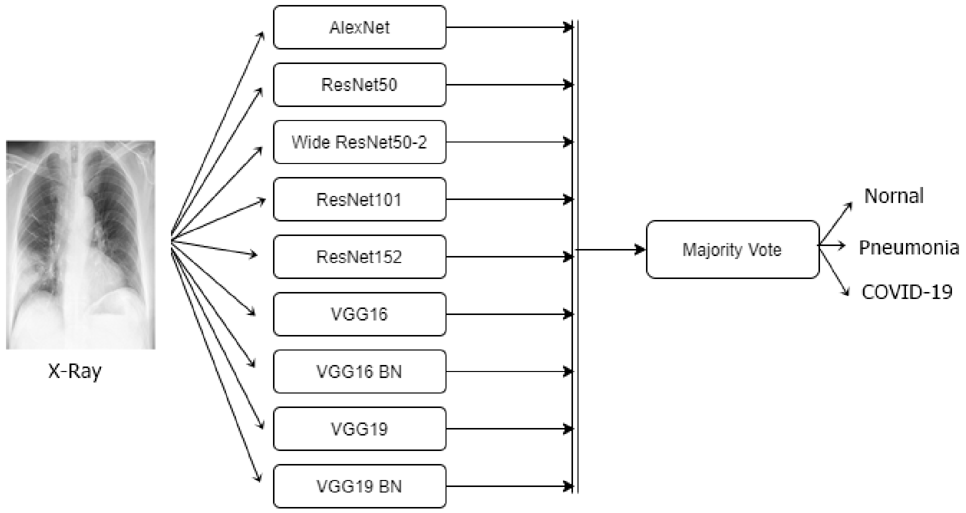

Figure. 1 The proposed system architecture

testings is using the KFold technique with 5 fold. In addition, using accuracy as a parameter to determine the performance, the others parameter like Sensitivity, Specificity, Precision, F1 – Score also included. Then all models will compare with this parameter to know the best model.

2. The methodology of proposed models

In the model proposed by the researcher, the researcher will use X-Ray image evaluation techniques on the subject's lungs by using CNN and the majority vote. This proposed system consists of several nine architectures of Convolutional Neural Network (CNN) that are used together to evaluate whether the subject's X-Ray images are to indicate Coronavirus infection or not. By assessing each architecture, then the results of each CNN architecture are put together to get one conclusion. The conclusion is in the form of information relating to whether the X-Ray image contained the Coronavirus or not. For more details, see Fig. 1.

In Fig. 1, it can be seen that the researchers used nine CNN architectures. Related to the architecture formed, the authors did not change the original structure of each of the CNN architectures used. All images entered into each architecture will be adjusted to the input image size on each architecture, while the output of each architecture consists of two classes, namely normal and COVID-19. The reason why the authors chose the architecture is that the architecture has been widely used in the medical world, especially in solving problems in radiology images, especially in previous COVID-19 studies [29, 32, 42]. For each architecture used by researchers, researchers will use pre-trained data and does not make any changes from the original architectures.

In the previous explanation, it has been stated that the system built is a system with more than one architecture and does not make any change from the original. Nine CNN builds with the architectures used: AlexNet, ResNet 50, Wide ResNet 50 – 2, ResNet 101, ResNet 152, VGG16, VGG16 Batch, Normalization (BN), VGG19, and VGG19 Batch Normalization (BN). Cause many decisions will be produced from that nine CNN, and the final decision must be produced one decision only. Therefore it is necessary to have a technique used to infer the results and made only one final decision. This can be overcome by using the majority vote technique. In this study, there are three types of Majority Vote used in this study, including Hard Majority Vote, Average-Majority Vote, and Soft (Weighted) Majority Vote. All of these techniques will be used separately. The purpose of doing this separation is to find out which method can maximize the performance of the system compiled using these nine CNN architectures so that the accuracy of the classification of species increases. In the proposed system, researchers detected only three classes, namely normal, Pneumonia, and COVID-19. Then the final output of the Majority Vote was used in these three classes.

First is the Hard Majority Vote technique. This technique is the simplest of the three techniques mentioned earlier. This technique will make a decision based on the most decisions in several architectures. So the final decision is based on the most votes in one class. For the equation of this technique, it can be seen in Eq. (1).

$$y = \max\{C_1(x), C_2(x), C_3(x), \dots, C_m(x)\} \quad (1)$$

Where y is the result of the final decision, and C_j is the final result of each classifier.

If assumed as follows:
Classifier 1 (C_1) → class 1
Classifier 2 (C_2) → class 0
Classifier 3 (C_3) → class 1

$$y = \max\{1,0,1\} = 1 \quad (2)$$

The second is the Average-Majority Vote technique. For the Average-Majority Vote technique used is to calculate the average of each class probability generated by each classifier or CNN architecture used. Then, to determine the final result of this technique is based on the most significant probability in one of the classes that have been averaged. If written in the equation, it can be seen as contained in Eq. (2):

$$yi = \frac{\sum_{j=1}^{m} p_{ij}}{m} \quad (3)$$

$$\arg max = yi \quad (4)$$

Where y is the result, i is the class label, j is the jth classifier, and m is the total classifier.
If assumed as follows:
Classifier 1 (C_1) → {class 0 (70%), class 1 (10%)}
Classifier 2 (C_2) → {class 0 (20%), class 1 (50%)}
Classifier 3 (C_3) → {class 0 (40%), class 1 (60%)}

$$y_{(class\ 0)} = \frac{70+20+40}{3} = 43.3 \quad (5)$$

$$y_{(class\ 1)} = \frac{10+50+60}{3} = 40 \quad (6)$$

$$y = max\{class\ 0(43.3), class\ 1(40)\} = class\ 0\ (43.3) \quad (7)$$

Next up is the Soft (Weighted) Majority Vote technique. This technique is also known as Weighted Majority Vote because there is a weighting value for each classifier used.

$$y = arg\, max_i \sum_{j=1}^{m} w_j P_{ij} \quad (8)$$

Where y is the result, i is the class label, j is the jth classifier, m is the total classifier, w is Weight, and P is probabilities.
If assumed as follows:
Classifier 1 (C_1) → {class 0 (70%), class 1 (10%)}, Weight 1
Classifier 2 (C_2) → {class 0 (20%), class 1 (50%)}, Weight 4
Classifier 3 (C_3) → {class 0 (40%), class 1 (60%)}, Weight 2

$$y_{(class\ 0)} = (1\ x\ 70) + (4\ x\ 20) + (2\ x\ 40) = 230 \quad (9)$$

$$y_{(class\ 1)} = (1\ x\ 10) + (4\ x\ 50) + (2\ x\ 60) = 330 \quad (10)$$

$$y = max\{class\ 0(230), class\ 1(330)\} = class\ 1\ (330) \quad (11)$$

To find the right weighting, one can use the Grid Search technique where the weight tuning is given a brute force value to find the best accuracy value in a tuning loop.

3. Dataset description and experimental setup

To be able to test the model tested in this study, a dataset is used. The dataset used is the dataset, which is the winner of the COVID-19 Dataset Award provided by Kaggle Repository [44]. This data is validated by a team of researchers from Qatar University, the University of Dhaka (Bangladesh), along with their collaborators from Pakistan and Malaysia in collaboration with medical doctors. The data X-Ray provided in this repository has 2905 images with there are 1345 viral pneumonia, 1341 normal images, and 219 COVID-19 positive images. For the examples of the data used it can be seen in Fig. 2.

From Fig. 2, it can know that the data will be tested by using K-Fold techniques, which in this study use 5 K-Fold. The data will be trained in this technique individually to produce the best model for each architecture. Then, after the data trained in 1 K-Fold, all models combined with the three models of majority vote then tested with used this model, not as individually of CNN architecture. The result of the classification will be store to the datalogger and then will be calculated accuracy, sensitivity, and all performance parameter used at the end of the 5 Fold. So, this process will be running until it reaches 5 K-Fold.

However, if seen in the previous explanation, which is precisely in the Methodology of Proposed Models section, to be able to use the Soft Majority Vote technique, it is necessary to do the tuning on the Weight. Therefore, specifically for the tuning process in the Majority Vote, the author tuned outside the K-Fold process. The trick is to use 80% data used in the K-Fold process, which is 2324 images. But the data is divided again into 80% for training (1859 images) and 20% for testing (465 images). By using the testing data, the author then performs the tuning to

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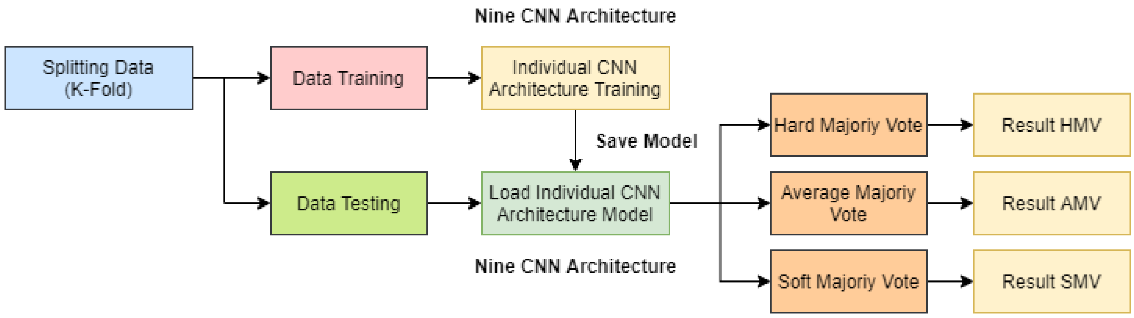

Figure. 2 The scheme of 1 K-Fold process

Table 1. The weight after tuned by using a grid search

Architecture	Weight
AlexNet	3
VGG16	4
VGG16 Batch Normalization	2
VGG19	5
VGG19 Batch Normalization	5
ResNet101	5
ResNet152	5
ResNet50	5
Wide Resnet50-2	1

get the best accuracy value using Grid Search techniques. The predetermined load results will then be implemented in the overall test using the 5 K-Fold methods. The results of the Weight obtained from the tuning results can be seen in Table 1. Table 1. The Weight after tuned by using a Grid Search.

As previously stated, that performance testing on this system will be seen in several aspects, namely Sensitivity, Specificity, Precision, F1-Score, and Accuracy, it is necessary to calculate. For the calculations used, it can be seen in Eq. (12)- (16). While the variables or parameters used to calculate are True Positive (TP), False Negative (FN), True Negative (TN), and False Positive (FP).

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{12}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{13}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{14}$$

$$\text{F1 Score} = \frac{2TP}{2TP+FP+FN} \tag{15}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{16}$$

4. Result and discussion

In this section, the system will be tested according to the test scenarios contained in the discussion in the previous section, using the 5 K-Fold technique. Each test will take five parameters. Among the five parameters are Sensitivity, Specificity, Precision, F1-Score, and Accuracy. Because there are three proposed Majority Vote models, the performance of each of these models is separated into Table 2.

From the results obtained, as shown in Table 2 and the results of the performance comparison found in Fig. 3, it can be seen that Soft Majority Vote has higher average performance compared to the other models. This can be seen in all the measured performance parameters. It also means that the Soft Majority Vote also has low misclass in each fold tested.

The reason for the low value of the misclass contained in the Average Majority Vote is due to this technique. The final decision is not based on the absolute value, as found in the Hard Majority Vote. Also, it does not make the same as in the Average Majority Vote technique that the final decision is based on the highest average output probability for each classifier. In the Average Majority Vote technique, each classifier is asked to issue a probability value for each class. After that, each of these probabilities will be calculated. Then the final decision on this technique is determined on the highest average probability. This is the opposite of Hard Majority Vote. In the Hard Majority Vote technique, the problem of misclasses arises because each architecture will only be asked to give a firm value to one class that only has the highest probability decision on the classification. Then Hard Majority Vote will determine the final decision based on the majority vote in each of its classifier. This has proven to be effective, as shown in Fig. 5 and Table 2, where the image that should have been detected as normal and detected as COVID-19 or Pneumonia and vice

Table 2. Comparison performance of each technique

Technique	Sensitivity	Specificity	Precision	F1 - Score	Accuracy
Hard Majority Vote	0.992	0.846	0.971	0.979	0.971
Average Majority Vote	0.997	0.83	0.967	0.98	0.973
Soft Majority Vote	0.994	0.99	0.991	0.992	0.993

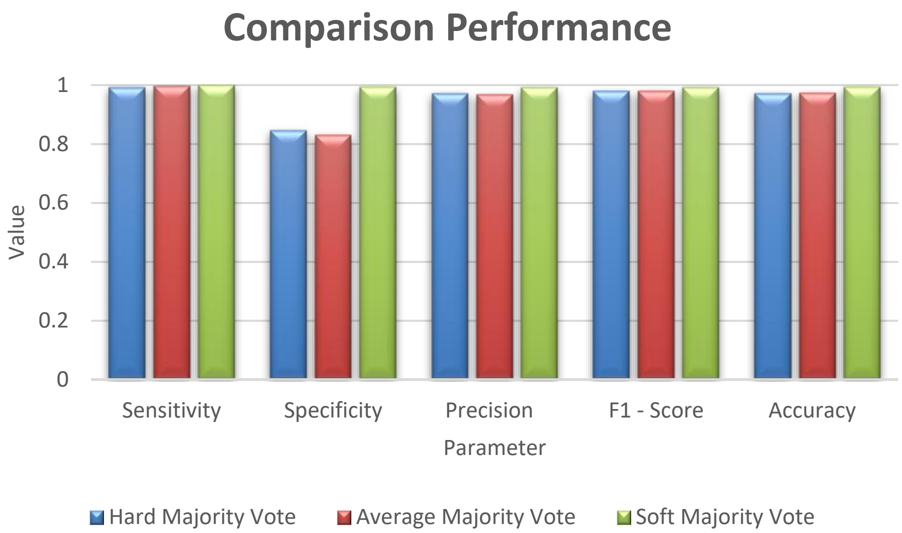

Figure 3. Head to head of model performance

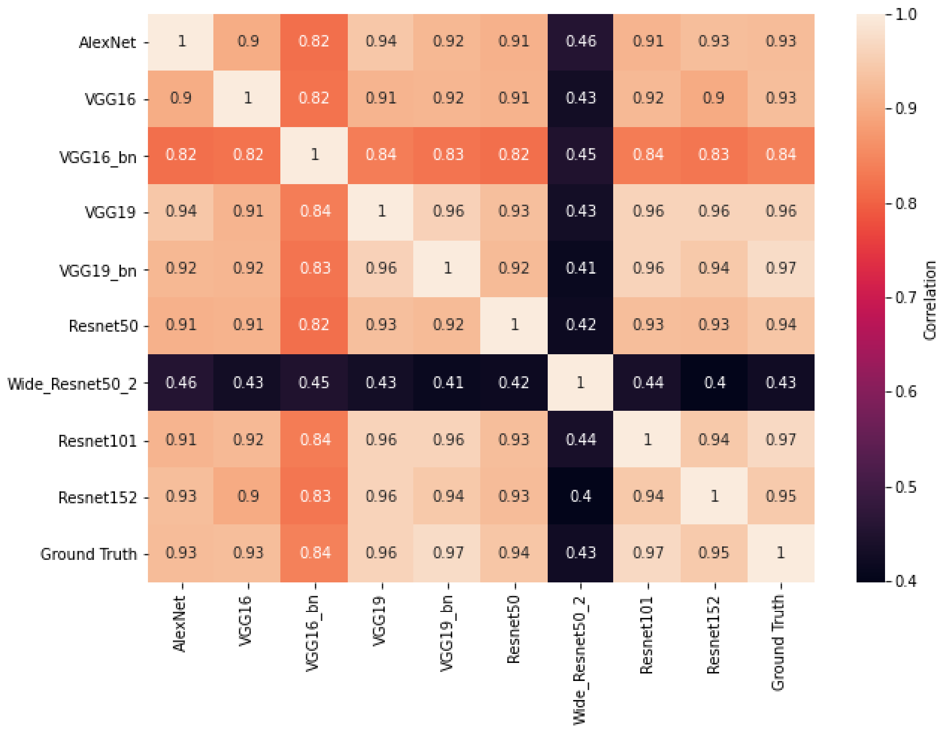

Figure 4. Matrix correlation of each CNN architecture with the ground truth in fold 4

versa on the Hard Majority Vote has been successfully corrected in the Average Majority Vote with increasing of accuracy parameter.

As for the reasons why in Soft Majority Vote, each performance parameter tested, the model has a better performance compared to other Majority Vote models. This happens because each architecture will be maximized based on the tendency of success in the classification. Classifiers that have excellent performance will get high priority compared to other classifiers. These priorities are manifested in the form of granting Weight. Therefore, the misclass problem can be overcome. For a complete explanation of this phenomenon it can be seen after Fig. 4 showed. Fig. 4 is the Correlation Matrix, which represents the relationship between individual CNN architectures (it can be called as conventional techniques) and Ground Truth.

If seen in Fig. 4, it can be seen that by using the Majority Vote model, it has succeeded in improving the performance of the final classification decision. This is marked by the achievement of a higher classification accuracy than when the CNN architecture worked alone (conventional techniques). Even more so with the Soft Majority Vote. If seen in Fig. 4, only a few CNN architectures have excellent performance (above 90%) compared to other architectures. Therefore, by giving priority rights to specific architectures that have performed well in the previous session (Grid Searching session using validation data), the misclass error will be reduced. So with this fact, architecture can work optimally (with performance up to 90%), namelyVGG19, VGG19 Batch Normalization, ResNet101, ResNet152, and ResNet50, have maximum Weight in the Soft Majority Vote (Table 1). This is different from the average-majority vote, which in its determination, is based on the average probability of the results of the classification process for each class. Whereas in Soft Majority Vote, performance can be maximized because there is a weighting process in making decisions. As a result, the architecture that has a better performance compared to the others will be able to work optimal because there is weighting that is done on the final verdict.

5. Conclusion

The COVID-19 pandemic has shocked the world with high rates of virus transmission and the number of victims affected. Therefore, many researchers in various countries to focus their research related to tackling this pandemic. One of the things done is fast screening on X-Ray images of lungs using Deep Learning. In this study, the author has formed a Deep Learning that is used to diagnose X-Ray images of the human lungs. The system developed is a Deep Learning multi-classifier system. This means that there is more than one classifier (Deep Learning) used. The method developed in this study consists of nine Deep Learning in the form of a Convolutional Neural Network (CNN). The whole Deep Learning architecture is used in one X-Ray image diagnosis, which is then combined with three Majority Vote Techniques that will be compared in this study to get maximum performance. The results obtained indicate that the Soft (Weighted) Majority Vote Technique has the best performance in this study with an accuracy value average F1-Score 0.992 and Accuracy 0.993, according to 5 K-Fold. But the resulting technique needs to be tested using another CNN architecture or using a preprocessing image or image augmentation to enhance the result.

Conflicts of Interest

The data used in this research comes from open access data from Kaggle. This dataset is the winner of the COVID-19 dataset award provided by Kaggle Repository. The authors declare no conflict of interest.

Author Contributions

The research is performed by the author, and the individual contributions are provided as follows: conceptualization, writing, and draft preparation Ike Fibriani, Widjonarko; data investigation, and validation Aris Prasetyo, Angga Mardro Raharjo; methodology, review, and editing Dasapta Erwin Irawan.

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