Detection of Covid-19 in Chest X-ray Image by Using Convolutional Network Trained with Walsh Functions

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Abstract

Covid-19 is a highly contagious disease with devastating problems, comprised of many deaths, heavy costs incurred during the treatment, physiological and psychological problems, and still affects many people all over the world. Several approaches are widely used to either stop or narrow the number of people infected. Chest x-ray images can be also used as a leading indicator once the person gets infected with Covid-19. In image classification, deep neural network structure, including a convolutional neural network in the position of feature extractor and fully connected neural network, is commonly preferred to be able to classify the image among the group. In FCNN, aside from laborious hyperparameter determinations, it also demands high computational load and high memory. The proposed method aims to use a minimum distance classifier with Walsh functions instead of a fully connected neural network. By doing so, many problems such as long training time, high memory requirement coming along with FCNN would be resolved. X-ray images in the dataset have been labeled as Covid-19, lung opacity, normal and viral pneumonia provided by public resources. The proposed small-size model is observed to be able to classify the images at a 92% accuracy rate without benefitting from a highly complex fully connected neural network section.

Keywords: Chest X-ray image classification, Covid-19, deep neural networks, Walsh matrix, Convolutional Neural Network

1. Introduction

It is known that Covid-19 disease affects the lungs before infected patients give symptoms, pain in the throat and difficulty in breathing (Weng et al., 2021), so first examining this area of the body provides to control of spreading before too late. With early diagnosis, patients can be separated from healthy people by screening approaches and one of which is radiology examination using chest radiography, where chest radiography imaging or tomography is taken and analyzed by radiologists to look for visual indicators associated with Covid-19 viral. This situation caused many problems for the countries that have not properly worked health systems, enough physicians, sufficient amount of equipment for fighting the disease caused serious deaths. Moreover, infected people even in developed countries may accelerate the spreading of the disease due to the relatively long-time requirement of test results, ranging from 3 to 48 hours which is likely to be longer in underdeveloped regions (Larremore et al., 2020). On the other hand, when more capacity is needed, or in countries that cannot purchase laboratory kits for testing makes the whole process is more difficult and the cost is also so effective.

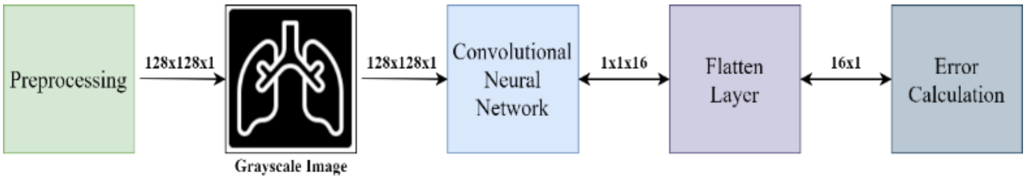
So, considering the time and financial costs required for the diagnosis of laboratory kits canalizes the ways to AI researches and applications. Also, computer-aided diagnostic systems, one of the fastest and safest ways to diagnose inside of the methods, can help radiologists by providing accurate results, using the images to detect the cases even in uncertain situations that normally would not be recognized by radiologists. If these systems can achieve desired performance in the classification, the contribution of the findings to the coronavirus pandemic would be significant.

In this field, the deep learning method plays a dominant role as high-performance classifier in the detection of disease. Since deep neural network (DNN) models are expected to train with a low amount of computational load in a short time due to the current economic conditions for each country, fully connected neural networks, the one part of the deep neural network (DNN), has several bottlenecks. In this study, the proposed method, which is modified by adding new connections and removing DNN from the traditional deep neural networks, aims to develop a light version of convolutional neural network (CNN) for Covid-19 classification using chest X-ray images, containing 4 different classes.

In general, CNN illustrates the mission of the feature extractor, while FCNN, the classifier (POLAT et al., 2021). Many parameters need to be regulated in order to increase the model performance such as learning rate, filter size, optimizer type, batch size, number of hidden layers and neurons inside of hidden layers. By removing the FCNN, automatically, there is no need to single out related hyperparameters relating to FCNN which leads to converging the model by changing fewer parameters. During the training, kernels are updated themselves according to the error value, arising from the operation between vectors of Walsh matrix and outputs. This value after the error calculation is normally expected to be lower in the same class and higher in different classes. In the feature extraction part, the proposed structure consists of convolution operation, batch normalization, max pooling and dropouts respectively.

To explain briefly, convolution operation has the learnable filter in backpropagation, batch normalization allows us to avoid destabilization of nodes, max-pooling reduces the size by preserving properties and providing significant time, dropouts are used to avoid overfitting during the training.

Figure 1: The general training process of the proposed model, containing the steps from pre-processing to error calculation as well as dimensions of outputs respectively.

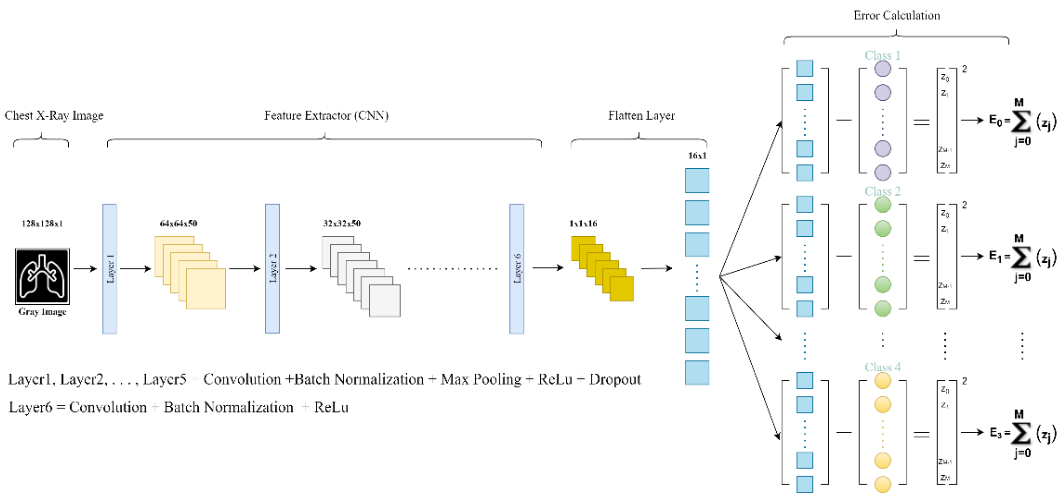


The general steps followed by the proposed model are shown in Fig. 1. Images that are sent to CNN follow this process respectively. Firstly, it requires pre-processing because all images in the dataset do have not the same size, 128x128x1, and property. Afterward, grayscale images suitable for the model structure are sent to the convolutional neural network, after the training process, the output of the model, 1x1x16, is flattened to be the same size as the Walsh vector, 16x1. In the final part, the class is selected with the lowest error and backpropagation is started after checking the accuracy.

2. Method

In order to reduce the 128x128x1 image to 1x1x16, a total of 6 layers were used and the layers from first to fifth contain convolution, batch normalization, max pooling, ReLu, dropout, respectively. In the last layer, Layer 6, max pooling and dropout have been removed. The detailed overview of the proposed model is as follows.

Figure 2: The expanded training process of proposed model after pre-processing which include mainly feature extractor, flatten layer and error calculation section



In this study, since there are 4 classes, the error calculation part compares the output with 4 class Walsh vectors and the lowest error is accepted as the model output.

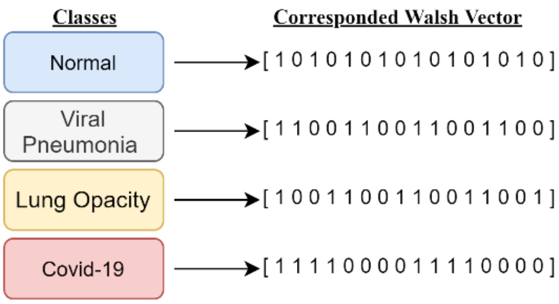
2.1 Walsh Matrix

The Walsh matrix is the set of the vectors with the longest distance from each other, referring that rows and columns being orthogonal to each other, meaning their dot products are 0 (Yuan & Cai, 2021). The elements of this set consist of +1 and -1, but since ReLu is used as an activation function, it is replaced by -1s with 0s (POLAT et al., 2021). This effective method is used in signal processing operations successfully. The following matrices show the modified Walsh matrices for two, four, eight and sixteen-dimensional spaces.

$$W_2=\begin{bmatrix}1&1\\1&0\end{bmatrix}\; W_4=\begin{bmatrix}1&1&1&1\\1&0&1&0\\1&1&0&0\\1&0&0&1\end{bmatrix}\; W_8=\begin{bmatrix}1&1&1&1&1&1&1&1\\1&0&1&0&1&0&1&0\\1&1&0&0&1&1&0&0\\1&0&0&1&1&0&0&1\\1&1&1&1&0&0&0&0\\1&0&1&0&0&1&0&1\\1&1&0&0&0&0&1&1\\1&0&0&1&0&1&1&0\end{bmatrix}\; W_{16}=\begin{bmatrix}1&1&1&1&1&1&1&1&1&1&1&1&1&1&1&1\\1&0&1&0&1&0&1&0&1&0&1&0&1&0&1&0\\1&1&0&0&1&1&0&0&1&1&0&0&1&1&0&0\\1&0&0&1&1&0&0&1&1&0&0&1&1&0&0&1\\1&1&1&1&0&0&0&0&1&1&1&1&0&0&0&0\\1&0&1&0&0&1&0&1&1&0&1&0&0&1&0&1\\1&1&0&0&0&0&1&1&1&1&0&0&0&0&1&1\\1&0&0&1&0&1&1&0&1&0&0&1&0&1&1&0\\1&1&1&1&1&1&1&1&0&0&0&0&0&0&0&0\\1&0&1&0&1&0&1&0&0&1&0&1&0&1&0&1\\1&1&0&0&1&1&0&0&0&0&1&1&0&0&1&1\\1&0&0&1&1&0&0&1&0&1&1&0&0&1&1&0\\1&1&1&1&0&0&0&0&0&0&0&0&1&1&1&1\\1&0&1&0&0&1&0&1&0&1&0&1&1&0&1&0\\1&1&0&0&0&0&1&1&0&0&1&1&1&1&0&0\\1&0&0&1&0&1&1&0&0&1&1&0&1&0&0&1\end{bmatrix} \tag{1}$$

In this study, Walsh matrix rank was chosen as 16 for 4 classes. The 4 rows in the Walsh matrix can be selected randomly, with the exception of the first row, consisting of only 1s, to refer to the classes.

Figure 3: Each class and corresponded Walsh vector, used in error calculation with the output of the model.



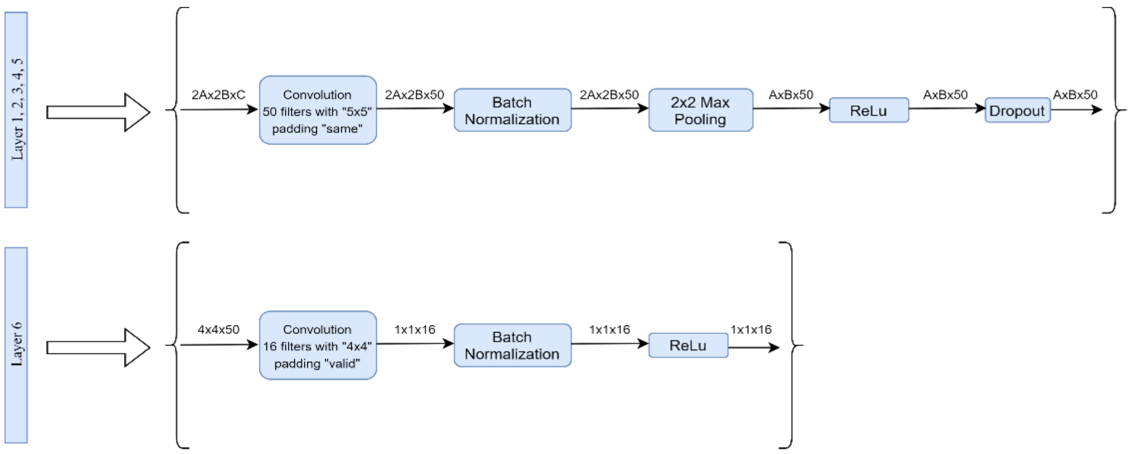
2.2 Convolutional Neural Network

This part constitutes the main learning part and the error value of the model is gradually decreasing by means of the learnable kernels.

Since Layer 6 is the last layer, it has structural differences because the number of elements of the Walsh vector, which is 16 in this study, must be in the same size as the output of Layer 6, so padding, a number of filters and filter size have been changed to adjust the size.

In general, expanded layers follow the procedure as given in the figure below. It is aimed to be straightforward by showing the output dimensions after each operation, which are marked with A, B and C. Since Layer 6 is the only layer, original dimensions and corresponding values are given in Fig. 4.

Figure 4: Expanded view of 6 layers in feature extractor section namely Layer 1 Layer 2, Layer 3, Layer 4, Layer 5, and Layer 6.



2.3 Error Calculation

The changes made in this section, consisting of the error calculation part specified at the beginning of the methods section, Fig. 2, actually inspired this study. As can be seen in the figure, the flattened 16x1 array, model output, is used to find the closest class by subtracting output from each class Walsh vector, which is specified in section 2.1. Then, the error value is calculated by taking the squares of the differences, as in the squared error approach.

$$Error_j = \sum_{i=0}^{15}\left(Output_i - Classes_{j,i}\right)^2 \tag{2}$$

$$Selected\ Class = \min_{j}\left(Error_j\right) \tag{3}$$

Since the proposed Walsh vector contains 16 numbers, the variable of I in the equation starts from 0 to 15 and j represents the 4 classes in this study. The class chosen with minimum error represents the predicted class and the accuracy value is calculated according to the similarity between the original and predicted class.

3. Result and Discussion

Train and test sizes were determined as 80% and 20%. In pre-processing part, images are randomly cut to get more robust results. Afterward, histogram equalization was performed for the problems caused by images with different densities. As can be seen in Table 1, the best batch size was measured as 32 after several changes. Optimizer was set as Adam with a learning rate of 3e-3 and epsilon 1e-5. After 30 epochs, validation accuracy has increased to a %92 in Fig. 5 with the hyperparameters explained above. In literature, different model approaches have an %89.6 accuracy rate in 4 classes of chest x-ray classifications (Khan et al., 2020).

Figure 5: Training Accuracy Graph of Validation & Train Sets

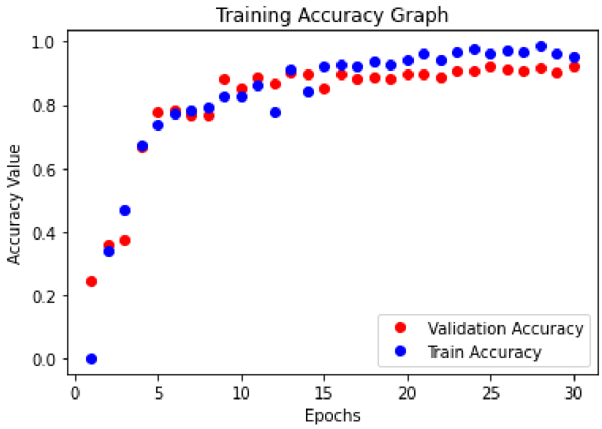


Table 1: Hyperparameters selected in the training part and applied in the validation part.

Hyperparameters	Value
Batch Size	32
Learning Rate	3e-3
Epsilon Value	1e-5
# of Epoch	30
Optimizer	Adam
# of Layer	6
Kernel size	5x5, (4x4 in the last layer)
# of Kernel	50, (16 in the last layer)

In this study, the main goal was to create a model with a high success rate and few parameters. Looking at the model parameters, which is 264,050 (Layer 1 containing 1x5x5x50 parameters, Layer 2 containing 50x5x5x50 parameters, Layer 3 containing 50x5x5x50 parameters, layer 4 containing 50x5x5x50 parameters, Layer 5 containing 50x5x5x50 parameters, Layer 6 containing 50x4x4x16 parameters), it appears to need at least 30 times fewer parameter, compared with GoogleNet 6,414,360 parameter, then pre-trained models. To extend this example, Alexnet has about 62 million, Vgg16 about 138 million, Resnet about 11 million parameters (Gönenç-Sorguç et al., 2018).

Table 2: Confusion matrix of Validation Set with overall and recall values

Class	Covid-19	Lung Opacity	Normal	Viral Pneumonia	Classification Overall	Accuracy
Covid-19	243	11	8	1	263	92.39%
Lung Opacity	5	257	18	0	280	91.78%
Normal	7	20	229	6	262	87.40%
Viral Pneumonia	2	2	3	248	255	97.25%
Truth Overall	257	290	258	255	1060	
Recall	94.55%	88.62%	88.76%	97.25%		

On the other hand, the proposed model required training time is relatively too little, providing more freedom to finetune for developers. Confusion matrix provides the related accuracy rates of the validation set, %20 of data is equal to 1060, which makes around 5300 in total.

4. Conclusion

In conclusion, it has been shown in the study that the models can be trained with high accuracy without fully connected neural network (FCNN) layers. There is no doubt that this ratio will be higher in cleaner images, but the high accuracy rate despite using a public dataset and preferring multiclass classification is promising to improve this research further. Regarding time consumption during the training, the proposed method by decreasing the nodes and parameters gives us impactful results.

However, the learning process is not as stable as the model with FCNN. In further works, it is aimed to develop more stable learning figures. Due to a large number of parameters and processing and memory load as well as accessing the high-powered computers, the proposed solution will alleviate the workload of researchers who are striving to produce a solution against such a contagious disease.

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