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Effect of Chest X-Ray Contrast Image Enhancement on Pneumonia Detection using Convolutional Neural Networks

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***Abstract*—The problem in pneumonia detection using a chest X-ray is the differences in the image quality due to the difference in the image acquisition procedure. To overcome the issue, the image enhancement technique is used in the preprocessing step. The purpose is to examine the effect of three image enhancement techniques to detect pneumonia, i.e. histogram equalization (HE), contrast limited adaptive HE and exposure fusion framework. These enhanced images are used as input images in pneumonia detection using VGG16 convolutional neural network architecture. In total, 3,151 chest X-ray images are used. The best performance is achieved by the exposure fusion framework image enhancement technique. The combination of exposure fusion framework and VGG16 give the training loss and accuracy of 0.2113 and 0.9451, and validation and accuracy loss of 0.6034 and 0.8670. Deeper analysis shows that the exposure fusion framework not only stretches the image intensity but also keeps the shape of the histogram remains. This technique will minimize the information loss in the enhanced image during the enhancement process.**

***Index Terms*—clahe, convolutional neural networks, exposure fusion framework, histogram equalization, image enhancement, pneumonia, ying**

I. Introduction

Pneumonia is the leading cause of infectious death in children worldwide, around 15% [1]. Nowadays, the use of machine learning in pneumonia detection is more common than traditional image processing, such as Convolutional Neural Networks (CNN). Several CNN architectures already use to detect pneumonia, i.e. Inception-v3; ResNet50; VGG19; and VGG16 that give accuracy around 71%; 78%; 88%; and 87% [2]. Other research shows that the accuracy of VGG16 architecture achieves 87% [3]. Moreover, AlexNet architecture that is utilized to detect pneumonia gives an accuracy of 72% [4]. Another approach is to combine weighted predictions from several CNN architectures, such as MobileNetV3; DenseNet121; InceptionV3; Xception; and ResNet18 [5]. Furthermore, the combination of InceptionV3 CNN architecture in feature extraction and several classification methods, e.g. Neural Network (NN), k-Nearest Neighbor (k-NN) and Support Vector Machine (SVM) is introduced in pneumonia diagnosis [6].

Another technique in detecting pneumonia using a Chest X-Ray (CXR) is combining machine learning and traditional image processing. The combination of lung segmentation as image preprocessing and CNN give better accuracy of 68% [7]. Another image preprocessing technique that combines image cropping to determine the Region of Interest and Histogram Equalization (HE) is used not only to reduce irrelevant information but also to enhance texture details of chest X-ray image [8]. This image enhancement technique can be addressed one of the main problems in CNN-based pneumonia detection using a CXR that is the image that has low contrast [8]. The combination of image preprocessing and deep CNN using transfer learning gives an accuracy of 90.16% and 85.3%, 87.8%, 83.7% and 78.3% for InceptionV3, Xception, ImageNet and ResNet [9].

To overcome this problem, this study tries to evaluate the effect of several contrast image enhancement techniques that are applied to chest X-ray images to detect pneumonia using CNN, such as HE and Contrast Limited Adaptive HE (CLAHE). Furthermore, this study implements a relatively new image enhancement technique based on the exposure fusion framework in pneumonia detection using a CXR. The goals of this study are not only to implement several image enhancement techniques but also to improve accuracy.

II. Methods

A. Dataset

The dataset is downloaded from one of the largest public datasets, kaggle.com. The dataset of Chest X-Ray Pneumonia images is provided by Kermany et al. [10]. To ensure the quality of the images in the dataset, the images are annotated by two expert physicians and rechecked by the third expert. In total, 3,151 chest X-ray images are used in the study. These images are divided into two classes, i.e. normal and pneumonia. Detail of the number of classes and the images are shown in Table I.

B. Contrast Enhancement

Three contrast image enhancement techniques are used in this study, i.e. HE, CLAHE and Exposure Fusion Framework

TABLE I
NUMBER OF CLASS AND THE DATA

	Class	
	Normal	*Pneumonia*
Training	1,341	1,186
Validation	234	390

(EFF) or Ying's Enhancement. The first and second techniques are the most common use in X-ray image enhancement [11]. The last technique is introduced in this study as an alternative image enhancement and it is expected that the performance of EFF is better than HE and CLAHE. The block diagram of the proposed system can be seen in Fig. 1.

1) Histogram Equalization: In this study, HE is utilized to enhance the chest X-ray image due to its simplicity. Using this technique, the most frequent intensity values are spreading out and distributed on histograms. In this study, OpenCV2 Library is used to process the image, particularly for image enhancement using HE and CLAHE. In HE, there is no parameter that should be adjusted. Fig. 2 gives an illustration of the image enhancement results and the histograms. The original image and its histogram are shown in Fig. 2. (a) and (b). While enhanced images using HE and its histogram can be seen in Fig. 2. (c) and (d). This HE-enhanced image has the highest contrast image among others, particularly in the clavicle and the edge of the upper ribs.

2) Contrast Limited Adaptive Histogram Equalization: The second contrast image enhancement technique that is implemented is CLAHE. In this study, CLAHE is chosen due to it successfully enhancing the chest X-ray image [12], [13]. CLAHE is the improvement of Adaptive Histogram Equalization (AHE) due to AHE tends to over-amplify the noise. There are three main processes in CLAHE, i.e. tiling the image; equalize the histogram and bilinear interpolation. In this study, the tile grid size is set to 8×8. In histogram

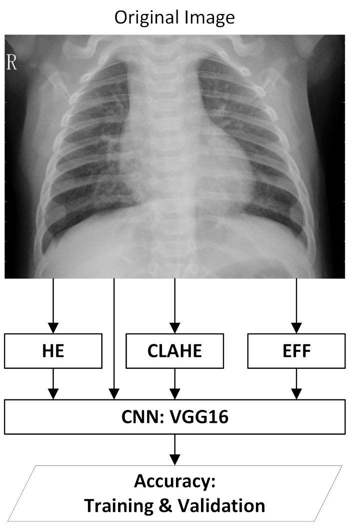

Fig. 1. Block diagram of the proposed pneumonia detection.

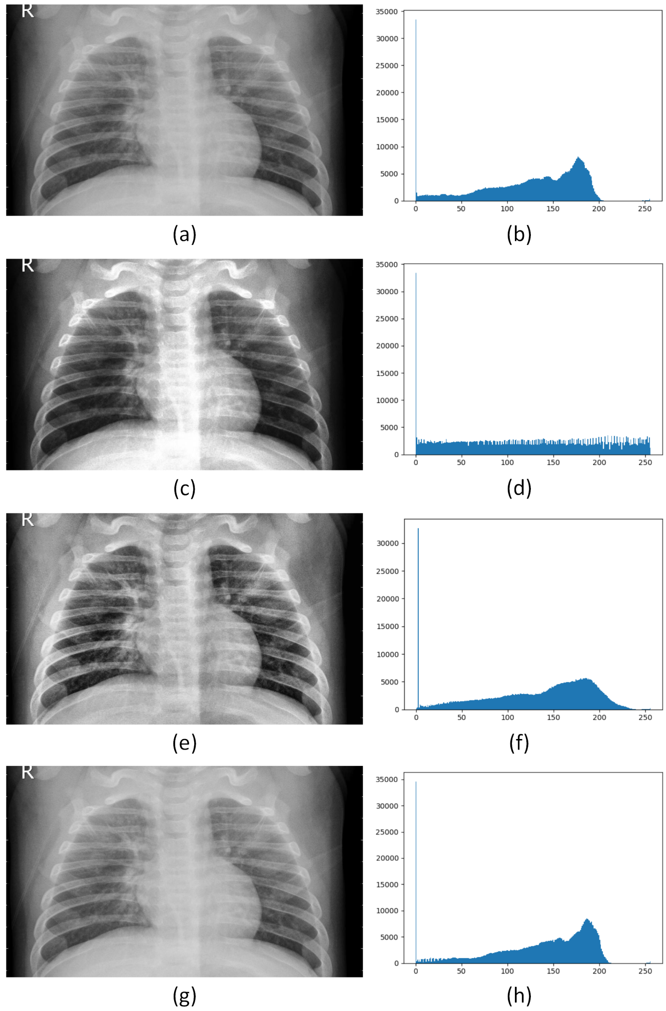

Fig. 2. Example of the images: (a) Original, (b) HE-enhanced, (c) CLAHE-enhanced, and (d) EFF-enhanced.

equalization of CLAHE, the clip limit is set to 2.0. Using CLAHE, HE process is adaptive and the noise amplification is reduced by limiting the contrast amplification. The enhanced image using CLAHE and its histogram is shown in Fig. 2. (e) and (f). Using this image enhancement technique, the contrast between soft and hard tissues is more clear.

3) Exposure Fusion Framework: This study introduced EFF to enhance the chest X-ray image [14]. Several steps are involved in this enhancement technique, i.e.:

- Designing the image fusion's weight matrix using estimation of illumination,
- Utilization of camera response model for synthesizing multi-exposure images,
- Obtaining the best exposure ratio,
- Image fusion using the weight matrix.

The enhanced image using EFF and its histogram is shown in Fig. 2. (g) and (h). From visual assessment, comparing the original and enhanced images, there are no such significant differences. The detailed examination by comparing the image histograms, the shape of these histograms are the same.

C. Convolutional Neural Network

This study utilizes VGG-16 that is developed by the Visual Geometric Group from Oxford University as CNN architecture due to its simplicity [15]. The input image is resized to 200×300 pixels to speed up the model building and minimize the computation load due to the limitation of computing resources. 50 epochs are implemented to build the model. In this study, the VGG16 architecture adapted from [16] due to it is powerful to build a model using very little data.

III. Results

In this study, four image types are used as CNN's input image, i.e. original; HE-enhanced; CLAHE-enhanced; and EFF-enhanced images. The graphics of training loss and validation loss are shown in Fig. 3. While Fig. 4 shows the training and validation accuracies of the original one. The performance of image contrast enhancement in pneumonia detection using CNN is measured using the model's loss and accuracy. The accuracy is calculated using formula as follow:

$$Accuracy = \frac{TP + TN}{AllData} \quad (1)$$

where TP is True Positive and TN is True Negative.

In this study, 50 epochs are chosen due to the limitation of computational resources. Furthermore, this study is used to explore the test and validation datasets distribution, whether it is overfitting or underfitting. Besides, the focus of the study is to explore the effect HE, CLAHE and EFF in CNN-based pneumonia detection. Therefore, the optimal number of epochs is not investigated further. In the last epoch, this original input image has a training accuracy of 0.9348 and a validation accuracy of 0.7532. Table II shows the performance of the four input image types. Even though the last training loss achieves 0.2096, the validation loss achieves 2.0537 which is higher than 2. It means that this is not a good model.

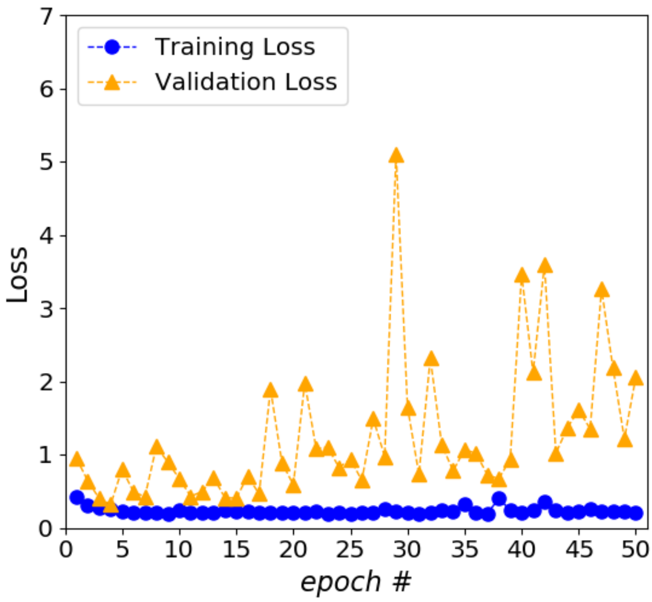

Fig. 3. Training loss and validation loss of the original image.

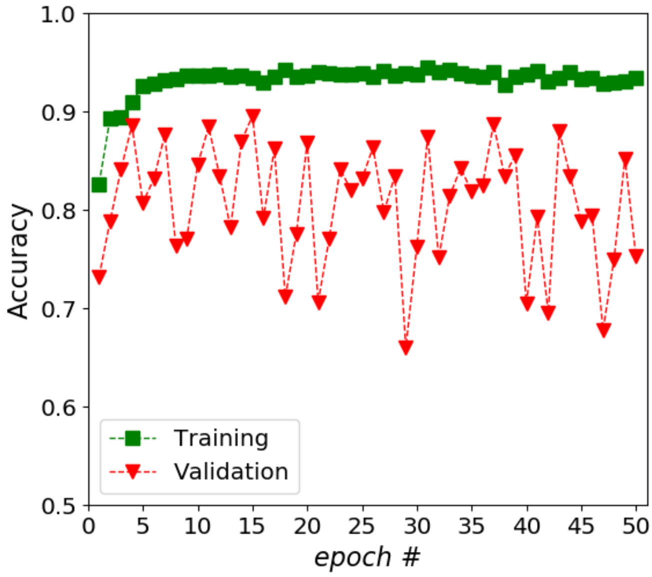

Fig. 4. Training accuracy and validation accuracy of the original image.

To improve the model performance, this study introduces the HE-enhanced image as CNN's input. Fig. 5 shows the training loss & validation loss graphics of the HE-enhanced image. While training and validation accuracies graphic of this input image are shown in Fig. 6. In the last epoch, the training loss achieves 0.1712, whereas the validation loss achieves 0.13861. While this scheme has a training accuracy of 0.9440 and 0.8077 for validation accuracy. The model performance that utilizes HE-enhanced as input image is better than the original one.

In this study, a CLAHE-enhanced image is used as CNN's input image. This scheme is introduced to prove the hypothesis that CLAHE has better performance than the original and HE-enhanced ones. In the last epoch, the training loss and validation loss achieve 0.3504 and 1.1497. The graphics of this CLAHE-enhanced loss are shown in Fig. 7. While Fig. 8 shows the training and validation accuracies graphics of the CLAHE-enhanced which achieve 0.9340 and 0.8301 in the last epoch. The performance of the CLAHE-enhanced scheme is better than the previous two schemes.

For the last scheme, an EFF-enhanced image is used as

TABLE II
Performance of Contrast Enhancement in CNN

Method	Performance			
	Loss	*Acc.*	*Val. Loss*	*Val. Acc.*
Original	0.2096	0.9348	2.0537	0.7532
HE	0.1712	0.9440	1.3861	0.8077
CLAHE	0.3504	0.9340	1.1497	0.8301
EFF	0.2113	0.9451	0.6034	0.8670

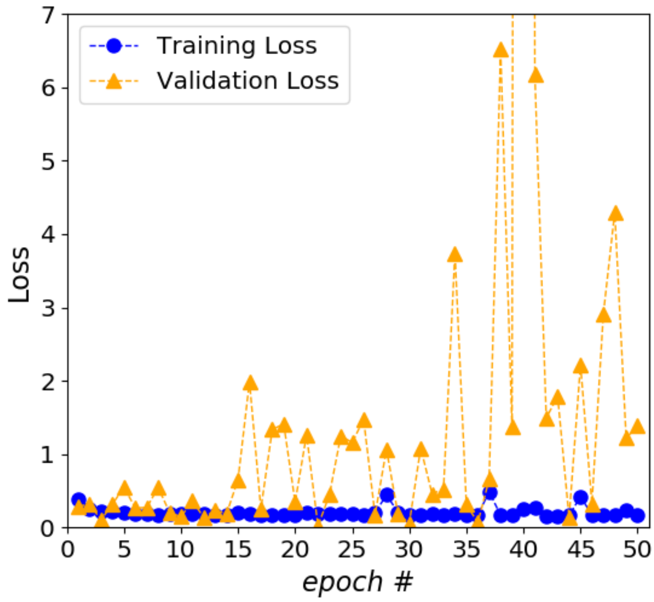

Fig. 5. Training loss and validation loss of the HE-enhanced image.

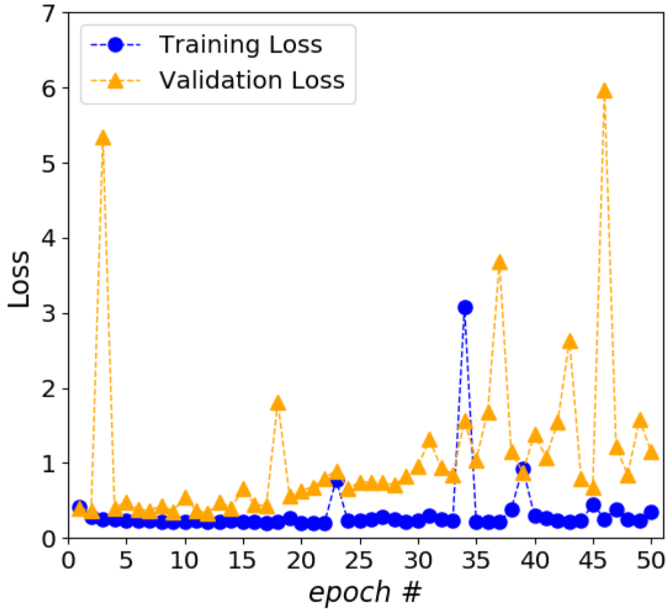

Fig. 7. Training loss and validation loss of the CLAHE-enhanced image.

CNN's input image. Even though the EFF image enhancement technique is developed in 2017, the utilization of this method is still limited, particularly for enhancing chest x-ray in pneumonia detection. The graphics of the training-validation loss and training-validation accuracy are shown in Fig. 9 and Fig. 10. Comparing results in Table II, the EFF-enhanced image scheme has the best performance than the other ones. Even though the training loss is higher than HE-enhanced, this scheme has the highest training and validation accuracies. Besides, it has smallest validation loss.

The validation loss in Fig. 3, 5, 7 and 9 have high magnitude variations due to the models being overfit. Further investigation in Fig. 4, 6, 8 and 10 show that the validation accuracies are lower than training accuracies. Furthermore, the validation accuracies in Fig. 4, 6, 8 and 10 tend to decrease.

The proposed method that combined EFF and VGG16 in detecting pneumonia using chest X-ray gives test and validation accuracy of about 94% and 87%, with the average accuracy of 91% While, the previous study that used only VGG16 gives an accuracy of 87% [2], [3].

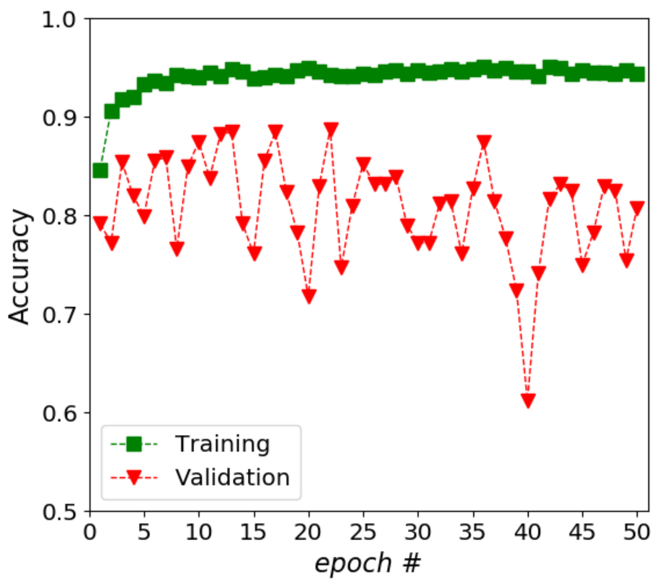

Fig. 6. Training and validation accuracies of the HE-enhanced image.

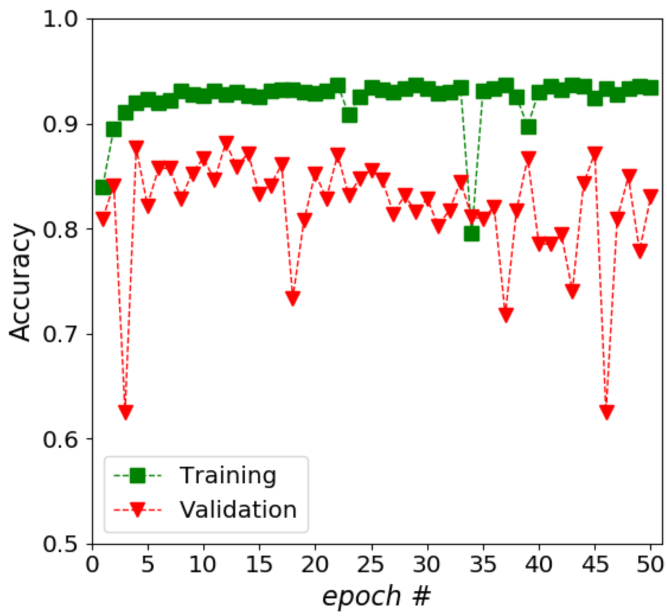

Fig. 8. Training and validation accuracies of the CLAHE-enhanced image.

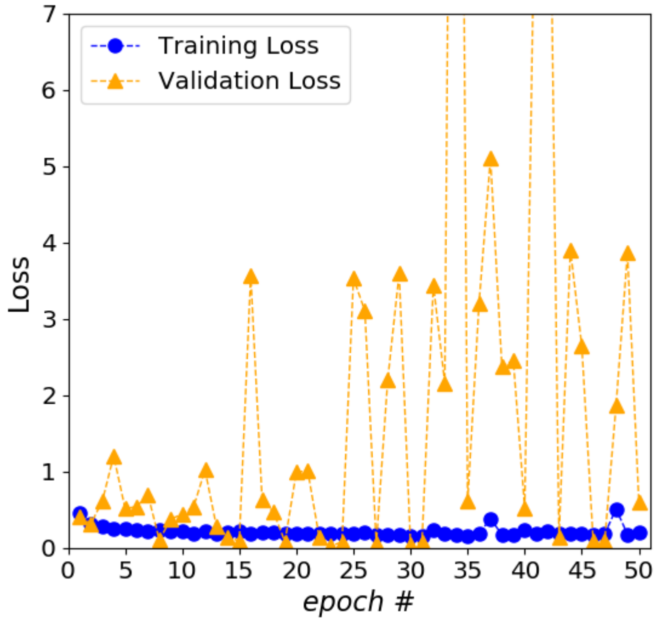

Fig. 9. Training and validation losses of the EFF-enhanced image.

IV. Conclusions

This study has implemented several image enhancement techniques, such as HE; CLAHE; and EFF. These three enhanced images are used as the input images for the VGG16-based CNN in pneumonia detection using a CXR. The best performance, in terms of training and validation losses and accuracies, is achieved using EFF image enhancement as a pre-processing technique. Even though from the visual assessment, there is a significant difference in the contrast between the EFF-enhanced and the original images, the validation loss and accuracy differ significantly. The validation loss has increased from 2.0537 to 0.6034 and 0.7532 to 0.8670 for validation accuracy. A deeper examination through its histograms reveals that the shape of the EFF-enhanced image histogram is still unchanged even though there is a little intensity stretching. This histogram shape is very different compare to the HE-enhanced and CLAHE-enhanced image histogram shapes in that there is deformation during the enhancement process. This study shows that one of the important aspects of the image enhancement process is not only intensity stretching but also keeping the shape of the histogram as closely as possible to the original one.

This study was limited by the existing computational resource. Therefore, Further development will focus on implementing other CNN architectures that have more computation load to improve the metrics performance. This preliminary study still needs further investigation, particularly to prevent over-fitting.

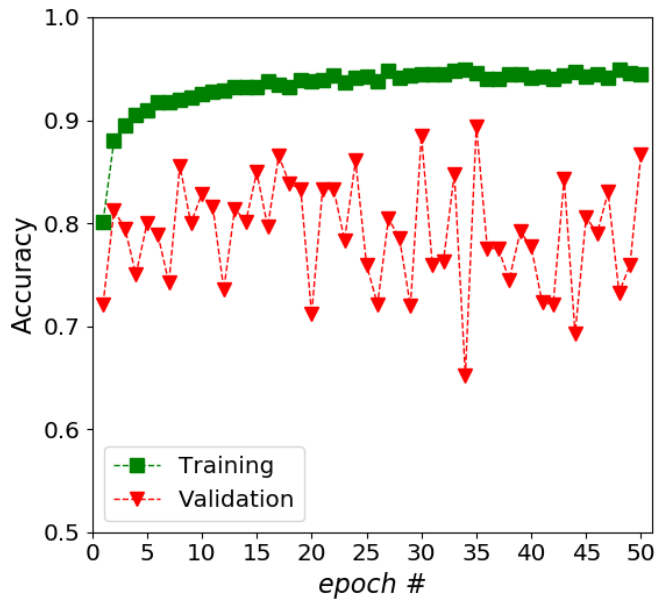

Fig. 10. Training and validation accuracies of the EFF-enhanced image.

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