Research Article

Iris recognition through transfer learning and exponential scaling

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Abstract:
In this paper, we investigate deep learning framework for iris recognition by embedding exponential scaling using transfer learning. By employing exponential scaling transformation technique, we examine the effect of in fine-tuned pre-trained MobileNetV2 model. The performance of the model is evaluated for various scaling techniques by conducting an experiment on well-known two public iris dataset. The results of the experiment show the exponential scaling operation outperforms in comparison with the linear scaling.

Keywords: Iris recognition, transfer learning, exponential scaling

Introduction:

Deep learning has gained prominence place for computer vision as traditional techniques, such as image thresholding, filtering, and edge detection, have been augmented by deep learning methods.Tillnow,there has beensizeableliteraturepublishedin all variety of reputed journals and magazines centered around deep learning. In this context,Convolution Neural Networks (CNNs) is the most important type of deep learning models as similar images are found by transforming an image into a feature vector, while doing prediction [1]. Various kinds of CNN based iris recognition systemhave beenproposed toimprove the performance of the system, see [2-4] and references therein.

In [5], it is shown that the features learned by the model on a generic dataset can be transferred to the specific dataset of interest. This technique is refereed as transfer learning. Typically, the models trained on millions of images are used to perform transfer learning and those pre-trained models are fine-tuned or customized to specific dataset of interest. Then, the newly created model for specific dataset is used to generate predictions.

As MobileNetV2 [6], by Google, is a very effective feature extractor for object detection and segmentation. The architecture of MobileNetV2 contains the initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers.In this work, we have considered it as the base model without the top layer and then add our custom fully including activation and softmax to constitute our final model for iris recognition task.We freeze the base model, but the top layer of the newly added components remains unfrozen.

For MobileNetV2, images, before being fed into the network, are of size 224 x 224 and rescaled by applying transformation $\frac{x-127.5}{127.5}$, where x denotes the pixel value. Thus, this scaling transformation, transforms every pixel value from range 0 (black) to 255 (white) into [-1, 1]. In this work, instead of pixel scaling in linear manner, we utilize exponential form for pixel scaling technique whose shape is flexibly determined by changing the scale and shape parameter a and b (See, equations (1) and (2))

$$f(x)=\frac{a}{1+\exp(bx)}-1 \tag{1}$$

$$f(x) = 1 - \frac{a}{1 + \exp(bx)} \tag{2}$$

By fixing the values for the parameters *a* and *b*, the changes in the pixel value (x) are shown in Figures 1-2. From Figure 1, convex decrease is observed for function defined in (1), whereas convex increase is seen for function defined in (2). By applying different transformations, the changes in the visual appearance of an image are shown in Figure 2. Transformation defined in (1)darkens the image, on the other hand, the image has exposed more and washed-out the appearance for the transformation defined in (2).

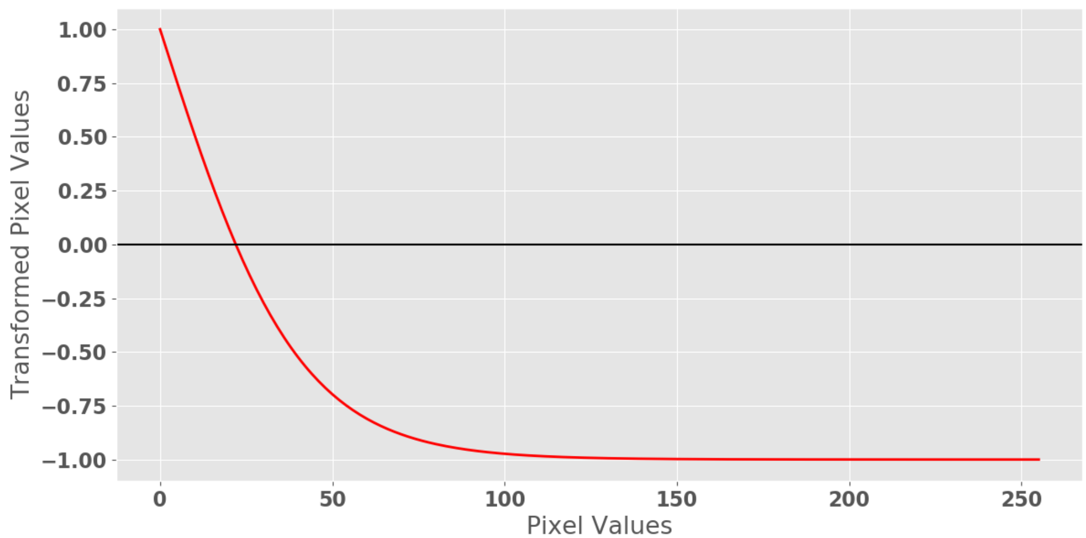

Figure 1: Scaling pixels using equation (1) for a = 4 and b = 0.05

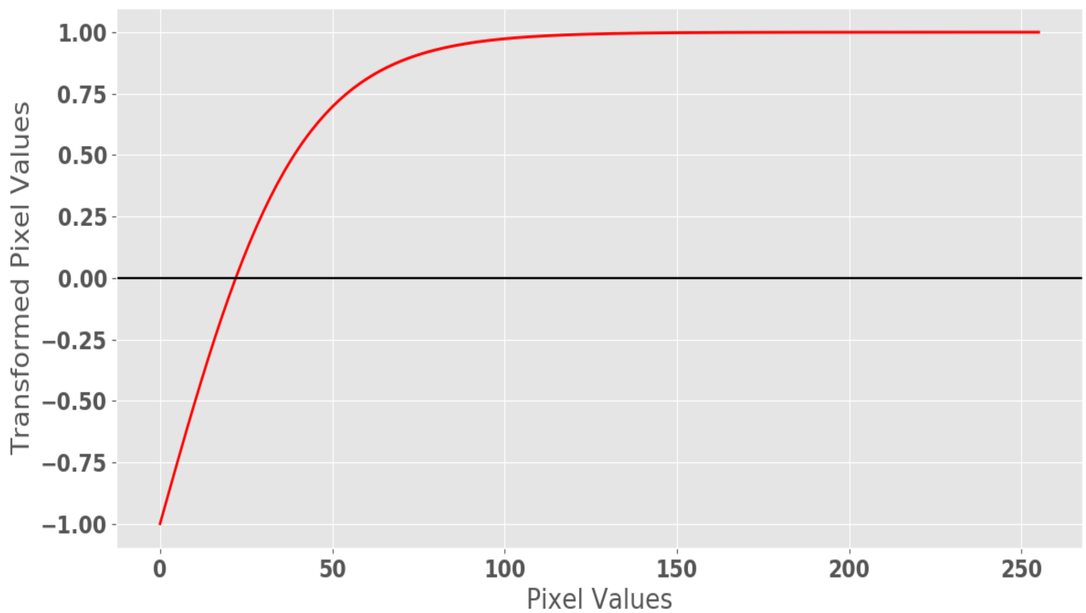

Figure 2: Scaling pixels using equation (2) for a = 4 and b = 0.05

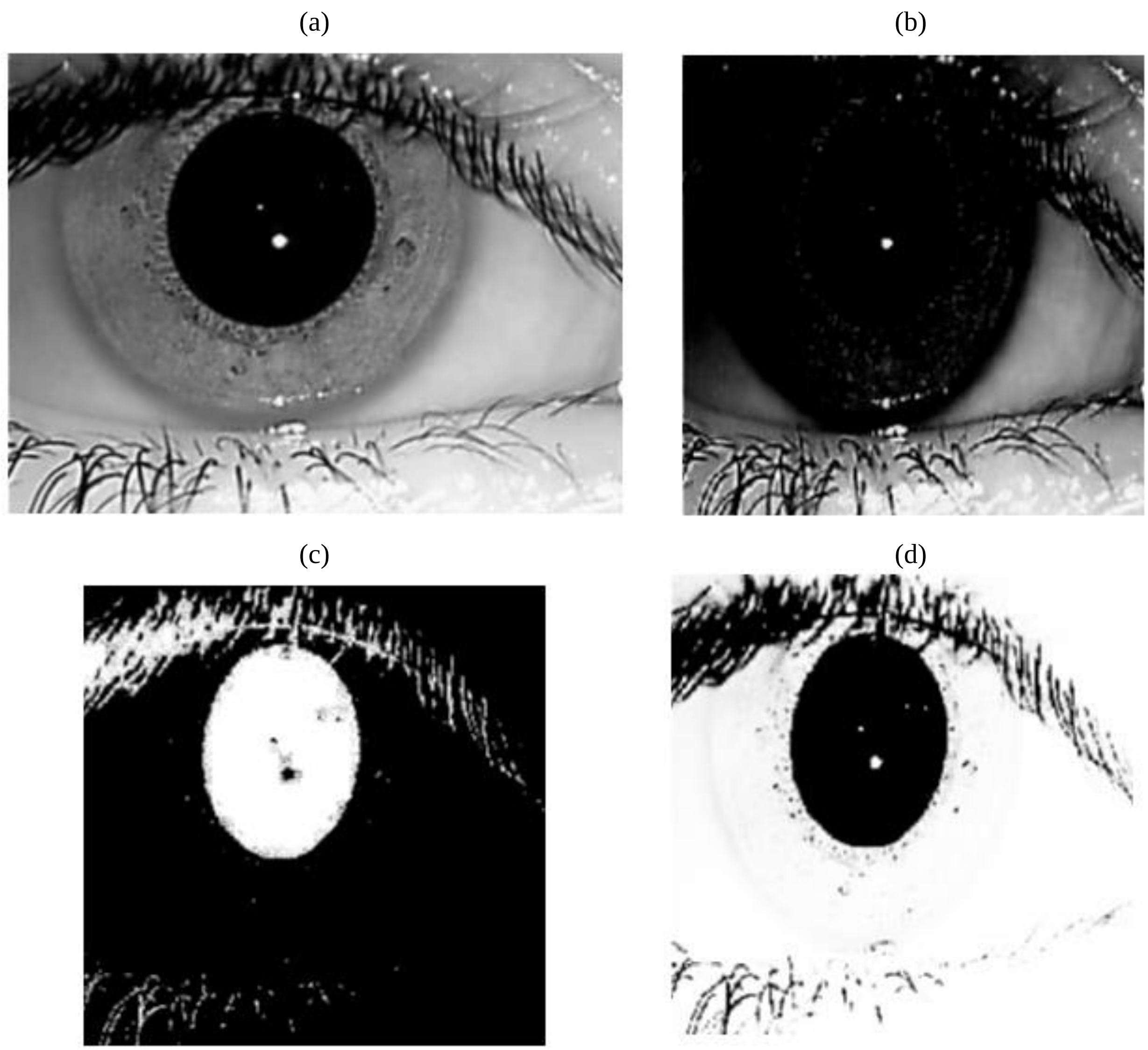

Figure 2:(a) a sample eye image of IIT Delhi of size 320 x 240, (b) pre-processed sample image for MobilNetV2 of size 224 x 224, (c) applying transformation defined in eq. (1) on sample image, (d) applying transformation defined in eq. (2) on sample image of size 224 x 224.

Proposed method:

In order to examine the effect of pixel scaling, we have followed the procedure comprises the following five steps.

Step 1:	Normalize the input images, respectively, (1) as used during the training of the pre-trained

	MobileNetV2 model, (2) applying exponential scaling defined in equation (1), and (3) applying exponential scaling defined in equation (2).
Step 2:	Employ the pre-trained MobileNetV2 model's architecture. Use the weights for this architecture that generatedbecause of being trained on a large dataset.
Step 3:	Discard the last layer of the pre-trained model.
Step 4:	Connect the truncated pre-trained model to a freshly initialized layer (or layers) where weights are randomly initialized. Ensure that the output of the last layer has as many neurons as the classes/outputs we would want to predict.
Step 5:	Update the trainable parameters over increasing epochs to fit a model.

We do not train the weights of the pre-trained model, as we assume those weights are already well learned for the task, and hence leverage the learning from a large model. In essence, we only learn the newly initialized layers for our dataset.Sparse categorical crossentropy loss is considered which is optimized using Nadam optimizer during the training of the model.After each training epoch, we compute the error on validation dataset and update the model that provides highest validation accuracy.

Experiment and results:

We have tested our model on two iris databases IIT Delhi and MMU.2. IIT Delhi database contains 2240 iris images in BMP format with resolution 320 x 240 captured from 224 different people. We have used 1957 images out of that from 195 subjects. MMU.2 iris database consists of 995 iris images which are stored in BMP format with resolution 320×240. We perform our experiments using TensorFlow 2.x framework with GPUs on Google Colaboratory. We split the dataset into training, testing and validation using stratified sampling. Loss and accuracy on the dataset are summarized in Table 1 and depicted in figures 3 – 8.

Table 1: Accuracy for different scaling

Scaling	IIT Delhi dataset	MMU.2 dataset
	Accuracy (train/valid/test)	Accuracy (train/valid/test)
Linear	0.9936/0.8279/0.8359	0.9937/0.8600/0.9000
Exponential defined in eq. (1)	1.0000/0.8474/0.8539	1.0000/0.8500/0.8900
Exponential defined in eq. (2)	0.9490/0.6526/0.7205	0.9887/0.8600/0.8400

It can be observed from the figures 3 – 8 that the accuracy increases steadily whereas the loss decreases for the training and validation dataset in few numbers of epoch. It is to be noted that higher training, testing, and validation accuracy is achieved for exponential scaling defined in (1) than the linear scaling for IIT Delhi dataset. On the other hand, for MMU.2 database, there is no significant variation is observed in terms of training, testing and validation accuracy between linear and exponential scaling defined in (1). Moreover, the exponential scaling defined in (2) does not produce good results in terms of accuracy for the datasets.

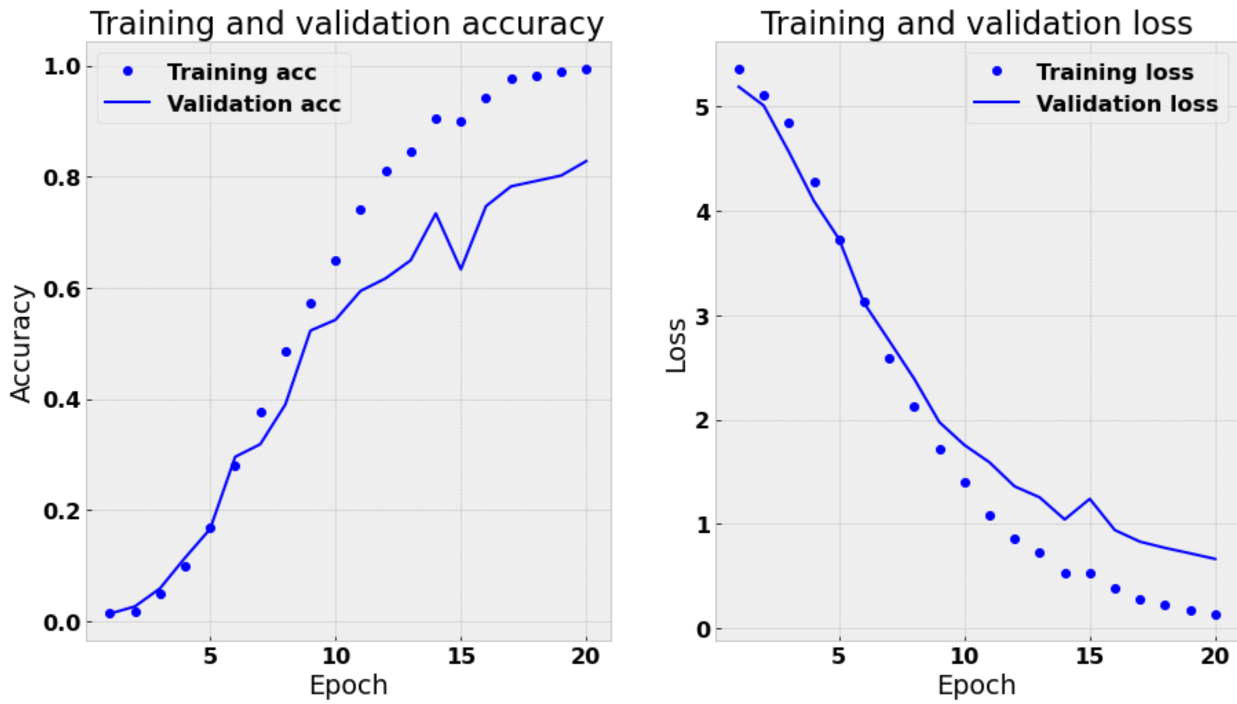

Figure 3: Loss and Accuracy for IIT Delhi datasetwhen images are rescaled using linear transformation

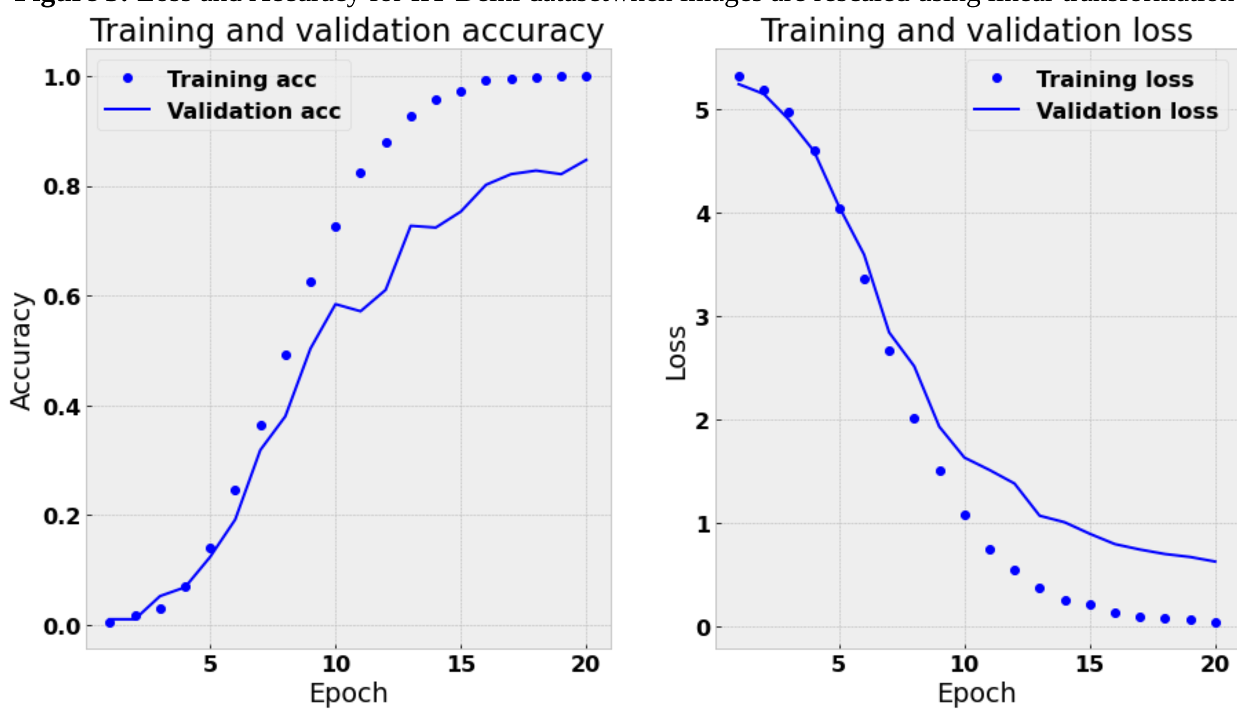

Figure 4: Loss and Accuracy for IIT Delhi dataset when images are rescaled using transformation defined in eq. (1)

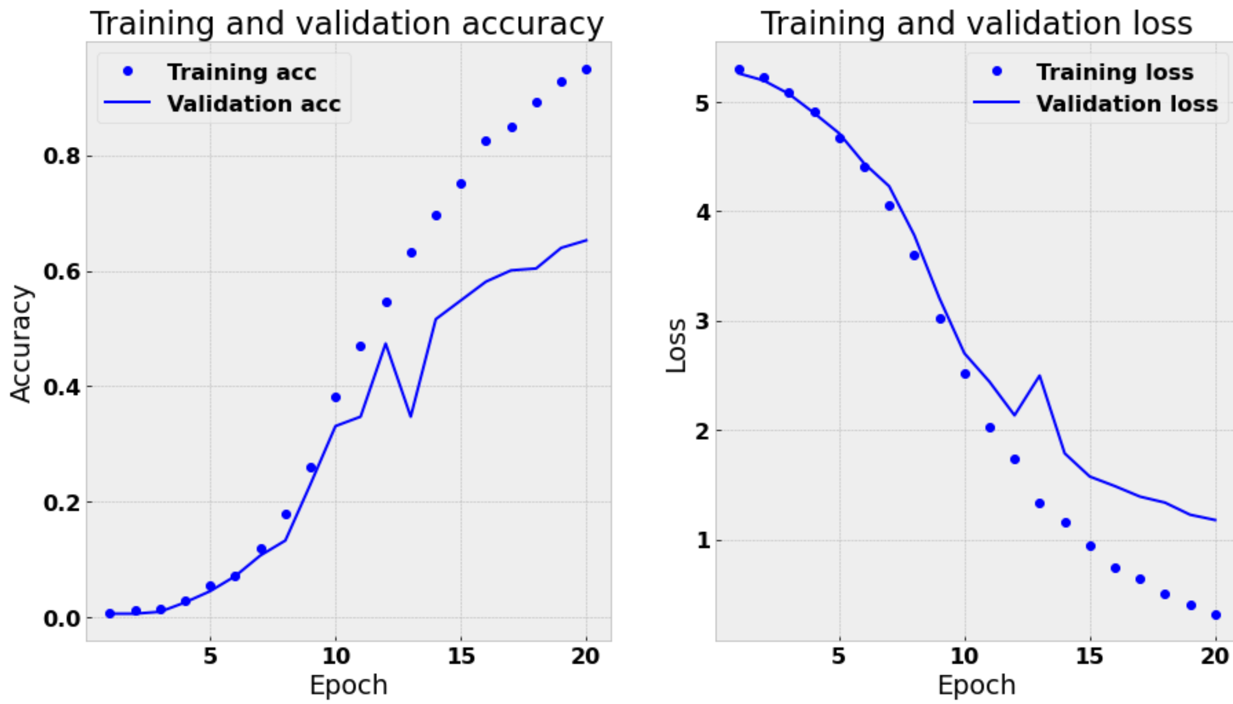

Figure 5: Loss and Accuracy for IIT Delhi dataset when images are rescaled using transformation defined in eq. (2)

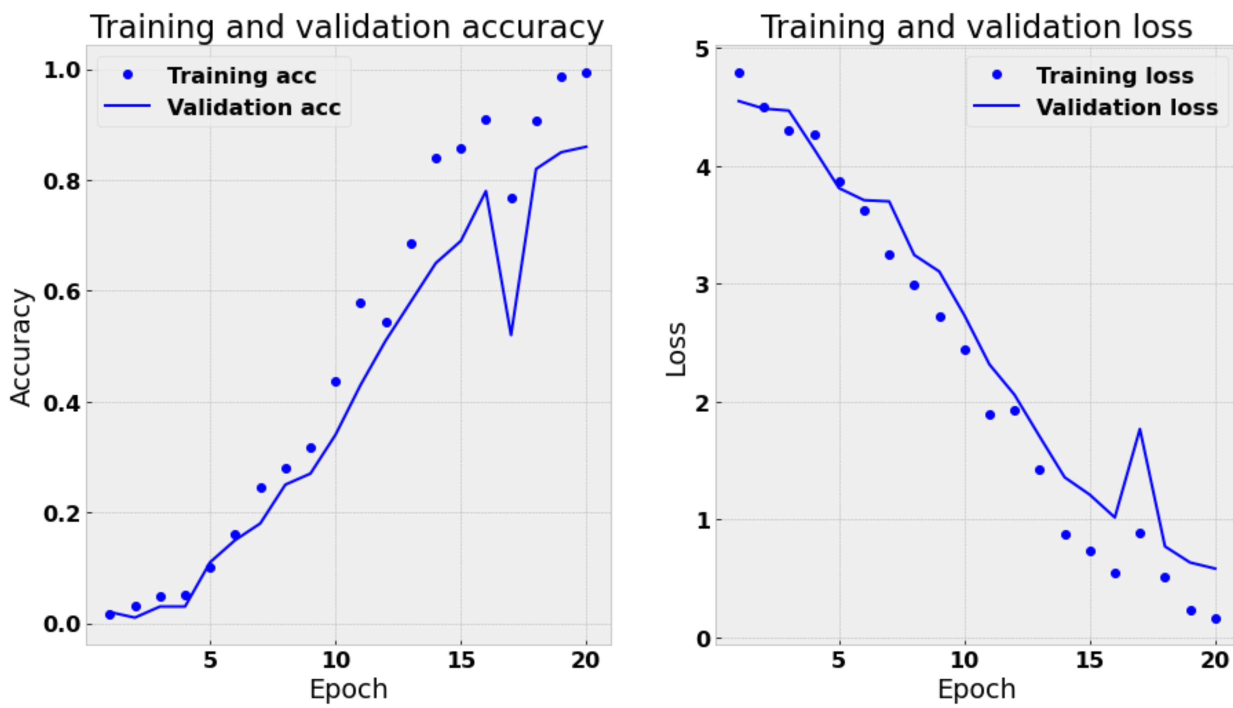

Figure 6: Loss and Accuracy for MMU.2 dataset when images are rescaled using linear transformation

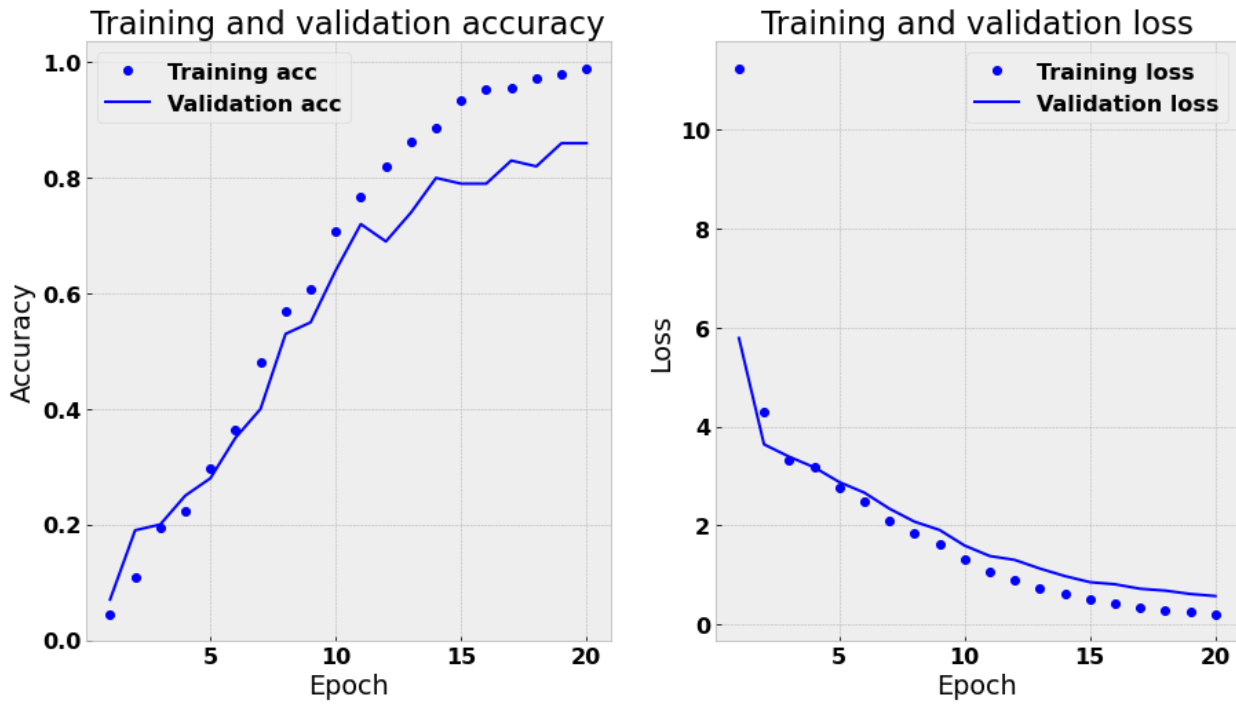

Figure 7: Loss and Accuracy for MMU.2 dataset when images are rescaled using transformation defined in eq. (1)

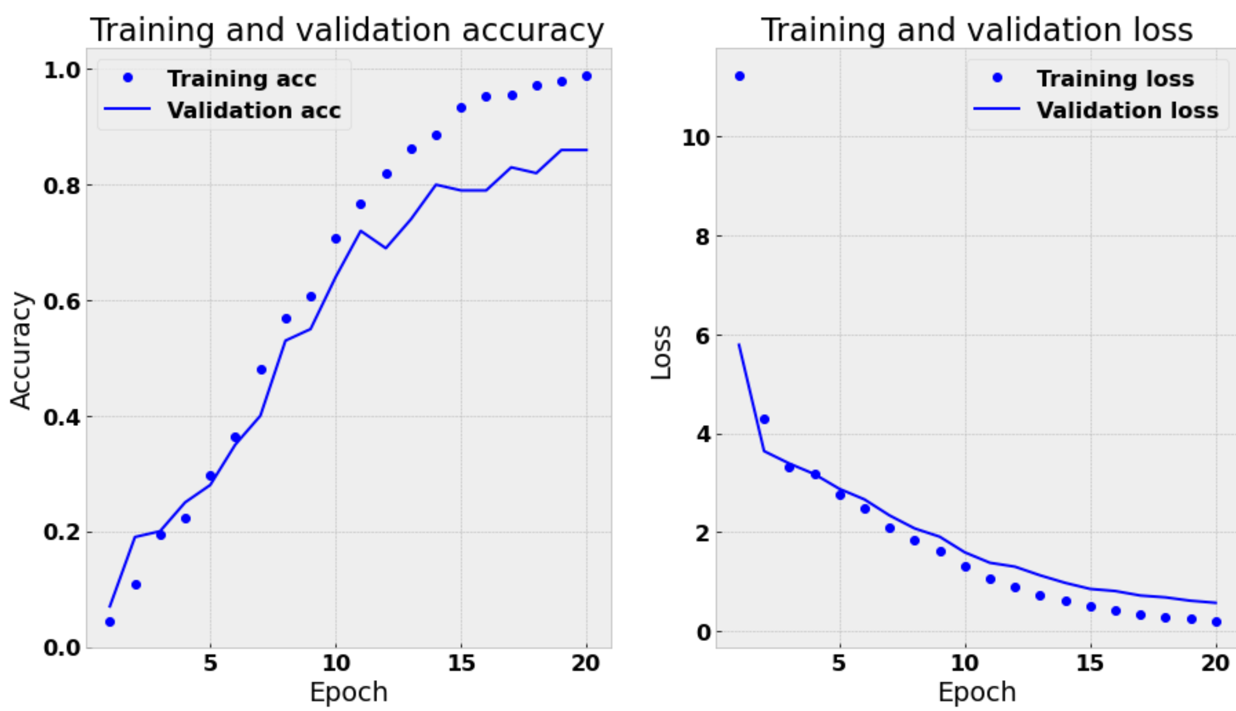

Figure 8: Loss and Accuracy for MMU.2 dataset when images are rescaled using transformation defined in eq. (2)

Conclusion:

In this paper, we propose deep learning framework by embedding exponential scaling in fine-tuned pre-trained convolution model ImageNet and analyze the performance of the model for iris recognition. The results of the experiments show the improvement in the performance of the CNN model when exponential scaling is employed. This research can be extended by applying different scaling techniques on another pre-trained model for iris recognition.

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7. Acknowledgement:
8. We would like to thank IIT Delhi for providing the iris database.