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The Performance of Deep Neural Networks in Deformed Iris Recognition System

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Abstract

Iris recognition system is a powerful tool for person identification based on their special iris traits which are unique for each individual. Besides hand-crafted techniques, modern deep learning algorithms can be implemented as a good feature extractor for iris recognition system. Deformed iris texture due to different pupil dilation of the same eye can cause negative impact on iris recognition performance. Hence in this paper, we study the effectiveness of deep learning algorithms on extracting deformed iris features from the normalized iris images. We compared the performance of 17 available deep learning algorithms which followed by a multi-class Support Vector Machine (SVM) algorithm to perform classification. We then utilized different epoch number on the model until a good accuracy is achieved. We also extracted features using different type of layers in order to identify which type of layers could extract good features. Simulation results of 92% by Darknet-19 on CASIA-Iris-Lamp dataset reveal the effectiveness of deep learning algorithms on extracting irregular features of deformed iris.

Key-words: Pupil dilation, deformed iris recognition system, deep learning algorithm

I. INTRODUCTION

Iris recognition is one of the robust recognition system due to high degree of freedom (DOF) in iris trait and does not affected with aging. Iris recognition system is usually implemented in numerous fields such as at BioID Technologies SA in Pakistan, Schiphol Airport Netherlands, United Arab Emirates Homeland Security Border Control and many more.

As any other security technology, iris recognition system also faces some challenges that influence its performance. Its challenges including capturing noisy iris images. The acquisition of human iris is quite difficult compared to other biometric traits because of its small size. The acquired images are seldom perfect even under a controlled environment due to various uncertainty factors. Reflections, defocus, motion blur, occlusion and pupil dilation are factors that cause to noisy iris images.

Among other factors that cause to noisy iris images, pupil dilation, or also known as iris deformation become a popular research topic in the past few years. Some causes such as alcohol, drugs, age, disease, psychology and light intensity changes has been proven to cause varying size of pupil dilation. In the issue of light intensity changes, there are two muscle systems which consists of several radial dilator muscles and a sphincter muscle that function to adjust the volume of light getting into the pupil by controlling the size of the iris. To widen pupil size, the dilator muscle fibers are radially arranged meanwhile to constrict pupil size, the sphincter muscle fibers are circumferentially arranged (Tomeo-Reyes, Ross, & Chandran, 2016).

Two eye images of the same person having different pupil size make the iris texture patterns dilate and contract according to the light intensity changes (Jeong et al., 2015), and the detectable features of the iris such as collarette, crypts and radial furrow change perceptibly (Tomeo-Reyes et al., 2016). The change of visible features of iris will increases the possibility of false non-matches, where the user is failed to be identified, hence lower the accuracy of the system (Hollingsworth, Bowyer, & Flynn, 2009; Pasula, 2016). Figure 1 shows example of two iris images with different degree of pupil dilation values having different visible iris features.

Recently, research on deep learning has been actively conducted (Almisreb, Jamil, Norzeli, & Din, 2020; Ibrahim, Abdul-Rahman, Hamid, & Shamsuddin, 2020) including deep learning based iris recognition system (Ying Chen, Zeng, Gan, & Zeng, 2021; Kashihara, 2020; MIN Beom Lee, Kang, Yoon, & Park, 2021; M. Omran & Alshemmary, 2020). This is due to its success in serving as good iris feature extractors. Deep learning algorithms enable the system to extract features, classify and detect patterns automatically without explicitly programming them.

In this paper, we analyzed the effectiveness of 17 available pre-trained deep neural networks on extracting deformed iris features. The system approach is implemented by fine-tuning deep neural networks for feature extraction and SVM for feature classification. The performance of the iris recognition system is evaluated on CASIA-Iris-Lamp dataset.

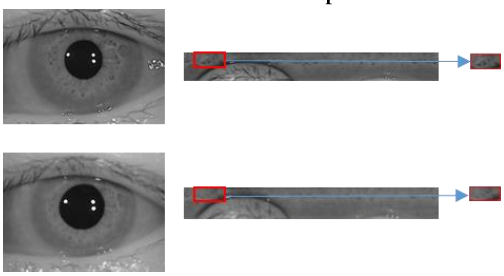

Figure 1 – Different iris texture of two eye images of same person due to changes in pupil size

II. RELATED WORK

In 1987, Leonard Flom and Aran Safir had proposed the first biometric identification using individual iris traits. Then, an algorithm to recognize iris based on image data had been proposed by Dougman (2004). Phases in iris recognition involves localization and segmentation of the iris from the eye image. The segmented iris is then being normalized from cartesian to polar coordinate. Iris features will be extracted from normalized iris in order to be recognized by either feature engineering, statistical or artificial neural network.

Many countermeasures had been proposed on enhancing deformed iris recognition system. Some of researchers proposed nonlinear iris normalization scheme to reduce intra-class variations (W. S. Chen, Li, Jeng, Hsieh, & Shih, 2010; Tomeo-Reyes et al., 2016) which in return got significant accuracy improvement. Some of them proposed selective matching scheme by using multiscale filter (Pasula, 2016). There is also previous work proposed feature extraction scheme that extract non-linear tensile properties of iris patterns (Jeong et al., 2015).

Deep learning networks on the other hand, gain much attention lately on iris recognition system. It is due to high accuracy performance obtained when implemented on iris datasets. Some researchers implemented deep learning algorithms to fuse iris features with other biometric traits in order to joint discriminant feature of iris and other biometric traits (Damer, Dimitrov, Braun, & Kuijper, 2019; Talreja, Soleymani, Valenti, & Nasrabadi, 2019; Talreja, Valenti, & Nasrabadi, 2021; Zhang, Li, Sun, & Tan, 2018).

Besides, it has been successfully applied to extract discriminative iris information. Deep convolutional neural networks were trained on a large number of iris sample images in order to learn and extract robust and discriminant iris features. There are various types of deep learning algorithm have been implemented to extract iris features such as AlexNet, Vgg-16, Vgg-19 and many more (Boyd, Czajka, & Bowyer, 2019; Chakraborty, Roy, Biswas, & Mitra, 2020; Yifeng Chen, Wu, & Wang, 2020; Y. W. Lee, Kim, Hoang, Arsalan, & Park, 2019; Nguyen, Fookes, Sridharan, & Ross, 2020; E. M. Omran et al., 2020; Rafik &

Boubaker, 2020; Singh, Gaurav, Vashist, Nigam, & Yadav, 2020; Tobji, Di, & Ayoub, 2019; Wei et al., 2019).

Deep learning algorithms are also used to segment pupil and iris including for irregular pupil and iris (Ganeeva & Myasnikov, 2020; Gunasekaran & Muthuraman, 2020; Kinnison, Trokielewicz, Carballo, Czajka, & Scheirer, 2019; Li, Huang, & Juan, 2019; Pathak, Srinivasu, & Bairagi, 2020; Wang, Muhammad, Wang, He, & Sun, 2020). Deep learning networks need to be tuned to perform the segmentation, in order to differentiate the region of iris and non-iris on digital images. This can be accomplished by training neural networks using proper dataset. Other than that, classification of iris images also can be done using deep learning approach since it is very effective to classify iris features (Alaslani & Elrefaei, 2018; Kaur, Singh, & Kumar, 2018; Min Beom Lee, Kim, & Park, 2019; Nawaz Ripon, Ershad Ali, Siddique, & Ma, 2019; Nguyen, Fookes, Ross, & Sridharan, 2017). Table 1 shows existing works of deep learning algorithms on noisy iris recognition system.

Based on previous works, most of researchers used less than five types of deep learning algorithms to show the effectiveness of such approach on iris recognition. To the best of our knowledge, there are no existing works that compare the performance of all deep learning neural networks on deformed iris recognition system. Hence, in this paper, we analyzed the effectiveness of 17 available pre-trained deep neural networks on extracting deformed iris features.

Tabel 1 – Existing works on Deep Learning based Iris Recognition

Author/s	Function of DNN	Type of DNN	Employed database
Talreja et al., (2021)	Feature fusion	VGG-19	WVU multimodal
Talreja et al., (2019)		VGG-19	-CASIA-Iris-Thousand -ND-Iris-0405
Damer et al., (2019)		deep CNN	-CASIA Thousand v4 -CASIA Lamp v4 -CASIA Interval v4 -BioSecure
Zhang et al., (2018)		CNN	-CASIA-Iris-M1-S3 -Bath -CASIA-IrisV4 (Thousand, Lamp and Interval) -CASIA-CSIR2015
E. M. Omran et al., (2020)	Feature extractor	-Alex net -Vgg16 -Vgg19	-CASIA-Iris V3 database (Interval, lamp, twins) -CASIA-Iris V3 database
Nguyen et al., (2020)		ComplexIrisNet	-ND-CrossSensor-Iris-2013 dataset -CASIA-Iris-Thousand dataset -UBIRIS.v2 iris dataset:
Chakraborty et al., (2020)		CNN	-CASIA.v4-Distance -CASIA.v4-Thousand
Boyd et al., (2019)		ResNet-50	-in-house iris data collected by the University of Notre Dame -CASIA-Iris-Thousand database
Rafik & Boubaker, (2020)		-VGG16 -DenseNet169 -Resnet50	MMU1
Yifeng Chen et al., (2020)		T-Center Loss	-ND-IRIS-0405 -CASIA-Thousand -IITD

Wei et al., (2019)		CNN	-Bath -CASIA-IrisV4 (Thousand, Lamp and Interval) -CASIA-CSIR2015.
Y. W. Lee et al., (2019)		ResNet	-CASIA Iris-Distance -CASIA-Iris-Lamp -CASIA-Iris-Thousand
Tobji et al., (2019)		FMnet	-CASIA-Iris-Thousand -UBIRIS.v2 -LG2200
Singh et al., (2020)		POFNet	-CASIA Lamp -CASIA-V3 Interval -IITD-V1 Iris -IITK Iris
Gunasekaran & Muthuraman, (2020)	Segmentation	HCNN	CASIA-Iris-V3 Interval
Ganeeva & Myasnikov, (2020)		-U-Net -LinkNet -FC- DenseNet	MMU
Wang et al., (2020)		IrisParseNet	-CASIA.v4-distance -UBIRIS.v2 -MICHE-I
Pathak et al., (2020)		E-CNN	UBIRIS.V2
Li et al., (2019)		Faster R-CNN	CASIA-Iris-Thousand
Kinnison et al., (2019)		FLoRIN	-Biosec baseline corpus -BATH -ND0405 -UBIRIS -CASIA-V4-Iris-Interval -proposed database of iris near-infrared videos, presenting various pupil sizes
Alaslani & Elrefaei, (2018)	Classifier	AlexNet	-IITD -CASIA Iris V1 -CASIA Iris thousand -CASIA Iris V3 Interval
Kaur et al., (2018)		KNN	-CASIA-IrisV4-Interval -IITD.v1 -UPOL -UBIRIS.v2 -IIITD-CLI
Nguyen et al., (2017)		-DenseNet -ResNet -Google Inception -VGG -AlexNet	-LG2200 ND-CrossSensor-Iris-2013 -CASIA-Iris-Thousand
Min Beom Lee et al., (2019)		cGAN	-NICE.II (selected from UBIRS.v2) -MICHE -CASIA-Iris-Distance
Nawaz Ripon et al., (2019)		-CNN -KELM	CASIA.v4 distance

III. EXPERIMENTAL SETUP

All experiments were conducted using the platform of Windows 10 with the configuration of Intel Core i7- 7500U CPU @ 2.7GHz with 12.0GB on NVIDIA GEFORCE GTX 950M. MATLAB R2020a simulation tool was used to evaluate the experiment and perform the feature extraction and classification task. The performance of the pre-trained convolutional neural network system is evaluated on the basis of the quality metric known as recognition accuracy. The accuracy is the fraction of the correct predicted labels.

We used the CASIA-Iris-Lamp dataset, which consist of 8 bit gray-level JPEG images to identify the robust pre-trained neural network on extracting deformed iris features. Those images are collected under near infrared illumination with 640 x 480-pixel resolution. The dataset comprises 16,212 iris images of left and right eyes of 411 subjects resulting in a total number of 819 different classes. In this work, only 100 classes were used, which comprises 700 iris images. At pre-processing the iris of a given sample image is detected, un-wrapped to an enhanced rectangular texture of 480 × 40 pixel. Software of Iris system from Libor Masek (2003) had been used to carry out pre-processing of iris images.

IV. MEASURING DILATION

Measuring pupil dilation size was the first step in this work in order to make sure that the database used consists of iris with varying pupil dilation sizes. Besides, this step is needed to ensure that all image classes consist of irregular iris structure due to varying pupil dilation sizes.

Both radii of iris and pupil are obtained from segmentation process. In order to measure pupil dilation, the radius of pupil is divided by the radius of iris. Since the iris radius is always larger than the pupil radius, dilation ratio value must be between 0 and 1 (Tomeo-reyes & Chandran, 2014). In this work, all dilation ratios were between 0.21 and 0.62. There are three types of dilation ratio based on three different range of values. According to Tomeo-reyes (2015), the range of value for constricted dilation ratio is $0.28 < \Delta \leq 0.35$. The range of value for normal dilation ratio is $0.35 < \Delta < 0.48$ while for dilated dilation ratio is $\Delta \geq 0.48$.

V. PERFORMANCE EVALUATION

A) Experiment 1:

The iris images are loaded as an image datastore. The data is then divided into training and testing data sets where 70% of the images is used for training and 30% for testing. For the pre-processing, the input images of normalized iris are automatically resized to a suitable size as required by each deep learning network. We also converted grey scale images to RGB images.

The last three layers of each network are by default configured for 1000 classes. Hence we fine-tuned these three layers according to our classification task. All layers from the pretrained network were extracted except the last three layers. A fully connected, a softmax and a classification output layer are used to replace the removed three layers. The options of the new fully connected layer had been specified according to our iris dataset. Since we used 100 classes in the iris dataset, the fully connected layer is set to 100.

For experiment 1, the number of maximum epochs was set to 4. The mini-batch size was set to 22 and the initial learning rate was set to 0.0001. The validation frequency was set to 3 during training. Then the network that consists of the transferred and new layers was trained using the specified training options.

The deeper the layers, the higher the features level it has, which in return should generate a better accuracy performance. Hence for this experiment, iris features are extracted using last learnable layers, either fully connected layer or convolutional layer. Then the extracted iris features are used as predictor variables. Trained SVM model was used to classify the test images using the extracted features from the test images. Figure 2 and Table 2 illustrate overall accuracy performance of 17 pre-trained neural networks on CASIA Iris Lamp Dataset.

We found that three pre-trained neural networks which are DarkNet-19, Squeezenet and

DarkNet-53 got accuracy of above 80%. This result shows that these type of pre-trained neural networks are robust to recognize deformed iris images. An overall accuracy below 40% from other types of networks such as Inception-v3 and NasnetMobile showing that these networks are not robust enough for recognizing irregular iris texture on deformed iris images compared to, for example, DarkNet-53 and DarkNet-19.

B) Experiment 2:

In experiment 2, we utilized five types of epoch number to analyze the effectiveness of pre-trained neural networks on iris dataset. We just chose 13 pre-trained neural networks with accuracy performance of above 45% for this experiment. All the setting remains the same except for the number of epochs used. We tested the models with 4, 8, 12, 16 and 20 epochs. Figure 3 and Table 3 illustrate

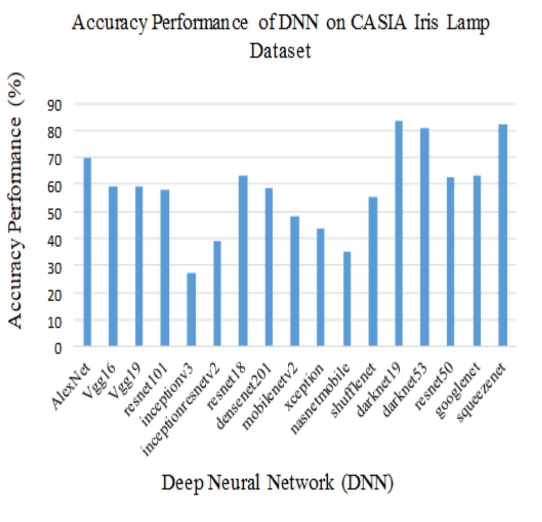

Figure 2 – Overall accuracy performance of 17 pre-trained Neural Networks on CASIA Iris Lamp dataset

Tabel 2 – Performance of 17 pre-trained Neural Networks on CASIA Iris Lamp dataset

Network	No of Epoch	Classification Accuracy (%)
Darknet-19	4	83.50
Squeezenet		82.00
Darknet-53		81.00
Alexnet		69.50
Resnet-18		63.00
Googlenet		63.00
Resnet-50		62.50
Vgg-16		59.50
Vgg-19		59.50
Densenet-201		58.50
Resnet-101		58.00
Shufflenet		55.50
Mobilenet-v2		48.00
Xception		43.50
Inceptionresnet-v2		39.00
Nasnetmobile		35.00
Inception-v3		27.50

Note: The deep neural networks are ranked in descending order based on the overall performance on the training and validation images

overall accuracy performance of 13 pre-trained neural networks when using different number of epochs.

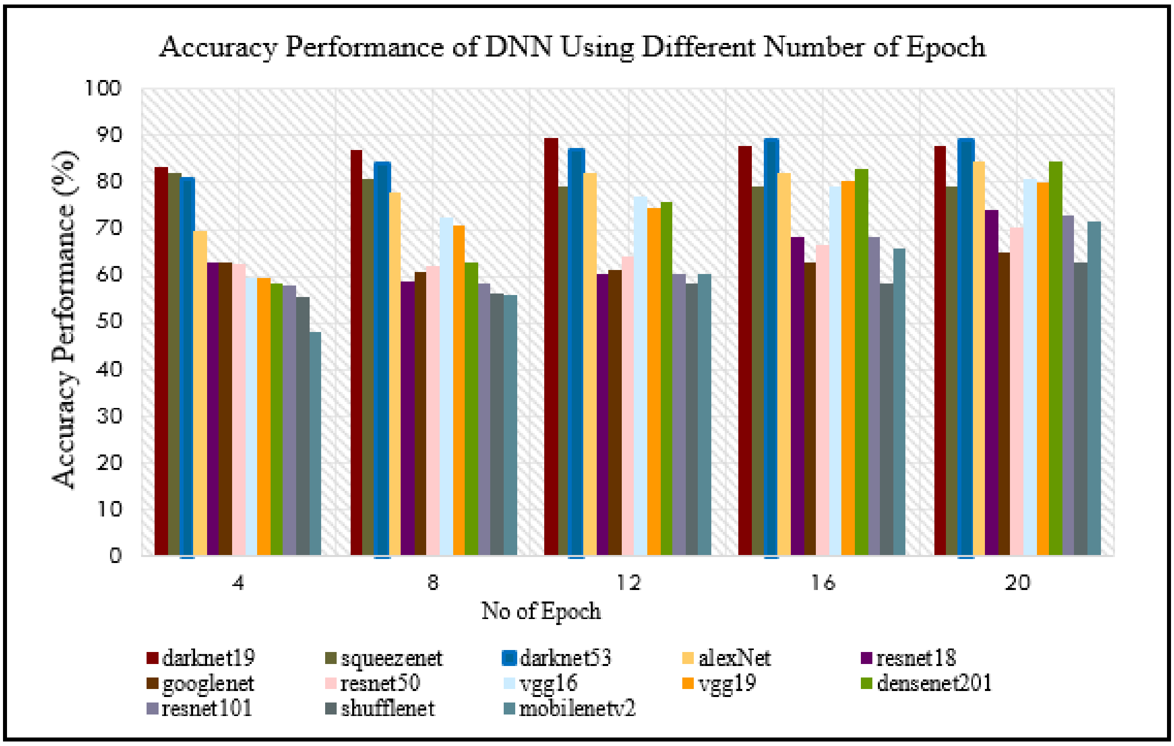

Figure 3 – Overall accuracy performance of 13 pre-trained Neural Networks using different number of epochs

Tabel 3 – Performance of 13 pre-trained Neural Networks using different number of epochs

Network	Classification Accuracy (%)				
	4	8	12	16	20
Darknet-19	83.50	87.00	89.50	88.00	88.00
Squeezenet	82.00	81.00	79.00	79.00	79.00
Darknet-53	81.00	84.00	87.00	89.00	89.00
Alexnet	69.50	78.00	82.00	82.00	84.50
Resnet-18	63.00	59.00	60.50	68.50	74.00
Googlenet	63.00	61.00	61.50	63.00	65.00
Resnet-50	62.50	62.00	64.00	66.50	70.50
Vgg-16	59.50	72.50	77.00	79.00	81.00
Vgg-19	59.50	71.00	74.50	80.50	80.00
Densenet-201	58.50	63.00	76.00	83.00	84.50
Resnet-101	58.00	58.50	60.50	68.50	73.00
Shufflenet	55.50	56.50	58.50	58.50	63.00
Mobilenet-v2	48.00	56.00	60.50	66.00	71.50

Based on the results obtained, we can see that there are several models such as AlexNet, Resnet-50 and Vgg-16 achieved higher accuracy performance as the number of epochs increased. However, there are also model that obtained higher accuracy performance when the amount of epochs decreased such as squeezenet. Besides, there are several models that shows irregular performance such as Darknet-19, Resnet-18 and Googlenet. Darknet-19 achieved highest performance of 89.50% compared to other models when using 12 epochs. It followed by Darknet-53 that achieved 89% of accuracy performance when using 16 and 12 epochs. This finding shows that the accuracy performance of iris recognition system using CASIA Iris Lamp Dataset is not depending on the number of epochs used.

C) Experiment 3:

To conduct this experiment, we chose pre-trained neural networks models that achieved accuracy performance of above 85% based on result from previous experiment. There are only two models that satisfied that performance, which are Darknet-19 with 8, 12, 16 and 20 epochs, and Darknet-53 with 12, 16 and 20 epochs. We used three different layers from both models to extract irregular iris features. All the setting remains the same except for the type of layers used.

Figure 4 and Table 4 illustrate accuracy performance of Darknet-19 using different type of layer on different number of epoch. For Darknet-19 network, the highest accuracy performance is obtained when extracting features using Convolution 18 layer for all types of epoch. This result clearly proved that Convolution 18 layer of Darknet-19 are robust to extract discriminant iris features. It followed by Convolution 17 layer where had the second highest recognition accuracy for all types of epoch. Meanwhile Convolution 19 layer had the lowest recognition accuracy for all types of epoch. As mentioned in previous section, the deeper the layers, the higher the features level it has, which in return should generate a better accuracy performance. However, this finding shows opposite results. The deepest layer of Darknet-19 had the lowest accuracy performance. It shows that the highest accuracy performance of Darknet-19 network on CASIA Iris Lamp Dataset is not depending on its deepest layer.

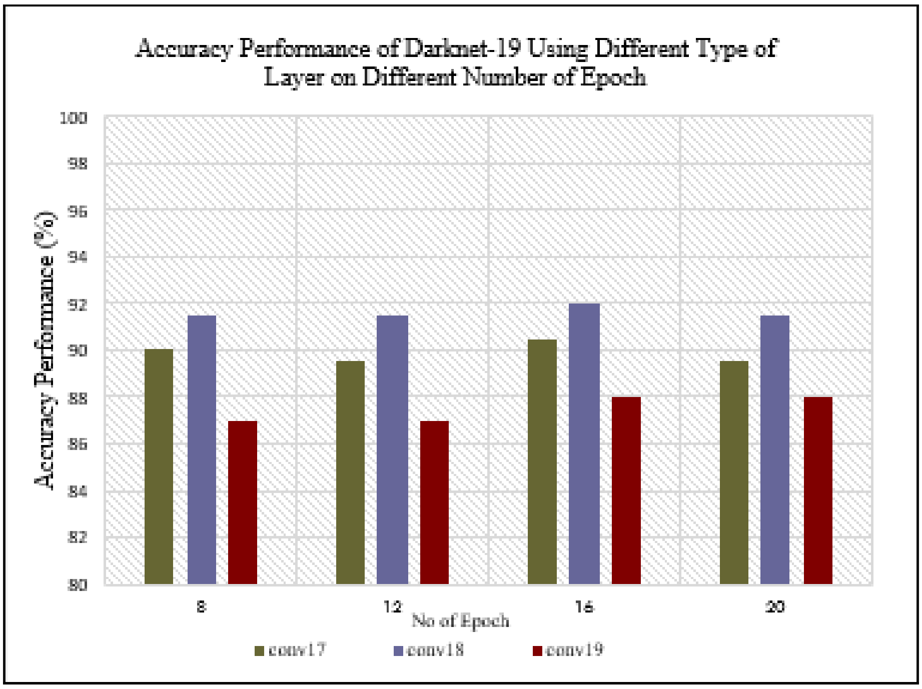

Figure 4 – Accuracy performance of Darknet-19 using different type of layer on different number of epoch

Tabel 4 – Performance of Darknet-19 using Different Type of Layer on Different Number of Epoch

Type of Layer	Classification Accuracy (%)			
	8	12	16	20
Conv17	90.00	89.50	90.50	89.50
Conv18	91.50	91.50	92.00	91.50
Conv19	87.00	87.00	88.00	88.00

Figure 5 and Table 5 illustrate accuracy performance of Darknet-53 using different type of layer on different number of epoch. For Darknet-53 network, the highest accuracy performance is obtained when extracting features using Convolution 52 layer for all types of epoch. This result clearly proved that Convolution 52 layer can be utilized to extract discriminant iris features. The accuracy performance of Darknet-53 shows similar pattern as Darknet-19, where the highest accuracy performance of Darknet-53 network on CASIA Iris Lamp Dataset is not depending on its deepest layer. Another finding on accuracy performance of Darknet-53 is the optimal number of epochs used. We found that the highest accuracy is achieved when using epoch 16. When tested the model with epoch 20, we got similar accuracy performance as epoch 16. Hence we can say that, by using epoch 16 is enough to achieved a good accuracy for Darknet-53 on CASIA Iris Lamp Dataset.

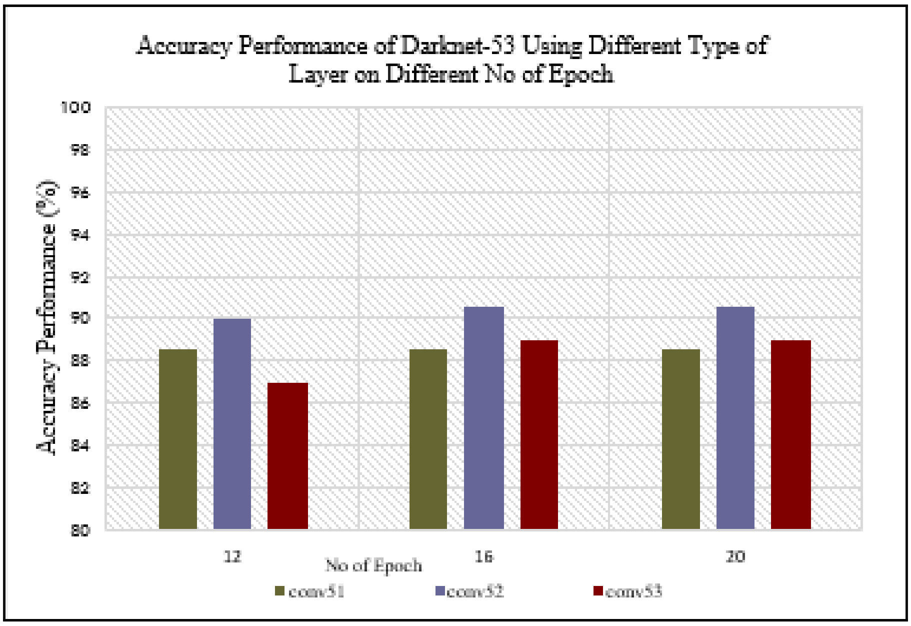

Figure 5 – Accuracy performance of Darknet-53 using different type of layer on different number of epoch

Tabel 5 – Performance of Darknet-53 using Different Type of Layer on Different Number of Epoch

Type of Layer	Classification Accuracy (%)		
	12	16	20
Conv51	88.50	88.50	88.50
Conv52	90.00	90.50	90.50
Conv53	87.00	89.00	89.00

VI. CONCLUSION AND FEATURE WORK

In this paper, the effectiveness of 17 available pre-trained deep neural networks on extracting deformed iris features had been analyzed. The system approach was implemented by fine-tuning deep neural networks to extract iris features and classify extracted features using SVM. The performance of the system was tested on CASIA-Iris-Lamp dataset. Three experiments had been conducted to analyze the effectiveness of deep neural networks on deformed iris recognition system.

Experiment 1 was conducted with objective of identifying which deep neural networks are robust to extract deformed iris features. Based on the results obtained, three pre-trained neural networks which are DarkNet-19, Squeezenet and DarkNet-53 got accuracy of above 80% during the training and validation phases.

For experiment 2, five types of epoch number were implemented to study the performance of neural networks. The obtained results showed that there are several models such as AlexNet, Resnet-50 and Vgg-16 achieved higher accuracy performance as the number of epochs increased. However, there are also model that obtained higher accuracy performance when the amount of epochs decreased such as squeezenet. Besides, there are several models that shows irregular performance such as Darknet-19, Resnet-18 and Googlenet.

For experiment 3, three different layers from Darknet-53 and Darknet-19 were used to extract irregular iris features. 8, 12, 16 and 20 epochs were set for Darknet-19, while 12, 16 and 20 epochs were set for Darknet-53. Based on the results obtained, accuracy performance of Darknet-53 and Darknet-19 had shown similar pattern, where the highest accuracy performance of both networks on CASIA Iris Lamp Dataset is not depending on their deepest layer. For Darknet-19, the highest accuracy performance was obtained when extracting features using Convolution 18 layer for all types of epoch. While for Darknet-53, the highest accuracy performance is obtained when extracting features using Convolution 52 layer for all types of epoch. Besides, epoch 16 is shown to be the optimal epoch number for Darknet-53 on CASIA Iris Lamp Dataset as highest accuracy performance was achieved.

For future work, we are going to extend this work by utilizing Convolution 18 layer and Convolution 52 layer of Darknet-19 and Darknet-53, respectively. Moreover, we could construct a new hybrid deep learning network based on Darknet-19 and Darknet-53 in order to enhance accuracy performance of deformed iris recognition.

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