Секция 5
ЗАЩИТА ИНФОРМАЦИИ И ТЕХНОЛОГИИ ИНФОРМАЦИОННОЙ БЕЗОПАСНОСТИ

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FINGER VEIN BIOMETRIC IDENTIFICATION USING TRANSFER LEARNING CONVNET MODEL

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Abstract. *The human brain, can easily perceive and differentiate the objects in an image. Subsequently the field of computer vision intent to mimic / simulate the human vision system. Finger vein-based user authentication has been used to control access and maintaining privacy of confidential data. The main challenges in the finger vein verification are the quality of an acquired images due to uneven illumination of light, quality of sensor, positional variation and environmental condition. In this article, we used Wiener filter, to improve the quality of finger vein images. Then we analysed the performance of these noise free images to some of popular pre trained ConvNet (convolutional neural networks) such as Alex Net, Squeeze Net, Google Net, Shuffle Net, Efficient Net, Mobile Net, Res Net, Dense Net and NAS Net for the finger vein based personal authentication to secure confidential data and maintain privacy. The finger vein images from Kaggle database are used for this research work. The experiment exhibits the outstanding performance of resnet101 with the 97.64% accuracy over its peer networks.*

Keywords: *Convolutional Neural Network, Finger Vein Authentication, Transfer Learning, Accuracy*

Introduction. Biometrics is an automated tool for user identification using their behavioural and biological characteristics [1]. It is universally accepted as most secured, trusted as well as fastest method for personal authentication by the defence service, immigration check, banking, governments, corporates, and other agencies, where security, safety and surveillance are the utmost priority. Recently, finger vein authentication (FVA) methods using Convolutional Neural Network (CNN) approach have replaced traditional authentication systems due to its accuracy and remarkable speed. However, FVA remains still less explored region in deep learning (DL). In deep learning, the relevant feature extraction is an automated process decided by machine itself whereas in traditional machine learning, the relevant features are extracted manually. DL uses two different approach which can be classified as: (a) Training from Scratch and (b) Transfer Learning.

Training from Scratch. CNN (Convolutional Neural Network) is broadly used for object identification and classification. It consists of net-works of neurons, which have some associated weights, bias and learning parameters. A neural network provided with large number of images as inputs, which are then processed with number of hidden layers by initializing some weights, that weights are needed to be adjusted during the course of training. The weights are adjusted to find patterns in order to make better predictions, then the model is evaluated for future prediction. CNN contains many convolutions, subsampling layers and fully connected layers.

Transfer Learning. It may take few weeks of training and requires a very huge dataset for efficient learning, for building a neural network from scratch. Fortunately, this time can be reduced by applying a transfer learning approach. Transfer learning is the process of applying acquired knowledge to new situations. The weights obtained from the pre-trained model can be directly applied for training processes on relatively new related but some other kind of similar applications.

1. Materials and methods. CNNs played a very important role in the popularity and evolution of neural networks and deep learning. In current article, we will perform transfer learning experiment, to compare the performance of some popular pre-trained architecture such as Alex Net, Squeeze Net, Google Net, Shuffle Net, Efficient Net, Mobil Net, Res Net, Dense Net and NAS Net.

To develop the CNN architecture for user authentication task, we applied a transfer learning approach in the subsequent manner: (a) Load the finger vein images. (b) Partition the data set into training dataset and testing dataset. (c) Train the model, by loading popular pre-trained CNN models. (d) Replace the feature learnable layer with the new training layer. (e) Checked for validation.

2. Experimental results and discussion. For the experiment, we have taken finger vein images from Kaggle dataset which consists of total 3816 images collected from106 persons in one session. The images are stored in 106 folders which are sub classified into left and right folders, each consisting of 18 images from index, middle, and ring finger of both hands. Simulation task of training all the CNN model is carried out in MATLAB R2021b.

For the first experiment, we have used 3816 images from Kaggle database and then noises were removed by using a Wiener filter. These noise-free images are then used to train popular CNN model. We split the dataset into two parts 70% for training and 30% for validation where the maximum number of the epoch equal to 6 and the mini-batch size equal to 267, maximum iteration=1602, learning rate is 0.0003. We repeat the second experiment by partitioning the dataset into 80% for training and 20% for testing, while keeping the rest of the parameters the same. After training, the networks can identify the person's finger vein and display prediction probability. Comparative analysis of finger vein recognition of CNN model are presented in Table.

Table. – Comparative FVR CNN

S. No	CNN Model	Layers	FVR CNN (70:30)		FVR CNN (80:20)	
			Accuracy in %	Time in minutes	Accuracy in %	Time in minutes
1	Alex net	25	82.17	14	84.95	15.29
2	Squeeze net	68	87.06	10.23	87.57	11.28
3	Google net	144	92.22	19.54	93.39	19.57
4	Shuffle net	172	92.05	26.1	90.31	27.43
5	Efficient net	290	87.59	73.23	86.78	75.57
6	Resnet101	347	97.64	83.29	97.64	89.56
7	Densenet201	708	97.2	236.34	96.34	192.21
8	Mobilenetv2	154	94.14	175.52	95.29	254.48
9	NAS net	913	82.87	251.37	89.92	300.1

From MATLAB simulation, results clearly demonstrate comparison of FVA CNN model in terms of computational time required for learning and accuracy by partitioning finger vein dataset in 70:30 and 80:20 ratios in figure1 and figure 2.

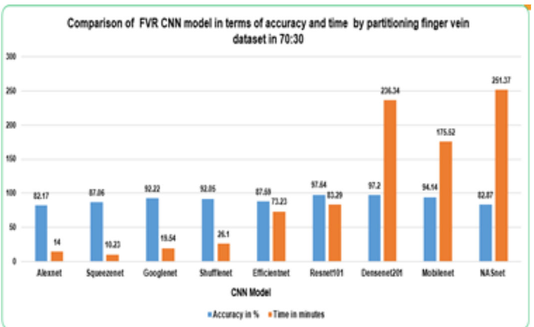

Figure 1. – Comparison of FVR CNN Model (70:30)

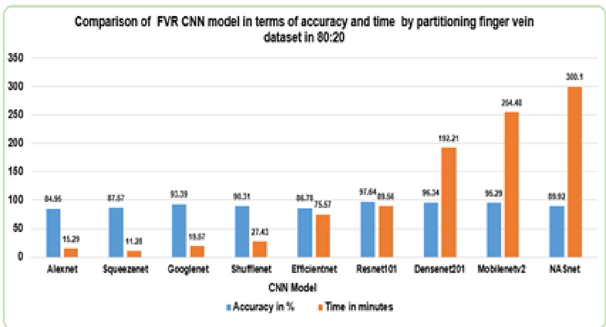

Figure 2. – Comparison of FVR CNN Model (80:20)

Conclusions. CNN has demonstrated outstanding performance in the field of image understanding and recognition. It has become very successful in the field of image processing. Current paper presented the concept of transfer learning for finger vein based personal authentication. Analysis of accuracy scores and execution time required for user verification demonstrate that ResNet101 has the best performance with the accuracy 97.64% among all. Based on above results, it is proposed to develop a real-time system which will have ability to identify finger veins in real time.

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