Transfer Learning based CNN Model for Personal Authentication using Finger Vein Biometric

Sapna Sharma[1] and Dr. Shikha Lohchab[2]
[1]*Research Scholar, School of Engineering, Computer Science and Engineering, G D Goenka University, Gurgaon*
[2] *Assistant Professor, School of Engineering, Computer Science and Engineering, G D Goenka University, Gurgaon*

***Abstract* - In this paper, the performance of CNN (convolutional neural networks) such as Alex net, Squeeze net and Google Net (Inception) are analyzed for the finger vein based personal authentication with respect to control, access to the confidential data. The finger vein images from SDUMLA HMT database are used for this research work. Using a wiener filter the noises are removed from the finger vein images. The noise free images are provided for training to Alex net, Squeeze net and Google net network to recognize persons for finger vein authentication. The finger vein authentication using the three pre-trained networks includes loading finger vein images dataset, loading pretrain network, training network through transfer learning, image classification and image validation. The experiment exhibits the outstanding performance of Google net over the Alex net and Squeeze net on several parameters including computation time, the initial learning, accuracy, number of layers and dropout.**

***Index Terms* - Accuracy, Alex net, Convolutional Neural Network, Google net, Transfer Learning, Squeeze net.**

I.INTRODUCTION

Vascular pattern-based finger vein biometrics has been used for control access and personal authentication due to its unique features like universality, acceptability, no aging effect, easy to enroll faster and higher accuracy [1]. Recently the conventional finger vein-based authentication system has been replaced by CNN based methods due to its precision and remarkable speed. Researchers used CNN for image classification and identification. However, finger vein based personal recognition and verification remains a relatively unexplored area in deep learning. This paper proposes a transfer learning approach for reliable finger vein based personal authentication.

Transfer learning is the process of applying acquired knowledge to new situations. In our day-to-day life we unknowingly transfer the knowledge of some task to the related one. Whenever we come across a new similar kind of related problem or task, first we recognize it and then try to apply the relevant past experience/knowledge in order to find a solution in a hassle-free manner.

Transfer learning approach not only shortens the required training time to train a newly developed model as compared to training a model from scratch but also lowers the generalization error. In this article, we will take a look at /compare the performance of some popular pre-trained architectures including the Alex net, Squeeze net and Google net. All these CNN models are trained on the huge dataset such as Image net dataset. The weights obtained from this training can be used for our customized neural network for personal finger vein authentication. For the experiment, we have taken the SDUMLA HMT image dataset for feature extraction and feature matching for previously enrolled finger vein images. The performances of all the three models will be compared using the confusion matrices and their average accuracies.

The rest of the paper structure is arranged as follows: In Section 2 we presented a short review of literature related to use of deep learning mechanisms for finger vein-based user reorganization with classification. Section 3 describes information of some popular CNN model architecture. Section 4 describes our proposed methodology as well as demonstrates the procedure of experiment carried out with their outcome. Section 5 visualized experimental results with discussion. Finally, we present our conclusions in section 6.

II. LITERATURE REVIEW

In the past few years, a few researchers have used convolution neural networks for vascular pattern based biometric for user authentication. CNN used for object identification and image processing for better interpretability.

In 2011 J.-D. Wu and C.-T. Liu [4] investigated principal component analysis techniques for convolution neural network-based finger vein identification. Hoshyar et al [5] has used multilayer perceptron and attained a good accuracy of 93 % but this is experimented with only on 7 subjects and 14 test templates. In 2012 Krizhevsky et al [6] became the winner of ILSVRC-2012 by developing a deep learning-based CNN model in large-scale image and video recognition. Wu et al [7] has achieved 96% accuracies over a database of 10 people with 80 images by applying SVM support vector machine. H. Qin et al [8] uses multi-features fusion based scale invariant feature transform (SIFT) techniques for finger-vein verification.

Simonyan and A. Zisserman [9] have addressed an important aspect of ConvNet architecture design and its depth by using large public image repositories, such as ImageNet. Khellat -Kihel et al. [10] has got a 98.75% accuracy by applying machine learning for finger vein classification method. Shareef et al [12] has proposed finger vein recognition using the HAAR Wavelet Transform method.

Radzi et al. [13] has been studying biometric identification using CNN and also introduced the four-layer CNN on finger vein in terms of reduced-complexity. Hong et al. [14] experimented with VGG-Net-16 pre-trained in order to achieve finger vein-based user verification. VGG-Net-16 consists of 13 convolutional layers, 5 pooling layers and 3 fully connected layers.

Hui Hu et al [15] has addressed the issue related to rotation and translation in finger vein imaging, and proposed a template based matching strategy for extracting the features with spatial information while designing the FV-net architecture. Das et al. [16] investigated capabilities of a CNN model containing five convolution layers and tested this architecture 95% accuracy with four publicly available databases. In 2020 George K. et al [18] were to write up a detailed systematic review of the feature extraction methods adapted for finger vein identification. The analysis spans over a period of 13 years (from 2008 to 2020).

III.CNN MODEL ARCHITECTURE

CNN has demonstrated outstanding performance in the field of image understanding and recognition. It has become very successful in the field of image processing. However, finger vein authentication (FVA) remains a comparatively unmapped area in deep learning. As it is a known fact that deep learning requires a very large data sample for efficient learning. Neural network (NN)consists of neurons that have weights, learning parameters and bias. CNN contains many convolutions, subsampling layers and frequently fully connected layers. In order to obtain speedy and accurate personal authentication we applied the concept of transfer learning. Now we will explore the three popular CNN model architectures namely 1. Alex net 2. Squeeze net and 3. Google net.

A Alex Net: Alex net was proposed by Alex Krizhevsky, Geoffrey Hinton, and Ilya Sutskever in 2012. This network was similar to LeNet-5 but has 8 layers deeper and with more filters, max pooling, stacked convolutional layers, data augmentation, dropout, ReLU (rectified linear unit) and SGD (Stochastic gradient descent) [6]. Alex Net architecture comprises eight layers which consist of 5 convolution layers and 3 fully connected layers. The network has an image input size of 227-by-227. The convolutional layers use 11 X 11 filters with a stride of 4 and the max pooling uses 3 X 3 filters with a stride of 2. Alex net consists of approximately 60 M parameters. It is a preeminent architecture for any object-detection task. It may have vast applications in computer vision and artificial intelligence problems [20]. Figure 1 exhibits the architecture of Alex net.

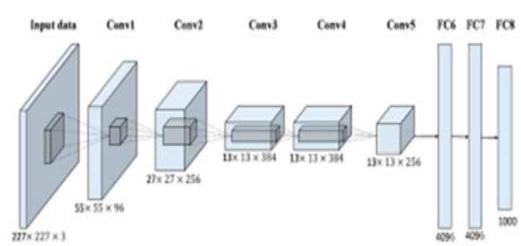

Fig1.: Alex Net Architecture [21]

B Squeeze Net: It is a deep neural network for computer vision that was released on February 22, 2016. Squeeze Net was developed by researchers at Deep Scale, University of California, Berkeley, and Stanford University. In designing Squeeze Net, the authors' goal was to create a smaller neural network with fewer parameters that can more easily fit into computer memory and can more easily be transmitted over a computer network. Squeeze Net is a CNN that has 18 layers deep. It has an input image size of 227-by-227. It can achieve Alex Net-level accuracy with 50x lesser parameters on ImageNet dataset [22]. Squeeze net architecture shown in figure 2.

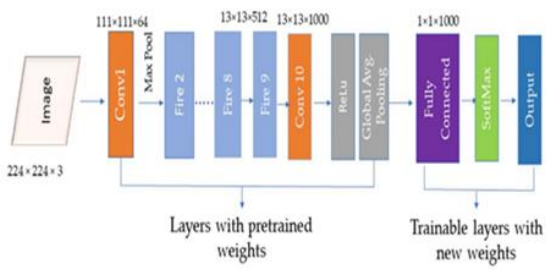

Fig 2. Squeeze Net Architecture [23]

C Google Net (Inception): It is better known as Inception net. Google Net is a convolutional neural network that is 22 layers deep. Inception nets use filters of 3 different sizes (i.e., 1X1, 3X3, 5X5) for the same image and combine the features to achieve robust output. It has 4 million parameters as compared to Alex Net which has 60 million parameters [24]. For dimension reduction it introduced 1x1 convolution and also found out the best weight in the course of training the network and naturally selected the appropriate features. The pretrained networks both have an image input size of 224-by-224. Google net architecture exhibited in figure 3.

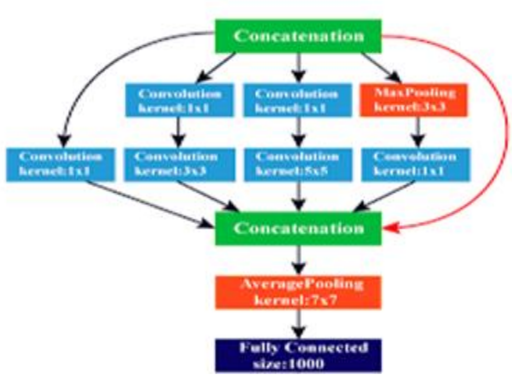

Fig 3. Google net Architecture [25]

Let us summarize each of these models by comparing their important features. Table1. Presented comparative analysis of Alex net Squeeze net and Google Net architecture.

Table.1. Feature Comparison of Different Transfer Learning Model

Table 1. Feature Comparison of Different Transfer Learning Model

CNN	Year	Developed by	No of layers	No. Of parameters	Top 5 error rate	Model size	Unique Feature
Alex net	2012	Alex Krizhevsky, Geoffrey, Hinton, Ilya Sutskever	8	60 million	15.3%	207.266MB	able to recognize off-center objects an
Squeeze net	2016	Forrest N. Iandola, Song Han, Matthew W. Moskewicz, Khalid Ashraf, William J. Dally, Kurt Keutzer	18	50x fewer parameters	16.4%	0.66 MB	smaller DNN architectures
Google net	2014	Matthew Zeller and Rob Fergus	22	4 million	6.67%	22MB	Replace large filters with small

IV. PROPOSED APPROACH

Here we will perform the transfer learning experiment with the use of three popular CNN architectures for the finger vein based personal authentication task and compare their performance. Transfer learning can be implemented in following steps: 1. Loading database 2. Split the dataset 3. Load pretrained model 4. Freeze the layer during training 5. Add new trainable layers 6. Train the network 7. Check for validation. Let us explore the architecture of popular pretrained models.

A The Dataset:

In this experiment, we will be using the publicly available SDUMLA HMT image dataset provided by the Shandong University China (2010). It consists of 3816 images collected from106 persons in one session. The images are stored in 106 folders which are further classified into two subfolders left and right, each consisting of 18 images from index, middle, and ring finger of both hands [2]. Alex Net Squeeze net and Google Net network are trained using MATLAB R2021b with a GPU system with the following specifications. Processor: Intel ® Core TM i5-6200 CPU @2.30GHZ ,12 GB RAM and Graphics Card: NVIDIA GeForce GTX 1060 6GB.Various parameters are taken into consideration to compare the performance of Google Net and Alex Net. Figure 4(a)-Figure 4(c) demonstrated the training and validation accuracy plot for Alex net, Squeeze net and Google net and their performance based on parameter like accuracy and loss in percentage, computation time, number of iterations per epoch =267, maximum iteration=1602, validation frequency=267 and learning rate = 3.00E-04.

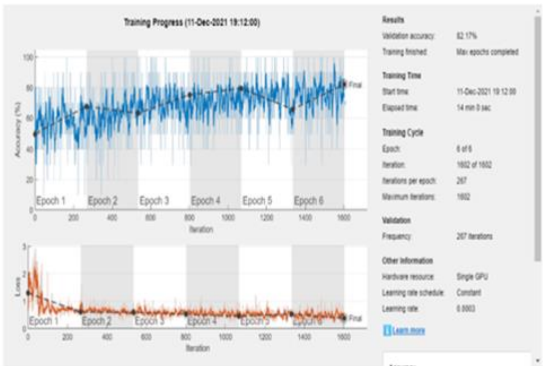

Fig 4(a). Feature extraction training & Validation (Alex net)

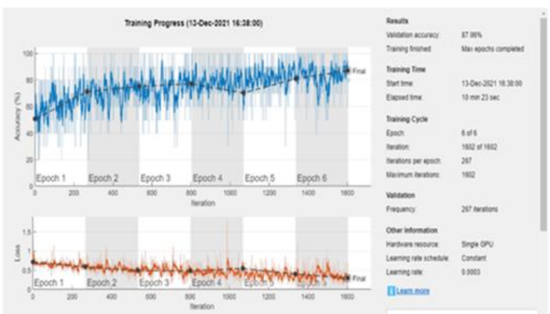

Fig 4(b). Feature extraction training & Validation (Squeeze net)

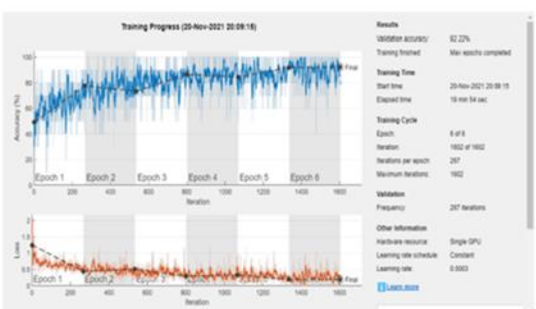

Fig 4(c). Feature extraction training & Validation (Google net)

V. EXPERIMENTAL RESULTS AND DISCUSSION

In order to obtain accurate and approvable results we applied deep learning in finger vein based personal authentication for image processing, feature extraction and classification. This task of transfer learning is carried out in following steps: first we acquired finger vein images from SDUMLA HMT database and then noises are removed by using a wiener filter. These noise-free images are used to train Alex net, Squeeze net and Google net networks. We partitioned the dataset into two parts for training 70% and for validation 30%. We had kept the learning rate of 0.0003 and maximum no of 6 epochs with 267 iterations in each epoch. After training, the networks can identify the person's finger vein and display the predicted label and prediction probability for the images in the dataset. Comparative analysis of Alex net Squeeze net and Google Net architecture in terms of features, computation time and validation accuracy are presented in Table 2.

Table.2. Comparative FVA CNN Model (70:30)

Table 2. Comparative FVA CNN (70:30)

S No.	CNN Model	Layers	Accuracy in %	Time in seconds
1	Alex net	8	82.17	14
2	Squeeze net	18	87.06	10.23
3	Google net	22	92.22	19.54

Comparison of FVA CNN model in terms of number of deep layers, computation time required for learning and accuracy by partitioning finger vein dataset in 70:30 is depicted in Figure5(a)-Figure 5(c).

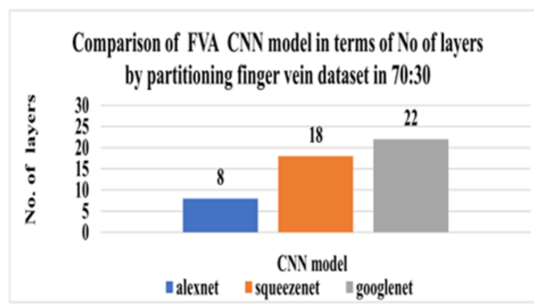

Fig 5(a). FVA CNN Number of layers

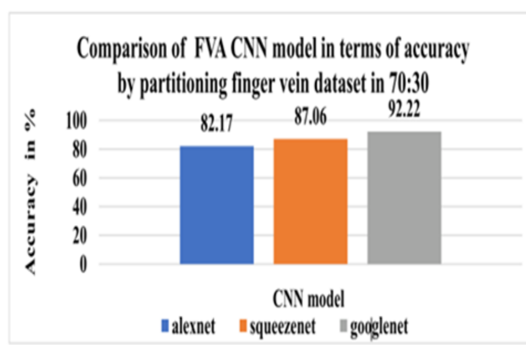

Fig 5(b). FVA CNN Accuracy in percentage

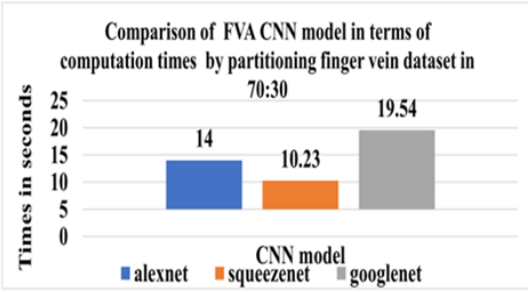

Fig 5(c). FVA CNN Times in seconds

VI. CONCLUSION

In this paper, we had investigated the concept of transfer learning for finger vein based personal authentication. We discussed the architectures of three popular convolution neural networks namely Alex net, Squeeze net and Google net. We also went through the comparisons of their features along with comparison with respect to number of deep layers, accuracies and computation time. By going through the comparisons as presented in both the tables above, we can clearly say that the Google net model outperforms its peers not only in terms of features but also in terms of classification and validation accuracy.

ACKNOWLEDGMENT

We would like to thank Dr. Karan Singh who provided significant guidance, suggestions to complete the experiment and for providing access to JNU ,computer lab.

FUNDING

The author(s) received no financial support for the research, authorship, and/or publication of this article

REFERENCES

[1] Lu, Yu, Shiqian Wu, Zhijun Fang, Naixue Xiong, Sook Yoon, and Dong Sun Park. "Exploring finger vein based personal authentication for secure IoT." Future Generation Computer Systems 77 (2017): 149-160.
[2] ImageNet. http://www.image-net.org
[3] http://mla.sdu.edu.cn/info/1006/1195.htm
[4] J.-D. Wu and C.-T. Liu, “Finger-vein pattern identification using principal component analysis and the neural network technique,” Expert Systems with Applications, vol. 38, no. 5, pp. 5423–5427, 2011.
[5] Hoshyar, Azadeh Noori, Riza Sulaiman, and Afsaneh Noori Houshyar. "Smart access control with finger vein authentication and neural network." J. Am. Sci 7.9 (2011).
[6] A. Krizhevsky, I. Sutskever and G. E. Hinton, “ImageNet classification with deep convolutional neural networks", Proc. 25th Int. Conf. Neural Inf. Process. Syst., vol. 1, pp. 1097-1105, 2012.
[7] J.-D. Wu and C.-T. Liu, "Finger-vein pattern identification using SVM and neural network technique", Expert Syst. Appl., vol. 38, no. 11, pp. 14284-14289, 2011.
[8] H. Qin, L. Qin, L. Xue, X. He, C. Yu, and X. Liang, “Finger-vein verification based on multi-features fusion,” Sensors, vol. 13, no. 11, pp. 15 048–15 067, 2013.
[9] K. Simonyan and A. Zisserman, Very deep convolutional networks for large-scale image recognition, 2014, [online] Available: https://arxiv.org/abs/1409.1556.
[10] S. Khellat-Kihel, R. Abrishambaf, N. Cardoso, J. Monteiro, and M. Benyettou, “Finger vein recognition using Gabor filter and support vector machine,” in Proceedings of the International Image Processing, Applications and Systems Conference, pp. 1–6, IEEE, Geneva, Italy, November 2015.
[11] Shareef A.Q., George L.E., Fadel R.E., “Finger Vein Recognition Using HAAR Wavelet Transform”. Int. J. Comput. Sci. Mob. Comput. 2015;4: l—7
[12] S. A. Radzi, M. Khalil-Hani and R. Bakhteri, "Finger-vein biometric identification using convolutional neural network", Turkish Journal of Electrical Engineering & Computer Sciences, vol. 24, no. 3, pp. 1863-1878, 2016.
[13] H. G. Hong, M. B. Lee and K. R. Park, "Convolutional neural network-based finger-vein recognition using NIR image sensors", Sensors, vol. 17, no. 6, pp. 1297, 2017.
[14] Meng, G., Fang, P., & Zhang, B. Finger vein recognition based on convolutional neural network. In MATEC Web of Conferences EDP Sciences. 2017.
[15] H. Hu, W. Kang, Y. Lu, Y. Fang, and F. Deng, “FV-Net: learning a finger-vein feature

representation based on a CNN," in Proceedings of the 2018 24th International Conference on Pattern Recognition (ICPR), pp. 3489–3494, Beijing, China, November 2018.
[16] R. Das, E. Piciucco, E. Maiorana and P. Campisi, "Convolutional Neural Network for Finger-Vein-based Biometric Identification", IEEE Transactions on Information Forensics and Security, vol. 14, no. 2, pp. 1-13, 2018.
[17] H. Huang, S. Liu, H. Zheng, L. Ni, Y. Zhang and W. Li, "Deep Vein: Novel finger vein verification methods based on deep convolutional neural networks", Proc. IEEE Int. Conf.Identity Secure. Behav. Anal., pp. 1-8, Feb. 2017.
[18] Sidiropoulos, George K., Polixeni Kiratsa, Petros Chatzipetrou, and George A. Papakostas."Feature Extraction for Finger-Vein-Based Identity Recognition." Journal of Imaging 7, no. 5 (2021): 89.
[19] Ferguson, Max & ak, Ronay & Tina Lee, Yung-Tsun & H. Law, Kincho. Automatic localization of casting defects with convolutional neural networks. 2017.
[20] https://en.wikipedia.org/wiki/AlexNet
[21] https://www.mdpi.com/remotesensing/remotesensing-09-00848/article_deploy/html/images/remotesensing-09-00848-g001.png.
[22] https://en.wikipedia.org/wiki/SqueezeNet
[23] https://www.mdpi.com/inventions/inventions-05-0016/articledeploy/html/images/inventions-05-00016-g002.png
[24] https://en.wikipedia.org/wiki/Inceptionv3.
[25] https://www.mdpi.com/diagnostics/diagnostics-10-00027/articledeploy/html/images/diagnostics-10-00027-g003.png.
[26] http://www.biometria.sk/en/principles-of-biometrics.htm
[27] R. Raghavendra and C. Busch, "Presentation attack detection algorithms for finger vein biometrics: A comprehensive study", Proc. 11th Int. Conf. Signal-Image Technol. Internet-Based Syst. (SITIS), pp. 628-632, Nov. 2015.
[28] A. Vedaldi and K. Lenc, "MatConvNet: Convolutional neural networks for MATLAB", Proc. 23rd ACM Int. Conf. Multimedia, pp. 689-692, 2015.
[29] C. He, Z. Li, L. Chen, and J. Peng, "Identification of finger vein using neural network recognition research based on PCA," in Proceedings of the IEEE International Conference on Cognitive Informatics & Cognitive Computing, pp. 456–460, IEEE, Beijing, China 2017.
[30] S. J. Pan and Q. Yang, "A survey on transfer learning," IEEE Transactions on Knowledge and Data Engineering, vol. 22, no. 10, pp. 1345–1359, 2010.
[31] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 4700–4708, San Francisco, CA, USA, July 2017.
[32] H.Qin and M. A. El-Yacoubi, "Deep representation-based feature extraction and recovering for finger-vein verification", IEEE Trans. Inf. Forensics Security, vol. 12, no. 8, pp. 1816-1829, Aug. 2017.

Author's Detail

Sapna Sharma received BE in Computer Science and Engineering from Amravati University, India in 1997, MTech in Computer Science from IETE, New Delhi in 2010, India. She worked as lecturer in Border Security Force STS-1, New Delhi and has a rich experience of 21 years. Prior to that she worked at Hitkarini College of Engineering and Technology, Jabalpur and Government College of Engineering, Jabalpur. Her research interests included biometric security, personal authentication, image processing, machine learning, and deep learning.

Dr. Shikha Lohchab is a Researcher with a background in Wireless Sensor Network. She is an expert with comprehensive knowledge of both Mobile Adhoc Network and Wireless Sensor Network, Technique Characterization of components by Dynamic Topologies, Bandwidth Constraints, Autonomous behavior, Limited Security etc. Shikha Lohchab has teaching experience of 6 years and prior to joining G D Goenka University, she joined as an Assistant professor at DPG Group of Institution, Gurugram. She completed her BE studies in Kurukshetra University and the Postgraduate in Amity University.