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ConvNet for Finger Vein based Personal Authentication

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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. These noise free images are provided for training to popular pretrained ConvNet architecture for user verification using finger vein biometric. Then we analysed the performance of ConvNet (convolutional neural networks) such as Alex Net, Squeeze Net, Google Net, Shuffle Net, Efficient Net, Mobile Net, Res Net, Dense Net and NASNet for the finger vein based personal authentication to secure confidential data and maintain privacy. The finger vein images from Kaggle database is 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

I. Introduction

Biometrics, an automated recognition of individuals based on their behavioural and biological characteristics [1]. It is globally 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 almost priority. Finger vein-based user authentication has been used to control access and maintaining privacy of confidential data. Finger vein authentication (FVA) can be classified into conventional, machine learning and hybrid methods. Currently, Convolutional Neural Network (CNN) based methods have replaced conventional systems due to its accuracy and remarkable speed. However, FVA remains still less explored region in deep learning (DL).

Deep learning models can be built using (NN) neural networks. In deep learning, the relevant feature exaltation 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
b. Transfer Learning

1.1 Training from Scratch

CNN (Convolutional Neural Network) is a kind of artificial neural network (ANN), which is broadly used for object identification and classification. ANN 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 need ed to be adjusted during the course of training. These input weights are adjusted by calculating error between the two inputs and their expected output response. The weights are adjusted to find patterns in order to make better predictions. Then the model evaluated for future prediction. CNN contains many convolutions, subsampling layers and fully connected layers.

It is a well-known fact that, DL requires a very huge dataset for efficient learning. Graphics processing unit (GPUs) are designed for parallel processing. The power of GPU accelerates high performance computing in deep learning. This compels deep learning algorithms run several times faster on a GPU as compared to CPU.

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1.2 Transfer Learning

Building a neural network from scratch may take few weeks of training and requires a huge /large database. Fortunately, this time can be reduced by applying a transfer learning approach. Transfer learning is a machine learning model for feature representation. 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. This approach not only shortened the required training time but also minimizes the generalization error. It is very beneficial in natural language processing (NLP).

In current article, we will perform experiment, to compare the performance of some popular pre-trained architecture including the Alex Net, Squeeze Net, Google Net, Shuffle Net, Efficient Net, Mobile Net, Res Net, Dense Net and NASNet. All these CNN models are trained using huge dataset, ImageNet. The weights obtained from this training can be used for our customized neural network for personal finger vein authentication.

The rest of paper are arranged as follows: Section 2 represents brief study of some popular CNN architectures. Section 3 describe our proposed methodology and experimental setup. Section 4 explain results with discussion. Section 5 presented conclusion

II. Materials And Methods

CNNs played a very crucial role in the popularity and evolution of neural networks and deep learning. It generally uses shift-invariant method for extracting learnable features to predict future outcome. In this study we will focus on the brief overview of some popular CNN architecture.

2.1 Alex Net

In 2012, Alex net was first introduced by Alex Krizhevsky, Geoffrey Hinton, and Ilya Sutskever. This network was similar to LeNet-5 but has 8 layers deeper and with larger number of filters, max pooling, stacked convolutional layers, data augmentation, dropout, ReLU (rectified linear unit) and SGD (Stochastic gradient descent) [3]. Alex Net architecture comprises eight layers which consists of 5 convolution layers and 3 fully connected layers. The network has an image input size 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 the computer vision and artificial intelligence problems [5]. Figure 1 exhibit the architecture of Alex net.

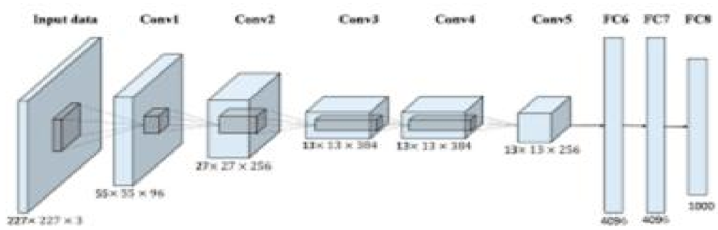

Figure 1: Alex Net Architecture [5]

2.2 Squeeze Net

It is a deep neural network was released on February 22, 2016 for computer vision. Squeeze Net was developed by researchers at Deep Scale, University of California, Berkeley and Stanford University. While designing Squeeze Net, the authors' objective was to create a smaller network with a smaller number of parameters that can more easily accommodate in computer memory and more efficiently transmitted over a network. Squeeze Net has 18 layers deep network. It has an input image size 227-by-227. It has achieved Alex Net-level accuracy with 50x lesser parameters on ImageNet dataset [7]. Figure 2 represents Squeeze net architecture.

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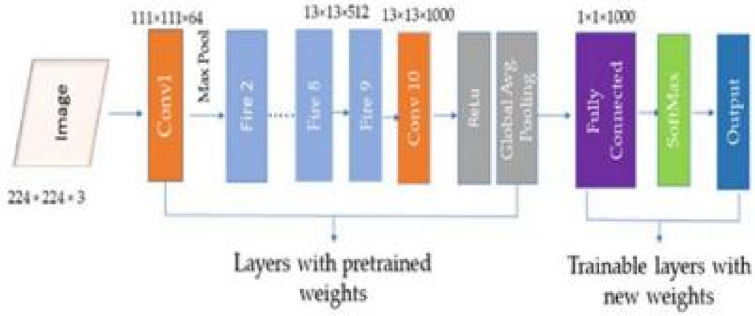

Figure 2: Squeeze Net Architecture [7]

2.3 Google Net (Inception)

It is better known as Inception net. Google Net architecture network has 22 layers depth. Inception nets uses filters of different sizes (i.e., 1 X 1, 3 X 3, 5 X 5) for the same images and combine features in order to achieve robust outcome. It has 4 million parameters as compare to Alex Net which has 60 million parameters [3,4]. For dimension reduction, it has introduced 1 x 1 convolution and also found out the best weight in the course of training network and naturally selected appropriate features. The pretrained networks both have an image size of 224-by-224. Figure 3 displays Google net architecture.

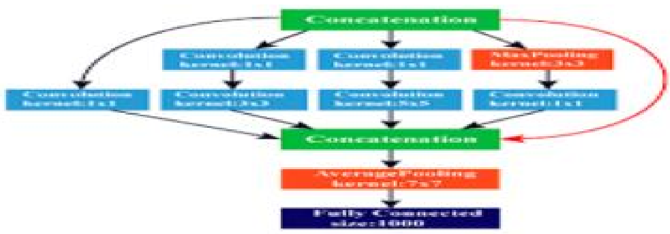

Figure 3: Google net Architecture [9]

2.4 Shuffle Net

Shuffle Net v2 was first introduced in the paper, "Shuffle Net V2: Practical Guidelines for Efficient CNN Architecture Design", in 2018.The paper is authored by Ningning Ma, Xiangyu Zhang, Hai-Tao Zheng, and Jian Sun. Shuffle Net v2 architecture uses metrics like speed or memory access cost in respect to measure the computational complexity. In addition to this, the direct metrics are also evaluated on the target platform [11]. Figure 4. demonstrates Shuffle net Architecture.

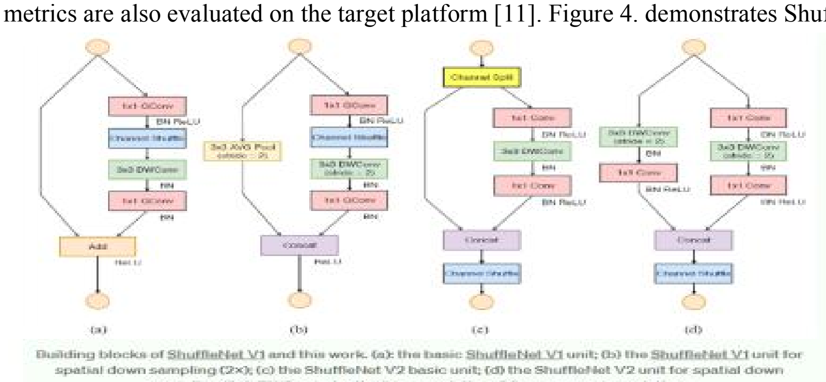

Figure 4: Shuffle net Architecture [12]

2.5 Efficient Net

Efficient Net model developed with the idea of focusing on to solve performance and computational efficiency problems with similar architecture. In [13] they proposed CNN architecture with three different parameters, namely (a) width (b) depth, and (c) resolution. Here, width represents the number of channels present in various layers, the depth refers to the number of layers and the resolution refers to the input size of images. They claimed that by keeping all these parameters small, one can create a competitive yet computationally efficient CNN model. They also claimed that higher accuracy can be achieved, just by increasing the value of these parameters. They are the first to introduce squeeze and excitation layers which create interactions across channels that are invariant to spatial information. This lowers the impact of less important channels, In order to improve performance, they rather proposed Swish activation in place of ReLU. Efficient Nets are performing the best classification models under different categories of computation, resource availability]. Efficient net Architecture shown in Figure 5.

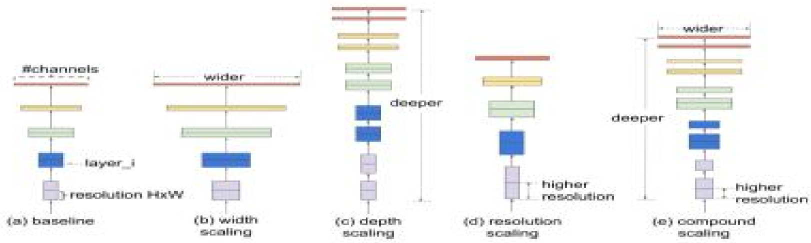

Figure 5: Efficient net Architecture [13]

2.6 Res Net

Residual Network (Resnet) architecture was first presented by He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in 2015 [18]. The main motivation behind Resnet was to obtain more accuracy by going on deeper layer. While training, gradient starts from the last layer and needs to travel through every layer in the middle before it reaches the initial layers. However, this causes a very common problem of vanishing gradient descent in deep learning, and making it more crucial /challenging to train the initial layers of the model. While training the deeper network another problem arises due to adding some new layer which may lead to higher training error. This is also known as the degradation problem. They solve these problems by skipping some connection where output from one layer is fed to another deeper layer. Thus, Resnet overcame the “vanishing gradient” problem, by constructing networks with up to thousands of convolutional layers, which outperform shallower networks. In an overall perspective this model is similar to LSTM (Long short-term memory in recurrent neural networks (RNN). The advantages of using Resnet can be summarized as :(a) ability to train a very deep network. (b) tackle the gradient vanishing problem (c) performance doesn’t degrade with a very deep network and (d) computation is cheaper. Figure 6. displays Resnet architecture

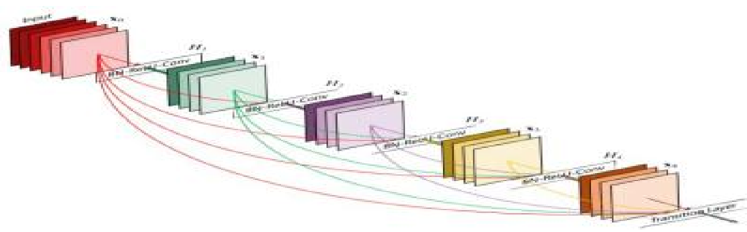

Figure 6: Resnet architecture [15]

2.7 Dense Net

Dense Net stands for Densely Connected Convolutional Networks was first introduced by Gao Huang, Zhuang Liu, and their team in 2017 at the CVPR Conference [16]. Traditional CNN convolutional networks have N layers have N connections - one between each layer and its following layer whereas in Dense Net, each layer connected to every other layer in a feed-forward pattern. This network has N (N+1) /2 direct connections. For each layer, the feature-maps of all preceding layers are used as inputs, and its own feature-maps are used as inputs into all subsequent layers. Dense Nets have some fascinating advantages can be summarized as (a) diversified features(b) fewer parameter and computational efficiency (c) reduce the gradient vanishing problem and (d)reduced complexity feature. Figure 7. displays dense net architecture

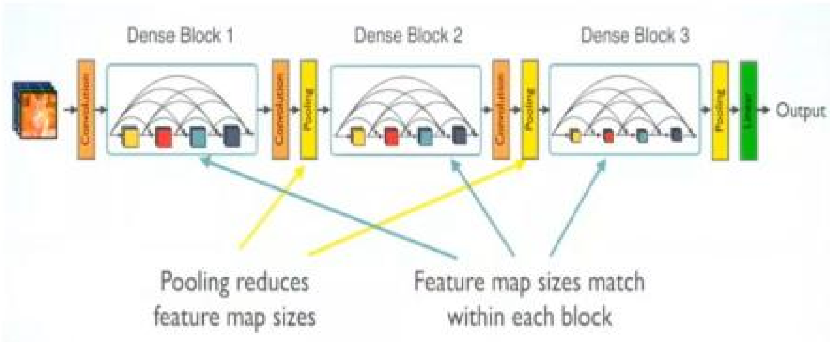

Figure 7: Dense net architecture [17]

2.8 NASNet

In concerned with respect to accuracy and latency metrics, so far developed conventional CNN mobile models, do not yield the desired outcome. The latency is frequently estimated using FLOPS, which unable to predict the accurate outcome. NASNet stands for Neural Architecture Search Network (NASNet). In 2019, It was first proposed by Andrew Howard, and Andrew Howard, from Google [18]. NASNet uses reinforcement learning techniques and incorporates a balance between enhancing accuracy and reducing latency. It outperforms when deployed into a mobile. Its working principles are different from existing models like Google Net. Soon it will bring a major advancement in the artificial intelligence domain. The network has an image input size of 224-by-224.NASnet can be classifying neural networks, including: normal convolutions, separable-convolutions, max-pooling, average-pooling, identity mapping, etc.it is capable of learning rich feature representations from a wide range of images. As a result, this network trained to classify one images out of different 1000 object categories. Figure 8. displays NASNet architecture

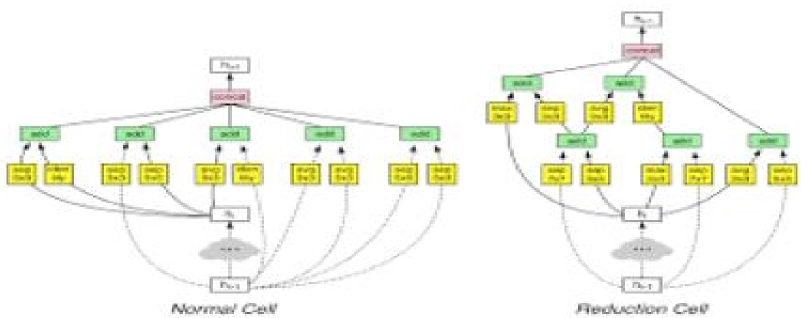

Figure 8: NASNet architecture [18]

2.9 Mobile Net

Mobile Net is designed for mobile and embedded vision applications. Mobile Net introduced the idea of depth wise separable convolutions [19]. Xception was the first to introduce the convolution block. Mobile net partitioned 2D convolution kernel into two separate convolutions: depth wise and pointwise. A pointwise convolution works on the spatial dimension of the feature maps and the input and output channels. The estimated computational cost given by $Df^2 * M * N * Dk^2$ Where M represents the number of I/Pt channels, N is number of O/P channels, Dk the kernel size and Df the dimension of the input feature maps. Whereas A depth wise convolution is responsible for collecting spatial information for every individual channel. Therefore, its number of output channels is the same as the number of input channels. Its computational cost calculated as $Df^2 * M * Dk^2$. Mobile net with residual connections and squeeze architecture, to build lightweight deep neural networks. Advantages of Mobile net can be summarized as(a) reduced network size (b) lesser number of parameters (c)faster performance and low latency. figure 9 exhibit the mobile net architecture

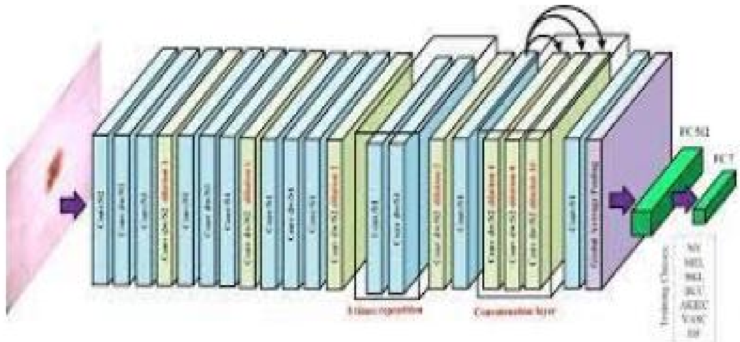

Figure 9: Mobile net architecture [19]

III. PROPOSED APPROACH

Here we will perform the transfer learning experiment with the use of nine popular CNN architecture for the finger vein based personal authentication task and compared their performance. Now in this research article, we will explore and compare the other popular transfer learning architectures, Alex Net, Squeeze Net, Google Net, Shuffle Net, Efficient Net, Mobil Net, Res Net, Dense Net and NASNet for the same task and compare their classification performance with respect to the elapsed time and their accuracies. To develop the CNN architecture for user authentication task we implemented a transfer learning approach in the following manner:

1. We upload the dataset images
2. Partition the data set into training dataset and testing dataset.
3. loading popular pre-trained CNN models for training
4. Replace the feature learnable layer with the new training layer accordingly.
5. Later on. test it for validation

3.1 Experiment Setup

For the experiment, we have taken the Kaggle image dataset that is a popular benchmark in finger vein image classification. It consists of total 3816 images collected from106 persons in one session. The images are arranged in 106 different folders which are further classified into two folders left and right, each consisting of 18 images from index, middle, and ring finger of both hands. Simulation task of training all the CNN model Alex Net, Squeeze Net, Google Net, Shuffle Net, Efficient Net, Mobil Net, Res Net, Dense Net and NASNet is carried out in MATLAB R2021b with a GPU system with following specifications. Processor: Intel ® Core TM i5-6200 CPU @2.30GHZ ,12 GB RAM and Graphics Card: NVIDIA GeForce GTX 1060 6GB

IV. EXPERIMENTAL RESULTS AND DISCUSSION

To obtain more accuracy and better performance, we applied a transfer learning approach. We experimented through various types of popular pre-trained CNN architecture and compared their performance to get a feasible result for finger vein based personal authentication.

4.1 Experiment 1

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 Alex Net, Squeeze Net, Google Net, Shuffle Net, Efficient Net, Mobil Net, Res Net, Dense Net and NASNet. 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. 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 are compared. Comparative analysis of Finger vein recognition of CNN model with respect to features, computation time and validation accuracy are presented in Table 1.

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Table1. Comparative FVR CNN (70:30)

Sno.	CNN Model	Accuracy in %	Time in minutes	Layers	Training	Testing	Learning rate	Epoch
1	Alexnet	82.17	14	25	2672	1144	3.00E-04	6
2	Squeezenet	87.06	10.23	68	2672	1144	3.00E-04	6
3	Googlenet	92.22	19.54	144	2672	1144	3.00E-04	6
4	Shufflenet	92.05	26.1	172	2672	1144	3.00E-04	6
5	Efficientnet	87.59	73.23	290	2672	1144	3.00E-04	6
6	Resnet101	97.64	83.29	347	2672	1144	3.00E-04	6
7	Densenet201	97.2	236.34	768	2672	1144	3.00E-04	6
8	Mobilenet	94.14	175.52	154	2672	1144	3.00E-04	6
9	NASnet	82.87	251.37	913	2672	1144	3.00E-04	6

From MATLAB simulation, results are in figure 10. 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

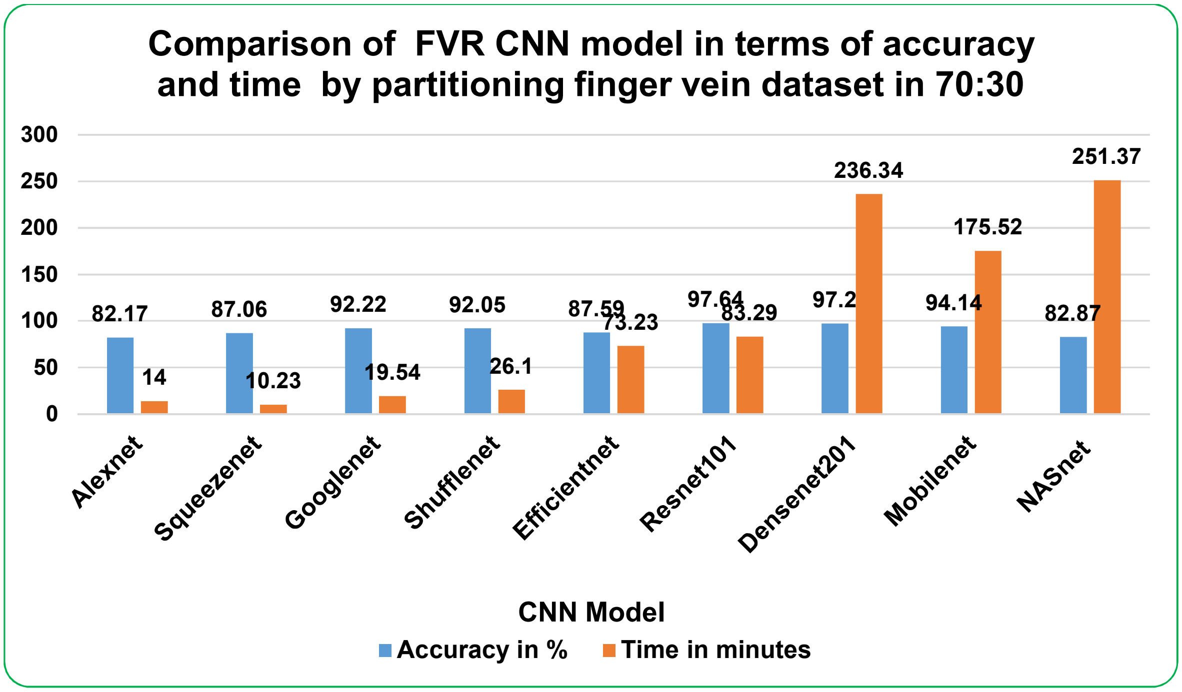

Figure 10: Comparison of FVR CNN Model (70:30)

As we can observed from the graph, he first experiment performance is really pleas-ant. A better model means lower the losses means better the accuracy. Accuracy value indicates how strong or poorly a specific model is performing after each iteration, However, from table 1. we can conclude that Google net performs better with the 92.22 % accuracy and time required is very less as 19.54 minutes whereas Resnet 101 performs outstanding with the accuracy 97.64 % but it takes much more time i.e., 83.29 minutes as compared with Google net.

4.2 Experiment 2

In the second experiment, we repeat the above 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. The results are presented in Table 2.

On the other hand, in second experiment, we used 3052 finger images for training the network and remaining 764 images for validation which took an execution time of 19.57 minutes for Google net, which is slightly higher than the previous experiment. Although the second experiment took a slightly higher time for processing the data, the predictive accuracy has increased to 93.39 % for Google net whereas in case of Res Net 101 for the similar accuracy of 97.64 % execution time is increased 89.56 minute which is much higher. so, we can conclude that depending on the application and our requirement we can choose any CNN model for an accurate user authentication. Simulated results are shown in figure 11.

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Comparative FVR CNN (80:20)								
Sno.	CNN Model	Accuracy in %	Time in minutes	Layers	Training	Testing	Learning rate	Epoch
1	Alexnet	84.95	15.29	25	3052	764	3.00E-04	6
2	Squeezenet	87.57	11.28	68	3052	764	3.00E-04	6
3	Googlenet	93.39	19.57	144	3052	764	3.00E-04	6
4	Shufflenet	90.31	27.43	172	3052	764	3.00E-04	6
5	Efficientnet	86.78	75.57	290	3052	764	3.00E-04	6
6	Resnet101	97.64	89.56	347	3052	764	3.00E-04	6
7	Densenet201	96.34	192.21	768	3052	764	3.00E-04	6
8	Mobilenetv2	95.29	254.48	154	3052	764	3.00E-04	6
9	NASnet	89.92	300.1	913	2672	1144	3.00E-04	6

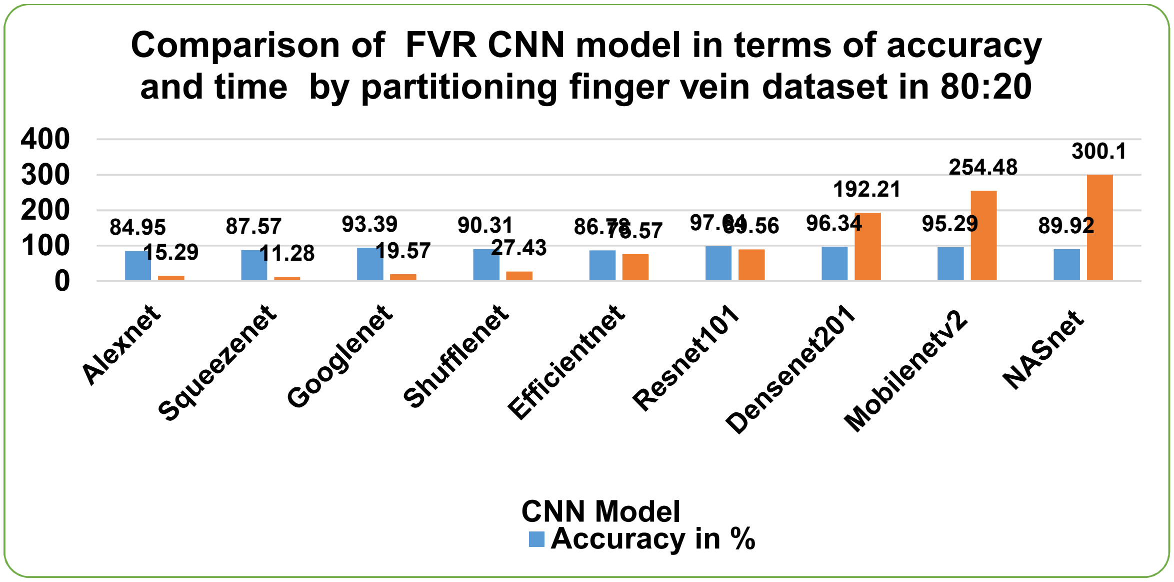

Figure 11: Comparison of FVR CNN Model (80:20)

V. Conclusion

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, and brief review of popular convolution neural networks architectures viz Alex Net, Squeeze Net, Google Net, Shuffle Net, Efficient Net, Mobil Net, Res Net, Dense Net and NASNet. Analysis of accuracy scores and execution time required for user verification demonstrate that ResNet101 has the best performance 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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BIOGRAPHY

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