IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⧖ Impact Factor 7.39 ⧖ Vol. 11, Issue 6, June 2022

DOI: 10.17148/IJARCCE.2022.11603

Design of FFA - CNN Face Recognition System

Yusuf Alhaji Salihu[1], Nuradeen, Ibrahim Mahmud[2], Bashar Umar Kangiwa[3]

Department of Computer Science, Federal Polytechnic Bida, Niger State, Nigeria[1]

Department of Computer Science, Kebbi State University of Science and Technology, Aliero, Nigeria[2]

Department of Computer Science, Kebbi State University of Science and Technology, Aliero, Nigeria[3]

Abstract: The importance of face recognition system in our world today is enormous. Issues that the existing face recognition systems had to solve emanated from in consistence in facial patterns which do not conform to the traditional facial patterns. Existing face recognition models which employed the use of genetic algorithm for modeling CNN have the problem of slow convergence and local minimal entrapment. Firefly algorithm (FA) has been found to produce consistent and better performance in terms of time and optimality than other algorithm. Firefly (FA) is therefore applied for modeling CNN face recognition system. Three models were used, FFA-CNN, CNN1, and CNN2. Where FFA-CNN is a CNN model designed to obtain optimized parameter using FFA as the optimizer, CNN1 and CNN2 are CNN model designed by Random model parameters. For each model a total number of 694 sample facial images which is about (70%) of total dataset were used for training and 299 sample of facial images which is about (30%) of total dataset were used for testing the trained system. 3 experiments were carried out. The result shows that FFA-CNN is 100% accurate while CNN1 and CNN2 are 30.10% and 81.61% respectively. With this excellent result, FFA-CNN model develop in this research work can be recommended for use in face recognition system. This research has contributed immensely to knowledge by developing an algorithm that improved the performance of CNN model for face recognition.

Keywords: Convolutional Neural Network, Face Recognition System, Firefly Algorithm, Optimized Parameter.

INTRODUCTION

Face recognition is a very challenging research area in computer vision and pattern recognition due to variations in facial expressions, poses and illumination. Recent advances in automated face analysis, pattern recognition and machine learning have made it possible to develop automatic face recognition systems to address these applications [1]. Several emerging applications, from law enforcement to commercial tasks, demand the industry to develop efficient and automated face recognition systems. Although, many researchers have worked on the problem of face recognition for many years still several challenges need to be solved. Difference in illumination of the scene, changes in pose, orientation and expression are examples of some of the issues to be dealt carefully [2]. Also, when size of face database increases the recognition time becomes a big constraint. Face recognition is one of the biometric methods that to have the merits of both high accuracy and low intrusiveness. It has the accuracy of a physiological approach without being intrusive. For this reason, the face recognition has drawn the attention of researchers in fields from security, Psychology, and image processing, to computer vision. Face recognition has also proven useful in other multimedia information processing areas. Facial recognition analyses the characteristics of a person's face images input through a digital video camera or online face capturing. Nowadays we need to maintain global security Information, in every organization or individual wants to improve their existing security system. Most of the people need better security system which gives complete security solution [3].

Modern surveillance networks are key tools for several different industrial applications. These include, but are not limited to, the monitoring of patients in hospitals, detecting violence in stadiums, and identifying lost baggage in airports [3]; [4]. Regardless of application, all of these systems have the same underlying goals: to observe and report interactions of interest. These systems, however, often require a human to monitor several camera feeds and react quickly if and when a situation arises. With growing numbers of cameras in surveillance systems, it has become unfeasible for a single human to monitor so many data streams simultaneously. While additional humans could monitor the increased number of camera feeds, this is costly and prone to error. This has led to the development of computer-based intelligent systems for monitoring [3]; [4].

Face Recognition is steadily making its way into commercial products. As such, the accuracy of face Recognition systems is becoming extremely crucial. In the firefly Algorithm, the brightness of the fireflies is used to measure attraction between a pair of unisex fireflies. The firefly algorithm (FA) was developed by Xin –She Yang in 2008 and is based on the flashing patterns and behavior of tropical fireflies. FA is simple, flexible, and easy to implement.

Using machine learning principles and modern computer vision algorithms, it is possible to accurately detect objects of interest in an image frame, and to classify them with above human-level ac- curacy [5]. To detect and categorize these

 ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁘ Impact Factor 7.39 ⁘ Vol. 11, Issue 6, June 2022

DOI: 10.17148/IJARCCE.2022.11603

images, state of the art methods leverages convolutional neural networks (CNNs) [6]. These net- works utilize a deep architecture consisting of convolutional layers, pooling layers, fully connected layers, and non-linear activation functions. This form of architecture transforms the input data into a 'deep' low-dimensional feature representation, which facilitates the classification task completed by the fully connected layers [5].

A limitation of these algorithms is the significantly increased processing requirements which result in higher costs for additional or faster hardware [5]. Despite the demonstrated benefits of using these algorithms [7]; [5], it is often cost-prohibitive to deploy them on large-scale camera net- works. In this work we propose that, with the proper attention to hardware and software integration, an efficient and effective automated surveillance processing system can be deployed with off- the-shelf algorithms and hardware.

I. RELATED WORK

Convolutional Neural Network (CNN)**:** It is a class of multilayer artificial neural networks that have successfully been applied to analyzing visual images through machine learning approach. CNNs are widely used in image and video recognition, recommender systems and natural language processing. The problem of applying these networks is one of the supervised learning tasks [8]. The process of training CNN has a great deal of parameters to be set up and adjusted, where the batch size is the most influential one [9]. This parameter represents a number of training samples that will be used during the training in order to make one update to the network parameters. Specifically, the batch size is used when fitting the model, and it controls how many predictions must be made at a time [10]. Summing up the above-mentioned considerations, the batch size impacts the CNN training both in terms of the time to converge and the amount of over fitting, that is, smaller batch size yields faster computation (with suitable implementations), but requires visiting more examples in order to reach the same error, since there are less updates per training iteration [10]. According [10] to the optimal batch size of 200 or greater on the basis of computational resources is desirable for CNN increased recognition patterns accuracy. The increased parameter values lead to increased better image recognition accuracy.

[10] proposed a CNN model named PSI-CNN for face recognition. The population stability index (PSI-CNN) model extracts untrained features from the image, and then fuses these features with original feature maps. The results of the experiments are shown in terms of matching accuracy, with the model outperforming the model derived from the VGG-Face model. Also, PSI-CNN was able to maintain stable performance when tested on low-resolution images acquired from CCTV cameras. In case of change in image resolution and quality, PSI-CNN is robust.

The quest to improve the face quality of video streams and processing speed of face recognition system motivated the work of [11]. The approach used frame selection of key-frames extraction engine and graphic processing unit (GPU) acceleration, which is used to extract key-frames of high quality, faces correctly and speedily. The outcomes improve the face recognition accuracy of the new CNN procedure.

To improve on the performance of recognition and authentication system of CNN, the layering of the convolutional and sampling layers collapsed into a single layer was proposed by [12]. The concept relied on the optimizing the parameters of face data through pre-training with fully connected layer and softmax classification layers. However, there is need for large-scale images during training phase.

II. APPLICATION OF FIREFLY ALGORITHM FOR FACE RECOGNITION

Face Recognition is steadily making its way into commercial products. As such, the accuracy of Face Recognition systems is becoming extremely crucial. In the Firefly Algorithm, the brightness of fireflies is used to measure attraction between a pair of unisex fireflies. The firefly with higher brightness attracts the less bright Firefly. The objective function is defined in proportion to the brightness, to define a maximization problem. This chapter aims to present the promising application of the Firefly Algorithm for Face Recognition. The Firefly Algorithm is used in hyper-dimensional feature space to select features that maximize the recognition accuracy. This also delineates how the Firefly Algorithm is suitable for selection of the features in a Face Recognition model. The Firefly Algorithm is then applied to this feature space to identify and select the best features. Fireflies are arbitrarily placed on various focal points of the image under consideration. The advantage of this approach is its fast convergence in selecting the best features and aim to evaluate the performance and viability of using the Firefly Algorithm for Face Recognition model [13].

III. CONVOLUTIONAL NEURAL NETWORK (CNN)

According to [14] and [15], a Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. CNNs are used for image classification and recognition because of its high accuracy. The CNN follows a hierarchical model which works on building a network, like a funnel, and finally gives

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⋇ Impact Factor 7.39 ⋇ Vol. 11, Issue 6, June 2022

DOI: 10.17148/IJARCCE.2022.11603

out a fully-connected layer where all the neurons are connected to each other and the output is processed. CNN is an efficient recognition algorithm which is widely used in pattern recognition and image processing. It has many features such as simple structure, less training parameters and adaptability. It has become a hot topic in voice analysis and image recognition.

IV. METHODOLOGY

Optimized CNN Model Design

To design the optimized CNN model, the CNN model was designed first. In this work, a pre-trained alexnet CNN model was used for training the faces by extracting features and classifying them using Softmax transfer learning classification layer in a one-vs-all approach.The choice of the model was based on its performance on several face recognition datasets [16].

The pre-processing was carried out on the raw images in order to remove the noise and redundancy for the purpose of making them fit for the next level of face recognition activities. The pre-processing also includes re-sizing and type conversions suitable for the CNN in order to properly train the images by generating the best features for the recognition stage of the CNN. The features extraction activity was performed in the convolutional layer from the pre-trained model by setting the filter parameters, max pooling layer and reshaping of convolutional layer of the CNN. The appropriate features in the pre-trained images generated were passed on to the fully connected layer and used for the face recognition block. The features extracted from the original image are used to train and evaluate the face recognition system, which serves as the outcome of the proposed system.

V. EXPERIMENT

Three experiments were conducted. In the first experiment, the optimized CNN model was developed using Firefly algorithm as the parameter optimizer. The model was called FFA-CNN model. A total of 994 images were used for training and testing the developed model. 695 for training and 299 images for testing, comprising of six images per individual. The FF algorithm was used to optimize two CNN parameters; the learning rate and maximum epoch because of their importance in model performance.

The second experiment was conducted using CNN model only with learning rate of 0.00001 and maximum epoch of 2 called CNN1 and the third experiment called CNN2 was developed using learning rate of 0.0001 and maximum of 2. The performance of the models was evaluated using accuracy and MAPE.

The FFA used for the optimization is shown in the flowchart in Figure 3.5. The processes include; defining the initial parameters and constraints of the algorithm including population sizes, light absorption coefficient (gamma), attraction coefficient (beta0), mutation coefficient (alpha). This followed by definition of the objective function. Accuracy was used as the objective function as shown in Equation 3.1 under sub-section 3.4.

Based on the fitness of fireflies, their light intensities are evaluated and the final solution is returned when the stopping criteria is reached. The parameters of the FFA include gamma (1), beta0 (2), alpha (0.2), population (10), and maximum iteration of 5.

Performance Evaluation

This research work is to evaluate the proposed face recognition and detection system using accuracy and Mean Absolute Percentage Error (MAPE).

A. **Accuracy**

Accuracy or classification accuracy measures the proportion of all correct classification for all individuals in the test dataset. The equation is given as;

$$\mathrm{Accuracy} = \left(\frac{\sum_{i}^{T}(C_i)}{T}\right) * 100\%$$

B. **MAPE**

This measures the percentage of wrongly classified samples of all test datasets.

$$\mathrm{MAPE} = \left(\frac{\sum_{i}^{T}(W_i)}{T}\right) * 100\%$$

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁜ Impact Factor 7.39 ⁜ Vol. 11, Issue 6, June 2022
DOI: 10.17148/IJARCCE.2022.11603

Where, C is the total number of correctly predicted faces of sample (i), T is the total number of test samples, W is the total number of wrongly predicted faces of sample (i).

VI. RESULTS AND DISCUSSION

The results described in this section include; training result, testing results and performance evaluation results for the three developed systems. The systems are; the proposed Firefly Algorithm and Convolutional Neural Network system (FFA-CNN), CNN-1 and CNN-2 systems respectively. CNN-1 and CNN-2 were designed using random model parameters while FFA-CNN was designed to obtain optimized parameters using FFA as the optimizer. For each model, a total of 694 sample facial images which is about 70% of total dataset were used for training and 299 sample facial images which is about 30% of total dataset were used for testing the trained systems.

TRAINING RESULTS

Figure 1 shows the training progress curve for FFA-CNN model. The curve shows the training accuracy, the training loss and the number of iterations the algorithm took to converge. From Figure 1, the training was completed in 12 mins 4 seconds in 40 iterations. The training accuracy reached 99% at the 35th iteration with a consequential near zero loss. An optimal Maximum epoch of 4 and learning rate of 0.0001 was obtained by the FF algorithm for the model.
Figure 2 and Figure 3 shows the training progress curves for CNN-1 and CNN-2 models. The curves show the training accuracy, the training loss and the number of iterations the algorithm took to converge. From the Figures, the training was completed in 5 min 26 seconds and 5 min 28 seconds in 20 iterations for both CNN-1 and CNN-2 respectively.

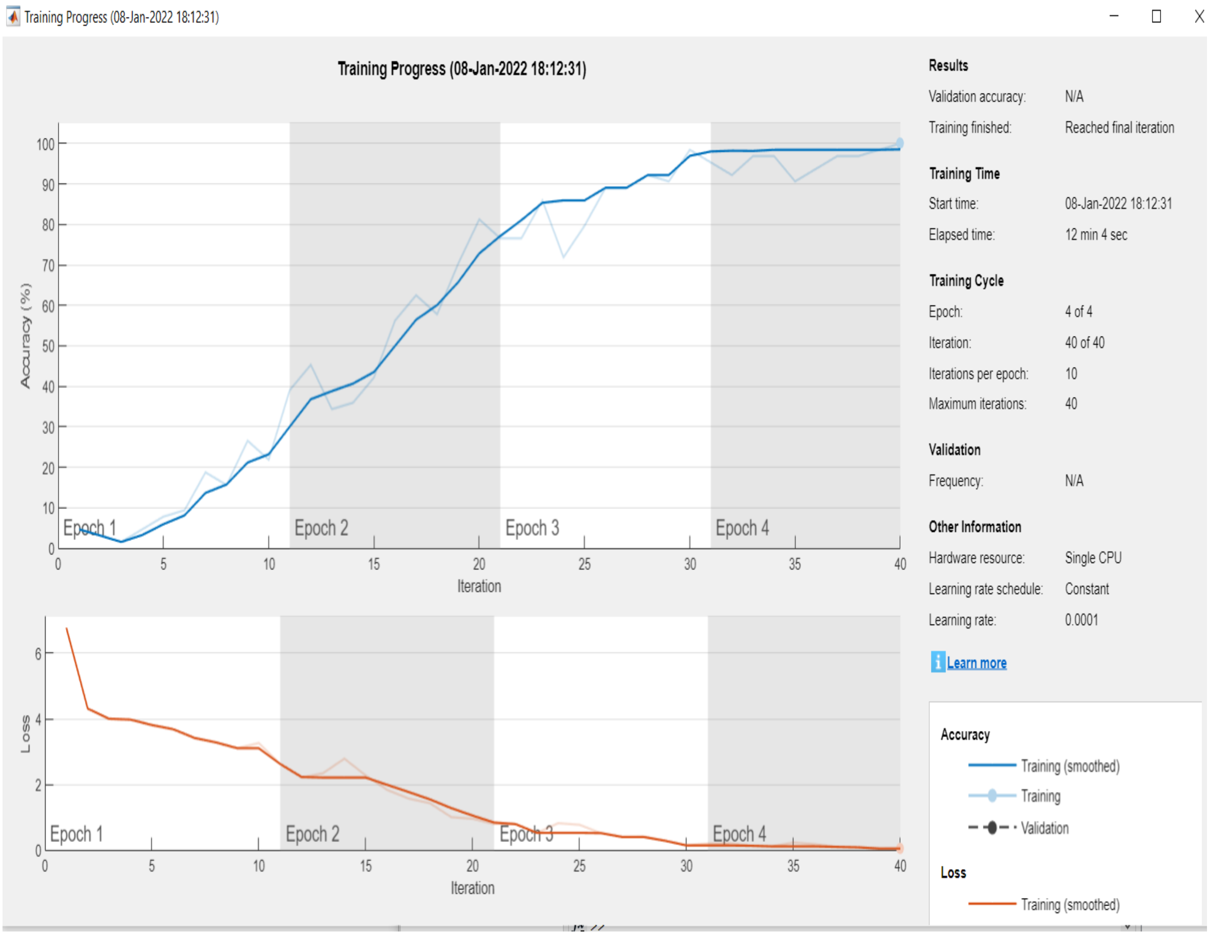

Figure 1: Training convergence curve for FFA-CNN

The training accuracy reached 10% at the 20th iteration and 70% at the 19th iteration respectively. A higher loss of 3.8 and 1.6 respectively was recorded.

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⁜ Impact Factor 7.39 ⁜ Vol. 11, Issue 6, June 2022
DOI: 10.17148/IJARCCE.2022.11603

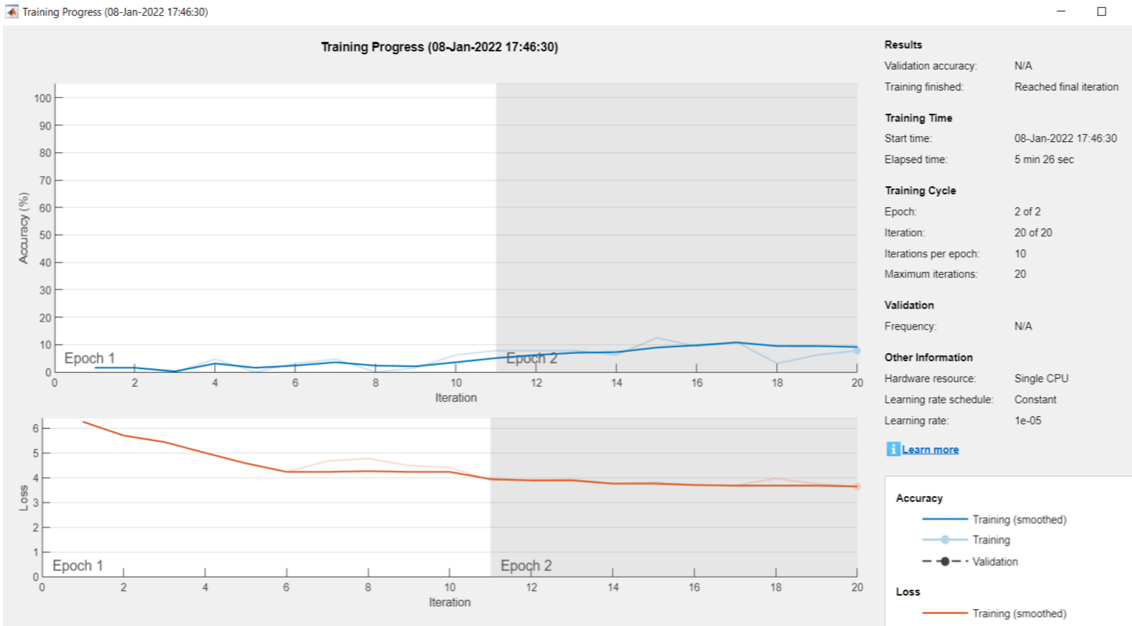

Figure 2: Training convergence curve for CNN1

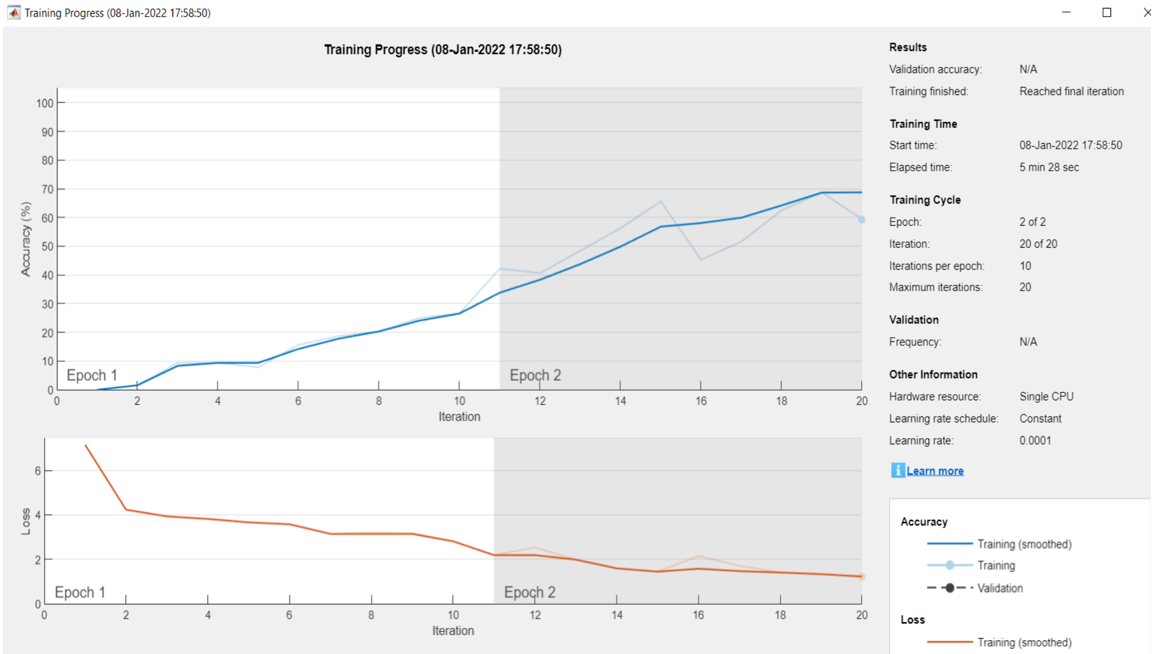

Figure 3: Training convergence curve for CNN2

TABLE 1: PERFORMANCE EVALUATION RESULTS

	FFA-CNN	CNN1	CNN2
Total Number of Correctly Predicted Labels	299	90	244
Total Number of Wrongly Predicted Labels	0	209	55
Accuracy	**100%**	30.10%	81.61%
MAPE	0%	69.90%	18.39%

Table 1, shows the performance evaluation results in terms of number correct and wrongly predicted faces of the system testing for the 3 experiments. The results show that FFA-CNN has the highest number of correct predicted faces shown in the first blue bar followed by CNN2 while CNN1 has the lowest.

DOI: 10.17148/IJARCCE.2022.11603

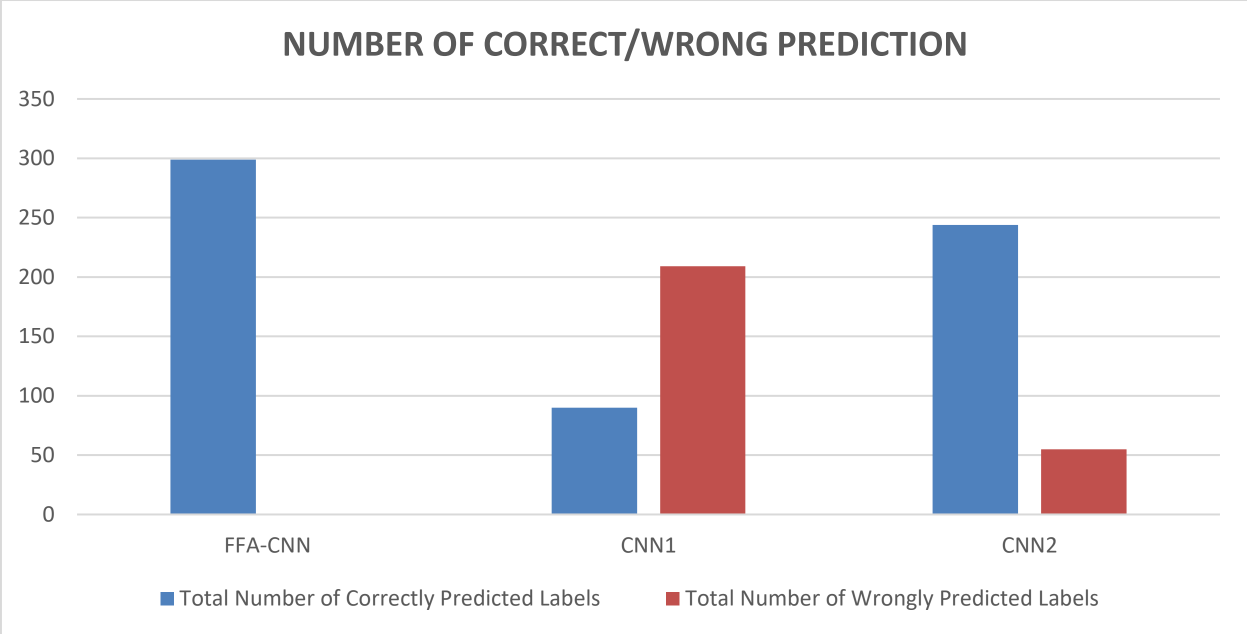

Figure 4: Prediction Count

Figure 5 shows the performance evaluation in terms of accuracy for the 3 models. This show that the accuracy of the proposed system (FFA-CNN) is 100%, while the accuracy for CNN1 30.10% and that of CNN2 is 81.61% respectively. It shows that the application of FFA for hyper-parameter optimization of the CNN model was very effective in improving the recognition rate of the system.

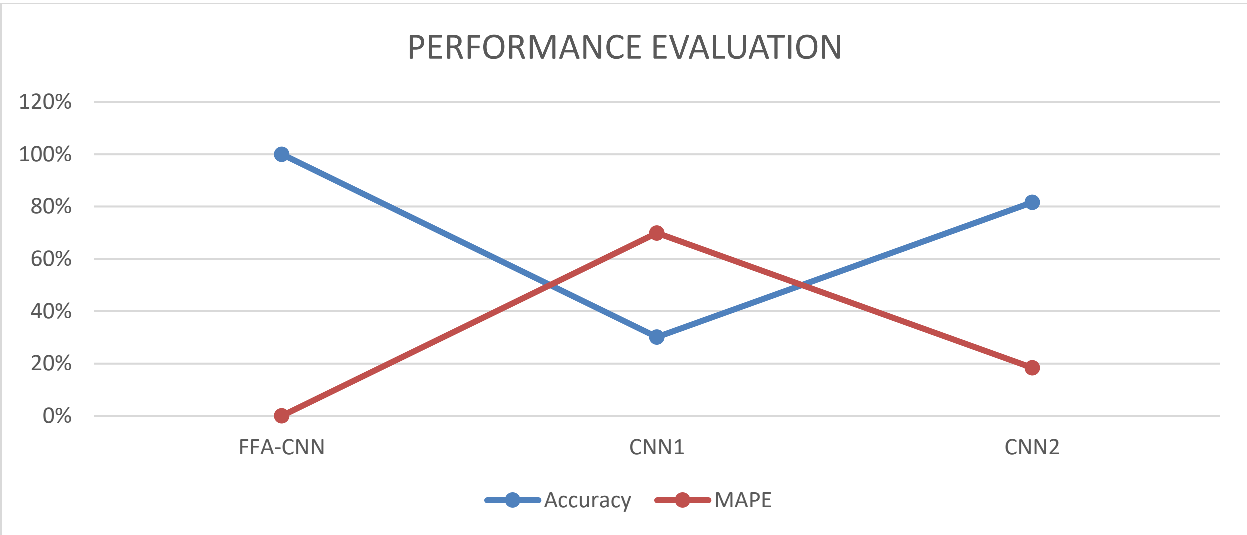

Figure 5: Performance Evaluation Graph

VII. CONCLUSION

In conclusion, the optimal learning rate for CNN models for face recognition systems is 0.0001 while the maximum epoch of 4 is appropriate. The obtained result shows that the application of FFA for hyper-parameter optimization of the CNN model was very effective in improving the recognition rate of the system. This research has contributed immensely to knowledge by developing an algorithm that improved the performance of CNN model for face recognition.

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.39 ⁜ Vol. 11, Issue 6, June 2022

DOI: 10.17148/IJARCCE.2022.11603

REFERENCES

[1] Wojcik, W., Gromaszek, K. & Junisbekov, M. "Face recognition: Issues, methods and alternative applications". Afolabi, A. O. & Adigun, A. A. IntechOpen, 1-23, (2012). Development of Crypto-Biometric E-Banking System. International Journal of Engineering and Technology, v.2(11), pp.1893-1900.

[2] Jan, A. "Deep learning based facial expression recognition and its applications". Unpublished PhD Thesis, Electronics and Computer Engineering, Brunel University London, UK. (2017).

[3] Kiewiet, N., Roodt, Y., Roos, H., & Clarke, W. "Automated surveillance and detection of foreign stationary objects". IEEE pp.1–6 doi:10.1109/AFRCON.2011.6072153. (2011).

[4] Ramachandran, U., Hong, K., Iftode, L., Jain, R., Kumar, R., Rothermel, K., & Sivaku- mar, R. "Large-scale situation awareness with camera networks and multimodal sensing". Proceedings of the IEEE, , v.100 (4), pp.878–892 (2012).

[5] Sze, V., Chen, Y. H., Yang, T. J., & Emer, J. S. "Efficient processing of deep neural networks: A tutorial and survey". Proceedings of the IEEE, v.105 (12), pp.2295– 2329,. (2017).

[6] LeCun, Y., Bengio, Y., & Hinton, G. "Deep learning". Nature, 521 (7553), pp.436– 444 (2015).

[7] Goodfellow, I., Bengio, Y., & Courville, A. "Deep learning". MIT Press (2016).

[8] Goyal, P., Dollar, P., Girshick, R., & Noordhuis, P. "Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour. Facebook AI Research (FAIR)", In CVPR, 2017.

[9] Ioffe, S., & Szegedy, C. "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift". Proceedings of the 32nd International Conference on Machine Learning, pp. 448–456. (2015).

[10] Radiuk, P. M. "Impact of Training Set Batch Size on the Performance of Convolutional Neural Networks for Diverse Datasets". Information Technology and Management Science, 20, 20-24. doi: 10.1515/itms-2017-0003.

[11] Qi, X., Liu, C. & Schuckers, S. "Boosting Face in Video Recognition via CNN based Key Frame Extraction". IEEE 4th International Conference on Identity, Security, and Behavior Analysis (ISBA), pp.451-462. (2018).

[12] Wang, J. and Li, Z. "Research on Face Recognition Based on CNN". IOP Conference, 2nd International Symposium on Resource Exploration and Environmental Science. Series: Earth and Environmental Science 170 (2018) 032110. (2018).

[13] Kotia J., Bharti R., Kotwal A., Mangrulkar R. "Application of Firefly Algorithm for Face Recognition". Springer, Singapore. (2020).

[14] Gibb, S., La, H. M., & Louis, S. A "Genetic Algorithm for Convolutional Network Structure Optimization for Concrete Crack Detection". 2018 IEEE Congress on Evolutionary Computation, CEC 2018 - Proceedings, 1–8. (2018).

[15] Li, S.; Dou, Y. Niu, X. Lv, Q. & Wang, Q. "A Fast and Memory Saved GPU Acceleration Algorithm of Convolutional Neural Networks for Target Detection". Neuro computing, v.230, pp.48–59. (2017).

[16] Almabdy, S., & Elrefaei, L. "Deep Convolutional Neural Network-Based Approaches for Face Recognition". (2019).