PREPROGRAMMED FACE RECOGNITION FOR ATTENDANCE MANAGEMENT

MOHAMMED ADIL S¹, ARUUNKUMARAN², ARIVAZHAGU UV³

¹UG Scholar, Department of CSE, Kingston College, Vellore-59 ² UG Scholar, Department of CSE, Kingston College, Vellore-59 ³ Asst.Professor, Department of CSE, Kingston College, Vellore-59

Abstract - Facial Recognition is a Deep Learning Technology, in which the system uses more than one photograph of a user or a set of faces that were captured as a video during training session to recognize and authenticate. It is an AI combined Deep Learning Technique which is a step forward in biometric authentication system. It consists of two algorithms

(i)CNN – Convolutional neural network

(ii)Ada Boost Algorithm

The Concept has a wide spectrum of applications like Attendance system in Educational institutions and organizations, deep face reaction monitor, privacy locks in hand held devices etc.

We also included a Comparative Facial match algorithm which uses multiple images of a user to authenticate and authorize to process further actions. These systems can detect person with an accuracy of 94.5% with the help of CNN & Ada Boosting algorithm, it also be used in an ATM or provisional store's surveillance camera to identify the thief by facial recognition and to alert nearby cops. The major advancement is that the system has improved security and data integrity in database, it's least likely possible for a person to breach the database.

Key Words: CNN, Ada Boost Algorithm, Open CV, TKinter, Comparative Facial match algorithm.

1. INTRODUCTION

Pandemic has almost changed everything in every aspect, to prevent the contact and to eliminate the spread of infection people adapted to use online attendance system using facial recognition, the major Algorithms we're implementing here is the most popular CNN (convolutional neural network), Ada Boosting Algorithm then finally the Comparative facial match Algorithm.

In the beginning phase the user face is registered in database as a multiple images and a set of videos using the training module. Once after the face is registered whenever the person is in-front of web camera, the recognition module automatically detects the person and compares the present image with the pre-existing image that found in the database. Whenever the face match is found accurate (i.e. that is more than 94.5% accurate using CNN) the system will mark present for the person in attendance, here CNN plays a vital role in matching

images as a set of matrix and producing an output with a perfect accuracy.

Then followed by Ada Boost Algorithm which ensures that the face detected has recognized efficiently without any deviations in results. So that the online attendance system will functional with high accuracy without any errors. The major advancement is that if the system is installed together with the surveillance camera of a store or an ATM it acts as a real-time security monitor. if any images that found in database is mentioned as wanted list, it alerts the cops as soon as possible whenever the person is detected in those surveillance camera.

The outcome is much effective and serves its purpose in terms of identifying the faces of a person using it



Figure 1: Example image for the dataset

2. RELATED WORKS

[1] The work done by author C Ding and D. Tao, "Trunk-branch ensemble convolutional neural networks for video-based face recognition", *IEEE transactions on pattern analysis and machine intelligence*, vol. 40, no. 4, pp. 1002-14, Apr 2018.

Human faces in surveillance videos often suffer from severe image blur, dramatic pose variations, and occlusion. In this paper, we propose a comprehensive framework based on Convolutional Neural Networks (CNN) to overcome challenges in video-based face recognition (VFR). First, to learn blur-robust face



representations, we artificially blur training data composed of clear still images to account for a shortfall in real-world video training data. Using training data composed of both still images and artificially blurred data, CNN is encouraged to learn blur-insensitive features automatically. Second, to enhance robustness of CNN features to pose variations and occlusion, we propose a Trunk-Branch Ensemble CNN model (TBE-CNN), which extracts complementary information from holistic face images and patches cropped around facial components. TBE-CNN is an end-to-end model that extracts features efficiently by sharing the low- and middle-level convolutional layers between the trunk and branch networks. Third, to further promote the discriminative power of the representations learnt by TBE-CNN, we propose an improved triplet loss function. Systematic experiments justify the effectiveness of the proposed techniques. Most impressively, TBE-CNN achieves state-of-the-art performance on three popular video face databases: PaSC, COX Face, and YouTube Faces. With the proposed techniques, we also obtain the first place in the BTAS 2016 Video Person Recognition Evaluation.

[2] The work done by another author Y Duan, J Lu, J Feng and J. Zhou, "Context-aware local binary feature learning for face recognition", *IEEE transactions on pattern analysis and machine intelligence*, vol. 40, no. 5, pp. 1139-53, May 2018.

In this paper, we propose a context-aware local binary feature learning (CA-LBFL) method for face recognition. Unlike existing learning-based local face descriptors such as discriminant face descriptor (DFD) and compact binary face descriptor (CBFD) which learn each feature code individually, our CA-LBFL exploits the contextual information of adjacent bits by constraining the number of shifts from different binary bits, so that more robust information can be exploited for face representation. Given a face image, we first extract pixel difference vectors (PDV) in local patches, and learn a discriminative mapping in an unsupervised manner to project each pixel difference vector into a context-aware binary vector. Then, we perform clustering on the learned binary codes to construct a codebook, and extract a histogram feature for each face image with the learned codebook as the final representation. In order to exploit local information from different scales, we propose a context-aware local binary multi-scale feature learning (CA-LBMFL) method to jointly learn multiple projection matrices for face representation. To make the proposed

methods applicable for heterogeneous face recognition, we present a coupled CA-LBFL (C-CA-LBFL) method and a coupled CA-LBMFL (C-CA-LBMFL) method to reduce the modality gap of corresponding heterogeneous faces in the feature level, respectively. Extensive experimental results on four widely used face datasets clearly show that our methods outperform most state-of-the-art face descriptors.

[3] The Research done by author W Xie and A. Zisserman, "Multicolumn networks for face recognition", *arXiv* preprint *arXiv*:1807.09192, Jul 2018.

The objective of this work is set-based face recognition, i.e. to decide if two sets of images of a face are of the same person or not. Conventionally, the setwise feature descriptor is computed as an average of the descriptors from individual face images within the set. In this paper, we design a neural network architecture that learns to aggregate based on both "visual" quality (resolution, illumination), and "content" quality (relative importance for discriminative classification). To this end, we propose a Multicolumn Network (MN) that takes a set of images (the number in the set can vary) as input, and learns to compute a fix-sized feature descriptor for the entire set. To encourage high-quality representations, each individual input image is first weighted by its "visual" quality, determined by a self-quality assessment module, and followed by a dynamic recalibration based on "content" qualities relative to the other images within the set. Both of these qualities are learnt implicitly during training for setwise classification. Comparing with the previous state-of-the-art architectures trained with the same dataset (VGGFace2), our Multicolumn Networks show an improvement of between 2-6% on the IARPA IJB face recognition benchmarks, and exceed the state of the art for all methods on these benchmarks.

3. METHODOLOGY PROPOSED

Methodologies used:

The face recognition system is pre equipped with the set of data that gathered from the google and the open cv, that is useful in training the module to attain the targeted accuracy. The major algorithms like CNN, Ada Boost and Comparative match is provided below as well as the detailed description of each module also provided.

The combination of those methodologies yields maximum of 94.5% accuracy in detecting and recognizing users.

GUI Interface:

GUI (Graphical User Interface) provides an interaction between the user and recognition machine. By importing the TKinter module the GUI application main window is created as shown in [Figure 2]. The GUI interface window consists three important stages

- 1. Training/Register face
- 2. Recognition and authenticate face
- 3. Exit



Figure 2: GUI Interface

Stage 1: Register the user face in database for training

To Recognize a person one has to train it's facial biometrics in the module as shown in the [Figure 1]. In this stage, the user registers their facial biometrics for the future recognition process. Ones the Biometrics are stored in the database the registration stage gets completed.



Figure 3: User Id info. Screen

Stage 2: To Recognize the live image and authenticate face

Through capturing the face in the web-camera, the recognition module authenticates the live facial image with the database facial biometrics to find the out whether the image matches with the targeted accuracy.



Figure 4: Feedback from training module and storing the data in the database

Stage 3: To Terminate the Recognition process

If the user chooses to move out from the GUI interface, Exit.

4. ARCHITECTURAL AND DATA FLOW DIAGRAM

Architectural diagram:

The architectural diagram consists of two parallel set of processes, in that one will fetch the pre-existing data's from the database and the other will fetch the live images of an user with the help of web-camera, now both the process will compare the data of one another, if the correct match found in an certain accuracy, it displays the result, else it produce output as "unknown" or "Image not matched".

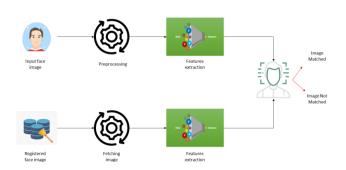


Figure 5: Architectural Diagram

Data Flow Diagram:

Generally, data flow diagram refers the flow of data and its functionality. In the program, these system starts with capturing the image of an user through the web camera[Figure 1] then followed by detecting and cropping out only the face and eliminating other things in an image[figure 3].

The detected face is then processed with Ada Boosting algorithm to extract and improvise the image quality. Now the image is compared with the pre-existing images from the database that were stored when the user is registered his face in training module. When the images of both training and recognizing module matches the system successfully produce the output as image matched. Else not.

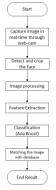


Figure 6: Data Flow Diagram

5.RESULTS AND OBSERVATIONS

The system worked well efficient in different scenarios

 While training the AI it is mandatory to look at the camera only by the respective person (if two or more person present while training the AI it may lead to confusion and misinterpretation of person).

- We can train the AI even by wearing the spectacles but it is advisable to remove the specs for clear image capturing.
- During the recognition process the auto-focus function focuses only the live face of a user to detect and identify. It won't consider any images or photographs that showed in-front of camera to recognize.

Training:



Figure 7: Training Module Example

Recognition:

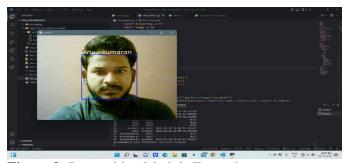


Figure 8: Recognition Module Example

6.CONCLUSION

In this work we've made two major modules one is training the AI and the other is recognizing the user. Both the modules works fine with the help of convolutional neural network(CNN) and also achieved a good amount of accuracy while detecting and recognizing faces. On considering the accuracy percentage of 94.5% it is good to go in any type of government, private and non-private surveillance cameras to detect and recognize the thieves or criminals who were been in wanted list but for that we need an authorization from officials to access their confidential data base. So for now we focus our project into online attendance system using facial recognition by using camera which yields a good success accuracy rate.



International Jo

ACKNOWLEDGEMENT

The authors would like to thank Dr. U.V Arivazhagu for his suggestions and excellent guidance throughout the project period.

REFERENCES

- [1] C Ding and D. Tao, "Trunk-branch ensemble convolutional neural networks for video-based face recognition", *IEEE transactions on pattern analysis and machine intelligence*, vol. 40, no. 4, pp. 1002-14, Apr 2018.
- [2] B. Rossion, "Humans are visual experts at unfamiliar face recognition", *Trends in cognitive sciences*, vol. 22, no. 6, pp. 471-2, Jun 2018.
- [3] Y Duan, J Lu, J Feng and J. Zhou, "Context-aware local binary feature learning for face recognition", *IEEE transactions on pattern analysis and machine intelligence*, vol. 40, no. 5, pp. 1139-53, May 2018.
- [4] W Xie and A. Zisserman, "Multicolumn networks for face recognition", *arXiv preprint arXiv:1807.09192*, Jul 2018.
- [5] S Bate, C Frowd, R Bennetts, N Hasshim, E Murray, AK Bobak, et al., "Applied screening tests for the detection of superior face recognition", *Cognitive research:* principles and implications, vol. 3, no. 1, pp. 22, Dec 2018.
- [6] X Liu, L Lu, Z Shen and K. Lu, "A novel face recognition algorithm via weighted kernel sparse representation", *Future Generation Computer Systems*, vol. 80, pp. 653-63, Mar 2018.
- [7] X Wu, R He, Z Sun and T. Tan, "A light CNN for deep face representation with noisy labels", *IEEE Transactions on Information Forensics and Security*, vol. 13, no. 11, pp. 2884-96, Nov 2018.
- [8] X Sun, P Wu and SC Hoi, "Face detection using deep learning: An improved faster RCNN approach", *Neurocomputing*, vol. 299, pp. 42-50, Jul 2018.
- [9] Soad Almabdy et al., "Deep Convolutional Neural Network-Based Approaches for Face Recognition", *Applied Science*, vol. 9, 2019.
- [10] Yichun Shi et al., *Probabilistic Face Embeddings*, Aug 2019.
- [11] R. Hartanto and M. N. Adji, "Face recognition for attendance system detection", 2018 10th International Conference on Information Technology and Electrical Engineering (ICITEE), pp. 376-381, 2018, [online] Available:
 - https://ieeexplore.ieee.org/document/8534942.
- [12] A. Ghofrani, R. M. Toroghi and S. Ghanbari, "Realtime Face-Detection and Emotion Recognition Using MTCNN and miniShuffleNet V2", 2019 5th Conference on Knowledge Based Engineering and Innovation (KBEI), pp. 817-821, 2019, [online] Available: https://ieeexplore.ieee.org/document/8734924.
- [13] W. Yang and Z. Jiachun, "Real-time face detection based on YOLO", 2018 1st IEEE International Conference on Knowledge Innovation and Invention (ICKII), pp. 221-224, 2018, [online] Available: https://ieeexplore.ieee.org/document/8569109.

- [14] S. Aryal, R. Singh, A. Sood and G. Thapa, "Automatic attendance system using deep learning", *SSRN Electron. J*, 2019, [online] Available: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3352376.
- [15] "Face Detection Neural Network Structure", *Mc.ai*, Jul 2018, [online] Available: https://mc.ai/face-detection-neural-network-structure/.
- [16] C.-F. Wang, "I implemented a face detection model. Here's how I did it", *Towards Data Science*, Jul 2018, [online] Available: https://towardsdatascience.com/mtcnn-face-detection-cdcb20448ce0.
- [17] C.-F. Wang, "How does A face detection program work? (using neural networks)", *Towards Data Science*, Jul 2018, [online] Available: https://towardsdatascience.com/how-does-a-face-detection-program-work-using-neural-networks-17896df8e6f.
- [18] A. Kathuria, "What's new in YOLO v3? Towards Data Science", *Towards Data Science*, Apr 2018, [online] Available: https://towardsdatascience.com/yolo-v3-object-detection-53fb7d3bfe6b.
- [19] R. Balsys, "YOLO v3 theory explained Analytics Vidhya - Medium", Analytics Vidhya, Jul 2019, [online] Available: https://medium.com/analytics-vidhya/yolo-v3-theory-explained-33100f6d193.
- [20] M. Deore, "FaceNet Architecture Analytics Vidhya Medium", Analytics Vidhya, Apr 2019, [online] Available: https://medium.com/analytics-vidhya/facenet-architecture-part-1-a062d5d918a1.
- [21] D. Kumar, "Introduction to FaceNet: A unified embedding for face recognition and clustering", *Analytics Vidhya*, Jul 2019, [online] Available: https://medium.com/analytics-vidhya/introduction-to-facenet-a-unified-embedding-for-face-recognition-and-clustering-dbdac8e6f02.
- [22] P. F. T. Madio, "A FaceNet-style approach to facial recognition on the Google coral development board", *Towards Data Science*, Aug 2019, [online] Available: https://towardsdatascience.com/a-facenet-style-approach-to-facial-recognition-dc0944efe8d1.
- [23] . Brownlee, "How to develop a face recognition system using FaceNet in keras", Machinelearningmastery.com, Jun 2019, [online] Available: https://machinelearningmastery.com/how-to-develop-a-face-recognition-system-using-facenet-in-keras-and-an-sym-classifier/.