Face Recognition in digital documents with live image

S. Priyanga[1], S. Sneha[2], Dr. P. Mohan Kumar[3]

[1,2] UG Student, Dept. of CSE, Jeppiaar SRR Engineering College, Chennai, Tamilnadu , India.
[3] Professor, Head of the department (CSE), Jeppiaar SRR Engineering College, Chennai

---

Abstract — *Our daily life requires us to verify who are we, showing our ID documents containing face images as passports and driver licenses, to humans. This process is slow, labor-intensive and unreliable. A system for matching ID document photo to live image(photo) in real-time is required for high accuracy. We propose face recognition in this paper to meet the objective. Initially, we show gradient methods that converge slowly of the under fitting of classifier weights as many classes have very few samples, of existing ID photo datasets. We propose dynamic weight imprinting to overcome the disadvantage of updating the classifier weights, for faster convergence and more generalized representations. A pair of sibling networks with partial shared parameters are trained to learn a unified face representation(photo) with specific domain parameters. Cross verification on an ID photo dataset shows that a publicly available general face identifier (Insight Face photo) only achieves a true accept rate (TAR) of 88.77 ± 1.30% at a false accept rate of 0.01% on the problem, Face recognition improves the TAR to 95.95 ± 0.53%.*

Keyword: Central Board Server, Dynamic Weight Imprinting, Face live Image, Blockchain1.

1. INTRODUCTION

The main aim of this project is to solve the problem of counter certificates, we are proposing a digital certificate system based on blockchain technology and to verify the traveler's identity using a live camera which allows faster convergence and more generalized representations. Daily life requires us to verify who are we, showing our ID documents containing face image passports, and driver licenses with human operators. This process is slow, labor-intensive and unreliable. So that an automated system for matching ID documents photos to live images in real-time with high accuracy is required. We propose face recognition in this paper to meet the objective. Initially, we show gradient methods that converge slowly of the under fitting of classifier weights as many classes have very few samples, of existing ID photo datasets. We propose dynamic weight imprinting to overcome the disadvantage of updating the classifier weights, for faster convergence and more generalized representations. A pair of sibling networks with partial shared parameters are trained to learn a unified face representation(photo) with specific domain parameters. Cross verification on an ID photo dataset shows that a publicly available general face identifier (Insight Face photo) only achieves a true accept rate (TAR) of 88.77 ± 1.30% at a false accept rate of 0.01% on the problem, Face recognition improves the TAR to 95.95 ± 0.53%. Initially, the documents are stored in a digital format using the blockchain technology. The photos in the document are trained using the python server. To check the identity our live image is captured and compared with the trained document photo, Using the KNN algorithm the closest match is found and if the images are matched the verification process will be successful. KNN is used for classification and regression problems. KNN is widely used in classification problems.

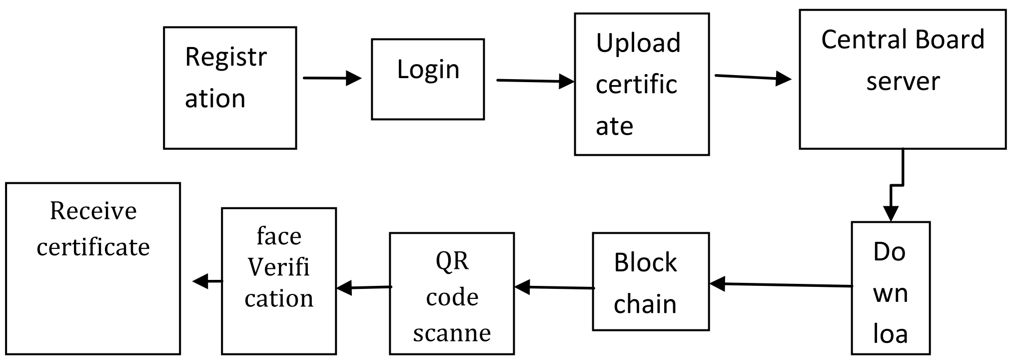
2. RELATED WORKS

Fen Wang and Xiang [1] "L2 Hyper sphere Embedding for Face Verification" -2017. To the recent developments of Convolutional Neural Networks, the performance of face verification has increased rapidly. Face verification methods, for boosting performance feature normalization is used. During training, this motivates us to introduce, and study normalization. This is non-trivial, despite normalization being differentiated. To study for issues related to normalization is through mathematical analysis, and it helps with settings of the parameter. The two strategies for training are using normalized features. The rest is a modification of soft max loss, which optimizes the similarity of cosine instead of inner-product. Formulation of learning by introducing a vector for each class is recommended. To show that both strategies, and small variants, improve consistently by between 0.20% to 0.40% on the labelled faces in the wild dataset based on the two models. It is significant because the performance of the two models on the dataset is close to saturation over at 98.0%. H�o Wang, Yitong Wang [2] "Large Margin Cosine Loss for Deep Face Recognition"- 2018. Face recognition has made brilliant progress in the advancement of deep convolutional neural networks. The main task of face recognition includes face verification and identity, which involves face feature discrimination. The soft max loss of deep CNN usually reduces the power of discrimination. In a recent survey, many loss functions like to middle loss, margin loss, and angular vector loss is proposed. All these losses have the same idea of maximizing inter-class and minimizing variances. In this paper, the proposed novel loss function is a large margin cosine loss function, to know this idea from a different perspective. The reformulation of the soft max loss as a cosine loss, by normalizing L2 both features and weight remove radial variations, based upon a cosine term to further maximize the decision margin in the annular space. The result is minimum and maximum class variances, which are achieved by normalization virtue and decision margin maximization of cosine. It refers to the model trained with as Cosine Face. Experimental evaluations conducted on public-domain datasets like challenge of mega face, YouTube Faces and Label Face in the Wild. Finally, it achieves state-of-the-art performance on the benchmarks, which shows the effectiveness of this approach. Yair Movshovitz-Attias and Alexander Toshev [3] “No Fuss Distance Metric Learning to use Proxies”-2017. It addresses the problem of distance metric learning. It is defined as learning a consistent notion of semantic similarity. Previously, for this problem it is expressed in the form of points that follow an ordinary relationship point x is similar to a set of positive points Y and dissimilar to a set of negative points Z, and a loss is defined as minimized. The optimization differs as we collectively call this Triplet's supervision and the methods that follow Triplet-Based methods. Those methods are quite challenging optimizing. The important issue is finding informative triplets, that is usually achieved by tricks such as increasing batch size, hard or semi-hard mining, etc. With these tricks, the rate of convergence is slow. To optimize the triplet loss on a different space consisting of anchor data point and similar, dissimilar proxy points that are well learned. The appropriate data points a triplet loss, over the proxy servers, which is an upper tight bond. This loss is usually better behaved. The conclusion of these losses of proxies generally improves for standard three zero-showed sets up to 15.11% points, converging faster as other triplet-based losses. Hang QI and Matthew Brown [4], “Low-Shot Learning with Imprinted Weights”-2018. Human vision is capable of immediately recognizing novel visual categories after seeing just one or more training examples. It describes adding a similar capability to Con Net classifiers by setting the final layer weights directly from novel training during low-shot learning(performance). The process used is called the imprinting of weights because it converts sets directly weights based on an appropriate copy of the embedded layer. The process of imprinting shows a complement in training with descent, and it provides good performance and a start-up for development in the future. This shows the imprinting process which is related to proxy-based(embedding). Moreover, it differs in a single printed weight is learned for each category of novel, then relying on a nearest-neighbor vector to train instances typically with embedding methods. Using averaging of imprinted weights provide a better generalization than using nearest-neighbor instance embeddings is shown by the experiments.

3. PROPOSED SYSTEM

Here in our proposed system a certificate system is used based on blockchain. Different nodes are used to store data. To modify particular internal data, the other nodes modifies it quickly. It achieves highly reliable system for data storing. An Ethereal blockchain is used for decentralized projection. Generally it is incorruptible, encrypted, and permits synchronization of data. The system improves the efficiency by integrating the features of a block chain and its operations at each level. This idea saves on paper, management cut costs, document forgery, and gives accurate and reliable information on digital certificates, and compare user live face with verified document photo. For traveler verification, a live face image is captured rather than scanned document photo. Our daily life requires us to verify who are we, showing our ID documents containing face images as passports, driver licenses to human operator. Access control, physical security and international border crossing require us to verify our access and our identities approach. It involves comparing an individual’s live face to the face image found in his/her ID document. The Smart Gate, read their e-Passport chips containing their digital photographs, and captures their face images using a camera.

4. DATAFLOW DIAGRAM



5.METHODOLOGY

1. REGISTRATION, LOGIN, UPLOADING — CENTRAL BOARD SERVER

Initially user need to register into his application. A request is sent to central board server for further authentication purposes. Until the central board server accepts the request of the user, the user cannot log in to the account. When central boards server accepts the request, a key(private key) will be generated so that user can log in to the account. After logging in, user needs to upload certificates such as pan card, Aadhar card, voter id, SSC certificates to the central board server. Central board server will review all the certificates. Then accept or decline the certificates based on its originality. If central board server accepts the certificate, the details are stored in electronic clearing service and in Blockchain technology or if central board server declines the certificate based on its originality. For updating if user needs certificate, request is sent to central board server. The central board server checks the user details to be genuine it accepts the request. It forwards a request to Authority where the certificate database is available. Authority responds and certificate are provided to the user. Authority verifies user live face(photo) with document photo and forwards to user via central board server. User can forward the QR code to the authority for verification and if all details are correct authority will issue the document.

2. KNN Algorithm

It is used for classification and regression problems. KNN is widely used in classification problems for solving it easily. It is used to evaluate any technique by three important aspects such as, Ease to interpret output, Overall calculation time, Predictive power. The following details show an example of KNN. KNN algorithm is true for all parameters of theory. Easy interpretation and low calculation time is the main advantage of this algorithm. A simple example, Consider a spread of red circles and green squares. You need to find out the class of the blue star. Blue Star can either be Red Circles or Green Square or empty. The "K" is the nearest neighbor for consideration. Let K be 3. Create a circle with Blue Star as center as big, to enclose three data points on the plane only. The three closest points to Blue Star is all Red Circles. We can say accurately that the Blue Star must belong to the class Red Circle. In this case the choice became very obvious, as all three votes from the closest neighbor went to Red Circle. The choice of K is crucial in this KNN algorithm.

3. CHOOSING K Factor

understand what K influence in the algorithm. Given that all the observation remain constant, we can make boundaries of each class with the given k value. The boundaries will segregate the circles. To see the effect of value, "K" in the class boundaries is defined. Different boundaries separating the two classes with k different values. The boundary becomes smoother of increasing value of K. K increasing valuing to infinity it becomes all blue or all red takes the count of majority. The error rate, the validation error rate are the two important parameters which need to access in different values of K. Error rate at k is one, is always zero for the training sample. Prediction is accurate with k as 1. If validation error curve is similar, the choice of K would be 1. At K as 1,were over fitting the boundaries. The error rate initially decreases then reaches minimal. After the minimal point, it increases with increasing K. The optimal value K, you can separate the training and validation from the initial dataset.

4. PSEUDO CODE

KNN model can be implemented by following the below steps

Load the given k value from one to total number of data points to get the predicted class. Find the distance between the data to be tested and training data of each row. Euclidean distance. Chebyshev, cosine, are the other networks that can be used. Based on distance values, sort the calculated distances in ascending order. From the sorted array, get top K row. Get the most used class. Predicted class can be returned.

6. ADVANTAGES

1. The proposed method is a dynamic weights imprinting, not only helps the loss converge, also leads to better generalization performance and also faster

2. It saves time.

3. It is faster than human operators.

7. CONCLUSION

In this paper, the method for matching ID documents photos to selfies is face recognition. A base model for unconstrained face recognition is used on a private ID-photo set called transfer training technique. The proposed dynamic weight imprinting to overcome the disadvantage of updating the classifier weights, for faster convergence and more generalized representations. A pair of sibling networks with partial shared parameters are trained to learn a unified face representation(photo) with specific domain parameters. Experiments show not only helps the loss converge much faster but also leads to better generalization performance. DWI is capable of capturing the global distribution of embeddings accurately as comparison with static methods.

REFERENCES

[1] D. White, R. I. Kemp, R. Jenkins, M. Matheson, and A. M. Burton, "Passport officers' errors in face matching," ONE, vol. 9, no. 8, 2014, Art. No. e103510.

[2] Wikipedia. (2018). Australia Smart gate. [Online]. Available: https://en.wikipedia.org/wiki/SmartGate.

[3] Wikipedia. (2018). E passport Gates. [Online]. Available:https://en.wikipedia.org/wiki/EPassport_gates.

[4] U.S. Customs and Border Protection. (2018). Automated Passport Control (APC). [Online]. Available: https://www.cbp.gov/travel/uscitizens/apc.

[5] Xinjiang Heng Perimeter security Equipment Company. (2018). What Is ID-Person Matching? [Online]. Available:http://www.xjhazj.com/xjhazj/vip_doc/8380983.html.

[6] Jumio. (2018). Netverify ID Verification. [Online]. Available:https://www.jumio.com/trustedidentity/netverify

[7] Mitek. (2018). Mitek ID Verification. [Online]. Available: https://www.miteksystems.com/mobile-verify.

[8] G. B. Huang, M. Ramesh, T. Berg, and E. Learned-Miller, "Labeled faces in the wild: A database for studying face recognition in unconstrained environments," Univ. Massachusetts, Amherst, MA, USA, Rep. 07-49, Oct. 2007 V. Starovoitov, D. Samal, and B. Sankur, "Matching of faces in camera images, and document photographs," in Pro. ICA SSP, 2000, pp. 2349–2352.

[9] X. Gao, J. Zhong, J. Li, and C. Tian, "Face sketch synthesis algorithm based on E-HMM and selective ensemble," IEEE Trans. Circuits System. A video Technology, vol. 18, no. 4, pp. 487–496, Apr. 2018.

[10] T. Bourlai, A. Ross, and A. Jain, "On matching digital face images against scanned passport photos," in Proc. IEEE Int. Conf. Biometrics Identity Security (BIDS), 2009, pp. 1–10.

[11] T. Bourlai, A. Ross, and A. K. Jain, "Restoring degraded face images: A case study in matching faxed, printed, and scanned photos," IEEE Trans. Inf. Forensics Security, vol. 6, no. 2, pp. 371–384, June. 2011.

[12] V. V. Starovoitov, D. I. Samal, and D. V. Briliuk, "Three approaches for face recognition," in Proc. Int. Conf. Pattern Recognit. Image Anal. 2002, pp. 707–711.

[13] Y. Shi and A. K. Jain, "DocFace: Matching ID documents photos to selfies," in Proc. BTAS, 2018, pp. 1–8.

[14] X. Zhu et al. "Large-scale bi sample learning on ID vs. spot face recognition," arXiv:1806.03018, 2018.

[15] Q. Cao, L. Shen, W. Xie, O. M. Parkhi, and A. Zisserman, "VGGFace2: A dataset for recognizing faces across pose and age," in Proc. IEEE Conf. Automation. Face Gesture Recognize, 2018, pp. 1–8.