MULTI- TASK CNN BASED CROSS-AGE FACE RECOGNITION

T.Hima Bindu PG Student, Department of CSE, Aditya Engineering College(A), Surampalem, AP.

M.Raja Babu Associate Professor, Department of IT, Aditya Engineering College(A), Surampalem, AP.

Email: himabindureddysss@gmail.com[1], rajababu.makineedi@aec.edu.in[2]

ABSTRACT:

Cross-age face recognition (CAFR) has gotten received more consideration in genuine applications, yet it is a challenging assignment because of complex facial aging process. One famous way is displaying CAFR as a traditional face classification issue.To classify person age using faces author using combination of two CNN where one CNN will extract face features which can help in identify changes in face over time and second CNN helps in predicting/classifying age and this combination of CNN is called as JOINT CNN. To implement this project we are using CACD2000 images dataset and after training we are getting JMCNN accuracy as 99%. In this paper author has not used any features selection algorithms so as extension work we are using GABOR features selection algorithm and this algorithm helps in extracting important features from faces and this important features helps CNN in identifying person in better way which can increase classification accuracy.

Keywords:CNN (Convolution Neural Network), JMCNN, JOINT CNN,GABOR.

INTRODUCTION:

CAFR as an arising research field got increasingly more consideration in academic and industry regions. For example, it very well may be applied to tracking down missing youngsters and identifying got away from criminals.In any case, it is a difficult assignment since maturing process after some time can considerably change facial appearance. The primary trouble is the means by which to adequately extract character sensitive features that are age insensitive.

To take care of this issue, a flood of strategies have been proposed and can be generally divided to three classes.The first one plans to construct generative model for synthesizing face image in various age ranges. Despite the fact that such methodologies, somewhat, make up for huge intra-individual changes brought about by maturing, they need to rely upon a few boundaries and cost a ton to prepare the model, which normally brings about unstable execution.An option is discriminative learning approach that intends to design face feature descriptor and utilize supervised learning algorithm to settle CAFR issue.

LITERATURE SURVEY:

Y. Qiao, K. Zhang. ***et al*** Face detection and alignment in unrestrainedsituation are challenging due to various poses, clarifications and occlusions. In this we recommend a deep cascaded multi-task framework which exploits the inherent correlation among detection and alignment to boost up their performance.

T. F. Cootes, A. Lanitis. ***et al*** We explain how the effects of aging on facial look can be explicated using learned age alterations and present experimental results to show that reasonably accurate estimates of age can be made for unseen images. We can improve our results by taking into account the fact that different individuals age in different ways and by considering the effect of daily life.

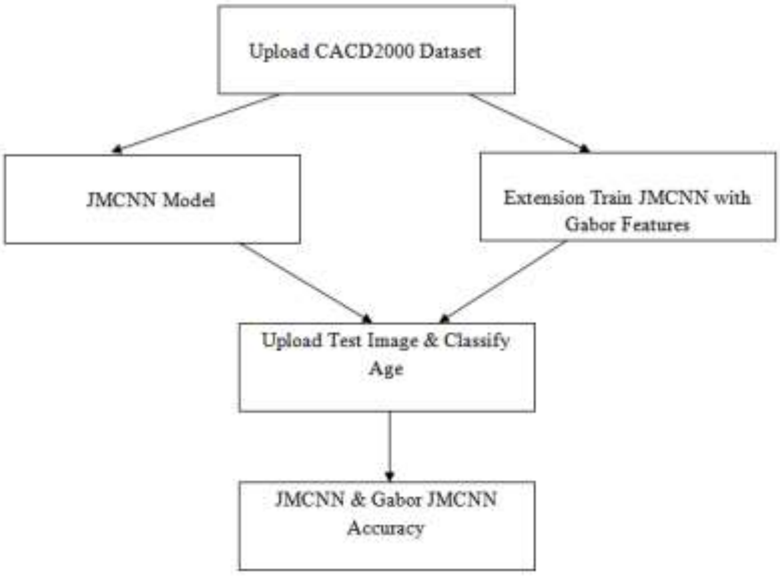
Y. Qiao,] Y. Wen. ***et al***we propose a novel deep face recognition framework to learn the ageinvariant deep face features through a carefully designed CNN model. To the best of our knowledge, this is the first attempt to show the effectiveness of deep CNNs in advancing the state-of-the-art of AIFR.

PROBLEM DEFINTION:

Cross-age face recognition as an emerging research field obtained more and more attention in academic and industry areas. For instance, it can be applied to finding missing children and identifying escaped criminals. However, it is a challenging task because aging process over time can substantially change facial appearance.

PROPOSED APPROACH:

A joint multi-task convolutional neural network (JMCNN) framework. It simultaneously models face recognition and age classification tasks by sharing a same CNN model and a regularization term, so that the interaction between identity sensitive features and age sensitive features are encouraged via the regularization loss.In this paper author has not used any features selection algorithms so as extension work we are using GABOR features selection algorithm and this algorithm helps in extracting important features from faces and this important features helps CNN in identifying person in better way which can increase classification accuracy.



PROPOSED METHODOLOGY:

DATASET:

To implement this project we are using CACD2000 images dataset and after training we are getting JMCNN accuracy as 99%. Training dataset saved inside CACD2000 folder and metadata of each image such as person name, birth date and identity can be obtained from 'celebrity2000_meta.mat' file. From dataset we are getting person birth year and we are getting his age by subtracting person birth date by 2021. For example if person birth year is 1950 the age is input to CNN as 2021 – 1950 = 71 years.

PREPROCESSING:

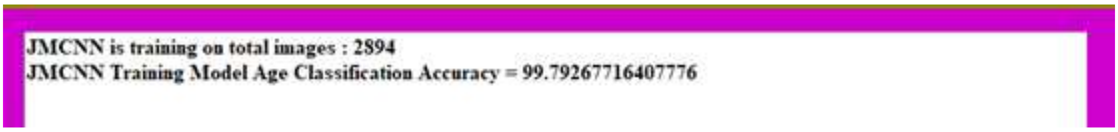
We can see each person names extracted from metadata file with his age and now images and age data is ready. JMCNN trained on total 2894 images and it got classification accuracy on test data is 99.79%

OPTIMIZATION:

The optimization for the model is implemented by stochastic gradient descent (SDG) and standard backpropagation algorithm. For the backward propagation, the derivative of L with respect to fI and fA need to be calculated.

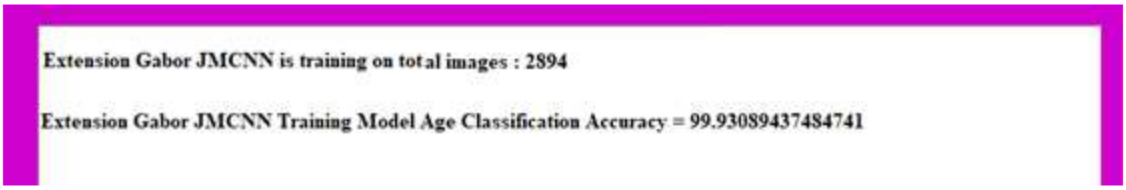
RESULTS:

Train JMCNN Model:


JMCNN is training on total images : 2894
JMCNN Training Model Age Classification Accuracy = 99.79267716407776

In above screen JMCNN trained on total 2894 images and it got classification accuracy on test data is 99.79%

Extension Train JMCNN with Gabor Features:


Extension Gabor JMCNN is training on total images : 2894

Extension Gabor JMCNN Training Model Age Classification Accuracy = 99.93089437484741

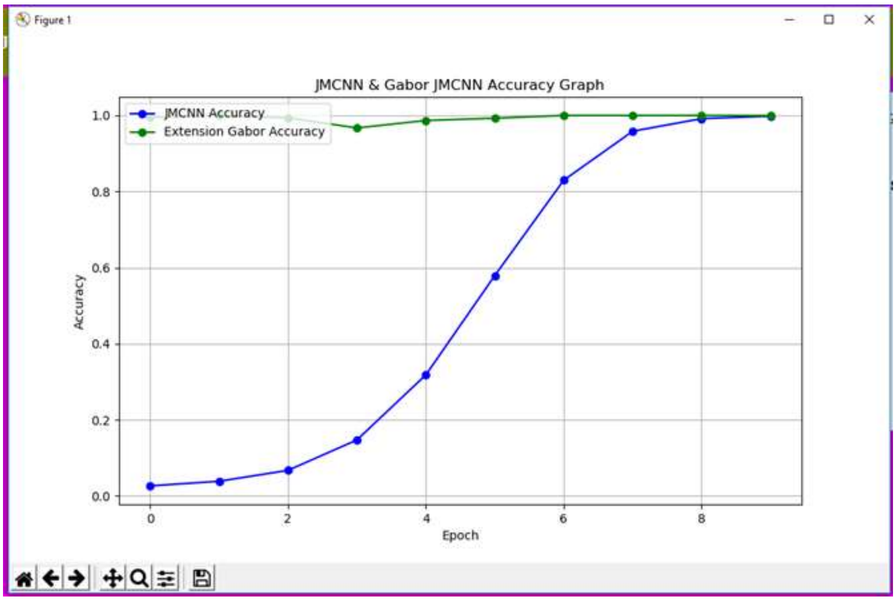
In above screen after applying GABOR we got JMCNN accuracy as 99.93 which is greater than plain JMCNN

Upload Test Image & Classify Age' CNN will predict age

In above screen age classified as 42

In above screen age classified as 54

JMCNN & Gabor JMCNN Accuracy Graph



In above graph x-axis represents epoch/iterations and y-axis represents accuracy and blue line represents JMCNN and green line represents extension GABOR features JMCNN accuracy. In above screen we can see both algorithms accuracy gets better upon each increasing epochs but extension Gabor features is better than normal JMCNN

CONCLUSION:

We presented a joint multi-task CNN for cross-age face recognition. Contrastinglots of existing deep learning techniques, the proposed technique simultaneously learn identity sensitive features and age sensitive features to get robust age-invariant features. As extension work we are using GABOR features selection algorithm and this algorithm helps in extracting important features from faces and this important features helps CNN in identifying person in better way which can increase classification accuracy.

REFERENCES:

[1] U. Park, Y. Tong, and A. K. Jain, “Age-invariant face recognition,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 32, pp. 947–954, 2010.

[2] J. Du, C. Zhai, and Y. Ye, “Face aging simulation based on nmf algorithm with sparseness constraints,” in International Conference on Intelligent Computing. Springer, 2011, pp. 516– 522.

[3] A. Lanitis, C. J. Taylor, and T. F. Cootes, “Toward automatic simulation of aging effects on face images,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, pp. 442–455, 2002.

[4] C. N. Duong, K. G. Quach, K. Luu, T. H. N. Le, and M. Savvides, “Temporal non-volume preserving approach to facial age-progression and age-invariant face recognition,” in Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 3755–3763.

[5] X. Shu, J. Tang, H. Lai, L. Liu, and S. Yan, “Personalized age progression with aging dictionary,” in Proceedings of the IEEE International Conference on Computer Vision, 2015, pp. 3970–3978.

[6] FG-NET, “Fg-net aging database,” (http://www-prima. inrialpes.fr/FGnet/html/home.html).

[7] H. Ling, S. Soatto, N. Ramanathan, and D. W. Jacobs, “Face verification across age progression using discriminative methods,” IEEE Transactions on Information Forensics and Security, vol. 5, pp. 82–91, 2010.

[8] Z. Li, U. Park, and A. K. Jain, “A discriminative model for age invariant face recognition,” IEEE Transactions on Information Forensics and Security, vol. 6, pp. 1028–1037, 2011.

[9] D. Gong, Z. Li, D. Lin, J. Liu, and X. Tang, “Hidden factor analysis for age invariant face recognition,” in Proceedings of the IEEE International Conference on Computer Vision, 2013, pp. 2872–2879.

[10] D. Gong, Z. Li, D. Tao, J. Liu, and X. Li, “A maximum entropy feature descriptor for age invariant face recognition,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 5289–5297.

[11] L. Du and H. Ling, “Cross-age face verification by coordinating with cross-face age verification,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 2329–2338.

[12] C. Xu, Q. Liu, and M. Ye, “Age invariant face recognition and retrieval by coupled auto-encoder networks,” Neurocomputing, vol. 222, pp. 62–71, 2017.

[13] L. Lin, G. Wang, W. Zuo, X. Feng, and L. Zhang, “Crossdomain visual matching via generalized similarity measure and feature learning,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, pp. 1089–1102, 2017.

[14] Y. Wen, Z. Li, and Y. Qiao, “Latent factor guided convolutional neural networks for age-invariant face recognition,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 4893–4901.

[15] T. Zheng, W. Deng, and J. Hu, “Age estimation guided convolutional neural network for age-invariant face recognition,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2017, pp. 1–9.

T. Hima Binduis a student pursuing her M.Tech (Computer Science and Engineering) at Aditya Engineering College(A), Surampalem, E.G Dt. She completed her B.Tech (IT) in Shri Vishnu Engineering College For Women, Bhimavaram in 2021. Her area of interest includes web applications, python and Object-Oriented Programming Languages in Computer Science.

M.RajaBabu received the B.Tech degree from MVGR College Of Engineering, Vizianagaram in 2003. He completed M.Tech in Information Technology from NCET, Vijayawada in 2010. He is having nearly 15 years of teaching experience. He worked as an Assistant Professor in RGM Engineering College, Nandyal in CSE Dept. from September 2005 to May 2008 and worked as an Assistant Professor in GIET Engineering College, Rajahmundry in CSE Dept. from June 2009 to November 2010. He is Currently working as Associate Professor& HOD, Dept of IT, Aditya Engineering College, Kakinada, Andhrapradesh, India. His research interest includes Image Processing, Information Retrieval and Machine Learning.. He is a life member of Computer Society of India(CSI)and Indian Science Congress Association(ISCA). He has published research papers in various National, Inter National Journals and conferences.