ISSN: 2321-7782 (Online)
Volume 4, Issue 2, February 2016
International Journal of Advance Research in Computer Science and Management Studies
Research Article / Survey Paper / Case Study
Available online at: www.ijarcsms.com

Automatic Age and Gender Recognition in Human Face Image Dataset using Convolutional Neural Network System

Subhani Shaik[1]
Assoc. Prof & Head of the Department
Department of CSE,
St.Mary's Group of Institutions Guntur
Chebrolu(V&M),Guntur(Dt),
Andhra Pradesh - India

Anto A. Micheal[2]
Associate Professor
Department of CSE,
St.Mary's Group of Institutions Guntur
Chebrolu(V&M),Guntur(Dt),
Andhra Pradesh - India

Abstract: Age and gender classification has become applicable to an extending measure of applications, particularly resulting to the ascent of social platforms and social media. Regardless, execution of existing strategies on real-world images is still fundamentally missing, especially when considered the immense bounced in execution starting late reported for the related task of face acknowledgment. In this paper we exhibit that by learning representations through the use of significant Convolutional Neural Systems (CNN), a huge augmentation in execution can be acquired on these errands. To this end, we propose a direct Convolutional Neural System engineering can be used despite when the measure of learning data is limited. We survey our procedure on the recent Adience benchmark for age and gender estimation and demonstrate it to radically outflank current state-of-the-art methods.

Keywords: Age Estimation; Gender Recognition; Classification; Human Face; Neural Network.

I. INTRODUCTION

Age and gender assume essential parts in social between activities. Dialects hold distinctive greetings and grammar rules for men or women, and frequently diverse vocabularies are utilized while tending to senior citizens compared to youngsters [1]. In spite of the essential parts these characteristics play in our everyday lives, the capacity to consequently assess them precisely and dependably from face image is still a long way from addressing the requirements of business applications. This is especially puzzling while considering late claims to super-human capacities in the related errand of face recognition. (e.g. [48]).

Past ways to deal with assessing or ordering these properties from face images have depended on contrasts in facial feature dimensions [29] or "customized" face descriptors (e.g., [10, 15, 32]). Most have utilized characterization plans composed especially for age or gender orientation estimation undertakings, including [4] and others. Few of these past strategies were intended to handle the numerous difficulties of unconstrained imaging conditions [10]. In addition, the machine learning strategies utilized by these frameworks did not completely abuse the huge quantities of image cases and information accessible through the Internet keeping in mind the end goal to enhance characterization capacities.

In this paper we endeavour to close the gap between automatic face recognition abilities and those of age and gender classification techniques. To this end, we take after the fruitful sample set around late face recognition frameworks: Face recognition systems portrayed in the most recent couple of years have demonstrated that gigantic advancement can be made by the utilization of profound convolutional neural networks (CNN) [31]. We show comparative additions with basic system engineering, composed by considering the somewhat constrained accessibility of precise age and gender classification names in existing face information sets.

II. Related Work

Before depicting the proposed strategy we brief review related systems for age and gender classification and give an outline of significant convolutional networks.

A. *Age and Gender Classification*

Age Classification: The issue of consequently extricating age related traits from facial images has got expanding consideration as of late and numerous strategies have been put forth. A point by point overview of such strategies can be found in [11] and, all the more as of late, in [21]. We take note of that regardless of our attention here on age group characterization as opposed to exact age estimation (i.e., age regression), the study incorporates strategies intended for either undertaking. Early techniques for age estimation depend on ascertaining proportions between various estimations of facial features [29]. When facial features (e.g. eyes, nose, mouth, jaw, and so forth.) are confined, their sizes and separations are measured, proportions between them are ascertained and utilized for arranging the face into various age classifications as indicated by hand-made principles [12]. All the more as of late, [41] utilizations a comparative way to deal with model age movement in subjects less than 18 years of age [22]. As those techniques require precise restriction of facial elements, testing issues are independent from anyone else, they are unacceptable for in-the-wild images which one might hope to discover on social platform.

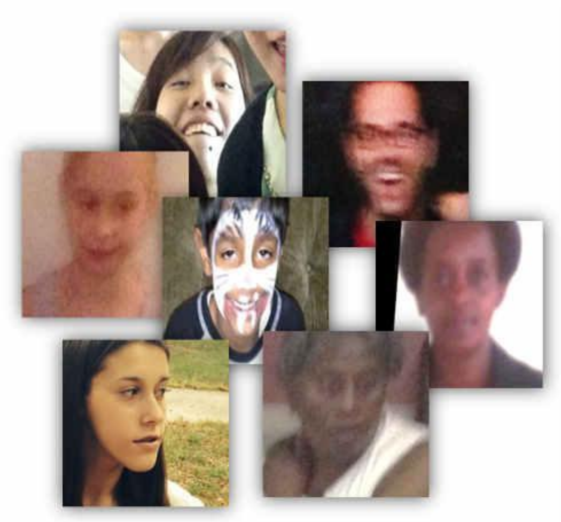


Fig. 1 Faces from the Adience benchmark for age and gender classification [10]

On a substitute calling are strategies that address the developing procedure as a subspace [16] or a complex [19]. An impediment of those systems is that they require information about the image to be close frontal and all that much balanced. These systems in like manner present test comes to fruition just on constrained data sets of close frontal images (e.g UIUC-IFP-Y [12, 19], FG-NET [30] and MORPH [43]). Again, accordingly, such strategies are ill-suited for unconstrained images. Not exactly the same as those depicted above are methods that usage adjacent components for identifying with face images. In [55] Gaussian Mixture Models (GMM) [13] were used to the scattering of facial patches. In [54] GMM were used again to speak to the scattering of close-by facial estimations, however effective descriptors were used as opposed to pixel patches. Finally, instead of GMM, Hidden-Markov-Model, super-vectors [40] was used as a piece of [56] face patch transports.

A different option for the neighbourhood image force patches are vigorous image descriptors: Gabor image descriptors [32] were utilized as a part of [15] alongside a Fuzzy-LDA classifier which considers a face images as fitting in with more than one age class. In [20] a blend of Biologically-Inspired Features (BIF) [44] and different complex learning techniques were utilized for age estimation. Gabor [32] and nearby twofold examples (LBP) [1] components were utilized as a part of [7] alongside a various leveled age classifier made out of Support Vector Machines (SVM) [9] to order the info image to an age-class took after by a bolster vector relapse [52] to appraise an exact age. At last, [4] proposed enhanced forms of important part investigation [3] and locally safeguarding projections [36]. Those techniques are utilized for separation learning and dimensionality diminishment, separately, with Active Appearance Models [8] as an image highlight. These techniques have demonstrated successful on little and/or obliged benchmarks for age estimation [26]. As far as anyone is concerned, the best performing techniques were shown on the Group Photos benchmark [14]. In [10] best in class execution on this benchmark was exhibited by utilizing LBP descriptor varieties [53] and a dropout-SVM classifier. We demonstrate our proposed technique to beat the outcomes they give an account of all more difficult Adience benchmark Fig. 1, intended for the same errand.

Gender Classification: A point by point study of gender classification arrangement techniques can be found in [34] and all the more as of late in [42]. Here we rapidly review significant strategies. One of the early techniques for gender classification characterization [17] utilized a neural network system prepared on a little arrangement of close frontal face images. In [37] the consolidated 3D structure of the head (acquired utilizing a laser scanner) and image intensities were utilized for grouping gender classification. SVM classifiers were utilized by [35], connected specifically to image intensities. Instead of utilizing SVM [2], utilized AdaBoost for the same reason, here once more, connected to image intensities. At long last, perspective invariant age and gender classification characterization was presented by [49]. All the more as of late, [51] utilized the Webers Local composition Descriptor [6] for gender classification acknowledgment, exhibiting close immaculate execution on the FERET benchmark [39]. In [38], power, shape and surface elements were utilized with shared data, again getting close immaculate results on the FERET benchmark.

A large portion of the strategies talked about the above utilized FERET benchmark [39] both to build up the proposed frameworks and to assess exhibitions. FERET images were taken under profoundly controlled condition and are along these lines considerably less difficult than in-the-wild face images. In addition, the outcomes got on this benchmark propose that it is soaked and not trying for present day strategies. It arrives fore hard to appraise the genuine relative advantage of these methods. As an outcome, [46] probed the prominent Labelled Faces in the Wild (LFW) [25] benchmark, basically utilized for face acknowledgment. Their technique is a blend of LBP components with an AdaBoost classifier. Likewise with age estimation, here as well, we concentrate on the Adience set which contains images more difficult than those gave by LFW, reporting execution utilizing a heartier framework, intended to better adventure data from monstrous illustration preparing sets.

B. *Deep Convolutional Neural Networks*

One of the primary utilizations of convolutional neural networks (CNN) is maybe the LeNet-5 system depicted by [31] for optical character acknowledgment. Contrasted with current profound CNN, their system was generally humble because of the restricted computational assets of the time and the algorithmic difficulties of preparing greater systems. In spite of the fact that much potential laid in more profound CNN designs (systems with more neuron layers), just as of late have they got to be predominant, after the emotional increment in both the computational force, the measure of preparing information promptly accessible on the Internet, and the improvement of more viable techniques for preparing such complex models. One later and remarkable case is the utilization of profound CNN for image classification based on the testing Image net benchmark [28]. Profound CNN have moreover been effectively connected to applications including human posture estimation [50], face parsing [33], facial key point identification [47], discourse acknowledgment [18] and activity characterization [27].

III. A CNN FOR AGE AND GENDER ESTIMATION

Gathering a substantial, marked image preparing set for age and gender estimation from social network image archives requires either access to individual data on the subjects showing up in the images, which is regularly private, or is tedious to physically name [28]. Information sets for age and gender estimation from true social network images are in this way moderately constrained in size and in a matter of seconds no match in size with the much larger image arrangement information sets (e.g. the Image net dataset [45]). Over fitting is normal issue, when machine learning construct strategies are utilized as a part of image accumulations. This issue is exacerbated while considering profound convolutional neural network systems because of their enormous quantities of model parameters. Care should in this way be taken with a specific end goal to stay away from over fitting under such circumstances.

A. *Network Architecture*

Our proposed system design is utilized all through our tests for both age and gender classification order. It is delineated in Fig. 2. The system contains just three convolutional layers and two completely associated layers with little number of neurons. This, by correlation with the much bigger models connected, for instance, in [28] and [5]. Our decision of a system outline is spurred both from our longing to lessen the danger of over fitting and in addition the way of the issues we are endeavoring to unravel: age grouping on the Adience set requires recognizing eight classes; gender classification needs just two classes [52]. This contrasted with, e.g., the ten thousand personality classes used to prepare the system utilized for face acknowledgment as a part of [48].

Each of the three shading channels is handled specifically by the system. Images are initially rescaled to 256 × 256 and a product of 227×227 is bolstered to the system. The three ensuing convolutional layers are then characterized as takes after.

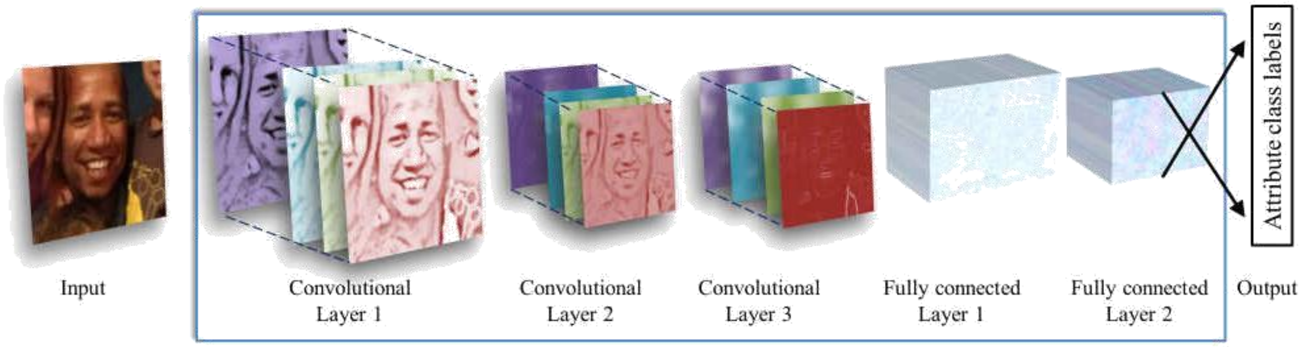


Fig. 2 Illustration of CNN architecture for age and gender classification

B. *Testing and Training*

Initialization:

1. 96 channels of size 3×7×7 pixels are connected to the information in the primary convolutional layer, trailed by an amended straight administrator (ReLU), a maximum pooling layer taking the maximal estimation of 3 × 3 areas with two-pixel strides and a nearby reaction standardization layer [28].

2. The 96 × 28 × 28 yield of the past layer is then handled by the second convolutional layer, containing 256 channels of size 96 × 5 × 5 pixels. Once more, this is trailed by ReLU, a maximum pooling layer and a local reaction standardization layer with the same hyper parameters as some time recently.

3. Finally, the third and keep going convolutional layer works on the 256 × 14 × 14 blob by applying an arrangement of 384 channels of size 256 × 3 × 3 pixels, trailed by ReLU and a maximum pooling layer.

The accompanying completely associated layers are then characterized by:

4. A first completely associated layer that gets the yield of the third convolutional layer and contains 512 neurons, trailed by a ReLU and a dropout layer.

5. A second completely associated layer that gets the 512-dimensional yield of the main completely associated layer and again contains 512 neurons, trailed by a ReLU and a dropout layer.

6. A third, completely associated layer which maps to the last classes for age or gender classification. At long last, the yield of the last completely associated layer is encouraged to a delicate max layer that doles out likelihood for every class. The forecast itself is made by bringing the class with the maximal likelihood for the given test image.

The weights in all layers are instated with irregular qualities from a zero mean Gaussian with standard deviation of 0.01. To stretch this, we don't utilize pre-prepared models for instating the system; the system is prepared, starting with no outside help, without utilizing any information outside of the images and the makes accessible by the benchmark. This, once more, ought to be contrasted and CNN executions utilized for face acknowledgment, where countless images are utilized for preparing [48].

Network Training:

Beside our utilization of incline system design, we apply two extra strategies as far as possible the danger of over fitting. To start with we apply dropout learning [24] (i.e. randomly setting the output value of network neurons to zero). The system incorporates two dropout layers with a dropout proportion of 0.5 (half risk of setting a neuron's yield worth to zero). Second, we utilize information growth by taking an arbitrary product of 227 × 227 pixels from the 256 × 256 image data and arbitrarily reflect it in each forward-backward training pass. This, likewise to the different yield and reflect varieties utilized by [48].

Prediction:

We tried different things with two techniques for utilizing the system as a part of request to create age and gender predictions for novel countenances:

- *Center Crop*: Feeding the system with the face image, edited to 227 × 227 around the face focus.
- *Over-Sampling*: We separate five 227 × 227 pixel crop districts, four from the sides of the 256 × 256 face image, and an extra yield area from the focal point of the face. The system is given every one of the five images, alongside their flat reflections. Its last forecast is taken to be the normal expectation esteem over every one of these varieties.

We have found that little misalignments in the Adience images, brought on by the numerous difficulties of these images (impediments, movement obscure, and so forth.) can noticeably affect the nature of our outcomes. This second, over-testing strategy is intended to adjust for these misalignments, bypassing the requirement for enhancing arrangement quality, yet rather specifically bolstering the system with different interpreted adaptations of the same face.

IV. Experiment

The Adience benchmark: We test the precision of our CNN plan utilizing the as of late discharged Adience benchmark [10], intended for age and gender classification. The Adience image set comprises of images consequently transferred to Flickr from PDA gadgets. Since these images were transferred without former manual sifting, as is ordinarily the case on media site pages (e.g., images from the LFW gathering [25]) or social network sites (the Group Image set [14]), the conditions in these images are exceedingly unconstrained, reflecting a significant number of this present difficulties of confronts showing up in networking images. Adience images along these lines catch compelling varieties in head posture, lightning conditions quality, and the sky is the limit from there.

The whole Adience image set gathering incorporates around 26K images of 2,284 subjects. Table 1 records the breakdown of the accumulation into the distinctive age classifications. Testing for both age and gender is performed utilizing a standard five-fold, subject-selective cross-approval convention, characterized in [10]. We utilize the in-plane adjusted adaptation of the countenances, initially utilized as a part of [10]. These images are utilized as opposed to more up to date arrangement procedures so as to highlight the execution pick up ascribed to the system design, as opposed to better pre-processing.

TABLE I
The Adience Faces Benchmark

Gender /Years	0-2	4-6	8-13	15-20	25-32	38-43	48-53	60-	Total
Male	745	928	934	734	2308	1294	392	442	8192
Female	682	1234	1360	919	2589	1056	433	427	9411
Both	1427	2162	2294	1653	4897	2350	825	869	19587

 ISSN: 2321-7782 (Online)

We test the time with same system design and utilized for all test folds of the benchmark and indeed, for both gender and age estimation assignments. This is performed with a specific end goal to guarantee the legitimacy of our outcomes crosswise over folds, additionally to show the sweeping statement of the system plan proposed here; the same engineering performs well crosswise over various, related issues. We contrast beforehand reported results with the outcomes processed by our system. Our outcomes incorporate two techniques for testing: center crop and over-sampling.

V. Results

Table 2 shows our outcomes for gender and age classification separately. Table 3 further gives a confusion matrix to our multi-class age grouping results. For age arrangement, we measure and look at both the exactness when the calculation gives the precise age-bunch order and when the algorithm is off by one nearby age-bunch (i.e., the subject fits in with the gathering instantly more seasoned or quickly more youthful than the anticipated gathering). This tails other people who have done as such before, and reflecting the instability natural to the errand – facial components frequently change next to no between most seasoned countenances in one age class and the most youthful appearances of the consequent class.

Both tables contrast execution and the strategies depicted in [10]. Table 2 additionally gives a correlation [23] which utilized the same gender classification pipeline of [10] connected to more compelling arrangement of the countenances; faces in their tests were artificially adjusted to show up confronting forward. Clearly, the proposed strategy beats the reported cutting edge on both assignments with impressive considerable gaps. Likewise, obvious is the commitment of the over-examining approach, which gives an extra execution support over the first system. This suggests better arrangement (e.g., frontalization [22, 23]) might give an extra support in execution.

The result of the age and gender estimated using the Conventional Neural Network (CNN) is shown in Fig. 3 and Fig. 4 respectively. We give a couple of samples of both gender and age misclassifications in Fig. 5 and Fig. 6, separately. These demonstrate that a large number of the errors made by our framework are because of a great degree testing seeing states of a percentage of the Adience benchmark images. Most outstanding are mix-ups brought on by obscure or low determination and impediments (especially from substantial cosmetics). Gender estimation confuses likewise habitually happen for images of infants or exceptionally youthful kids where evident gender traits are not yet noticeable.

TABLE II
Gender Estimation Results on the Adience Benchmark

Method	**Accuracy**
Support Vector Machine [10]	77.8±1.3
3D face shape estimation [23]	79.3±0.0
Proposed using single crop	85.9±1.4
Proposed using over-fitting	86.8±1.4

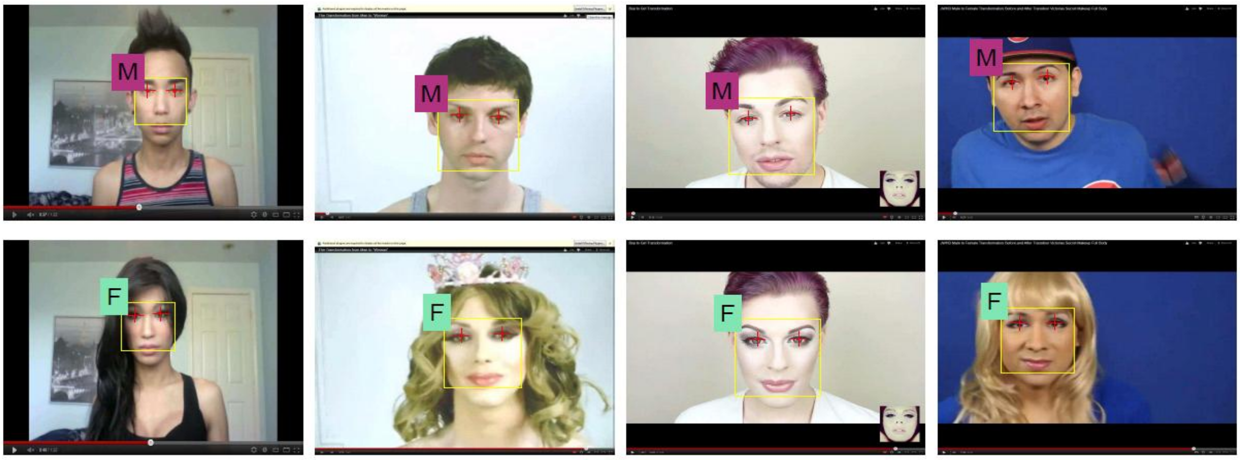
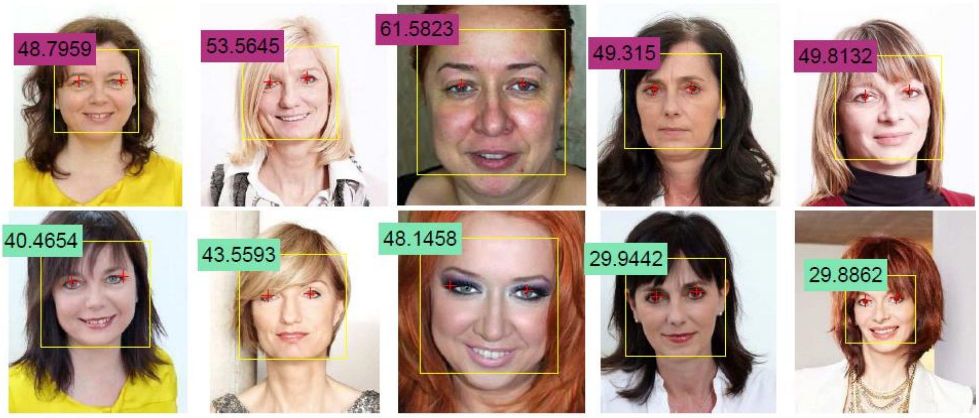


Fig. 1 The results of Automatic gender recognition using the proposed approach



(b) Fig. 4 The results of Automatic age estimation using the proposed approach

Fig. 5 Gender misclassifications. Top row: Female subjects mistakenly classified as males. Bottom row: Male subjects mistakenly classified as females

Fig. 6 Age misclassifications. Top row: Older subjects mistakenly classified as younger. Bottom row: Younger subjects mistakenly classified as older

TABLE III
Age Estimation Confusion Matrix on the Adience Benchmark

Age Range in Years	0-2	4-6	8-13	15-20	25-32	38-43	48-53	60-
0-2	**0.669**	0.147	0.028	0.006	0.005	0.008	0.007	0.009
4-6	0.256	**0.573**	0.166	0.023	0.010	0.011	0.010	0.005
8-13	0.027	0.223	**0.552**	0.150	0.091	0.068	0.055	0.061
15-20	0.003	0.019	0.081	**0.239**	0.106	0.055	0.049	0.028
25-32	0.006	0.029	0.138	0.510	**0.613**	0.461	0.260	0.108
38-43	0.004	0.007	0.023	0.058	0.149	**0.293**	0.339	0.268
48-53	0.002	0.001	0.004	0.007	0.017	0.055	**0.146**	0.165
60-	0.001	0.001	0.008	0.007	0.009	0.050	0.134	**0.357**

VI. CONCLUSION

In spite of the fact that numerous past techniques have tended to the issues of age and gender grouping, as of not long ago, quite a bit of this work has concentrated on obliged images taken in lab settings. Such settings don't sufficiently reflect appearance varieties normal to this present reality images in social networking sites and online archives. Web images, how-ever, are not just all the more difficult: they are likewise bounteous. The simple accessibility of tremendous image accumulations master videos advanced machine learning based frameworks with viably perpetual preparing information, however this information is not generally suitably named for directed learning.

Taking illustration from the related issue of face acknowledgment, we investigate how well profound CNN perform on these assignments utilizing Internet information. We provide results with an incline profound learning architecture designed to keep away from over fitting because of the impediment of constrained marked information. Our system is "shallow" contrasted with a portion of the late system designs, along these lines diminishing the quantity of its parameters and the chance for over fitting. We advance swell the extent of the preparation information by falsely including trimmed variants of the images in our preparation set. The subsequent framework was tried on the Adience benchmark of unfiltered images and appeared to fundamentally beat late cutting edge.

Two critical conclusions can be produced using our experimental outcomes. In the first place, CNN can be utilized to give enhanced age and gender arrangement results, notwithstanding considering the much little size of contemporary unconstrained image sets named for age and gender classification. Second, the straight forwardness of our model suggests that more involved frameworks utilizing all the more preparing information might well be able to do significantly enhancing results beyond the one reported here.

References

1. T. Ahonen, A. Hadid, and M. Pietikainen. “Face description with local binary patterns: Application to face recognition”, Trans. Pattern Anal. Mach. Intell., 28(12):2037–2041, 2006.
2. S. Baluja and H. A. Rowley. “Boosting sex identification performance”, Int. J. Comput. Vision, 71(1):111–119, 2007.
3. A. Bar-Hillel, T. Hertz, N. Shental, and D. Weinshall. “Learning distance functions using equivalence relations”, In Int. Conf. Mach. Learning, volume 3, pages 11–18, 2003.
4. W.L. Chao, J.-Z. Liu, and J.-J. Ding. “Facial age estimation based on label-sensitive learning and age-oriented regression”, Pattern Recognition, 46(3):628–641, 2013. 1, 2
5. K. Chatfield, K. Simonyan, A. Vedaldi, and A. Zisserman. “Return of the devil in the details: Developing deep into convolutional nets”, arXiv preprint arXiv:1405.3531, 2014.
6. J. Chen, S. Shan, C. He, G. Zhao, M. Pietikainen, X. Chen, and W. Gao. Wld: “A robust local image descriptor”, Trans. Pattern Anal. Mach. Intell.,

32(9):1705–1720, 2010.

7. S. E. Choi, Y. J. Lee, S. J. Lee, K. R. Park, and J. Kim. "Age estimation using a hierarchical classifier based on global and local facial features", Pattern Recognition, 44(6):1262–1281, 2011. 2
8. T. F. Cootes, G. J. Edwards, and C. J. Taylor. "Active appearance models", In European Conf. Comput. Vision, pages 484–498. Springer, 1998.
9. C. Cortes and V. Vapnik. "Support-vector networks", Machine learning, 20(3):273–297, 1995.
10. E. Eidinger, R. Enbar, and T. Hassner. "Age and gender estimation of unfiltered faces", Trans. on Inform. Forensics and Security, 9(12), 2014.
11. Y. Fu, G. Guo, and T. S. Huang. "Age synthesis and estimation via faces: A survey", Trans. Pattern Anal. Mach. Intell., 32(11):1955–1976, 2010.
12. Y. Fu and T. S. Huang. "Human age estimation with regression on discriminative aging manifold", Int. Conf. Multimedia, 10(4):578–584, 2008.
13. K. Fukunaga. "Introduction to statistical pattern recognition", Academic press, 1991.
14. A. C. Gallagher and T. Chen. "Understanding images of groups of people", In Proc. Conf. Comput. Vision Pattern Recognition, pages 256–263. IEEE, 2009.
15. F. Gao and H. Ai. "Face age classification on consumer images with gabor feature and fuzzy LDA method", In Advances in biometrics, pages 132–141. Springer, 2009.
16. X. Geng, Z.-H. Zhou, and K. Smith-Miles. "Automatic age estimation based on facial aging patterns", Trans. Pattern Anal. Mach. Intell., 29(12):2234–2240, 2007.
17. B. A. Golomb, D. T. Lawrence, and T. J. Sejnowski. Sexnet: "A neural network identifies sex from human faces", In Neural Inform. Process. Syst., pages 572–579, 1990.
18. A. Graves, A.-R. Mohamed, and G. Hinton. "Speech recognition with deep recurrent neural networks", In Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE Inter-national Conference on, pages 6645–6649. IEEE, 2013.
19. G. Guo, Y. Fu, C. R. Dyer, and T. S. "Huang. Image-based human age estimation by manifold learning and locally adjusted robust regression", Trans. Image Processing, 17(7):1178–1188, 2008. 2
20. G. Guo, G. Mu, Y. Fu, C. Dyer, and T. Huang. "A study on automatic age estimation using a large database", In Proc. Int. Conf. Comput. Vision, pages 1986–1991. IEEE, 2009.
21. H. Han, C. Otto, and A. K. Jain. "Age estimation from face images: Human vs. machine performance", In Biometrics (ICB), 2013 International Conference on. IEEE, 2013.
22. T. Hassner. "Viewing real-world faces in 3D", In Proc. Int. Conf. Comput. Vision, pages 3607–3614. IEEE, 2013.
23. T. Hassner, S. Harel, E. Paz, and R. Enbar. "Effective face frontalization in unconstrained images", Proc. Conf. Comput. Vision Pattern Recognition, 2015.
24. G. E. Hinton, N. Srivastava, A. Krizhevsky, I. Sutskever, and R. R. Salakhutdinov. "Improving neural networks by pre-venting co-adaptation of feature detectors", arXiv preprint arXiv:1207.0580, 2012.
25. 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", Technical re-port, Technical Report 07-49, University of Massachusetts, Amherst, 2007.
26. Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Gir-shick, S. Guadarrama, and T. Darrell. "Caffe: Convolutional architecture for fast feature embedding", arXiv preprint arXiv:1408.5093, 2014.
27. A. Karpathy, G. Toderici, S. Shetty, T. Leung, R. Sukthankar, and L. Fei-Fei. "Large-scale video classification with convolutional neural networks", In Proc. Conf. Comput. Vision Pattern Recognition, pages 1725–1732. IEEE, 2014.
28. A. Krizhevsky, I. Sutskever, and G. E. Hinton. "Image-net classification with deep convolutional neural networks", Neural Inform. Process. Syst., pages 1097–1105, 2012.
29. Y. H. Kwon and N. da Vitoria Lobo. "Age classification from facial images", In Proc. Conf. Comput. Vision Pattern Recognition, pages 762–767. IEEE, 1994.
30. A. Lanitis. "The FG-NET aging database, 2002", Available: www-prima.inrialpes.fr/FGnet/html/ benchmarks.html.
31. Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel. "Back-propagation applied to handwritten zip code recognition", Neural computation, 1(4):541–551, 1989.
32. C. Liu and H. Wechsler. "Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition", Trans. Image Processing, 11(4):467–476, 2002.
33. P. Luo, X. Wang, and X. Tang. "Hierarchical face parsing via deep learning", In Proc. Conf. Comput. Vision Pattern Recognition, pages 2480–2487. IEEE, 2012.
34. E. Makinen and R. Raisamo. "Evaluation of gender classification methods with automatically detected and aligned faces", Trans. Pattern Anal. Mach. Intell., 30(3):541–547, 2008.
35. B. Moghaddam and M.-H. Yang. "Learning gender with support faces", Trans. Pattern Anal. Mach. Intell., 24(5):707– 711, 2002.
36. X. Niyogi. "Locality preserving projections", In Neural In-form. Process. Syst., volume 16, page 153. MIT, 2004.
37. A. J. O'toole, T. Vetter, N. F. Troje, H. H. Bulthoff,¨ et al. "Sex classification is better with three-dimensional head structure than with image intensity information", Perception, 26:75–84, 1997.
38. C. Perez, J. Tapia, P. Estevez,´ and C. Held. "Gender classification from face images using mutual information and feature fusion", International Journal

of Optomechatronics, 6(1):92– 119, 2012.

39. P. J. Phillips, H. Wechsler, J. Huang, and P. J. Rauss. "The FERET database and evaluation procedure for face-recognition algorithms", Image and vision computing, 16(5):295–306, 1998.
40. L. Rabiner and B.-H. Juang. "An introduction to Hidden Markov Models", ASSP Magazine, IEEE, 3(1):4–16, 1986.
41. N. Ramanathan and R. Chellappa. "Modeling age progression in young faces", In Proc. Conf. Comput. Vision Pattern Recognition, volume 1, pages 387–394. IEEE, 2006.
42. D. Reid, S. Samangooei, C. Chen, M. Nixon, and A. Ross. "Soft biometrics for surveillance: an overview", Machine learning: theory and applications. Elsevier, pages 327–352, 2013.
43. K. Ricanek and T. Tesafaye. "Morph: A longitudinal image database of normal adult age-progression", In Int. Conf. on Automatic Face and Gesture Recognition, pages 341–345. IEEE, 2006.
44. M. Riesenhuber and T. Poggio. "Hierarchical models of object recognition in cortex", Nature neuroscience, 2(11):1019– 1025, 1999.
45. O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei. "Image Net Large Scale Visual Recognition Challenge", 2014.
46. C. Shan. "Learning local binary patterns for gender classification on real-world face images", Pattern Recognition Letters, 33(4):431–437, 2012.
47. Y. Sun, X. Wang, and X. Tang. "Deep convolutional network cascade for facial point detection", In Proc. Conf. Comput. Vision Pattern Recognition, pages 3476–3483. IEEE, 2013.
48. Y. Sun, X. Wang, and X. Tang. "Deep learning faces representation from predicting 10,000 classes", In Proc. Conf. Com-put. Vision Pattern Recognition, pages 1891–1898. IEEE, 2014.
49. M. Toews and T. Arbel. "Detection, localization, and sex classification of faces from arbitrary viewpoints and under occlusion", Trans. Pattern Anal. Mach. Intell., 31(9):1567–1581, 2009.
50. A. Toshev and C. Szegedy. Deeppose: "Human pose estimation via deep neural networks", In Proc. Conf. Comput. Vision Pattern Recognition, pages 1653–1660. IEEE, 2014.
51. I. Ullah, M. Hussain, G. Muhammad, H. Aboalsamh, G. Be-bis, and A. M. Mirza. "Gender recognition from face images with local world descriptor", In Systems, Signals and Image Processing, pages 417–420. IEEE, 2012.
52. V. N. Vapnik and V. Vapnik. "Statistical learning theory", volume 1. Wiley New York, 1998.
53. L. Wolf, T. Hassner, and Y. Taigman. "Descriptor based methods in the wild", In post-ECCV Faces in Real-Life Images Workshop, 2008.
54. S. Yan, M. Liu, and T. S. Huang. "Extracting age information from local spatially flexible patches", In Acoustics, Speech and Signal Processing, pages 737–740. IEEE, 2008.
55. S. Yan, X. Zhou, M. Liu, M. Hasegawa-Johnson, and T. S. Huang. "Regression from patch-kernel", In Proc. Conf. Com-put. Vision Pattern Recognition. IEEE, 2008.
56. X. Zhuang, X. Zhou, M. Hasegawa-Johnson, and T. Huang. "Face age estimation using patch-based Hidden Markov Model super vectors", In Int. Conf. Pattern Recognition. IEEE, 2008.

 ISSN: 2321-7782 (Online)