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AGE ESTIMATION AND GENDER CLASSIFICATION TECHNIQUES USING CNN: A SURVEY

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ABSTRACT
Now a day's Researchers have given more interest in soft biometrics area to fill the communication gaps between humans and machines. Soft-biometric consists of age, gender (sex), ethnicity, height, facial measurements and etc. The real- world application of computer vision has grown in recent years. This survey paper contains a detailed discussion about the contribution of the researchers in the area of age estimation and gender classification using CNN (Convolutional Neural Network). Different neural network model features, such as datasets, methodology, discoveries, accuracy measures, and results, are presented for further research. In this survey paper, we also reviewed various age and gender recognition strategies and summarize the tasks for future research aspects.

KEYWORDS— ***Soft Biometrics, Neural Network, CNN, Computer Vision, Gender recognition, Age estimation***

1. INTRODUCTION

Understanding age and gender from the human face plays an important role in social interaction. A human face can reveal details such as age, gender, emotions, ethnicity, and more. It is influenced by a range of dynamic qualities that change over time, such as age, hairstyle, facial hair, and expressions. Age and Gender are significant characteristics for identifying humans. Biometric recognition refers to the process of gathering data on a person's physiological and behavioural features for the purposes of identification and verification. Biometrics contains soft biometric (age, gender, ethnicity, height and facial measurements) and hard biometric (Physical, behavioural and biological). Soft biometric attributes such as skin color, hair color, facial hair, distance between eye and nose, face shape, and so on. It can be used to categorize unlabeled data based on age and gender.

Changes in the face caused by ageing have a greater impact on facial recognition systems. This idea is critical for the advancement of a new field of computer vision research. The age estimation procedure is widely used to find trends and variances, as well as to establish the best approach for estimating the numerous characteristics that must be considered.

Another characteristic is gender. Automatic gender classification is critical for a variety of applications, including surveillance and targeted advertising. This is done to differentiate between male and female based on physical traits.

Before deep neural network era, several approaches like local binary patterns (LBP), support vector machine (SVM), biologically inspired features (BIF), Principal Component Analysis (PCA), Histogram Analysis and Canonical Correlation Analysis (CCA) were used to estimate age and gender from face images. Deep CNNs are now achieving remarkable success in object categorization [1]. Now a day's Deep CNNs Model accomplishes high accuracy in age estimation and Gender Classification [2].

This literature elaborates on description and comparisons done by the author on numerous variables such as age and gender. Furthermore, the different approaches for extracting characteristics, classification, methodology used and evaluation for crucial research knowledge. This enables enthusiastic researchers to enroll in deep learning components of classifying age and gender through human face images.

2. AGE AND GENDER CLASSIFICATION CHALLENGES

The primary goal of age and gender classification is to predict age and gender for each individual based on face images captured by a camera and demographic data. This paper discusses the methods for predictions of age and gender based features extraction from human facials images [3]. It can be used to increase authentication accuracy using soft biometric approaches, improve user experience in gaming and mobile phone applications, recognize lost persons, and recognize aged people for identification purposes using past photographs.

Children's access to inappropriate information on televisions and the Internet can be limited by age classification. In terms of security and surveillance, prohibiting children's access to adult vending machines such as (alcohol and cigarettes) and adult websites and movies, as well as monitoring for fraud detection. Security control, surveillance monitoring, and targeted marketing systems have all lately included automatic face detection, tracking, and classification into their systems [4].

There are numerous issues with age and gender classification. It is difficult for machines to classify age and gender. As of today, several models have been created based on additional facial information such as hairstyle, body shape, facial hair, clothing and facial features etc. Accurate age grouping is still difficult to predict. Furthermore, good and relevant datasets for age and gender classification are limited. The images of dataset cover large variation in pose, facial expression, illumination, occlusion, resolution, etc.

3. CNN (CONVOLUTIONAL NEURAL NETWORK)

CNN models have been used in a many studies on age and gender classification models. CNN models are made up of different weights for each hidden neuron, which are expressed mathematically as a multi-dimensional matrix. CNN frameworks are built using a variety of layers, including narrow layers, sub sample layers, and fully connected layers. These layers are CNN building blocks that perform the basic function of convolution. Sub layers are utilized to control over fitting by reducing parameters and size through the use of max pooling. The fully connected layer of neurons that map to all of the activation functions of the previous layers. Also, an additional RELU layer is employed in CNN to implement the non-purity function and correction. Several CNN architectures have been proposed by researchers to classify age and gender, such as: AlexNet, ZFNet, VGG19, GoogleNet, ResNet, DenseNet etc.

Designing and testing models is costly and time-consuming due to the vastness and complexity of deep neural network architecture. When tackling an AI problem, a technique called as transfer learning might yield speedy results [5]. Transfer learning allows weights and Convolutional filters that are proficient at one task, can be reused for a different task requiring only a small amount of retraining. This entails taking a network design with preloaded weights, significantly altering it, and then retraining a portion or the entire model to generate predictions for the new task. The filters learned by one task, are used to extract features from images that can then be interpreted by the retrained portion of the neural network in order to perform its new task. Experiments will show that the transfer learning can efficiently adapt pre-trained networks to new unseen data [6].

4. AGE AND GENDER CLASSIFICATION BASED ON CNN

A review of the literature on gender and age classification of facial images using neural networks has been recorded and described as given below (TABLE 1).

TABLE-1:LITERATURE SURVEY

Sr. No	Paper Title	Year	Published In	References	Methodology	Dataset used	Tools and Technologies used	Results	Future Enhancement
1	Age and Gender Classification using Convolutional Neural Networks	2015	IEEE	Gil Levi et al. [7]	A new Deep CNN model for age and gender classification has been proposed. One output layer and three FC layers comprise the model. The neural network's output is dependent on the SoftMax layer, whose input is provided via the output of the previously associated layer.	Adience Benchmark	Caffe open-source Framework. Training was performed on an Amazon GPU Machine with 1,536 CUDA coresand 4GB of video memory.	The age Accuracy for proposed method is 85%.The gender accuracy For proposed method is 86%.	Elaborate systems usingmore trainingdata to Improve results.
2	Age group and Gender Estimation in the Wild with Deep ROR Architecture	2017	IEEE	Ke Zhang et al.[8]	A CNN-based approach for estimating age group and gender based on residual networks of residual networks(RoR) is proposed. This methodology consists primarily of four steps: Building RoR	ImageNet, IMDB-WIKI-101 and Adience	4c2f-CNN, VGG, Pre-ResNets, our Pre-RoR architectures	single-model accuracy of 66.91±2.51 %, and the 1-off accuracy of 97.49±0.76	Explores the application of RoR on large scale and high-resolution image

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					architecture, pre-training with gender and training with weighted loss layer to improve age group classification performance, pre-training on ImageNet and further tuning on IMDB-WIKI-101 data set to alleviate over fitting and improve model performance. In this model 64, 128, 256 and 512 filters were used in conversational layers.			% on Adience.	classifications.
3	Age Classification Using an Optimized CNN Architecture	2017	ResearchGate	M. Fatih Aydogdu et al. [9]	An optimised CNN architecture for the age categorization problem is proposed. A number of different CNN architectures are tested. The CNN architecture involving 4 Convolutional layers and 2 fully connected layers. It is found to be superior to the other CNN-based architectures with different number of layers based on the fitness of the age classification results in terms of success-error ratios, training times, and standard deviations of success rates; using exact, top-3, and 1-off criterion.	MORPH face database	CNN and NVIDIA Quadro K4000 192 bit GPU with 3GB memory.	Exact Success % of CNN with 2 Convolutional layers and 4 fully connected layers with respect to age classes is 46.39 %.	Plan to use larger datasets to perform more comprehensive tests.
4	Deep Age Estimation: From Classification to Ranking	2017	IEEE	Shixing Chen et al.[10]	Ranking CNN for age estimation is proposed. To create the final age estimation, the binary output of basic CNNs is combined. They created a substantially tighter error constraint for ranking-based age estimation from a theoretical perspective. Three theorems were proven: 1) reduce binary error, 2) softmax and ranking CNN are highly correlated and 3) for ranking CNN, specify a unique upper bound for precise error.	MORPH-2, FG - NET and Adience Faces benchmark	Uses a single GTX 980 graphics card (including 2,048 CUDA cores), i7 4790K CPU, 32GB RAM, and 2TB hard disk drive.	Ranking CNN estimates 89.90% for L = 6 and 92.93% for L = 7 and 2.96 for mean absolute error score.	Literature specific features were not manually selected but automatically selected by CNN ranking-model.
5	Age and Gender Recognition in the	2017	Science Direct	Rodriguex et al.[11]	Presents a feed forward strategy for age and gender recognition (1) Attention CNN	Adience, Imagesof	Tesla K40 GPU and a GTX TITAN GPU are used.	Adding attention results in 2.56 MAE,	Proposed model fails with the youngest

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	Wild with Deep Attention				("where"), which expects the best attention map to offer a glimpse, (2) a patch CNN ("what"), which is expected by the attention grid generated on its relevance, Evaluates high-resolution patches in conjunction with (3) a Multi-Layer Perceptron (MLP) that incorporates statistics extracted from CNNs before finalization.	Groups, and MORPH II	Models are optimized with sgd for 30 epochs, the learning rate is initially set to 0.0001 and divided by 10 every ten epochs.	a relative 4.47% improvement with respect to the state of the art.	ages, which are difficult to be distinguished even by humans. In future focus on that.
6	Age and Gender Classification Using Wide Convolutional Neural Network and Gabor Filter	2018	IEEE	Sepidehsadat Hosseini et al. [12]	A CNN-based architecture for combined age-gender classification is proposed, with Gabor filter responses utilised as input. Back-propagation in an end-to-end architecture is used to learn the weighting of Gabor-filter replies. Additionally, expanding the diameter of the neural network would improve overall system accuracy.	Adience dataset	Experiments have been done using five-fold subject exclusive protocol. Nvidia GeForce TX 1060 6G 192 GPU used for network.	Age accuracy is 61.3% and Gender accuracy is 88.9%	More useful features could be adopted.
7	Deep Facial Age Estimation Using Conditional Multitask Learning with Weak Label Expansion	2018	IEEE	ByungIn Yoo et al. [13]	A label expansion strategy is proposed that enhances the number of accurate labels from weakly supervised categorical labels. Conduct extensive tests on the publicly accessible MORPH-II and FG-NET datasets to test the generality of the proposed technique. This method confirmed by testing the performance benefits on well-known deep network designs such as VGG-16, CASIA-WebFace, and Alexnet.	MORPH-II, FG-NET and CASIA-WebFace	Experiments were run on K80 GPUs with a CAFFE framework	With Mean of 3.04	Improve the accuracy in predicting age.
8	A hybrid deep learning CNN–ELM for age and gender classification	2018	Elsevier	Mingxing Duan et al. [14]	Introduce a hybrid structure that includes two classifiers, Convolutional Neural Network (CNN) and Extreme Learning Machine (ELM) to cope with age and gender classification. CNN was used to extract features from the input photos, while ELM was used to	MORPH- II and Adience Benchmark	Method is implemented using the publicly available code of cuda – convent and Caffe . The whole networks was rained on a single GeForce GTX 750.	Proposed model gives 52.3% age accuracy and 88.2% gender accuracy.	Most of the errors caused by blur or low resolution and heavy makeup. In future resolve this mistakes.

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					classify the intermediate findings.				
9	Fine-Grained Age Estimation in the Wild with Attention LSTM Networks	2020	IEEE	Ke Zhang et al. [15]	Proposed an AL-ResNets and an AL-RoR architectures based on the attention LSTM network for the task of facial age estimation. The fine-grained age estimation approach learns the discriminative local characteristics of the age sensitive areas obtained by the attention LSTM unit efficiently. It improves performance by combining global and local features from target age datasets.	Adience, MORPH-2, FG-NET and 15/16LAP	Torch 7 with one NVIDIA GeForce GTX Titan X. And use scale and aspect ratio augmentation, for data augmentation. The learning rate is set to 0.001, and is divided by a factor of 10 after epoch 30.	Age classification results with AL-RoR-34 =65.77 % accuracy and 97.01% 1-off accuracy, AL-ResNets-34= 66.03% accuracy and 97.12% 1-off accuracy.	Improve the accuracy in predicting low age group.
10	GRA_Net: A Deep Learning Model for Classification of Age and Gender From Facial Images	2021	IEEE	Avishek Garain et al. [16]	Designed a deep learning based model, called GRA_Net (Gated Residual Attention Network), for the prediction of age and gender from the facial images. This is a modified and improved version of Residual Attention Network where they have included the concept of Gate in the architecture.	FG-Net, Wikipedia, AFAD, UTKFace And Adience DB	Used pre-activation Residual Unit and ResNet with gated activation as Gated Residual Attention Network's basic unit to construct Attention block.	Proposed model gives 65.1±2.1% age accuracy and 81.4±0.6 % gender accuracy with Adience dataset	Make the model more adept when images are obstructive, partially viewed, bearing hat/glass/wig, and wearing some unusual make-up etc.
11	Age, Gender Prediction and Emotion recognition using Convolutional Neural Network	2021	Elsevier	Arjun Singh et al.[17]	Proposed work has two models, one for age-gender prediction using wide resnet architecture and the other model is trained for emotion recognition using conventional CNN architecture. For age and Gender classification, Multi task learning (parallel learning) is used to avoid overfitting and training more than one task using shared structure.	IMDB-WIKI for age-gender and Fer 2013 dataset for emotion recognition	wide-resnet architecture and CNN	Accuracy of the wide-resnet model is 96.26% and for the emotion recognition model accuracy is 69.2%.	Entity recognition, the residual architecture can be more efficient by hyper parameter tuning, addition of more Convolutional layers per block.

5. DATASETS USED

Literature survey shows that most of the researcher used Adience Benchmark, IMDB-WIKI, MORPH II, FG-NET, IoG, CASIA-WebFace, 15/16LAP, AFAD, UTKFace databases for their research. All these databases contain facial images.

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Some popular datasets for facial recognition and analysis are given below.

- Adience Benchmark: It contains 26,580 images from 2,284 people, each with a binary gender label and eight age group labels.
- IMDB-WIKI: It is largest publicly available dataset of human faces with gender, age, and name. It has almost 500 thousand photos with all of the Meta information.
- MORPH-II: It is a facial age estimation dataset containing 55,134 facial photos of 13,617 people ranging in age from 16 to 77 years.
- FG-NET: It is a dataset for estimating age and recognizing faces across ages. It contains 1,002 images of 82 persons ranging in age from 0 to 69, with a 45-year age gap.
- IoG: Images of groups dataset contains 5,080 images containing 28,231 faces are labeled with age and gender. It contains labeled each face as being in one of seven age categories: 0-2, 3-7, 8-12, 13-19, 20-36, 37-65, and 66+.
- CASIA-WebFace: It is used for face verification and face identification tasks. This dataset contains 494,414 face images of 10,575 genuine people gathered from the internet.
- 15/16LAP: LAP is the labeled dataset which contains 7591 face images.
- AFAD: The Asian Face Age Dataset (AFAD) is a new dataset proposed for evaluating the performance of age estimation, which contains more than 160K facial images with age and gender labels.
- UTKFace: It is a large-scale face dataset with long age range from 0 to 116 years old. The dataset contains over 20,000 face images with age, gender, and ethnicity labels.

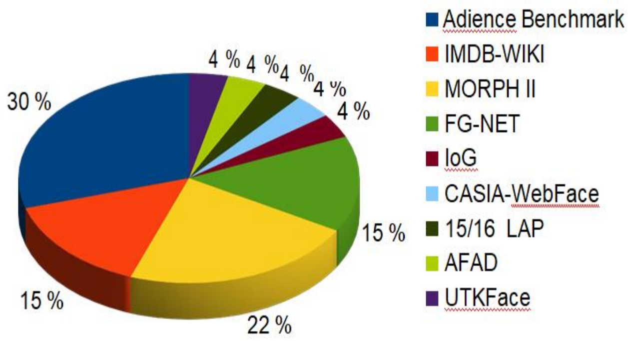

Fig-1: Datasets Popularity In (%)

6. DISCUSSION

Age and gender classification models from facial images using CNN-architecture have been done in the literature survey (Table 1). In a pie chart, the survey displays the ratio of databases used in various references (Fig 1). The Audience benchmark dataset is the most commonly used dataset.

The majority of the references used accuracy matrix to evaluate their work's performance. Accuracy can be achieved from the right sample of the population to regulate the precision and accurate the outcomes. Some references have used Mean Absolute Error (MAE), Mean Squared Error (MSE), 1-off accuracy and confusion matrix.

7. CONCLUSION AND FUTURE WORK

Overall, gender classification and age prediction research can be applied to solve real-time application challenges. Most Research analysis conducted in this paper were used Convolutional Neural Networks (CNN). All neural networks are formed with their MAE and MSE model accuracy. Furthermore, by separating a few functions, feature extraction is accomplished using a single element extractor or a one-time classifier, as well as countless additional works, fusion is performed to differentiate or extract attributes.

In future, we can continue to build the Convolutional neural network with transfer learning or encoder-decoder technique for age and gender classification to improve reliability. It will also affective for behavioral analysis, ethnicity estimation and demographic features etc. Also use the databases with 2D and 3D facial images.

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9. REFERENCES

1. *J. -H. Lee, Y. -M. Chan, T. -Y. Chen and C. -S. Chen, "Joint Estimation of Age and Gender from Unconstrained Face Images Using Lightweight Multi-Task CNN for Mobile Applications," 2018 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), Miami, FL, USA, 2018, pp. 162-165, doi: 10.1109/MIPR.2018.00036.*
2. *Mustapha, Muhammad & Mohamad, Nur & Osman, Ghazali & Hamid, Siti. (2021). "Age Group Classification using Convolutional Neural Network (CNN)." Journal of Physics: Conference Series. 2084. 012028, DOI:10.1088/1742-6596/2084/1/012028.*
3. *Carletti, A. Greco, G. Percannella, and M. Vento, "Age from Faces in the Deep Learning Revolution," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 42, no. 9, pp. 2113–2132, Sep. 2020.*
4. *Suu, Khaing & Sein, Myint. (2020), "Effective Marketing Analysis on Gender and Age Classification with Hyperparameter Tuning.", 247-248, DOI:10.1109/LifeTech48969.2020.1570616797.*
5. *P. Smith and C. Chen, "Transfer Learning with Deep CNNs for Gender Recognition and Age Estimation," 2018 IEEE International Conference on Big Data (Big Data), Seattle, WA, USA, 2018, pp. 2564-2571, doi: 10.1109/BigData.2018.8621891.*

6. *Dornaika, F., Arganda-Carreras, I. & Belver, C., "Age estimation in facial images through transfer learning", Machine Vision and Applications **30**, 177–187 (2019), doi:10.1007/s00138-018-0976-1.*
7. *Gil Levi and Tal Hassner, "Age and Gender Classification using Convolutional Neural Networks", Intelligence Advanced Research Projects Activity (IARPA) 2015.*
8. *Ke Zhang, Liru Guo, Miao Sun, Xingfang Yuan, TonyX. Han, Zhenbing Zhao and Baogang Li, "Age Group and Gender Estimation in the Wild with Deep RoR Architecture", IEEE Access COMPUTER VISION BASED ON CHINESE CONFERENCE ON COMPUTER VISION Volume 5 (CCCV) 2017.*
9. *M. Fatih Aydogdu and M. Fatih Demirci, "Age Classification Using an Optimized CNN Architecture", Association for Computing Machinery 2017.*
10. *Shixing Chen, Caojin Zhang and Ming Dong, "Deep Age Estimation: From Classification to Ranking", TRANSACTIONS ON MULTIMEDIA 2017.*
11. *Pau Rodrıguez, Guillem Cucurull, Josep M. Gonfaus, F. Xavier Roca, and Jordi Gonzale, "Age and Gender Recognition in the Wild with Deep Attention", Pattern Recognition 2017.*
12. *Sepidehsadat Hosseini, Seok Hee Lee, Hyuk Jin Kwon, Hyung Ii Koo and Nam Ik Cho, "Age and Gender Classification Using Wide Convolutional Neural Network and Gabor Filter", Institute for Information and communications Technology Promotion (IITP) 2018.*
13. *ByungIn Yoo, Youngjun Kwak, Youngsung Kim, Changkyu Choi and Junmo Kim, "Deep Facial Age Estimation Using Conditional Multitask Learning with Weak Label Expansion", SIGNAL PROCESSING LETTERS, VOL. 25, NO. 6 2018.*
14. *Mingxing Duan, Kenli Li, Canqun Yang and Keqin Li, "A hybrid deep learning CNN–ELM for age and gender classification", Neu-rocomputing 275 (448-461) 2018.*
15. *K. Zhang, N. Liu, X. Yuan, X. Guo, C. Gao, Z. Zhao, and Z. Ma, ``Fine-grained age estimation in the wild with attention LSTM networks,'' IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 9, pp. 31403152, Sep. 2020, doi: 10.1109/TCSVT.2019.2936410.*
16. *Garain, B. Ray, P. K. Singh, A. Ahmadian, N. Senu and R. Sarkar, "GRA_Net: A Deep Learning Model for Classification of Age and Gender From Facial Images," in , vol. 9, pp. 85672-85689, 2021, doi: 10.1109/ACCESS.2021.3085971.*
17. *Singh, Arjun, Nishant Rai, Prateek Sharma, Preeti Nagrath, and Rachna Jain, "Age, gender prediction and emotion recognition using convolutional neural network." Proceedings of the International Conference on Innovative Computing & Communication (ICICC) 2021.*