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A Review on Age and Gender Recognition UsingVarious Datasets and Deep Learning Models

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Abstract: Age and Gender are two facial potentials play a principalrole in the society. An instinctive age and gender appreciation have a massive numeral of real-world uses that comprises a consumer facility, the priority voting system, medical diagnosis, the human computer communication. Deep learning methods are usually used in utmost researches and attained to progress the performance too. Relating dissimilar deep education models and evaluating the enhancement in exactness leads to complementary studies. The chief aim of this paper is to achieve detailed examination of age and gender credentials through numerous datasets and deep learning prototypes. In this paper, the growth made by, deep learning prototypes are highlighting the assistances addressed; the prototypes and dataset used are estimating the acclaimed method with the concerns attained.
Keywords: Deep neural network, Datasets, Age and gender Classification, Deep learning.

I. INTRODUCTION

Age and gender ordering is the mission of recognizing a person's age and gender from an image or video. Age and gender play a chief role in detecting a person. With the advent of social media, there may be developing attention in automatic classification of age and gender with the aid of using facial images. Age and gender are the maximum fundamental facial features in social interaction. Human face contains characteristicsthat determine identity, age, gender, emotions, and ethnicity. Therefore, the process of age and gender assessment is a significant step for many presentations. Some real-world displaysare visible surveillance, digital customer, crowd conduct analysis, online advertisement, item recommendation, regulation enforcement, prevent juveniles from shopping banned pills from shops, prevent kid's from browsing dangerous websites, forensic, anti-aging treatment, beauty products production, film function casting etc. With the assist of human eye, it's far tough to estimateage due to the fact from the center age to antique age, the facial functions end up key time-various because of pores and skin transformation. In adolescent, due to growth. Age and gender identity will become a not unusual place open project for researchers due to a few not unusual place problems.

So, computer vision steps ahead to clear up all of these problems. Computer vision is an artificial intelligence (AI) that allows computer systems and structures to derive significant information from virtual images, videos, and different visible inputs, and to do so and make proposals primarily based on that information. So, the need of an effectual model for age and gender approximation responsibilities may be very essential. In most of the past researches, individually intended characteristics with the models. Machine education models are popularly used. Machine learning as the study of computer procedures that can be improved automatically through the use of involvement and data. These machine learning models i.e., exclusively designed characteristics represented efficiently on some datasets, and it fails to yield foreseeable outcomes.

Deep learning models is merely a subset of machine learning. While associating with simple machine learning concepts deep learning works to imitate how individuals ponder and learn. Deep learning makes the processes easier and faster. Facial age and gender recognition is one of the supreme applications of deep learning. Convolutional neural network has one or more convolutional layers and has some specific functions too. Some of the common drawbacks of age and gender recognition are Dataset problem that affects the performance, machine learning depends on quality of data. Mislabeled data excessive noise can causethe models to start learning wrong things.2.Traditional Classification algorithms can't learn the complicated nonlinear relationship in image data.3. Deep Neural Network extract features in images is not much efficient and accurate i.e. particular model extract only one type of feature.4.Minor change in alignment which affects the performance.5.Problem of misclassification 6.Problem obstruction, pose, illumination, resolution, facial expression etc. in images.

II. LITERATURE SURVEY

In 2017, [2] k. Zang, et al. projected Residual linkage of Residual system for instinctive forecast of age and gender from face pictures of unconstrained situation. The design is for high perseverance facial pictures age and gender grouping. Two mechanisms such as connected by gender and preparation with weighted damage level, and used to progress the presentation of age assessment. In order to advance the presentation and improve over fitting problem, ROR is concerned on Image Net, then it is fine-tuned on IMBD-WIKI 101dataset for additional learning the structures of face images and finally altered on Audience dataset. Excessive exactness is attained for gender cataloguing task works well for excessive determination facial images. Age assessment accurateness of 67.37% andgender approximation accurateness of 93.27%. Lesser age approximation accurateness and ROR model is slower than other models make this stimulating. Accurateness of age approximation occasionally distress due to slight alteration in configuration. Concern of dataset. Audience. Works fine on some precise structures only.

In 2018,[3] Philip smith, et al., transfer learning is active to tackle the problem of identifying a person's age and gender from an image by deep CNNs. Transfer learning to use VGG19 and VGGFace related prototypes are used to upsurge the competence. Training methods such as input standardization, data extension, label distribution age encoding is associated. In 2019, [4] Ningning Yu, et al. proposed an ensemble learning used for facial age estimation within non-ideal facial imagery in Fig[1] .The method consists of mainly image preprocessing, featureextraction, and age predication. Separately, the input face image is preprocessed in RGB Stream, Luminance Modified Stream, and YIQ Stream. Three different pertained DCNNs equipped with softmax are wont to implement feature extraction and age estimation because theweak classifiers. Finally, the ensemble learning module fuses the three weak classifiers to get a more accurate estimation. Dataset usedis IMBD-WIKI from Wikipedia.

Three stream technique advances the presentation. To produce supplementary precise organization, ensemble learning to fuse the weak classifiers. To estimate the performance of classification, some evaluation indexes such as AEMand. With ensemblemethod, AEM of 45.57% and AEO of 88.20%.

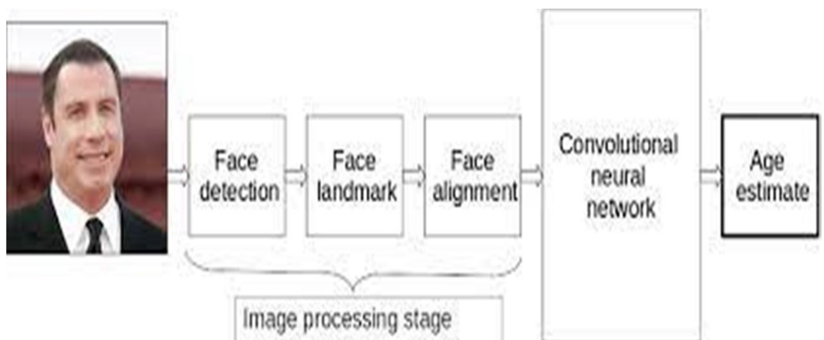

Fig.1. Block diagram for Lightweight CNN Age approximation

In 2020, [5] Olatunbosun, et al. projected a Lightweight Convolutional neural network for real and apparent age estimation ofhuman faces in Fig [1]. Real and apparent age estimation has numerous real-world applications such as medical diagnosis, forensic, facial beauty product production. CNN model is larger, more complex, too large network parameters and layers, training times long, huge training dataset.In which computation price upsurges and storage overhead. Incurs so, proposed to design a light weight CNN layer of fewer layers to estimate real and apparent age. Input is real world face image.

First step is, image preprocessing. Face detection and alignment. Then, followed by image augmentation where random scaling, random horizontal flipping, color channel shifting, standard color jittering, random rotation and also generate an alter copies of every training image.

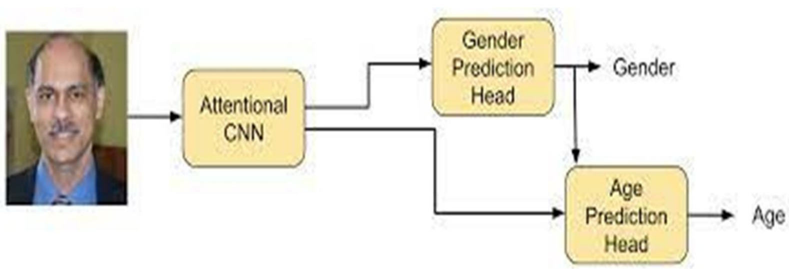

Fig.2. Block diagram of GRANET model

In 2021 [1] Avishek Garain, et al. proposed a model GRANET (Gated Residual Attention Network) for organization of age and gender from facial images in Fig [2]. Some normal deficiencies of previous researches are: higher MAE, lower age estimation accuracy,

A. Age And Gender Recognition Technology

1) Deep Neural Network and Transfer learning:

Neural networkstructures like human intelligence, and it comprises nodes. It consistsof input layer, hidden layer and output. Images as input and multiplehidden layers the node multiply the inputs with random weights, calculate them and pass to output layer. Some major algorithms usedin deep learning are: Convolutional Neural Networks, Long Short- Term Memory Networks, and Recurrent Neural Networks. Convolutional Neural Networks have multiple layers that process and extract features from data.

The training testing of model is very vital factor in deep knowledge. Datasets play a chief role in preparation and testing. The obtainability of diverse age and gender recognition datasets are great support for investigators. Each of the datasets has dissimilar featurestoo.

2) IMBD Wiki Dataset

The largest face dataset with gender, a name and age evidence. It contains 500 thousand images of faces. In total 460,723 face images from 20,284 celebrities from IMBD and 62,328 from Wikipedia, thus total of 523,051. Some glitches of the dataset are: all images are dissimilar size, some ages are inacceptable,and there are more male faces than female faces.

3) Dataset of MORP II

A facial age estimation dataset which contains 55,134 facial images of 13,617 subjects ranging from 16 to 77 years old. Images of 84.6% are males and 77.2% are of black.

4) IMAGENET

An image database organized according to WorldNet hierarchy. ImageNet contains more than 20,000 categories such as a strawberry, a balloon and several other objects.

5) Dataset Of FG Net Aging

The dataset consists of 1002 images of 82 different subjects with their ages varying from a baby to69 years old. Images from the photographs of the personal collections. Some challenges are: the quality of images, the quality of photographic paper, affect some Variability in the quality, an illumination, the resolution, the viewpoint, an expression, presence ofan occlusion in the form of facial hairs, spectacles, hats.

6) Dataset Of AFAD

The Asian Face Age Dataset for evaluating the presentation of various age estimation. It contains more than 160Kfacial images along with their corresponding age labels. The dataset has been designed for an age estimation on Asian faces. There are labeled prints in the AFAD dataset with the ages varying from 15to 40. The AFAD dataset was constructed by collecting shots of users from a particular social network.

7) Dataset Of Wikipedia Age

The publicly available dataset comprises facial images. Images of various celebrities are available in this dataset. The images which were the date when the photo was taken was removed as they will not have any age information in them. In total, 62,328 face images from 20,284 celebrities were obtained from Wikipedia.

8) Dataset of UTK Face

The large-scale dataset which contains face images with a very long span range from 0 to 116. It contains more than the 20k face images. It comprises labels of a face age, genderand ethnicity. The images cover huge variation in illumination, pose,occlusion, facial expression, resolution etc. The dataset contributes advantage over face detection, age assessment to age advancement orregression and landmark localization.

Fig.3.Sample images of UTKFace dataset.

9) Dataset Of Adience

The Adience dataset comprises pics occupied through a digital digicam from a phone or tablets. The pictures of the dataset grab severe deviations, together with a severe blur (low- resolution), occlusions, out-of-plane, pose variations, expressions.

10) BIAS Estimate in Face Analytics

Bias Estimate in face analytics encompasses13431 test pictures were determines age, gender.

III. ASSESSMENT AND CONVERSATION OF PREVIOUS RESEARCHES

Table 1: Relational learning of age and gender identification grounded on preceding investigates.

Prototype	Datasets	Benefits	Drawbacks
CNN[13]	Adiencedataset	High accurateness in gender approximation task is 86.8%. Dropping the probabilities of over fitting because condensed Number of parameters.	Lesser age appreciation accurateness is, 50.7% dueto its modest design.
ROR[12]	ImageNet dataset., IMBD WIKI dataset,	Great accurateness attainmentin gender orderingand is 93.24%. Works wellon great tenacitypictures	Lower age identification accurateness is 67.34%.
CNN[11]	WEAFD Dataset	Gender grouping accurateness is quite noble accurateness is 88%. Used Labelled face Images for classification.	Age discoveryaccurateness is very petite 38%.

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MT CNN[7]	UTK Face dataset, BEFA dataset	Produces great gender ordering accurateness for UTK Facedataset is 98.23%, and for BEFA dataset it is 93.72%.	Due to inadequateamount of facial attributes. Lesser accurateness of the age ordering task for UTK Face dataset is 70.1% and for the BEFA dataset is 71.83%.
VGG19, VGG Face[3]	MORP-II Dataset	VGG Face is superior. High gender gathering accurateness is 98.7%.	Age approximation yields higher MAE of 4.1 years. Trivial alteration affects the forecast task.
CNN[10]	Adiencedataset	Produces enhanced genderchecking, Accurateness is, 88%. The model emphases on useful and vital structures.	Lower agerecognition, accurateness is 61%.
LMT CNN[9]	Adiencedataset	Gender ordering accurateness is noble is, 85%.	Lower agedetection, accuracy is, 44%. Greater size does not work well with unrestricted faces.
CNN[8]	UTK Facedataset	High accurateness for gender groupingis, 94.1%.	Age approximation produces greater MAE of 5.44 years.
GRANET[1]	FG-NET dataset,AFAD Dataset, Wikipedia dataset, UTK Face dataset, Adience DB dataset.	UTKFace performs better and produce gender appreciation accuracy of99.2%. Produce fewerage approximation MAE of 1.07.	Produces ageappreciation accurateness of 93.7%. Difficulty in misclassification.

Presently there are numerous current exploration prototypes for identifying the age and the gender. While associating with specific initial investigates presentation of gender recognition is quite praiseworthy, but the age approximation is not well. While associating some researches model using UTK Face Dataset, Facenet prototype yield gender identification accurateness of 91.2% and age approximation accurateness of 56.9%. Next Fine-tuned Facenet produce gender recognition accuracy of 96.1% and age estimation accurateness of 64%. Then [7] Multitask cascaded convolutional neural networks (MTCNN) produces accurateness amounts on gender and age is 98.23% and 70.1%. Then [6] Residual attention network model yield accuracy on gender is 97.5% and age approximation accuracy is 85.4%.RAN model on AFAD dataset age estimation MAE of 3.42 and FG-NET dataset age estimation MAE of 4.05 In the latest research, using [1] GRANET model on five publicly available datasets. MAE over FG-NET, AFAD, Wikipedia, UTKFace, Adience are 3.23, 3.10,5.45, 1.07, 10.57 respectively. UTK Face produces better gender recognition accuracy of 99.2% and age estimation accuracy of 93.7%. Table 1 demonstrates the relative study of preceding investigates. From the above investigates it is clear that deep learning modelsare superior and yields effective presentations. Lastly, hypothesis from amongst all the datasets that UTK Face is superior one. UTK Face dataset covers huge brightness, pose, occlusion, facial appearance, firmness etc.

IV. CONCLUSION

The facial age and gender identification is a compound task. Butit was very significant to the civilization where, it has several real world presentations. Age and gender identification with exclusivelyintended structures and the machine learning fail. In the old-fashioned organization method cannot study non-linear association in pictures. So, the advent of deep learning models is very noteworthy. Deep learning models accomplished superior from proceeding investigates and also expands the enactment. In gender cataloguing tasks most of the researches accomplish enhanced and accomplishes better outcomes. But an enhancement is very essentialin the case of an age approximation. The single model extracts onlyone type of structures, and it powerfully affects the presentation. So, essential to present an ensemble technique by means of numerous deep learning models to advance the presentation on age and gender reorganization in future.

REFERENCES

[1] A Garain, B Ray," GRANet: A Deep Learning Model forClassification of Age and Gender From Facial Images" IEEE Access, vol.9, pp.85672-85689, 2021.
[2] K. Zhang, C. Gao, L. Guo, M. Sun, X. Yuan, T. X. Han,Z. Zhao, and B. Li,``Age group and gender estimation in the wild with deep RoR architecture,"IEEE Access, vol. 5,pp.22492-22503, 2017.
[3] P. Smith and C. Chen, ``Transfer learning with deep CNNsfor gender recognition and age estimation," in Proc. IEE Int. Conf. Big Data (Big Data),Dec. 2018, pp. 2564-2571.
[4] Ningning yu, l. qian, y. huang, and yuan wu," Ensemble Learning for Facial Age Estimation Within Non-IdealImagery" Facial, IEEE Access, vo.7, pp.97938-97948,2019.
[5] Olatunbosun agbo-ajala and Serestina viriri" A Lightweight Convolutional Neural Network for Real and Apparent Age Estimation in Unconstrained Face Images",IEEE Access, vol.8, pp.162800-162808,2020.
[6] F. Wang, M. Jiang, C. Qian, S. Yang, C. Li, H. Zhang, X.Wang, and X. Tang "Residual attention network for imageclassification," in Proc. IEEE Conf.Comput. Vis. Pattern Recognit. (CVPR), Jul. 2017, pp. 3156-3164.
[7] A. Das, A. Dantcheva, and F. Bremond, ``Mitigating bias in gender, age, and ethnicity classification: A multi-task convolution neural network approach," in Proc. Eur. Conf.Comput. Vis. (ECCV) Workshops, 2018, pp. 1-13.
[8] A.V. Savchenko,"Efficient facial representations for age, gender and identity recognition in organizing photo albumsusing multi-output ConvNet,"PeerJ Comput. Sci., vol. 5, p.e197, Jun. 2019, doi: 10.7717/peerj-cs.197.
[9] J. H. Lee, Y. M. Chan, T. Y. Chen, and C. S. Chen, ``Jointestimation of age and gender from unconstrained face images using lightweight multitask CNN for mobile applications," in Proc. IEEE Conf. Multimedia Inf.Process.Retr. (MIPR), Apr. 2018, Art. no. 17877533.
[10] S. Hosseini, S. H. Lee, H. J. Kwon, H. I. Koo, and N. I. Cho,``Age and gender classification using wide convolutional neural network and Gabor filter," in Proc. Int. Workshop Adv. Image Technol., 2018, pp. 1-3, doi:10.1109/IWAIT.2018.8369721.
[11] N. Srinivas, H. Atwal, D. C. Rose, G. Mahalingam, K. Ricanek, and D. S. Bolme, "Age, gender, and _ne-grained ethnicity prediction using convolutional neural networks for the East Asian face dataset," in Proc. 12th IEEE Int. Conf. Autom. Face Gesture Recognit. (FG), May 2017,pp. 953-960, doi: 10.1109/FG.2017.118.
[12] K. Zhang, C. Gao, L. Guo, M. Sun, X. Yuan, T. X. Han, Z.Zhao,and B. Li, ``Age group and gender estimation in thewild with deep RoR architecture," IEEE Access, vol. 5,pp.22492-22503,2017, doi:10.1109/ACCESS.2017.2761849.
[13] G. Levi and T. Hassner, "Age and gender classification using convolutional neural networks," in Proc. IEEE Conf.Comput. Vis. Pattern Recognit.Workshops, Jun. 2015, pp. 34-42, doi: 10.1109/CVPRW.2015.7301352.