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### **Survey on Human Age and Gender Prediction**

Jayaprada S. Hiremath, Dr. Shantakumar B. Patil, Dr. Premjyoti S. Patil

Research Scholar, Dept. of Computer Science and Engineering, VTU, Belgaum, India

Professor, Dept. of Computer Science and Engineering, Sai Vidya Institute of Technology, Bengaluru, India

Professor, Dept. of Electronics and Communication Engineering, Nagarjuna College of Engineering and Technology,

Bengaluru, India

**ABSTRACT**:From the past few years, much exertion has been carried out for age assessment & recognition of gender through face images. The images of Human's faces uncover different data like gender, age, and nationality. Computer vision and pattern recognition in the discipline of computer vision represent an ideal role in human beings through automatic detection of face, recognition of gesture and face, and finding age and gender. Here through the paper describes a survey on predicting age and gender using face images. Various research has been developed on age and gender prediction using various features like face features, body pose, MRI brain images, giants, and pam. The face features can give more features for age and gender identification.

KEYWORDS: Age Recognition, Classification, Feature Extraction, Face Identification, Gender Prediction, SVM.

#### I. INTRODUCTION

From the most recent decade, the pace of image transfer to the web has been designed at a remarkable rate. This newfound higher amount of data has engaged research scholars to solve computer vision problems that are already superfluous or immovable [23].

Automatic age and gender classification have reached an essential stage for extending use, mainly as old age belongs to social stages and online dependent media. Yet, the efficiency of current strategies based on real-time images is absent, mainly while comparing with the huge jumps in performance as of late detailed for the connected task recognition of a face.

Consequently, several types of research are done on exact and robust facial detection. The application of this face identification system is improved by extending the research by using face feature identification of age and gender.

We cannot have two faces exactly look-a-like. This assertion is genuine because facial appearance changes progressively. They are influenced by few variables: posture, facial appearance, head contour, lighting, aging, obstruction, mustache, beards, makeup (cosmetics), and hair cut. Primary considerations which impact facial aging adds gravity, openness to ultraviolet (UV) beams arising from sun, development of delicate tissues, bone re-organizing, and facial muscular exercises. These elements brings varieties in face appearance. For example, a face shown in blue spotlight is shocking when viewed concerning red spotlight. The second element is stable at all-time due to varieties in facial representation as ages.

An aging factor of humans and other life is an unavoidable stochastic process that contributes an important part in facial appearance. The aging of human lives depends on both the factor like differences in softer and bony face shape. Based on which age, face appearances differ a lot. A face appears differently at different ages. Hence it's necessary to develop a system to recognize age and gender-based on facial features.

Identification of gender-based on-face features is broadly utilized in much human computer-depended intercommunication. It also includes various exciting applications, from identifying the gender automatically to search images through the internet. Researchers have carried out gender identification using various tricks like face image, audio, and 3D face data [22].

Many dilemmas in age and gender classification are yet unlocked issues. Predictions of age and gender on natural reallife faces are still to encounter the needs of business and real-world implementations despite the advance the computer vision sections stay with constant development of latest techniques that upgrade the state-of-the-art.



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This paper convey a complete research about various algorithms and configurations for measuring age and gender predictions. In specific, newlyfound common framework is the foundation of the study: Humans can determine people's gender almost instantaneously utilizing facial elements. Even though it is tough for machines to carry out the similar job, unbelievableadvancement is made in automatically predicting face images in the past decade. The project identifies or detects the gender through the input face images. The project has been inspired by absence of security, fraud, child molestation, robbery, criminal identification.

#### II. LITERATURE SURVEY

This section describes a literature survey on age and gender recognition using different techniques and algorithms. The survey was conducted on face detection, feature extraction, classification of age, and gender, as shown in figure 1. The human face images are considered as an input database for age and gender recognition. In computer vision-based image processing, the following steps are carried out, pre-processing of input images, face identification, extracting different features, and classifying.

#### A. Face Detection

The concept of a face recognition system deals with all humans having unique identities like face, fingerprint, a subject face having different unique shapes and different features. Authentication and identification of face are more complex problems. For face identification systems should have been accurate, having more precision and accuracy. Face images considered in different expression or lighting circumstances lead to a higher challenge for robust and accurate systems.

Dong Chen et al. [01]has expressed a new cascading convolutional neural network, allies named as supervised transformer network, in the system 1st step is multiple jobs of Region Proposal Network (RPN) that assists to guess the face area and also landmarks present in the face, i.e., from the giveninput image. Using which candidate face regionsare wrapped the mapping of face structure. In the next stage, RCNN validates the wrapped candidate's areas are validated as the face or not. This knowledge-based learning of the conversion automatically chooses the better scale to differentiate face with non-face regions.

Kaifeng Zhang et al. [02] have described a face recognition and alignment system using an unconstrained environment. Deep learning cascading multiple-layer architecture finds the network's inherent correlation to increase their performance. Different poses, illumination conditions, and occlusions are significantly challenging in the face detection system. The deep convolution detects the face and landmarks of the face. In learning, a new approach forcomplex online testing through mining increased the efficiency automatically without any interaction support of selecting the samples.

Baosheng Yuet al. [03] presented a robust and anchor-dependent cascading architecture known as anchor cascade. To increase the detection rate by discovering contextual data using a context pyramid max-out strategy for anchor cascading as proposed. Therefore, anchor-based cascading can be a robust face identification method that produces greater detection rate accuracy. Generally comparing with a famous convolutional neural network depended cascading face identifier MTCNN, the proposed anchor-based cascading face recognition achieved a higher accuracy rate.

NURULHUDA ISMAIL, MAS IDAYU MD. [25] In this paper, we present a review on the most successful existing algorithms or methods for facerecognition technology to encourage researchers to embark on this topic. A brief on general information ofthis topic is also included to compose an overall review. This review is written by investigating past andongoing studies done by other researchers related to the same subject. Five different algorithms have beenpreferred based on the most widely used criteria. The algorithms are Principal Component Analysis (PCA),Linear Discriminant Analysis (LDA), skin colour, wavelet and Artificial Neural Network (ANN). Certainparameters have been taken into account for the algorithms' review. The parameters are size and types ofdatabases, illumination tolerance, facial expressions variations and pose variations. However, no specific justification can be claimed as it is only a review paper based on other researches.



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TABLE I. SURVEY ON FACE DETECTION ALGORITHMS

SL No.	Title	Year	Algorithm	Result
01	SupervisedTransformer Network for Efficient Face Detection [01]	2016	Multi-task Region Proposal Network [RPN]	Speeds up face detector 3x on CPU with little recall drop
02	Joint Face Detection and Alignment using Multi-task Cascaded Convolutional Network [02]	2016	Multi-task Cascaded Convolutional Network [CNN]	The system as reached fastest speed along with face recognition and alignment. It takes 16fps on a 2.60GHz CPU and 99fps on GPU.
03	Anchor Cascade for Efficient Face Detection [03]	2019	Anchor cascade	Accuracy improved as 0.9435 to 0.9704 at 1k false positives on face detection benchmarks
04	Face Detection using Deep Leaming: An Improved Faster RCNN Approach [04]	2017	RCNN	Achieved the state-of-the-art results which ranked the best among existing methods.
05	Progressively Refined Face Detection Through Semantics- Enriched Representation Learning [05]	2015	Centralized Attention Feature (CAF) and Distributed Attention Feature (DAF)	CAF and DAF significantly outperform state-of-the-art face detection methods



Fig. 1. Overview of age and gender recognition using facial features.



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Zhihang Li et al. [05] structured a system for face detection. The system detects the faces even when so many tiny faces are present in the crowd. Structure of a profound progressive refined loss (DPRL) for precisely comprises feature intrusions. The 2 primary architectures, namely Centralized Attention Feature (CAF) and DistributedAttention Feature (DAF), are approached for face identification.CAF and DAF thus increases the average precisions range from 99.85% to 99.89% and from 99.85% to 99.90%

#### B. Feature Extraction

Hiranmoy Royet al. [06] have explained that a powerful gravitational force depended on an illumination-invariant face recognition approach known as LG-face, which is as well ascapable to manage with lightingchanges and heterogeneous face recognition. It uses the local gravitational force anglescalculated in local neighbourhoods to automatically eliminate the L component of an image using the division method and improve the local R component by preserving the edges. It is more flexible to local variations in illumination and produce better results than other existing methods. LG-face can easily be used as a pre-processing tool to eliminate variations in illumination, shadows, and facial expression and increase facial edge features. Thus, an extensive range of potential applications, from coping with illumination differences to heterogeneous face identification.

SL No.	Title	Year	Algorithm	Result
01	Local-Gravity-Face (LG-face) for Illumination-Invariant and Heterogeneous Face Recognition [06]		LocalGravity-Face (LG-face) for illumination-invariant and heterogeneous face recognition (HFR)	Recognition rates of 97.78% on the CMU-PIE database and 97.31% on the Extended Yale B database are achieved under varying illumination
02	Progressively Refined Face Detection Through Semantics- Enriched Representation Learning [07]	2015	Centralized Attention Feature (CAF) and Distributed Attention Feature (DAF)	CAF and DAF significantly outperform state-of-the-art face detection methods
03	Gender Identification via Reposting Behaviours in Social Media [08]	2018	Homophily based gender identification 1. Individual Arithmetic Average (IAA) 2. Community Arithmetic Average (CAA) 3. Weighted Average (WA) 4. Majority Voting (MV)	The data base, considered, as obtained from Sina Weibo and includes 1039 samples test and 528k user profiles, methods perform with 86.7% accuracy.
04	Gender identification based on human brain structural MRI with a multi-layer 3D convolution extreme learning machine [09]	2018	Multi-layer 3D convolution extreme learning machine	The results show that the human brain can be separated into two different classes, male and female brains
05	Detection of Age-Induced Makeup Attacks on Face Recognition Systems Using Multi-Layer Deep Features [10]	2019	deep learning-based presentation attack detection (PAD)itidentifies facial makeupsand Convolutional neural network (CNN) for feature extraction	Average classification error rateof 6.6%

#### TABLE II. SURVEY ON FEATURE EXTRACTION ALGORITHMS

Zhihang Li et al. [07] proposed a focus instructed similar quality feature concatenate system for learning a feature pyramid with efficient meanings for all the ranges for face identification. Two architectures, namely Centralized Attention Feature (CAF) and Distributed Attention Feature (DAF), are utilized for face identification. Deep Progressive Refined Loss (DPRL) adopts more contexts for detecting face robustly coarse to acceptable.

Dongxu Llet.al [08]has presented a gender identification based on behaviours on social networks. The method is divided into 3 steps: it captures the homophily contained in online content diffusion routes. The system is language-based. The 2nd step used a semi-supervised method and reduced the unnecessary features. 3rd step is to test thesystem's performance, which is evaluated using a small dataset and gives a competitive performancewith 86.7% accuracy.



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Dewen Huet al. [09] described a multiple-layer 3D convolution extreme learning machine (MCN-ELM) for classifying brains as male and female brains depending on the structural MRI grey matter (GM) information. In the 1st step, multiple features are extracted using three different ranges of multiple layered 3D convolution neural networks (CNNs) without changing the elements of convolution kernels. Thesystem classifies the brain of males and females with an accuracy of 98.06%.

Ketan Kotwalet al. [10]have proposed an age detection with identifying the face makeup. The get the features of the face, the convolutional neural network (CNN) is used. The feature descriptors are based on the shape and texture feature of the face, and it is built through different intermediate layers of a network CNN. The dataset utilized in the system to analyse the function of the method is the AIM (Age Induced Makeups) dataset, made up of 200 more videos showing old-age makeups and bona-fide (without makeup). 93% accuracy is achieved in the system.

#### C. Classification

AlenSalibbasicet al.[11] have presented a detailed explanation about the system of gender, age, and face identification methods for Android-based mobile devices. The system is developed using the OpenCV library. A feature LBP of face classifier is utilized for face detection, and the LBPH method is applied for face identification. The achievement concerning age and gender recognition is a deep neural network that utilizes identifying properties without catching the images and training gender and age recognition models.

Salah EddineBekhoucheet.al [12]has presented an age and gender estimation using multiple-level local phase quantization (ML-LPQ). The features using a standard face image. To guess the age group and person gender, two various types of SVM methods are used.

Hazarika, B. B., & Gupta, al [24] the famous SVM and LSSVM systems are boosted with the density-weighted notion, and two novel methods are proposed as DSVM-CIL and IDLSSVMCIL.

Edgar A. Torreset. Al [13]has presented an age and gender identification depending on the face structure. The system gains a shape structure to identify the face and upper body and later uses feature extraction and analysis based on spatialassociations and angles formed among characteristics. To classify the male and female, an SVM algorithm is used. Theyreached an accuracy of 93.2% and 87.2% in the classification of gender and age, respectively.

Sindi Amilia1 et al. [14] have proposed a face verification system. The system includes 3 basics steps (1) image processing, (2) feature extraction, and (3) classification. LBP is used to highlight the features from face processed images. Gradient filter is used to face outline. HOG method is utilized for extracting the features. PCA is applied for a reduction in feature dimensions of the extracted feature. A neural network is used to train the system using the extracted features.

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SL No.	Title	Year	Algorithm	Result
01	Development of Android Application for Gender, Age and Face Recognition Using OpenCV [11]	2019	<ol> <li>LBP Face Features         Classification for Face Detection         LBPH Model is Used for Face Recognition         Gender and AgeRecognition is Done Using Deep Neural Network     </li> </ol>	The result of the age estimation isdescribed in the form of output valuesfrom 0 to 7, where each valuerepresents a particular age group; 0-2, 4-6, 8- 13, 15-20, 25-32, 38-43, 48-53, 60+
02	Facial age estimation and gender classification using Multi Level Local Phase Quantization [12]		<ol> <li>Multi-Level Local Phase Quantization (ML- LPQ) for features extraction</li> <li>Support Vector Machines (SVM) for age and gender prediction</li> </ol>	<ul> <li>Accuracy of an exact match (AEM)56%</li> <li>Accuracy of error one (AEO)88.8%</li> <li>Gender classification confusion matrix accuracy of 79.1%</li> </ul>
03	Gender and age classification based on human features to detect illicit activity in suspicious sites [13]		<ol> <li>Haar-like features for the extraction of characteristics</li> <li>SVM for Classification of male and female</li> </ol>	SVM classifiers for gender classification, attained an accuracy of 93,2%, and, for age group classification attained an accuracy of 87,2%.
04	Face Image-Based Gender Recognition Using Complex- Valued Neural Network [14]	2015	<ol> <li>Viola-Jones face detection</li> <li>Complex-valued neural network as a classifier to recognize human gender</li> </ol>	Accuracy rate of 80%
05	Combining Facial Dynamics with Appearance for Age Estimation [15]	2015	<ol> <li>Dynamic Features selection Min- Redundancy Max- Relevance (mRMR) algorithm</li> <li>Features reduction using Principal Component Analysis (PCA)</li> <li>SVM classifier and regression for age estimation</li> </ol>	<ul> <li>Improves the classification accuracy of age groups. When smile videos are used, mean accuracy improvement for 7 and 5 age groups are 9.58%, and 13.03%</li> <li>When disgust videos are used, mean accuracy improvement for 7 and 5 age groups are 11.78%, and 11.83%</li> </ul>

#### D. Age and Gender Recognition

Mahmoud Afifet al. [16] is developed gender identification depended on hand images. Usually, the hand is considered a primary biometric for the identification of a person. The system uses the handset dataset of both sides. CNN is trained effectively for gender identification. Two types of CNN are trained for gender recognition. Both thesides of the hands give better features for gender identification.

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ShivanandGornaleet. AI [17] has developed a system for gender identification depending on palmprint images. The palmprint of persons contains enough necessary data: (1) rides, (2) wrinkles, and (3) main lines. On structuring, this feature automatic gender identification system is proposed. The system includes 3 stages, namely: ROI of extraction, computation of feature, and classification. To extract thefeatures from the palmprint, the Gabor wavelet is used. The analysis of the system is examined using a KNN classifier. The publicly available CASIA dataset is used to evaluate the system. Accuracy of 97.90% is achieved with 10 fold cross-validation

E.-S. M. El-Alfyet al. [18] proposed an automated gait basedon gender recognition based on fuzzy local binary patterns. To analysis the texture patterns, a fuzzy local binary is used. The movement of a person's silhouette is removed, and a texture-based image is structured for concluding systematic and dynamic differences given in the gait cycle. Later, histograms designed for soft pattern differences are building and utilized as feature vectors. Finally, SVM is used for gender classification

Ke Zhanget al. [19] have presented a novel CNN-dependent approach based on gait for age and gender identification. In this system, two types of convolutional appearance network (CAN) for facial appearance feature and deep geometry network (DGN) for facial geometric feature extraction. To improve the classification purpose of age and gender accuracy, both models are integrated. The dataset images are classified into 3 different groups young, adult, and elder group.

Jun Beom Kho et al. [20] have proposeda Multi-expert Gender Classification on Age Group (MGA), an end-to-end multi-task learning scheme of age estimation and gender classification. First, two types of deep neural networks areutilized; Convolutional Appearance Network (CAN) for facial appearance and Deep Geometry Network (DGN) for the geometric facial feature. Then, CAN and DGN are integrated by the presented model integration strategy and fine-tuned to improve age and gender classification accuracy. The facial images are categorized into any of the 3 groups of age, i.e., young, adult, and elder group based on their estimated age, and the system makes a gender classification according to the average fusion strategy of three gender classification experts, which are trained to fit gender characteristics of each age group. Rigorous analysis results on the challenging databases suggest that the approached MGA outperforms several prior arts with little computational cost.

InshaRafiqueet.al [21] has proposed a deep CNN to increase age and gender guess using essential outcomes can be resulted and as increased development are viewed in different work like face recognition. A robust convolutional network system is approached for remarkable changes in the platform utilizing existing approaches. Adopting deep CNN, architecture is practiced to reach the precision of Age and Gender reached 79% based on HAAR Feature-based Cascading Classifiers. It is a machine learning-dependent method in which cascading task is practiced with moreaccurate and false images. It is future applied for object detection in images.

#### III. CONCLUSION

Analysis of face has reached more identification in the community of computer vision community from few past years. The human face region includes charters tics properties like (1) identity, (2) age, (3) gender, (4) emotions, and (5) ethnicity. From the above features, classification of age and gender has many benefits in real-time applications: security and video surveillance, electronic-based CRM, biometrics, electronic vending machines, human-computer interaction, entertainment, cosmetology, and forensic art. Guessing Ageand gender rises business and real-time implementations even in the improvement of a community of computer vision tries building with the consistent performance with today's strategy by improving state of the art. This paper presents the survey on different algorithms; techniques adopted prediction of age and gender using face features. The survey concludes that the accuracy of the system is still lagging in prediction.

The similar system can be trained to predict emotion, age, ethnicity, etc. The classification of gender can predict gender in unconstrained real-time scenarios such as railway stations, banks, bus stops, airports.

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