JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A REVIEW ON GENDER CLASSIFICATION AND AGE DETECTION USING FACE RECOGNITION

[1]**Miss Aarti Deepak Bakare** [2]**Mr. Suraj Shivaji Redekar**

Postgraduate Student **Assistant Professor**

Computer Science and Engineering Department

Ashokrao Mane Group of Institutions, Wathar Tarf Vadgaon,Kolhapur

Affiliated to DBATU University, Lonere, Maharashtra, India

Abstract: With many real-world applications, including targeted advertising, security systems, and human-computer interaction, gender classification and age detection using face recognition have become pivotal tasks. The paper also examines the datasets typically used for training and evaluating gender classification and age detection models, highlighting the importance of representative and diverse data to guarantee objective results. Future research directions are also outlined in the review, such as the need to address algorithmic bias, improve interpretability, and deal with real-world complexities such as facial occlusions and age-related changes. This review serves as an invaluable resource for researchers, practitioners, and developers who wish to improve the accuracy and usability of gender classification and age detection using face recognition by offering a thorough analysis of the current state-of-the-art techniques.

Keywords: Mask RCNN, convolutional neural networks, deep learning, segmentation, object detection,

1. Introduction

In the current digital era, facial recognition technology has made incredible strides and transformed many fields and applications. Due to their potential in marketing, security, and personalised experiences, applications of gender classification and age recognition in facial recognition have attracted much attention. This review aims to present a thorough analysis of the existing literature, methodologies, and difficulties in gender classification based on face recognition and age detection. By analysing the latest research and methodologies, we aim to gain insight into the progress made and identify areas that still need improvement. The ability to correctly identify gender and age from facial images has implications for targeted advertising, human-computer interaction, and public safety. Our main purpose in writing this review is to advance knowledge in this dynamic field and to serve as a catalyst for new advances in age and gender identification based on face recognition. Gender classification is the process of determining whether an individual is male or female based on facial features. It has a wide range of applications, including targeted advertising, customer behaviour analysis, and personalised user experiences. Researchers have explored different approaches to solving gender classification, including traditional machine learning algorithms, deep learning models, and hybrid techniques. This review will discuss the strengths and limitations of these methods and highlight their performance in terms of accuracy, robustness, and efficiency.

The goal of age detection, on the other hand, is to determine a person's exact age or age range from their facial features. Personalised healthcare, age-specific marketing, and social robotics are three areas where accurate age detection has a big impact. This review will take an in-depth look at age estimation methodologies, including statistical models, regression-based methods, and deep learning architectures. It will focus on age detection issues such as facial ageing variations, biases in datasets, and privacy issues.

This review will also look at datasets typically used for developing and testing gender classification and age detection models. The diversity, size, and representativeness of these datasets will be explored, focusing on the importance of objective and inclusive data collection to reduce algorithmic biases. Finally, we discuss current issues and future directions in gender classification based on face recognition and age detection. Addressing ingrained biases, improving model interpretability, handling facial variations and occlusions, and exploring the intersections of gender and age with other demographic characteristics are some of these.

2. Literary survey

In 1: A gender and age estimation system from face images in Conference: SICE 2003 Annual Conference Volume: 1 by Gentaro Fukano of Yokogawa Electric Corporation:

This paper basically talks about face candidate extraction and includes point discovery. The candidate face localization is extracted based on skin colour data from the input image and 37 foci, i.e., 8 points on both eyebrows, 10 points on both eyes, 4 points on the nose, 8 points on the mouth, and 7 points on the face. diagram, are marked as including foci. Highlights for estimation are extracted based on recognised highlight orientations and assessed for gender orientation and age. The transformation equation from the RGB colour frame to the adjusted HSV colour frame is composed as Equation (1), where each calculation of H, Qc, and I is tone, altered dip, and scaled, and communicates colour, dip, and luminance separately. Qc maintains a strategic distance from the problem that a colour comparable to dark, whose immersion in the HSV colour frame must be moo, appears as having high immersion.

The modified framework is impressive in dividing the skin and hair environments. The computation for face candidate localization extraction is as follows:

(1) Calculate the contrast between the processed base image and the input image and binarize the subtracted image with a limit.

(2) Extract the locations whose H and Qc components are within a range of consistent values from the unmasked locations in the input image.

(3) The national environment that has the largest area of the extracted sites is respected as the national environment.

(4) Fill in the gaps in the skin colour area.

(5) The extracted location is tested to see if it is likely to be a face location with geometric highlights, i.e., zone, circularity, and aspect ratio. The rectangular area bounded by the local area is used as the candidate face location. 2.3 Discovery of face highlighting We used a Gabor Wavelet Transform (GWT) graph coordination strategy in the arrangement to identify the exact position of the face and parts by identifying highlighted foci.

In 2 Facial Age Estimation by Curriculum Learning by Wei Wang at Graduate School of Fundamental Science and Engineering, Takaaki Ishikawa at Global Information and Telecommunication Institute Hiroshi Watanabe:

In this article, we consolidate learning modules into age estimation. The test result of the proposed strategy on the AFAD database for age prediction shows a significant reduction in error prediction compared to the conventional training procedure.

Past work focuses on hand-crafted highlights using selection trees and heuristic contour preparation, while current work is engineering convolutional neural systems that have proven successful in large-scale image classification tasks. In short, curriculum teaching preparation is the dissemination of training information at several complex levels, which allows the demonstration to remember easier data at the beginning, which can avoid premature presentations out loud. The proposed strategy, the main ideal of learning the curriculum, is to divide the preparatory information into a series of complex levels, which allows the demonstration to remember the simpler information at the beginning and then constantly expand the difficulty.Curriculum Plan Two assumptions are suggested in age estimation assignments: (a) the complexity of tests within a single category is varied. In curriculum design, the biggest challenge is calculating the clustering centre using the density-distance clustering strategy.

- After pre-processing, the test will be transferred to the InceptionResNet-V2 model to incorporate the vectors into the fc_256 layer.

As part of the opening, the least demanding information will be used for the preparation of the sample so that the sample learns the essentials in the given category.

After that, in the event that the result of the validation data does not evolve in the epochs, the demonstration starts to learn more difficult training modules.

1. Datasets and Preprocessing: The database used in our tests is AFAD, which is Asia's largest face dataset for age estimation and contains more than 160 thousand face images and compares age names in the range of 15–40 years long-term.
2. Convolutional Neural Network Architectures: In order to test the learning capacity of the curriculum for the AFAD dataset of the age estimation framework, the state-of-the-art ResNet-34 CNN architecture was chosen in our experiment, which has been shown to be capable of a range of image classification assignments from a remaining learning framework that can untangle the preparation of systems that are deeper than past networks.

In 3 Age Prediction Based on Feature Selection by Yanhong Wang, Wei Song, Lizhen liu, at Information and Engineering College of Capital Normal University:

This article analyses the age of traffic among Microblog clients in terms of feature selection. It proposes a modern feature selection technique to enhance the existing strategy based on word repetition and includes time features to check the user's age range. In addition, it raises two primary questions: Is there a point in time that shows that there is a much better dividing line between the pre-80s era, the post-80s era, and the post-90s era? This work tests ternary classification into age groups and finds that selected n-grammes have a significant effect on age prediction. It builds a model to automatically recognise the age of Microblog users based on viable features selected from Microblog data.

The existing research has its core in two regions: the English blog and the social network. The survey results showed that unigram functions can achieve the desired regression performance. The paper also proposes a regression model based on three distinct types of information.

In 4 Mask R-CNN by Kaiming He, Georgia Gkioxari, Piotr Doll´ar, Ross Girshick on Facebook AI Research (FAIR):

The Mask R-CNN system is a conceptually straightforward, adaptable, and common system for segmenting question instances. It enhances faster R-CNN by including a question veil prediction department in parallel with the existing bounding box confirmation department. The R-CNN mask is a basic preparation and includes a small overhead for the faster R-CNN, running at 5 frames per second. It appears best in all three series of the COCO challenge set: counting instance segmentation, finding bounding box questions, and finding single key points. The vision community has made rapid progress in query positioning and semantic partitioning, driven by efficient pattern frameworks such as Fast/Faster R-CNN and Completely Convolutional Organise (FCN) systems.

The R-CNN mask combines components from the classic computer vision task of protest discovery, where the goal is to classify person objects and locate each using a bounding box, and RoIAlign semantic class partitioning, where the goal is to classify each pixel into a fixed set of categories without separating questions on positions. Mask R-CNN is a strategy that enhances Faster R-CNN by including a separation to predict segmentation masks in each region of interest (RoI). The mask separation can be a small FCN attached to each ROI, predicting the segmentation mask in a pixel-to-pixel manner. The R-CNN mask can be easily updated and prepared thanks to the Faster R-CNN system, which supports a wide range of adaptable engineering plans. Despite being Adapted from the common wording, we use protest discovery to denote discovery using bounding boxes rather than masks and semantic segmentation to denote pixel-wise classification without separating occurrences. The R-CNN mask outperforms all past state-of-the-art individual models created on the occasion of the COCO division and surpasses expectations for the task of COCO question detection. Finally, Mask R-CNN outperforms expectations on the COCO key dataset.

In 5 Age Detection in 5 with Face Mask using Deep Learning and FaceMaskNet-9:

The COVID-19 pandemic has made it difficult to identify the age of an individual with a face mask. To overcome this problem, we proposed a framework for performing age determination using FaceMaskNet-9, a deep learning network that identifies an individual's age using a face mask. FaceMaskNet-9 improves assignment accuracy and accurately classifies individuals with masked faces into distinct age groups. This framework can be used to limit access to certain content on social media and provide additional benefits to individuals depending on their age. The main points of interest

in this content are the strategies used to distinguish the age of an individual with a face mask. These strategies include using a Haar cascade classifier to recognise a specific protest from a webcam using a dataset of 10,000 images used to train a CNN, using Gaborlter with a CNN to target facial wrinkles, and using convolutional neural systems to accurately predict a person's age. In any case, determining the age of individuals with face masks is problematic because most vital features, such as wrinkles on the cheeks, closed mouths, and under the eyes, are not obvious.

The most important point of interest in this content is that a large dataset containing an assortment of images, including individuals of different age groups with different kinds of masks and people without masks, was used to prepare the network. The deep learning-based face detector has been updated to maintain the strength and accuracy of the framework, and a deep learning-based age finder has been added to accurately distinguish a person's age. The proposed framework included three stages: masked face detection from an input image or live video stream, region of interest (ROI) extraction, and subject age prediction. This caused the age detector to accurately identify a person's age.

In 6 Gender Classification using Face Recognition by Terishka Bissoon and Serestina Viriri from the School of Mathematics, Statistics, and Computer Science at the University of KwaZulu-Natal:

This article deals with the issue of gender classification using principal component analysis (PCA) and linear discriminant analysis (LDA). The PCA algorithm has a maximum win rate of 82%, while the LDA algorithm has a win rate of 85%. The FER database is used for training and testing images. Gender classification is a dual classification problem in which an image has to be predicted as male or female. This paper examines optional gender classification methods using face highlights to determine whether highlights extracted from computer vision methods for face recognition can be extended to gender classification. The computer vision techniques used in this paper include PCA and LDA. This paper presents a hybrid approach to gender classification that consists of three modules. The primary module normalises a given face image, while the second module removes features from the normalised image and creates a vector for embedding. The third module uses the highlight vector as input, and the output of the module comes to the conclusion. This gender classification is based on face images using dimensionality reduction strategies such as principal component analysis (PCA) and independent component exploratory (ICA), along with support vector machines (SVM). The impact of performing focused image normalisation, histogram equalisation, and input scaling is monitored. Include an extraction-based Face Recognition, Gender, and Age Classification (FEBFRGAC) algorithm with seemingly small training sets that produced great results. The Canny edge manager was used, and based on the surface and shape data, gender classification was performed using posteriori class probability with a win rate of around 98%. The preprocessing strategies used in this paper consisted of converting a colour image to a grayscale image and then applying histogram equalisation to the image. Histogram equalisation involves transforming the grayscale image into an unused one that is linearized in the respect range. The modern image is characterised by delineating the values back into their unique run after change.

In7 Deep Learning for Gender Recognition by Qili Deng and Yong Xu of the Bio-Computing Research Centre, Shenzhen Graduate School, Harbin Institute of Technology, Jinghua Wang of the School of Electrical and Electronic Engineering, Nanyang Technological University, and Kai Sun of Shenzhen Sunwin Intelligent Corporation, Shenzhen, China:

This study proposes the use of a comprehensive dataset that includes as many typical variations of facial photographs as possible to train a deep neural network-based gender detection model. On the most difficult public database, labelled faces in the wild (LFW), the model achieved 67%. Successful building blocks, including the rectified arunit line (ReLU), fine filter, dropout learning, and very deep architecture, were used to create the network. The main focus of conventional gender recognition techniques is on changes in position, illumination, and occlusion. However, the accuracy of gender recognition can also be affected by other differences, including age, hormonal differences between the sexes, racial differences, and dress style. A straightforward solution to this problem is to create a comprehensive dataset by including photographs of wild faces of different ages, races, occupations, and styles of dress. The CASIA WebFace database, which contains 10,575 subjects and 500,000 photos, serves as the basic building block of the training set.

3. Proposed work

A region-based convolutional neural network (Mask R-CNN) is used in the proposed work to improve gender and age detection. Accurate gender and age detection algorithms are challenged by the common use of face masks for various reasons, including the COVID-19 epidemic. We want to address this problem and increase the robustness and accuracy of gender and age classification in masked faces by exploiting the mask features of R-CNN, which combines object detection and instance segmentation. The proposed task entails a number of fundamental procedures. First, a dataset of masked faces will be collected and labelled for gender and age. To ensure the generalizability of the model, this dataset will be broad, including a range of mask styles, poses, lighting scenarios, and ethnicities. This review paper proposes a new approach for gender and age detection using the Mask R-CNN system. The goal of this study is to advance the

accuracy and robustness of gender classification and age detection frameworks, especially in mask-dominant scenarios such as pandemics and survey situations.

The proposed strategy involves adapting the Mask R-CNN system, originally developed for segmentation, to handle gender and age detection tasks. The system combines object discovery and semantic segmentation for accurate face recognition and classification while capturing gender- and age-related highlights. To achieve this, the proposed work includes several key steps. First, a complex dataset containing various facial images annotated with gender and age data is collected or edited, counting individuals with masks. The dataset has been carefully edited to reduce mutilation and guarantee an accurate display. At this point, a sample R-CNN mask is prepared on the dataset to remember the gender- and age-specific characteristics. The show undergoes iterative preparation and fine-tuning to optimise face recognition and classification performance regardless of the proximity of enclosures. Extensive tests using benchmark datasets are performed to assess the proposed approach and compare it to existing state-of-the-art gender and age detection strategies. Performance metrics such as accuracy, precision, reviews, and F1 scores are used to evaluate the adequacy of a proposed show.

By extension, the proposed study also investigates the effects of various components, such as mask sorting, obstacles, and lighting conditions, on the accuracy of gender and age detection. Techniques for solving these problems, such as information augmentation methods and linking relevant data, are explored. The extreme goal of this proposed consideration is to create a strong and accurate gender and age location framework that can actually work successfully near confrontation shelters. The emergence of this inquiry has potential applications in a variety of fields, such as observational frameworks, open-ended well-being, and social behaviour research. The proposed work contributes to the advancement of gender and age detection innovation and addresses the evolving need for robust and versatile frameworks in the enforcement of social orders.

4. Conclusion

In conclusion, this overview work provided a comprehensive overview of the current state of gender and age detection. We have explored various techniques and advances in feature extraction and classification methods, with a particular focus on deep learning models such as convolutional neural networks. The review highlighted the challenges and limitations we face in determining gender and age, including biases and ethical considerations. He emphasised the importance of data diversity, balanced representation, and addressing privacy issues. In addition, we discussed the real-world applications of gender and age detection and identified the need for further research into multimodal approaches, fusion techniques, and comprehensive reference datasets. Overall, this review serves as a valuable resource for researchers, practitioners, and policymakers, paving the way for the advancement of gender and age detection technologies and their responsible use in various fields.

Reference:

1) A gender and age estimation system from face images in Conference: SICE 2003 Annual Conference Volume: 1 by Gentaro Fukano of Yokogawa Electric Corporation
2) Research paper of Mask R-CNN by Kaiming He, Georgia Gkioxari, Piotr Doll´ar, Ross Girshick on Facebook AI Research (FAIR)
3) Age Prediction Based on Feature Selection by Yanhong Wang, Wei Song, Lizhen liu, at Information and Engineering College of Capital Normal University
4) Facial Age Estimation by Curriculum Learning by Wei Wang at Graduate School of Fundamental Science and Engineering, Takaaki Ishikawa at Global Information and Telecommunication Institute Hiroshi Watanabe
5) Gender Classification using Face Recognition by Terishka Bissoon and Serestina Viriri from School of Mathematics, Statistics and Computer Science University of KwaZulu-Natal
6) Deep Learning for Gender Recognition by Qili Deng and Yong Xu of Bio-Computing Research Center, Shenzhen Graduate School, Harbin Institute of Technology, Jinghua Wang of School of Electrical and Electronic Engineering, Nanyang Technological University, and Kai Sun of Shenzhen Sunwin Intelligent Corporation , Shenzhen, China
7) Age detection in 5 with face mask using deep learning and FaceMaskNet-9
8) https://opencv.org/
9) https://www.geeksforgeeks.org/opencv-python-tutorial/
10) https://viso.ai/deep-learning/mask-r-cnn/
11) https://developers.arcgis.com/python/guide/how-maskrcnn-works/
12) https://paperswithcode.com/paper/mask-r-cnn
13) https://www.geeksforgeeks.org/mask-r-cnn-ml/
14) https://www.mathworks.com/help/vision/ug/getting-started-with-mask-r-cnn-for-instance-segmentation.html
15) https://tensorflow-object-detection-api-tutorial.readthedocs.io/en/latest/

16) https://www.tensorflow.org/hub/tutorials/object_detection