WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Age and Gender Detection Using Python

SWASTIKA SHARDUL[1],TWINKAL SAHU[2], VAIBHAV CHANDRAKAR[3]

(**twinkalsahu2004@gmail.com**)
(**vchandrakar98@gmail.com**)
shri shankracharya technical campus

ABSTRACT :

In this paper, the author has worked on a technique for age and gender classification using python algorithm. Human identification and classification are being utilized in various field for a very long time. Fields like Government ID Cards, Verification procedures etc. We have already developed techniques like retina scan, iris scans, fingerprint and other sophisticated systems such as DNA fingerprinting to identify the individuals. Although these already built methods works efficiently, the hardware, software and human proficiency requirement are way too demanding for several simpler task which may or may not require a professional efficiency. Technique reported in this paper is simple and easy for human classification which can be performed using only a webcam and a decent computer system. Keywords: Age Estimation, Gender Detection, Python Deep Learning, Convolutional Neural Network, Webcam

Introduction

A. Background Information

With the proliferation of smart devices and surveillance systems, automatic facial analysis has emerged as a key application area in computer vision. Age and gender detection from images has applications in security, marketing, user profiling, and access control. Traditionally, these attributes were identified manually or required physical documentation, but deep learning offers a non-intrusive, real-time solution.

B. Research Problem or Question

Can Python-based deep learning models accurately detect age and gender from facial images in real-time applications, and what factors influence the accuracy and generalization of these models?

C. Significance of the Research

Automated age and gender detection offers significant societal and commercial benefits. However, model performance and fairness must be continually evaluated, especially across diverse populations and environments. This study contributes to understanding how Python-based tools perform in real-world conditions and how to enhance their reliability.

II. Literature Review

A. Overview of Relevant Literature

Several studies have demonstrated the effectiveness of convolutional neural networks (CNNs) in age and gender classification tasks. Datasets such as IMDB-WIKI, UTKFace, and Adience are widely used in academic research. Transfer learning using pre-trained models like VGGFace and MobileNet has shown promising results in improving accuracy with less training data.

B. Key Theories or Concepts

- **Facial Recognition**: Detecting and cropping facial regions using algorithms like MTCNN or OpenCV's Haar cascades.
- **Deep Learning**: CNNs automatically learn features from images, which are crucial for classification.
- **Transfer Learning**: Using a pre-trained model for a new, similar task to save computational resources.
- **Softmax Classification**: Used in the final layer of a neural network for multi-class prediction.

C. Gaps or Controversies in the Literature

- **Bias**: Models often underperform on minorities or underrepresented age groups.
- **Overfitting**: High accuracy on training data but poor generalization.
- **Interpretability**: Black-box nature of CNNs makes it difficult to explain decisions.

III. Methodology

A. Research Design

A CNN-based classification model was developed using Python, TensorFlow/Keras, and OpenCV. The design included image preprocessing, model training, and evaluation.

B. Data Collection Methods

The UTKFace dataset was used, which contains over 20,000 face images labeled with age, gender, and ethnicity. Images were collected under uncontrolled conditions, offering a realistic training scenario.

C. Sample Selection

A stratified sampling approach ensured balanced age and gender distributions. Images were resized to 200x200 pixels and normalized.

D. Data Analysis Techniques

Evaluation metrics included accuracy, precision, recall, and confusion matrices. Training/validation/testing was split 70/15/15. Model robustness was also tested using images with different lighting and occlusion.

IV. Results

A. Presentation of Findings

- **Gender Prediction Accuracy**: 93.6%
- **Age Estimation Accuracy (within ±5 years)**: 67.4%
- **Model Size**: 18 MB
- **Inference Speed**: ~50 ms per image on CPU

B. Data Analysis and Interpretation

Gender classification showed consistent accuracy across age groups, while age prediction had variability, especially for older adults and teenagers. The confusion matrix for age estimation revealed that nearby age groups were frequently confused.

C. Support for Research Question or Hypothesis

Findings validate that Python-based CNN models can effectively detect gender with high accuracy and provide usable age estimates. Performance declines with age range granularity or when generalizing to new faces.

V. Discussion

A. Interpretation of Results

High accuracy in gender classification suggests the model learned robust features. Lower performance in age estimation is attributed to subjective labeling and facial variation.

B. Comparison with Existing Literature

Our gender prediction accuracy matches or exceeds many benchmark studies using the UTKFace dataset. Age estimation accuracy, although slightly lower, is consistent with known challenges in this task.

C. Implications and Limitations of the Study

- **Limitations**: Dataset bias, uncontrolled lighting, limited diversity.
- **Implications**: Highlights the feasibility of real-time demographic prediction and the need for continuous retraining or adaptive learning.

V. Discussion

A. Interpretation of Results

While gender prediction is robust, age classification suffers from class ambiguity and dataset imbalance.

B. Comparison with Existing Literature

Findings are consistent with similar works but show improvement in processing time using optimized Python implementations.

C. Implications and Limitations of the Study

Limitations include dataset generalizability and reliance on facial visibility. Results are promising for commercial and academic applications.

VI. Conclusion

"Human Age and gender classification" are two of the many important information gathering resource from and individual. Human faces provide enough data which may be used for many purposes. In order to reach the correct audience human age and gender classification is very essential. Here we tried to do the same process but with general equipment. The efficiency of the algorithm depends on several factor but the main motif of this project is being easy and faster while also being as accurate as possible. Work is being done to the improve the efficiency of the algorithm. Some future improvements include discarding the face like non-human objects, more datasets for people belonging to different ethnic groups and more granular control over the workflow of the algorithm.

VII. REFERENCES

1. Redmon, Joseph, et al. "You only look once: Unified, real-time object detection." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.
2. Liu, Wei, et al. "Ssd: Single shot multibox detector." Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part I 14. Springer International Publishing, 2016.
3. Othmani, Alice, et al. "Age estimation from faces using deep learning: A comparative analysis." Computer Vision and Image Understanding 196 (2020): 102961.
4. Zhang, Kaipeng, et al. "Joint face detection and alignment using multitask cascaded convolutional networks." IEEE signal processing letters 23.10 (2016): 1499-1503
5. Hassner, Tal, et al. "Effective face frontalization in unconstrained images." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.
6. Xu, Wen, et al. Advances in convolutional neural networks. London, UK: Intech Open, 2020.
7. Yang, Shuo, et al. "Wider face: A face detection benchmark." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.
8. Levi, Gil, and Tal Hassner. "Age and gender classification using convolutional neural networks." Proceedings of the IEEE conference on computer vision and pattern recognition workshops. 2015.
9. Ranjan, Rajeev, Vishal M. Patel, and Rama Chellappa. "Hyperface: A deep multi-task learning framework for face detection, landmark localization, pose estimation, and gender recognition." IEEE transactions on pattern analysis and machine intelligence 41.1 (2017): 121-135.
10. Rasmus, Radu Timofte, and Luc Van Gool. "Deep expectation of real and apparent age from a single image without facial landmarks." International Journal of Computer Vision 126.2 (2018): 144-157.
11. M. M. Ranzato et al., "Face Recognition with Unsupervised Feature Learning," in Proceedings of the 2012 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2012.
12. Nair, Vinod, and Geoffrey E. Hinton. "Rectified linear units improve restricted boltzmann machines." Proceedings of the 27th international conference on machine learning (ICML-10). 2010.
13. LeCun, Yann, et al. "Gradient-based learning applied to document recognition." Proceedings of the IEEE 86.11 (1998): 2278 2324.
14. Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 779-788).
15. He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision