

Face Age Prediction Based on Machine Learning

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Abstract. Age recognition, an essential attribute of human identity, plays a pivotal role in various social and medical applications. Due to the influences of photography equipment, lighting, and angles, age recognition based on facial images has always been a challenging topic. Fortunately, with the development of machine learning, especially the breakthroughs achieved by neural network models in image-related fields, researchers have applied machine learning to age recognition. From the perspective of research methodologies, age prediction can be regarded as either a regression or classification task. Therefore, this article analyzes from both regression and classification perspectives. Firstly, it introduces the commonly used datasets in the field of facial recognition. Then, it discusses the commonly used regression models, classification models, and optimization methods in age recognition tasks. Finally, the article summarizes the entire text and proposes future research ideas, providing references for researchers in related fields.

Keywords: Age Recognition; Face Recognition; Machine Learning; Deep Learning.

1. Introduction

The attribute of age stands as a cornerstone of identity in the human saga, its estimation transcending beyond mere chronological measurement to become a cipher of social, biological, and psychological narratives. The impetus to discern age from facial features has burgeoned within the confluence of social networking, digital marketing, and medical diagnostics, making it a pivotal element of contemporary analytics. The emergence of facial recognition technology has fostered development in various sectors, especially in medical and commercial applications. In the healthcare domain, accurate age estimation could be instrumental in patient management, aiding in the diagnosis and monitoring of age-related diseases. Retailers, too, harness the subtleties of age data to tailor marketing campaigns and refine customer segmentation, thereby fostering a more personalized consumer interaction. Therefore, efficient, and accurate facial age prediction algorithms have attracted widespread attention from researchers.

However, age prediction from facial images encapsulates complex variables, posing significant challenges due to the diversity in facial aging influenced by genetics and environmental factors. Lighting, camera quality, and angles can affect age perception from images, with lighting potentially obscuring aging features and angles distorting images. Makeup and hairstyles can alter perceived age, while facial expressions and occlusions like glasses may temporarily change age markers. Ethnic and gender differences are crucial as aging signs manifest differently, requiring unbiased algorithms. Additionally, real-world dataset's varied expressions and conditions increase the complexity of developing robust models. Despite these challenges, advancements in machine learning, especially with large data-based model training, are improving the accuracy of age recognition. Age recognition algorithms can be divided into regression models and classification models based on their design. Regression models predict age as a continuous value, which is then fine-tuned through scaling coefficients to achieve precise age prediction. Classification models discretize age, predicting age by directly identifying age categories.

In the following content, Chapter 2 introduces the datasets used for age recognition and methods for calculating age prediction error. Chapter 3 discusses commonly used regression models, classification models, and optimization methods in age prediction. Finally, the paper concludes with a summary and a look forward to future research directions.

2. Dataset

In age prediction research, widely used datasets include FG-NET (Face and Gesture Recognition Network) [1] and MORPH (Mugshot Identification Biometric) [2]. The FG-NET dataset contains 1,002 color and grayscale face photos taken in a controlled environment. These photos represent 82 individuals, with an average of 12 different photos taken per person. The age range is from 0 to 69 years old, and each photo has a corresponding actual age label, making it one of the datasets with the youngest group's real age. As depicted in Figure 1 from the FG-NET dataset, the images of a single individual taken over different years exhibit significant variations in angle, lighting, and color—factors that greatly complicate the task of age estimation. Additionally, due to the differences between data, it is necessary to research simple and reliable data preprocessing methods in order to achieve good training results. Due to the limited size of the dataset, researchers usually use Leave-One-Out Cross-Validation (LOOCV) to divide the training and testing sets, i.e., all images of one person are randomly selected from the 82 people to form the test set, and the photos of the remaining people are used as the training set.

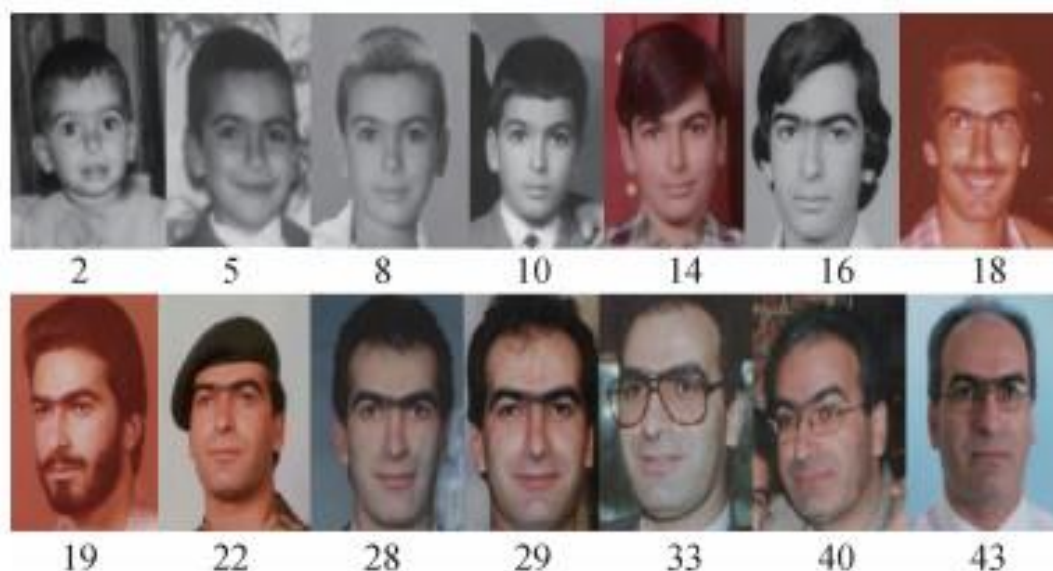


Figure 1. Images of the FG-NET Dataset [1].



Figure 2. Images of the MORPH Album 2 dataset [2].

The MORPH dataset was compiled by the face age research team at the University of North Carolina and is a real-age dataset collected under specific conditions, divided into two series: Album 1 and Album 2. The first series, Album 1, contains 1,690 photos of 515 individuals, taken from 1962 to 1998, covering ages 15 to 68, with each photo accurately age labeled. The second series, Album 2, significantly expands the data size, including images of 55,134 from 13,618 people, taken from 2003 to 2007, and the age range extends from 16 to 77, with each image also labeled with an age value. Figure 2 shows sample images from the MORPH dataset Album 2. Given the much larger number of images in Album 2 than in Album 1, most face age estimation studies based on this dataset tend to use Album 2 for experiments. When dividing the MORPH dataset into training and testing sets, a k-fold cross-validation strategy is usually adopted.

In age prediction research involving facial images, evaluation metrics are crucial for measuring the accuracy of model predictions. These metrics include the Mean Absolute Error (MAE) and Cumulative Score (CS). MAE measures the average difference between the predicted age and the actual age across all test images, calculated by dividing the total sum of prediction errors by the number of images. A lower MAE value indicates a higher accuracy of the model.

Cumulative Score (CS) is another metric that quantifies the percentage of images where the prediction error falls within a certain threshold. For instance, CS (5) represents the percentage of images where the predicted age is no more than 5 years different from the actual age. The higher the CS value, the more accurate the model is considered.

When employing these evaluation metrics, researchers typically perform cross-validation across different datasets to ensure the robustness and generalizability of the model. These metrics allow researchers to compare the performance of various models and identify areas needing improvement. The selection and application of evaluation metrics are vital for advancing age prediction technology; they provide a standardized measure of model performance, helping researchers optimize algorithms for greater predictive accuracy.

3. Methods

This section delves into the methodologies employed in face age prediction, categorizing them into regression and classification models, and explicating their development, performance, and potential areas for enhancement.

3.1. Regression Models

Direct regression models consider age prediction as a continuous variable estimation. Wang et al. [3] have articulated the use of adaptive layered regression for robust age estimation, which addresses the issue of non-linearity in age progression. This approach assigns age prediction as a regression problem, scaling the output between 0 and 1, and subsequently multiplying by an age coefficient to derive an individual's exact age. Moreover, the integration of multiple facial landmarks to align facial patches before inputting them into CNN models, as proposed by Li and Wechsler [4], has enhanced accuracy by providing a localized and structured approach to feature extraction.

In addition to the landmark-based methods, multitask learning frameworks have been employed to concurrently predict age alongside other demographic attributes such as gender and ethnicity, as noted by Moreno and Reddy [5]. These methods benefit from shared representation learning, which can lead to more generalized and robust models. However, when juxtaposed with single-task learning models, multitask frameworks often require more complex architectures and fine-tuning to avoid task interference.

3.2. Classification Regression Models

Classification regression models approach the prediction of age by discretizing it into categorical classes. Rothe et al. [6] demonstrated that training CNNs using classification, with age split into 100 distinct categories corresponding to each year of age, stabilizes the training process and can lead to

improved performance. Their DEX model, which averages the predictions of multiple CNNs, each trained on different age intervals, displayed state-of-the-art results on both biological and apparent age estimation on various datasets.

Further exploring classification-regression models, Thompson and Ghosh [7] introduced AgeNet, which employs deep learning to predict age from facial images. They posited that classifying age into a finite number of categories and then applying regression techniques to these categories can lead to a more refined estimation of age. This hybrid approach allows for the exploitation of the strengths of both classification and regression methodologies, potentially reducing the margin of error. Due to discretization of continuous temporal ages, age prediction with higher accuracy cannot be achieved when making age predictions, such as a child's age at 3 years and 5 months.

3.3. Model Optimization Methods

The enhancement of prediction accuracy is a critical objective in age prediction research. In terms of model optimization, researchers have proposed the method of fine-tuning pretrained Convolutional Neural Networks (CNNs) on specific datasets [8], while others have suggested the use of ensemble methods for robust age prediction [4]. Fine-tuning allows for the adaptation of models to the specific characteristics of age-related features in facial images, while ensemble methods combine the predictions of multiple models to mitigate the weaknesses of individual predictors.

In addition, an often-overlooked aspect in age prediction is the influence of race and gender on the accuracy of age estimates. Guo and Mu [9] have highlighted the importance of considering these demographic factors to develop unbiased age prediction models. Levi and Hassner [10] further investigated the classification of age and gender using CNNs, emphasizing the need for balanced datasets that represent a diverse range of ethnicities and genders to ensure the fairness and generalizability of the prediction models.

4. Conclusion

The age prediction method based on machine learning has achieved good results. This paper has dissected the subject from the dual perspectives of data and algorithms. It has illuminated the commonly used datasets in age recognition, as well as the prevalent methods of age prediction based on regression and classification. While these techniques have achieved commendable performance, they are not without their limitations. There is an ongoing endeavor to refine these methods.

Looking forward, the synergy between deep learning and AI portends a bright future for age recognition technology. The emphasis is migrating towards devising models that not only assess age with higher accuracy but also discern the nuanced age-related transformations in facial features. This evolution promises to yield more nuanced and precise age predictions. Moreover, as edge computing ascends, there is a burgeoning need for optimized models that can execute real-time age estimation on less powerful devices. Yet, as we advance, ethical implications must be rigorously considered. Privacy, data security, and the potential for misuse must stay at the forefront of this technological progression. It is incumbent upon researchers and developers to navigate these issues diligently, ensuring that age-recognition technology advances with a commitment to responsibility and ethical integrity.

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