© DEC 2023 | IRE Journals | Volume 7 Issue 6 | ISSN: 2456-8880

Age Estimation from Facial Images of Human Beings

OLATUNDE OLUKEMI VICTORIA[1], OLAGUNJU OLABISI KAYODE[2]

[1]*Software Engineering Department, Federal University of Technology, Akure, Nigeria*

[2]*Computer Science Department, Federal University of Technology, Akure, Nigeria*

Abstract— Real-time age estimation applications are prevalent in biometrics, security, and healthcare fields. These applications support various elements for confirming or authenticating an individual's identification, including age simulation, electronic customer relationship management, access control, surveillance, and age-specific human-computer interaction. The measure of how long a person or an object has existed is known as age, an age estimation system aims to attribute a certain age or age range to a given face image, with facial features, and the human face provides crucial data about a person's traits, including identity, expression, age, beauty, and gender, a person's age and identification can be estimated using facial recognition technology. This study proposed an innovative machine learning approach for classifying a person's age according to their facial image, thereby reducing reliance on sensitive identification data.

Indexed Terms— Age, Age Estimation, Facial Images, Machine Learning

I. INTRODUCTION

The human face provides crucial data about a person's traits, including identity, expression, age, beauty, and gender. This data has many practical applications, like video surveillance, customer profiling, human-computer interaction, and person identification. Among these issues, creating automatic age estimation systems has recently emerged as an interesting but complex subject.

An age estimation system aims to attribute a certain age or age range to a given face image. A cross-age facial task is a cross-domain challenge because the aging process brings considerable intraclass differences in facial looks. Age features must be accurately and robustly represented. It can also be used as forensic art for information retrieval to determine the best match for missing people [1], [2].

Automatic labeling of a face image with the age range or exact age can either be a classification problem if the model predicts an age range or a regression problem if the model predicts an exact age. Age estimation data offers extra information about users' identity and it can provide additional identifying information about the users. The system's performance might be enhanced, and the primary biometric traits, such as the face, fingerprint, and iris, could be supplemented with the data obtained from the Age estimation system. Age estimation models can be divided into groups according to the algorithm employed as the age estimate's final stage. In this way, the age estimation problem is considered to be a multiclassification task, if the ages are regarded as distinct class labels, and the absolute age is deduced using classifiers trained on labeled data, such as Support Vector Machine (SVM). On the other hand, the problem is considered a regression problem, if the labels were viewed as numerical values. However, a more robust system can be built by combining both methods [3].

II. AGE ESTIMATION

A. Age estimation system

Age estimation is a process of automatically labeling a human face with an exact age or age group, which can be either the actual age, perceived age, or estimated age. Age estimation is flexible and can be divided into groups according to the algorithm employed at the age estimate's final stage. In this way, the age estimation problem is considered to be a multiclassification task, if the ages are regarded as distinct class labels, and the absolute age is deduced using classifiers trained on labeled data, such as Support Vector Machine (SVM). On the other hand, the problem is considered a regression problem, if the labels were viewed as numerical values. A more robust hybrid system can be built by combining both methods [3], [4]. Fig. 1 is an overview of an age estimation system.

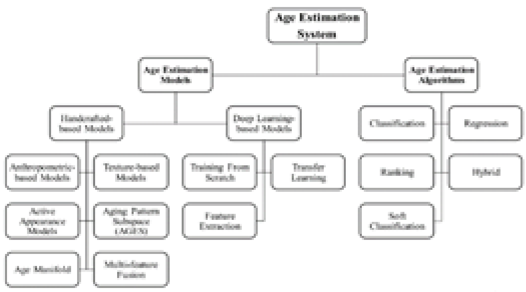

Figure 1. An overview of age estimation

B. Age estimation models

Age estimation can be classified as handcrafted and deep learning-based models. Handcrafted-based methods process of features selection and extraction is usually done manually, and usually combine filters to extract shapes and edges from a facial image, such filter include Local Binary Pattern (LBP) or Histogram of Oriented Gradients (HOG). A learning algorithm such as support vector machine or K-nearest neighbor is added to learn the extracted features. However, handcrafted methods tend to be time-consuming and less accurate; but it is usually less computationally expensive. Fig. 2. Shows the general framework of a handcrafted-based model, and Fig. 3 shows an overview of training a typical age estimation model.

The deep learning-based model process of feature selection and extraction is usually done automatically without human intervention and usually depends more on using algorithms such as convolutional neural networks (CNNs) or Multilayer preceptors (MLPs) to extract useful information from a given image. In deep learning-based methods, a fully connected neural network is employed to learn the extracted features. Deep learning models are computationally expensive in image processing, but they are more accurate compared to handcrafted models.

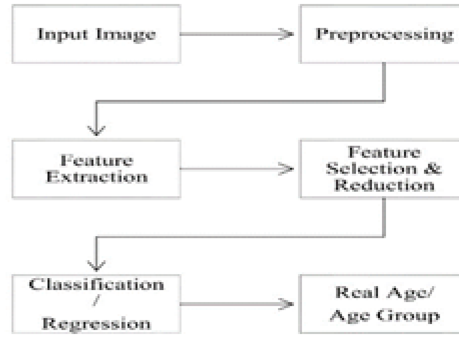

Fig. 2. General framework for handcrafted-based model

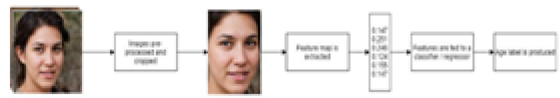

Fig. 3. Overview of a typical training of age estimation model

C. Age estimation parameters

To assess the effectiveness of the age estimation system, two primary metrics are used for this objective, which are the Mean Absolute Error and the Cumulative score.

The Mean Absolute Error (MAE) stands as the prevalent evaluation measure in the existing literature for age estimation. It is defined as in eq. (1).

$$MAE = \sum_{i=1}^{n} \frac{|\hat{x} - x_1|}{N} \qquad (1)$$

Where $\hat{x}$ represents the estimated age, the actual age is represented by x_i and N is the number of testing samples.

The Cumulative score (CS) is another metric in age estimation, which can be defined as in eq. (2)

$$CS(\theta) = \frac{N_\theta}{N} \qquad (2)$$

Where N_θ represents the number of test images whose absolute error between the estimated result and the ground truth is not higher than θ years.

III. RELATED LITERATURE

Age estimation from facial images is a complex one and several researchers have explored various methods. [5] presented an age estimation machine learning approach to predict user age from facial images without collecting all sensitive user data. The proposed model employed ResNet and MobileNet, to process facial images and predict user age. [6] proposed the use of post-processing strategies for features extraction using pretrained deep networks in age estimation. A review and comparative analysis of some of the modern approaches and techniques for the apparent age estimation task was presented by [7], and [8] proposed a new facial age estimation strategy that aims to improve accuracy by exploiting the relationships between facial feature representations and cumulative attribute coding in a unified model objective. [9] carried out an evaluation of the effectiveness of CNN models in accurate age estimation based on orthopantomogram images and compared them to traditional manual methods. The study aims to determine if CNN models have the potential to surpass human accuracy in age classification, which has implications in forensic science, immigration, and clinical treatments.

IV. DATASET

APPA and the UTKFace datasets with their corresponding age labels are publicly available online datasets that were employed in this study, Fig. 3 and Fig. 4 captured the faces of photos of people in our dataset(APPA-REAL) and their real ages; and the various people present in the UTK Face dataset respectively.

Fig. 3. people in our dataset (APPA-REAL) and their real ages

Fig. 4. various people present in the UTK Face dataset

The datasets were split into training, testing, and validation; preprocessed by resizing all the facial images to a fixed size of 224 x 224 to ensure consistency and normalized the pixel values to a suitable range of [0, 1] in preparation for machine learning training.

The training data were augmented by applying random transformations such as rotation, scaling, and flipping to increase the dataset's diversity.

Pretrained ResNet model was used as the based architecture where the last layer was removed, and a new layer to adapt the model for age estimation was added. Some layers of the ResNet were frozen during the training to prevent them from updating during the training. The model's weights were initialized, mean squared error (MSE) loss function was defined, ADAM was used as an optimizer, and its hyperparameters were set.

V. METHODOLOGY

In this study, a deep learning-based model Convolutional Neural Network (CNN) was employed for image analysis due to its exceptional performance in capturing complex spatial patterns and hierarchical features.

A CNN consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. These layers work together to extract meaningful features from images and make predictions. A high-level overview of how CNNs are applied to age estimation from facial images are stated below:

- Convolutional Layers: CNNs use convolutional layers to perform local feature extraction. These layers consist of multiple filters that convolve across the input image, capturing spatial patterns and features. The filters learn to detect edges, corners, textures, and other low-level features.
- Pooling Layers: After each convolutional layer, pooling layers are used to down sample the spatial dimensions of the feature maps. This helps reduce the computational complexity and focuses on the most informative features by retaining the dominant activations.
- Fully Connected Layers: The extracted features are then flattened and passed through fully connected layers, which learn high-level representations and make predictions. These layers map the features to the desired output, such as age labels in age estimation tasks.

VI. MODEL IMPLEMENTATION

A. TRAINING THE MODEL

In this study, a deep learning-based model Convolutional Neural Network (CNN) was employed for image analysis due to its exceptional performance in capturing complex spatial patterns and hierarchical features.

The model was trained on the training set using mini-batch gradient descent, and the model's performance was monitored on the validation set; adjusting its hyperparameters where necessary. The training process was repeated until the model converged or reached a satisfactory performance level.

Once the model achieved satisfactory performance, the trained weights were saved and integrated the model into an application.

The age estimation model was implemented on Microsoft Windows 11 professional 64-bit operating system Personal computer with intel core i5, CPU 2.40GHz processor, 16GB RAM, and 500GB hard disk storage. Kaggle development environment, which provides a platform for data analysis and machine learning tasks was utilized in implementing our model

B. BUILDING THE MODEL

This model contains three convolutional layers, one batch normalization layer, three MaxPooling2D layers, one flatten layer, three dense layers, and two dropout layers. With this model, there are 11,020,546 total parameters, and 11,020,418 of them are trainable parameters. The Adam optimizer with binary cross entropy and MAE loss was employed.

VII. RESULTS AND DISCUSSION

An innovative approach for classifying person age according to their facial image was proposed in this study, Fig. 4. Shows the age loss function of the UTK Face dataset; and Fig. 5 depict the model performance at predicting ages of people in the APPA-REAL dataset. The plot shows the age prediction accuracy. Surprisingly, the accuracy of both train and validation sets decreased significantly after the first epoch. Moreover, both tended to fluctuate greatly across epochs. The best accuracy for the train set was 0.0427 at epoch=1. The best accuracy for the validation set was 0.0474 at epoch=1

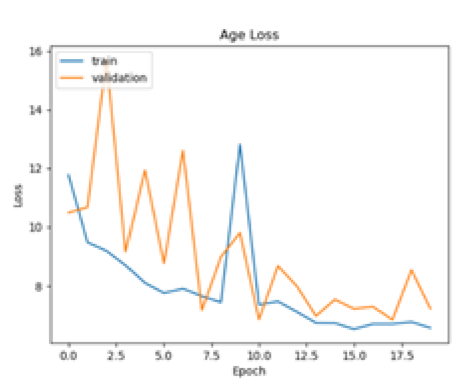

Fig.5 age loss function of the UTK Face dataset

Fig.6 Model performance at predicting ages of people in the APPA-REAL dataset

CONCLUSION

A machine learning method for classifying a person's age according to their facial image to reduce reliance on sensitive identification data was proposed, although the model did not reach its intended performance, the methodology and foundational understanding developed in this study could serve as a resource for practitioners aiming to integrate machine learning based age verification solutions into their system.

REFERENCES

[1] W. Li, J. Lu, J. Feng, C. Xu, J. Zhou, Q. & Tian BridgeNet: A continuity-aware probabilistic network for age estimation. *In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2019, pp.1145-1154.

[2] S. K. Gupta, and N. Nain. Review: Single attribute and multi attribute facial gender and age estimation. *Multimedia Tools and Applications*, 4: 82(1): 1289-131: 2023.

[3] A. S. Al-Shannaq and L. A. Elrefaei, "Comprehensive Analysis of the Literature for Age Estimation From Facial Images," *in IEEE Access,* vol. 7, pp. 93229-93249, 2019.

[4] R. Angulu, J. R. Tapamo, and A. O. Adewumi. Age estimation via face images: a survey. *J Image Video Proc.* (2018) 2018:42

[5] D. C. Nguyen. Age Estimation from Facial Images Using Machine Learning. Oulu University of Applied Sciences 2022

[6] A. Anand, R. D. Labati, A. Genovese, E. Muñoz, V. Piuri and F. Scotti, "Age estimation based on face images and pre-trained convolutional neural networks," *2017 IEEE Symposium Series on Computational Intelligence (SSCI), Honolulu, HI, USA*, 2017, pp. 1-7.

[7] O. Agbo-Ajala, S. Viriri, M. Oloko-Oba, O. Ekundayo, and R. Heymann – Apparent age prediction from faces: A survey of modern approaches. *Front. Big Data* 5:1025806. 2022.

[8] Q. Tian, M. Cao, H. Sun, L. Qi, J. Mao, Y. Cao, and J. Tang – Facial age estimation with bilateral relationships exploitation. *Neurocomputing* 144 pp 158 – 169.

[9] Y. Guo, M. Han, Y. Chi, H. Long, D. Zhang, J. Yang, Y. Yang, T. Chen, and S. Du. – Accurate age classification using manual method and deep convolutional neural network based on orthopantomogram images. *International Journal of Legal Medicine*. 135. pp 1-9. 2021.