# A Survey on Age Estimation using Facial Images

*Abstract*—**Numerous applications heavily rely on age estimation, including security management, multimedia communication, human-machine interface, and monitoring task. Because of this, research on age estimation has recently gained increased attention. This paper provides an overview of different methods and datasets used to estimate age from facial images. We present a summary of 13 papers that we reviewed. This paper shows that machine learning models work better in age prediction from image datasets. It will be beneficial for researchers to have a better grasp of the methods used for estimating age. We anticipate that our review will encourage researchers to continue developing and enhancing different techniques for age estimation.**

*Index Terms*—**Age Estimation, Facial Images, Face detection, Facial Features, Face , Age classification**

## I. Introduction

When we first glance at someone, we usually focus on their face. In the world, it is quite difficult to find different people with the same face. According to an article, there is a one in one trillion probability that two people will have exactly the same eight characteristics of the face. This is because many characteristics, such as age, gender, facial expression, various styles, and makeup, have an impact on how the face looks. People of different age groups have different facial features. For example, a person's facial features as an adult and as a child are very different from one another.

Age estimation is the process of identifying a person's age using biological characteristics. It is a useful feature for face image recognition and classification tasks. A person's age can be predicted based on some internal and external characteristics. Some internal characteristics of humans are sex, different genes, blood cells, diseases, etc. Contrarily, external influences include things like a person's weight, surroundings, and personal habits like smoking, drug use, etc.

There are a number of well-known global applications that directly or indirectly deal with facial age estimates. For example, face recognition is one popular method of identifying legitimate users in security systems. In forensic systems, it aids in distinguishing a person from unidentified dead bodies. Age is a consideration when hiring candidates for police and military positions. Age estimation will make it easier to verify candidates' ages during the hiring process. Moreover, it is additionally widely utilized in a variety of digital gadgets, automatic home systems, and law enforcement.

In this research, we reviewed 13 papers on age estimation from facial images. This research has focused on different models and dataset used in age prediction tasks. It will help to compare different models which work better in age estimation among other used models. We have also analyzed the performance of different models in the age estimation task. Our research will help other researchers in choosing a method for predicting age more accurately.

In the next section of our paper, we discussed the summary of the related works in this field. The dataset used in different research works is mentioned in Section III. Age estimation techniques and preprocessing tasks are described in Section IV. Next, the result part is introduced in Section V. Finally, in section VI we have concluded our paper.

## II. Related Works

In human-machine interaction tasks, age estimation plays a vital role. In the previous few decades, numerous studies have attempted to estimate the age from facial images. In this paper, we have analyzed 13 papers of the age estimation field. In a research paper by Sarah et al.[1] MLP is used to extract features from facial images to determine the age. They have used fine-tuned age ranges to estimate the age. The image dataset used in this approach is collected from their friends and family members. They have extracted features from the images by using 94 points from the eyes, nose, eyebrow, face contour, and mouth. Their model achieves around 88.29% accuracy during estimating age using the MLP model.

Another research article by Jamal et al. [2] used Linear Discriminant Analysis to predict the age from facial features. They have used the FG-NET dataset in their research work. The first step of their proposed model was face detection. They have used the Viola-Jones algorithm for this task. After that, they extracted features from the face image. After extracting the features, they used the J48 classification method to classify the features to estimate age. Their system achieved around 90.45% precision while estimating age from the facial image dataset.

In an article on age estimation [3], authors have used the Viola-Jones algorithm with the SVM model to extract features from facial images. The database used in their research work contains ninety images of different age group peoples with six different classes. Before performing the feature extraction task, they preprocessed their image dataset by resizing and converting it to grayscale images. Using the SVM technique, their model classifies age groups with an accuracy of 98.89%.

A recent paper by Xinhua et al [4] proposed ShuffleNetV2 model which is based on a lightweight CNN model to estimate age from facial images. They have used the MORPH2 dataset and FG-NET dataset for their research purpose. They have merged classification and regression methods which help to get higher accuracy in age estimation tasks. Their mixed ShuffelNetV2 produces only 3.81 mean absolute error while predicting age from facial features.

In a thesis paper by Prottoy et al [5], the goal was to investigate Convolutional Neural Network approaches to improve age classification accuracy. They employed a few pre-existing models and pre-trained weights like vgg16, Resnet50, and Senet50 and weighed face detection with VGG-Face that are trained on Wild and YouTube face datasets to get greater accuracy. They also employed k-fold validation and fine-tuned the model. This process demonstrated more precision. They used the UTKFace dataset to train their model. Then they contrasted their work with previously published publications. In other words, they sought to improve age classification accuracy. To demonstrate how well their model performed in comparison to other models, they also compared their work to previously published papers.

A research paper by Asthana et al. [6], attempted to demonstrate that a computer can categorize people's ages based on features collected from images of people's faces using SVM. They presented a Support Vector Machine-based technique for classifying people's ages based on facial features. They categorized the population's age into three categories: young, middle-aged, and old. Collected data, feature extraction, and system training and testing by the SVM are all phases in the development process. They used the website-derived dataset to train and test the system. The proper percentage for identifying children in the test images is 83.3333%, adults at 68.75 %, and the elderly at 61.4583%. After a detailed analysis of the factors affecting the classifier's performance, the authors conclude by outlining a few key ones. For instance, the photographer frequently smoothes out facial wrinkles or the effects of various cosmetics on the faces. Additionally, some essential details are lost due to the overwhelming power of some light sources. Additionally, beards and spectacles obscure several important characteristics.

In a study by Can et al. [7], they have developed a collection of deep learning models for estimating perceived age. This ensemble model allows for the erroneous, unclear appearance of the face images age labels in addition to age groupings. Instead of utilizing the highlighted facial image's average age as the class categorization, The images of faces have been grouped that fall inside a given age category to allow for numerous labels per image. They have trained age categories and age-shifted categories in a number of deep learning. Finding and utilizing five face landmark points for 2-D alignment before a facial image input is fed to a deep learning network. The IMDB-WIKI dataset was used to pre-train convolutional neural networks based on VGG-16 architecture. Combining the results of various deep learning models provides the final estimate. In the last test set for the ChaLearn LAP 2016 challenge, the proposed approach obtains 0.3668 error.

A final project by Kjaerran et al [8], presented a proposal to solve the age estimation problem. To identify a person's age from photographs, they introduced a deep convolutional neural network including three fully connected layers and five convolutional layers. Three separate datasets (APPA, UTK, and IMDB dataset) are combined to serve as training data, and the model is completely trained from scratch. A face-recognition program was used to pre-process the images. The model is assessed using the Adience benchmark as well as a held-out test set. The model obtains a categorical accuracy of 0.52 on the test set. Their model performs lower than another model on the Adience benchmark, with an exact accuracy of 0.30 and a one-off accuracy of 0.46. Additionally, a software was developed that enables users to estimate their age right on their webcam.

TABLE I
RELATED WORKS IN AGE ESTIMATION FROM FACIAL IMAGES

| **Paper** | **Applied Models** | **Dataset** |
|---|---|---|
| Sarah et al.[1] | Multilayer Perceptron (MLP) | A set of 300 images |
| Jamal et al. [2] | Linear Discriminant Analysis | FG-NET Dataset |
| Ingole et al.[3] | Viola-Jones Algorithm<br>SVM model | 90 images with 6 different age groups |
| Xinhua et al. [4] | Lightweight CNN<br>ShuffleNetV2 | MORPH2 Dataset<br>FG-NET Dataset |
| Ranjan et al.[9] | Fuzzy c-means clustering algorithm | 95 frontal face images captured using Digital Camera |
| Khryashchev et al.[10] | Local Binary Pattern<br>SVM | MORPH<br>FG-NET<br>RUS-FD |
| Malli et al.[7] | Deep CNN<br>VGG-16 | The ChaLearn LAP dataset. |
| Aparna et al.[6] | SVM model | 432 gray-scale facial images taken from a website |
| Adrian et al [8] | CNN | The APPA Dataset<br>The UTK Dataset<br>The IMDB Dataset |
| Mahruf et al.[11] | Transfer Learning<br>K-fold cross validation | The UTKFace |

## III. DATASET

To estimate age from facial images, the researchers used different datasets in their research work. In research paper [2], the researchers have used FG-NET dataset. This dataset contains 1,002 face images of both male and female. On the other hand, an article [4] used MORPH dataset in their research work which contains 55,000 unique images of different community peoples. Another paper used UTKFace image dataset which contains images of age range 0 to 106 years old. The number of images of each dataset used by different researchers in their research paper is shown below in table II.

TABLE II
COMPARISON OF DATASETS

| Image Dataset | Number of Images | Age Range |
|---|---|---|
| FG-NET | 1,002 | 0 to 69 years |
| MORPH | 55,000 | 16 to 77 years |
| UTKFace | 20,000 | 0 to 116 years |
| IMDB-Wiki | 5,23,051 | 0 to 60+ years |
| APPA | 7,591 | 0 to 90 years |
| ChaLearn Lap | 4,699 | 0 to 100 years |
| RUS-FD | 8,100 | 6 to 60 years |
| YGA | 1,600 | 0 to 93 years |
| AI and R Asian | 34 | 22 to 61 years |
| WIT-DB | 12,008 | 3 to 85 years |

In below Figure 1, Figure 2 and Figure 3 we have shown some images from VG-NET, MORPH and IMDB-Wiki dataset.

Fig. 1. Example of VG-NET Dataset

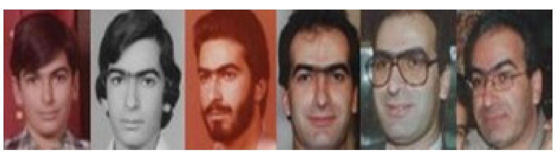

Fig. 2. Example of MORPH Dataset

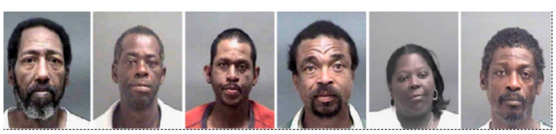

Fig. 3. Example of IMDB-Wiki Dataset

## IV. Methodology

### A. Data Pre-processing

Before training and testing, the dataset needs to be pre-processed.Different authors applied different steps in the preprocessing task. For example, in the preprocessing step, [2] converted the real image into a gray scale image using RGB to gray scale converter. After that, they used histogram equalization to reduce the noise from the converted images. Another paper [3] at first resized the images into 300x300 pixel size and then converted it into gray scale images. Using a face detector, [7] detected face from the images in their preprocessing step. After that, based on some landmarks, faces were aligned. Finally, cropped the images with sixty percent extra margin. Other preprocessing steps followed by other researchers are scaling, transformation of color space, crop and reshape resolution, grouping images into bins, data augmentation etc.

### B. Feature Extraction

Prottoy et al. [5] mentioned two types of feature extraction methods in their research work. Deep feature extraction and handcrafted feature extraction are two types of feature extraction methods. They have applied LBP which is a hand-crafted feature extraction method in their research. Ranjan et al.[9] extracted some global and local features from the facial images. The global features include the distance ratio of eyeballs, chin, lip, nose, etc. On the other hand, local features include wrinkles from some portions of the face like the corner of the eyes, forehead region, etc. Another paper used Viola-Jones algorithm to extract features. Moreover, hybrid attention mechanism is added to improve the feature extraction quality in another research paper. SURF is also used in [3] to detect features from the facial images.

### C. Age Estimation Algorithms

The final step of age prediction is to classify the facial features into different age groups. Logistic model tree classifier, MLP, SVM methods are used in different papers for the classification task . Another paper used a hybrid method for classification and regression task. Some machine learning models like VGG-16, Senet50, ResNet50 are used in the paper of Prottoy et al. [5]. Fuzzy C-Means clustering algorithm is used in another paper to classify wrinkle features from facial images. Some papers also used some hybrid approach by combining both classification and regression task in predicting age. This method helps in establishing a connection between the age labels and the feature vectors. Guo et al. [12] used a combined approach of classification and regression task predicting age. Some other age estimation algorithms are ANN, SVR regressor, LARR method used in different research papers [13].

## V. Result and Analysis

Performance measurement of different applied models on age estimation is shown in the below Table III. From the table we can see that, using CNN model, around 56% accuracy is achieved in age prediction task. When SVM model is used, it scored 83.33% accuracy. But when SVM model with Viola Jones algorithm are combinedly used, it scored 98.89% accuracy which is the highest accuracy among the other applied models.

TABLE III
PERFORMANCE ANALYSIS

| Applied Model | Performance Measure and Accuracy |
|---|---|
| CNN | 56% |
| SVM | 83.33% |
| ResNet50 | 71.84% |
| LBP | CS 42% |
| MLP | 88.29% |
| SVM+Viola Jones | 98.89% |
| VGG-16 | MAE 0.3668 |
| MA-SFV2 | MAE 3.81 |
| LDA | MAE 1.41<br>Precision 90.45% |

## VI. CONCLUSION

Age estimation is the technique to determine a person's age based on some features. In this paper, we have provided a survey on different age estimation techniques. We have reviewed a total to 13 papers where different models and datasets are used for age estimation. Different dataset of facial images and their characteristics are also reviewed in our paper. From our research, we found that among different machine learning models, SVM performs better in predicting age with an accuracy of 98.89%. Our survey will encourage researchers to continue developing and enhancing different techniques for age estimation. Moreover, it will help future researchers to have an idea of age estimation techniques before choosing models for age estimation. In future, we will work on predicting age from videos using hybrid models.

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