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Age Estimation from Facial Image:A Survey

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Abstract-In recent years, Age estimation approaches are challenging and time consuming. Age estimation has a lot of applications such as minimum driving age, cosmetology, finding lost people, etc. There are different models and algorithms for age estimation techniques. In this survey paper, we review the previous research papers and analyze their age estimation methods. We are shortly analyzing the classification and regression techniques.A comprehensive summary of analyzing methods is introduced with popular datasets.

Keywords-Age Estimation, feature extraction, age estimation techniques, comprehensive analysis.

I. INTRODUCTION

Each person has unique facial features. Biological facial features basically categorize the human with a different age. During previous years, the research area of age estimation has been more observed with lots of articles, journals and conference papers published. Age is a crucial property useful in many applications such as minimum **I.** driving age, preventing purchase of alcohol, legal smoking age, human-computer interaction, finding lost people, age based access control, social security, internet access, entertainment, cosmetology etc.

The most challenging thing is the human face could be different at different ages, related to its shape of facial features; the skin around the eyes gets wrinkles and changes in figuration and among others. This could be affected by two factors. One is an external factor (sun and living exposure, cigarette smoking, health) and, second, is the internal factor (gender, genetics and surgical operation). Age estimation is defined as "Automatically labelling a human face image with respect to their age range or age value".

Several techniques are available for solving the age estimation problem, but few problems are still remaining unsolved because the human aging process is not controllable. It is different from one person to another one. In this survey, our goal is to explain and analyze different age estimation techniques and comparison between them. Different datasets have a wide variety in terms of number of images. Section II describes literature review of age estimation technique.

In Section III we analyze the background of age estimation. Section IV defines the different age estimation techniques. Primarily, we are discussing supervised learning techniques – classification, regression, support vector machine. Then we are defining age estimation, learning techniques. Section V contains a table of comparative analysis between different age estimation techniques. Section VI defines datasets which are used to train the algorithms. The conclusion is described in section VII.

II. LITERATURE REVIEW

In recent times, a researcher has shown interests in the age estimation system due to its wide participation in real life applications. We are analyzing previous research to understand which type of methods can be suitable for age determination.

Hao Liu et al. [1], introduce an ordinal deep feature learning (ODFL) method. Work of this method is to learn feature description for facial image representation which is directly from raw pixel images. The ODFL method features extraction and age estimation both arelearned independently. In such work, we further introduce an ordinal deep learning (ODL) framework, which is used for exact age prediction. A back-propagation algorithm is used to optimize network parameters.

Marcus de Assis Angeloni et al. [3], introduce multi-stream convolutional neural network architecture. This architecture is designed for age estimation using facial parts (eyes, nose, eyebrows, and mouth) which is cropped from the input image. In this approach, each facial part feeds an individual stream and the Adam algorithm is used for optimization. Experimental results can be obtained in the adience benchmark dataset.

Yi-Lei Chen et al. [4], presents pairwise age ranking and introduces aflexible subspace learning method to specify the age-based features. The proposed subspace learning methodsolves a sequence of constrained optimization problems. The result of age estimation shows that the proposed method outperforms from the point of view of basic subspace learning, and the semi-supervised learning that successfully affiliatedunlabeled data with age ranks under a variety of scales and sources of data set. In this paper, the regression problem is used for the estimation stage and to estimate the regression function by support vector regression (SVR). Aging manifold, which is used for accurate age labels, and the age ranks both are jointly fixed in the proposed subspace method. Researchers use LOPO (leave-one-person-out) protocol for theFG-NET database. As for MORPH datasets, as it contains hundreds of images with few individual images, the LOPO strategy is not suitable.

Hu et al. [5], in this paper, researchers applied K-L (kullback-leibler)/raw intensities for human face identification. The K-L is present on the top layer of the CNN for age estimation. In this method, for unlabeled images, combinesimilar subject images into pairs and take the individual years as the age difference. Using the pairs of images, researchersrefine an already trained intensive age estimator. In this approach,entropy, cross entropy, and K-L divergence distance loss functions are present on top of the softmax layer, which is known as the representation of age difference.

Table 1.

Authers	Methods	Dataset	Protoc ol	Optimization algorithm
Shahram Taheri et al. [6]	DAG-CNN +average pooling	MORPH II + FG-NET	nil	Adam
Hu et.al [5]	CNN + K-L divergence	MORPH II + FG-NET + Year labeled dataset	nil	nil
Yi-Lei Chen et al.[4]	Subspace Learning + Age manifold + Semi-supervised learning	MORPH II + FG-NET	LOPO	nil
Marcus de Assis Angeloni et al. [3]	Multi-stream CNN + Max-pooling	Adience Benchmark	Standa rd 5-fold	Adam
Hao Liu et al. [1],	ODFL+ODL + supervised learning	MORPH II+ FG-NET + FACES + LIFESPAN + Apparent facial age estimation datasets	LOPO	Stochastic Gradient Descent via Backpropaga tion

Shahram Taheri et al. [6], introduce a new deep learning architecture DAG-CNN (directed acyclic graph CNN) for age estimation from facial image. DAG-CNN works on multi-level learned features from different layers of VGG-16 CNN and GoogLeNet models.

III. BACKGROUND

Aging is a time-dependent, inescapable, and irrevocable process that makes changes in facial shape and texture. Each person has different aging patterns. Age estimation system consists of two main terms: first one is feature extraction and the second is learning method. After extracting the useful features, estimate the age of the human with accurate age or labelled age group. Initially we describe image representation. After representing an image, feature extraction is performed.Select the useful features, Age estimation process is performed.

According to M. Mahmoud Badr et al. [2], researchers discuss three important areas focusedon aging research. Initially discussed aboutage invariant face recognition. Second is age synthesis and the third one is to estimate the age with labels. The main challenging job of a learning technique is to bridge the gap between the actual age and determined age. Generally, the age estimation models are of two types.

First one is handcrafted algorithms and the second one is deep learning technology. The handcrafted modelswhich are the process of features extraction and selection both are accomplished manually. Whereas thedeep learning process happens automatically without any human interference.

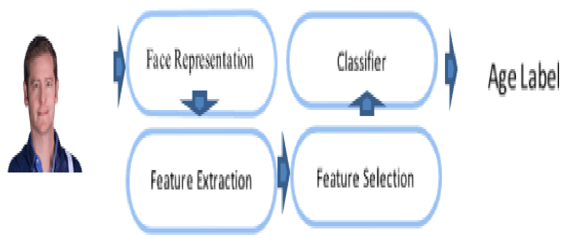

Fig 1. Basic block diagram of Age Estimation Process.

IV. AGE ESTIMATION TECHNIQUE

Once the aging factors are extracted subsequent processes are age estimation. As we know, the machine cannot calculate the accurate age of the human even if the human brain also fails in some time. In this case we train machines using labelled data which is trying to achieve the nearest value of human age. There are different algorithms in machine learning which are helpful for predicting the nearest person's age, such as classification, regression and SVM (support vector machine).

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1. Classification:
Classification is a supervised learning algorithm which is applied for prediction and work on labelled datasets. Classification is a technique to find an appropriate function which helps to separate different classes based on a parameter. In this process the model or computer program is trained using the training datasets and based on this type of training, it categorizes the datasets into classes. In an age estimation process, classify the different age labels such as child, adult, old and separate age ranges (0-3, 5-8, 11-14, 16-20…….).

This is a classification problem. Marcus de Assis Angeloni et al. [3], researchers used classification techniques. In this approach, the classification is done not only by the last layer, but also by each stream individually. Shahram Taheri et al. [6], used an SVM classifier for predicting an output label.

2. Regression:
Regression is also a supervised learning algorithm which is applied for statistical methods. In this analysis, target (dependent) variable and predictor (independent) variables both establish a strong relationshipwith more predictor variables. Regression analysis algorithms are used to predict the mathematical continuous values just like a price, age etc. Hao Liu et al. [1], applied ordinal regression for binary outputs of age labels. Yi-Lei Chen et al. [4], used semi-supervised subspace learning with support vector regression because the aging ranking process is a binary decision and SVR automatically classifies the age rank.

3. Support Vector Machine:
Support vector machine algorithm is a supervised learning which is used in both classification and regression problems. Initially, SVM is applied onclassification problems. SVM creates a decision boundary that can separate n-dimensional space into classes. The best decision boundary is also known as hyperplane. Support vector machine for regression is called support vector regression. The idea behind SVR is to identify the best fit line which is the hyperplane that has the maximum number of points.

4. Subspace learning:
Subspace learning is a handcrafted based method in which feature selection and extraction are completed in manual order. In this method, face images are encoded with the AAM (active appearance model) parameter. In the subspace learning method, it requires multiple existing faces of the same subject (human) with different ages and learned relative aging patterns of the same person image which are available on datasets.

The AAM parameters are manipulated using the combination of shape model and the texture model (gray scale image) coefficient.

The AAM parameter cannot identify the face wrinkles. And another drawback is, it is difficult to find the large dataset containing the multiple faces of the same person with a different age. Figure 2 depicts the image series of the same subject.

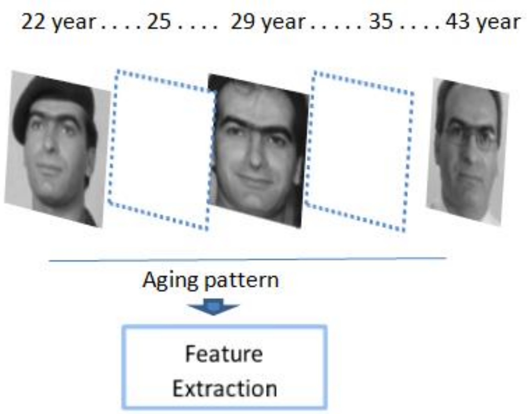

Fig 2. Image series of the same person.

5. Age Manifold:
In the age manifold technique, a similaraging pattern is identified from multiple faces of the same age and different ages of the same person. In this approach, each person's image may be one or more with the same or different ages. The images of this individual form a set called a manifold that forms points in a high-dimensional vector space. Face representation using age manifold learning is flexible as compared to subspace learning. The drawback of age manifold technique is that it requires lots of computational time.

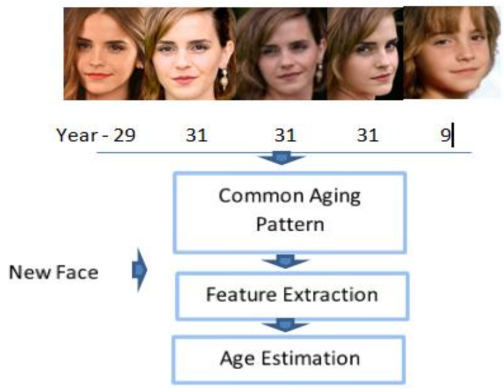

Fig 3. Basic Age manifold model.

6. Deep Learning models:
In deep learning techniques, feature learning and classification both are performed simultaneously without any interference of humans. As compared to other traditional handcrafted methods, deep learning techniques are quite less time consuming. In other words, Computation time is less and provides higher accuracy. It is an intelligent deep neural network. Deep learning algorithms train machines by learning using large

amounts of labelled and unlabeled data. Most popular deep learning algorithms (CNN, RNN, LSTMS etc.) are used for different purposes. CNN algorithm is mainly used for image classification and object detection.

V. CNN ARCHITECTURE

A deep convolutional neural network, which is applied on facial analyzing tasks defined as face detection, face alignment and face recognition. Compare the CNN model with traditional hand-crafts based models, the features are extracted at the training process automatically, instead of creating and defining algorithms. Thus, this is the reason to replace the traditional methods with Deep learning models. CNN architecture consists of layers: convolution layer, pooling layer and fully connected layer that can process and extract features from input images. In this architecture input is present in pixel format.

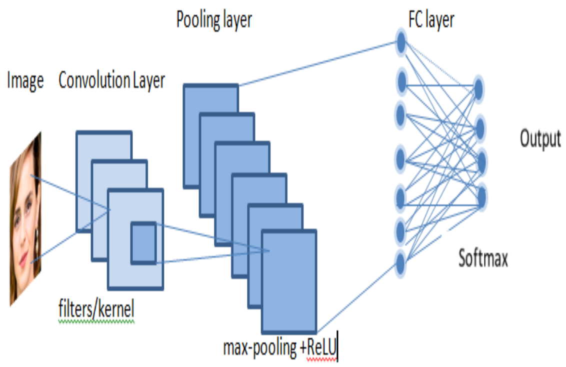

Fig 4. General Architecture of CNN Model.

VI. DAG-CNN ARCHITECTURE

The directed acyclic graph convolutional neural network is complex network architectures consisting of linear series of layers as compared to simple ones. Multi-stage DAG-CNN architecture consists of multiple layers: convolution layer, multi-output layer (ReLU), normalization layer, pooling layer. In this architecture, each ReLU layer is directly linked with an average pooling layer. Average pooling layer used to reduce feature dimension. The add layer work is to combine the output taken from different stages and feed into the Softmax layer which produces the final predicted output.

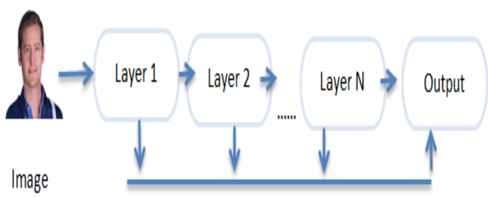

Fig 5. Basic information of DAG-CNN Model.

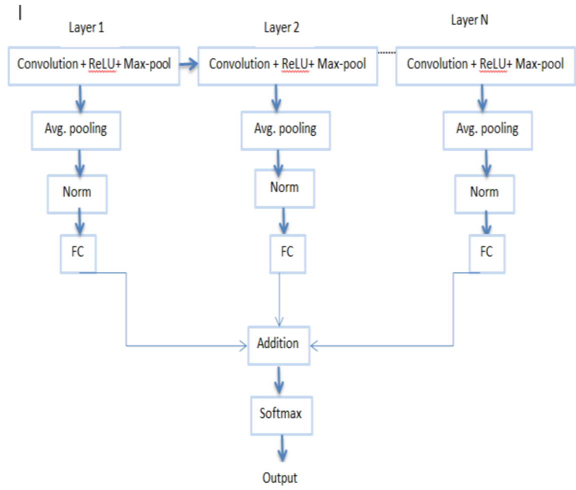

Fig 6. Basic Block diagram of DAG-CNN Model.

VII. COMPARATIVE ANALYSIS

Table 2.

Authors	Datasets	Used Algorithm	MEA	Accuracy (%)	1-Off (%) Accuracy
Hao Liu et al. [1]	FG-NET	ODFL+ODL+ cross entropy	2.92	nil	nil
M. de Assis Angeloni et al.[3]	Adience benchmark	Multi-stream CNN	nil	51.03	83.41
Yi-Lei Chen et al.[4]	FG-NET	Semi-Supervised Subspace Learning+ Age manifold	4.54	nil	82.10%
	MORPH		4.42	nil	81.57%
Hu et al. (2016) [5]	FG-NET	K-L divergence+CNN	2.8	nil	nil
	MORPH		2.78	nil	nil
Shahram Taheri et al., 2019 [6]	MORPH	DAG-CNNs / DAG-VGG 16	2.81	nil	nil

VIII. COMPARISON BETWEEN DATASET

Algorithms work more efficiently if we train on lots of labelled data. Different types of datasets are available for the age estimation system. We are defining FG-NET, MORPH, Adience Benchmark, CACD, IMDB-WIKI datasets.

FG-NET dataset used for age identification and image recognition. It was introduced by andreaslanitis and others. The dataset containing 1002 images of 82 people with age ranges from 0 to 69 years and each person has a maximum 45 yearsage gap. Both color and grayscale images are stored in this dataset. This dataset is unused for large scale projects because that type of project requires higher accuracy.

MORPH is a publically available facial age determination dataset. It contains 55134 images of 13617 people from the 16 to 77 year old range. That record was taken from a public site between October 26, 1962 and April 7, 1998. The images were converted into grayscale images. According to Karl Ricanek Jr.[7], MORPH contain Identification number for eachpicture ,the number of the picture, DOB, date of acquisition (data photo taken), weight and height of the each images, race -caucasian, hispanic, asian, or african ,american ,gender- male or female.

ADIENCE BENCHMARK dataset build on age and gender classification for face images captured in real-world situation. The Adience benchmark dataset consist of unconstrained facial images which are uploaded without applying any filter. In the dataset, images are automatically uploaded to Flickr.com from smartphone devices or mobile phone.It is published in 2014. The dataset contains 26,580 images across 2,284 persons with a 2 gender label and eight different age groups, partitioned into five splits. The age range from 0 to 60+ years old.

CACD is a cross-age celebrity dataset.It contains 163,446 images from 2,000 celebrities collected from the Internet. The dataset contains celebrity name and is taken from year (2004-2013). The IMDB-WIKI dataset is the dataset of face images with gender and age labels for training. It is the largest publically available data. It contains 460,723 images from 20,284 celebrities from imdb and 62,328 from Wikipedia, thus 523,051 in total.

IX. CONCLUSION

In this survey, we introduce an aging factor in analyzing facial images. We notice that lots of applications are required in real life scenarios. In past years, many researchers have used many techniques for age estimation. We have summarized these techniques such as subspace learning, age manifold, and deep learning techniques.

Further we have explained CNN, DAG-CNN architecture. A deep learning method is quite more efficient than a handcrafted method. We briefly introduce supervised learning algorithms such as classification, regression and SVM. Such .We analyzed comparative study of different methods along with mean absolute error, accuracy.After analyzing algorithms, we have studied age estimation dataset such as FG-NET, MORPH, Adience Benchmark, CACD, IMDB-WIKI.

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