A Survey on Neural Networks for Face Age Estimation

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Abstract. *Age estimation is an important task and challenge in computer vision. It can be defined as determining real or apparent age or age group of a person in an image. Through recent years, a large number of age estimation algorithms have been developed and multiple approaches to age estimation have been presented. Nowadays neural networks, especially Convolutional Neural Networks (CNN) have become a standard for age estimation. This paper gives an overview of recent advances in age estimation with focus on neural networks and identifies future research directions. It answers the research questions such as: (RQ1) Which models for age estimation have been used? (RQ2) Which are the most commonly used datasets for testing age estimation algorithms using neural networks? (RQ3) Which performance measures and evaluation protocols are prevalent in age estimation algorithms testing? (RQ4) What is the current state of the art performance for age estimation algorithms using neural networks?*

Keywords. artificial neural networks, convolutional neural networks, age estimation, age classification, face ageing

1 Introduction

When talking about biometrics, one of the areas often overlooked is soft biometrics. Soft biometric traits are "physical, behavioural, or material accessories, which are associated with an individual, and which can be useful for recognising an individual. These attributes are typically gleaned from primary biometric data, are classifiable in pre-defined human understandable categories, and can be extracted in an automated manner" (Dantcheva et al., 2016). In recent years, soft biometrics has become one of the more prolific fields of research, with its widely spread applications. Soft biometric can refer to demographic attributes (age, gender, ethnicity, eye colour, hair colour, skin colour), anthropometric and geometric attributes (body geometry and face geometry), medical attributes (health condition, BMI, body weight, wrinkles), material and behavioural attributes (hats, scarfs, bags, clothes, lenses, and glasses) (Tomičić et al., 2018). The soft biometric trait this paper focuses on is the age of a person.

Age estimation has an important role in classifying face images. It can be defined as the determination of the age of the person or his/her age group (Grd, 2015). According to previous research (Geng et al.,2010), there are four types of age: chronological age (the number of years a person has lived), appearance age (age information defined by appearance of the person), perceived age (defined by people based on the appearance of the person) and estimated age (defined by the computer from the way a person looks). The age estimation problem can be described as predicting estimated age from the visual appearance of the face.

The field of age estimation has been extensively studied in recent years mostly due to its numerous application areas (Wang et al., 2015), (Angulu et al., 2018), (Punyani et al., 2020) such as: forensic science, electronic customer relationship management, security control and surveillance monitoring, biometrics, entertainment and cosmetology, human-computer interaction, age simulation, employment, content access etc. As much as it is an important task in computer vision it is also a difficult task. Some of the problems are: (i) a large number of variations in human face (race, gender, illumination, pose, makeup) which makes selecting discriminative features complex, (ii) difficulty of collecting and labelling comprehensive face databases with age annotations.

Through recent years, a large number of age estimation algorithms have been developed and multiple approaches to age estimation have been presented. The thing most of the algorithms have in common is that they are made of two main parts: face representation model and aging function learning method. Angulu et al. (2018) and Punyani et al. (2020) distinguish between seven face representation models: anthropometric model, active appearance model (AAM), active shape model (ASM), aging pattern subspace model (AGES), age manifold model, appearance model and hybrid models. The same authors approach age estimation as a multi-class classification problem, a regression problem or as a hybrid between classification and regression.

Nowadays, deep learning methods mostly integrate both stages to one framework (Gao et al., 2018).

With the development of hardware resources and large increase in the number of face databases with age annotations, neural networks especially CNNs have become a standard for age estimation. They most commonly include an input layer, multiple hidden layers and an output layer and employ supervised learning for age estimation. The main idea of using CNNs for age estimation is to extract local features from face images, following layers combine the aforementioned features and create a one-dimensional vector which is then forwarded to the classifier (Duan et al., 2018).

The goal of this paper is to give an overview of recent advances in age estimation with focus on neural networks and identify future research directions. It also answers the research questions such as: (RQ1) Which models for age estimation have been used? (RQ2) Which are the most commonly used datasets for testing age estimation algorithms using neural networks? (RQ3) Which performance measures and evaluation protocols are prevalent in age estimation algorithms testing? (RQ4) What is the current state of the art performance for age estimation algorithms using neural networks? To answer these research questions, the most important papers on age estimation using neural networks are surveyed and different approaches are then compared in Section 2. The results of the survey are analysed and research questions answered and discussed in Section 3. Section 4 gives the conclusion and directions for future research.

2 Literature Review

When talking about using neural networks for age estimation, it is important to distinguish between different types of neural networks. There are three most often used types: Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). In recent years, when using neural networks for age estimation, CNNs are almost exclusively used. CNNs include an input layer, multiple hidden layers and an output layer and often have two parts: automatic feature extractor and trainable classifier (Duan et al., 2018).

As mentioned earlier, the goal of this paper is to give an overview of recent advances in age estimation with focus on neural networks and to identify future research directions. To this end, four research questions have been defined with the main motivation behind each question. (Table 1).

Table 1. Research questions and motivation

No.	Research question	Motivation
(RQ1)	Which models for age estimation have been used?	To identify the gaps in state of the art in age estimation using neural networks and the base NN for each model
(RQ2)	Which are the most commonly used datasets for testing age estimation algorithms using neural networks?	To identify the datasets appropriate for testing the age estimation algorithms using neural networks
(RQ3)	Which performance measures and evaluation protocols are prevalent in age estimation algorithms testing?	To identify evaluation protocols and performance measures prevalent in age estimation algorithm testing
(RQ4)	What is the current state of the art performance for age estimation algorithms using neural networks?	To compare the performances of state of the art algorithms and identify the best performance

After defining the research questions, next step was finding the research relevant for answering the posed questions. The sources searched were IEEE Xplore, Science Direct, Springer Link and Web of Science. The search string used (slightly modified for each source) was: (age estimat* OR age classif* OR age asses* OR fac* age estimat* OR fac* age classif*) AND (neural network OR ann OR cnn). The research was limited to the papers published in the last six years.

All of the papers found by this search were not relevant for the proposed research questions and there were some duplicate entries which were removed in first screening. This resulted in thirty-eight papers which entered the second screening phase which consisted of excluding the papers which had not presented new algorithms or where algorithms have not been tested or results have not been published. This resulted with eighteen papers that were analysed and described in detail. The summary of the eighteen paper selected can be seen in Table 2.

Table 2. Summary of age estimation studies

Paper	CNN model	Age estimation type	Age type	Dataset	Evaluation protocol	Evaluation metrics	Performance
Ranjan et al. (2015)	DCNN with Deep Pyramid Deformable Parts Model	Estimation	Apparent	LAP15	Holdout	Error rate	35.90%
Wang and Kambhamettu (2015)	Hierarchical Unsupervised Neural Network	Estimation	Real	FG-NET	LOPO	MAE	4.11
			Real	MORPH 2	Holdout	MAE	3.81
Qawaqneh et al. (2017)	Joint fine-tuned DNNs	Classification (8 classes)	Real	Adience		Accuracy	62.37%
						1-off Accuracy	94.46%
Zhang et al. (2017)	Deep CNN, Residual Network of Residual Networks	Classification (8 classes)	Real	Adience	Five-fold CV	Accuracy	67.34% +-3.56
						1-off Accuracy	97.51% +-0.67
Anand et al. (2017)	Multiple Deep CNNs	Estimation	Real	AmI-Face	Five-fold CV	MAE	3.3
		Classification (8 classes)	Real	Adience	Five-fold CV	Accuracy	58.49%
Agustsson et al. (2017)	Anchored Regression Network	Estimation	Apparent	LAP15	Holdout	MAE	3.153
			Real	MORPH 2		MAE	3
Ranjan et al. (2017)	Multipurpose single deep CNN	Estimation	Apparent	LAP15	Holdout	ϵ-error	0.293
			Real	FG-NET		MAE	2
Li et al. (2017)	Deep cumulatively and comparatively supervised age estimation model	Estimation	Real	MORPH 2	Holdout	MAE	3.06
			Real	WebFace	Four-fold CV	MAE	6.04
Xing et al. (2017)	Deep multi-task age estimation model	Estimation	Real	MORPH 2	Holdout	MAE	2.96
			Real	WebFace	Four-fold CV	MAE	5.75
Antipov et al. (2017)	Deep CNN with Label Distribution Age Encoding	Estimation	Real	FG-NET		MAE	2.84
			Real	MORPH 2		MAE	2.99
Liu et al. (2017)	Ordinal Deep feature learning for CNN	Estimation	Real	MORPH 2	Ten-fold CV	MAE	3.12
			Real	FG-NET	LOPO	MAE	3.89
			Apparent	LAP15	Holdout	MAE	4.12
Chen et al. (2017)	Ranking CNN with a series of binary CNNs for each age class	Estimation	Real	MORPH 2	Five-fold CV	MAE	2.96
Gao et al. (2018)	Deep Label Distribution Learning	Estimation	Apparent	LAP15	Holdout	MAE, ϵ-error	3.135, 0.272
			Apparent	LAP16	Holdout	MAE, ϵ-error	3.452, 0.267
			Real	MORPH 2	Holdout	MAE	1.969

Liu et al. (2018)	Depthwise Separable CNN, with Depthwise Separable Convolution and Support Vector Machines	Estimation	Real	IMDB-WIKI	Holdout	MAE	5.8865
			Real	MORPH 2	Holdout	MAE	3.08
			Apparent	LAP15	Holdout	ϵ-error	0.289579
			Apparent	LAP16	Holdout	ϵ-error	0.3478
Duan et al. (2018)	CNN and Extreme Learning Machine	Estimation	Real	MORPH 2	Four-fold CV	MAE	2.61
		Classification (8 classes)	Real	Adience		Accuracy	66.49% +- 5.08%
		Estimation	Apparent	LAP16	Holdout	MAE, ϵ-error	3.67, 0.3250
Pan et al. (2018)	CNN with Mean-Variance Loss function	Estimation	Real	MORPH 2	Five-fold CV	MAE	2.16
			Real	FG-NET	LOPO	MAE	2.68
			Apparent	LAP16	Holdout	ϵ-error	0.2867
Zhang et al. (2020)	ResNet with Attention long short-term memory (LSTM) and RoR with LSTM	Classification (8 classes)	Real	Adience	Holdout	Accuracy, 1-off Accuracy	66.82% +-2.79, 97.36% +-0.70
		Estimation	Real	MORPH 2	Five-fold CV	MAE	2.36
			Real	FG-NET	LOPO	MAE	2.39
			Apparent	LAP15	Holdout	MAE, ϵ-error	3.137, 0.2548
			Apparent	LAP16	Holdout	ϵ-error	0.2859
Zeng et al. (2020)	CNN based on ResNet-34 with a Global Average Pooling	Estimation	Real	MORPH 2	Five-fold CV	MAE	1.74
			Real	AgeDB	Five-fold CV	MAE	4.75
			Apparent	LAP15	Holdout	ϵ-error	0.232
			Apparent	LAP16	Holdout	ϵ-error	0.232

3 Discussion

After analysing the eighteen selected studies on age estimation using neural networks, different aspects of age estimation have been identified. When estimating a person's age, estimation can be precise or an age group could be classified (Figure 1). Nowadays, most research focuses on precise age estimation of each person (72.2%) and only a small number of papers focuses on age group estimation or classification (11.1%) where some papers (16.7%) test their algorithms for both precise age estimation and age group classification. The beginning research on age estimation focused on age group classification, but with the rise of neural networks popularity, the focus shifts almost exclusively on precise age estimation.

Other aspect that emerged was the type of age estimated. As mentioned earlier, there are four types of ages: chronological or real age, appearance age, perceived age and estimated age. From the eighteen selected studies, most of them (50%) test their algorithms for both real and apparent age, whereas 44.4% of the studies test their algorithm only for real age. Only one study focuses on apparent age estimation exclusively (Figure 2). This shows that real age estimation still has prevalence in age estimation research.

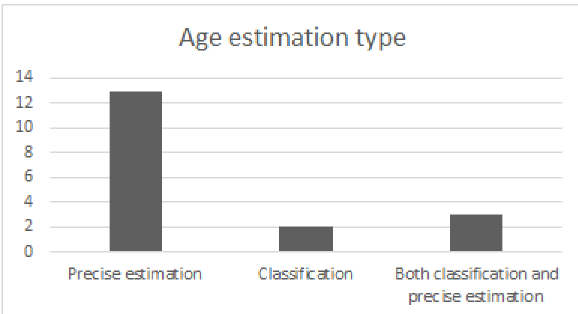

Figure 1. Number of papers per age estimation type

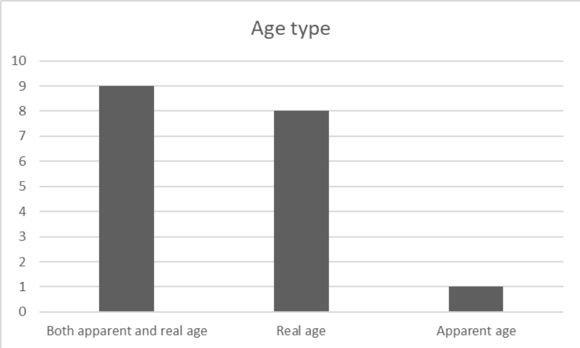

Figure 2. Number of papers per age type

3.1 RQ1: Which models for age estimation have been used?

Each of the proposed age estimation algorithm uses a type of CNN for age estimation. The three most common CNN architectures were used as a basis for the development of a new CNN for age estimation in the analysed papers: AlexNet (Krizhevsky et al., 2012), VGG-16 (Simonyan and Zisserman, 2015) and ResNet (He et al., 2015). Most of the papers (72.2%) use one of the popular CNN architectures as the basis for their research, with VGG-16 used in 33.3% of the papers, ResNet in 22.2% and AlexNet in 16.7% (Figure 3). In other papers, the base CNN has not been reported or it has been built from the ground up. The CNNs with the best performance in age estimation to date were using ResNet as the base architecture.

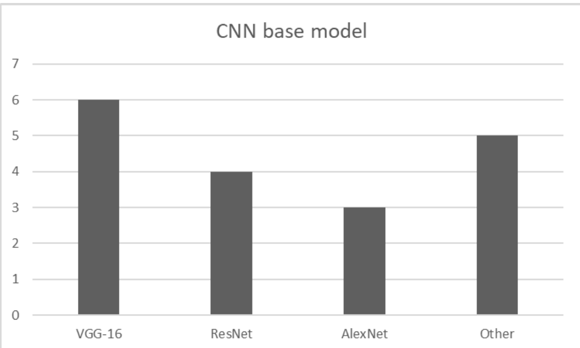

Figure 3. Number of papers per CNN base model

3.2 RQ2: Which are the most commonly used datasets for testing age estimation algorithms using neural networks?

In order to estimate the precise age or age-group of a person, a dataset of quality images with age annotations is needed. The process of creating a face age database is time consuming and complicated and requires a series of chronological images of a person. For this reason, most of the research on age estimation uses previously collected public datasets. There are a number of available face age estimation datasets and an overview of most often used datasets can be seen in Table 3.

Table 3. Summary of face age datasets

Dataset	Age type	No. of subjects	No. of images	Age
FG-NET	Real	82	1,002	0-69
MORPH 2	Real	13,618	55,134	16-77
LAP15	App.	5,500	5,500	0-100
LAP16	App.	8,000	8,000	0-100
ADIENCE	Real	2,284	26,580	0-60+
AgeDB	Real	568	16,488	0-100
IMDB-WIKI	Real	20,284	523,051	0-100
AmI-Face	Real	16	4,535	-
WebFace	Real	-	59,930	1-80

The FG-NET and MORPH 2 datasets have become a standard for testing age estimation algorithms in general but also for age estimation using neural networks specifically. This can be seen in Figure 4 which shows the distribution of datasets for age estimation using neural networks in the analysed papers. The exception are papers which estimate apparent age, where MORPH 2 database cannot be used, and to this end LAP15 and LAP16 databases are used exclusively.

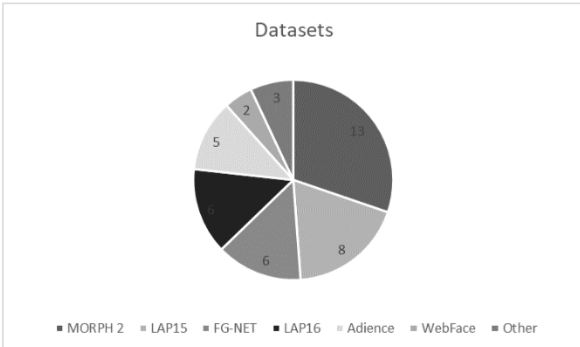

Figure 4. Distribution of datasets used for evaluation

Each of the described datasets have their advantages and drawbacks. The major drawback of FG-NET dataset is its small number of subjects. MORPH 2, while used most often, lacks in images of persons from age 0 to 15. Other example is ADIENCE dataset that does not have precise age annotations, only age group annotation. The largest dataset, IMDB-WIKI uses faces in the wild, but age annotations are made by hand based on the time the images were published and not the chronological age of a person in an image. This shows that, although in recent years many large datasets appropriate for age estimation appeared, there is still room for improvement.

3.3 RQ3: Which performance measures and evaluation protocols are prevalent in age estimation algorithms testing?

In order to measure the performance of different age estimation algorithms it is important to use the most appropriate evaluation protocol for the dataset used for testing. Evaluation protocols determine the testing protocol, criteria for selecting test data and system performance measure (Angulu et al., 2018). It is important for testing to be done on previously unseen images in order to get the most accurate performance estimation. The most popular evaluation protocol is cross-validation. Cross-Validation is a "statistical method of evaluating and comparing learning algorithms by dividing data into two segments: one used to learn or train a model and the other used to validate the model" (Refaeilzadeh et al., 2009). There are different types of cross-validation classified in two categories: exhaustive and non-exhaustive cross-validation. In age estimation three evaluation protocols are used: Leave One Person Out (LOPO), holdout and k-fold cross validation. LOPO is a type of exhaustive cross-validation, more specifically, a variant of Leave p-out cross-validation that involves using p-observation as validation data, and remaining data is used to train the model. This is repeated in all ways to cut the original sample on a validation set of p observations and a training set (Kumar, 2021). In LOPO, images of one person are used for testing iteratively. The holdout cross-validation is a non-exhaustive cross-validation method, that randomly splits the dataset into train and test data where training set is larger than test set. The training data is used to train the model and test data is used to evaluate the model performance (Kumar, 2021). In k-fold cross-validation, the original dataset is equally partitioned into k groups and for each iteration, one group is selected as test data, and the remaining groups are selected as training data. The process is repeated for k times until each group is treated as test and others as training data (Kumar, 2021).

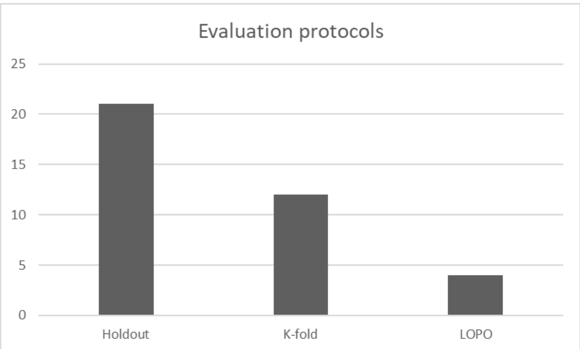

Figure 5. Distribution of evaluation protocols

In total, there were forty-three different tests conducted in eighteen selected papers. Out of forty-three, in five of them the evaluation protocol has not been reported, in 48.8% of the cases holdout evaluation protocol was used, in 27.9% k-fold cross validation and in 1% of the cases LOPO evaluation protocol was used (Figure 5). The protocol used largely depends on the dataset used for testing. Figure 6 shows the distribution of evaluation protocols according to dataset. Some datasets have a pre-defined protocol that is used for every performance evaluation, such as LAP15 and LAP16 that have a pre-determined set for training, validation and testing or FG-NET that uses LOPO evaluation protocol exclusively, mostly because of the small number of available images.

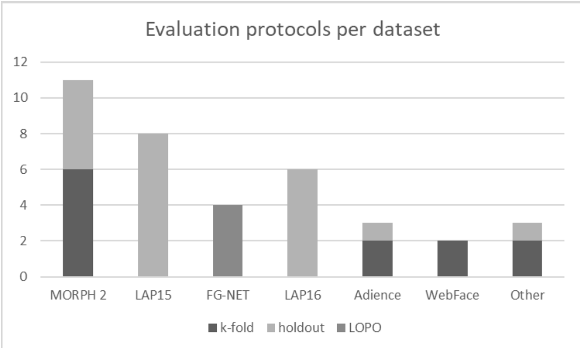

Figure 6. Distribution of evaluation protocols per dataset used for evaluation

Defining the evaluation protocols is not enough to compare different algorithms for age estimation. Other than evaluation protocol, performance measure needs to be defined. Performance measures used depend on the type of age estimation (precise age estimation or age group classification) and the type of age. When precise age estimation is conducted, if real age is estimated, Mean Absolute Error (MAE) and Cumulative score (CS) are used to evaluate the algorithm performance. MAE is computed as:

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

where $\hat{x}_i$ is estimated age and x_i is real or apparent age of n-th image in the test set and N is the total number of images in the test set (Zeng et al., 2020). The CS metric is defined as the proportion of test images such that the absolute error is not higher than an integer j:

$$CS(j) = \frac{N_{e\leq j}}{N_x} * 100\% \qquad (2)$$

where $N_{e\leq j}$ is the number of test images on which the absolute error in age estimation is within *j* years (Grd, 2015).

If apparent precise age is estimated, MAE, ϵ-error and error rate are used for evaluation. ϵ-error is used for apparent age estimation which is computed as:

$$\epsilon - \text{error} = \frac{1}{N}\sum_{n=1}^{N}(1 - \exp(-\frac{(\widehat{x}_i - x_i)^2}{2\sigma_n^2})) \qquad (3)$$

where is σ_n is the standard variance of the annotations for the n-th image in the test set and N is the total number of images in the test set (Zeng et al., 2020). MAE has become a standard for real age estimation and every paper analyzed that estimates the real age of a person uses MAE as a performance measure for comparison with other algorithms. Performance of apparent age estimation algorithms mostly uses ϵ-error (78.6%), but some of them (42.9%) use MAE also (Figure 7).

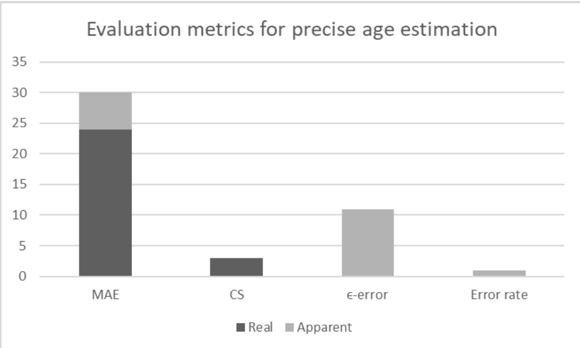

Figure 7. Distribution of evaluation protocols per dataset used for evaluation

When age group classification is conducted, accuracy and 1-off accuracy are calculated. Accuracy is defined as the correct age group prediction, and 1-off accuracy is when correct age group or adjacent age group was predicted (Zhang et al., 2017). From the papers analyzed it can be seen that all the papers that perform age group classification report the accuracy of their algorithm, but some of them report 1-off accuracy also.

3.4 RQ4: What is the current state of the art performance for age estimation algorithms using neural networks?

To compare the performance of different algorithms, it is important for those algorithms to be tested on the same dataset and using the same performance measure. As the previous research discovered, MORPH 2 dataset is most often used for real age estimation and MAE is the standard measure for estimating the algorithm performance. Because of this, MORPH 2 dataset and MAE will be used to compare the algorithm performance. The complete comparison can be seen in Table 4. Currently, the CNN with the best performance for real age estimation is the one with the smallest MAE, which is CNN based on ResNet-34 with a Global Average Pooling (Zeng et al., 2020) which has MAE of 1.74.

For apparent age estimation, standard datasets used are LAP15 and LAP16 with the most common performance measure being ϵ-error. The algorithm with the best performance on both datasets (Table 5) is the same algorithm which has the best performance for real age estimation CNN based on ResNet-34 with a Global Average Pooling (Zeng et al., 2020) with ϵ-error of 0.232. This shows that the same algorithms can be used for both real and apparent age estimation without significantly reducing the performance of those algorithms.

Table 4. MAE results of different real age estimation algorithms on MORPH 2 dataset

Paper	MAE
Wang and Kambhamettu (2015)	3.81
Liu et al. (2017)	3.12
Liu et al. (2018)	3.08
Li et al. (2017)	3.06
Agustsson et al. (2017)	3
Antipov et al. (2017)	2.99
Xing et al. (2017)	2.96
Chen et al. (2017)	2.96
Duan et al. (2018)	2.61
Zhang et al. (2020)	2.36
Pan et al. (2018)	2.16
Gao et al. (2018)	1.969
Zeng et al. (2020)	1.74

Table 5. ϵ-error results of different apparent age estimation algorithms on LAP15 and LAP16 dataset

Paper	Dataset	ϵ-error
Liu et al. (2018)	LAP16	0.3478
Duan et al. (2018)	LAP16	0.325
Ranjan et al. (2017)	LAP15	0.293
Liu et al. (2018)	LAP15	0.2896
Pan et al. (2018)	LAP16	0.2867
Zhang et al. (2020)	LAP16	0.2859
Gao et al. (2018)	LAP15	0.272
Gao et al. (2018)	LAP16	0.267
Zhang et al. (2020)	LAP15	0.2548
Zeng et al. (2020)	LAP15	0.232
Zeng et al. (2020)	LAP16	0.232

4 Conclusion

Through this paper, a number of studies on application of neural networks for age estimation have been presented. At the beginning of the paper, research questions have been defined which have been answered throughout the text. Thirty-eight studies on neural networks in age estimation have been identified and eighteen of them were selected for this survey. The goal of the paper was to give an overview of state of the art research and identify future research directions.

Most of the papers analysed use CNNs for age estimation. Three most common CNNs are often used as the basis for the development a new CNN for age estimation: AlexNet, VGG-16 and ResNet. The developed CNNs were tested on different datasets depending if the estimated age was real age or apparent age. For real age, most commonly used dataset was MORPH 2 (27.9%) and for apparent age, LAP15 dataset (18.6%). When talking about performance measures and evaluation protocols, each dataset has a recommended testing protocol, but in general, most of the testing (48.8%) utilizes holdout evaluation method, followed by k-fold cross validation (27.9%). MAE is used for real age estimation in all papers and ϵ-error is most often used for apparent age estimation. The current state of the art performance has MAE of 1.74 for real age estimation and ϵ-error of 0.232 for apparent age estimation.

Through the described survey, gaps in research have been identified. There is a lack of papers that take into account the computational speed and complexity of different age estimation methods. Also, most of the papers use large datasets that need a significant amount of time for neural network training. There is also a lack of research on fusing other biometric traits with face images in order to accomplish better age estimation accuracy. Future research will focus on comparing other age estimation methods with age estimation using neural networks to analyse the differences in performance, not only in different error rates, but also in computational speed and required dataset sizes. Also, different biometric traits will be analysed to identify their suitability for age estimation and possibilities of fusing the results with face age estimation.

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