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Evaluation of Classification and Regression Models Using Facial Images for Human Age Estimation

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Abstract: The growing interest in automatic age prediction from facial images stems from its security control, potential applications in law enforcement and Human-Computer Interaction (HCI). However, despite notable advancements in this field, automatic age estimation remains a formidable challenge. This complexity arises because the face aging process is influenced not only by intrinsic factors such as genetic components but also by extrinsic factors like lifestyle, expressions, and environmental conditions. Consequently, individuals of the same age may exhibit markedly different appearances due to varying rates of facial aging. In response to these challenges, we propose an experimental approach for automatic age estimation.In literature, researchers carried their research work using pre-trained models as these models saves time, cost and computational resources, avoids over-fitting with increased accuracy but these models are domain specific and acts as black box which makes fine-tuning difficult. In our research, we designed a Convolution Neural Networks model for age estimation and analyzed the performance on the publicly available FGNET, Adience, APPA-REAL, UTKFace, and All-Age-Face datasets by considering age estimation as classification and regression problem. Then compared the proposed model performance with the existing pre-trained models and observed both classification and regression results are in par with the performance of the existing pre-trained models.

Keywords : *Convolutional Neural Network, Regression, Classification*

1. Introduction

With the rapid advancements in computer vision, pattern recognition, and biometrics, there has been a growing focus on computer-based human facial age estimation. This technique proves invaluable when age information is required without divulging other irrelevant personal details. Its applications span a wide spectrum within computer vision, encompassing security surveillance, forensics, biometrics, Human Computer Interaction (HCI), electronic customer information management, age-specific precision marketing (such as age-based visual advertisement), and entertainment, among others. Numerous practical scenarios benefit from facial age estimation, such as using monitoring cameras to warn or prevent juveniles from purchasing cigarettes or prohibited drugs from vending machines. Restricting underage entry into wine bars and the purchase of alcohol, cautioning elders about high-risk theme park rides, and curbing children's access to harmful websites are just a few examples.

Nevertheless, it is undeniable that facial age estimation is a formidable and challenging task [1]. The challenges in computer-based facial age estimation manifest in several aspects [2]. Firstly, the diverse aging processes among individuals, influenced by factors like living environment, ethnic group, gender, lifestyle, social interactions, health conditions, and genetic diversity, contribute to variations in the aging speed. Secondly, the changing shapes or textures associated with different age levels present complexities. From infancy to adolescence, craniofacial growth dominates, while in the adult period to old age, skin transformation becomes more prominent. Thirdly, data insufficiency is a significant hurdle, with limited aging datasets covering the entire age range. Lastly, external factors, such as the desire for youthfulness leading to the use of cosmetics, accessories, and plastic surgery, can significantly interfere with accurate age estimation results.Given the significance of both research and practical applications, facial age estimation holds importance within the computer vision community. The importance of automatically estimating age from unconstrained, real-world facial photos is growing exponentially. This research suggests age prediction method using facial features based on the Convolution Neural Network (CNN) model to estimate age by utilizing age regression and classification models. This model is rigorously trained to estimate age in large-scale scenarios using five different datasets that are collected under constrained (FGNET) and unconstrained (UTKFace, All-Age-Face, APPA-REAL, and Adience) environments. The study precisely determines an individual's age from facial images, and provides insights into the performance and reliability of age estimation models.

The existing research focus on estimating the human age using pre-trained models as these models are time and

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cost effective, provides better accuracy, reduces over-fitting and easy to implement. But these models are domain-specific, trained on large datasets with fixed input size and used as black box. These models have limited adaptability, makes fine tuning difficult as these models have millions of trainable parameters. In this paper, we designed a convolution Neural Network (CNN) model for age estimation to analyze the performance of classification and regression using publicly available five datasets, FGNET, Adience, APPA-REAL, UTKFace, and All-Age-Face along the model training time for each dataset. Model over-fitting is controlled by adding dropout at hidden layers and dense layers. We observed that the proposed CNN model performance is in par with the pre-trained model performance for both classification and regression.

The following sections of this paper are structured as follows: The previous study in this field that served as our inspiration is covered in Section 2. Section 3 delves into the datasets employed for our study. Section 4 elaborates on the technical specifics of our research work. Section 5 presents the experiments conducted and their corresponding results. The paper is finally concluded in Section 6, which provides a summary of our findings and recommendations for further work.

2. Literature Review

Age estimate is a popular and always developing field of study in the computer vision community, forensics, HCI, electronic customer information management systems, as highlighted in literature [20-21].

UTKFace dataset covers wide range of age from newborn to centenarians and publicly available facial images collected under uncontrolled conditions, many research works had used it for age and gender estimation. George et al. [3] used pre-trained model to achieve an impressive performance of 1.76 as MAE value but the scope of this work is limited to 5 – 30 age group of UTKFace dataset with 450 images for each age group. This limits the generalization of the model. In another study [4], Puc et al. considered gender for estimating the age of a person and concluded that the gender imbalance impacts the performance of the age estimation model. The dataset consist of 58% of male and 42% of female faces and model shows better estimation results to male faces as compared to female face images. Meghana et al. [5] used the dataset for classification with 5 class label and achieved an accuracy of 60% when tested with real-world images. On the other hand, Sheoran et al. [7] used CNN model and transfer learning for age estimation as classification and regression and achieved 79.1% and 5.49 of MAE for classification and regression performance respectively. The authors conclude that the pre-trained model shows better performance than their CNN model. Ghildiyal et al. [6] resized the images to 32x32 to achieve 61.7% accuracy using ANN and CovNet as pre-trained models. Raman et al. [14] obtained an accuracy of 80.76% using pre-trained models based on gender specific features.

Adience is widely used face dataset for age and gender classification as the images shows challenges with respect to pose, orientation and illumination as the images are captured from internet. Ekmekji in [22] used high performance computational machine to achieve an accuracy of 50.2% on average by fine-tuning these models and Levi et al. of [23] achieved improved the performance by 50.7% of accuracy after optimizing the model. Lapuschkin et al. [10] used pre-trained models like AdienceNet, CaffeNet, Googlenet and VGG-16 by performing Layer-wise Relevance Propagation to achieve and maximum accuracy of 62.8% and 53.6% for training and testing pre-training models. Qawaqneh et al. in [8] concluded the performance age estimation using pre-trained models depends on the number of available images and also the number of subjects. In [24], Anand et al. extracted the features using statistical measures, reduced the dimensions and then fed to the pre-trained model like FeedForwardNeuralNetwork to obtain better performance.

FGNET is the facial image dataset collected under controlled conditions for age estimation in the range of newborn to 69 year old persons. The advantage of this dataset is small in size with multiple images per person. Xie et al. trained the model using an ensemble learning strategy, and their results showed an MAE of 3.14 [25]. Before feeding the DAG-CNN model with fused multi-stage features, Taheri et al. found a minimum MAE of 3.05 [26]. The age estimate model developed by the authors in [27] was trained using Local Direction and Moment Pattern (LDMP) as aging feature descriptor for encoding the facial aging signs. Deng et al. in [13] extracted Gabor features based on age, gender and race and trained their model to get 2.59 MAE. Raman et al. [14] used this dataset for classification to obtain an accuracy of 60.50% using pre-trained models based on gender specific features.

APPA-REAL face dataset was designed to identify the real and apparent age of the person. This dataset is mainly used for predicting the age of a person as regression problem. Puc et al. in [4] used various deep learning techniques to estimate the exact age of a person.

3. Face aging database

In this present study, the experiments are carried out using five different datasets, UTKFace [15], FGNET [16], AAF [17], APPA-REAL [18] and Adience [19] face databases and the images are captured under controlled and uncontrolled conditions.

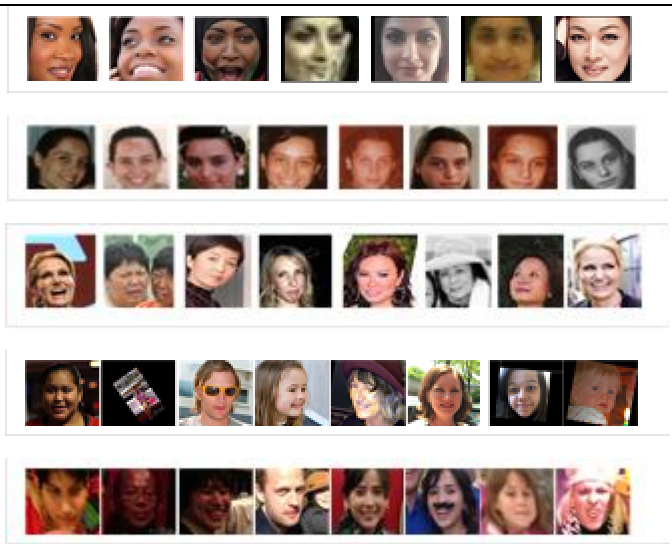


Fig.1 Sample datasets (row-wise: UTKFace, FGNET, AAF, APPA-REAL and Adience)

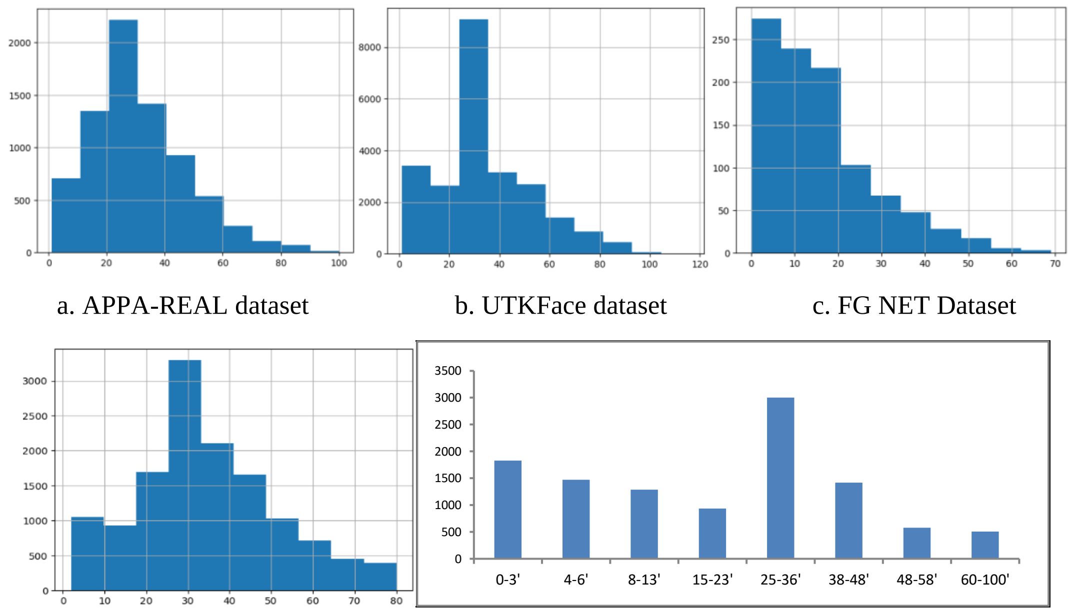
In Fig.1, the samples from each dataset demonstrate the diverse nature of images, including variations in poses, expressions, lighting conditions, and resolutions. These factors pose significant challenges for training models in age prediction tasks, as they must adapt to a wide range of image characteristics.

Additionally, other factors such as object distance from the camera, the number of subjects in the image, image size, and other environmental conditions contribute to the complexity of age prediction models. It is essential to consider these challenges while developing and evaluating models, as they directly impact the models' ability to generalize and perform accurately. Table 1 provides an overview of the five datasets mentioned in the context, highlighting the number of subjects, the number of images per subject, and the age range covered by each dataset. These datasets serve as valuable resources for researchers to train and test their models, aiming to improve age prediction performance despite the challenges mentioned above.

Table 1. Details about the dataset considered for the research

Dataset	**1.** **2.** **3.**	**Age range** **Data size** **condition**	**Description and Observations**
UTKFace	1. 2. 3.	0 - 116 23708 uncontrolled	- Widely used for gender, age and race estimation - Aligned Front faced images - Contains more male photos than female - Single image per person collected from internet sources
Adience	1. 2. 3.	0 - 100 26580 uncontrolled	- Includes a variety of real-world imaging situations, such as noise, lighting, pose, and look. - Used as a standard for face pictures. - Widely considered for age classification as the existing models performance is not as expected - Multiple images per person
FGNET	1. 2. 3.	0 - 69 1002 controlled	- Very small dataset and captures under controlled environment - Multiple images per person at various age span - Used for age estimation
APPA-REAL	1. 2. 3.	1-80 7951 uncontrolled	- Faces are of different orientations and the labels are available in CSV file separately - Images are of different size and taken from varying distances - Used mainly for age estimation
AAF	1. 2.	2 - 80 13322	- Used for gender and age estimation

3.	uncontrolled	-	Contains more female photos than male
		-	Front faced images
		-	Single image per person



a. APPA-REAL dataset b. UTKFace dataset c. FG NET Dataset

d. All Age Face dataset e. Adience dataset

Fig. 2. Age distribution for the datasets used for the research

Fig. 2 illustrates the age distribution across the datasets, where the x-axis represents the age or age group, and the y-axis denotes the image count for each age category. We can observe that the available data samples are not equally distributed for all the age labels. It is evident that the age distribution varies significantly among the datasets, although most datasets have a considerable number of samples in the age range of 25-35 years.

4. Research Methodology

The literature inferred pre-trained models show better performance with reduced complexity. Many studies focused on age estimation using classification and regression models. In our study, we have proposed a customized age estimation model, as shown in Fig. 3.

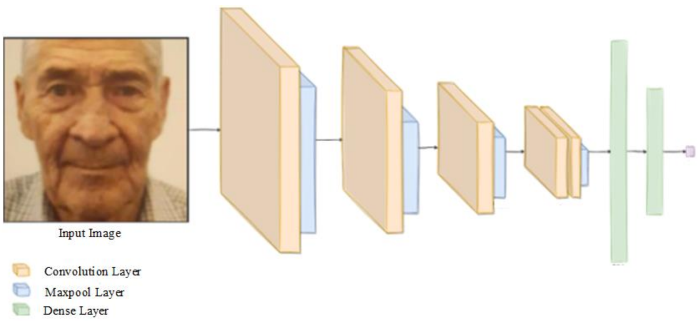


Fig. 3: Proposed age estimation model

The proposed model input is pre-processed to extract the face from the image using the HAAR cascade and resized before feeding to the model. The model consists of a set of three layers: a convolution layer, BatchNormalization and MaxPooling layer and repeated for five times, followed by three dense layers with a 0.4 dropout rate to overcome the over-fitting during training. The model is trained on average of 80 epochs by setting the hyper-parameter values as shown in table 2 for the optimal performance of the classifier and regression respectively.

Table 2. The proposed model's Hyper-parameters

Hyperparameter	Regression model	Classification model
Optimizer	SGD	Adam
Activation function	Relu and Sigmoid	Relu
Batch size	64	32
Learning rate	0.01	0.001
Strides	1x1	1x1
Dropout rate	0.2	0.5

The proposed regression model has a total of 674,049 parameters with 672,769 trainable parameters, whereas the classification model has a total of 13,182,594 parameters with 13,179,842 trainable parameters. The literature studies are focused on pre-trained models as these models are time and cost effective. In this research study, we focused on the performance of the CNN model with time taken for training the model for five different datasets. The proposed model shows competitive results with pre-trained models used in the literature with minimum computation time and computational resources.

5. Results and Discussions

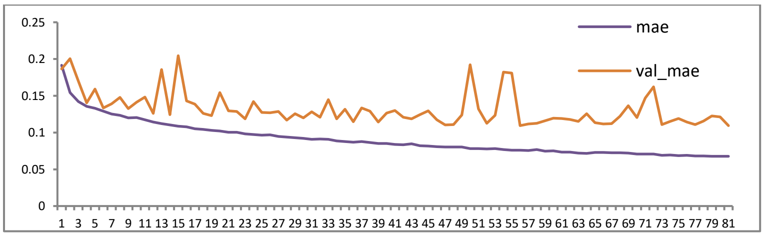
For apparent age estimation, the ϵ-Error, also known as the Normal Score, serves as a crucial metric, providing a quantitative measure of predicted age accuracy relative to the ground truth. Together, these metrics form a robust evaluation framework, enabling a comprehensive assessment of facial age estimation models and guiding advancements in the field. In the evaluation of various facial age estimation algorithms, a prevalent and widely adopted metric is the MAE, consistently utilized across numerous research papers. The MAE is defined as the average absolute error between the estimated age and the chronological age of individuals [21]. A lower MAE value signifies higher accuracy, making it a pivotal metric for gauging the performance of these algorithms.

The average absolute difference between the target values and the projected values is measured by the MAE, a potent statistic used to assess the accuracy of regression models. In contrast to other metrics, MAE assigns equal weight to all errors, regardless of direction, as it does not square the errors and the formula is given as in Eq.(1):

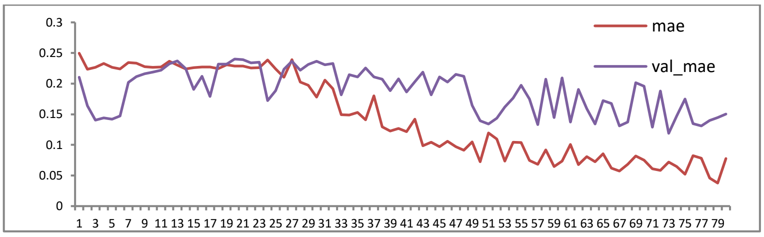
$$MAE = \frac{1}{m}\sum_{i=1}^{m}|x_i - y_i| \quad (1)$$

where m is the number of data points, xi and yi represent the actual target value and the model predicted value for data point i, respectively. The model's predictions match the real data more closely when the MAE is lower. Similarly, accuracy shows the classification model's performance; it is the ratio of the correct prediction to the total number of samples.

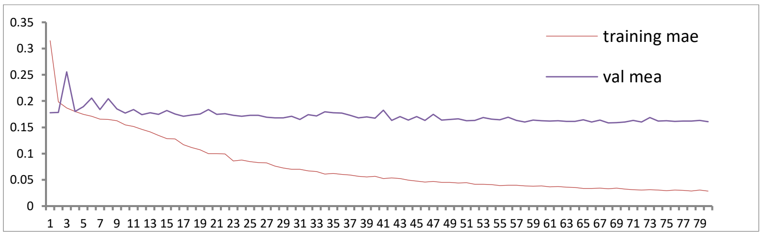
The performance of our proposed method in individual facial age estimation using a regression model is depicted in Fig. 4(a–d) and the classification model in Fig. 5(a–b). In Figure 4, we notice a smooth training curve depicted, while validation outcomes exhibit varying degrees of smoothness across different datasets as the datasets are not balanced across all age groups. FGNET dataset shows non-smooth curve because of small data size with minimum number of subjects, i.e. the data size and the number of subjects for the images will impact the performance of the model. This trend is also evident in Figure 5 for classification.



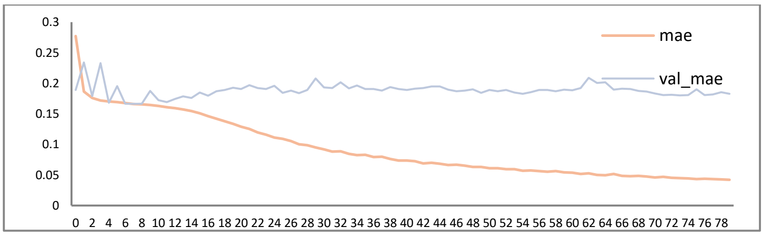
a. UTKFace dataset regression model results



b. FGNET regression results

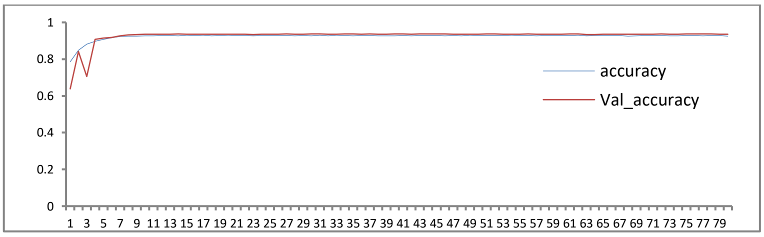


c. APPA-REAL dataset regression model results

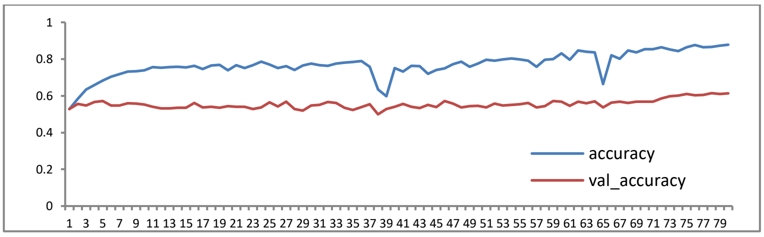


d. AAF dataset regression model results

Fig. 4 (a-d). Regression model results



a. UTKFace accuracy rate



b. Adience accuracy rate

Fig.5(a-b). Age classification model

For our experiments, the age estimation model is trained on average for 80 epochs for each individual dataset and measured accuracy as metrics for classification and MAE for regression, along with the overall model loss with respect to time, and the outcomes are tabulated in Table 3(a–b). The performances of the proposed approach are comparable to those of pre-trained models from the relevant literature.

Table 3. Age estimation model results a. Regression model results (loss and MAE)

Dataset	loss	mae	val_loss	val_mae	Time taken (sec)
APPA-REAL	0.277	2.853	8.006	15.840	49391.9347
FGNET	0.484	3.767	5.784	11.886	7350.091
UTKFace	0.763	6.769	2.087	10.937	139652.797
AllAgeFace	0.600	4.210	9.264	16.636	117220.829

b. Classification model results

Dataset	Accuracy	Testing Accuracy	Time taken (sec)
Adience	93.844	62.458	31904.52
UTKFace	93.025	93.733	55462.58

The proposed model's performance is compared with the existing pre-trained models performance as listed in table 4. The authors, Meghana et al. in [5] had used ResNet50, and inception ResNetV2 pre-trained models on UTKFace dataset to achieve an accuracy of 60% with 5 class labels. In another research [6], Ghildiyal et al. used ANN and Covnet pre-trained model to achieve an accuracy of 61.7 %, and Sheoran et al. of [7] used VGG16, ResNet50 and SENet50 pre-trained models to achieve 79.12%. And we achieved 93.7% of accuracy with proposed model using UTKFace with 8 class labels (0-3, 4-7, 8-14, 15-24, 25-37, 38-47, 48-59, 60+). Similar results are observed for Adience dataset. Lapuschkin [10] used four different DNN models to compare the layer-wise outcome and achieved an accuracy of 59.7%. Whereas, Benkaddour in [9] defined a model to achieve and accuracy of 91.75% by training model for 40,000 to 80,000 epochs. Our proposed model achieved a maximum accuracy of 93.8%.

The regressions models in the literature used pre-trained models and results are tabulated in table 4. The authors, Sheoran et al. in [7] used VGG16, ResNet50 and SENet50 to get a MAE of 5.49. Puc et al. of [4] achieved MAE of 7.25, 6.33 and 7.03 for UTKFace, FGNET and APPA-REAL dataset using WideResNet and FaceNet pre-trained models, authors tabulated the results based on Gender and Race. The researchers in [25-30] used FGNET dataset and measured the model performance in terms of MAE as shown in table 4. Xie et.al used ResNet model with emsemble learning approach for traing and achieved a MAE of 3.14 [25]. Taheri et.al extracted and fused multi-stage features before feeding to DAG-CNN model (Directed Acyclic Graph Convolutional Neural Networks) by fine-tuning pretrained VGG16 & GoogleNet models and obtained a minimum MAE of 3.05 [26]. The authors, Sawant et al. [27] used local direction and moment pattern features to train age estimation model and their model's enhanced performance was 3.9 MAE. Ng et al. [28] extracted wrinkled based features using LBP texture feature extractor and Hybrid Ageing Pattern feature descriptors and then fused to train their model to achieve a minimum MAE of 5.39. Pontes et al. [30] used facial landmark descriptors like facial contour, left and right eyebrow etc and then combined local and global feature to train the model to measure the MAE of 4.5. We also observe from the table 4, the pretrained models outperform when fine-tuned rather than using as black box [25-27].

Table 4. Comparing the proposed model's performance to existing models

Dataset	Researchers	Classification model (Accuracy) (%)	Regression Model (MAE)
UTKFace	Meghana et al. [5]	60	-
	Ghildiyal et al. [4]	61.7	-
	Sheoran et al. [5]	79.12	4.58
	Puc et al. [4]	-	7.25
	Raman et al. [14]	80.76	-
	Proposed model	**93.7**	**4.2**
	Ekmekji [23]	50.2	-
Adience	Levi et al. [22]	50.7	-

	Lapuschkin et al.[10]	53.6	-
	Qawaqneh et al.[8]	59.9	-
	Lu et al. [12]	60.0	-
	Duan et al. [11]	66.49	-
	Benkaddour [7]	91.75	-
	Proposed model	**93.8**	**-**
FGNET	Raman et al. [14]	66.50	-
	Puc et al. [4]	-	6.33
	Xie et al. [25]	-	3.14
	Taheri & Toygar[26]	-	3.05
	Sawant et al. [27]	-	3.9
	Ng et al. [28]	-	5.39
	Chen et al. [29]	-	4.13
	Pontes et al.[30]	-	4.50
	Proposed model	**-**	**3.76**
APPA-REAL	Puc et al. [4]	-	7.03
	Proposed model	**-**	**2.85**
AAF	**Proposed model**	**-**	**4.21**

Further, the classification model's performance is improved by increasing the number of classes, as shown in Table 5. In the proposed model, the dataset is categorized into 8 classes for both the UTKFace and Adience datasets and achieves better results than the existing models proposed in [5] and [9].

Table 5. Classification models performance with the number of class labels.

Author	**Dataset**	**No. of classes**	**Age group range**	**Accuracy (%)**
Meghana et al. [5]	UTKFace	5	0-14, 14-25, 25-40, 40-60, 60+	61.7
Proposed model		8	0-3, 4-7, 8-14, 15-24, 25-37, 38-47, 48-59, 60+	**93.7**
Benkaddour [9]	Adience	6	0-6, 8-20, 25-32, 38-43, 48-53, 60+	91.75
Proposed model		8	0-3, 4-7, 8-14, 15-24, 25-37, 38-47, 48-59, 60+	**93.84**

Our model shows a minimum computation time of 7350.091 sec. for the FGNET dataset, where the images are captured under controlled conditions as compared with the images captured in an uncontrolled environment, and also has an average of 12 images per person which makes faster learning. The model's training time increases with the size of the dataset and the number of individuals whose faces are considered for age estimation.

6. Conclusion

Facial age estimation models are rigorously evaluated using standard metrics to ascertain their accuracy and effectiveness. In the realm of real age estimation, the MAE stands as a fundamental metric, quantifying the average absolute differences between predicted and actual ages.

The comparison of these algorithms often centers on the assessment of MAE, emphasizing the importance of minimizing age prediction errors. This paper leverages datasets such as the UTKFace, FGNET, AAF, APPA-REAL, and Adience Face datasets commonly used benchmarks in this context, and the performance is compared with the pre-trained models in the literature. In this work, the age estimation is considered as regression and classification problem. Our model achieved an accuracy of 93.7% for UTKFace dataset for classification and minimum MAE of 2.85 for APPA-REAL dataset. The proposed models performance is superior than the existing pre-trained models because our model has minimum trainable parameters as compared to that of pre-trained model, we have repeated the convolution layers only for five times which reduces the models computation time with reduced resource utilization but can be improved further by using more data and improving the network design by varying the hyper-parameters. This research will be extended to other facial features like gender and race for the estimation of age along with the raw pixel information to generalize the model independent of the dataset and apply it to real-time applications.

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