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CNN Based Age Estimation Using Cross-Dataset Learning

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Abstract: In computer vision and pattern recognition, estimating age from a single Image of human face is a crucial but challenging job. The quantity of training data gathered has a direct impact on how well a learning algorithm performs. Research in this area is primarily concentrated on enhancing results by training and testing using a single dataset. Despite the high accuracy results on this task using recent deep learning approaches, due to the diversity of human characteristics such as race and nationality, and variations in capture circumstances, these approaches lack generality when applied to unseen Images. Poor image quality, insufficient image counts, and low precision data limit the effectiveness of current learning methods. In this process of age prediction using Mean Absolute Error (MAE), we adopted CNNs with VGG-16, Resnet-50 and DenseNet-201 architectures to estimate age of a person by treating it as classification problem. As part of this investigation, we extensively analyzed the UTK Face, FGNET, CACD, and AS-23 datasets. In the last stage, merged dataset is cross validated with an additional dataset that have not been investigated before. As a result of this process, it is discovered that VGG-16 has the best accuracy with an MAE value of 2.2 with cross data learning, whereas the MAE for the Merged dataset associated with VGG-16 was1.71. The MAE values achieved with VGG-16 model are the best among all the experimental values for estimating age. In comparison to training on an independent dataset, the results demonstrate that multi-dataset simultaneously training network results in a more notable performance. The proposed method, according to experimental findings, demonstrated that the it outperforms almost all previous methods on age estimation with an MAE of 1.71 years.

Keywords*— Age Estimation, Convolutional Neural Networks, Merged Datasets, Cross-Dataset training.*

1. Introduction

Images of human faces show a variety of characteristics such as age, race, gender, emotions and other characteristics related to health. Age estimation has emerged as the most difficult and crucial characteristic of all. People of the same age typically exhibit a variety of facial appearances because the ageing process is quite unique in each individual. In recent years, there has been a lot of attention paid in the age estimation of facial images using CNN in particular, because it can process enormous amounts of data to acquire a compact and discriminative feature representation. Most of the earlier age estimation techniques [3,4] were developed to give an accurate estimate of the actual age. However, it can be difficult to determine a precise age because of the specialization of ageing effects on the face. People age in different ways depending on a range of internal as well as external factors including their ethnicity, heredity, health, surroundings, and lifestyle. As a result, ageing is uncontrollable, making age estimation challenging for both humans and computer vision systems.

The accuracy of age estimation is also impacted by additional factors like pose variations, lighting conditions and facial expressions. The accuracy and reliability of the performance of the current methods still fall below the level of reality in spite of significant advances and ample work on age estimation The majority of the published work on age estimation simplifies the process by focusing on optimization of results obtained when applying methods to individual or merged datasets and evaluated on same dataset. These methods are therefore not enough to be used with new images when used in real-world situations. Combining various datasets for the training can solve this issue, but standardizing images is a challenging task.

In this paper, we propose cross validation approach to achieve more accurate age estimation results. The main goal of this research is to determine whether combining data from various datasets helps significantly in training. In order to analyze the accuracy of a proposed CNN-based system using Merged, Cross Datasets as well as single datasets, we present an approach for joining multiple datasets to create a Merged Dataset. The findings of all three CNN models are compared, and the best CNN model and optimized model are used to predict age. The following is a summary of this article's contributions:

(1) We outline a procedure for choosing and combining various datasets to produce a merged dataset that can be the basis for a single learning step.

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(2) Using the four public datasets and a new live dataset AS-23, we present an in-depth evaluation of CNN models (VGG-16, DensNet-201, and Resnet-50)

(3) The extensive investigative experiments are conducted by evaluating three CNN models on Individual, Merged and Cross Datasets.

(3) Finally, all the experiments which are conducted from CNNs are compare the performance MAE.

The rest of this paper is structured as follows: The related works are reviewed in Section 2, our proposed learning method is introduced in Section 3 along with implementation details, the experimental results are discussed in Section 4, and the conclusion and future issues are discussed in Section 5.

2. Related Work

Early methods for estimating age [1,2] rely on manually extracting features like PCA, LBP, Gabor, LDA and SFP. We can use a classification or regression algorithm to estimate facial age after these feature extractions. The use of CNNs [9] for age estimation and face identification has been gaining popularity because they are highly accurate and produce accurate results when tested on facial images that have been tilted, occluded and brightened.

The Active Appearance Model (AAM) was first used to investigate face age estimation by Lanitis et al. [5].Age estimation was performed using a quadratic regression algorithm based on AAM features. Dong et al. [6] designed a fully learned age estimation system with CNN for age estimation. This method improves CNN performance by incorporating the multi scale analysis strategy. A new frame work for feature extraction using deep learning algorithm and the Deep Learned Ageing pattern (DLA), was developed by Wang et al. [7] to enhance age estimation performance. A more advanced technique using distribution based (KL divergence) loss functions was proposed by the authors in Huo et al. [8]. Two deep CNNs with distinct architectures, the VGG-16 and Novel architectures, are used in the architecture as two streams. The VGG-16 CNN Model was optimized among the different datasets. The second model, which was used to train this novel CNN model, used various kinds of inputs from various augmentation techniques. Antipov et al. [10] proposed another technique that makes use of pre-trained algorithms to determine age and gender from facial images. They achieved the best accuracy with an MAE of 2.84 and 2.99 respectively on FG-NET and MORPH-II datasets.

For the purpose of estimating facial age, Liu et al. [11] proposed an Ordinal Deep Feature Learning (ODFL) and an Ordinal Deep Learning (ODL) framework. Deep CNN was developed by ODFL to investigate face descriptors with CNN and use the topology relation for face description. On five face ageing datasets, they presented extensive experimental findings that demonstrated that both ODFL and ODL outperformed the majority of the most recent methods. Duan et al.[12] created a CNN with hybrid structure and hierarchical style Extreme Learning Machine (ELM) for age estimation .The experiments on the MORPH-II and adience benchmarks demonstrated that the hybrid framework outperformed other approaches on the same face ageing datasets. Sawant and Bhurchandi[13] proposed a hierarchical Gaussian process for facial age estimation. They also proposed Warped Gaussian Process(WGP) regression to simulate group-specific ageing patterns. For the task of estimating facial age, Zhang et al. [9] proposed AL-ResNets and an AL-RoR architecture based on the attention LSTM network. The proposed approach performed better on the MORPH Album 2 and FG-NET datasets as well. A multi-stage estimation model using a pre-trained VGG-19 model was developed by Fang et al. [15]. The implementation of the saliency detection network, helped the authors to record an MAE of 1.84 years by extracting only faces. A lightweight CNN network (ShuffeNetV2) was developed by Liu et al. [16] based on mixed attention Mechanism (MA-SFV2). Testing on MORPH-II and FG-NET datasets, the authors obtained an MAE of 2.68 years. A deep CNN-based model that reconstructs low-resolution faces as high-resolution faces was developed by Nam et al. [17] to address the issue of age prediction in low-resolution facial images. The proposed method's effectiveness for high-resolution reconstruction is demonstrated by results from experiments on the PAL, MORPH, and FG-NET databases.

In order to determine age and gender from facial images, Garain et al. [18] developed the GRA_Net (Gated Residual Attention Network) deep learning model. They used five standard datasets (Wikipedia, FG-Net, AFAD, UTKFace and Adience DB) and demonstrated that it is effective for dividing people into groups based on their gender and age. Mustapha et al. [19] developed a method for CNN based age group classification on All-Age Face (AAF) dataset and they reported 84.90% training accuracy and 85.12% testing accuracy. The cross-dataset training CNN(CDCNN), developed by Zhang et al. [20], uses a normal architecture for age estimation using cross dataset validation. They used CNN pre-trained on ImageNet with VGG-16 architectures by implementing age estimation as a classification problem. The AFAD dataset with cross-dataset training reported an MAE of 3.11 years.

3. Materials and Methods

This section presents a brief summary of our proposed approach, which is explained in figures 1 and 2. We begin by outlining the datasets that were used to train and evaluate the CNN. Second, we describe the underlying three CNN models. The detailed explanation of block diagrams of figure1 &2 described in detail as follows:

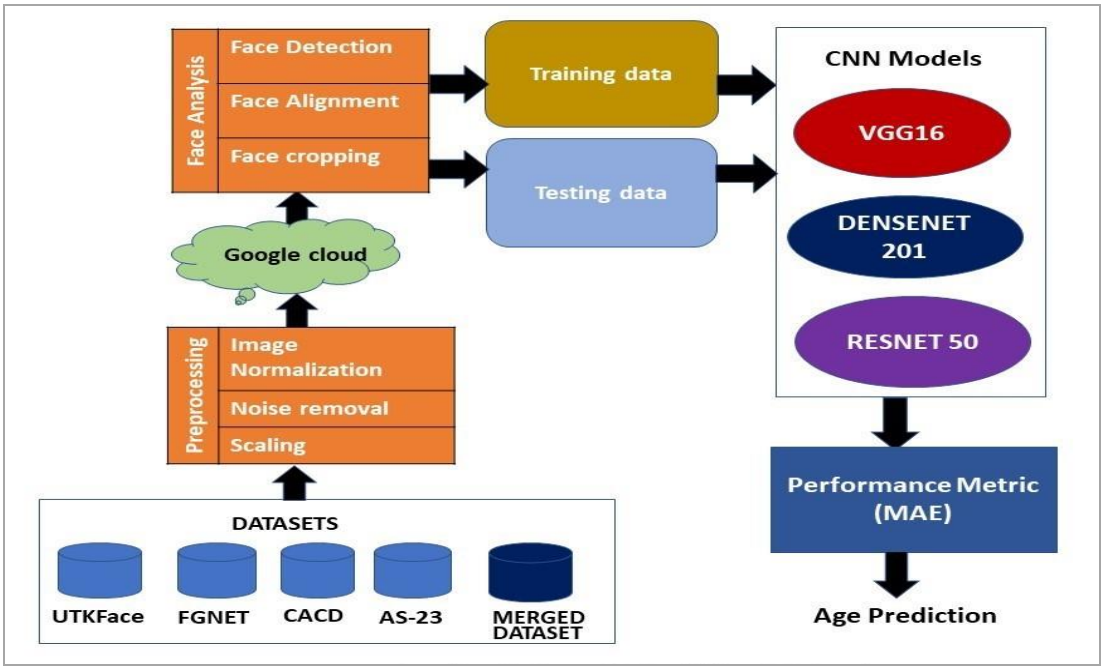

Fig.1. Age prediction with Individual Datasets

A. Description of Stages

The proposed system functioning depends on the following stages:

1)Prepare the Pre-processed image datasets for experimentation.

2)Create merged dataset from the images of four datasets.

3)Predict age of a person using best pre trained CNN Models.

4)The aforementioned CNN models are compared with the performance measures on individual, merged and Cross datasets and taken the best CNN model using the performance metric (MAE).

5) Finally, the identified CNN Models are applied to the SoftMax classification for multiclass classification in order predict age, and the best dataset has been selected in order to achieve the highest estimation accuracy

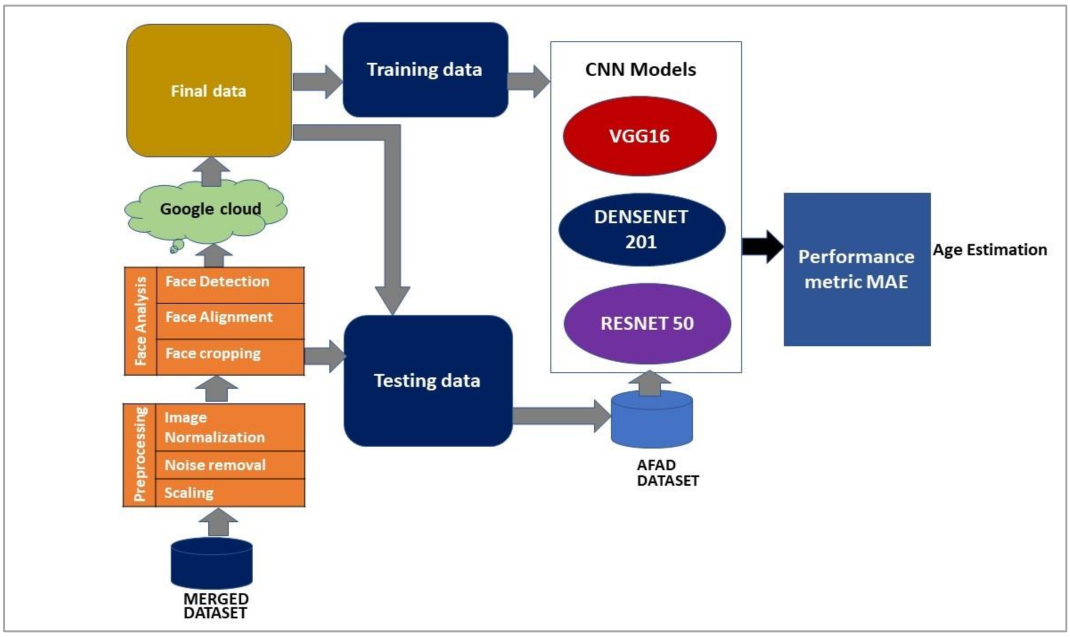

Fig.2. Age prediction with cross Data validation

B. Datasets

The proposed method is evaluated on three public datasets UTKFace, FGNET, CACD and a live dataset AS-23. The UTKFace [21] is a large dataset which consists of face images with a very long age span. It consists of more than 20K face images with metadata annotations of age, gender, and ethnicity. There were a total of 1,002 images in the

FGNET [22] dataset from 82 different individuals. With a broad range between 6 and 18 images, each person has an average of 12 images. One significant drawback is the small FG-NET collection with less number of people.Over half of FG-NET participants are under the age of 13, even though their ages vary from 0 to 69. In this dataset, out of the 82 individuals' 1002 images, the top 10 individuals' 150 images are taken into consideration for experimentation. There are a total of 2000 subjects in CACD [23] and there are 163,446 celebrity images of those subjects in the age range 12-62.

The college student dataset AS-23 contains images of students from the ages of 2 to 21. There are a total of 100 subjects, and there are 10,000 images of each subject as a student. The complete collection was recorded between 2003 and 2023. For experimentation, the top 10 students and 100 images out of the 100 students in this dataset are taken into consideration. Figure 3 displays the sample images from the four datasets.

The images from the various datasets were simply combined to create a single large Dataset (1,98,153 Images). The Cross-dataset evaluation using one unseen dataset the Asian Face Age Dataset (AFAD)[24] is performed on Merged dataset and later the results are compared. In this Dataset, there are 1,64,432 labelled images in this for testing only 10000 images have been considered with the ages varying from 15 to 40.

Fig. 3. Sample images from (a)UTKFace (b) FG-NET (c) CACD (d) AS-23

C. Preprocessing

The pre-processing is one of the crucial steps, when CNNs are adopted for any task. We use the following techniques to improve the quality of images and enhance the features that can be extracted from them.

- *Normalization*

Image normalization is a technique used to adjust the contrast and brightness of an image. The aim is to make the image more visually consistent by scaling the pixel values to a specific range or by adjusting the mean and variance of the pixel values.

- *Noise removal*

Noise in images can arise from various sources, including sensor noise, compression artifacts, or environmental factors. Noise removal techniques aim to reduce or eliminate unwanted noise in images. In our method, Median filtering and Gaussian filtering techniques are used. Median filtering replaces each pixel value with the median value of the neighboring pixels and Gaussian filtering uses a weighted average of neighboring pixels to smooth the image while preserving edges.

- *Scaling*

Scaling is a technique used to resize an image to a different size or resolution. Images in the training dataset had differing sizes, therefore images had to be resized to 224 X 224 before being used as input to the model.

D. Google cloud

Google Cloud Storage is a service within the Google Cloud Platform. The face images remain stored in Google cloud storage. To perform in-depth research and analyse the findings, the Google Co-Lab was used. The robust computing tools offered by Google Cloud were accessed and used through Google Colab.

E. Face Analysis

Once the datasets are ready, we perform face analysis using the following techniques:

- *Face Detection*

Face detection is the process of identifying the presence of faces in an image or a video. It is typically using Haar cascade face detection algorithm to detect facial features such as eyes, nose and mouth, and use them to identify the presence of a face.

- *Face Alignment*

Face alignment is the process of adjusting the position and orientation of a face in an image so that it is aligned with a predefined reference frame. The purpose of face alignment is to normalize the face pose and make it easier to extract facial features for further analysis. Here we used facial landmark detection technique for detecting specific facial features such as the eyes, nose and mouth, and using them to calculate the position and orientation of the face.

- *Face Cropping*

Once the face has been detected and aligned, it can then be cropped out of the original image to create a new image that focuses specifically on the face. Here we applied a simple Geometric Transformation called “Bounding Box Cropping” for drawing a bounding box around the face in an image and then cropping out the area inside the box.

F. Training and Testing

In this experiment, the three CNN Models are evaluated first individually on each dataset (UTKFace, FGNET, CACD, AS-23, and Merged Dataset) with 70:30 split ratio. Next, these CNN models are evaluated using cross dataset validation where Merged Dataset is training set and an unseen dataset AFAD is testing set (10,000 images). The size of each Dataset is shown in Table 1, along with the split distribution for training and testing.

Table 1. Training And Test Data split of five Datasets

S.No.	Dataset	#Training	#Testing	#Total
1	UTKFace	16594	7111	23705
2	FGNET	701	301	1002
3	CACD	114412	49034	163446
4	AS-23	3000	7000	10000
5	Merged Dataset	134707	63446	198153

G. Face age prediction using CNNs

A key element of the proposed approach is CNNs. The network inputs facial images and outputs data for age prediction. The CNN models used in this case are VGG-16[25], DenseNet-201[27,28], and ResNet-50[26]. Figure 3 shows the CNN used to determine age from the datasets. The four facial datasets UTKFace, FGNET, CACD, and AS-23 can all be used as input. The Convolutional Layers apply convolutional filters to extract features from the input images. Pooling layers down sample the feature maps generated by the convolutional layers. The final fully connected layer outputs the predicted age, typically as a probability distribution across different age groups.

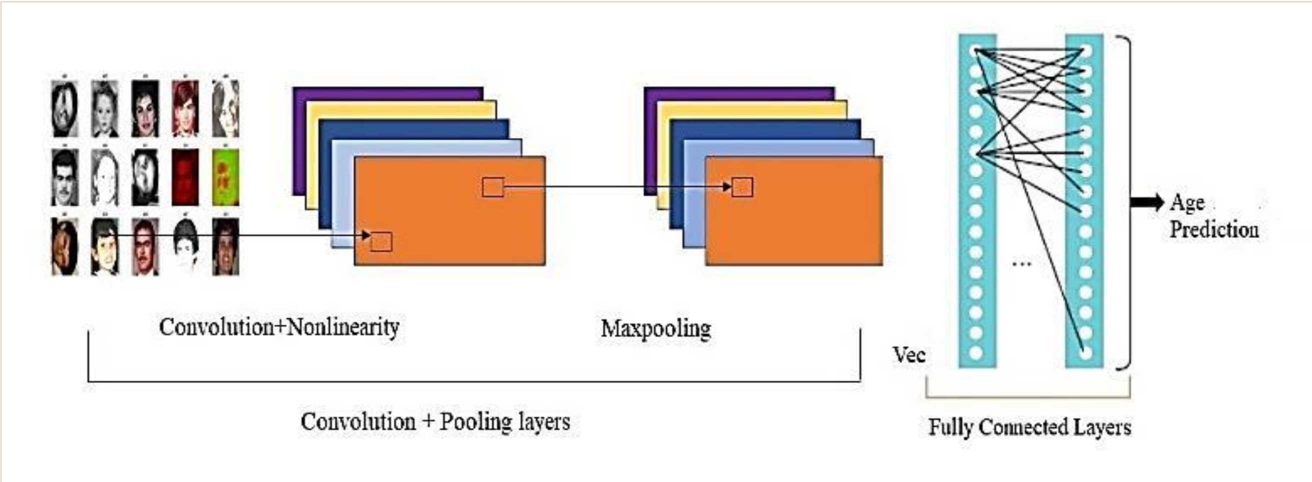

Fig. 3. Convolutional Neural Network architecture

H. Cross Dataset Validation

Before starting the cross dataset validation, it is crucial to perform merging of datasets. In this experiment, first the CNN models are evaluated on Merged Dataset using 70:30 split ratio. Next, using cross dataset validation the same Models are evaluated with Merged dataset as training set and unseen AFRD dataset as testing set.

I. Performance Metric

Different age estimation algorithms are evaluated using the widely used performance metric, the Mean Absolute Error (MAE). MAE calculates the absolute error between actual age and predicted age as defined by the equation (1).

$$\boldsymbol{MAE} = \frac{\mathbf{1}}{\boldsymbol{n}}\sum_{i=1}^{n} |\, \hat{y}i - yi \,| \qquad (1)$$

where n denotes the total number of data samples, yi denotes the actual age, and ŷi denotes the predicted age of the i-th sample. Better age prediction success by the model is indicated by a lower MAE value.

4. Results

This experimentation was carried out in two stages on four face datasets (UTKFace, FGNET, CACD and AS-23) and a Merged dataset. In the first stage, the three CNN models are evaluated on individual datasets. In the second stage, the same CNN models are evaluated using cross dataset validation approach where merged dataset is training set and an unseen AFRD dataset is testing set. The Performance (MAE) comparison results on four datasets and MAE comparison on merged datasets and cross-dataset training are presented in Table 2&3. The description of the comparative metrics study using three CNN models is shown in Figures 4 and 5.

Table 2. Performance (MAE) Comparison On four Datasets

Model	Performance (MAE)			
	UTKFace	FGNET	CACD	AS-23
VGG-16	2.1	2.46	2.97	1.95
Densenet-201	2.71	2.56	4.77	2.49
ResNet 50	2.4	4.2	3.27	4.53

Table 3. Performance (MAE) comparison with cross Dataset Validation.

Model	Performance (MAE)	
	Merged Dataset	Cross Dataset
VGG-16	1.81	2.2
Densenet-201	1.85	2.37
ResNet 50	2.11	2.34

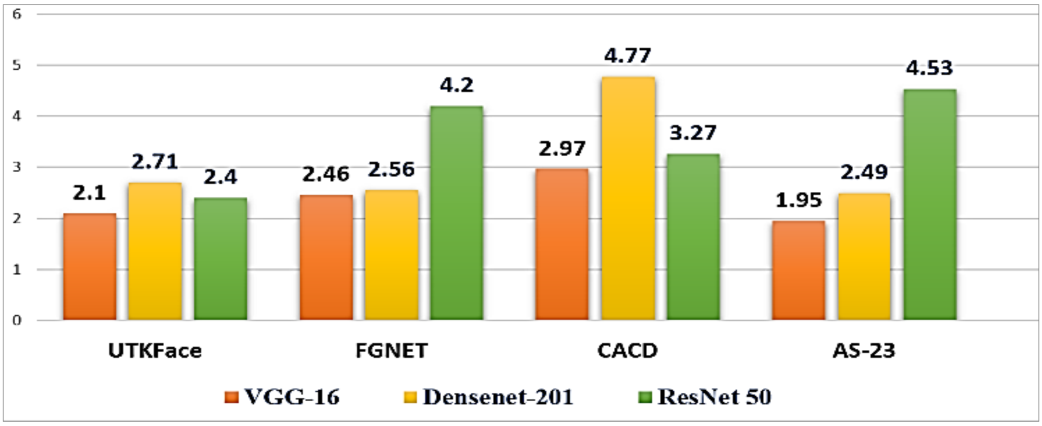

Fig. 4. Comparative analysis of MAE with three CNN models

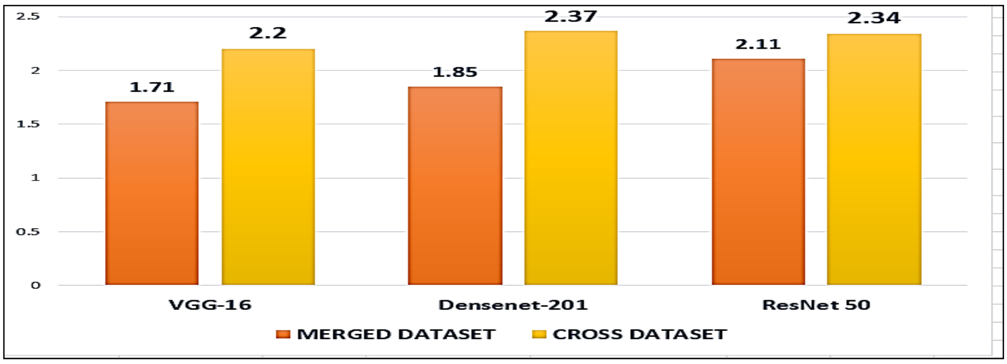

Fig. 5. Analysis of Comparative Metric (MAE) with cross dataset validation

J. Result analysis

The VGG-16 CNN model achieves a best accuracy on UTKFace with an MAE value of 2.1 of 2.46 on FGNET with MAE value of 2.46,CACD with an MAE of 2.97 and AS-23 with an MAE value of 1.95.For Merged dataset, the VGG-16 CNN model achieves an MAE value of 1.81.The VGG-16 CNN Model obtained the highest accuracy among all experimentation findings on five datasets, with an MAE of 1.81 on the Merged dataset. Finally with cross dataset valuation, The sameVGG-16 model achieves a better MAE value of 2.2 years when training on the Merged Dataset and testing on new unseen AFAD test set

K. Discussions

The performance comparison between our proposed method and other state of the art methods on FG-NET and CACD datasets is shown in Table 4. Our method is trained on Merged dataset with and without cross dataset Learning and improves the results by nearly 0.1 years compared to those of the state-of-the-art approaches.

Table 4 Comparison of age estimation results

Author	Method	Dataset	MAE
Zhang et al.[20]	CDCNN	CACD	3.96
Garain et al.[18]	GRA_Net	FG-NET	3.23
Liu et al.[16]	MA-SFV2	FG-NET	3.81
Zhang et al.[9]	AL-RoR-34	FG-NET	2.39
Nam et al.[17]	CNN with GAN	FG-NET	8.3
Liu et al.[11]	ODFAL	FG-NET	3.89
Fang et al.[15]	Multi Stage Learning	FGNET, CACD	1.81
Ours	Proposed Method (With Cross Dataset Validation)	Merged Dataset	2.2
Ours	Proposed Method (Without Cross Dataset Validation)	Merged Dataset	1.71

5. Conclusions

We propose this cross-validation method for age estimation task, that trains merged dataset mainly to solve the problem of poor quality and insufficient numbers of training images in face datasets and to help the training task with merging information from diverse datasets. This work presented an extensive evaluation of CNN Models using both single and cross-datasets approaches on UTKFace, FGNET, CACD, AS-23 Datasets. The proposed method improves the performance on AS-23 and Cross Datasets with lower MAE values of 1.95 and 1.71 respectively on evaluating on best performed VGG-16 CNN Model. Obtained results for both the tasks have **significantly** outperform many state-of-the-art approaches. In future works, we will use the best performed CNN models to implement Multi-Task Learning (MTL) mainly to perform face recognition and age classification tasks simultaneously.

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