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Human Age Estimation from Face Images with Deep Convolutional Neural Networks Using Transfer Learning

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Abstract: In recent years, there has been a growing interest in the prediction of facial age due to its diverse applications in fields such as security, entertainment, and healthcare. The current scourge of underaged voting in Nigeria is a problem and this research delves into the realm of facial age prediction by employing four well-known convolutional neural network (CNN) architectures, namely VGG16, ResNet50, Mobile Net, and VGG19 to predict chronological ages from facial pictures of person. The objective is to achieve precise age estimation from facial images, utilizing two datasets: UTKFace and CASIA African Facial Datasets. The results of this investigation are noteworthy. Specifically, the VGG16 model which demonstrated remarkable performance, yielding a Mean Absolute Error (MAE) of 1.76 when applied to the UTK-Face dataset. Additionally, when utilizing Mobile-Net, an unprecedented MAE of 1.10 was achieved for the Casia Africa Face Dataset. Notably, this marks the first instance of employing the dataset for facial age detection with CNNs, and this approach outperformed previous works, yielding the lowest MAE among all the studies reviewed.

Keywords: convolution neural network; deep learning; facial age; regression; transfer learning

1. Introduction

The task of automatically estimating age has gained popularity due to the many industries it may be applied to, particularly social media and e-commerce. Currently, various e-commerce websites may provide product recommendations to their users based on their historical preferences; with seeming age, more practical recommendations are likely. Facial age prediction is a challenging task due to the inherent complexity and variations in facial appearances caused by factors such as genetics, lifestyle, and environmental factors. Convolutional neural networks (CNNs) have shown remarkable success in various computer vision tasks, including facial age prediction. This paper focuses on utilizing transfer learning with VGG16[1], VGG19[2], ResNet50[3] and Mobile Net [5] which are deep CNN architectures widely adopted for image recognition tasks, to improve the accuracy of facial age prediction. Age can be expressed as an integer or a floating-point number, but it also has some coherence,[4] making it possible to compare a person's facial features across a few age groups (for instance, age 20-22). Hence, we can look at the age problem as either regression where a specific age is predicted or classification where different images are grouped into different age groups. We focus on age as a regression problem in this study. It is demonstrated that the suggested technique performs remarkably well on the UTK facial and IMDB-Wiki images benchmark datasets. In this article, we used transfer learning models to estimate facial photos on two facial datasets which are UTK face and Casia African facial dataset. In this approach, transfer learning is used to coordinate a variety of pre-trained deep CNNs VGG16, ResNet50, Mobile Net and VGG19. The only layers that are modified for age estimation are those that are added to the pre-trained model which are the fully connected layer s (FC). Underage voting can be said to be when a person less than the approved age for voting i.e. 18 years of age is engaged in voting exercises, this work aims to develop a facial age detector that can be used to prevent the problem of underaged voting and other age-related vices [18]. The following is the paper's outline: A quick summary of literature reviewed is found in the literature and related work is presented in Section 2. The proposed method for facial age classification

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is described in Section 3, Section 4 describes our result estimates, and Section 5 compares our findings to current state-of-the-art approaches.

2. Materials and Methods

2.1. Dataset

For facial age prediction, a dataset comprising facial images with corresponding age labels is required for that we selected the UTK and Casia African facial dataset which is openly available from the following links

1. https://www.kaggle.com/datasets/jangedoo/utkface-new.
2. https.//www.idealtest.org/#/datasetDetail/24

The dataset can be preprocessed by applying standard techniques such as face detection, alignment, and normalization. Data augmentation techniques like rotation, scaling, and flipping was also employed to enhance the diversity of the training set.

2.1.1. UTK facial dataset

One of the most used datasets created for age determination from facial photos is the UTK image benchmark. The dataset is one of the largest-scale facial dataset with a wide age range (from 0 to 116 years old), it has over 20,000 facial photos with annotations for age, gender, and ethnicity. There is a wide range of poses, facial expressions, lighting, occlusion and resolution. Several tasks, including face detection, age estimation, age progression and regression, and landmark localization could be performed using this dataset. We used pictures from ages 5-30, each consisting of 450 images which made a total of 11400 images.

Figure 1. image showing example of facial images in the UTK dataset.

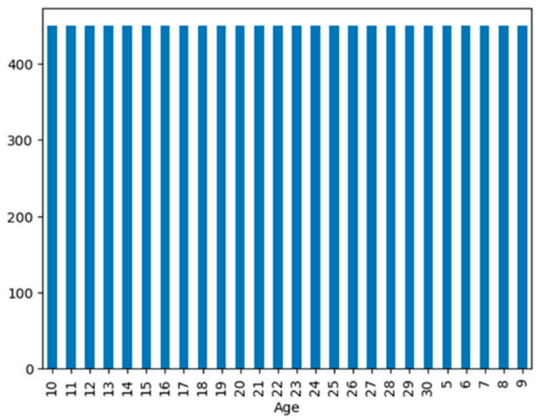

Figure 2. image showing the distribution of from ages 5-30 from the UTK Facial dataset used for the experiments.

2.1.2. CASIA African facial dataset

The images in the database were taken in Kaduna [27], Nigeria, which is an African country. Approximately 1150 individuals took part in the practice of capture. The dataset has different ethnic Nigeria tribes, for this experiment, we made use of the Hausa ethnic group. The images in the

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database comprise a total of 38,546 images from 1,183 subjects. We made use of a total of 10921 facial images distributed to ages 10-30, table 2 shows the age distribution of the dataset.

Figure 3. images showing example of facial images in the CASIA African dataset.

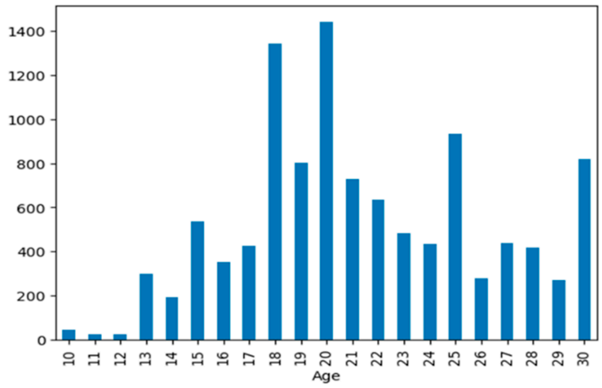

Figure 4. image showing the distribution of from ages 5-30 from the WIKI Facial dataset used for the experiments.

Training

The input image was rescaled to 120 X 120 pixels and we used the optimization function Adam, and a dropout of the fully connected layer of 0.2 which was to regularize the network while training. We downloaded the various deep learning models from the TensorFlow keras library, and then we froze the convolutional layers and added our fully connected layers for the prediction to take place, we used three dense layers which had 50, 20 and 1 outputs hence for prediction. We then specified the activation function at the last dense layer which is linear for the experiments. We also used the early stopping function to stop training once there are no improvements in accuracy, the RGB image is passed to the convolution area for feature extraction (pre-trained) and then passed to the fully connected layer which is then passed to the output layer where the probability of the output layer is calculated. We used a total of 11700 images which had 450 images in each age label i.e., 5-30 for the UTK dataset, we used a total of 10921 images from the CASIA dataset [27]. we then used the Python function" train_test_split()" to split the X images and labels into training and test set, using the ration of 70.30 for facial datasets.

Transfer Learning Workflow

The transfer learning workflow involves the following steps.

a. Preparing the dataset. Splitting the dataset into training, validation, and testing sets.

b. Pre-training. Utilizing the pre-trained (i.e. VGG16) model, which is trained on a large-scale image classification task such as ImageNet, to extract features from facial images.

c. Fine-tuning. Modifying the last few layers of the pre-trained model or adding new fully connected layers to adapt the model for age prediction. These layers are initialized. Randomly and trained on the specific age prediction task as seen in fig6.

d. Training and Evaluation. Training the modified model using the training set and evaluating its performance on the validation set. Iterative optimization techniques such as gradient descent and backpropagation are applied.

e. Testing. Assessing the final model's accuracy by evaluating it on the testing set.

Metrics such as mean absolute error (MAE) and mean squared error (MSE) can be used to quantify the prediction accuracy. In this work, we utilize the MAE as our evaluation metric.

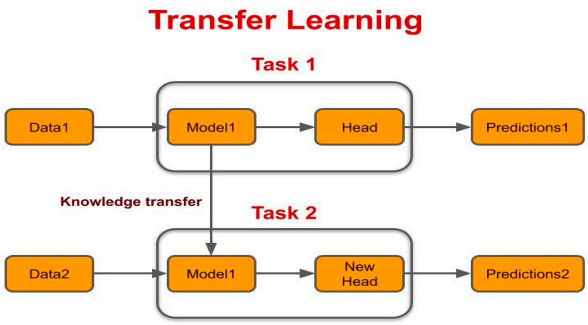

Figure 5. shows the transfer learning concept.

$$\boldsymbol{MAE}=\mathbf{0}\boldsymbol{Ny}-\boldsymbol{yN} \quad (3)$$

In a regression model, R-Squared (also known as R^2 or the coefficient of determination) is a statistical metric that quantifies how much of the variance in the dependent variable can be accounted for by the independent variable. R-squared, or the "goodness of fit," measures how well the data match the regression model. A greater r-squared shows that the model can explain more variability. R-Squared ranges from 0-1

$$\boldsymbol{R2} = \frac{\boldsymbol{SSr}}{\boldsymbol{SSt}} \quad (4)$$

where SSt represents the total sum of squares and SSr represents the residual sum of squares. We would be using both MAE and R2 to determine how well the models performed. The suggested age prediction system using deep CNNs and transfer learning is shown in Fig 7. One of the deep learning models would be attached to the base model with fully connected layers and an output. in Fig.7, a deep CNN model is initially imported with its pre-trained weights. The architectures were developed for the ImageNet object classification problem, so each deep CNN has 1000 units in its last layer. Hence, we remove its fully connected layers and added our custom fully connected layer with one output for age prediction using an activation function of either ReLu or Linear.

Experimental setup

Using Jupiter Notebook, we put the suggested strategy into practice. Intel 12 gen I-core 7 with 10 cores has been used for training the networks. For regression, the learning rate was set to 0.001 and the momentum to 0.9. We used mean absolute error (MAE) for regression in the performance metric. Human age exhibits some coherence, and facial shape can vary slightly but not enough for the human eye to notice. For instance, the age patterns of people who are 21 and 23 years old may be similar, and in some instances, it may be difficult for a human to tell them apart. On the other hand, for regression, we minimized MAE.

Training

The input image was rescaled to 224 X 224 pixels and we used the optimization function Adam, we used a dropout rate of 0.2 for convolutional layer and a dropout of the fully connected layer of 0.2 which was to regularize the network while training. We also used the early stopping function to stop training once there is no improvements in accuracy, the ‘rgb’ image is passed to the convolution area for feature extraction and then passed to the fully connected layer which is then passed to output layer where the probability of the output layer is calculated. We used a total of 11700 images which

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had 450 images in each age label i.e. 5-30 for the UTK-face dataset and the Casia dataset we had an unbalanced dataset due to the fact that some of the ages were in small amount in the dataset , we then used the python function train_test_split() to split the X images and labels into training and test set, using the ration 70:30 and the last layer had 1 output for the age value using linear activation function.

Figure 6, a deep CNN model is initially imported with its pre-trained weights. Ever since the architectures were developed for the ImageNet object classification problem, Deep CNN has had 1000 units in its last layer.

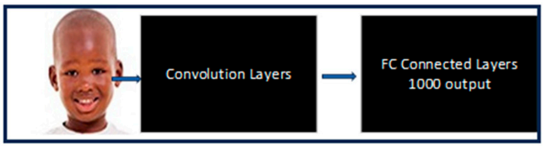

Figure 6. shows the initial transfer learning model without fine tuning.

The next step is to freeze it convolutional layers and three more fully connected layers added. The first FC layer has 1254450 units, and the second layer has 1024 units and the last fully connected layer has 1 unit for the number of classes, which in our case is 1 due to the regression problem we are dealing with. After training the final three layers in (b), the entire design is fine-tuned.

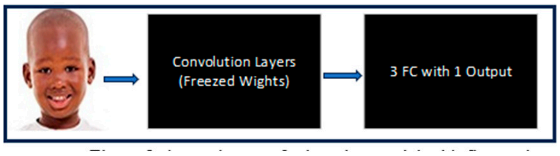

Figure 7. shows the transfer learning model with fine tuning.

Contribution to Knowledge

Our work Has examined the use of transfer learning approach on age prediction from facial images, this shows that with the aid of transfer learning we can build ready-to-go models which can be adopted in the real world specifically in Nigeria, for process such as under age detection during election and other access control functions.

3. Results

In Table 1 below we show the MAE and R2 of our experiments using the various transfer learning models .

Table 1. Regression results obtained from experiment using the UTK and CASIA facial dataset.

Method	MAE	R^2	Dataset
Resnet50	4.60	0.38	UTK
Mobile net	2.01	0.80	UTK
VGG16	1.75	0.85	UTK
VGG19	2.22	0.80	UTK
VGG19	1.34	0.19	CASIA
ResNet 50	3.19	0.28	CASIA
Mobile Net	1.10	0.88	CASIA
VGG16	1.21	0.85	CASIA

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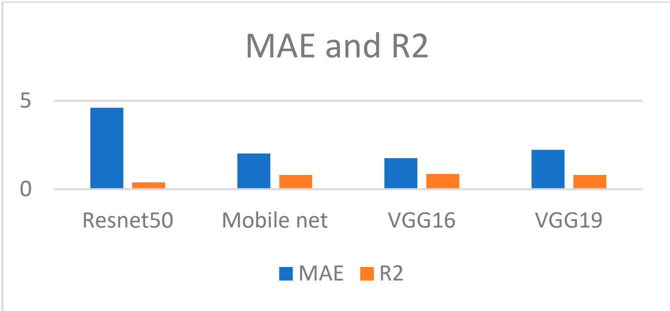


Figure 8. the performance of the models on the UTK face dataset.

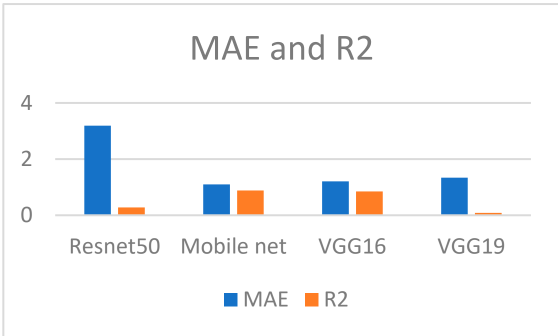
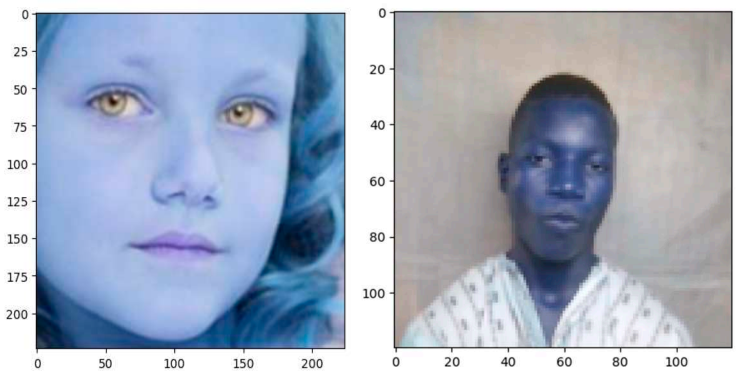


Figure 9. the performance of the models on the Casia Facial dataset.



Actual Age 6 Predicted Age 6.7: Actual Age 15 Predicted Age 16.25

Figure 10. shows a test image and the VGG 16 predicted result on the UTK image Dataset and Mobile-Net predicted result on the CASIA Facial dataset.

4. Discussion

From the results in our experiments, we obtained very impressive MAE and R^2, for the UTK Facial we obtained an MAE of 1.76 in years using VGG16 while for CASIA facial Dataset we obtained an MAE of 1.1 in years using Mobile-Net, which was the best in terms of performance. We also compare our work we some of the literatures using transfer learning models, in Table 2.

Authors	Method	Result	Dataset(s)
Akhand et al (2020)	Transfer-Learning (ResNet 18,ResNet -34,ResNet-50,InceptionNet and Den seNet	CACD:5-year Grouping (85%). 10-Year Grouping (93%) Regression (MAE of5.17) UTK Face:5-year Grouping (97%). 10-Year Grouping (99%) Regression	UTKFace,CACD and FGNet datasets

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		(MAE of 9.19) FG-Net:5-year Grouping (100%). 10-Year Grouping (100%) Regression (MAE of 2.64)	
[19] fang et al,(2019)	Trnasfer-Learning VGG 19	Adience:94% on classification. Regression 1.84 MAE CACD: 95% on classification. Regression 5.38 MAE	Adience,CACD
[20] Irhebhude et al,(2021)	Principal Component Analysis and support Vector Machine	10-Year Grouping (95% and 96%)(4 classes) .	Local Dataset and FG-Net
[21] Jiang et al (2018)	Caffe DL framwork,CNN	MAE:2.94	FG-NET and MORPH
[22]Ahmed & Viriri (2020)	Transfer-Learning and Bayesian Optimization	MAE) of 1.2 and 2.67	FERET and FG-NET
[23] Ahmed & Viriri (2020)	CNN& Bayesian Optimization	MAE of 2.88 and 1.3 and 3.01	MORPH, FG-NET and FERET
[24] Dagher & Barbara (2021)	transfer learning (pre-trained CNNs, namely VGG, Res-Net, Google-Net, and Alex-Net)	Googlenet (5-year Grouping 74%)	FGNET and the MORPH
		Googlenet (10-year Grouping 85%) Googlenet (15-year Grouping 87%) Googlenet (20-year Grouping 89%)	
[25] Ito& Kawai(2018)	transfer learning (AlexNet, VGG16, ResNet152, WideResNet-16-8) single task (STL) learning and multi task learning (MTL)	WRN + STL MAE(7.3)	IMDB
		WRN+MTL MAE(7.2)	Wide ResidualNe
[8]	ResNet18	2.66	UTKFace
[8]	ResNet34	2.64	FGNet
[8]	Inceptionv3	5	Cross-Age-Celebrity-Dataset
[8]	DenseNet	3.19	UTKFace
[8]	ResNet50	3.94	FGNet
[9]	GoogleNet	2.94	MORPH
[9]	GoogleNet	2.97	FGNET
[10]	CRCNN	3.74	MORPH
[10]	CRCNN	4.13	FGNET
[11]	RED+SVM	6.33	
Our Work	VGG19	2.22	CASIA African Facial Dataset
Our work	ResNet 152	4.08	CASIA African Facial Dataset
Our work	Mobile Net	1.10	CASIA African Facial Dataset
Our Work	VGG16	1.76	CASIA African Facial Dataset
Our Work	Resnet50	4.60	UTK Facial
Our Work	Mobile net	2.01	UTK Facial
Our Work	VGG16	1.75	UTK Facial
Our Work	VGG19	2.22	UTK Facial

5. Conclusion

The study showcases the effectiveness of employing transfer learning with popular models such as VGG16, ResNet50, Mobile Net, and VGG19 for facial age prediction. Leveraging pre-trained models along with fine-tuning techniques enhances generalization and accuracy, even when dealing with limited data. The research paper concludes by highlighting potential applications and future avenues for further refining facial age prediction through transfer learning.

The obtained results demonstrate VGG16's regression Mean Absolute Error (MAE) of 1.76 on the UT Face dataset and a 1.1 MAE when utilizing Mobile Net on the CASIA facial dataset. Predicting age through deep learning represents a challenging yet essential task. This study leveraged transfer learning within deep Convolutional Neural Network (CNN) models to devise an efficient approach for age prediction based on facial photographs. Age can be represented either as an integer or grouped into age brackets; in this work, regression techniques using deep learning were employed.

On benchmark face image datasets such as UTK-Face and CASIA African Dataset, which had not been previously used for age prediction in the existing literature, our proposed method demonstrated noteworthy performance, surpassing other approaches. This method exhibits significant potential for extension to real-time age estimation by extracting facial images from live recordings, such as those from webcams or security cameras—a promising avenue for future research. It consistently performs well on currently available benchmark datasets.

Funding: This research received no external funding

Informed Consent Statement: informed consents were taken from all the human subjects in this work by the respective researchers who developed the dataset.

Data Availability Statement: data used in this work can be publicly accessed and downloaded from Kaggle using the link: https://www.kaggle.com/datasets/abhikjha/utk-face-cropped for UTK Face dataset and http://biometrics.idealtest.org/dbDetailForUser.do?id=6#/datasetDetail/24 for Africa CASIA Face.

Conflicts of Interest: the authors declare no conflict of interest.

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