


REGRESSION AND CLASSIFICATION MODELS FOR HUMAN AGE PREDICTIONBhuvaneshwari Patil^{1,*} , Shivanand S. Rumma², Mallikarjun Hangarge³¹ Research Scholar, Department of Computer Science, Gulbarga University, Kalaburgi, India² Chairman, Department of Computer Science, Gulbarga University, Kalaburgi, India³ Professor, Department of Computer Science, Karnatak Arts Science and Commerce College, Bidar, IndiaCorresponding author email: bsp14052001@gmail.com**Article Info**

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Abstract

This study aims to enhance automated age prediction from facial images, a task with significant potential in security, law enforcement, and Human-Computer Interaction (HCI). While age estimation has seen progress, it remains a challenging problem due to the diverse factors influencing facial aging, such as genetics, environment, lifestyle, and facial expressions. These variations result in individuals of the same chronological age looking markedly different. Most existing age estimation methods rely on computationally intensive pre-trained models, often treated as “black boxes” with predefined input sizes and limited flexibility. To address these limitations, we propose using Convolutional Neural Networks (CNNs) for age prediction. Our approach combines classification and regression techniques to predict age more accurately. We applied our model to publicly available datasets, including FGNET, Adience, APPA-REAL, UTKFace, and All-Age-Face, encompassing images from constrained and unconstrained environments. The proposed CNN model was evaluated against existing pre-trained models, demonstrating comparable performance in age prediction tasks. Both classification and regression results underscored the model's accuracy, offering additional benefits in reduced computational complexity, increased flexibility, and adaptability. This study introduces a CNN-based approach as a viable alternative to pre-trained models for automated age prediction. It offers competitive accuracy while addressing critical limitations of current models, such as computational demands and lack of flexibility, thus contributing a more efficient solution for age estimation tasks in various real-world applications.

Keywords: Classification, Convolutional Neural Network, Regression

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INTRODUCTION

A increasing number of studies are focusing on computer-based human facial age assessment due to the quick advances in biometrics, pattern recognition, and computer vision. When age information is needed without disclosing other unnecessary personal details, this method is invaluable. Applications for computer vision are numerous and include electronic customer information management (ECIM), biometrics, security surveillance, forensics, Human Computer Interaction (HCI),

entertainment, and age-specific precision marketing (e.g., age-based visual advertisements). Facial age estimation has great applications in real-world situations. For example, monitoring cameras can be used to alert or stop minors from buying cigarettes or illegal narcotics from vending machines. A few examples include preventing minors from accessing dangerous websites, warning seniors about high-risk theme park rides, and prohibiting underage alcohol sales and entrance.

However, it is indisputable that estimating a person's age from their face is a difficult and demanding endeavor (Huerta, 2015). Numerous factors contribute to the difficulties in computer-based face age estimate (Drobnyh, 2017; Kusuma, 2020; Suwarni, 2021). First of all, differences in aging pace are a result of the different aging processes that each person experiences. These processes are impacted by a variety of factors, including living environment, ethnic group, gender, lifestyle, social interactions, health issues, and genetic variability. Second, there are intricacies in the shifting forms or textures connected to various age groups. For example, craniofacial growth, development of skull and facial bone primarily occurs during childhood to adolescence, at the same time, change in the facial skin is more noticeable during adulthood to old age. Thirdly, the urge to make an appearance of young may lead to use cosmetics, plastic surgery and other beauty products may substantially distort the results of age estimation model.

Using five distinct datasets gathered under constrained (FGNET) and unconstrained (UTKFace, All-Age-Face, APPA-REAL, and Adience) contexts, this model is thoroughly trained to estimate age in large-scale scenarios. The research accurately ascertains a person's age from face photos and offers perceptions into the efficacy and dependability of age estimation algorithms. In order to reduce overfitting, improve accuracy, save valuable resources, and make the models easier to use, pre-trained models are the focus of most current research on predicting human age. These models, however, are employed as black boxes, domain-specific, and trained on enormous datasets with predefined input sizes. Due of their millions of trainable parameters, these models are not very adaptive, which makes fine tuning challenging. We used five publically available datasets (FGNET, Adience, APPA-REAL, UTKFace, and All-Age-Face) to train a convolution neural network (CNN) model for age estimation and examine the results of classification and regression during the course of the datasets' training and testing. Dropout at thick and buried layers stabilizes the model and prevents overfitting. We found that, for both regression and classification, the performance of the suggested CNN model is comparable to that of the pre-trained model.

Better facial age estimation is needed for applications in forensics, security, and human-computer interaction. More accuracy and flexibility are needed in current models in order to meet real-world expectations. This study proposes the development of a Convolutional Neural Network (CNN) model for age estimation using both regression and classification. With the goal of improving upon the drawbacks of existing pre-trained models, the model's performance and generalizability will be assessed across five datasets. Utilizing the FGNET, UTKFace, All-Age-Face, APPA-REAL, and Adience datasets, the primary goals of this work are to build a CNN model that estimates the age of a face through regression and classification, and evaluate the model's performance. Here, an attempt has been made to achieve the state-of-the-art with the least amount of space and time complexity, on par with the performance of pre-trained models.

LITERATURE REVIEW

Although age estimation in computer vision has made great strides, there are still a number of gaps that point to areas in need of more study and improvement. The research gap is carried in three parts with respect to dataset, existing methodologies and future progress direction.

Constraints on the Dataset

While the UTKFace dataset is widely used for age and gender estimates, spanning from newborns to centenarians, research like George's (2024) is restricted to a small age group (5–30 years), with just 450 photos per group. The models trained on this dataset are less generalizable due to this restricted emphasis. Moreover, gender imbalance in datasets often results in models performing better on male faces than on female ones, as Puc (2020) reports.

The Adience dataset contains posture, orientation, and illumination problems because it was created from photographs from the internet. Gain in confidence in performance achieved through refining and perfecting research investigations, including those by Levi (2017) and Ekmekji (2016). Lapuschkin (2017) found 53.6% accuracy even with pre-trained models like AdienceNet, CaffeNet,

GoogLeNet, and VGG-16, with training accuracy of roughly 62.8% and testing accuracy of 50%. This demonstrates the difficulty of obtaining high accuracy with Adience data, especially in real-world settings. Despite being collected in a controlled setting and spanning from birth to 69 years of age, the FGNET dataset has limitations because of its small size and limited number of images per subject. Studies by Taheri (2019), Xie (2020), and Deng (2021), among others, have verified inconsistent outcomes with MAE ranging from 2.59 to 3.14, indicating that while controlled environments are beneficial, the size of the dataset and feature extraction techniques still have limitations.

The APPA-REAL dataset was primarily created for regression issues and attempts to estimate ages, both apparent and real. Although deep learning techniques for age estimate have been explored, Puc (2020)'s focus on real vs. perceived age in the dataset raises several challenges that are not fully addressed in current models.

Model Performance and Methodologies

Pre-Trained Models: To get a range of performance levels, pre-trained models have been employed in numerous studies. For example, Raman (2022) found 80.76% accuracy with gender-specific characteristics using pre-trained models. However, pre-trained models often struggle with generalization across different datasets and scenarios. The transfer learning model used by Sheoran et al. showed competitive performance for classification with 79.1% and regression with 5.49 MAE. The authors conclude that the pretrained model performs better than their custom neural network model.

Feature mining and classification: A series of feature extraction methods are employed by Sawant (2019) and Ghildiyal (2020) for feature mining and classification. In their research, they applied LDMP (Local Direction and Moment Pattern) for scaled images. The researchers stressed on the need for effective feature extraction approach for improving the performance measures of age estimation model for both classification and regression.

Context and Prospective Approaches

Integration of Features: The model accuracy can be enhanced by adding other features like age, gender and race, for model generalization. The existing models are dataset specific models which causes difficulty for the realtime applications. **Optimizing the model and extending the dataset:** The model ability to adapt to the enhancement is possible by augmenting the data samples to incorporate more extensive demographic range. Furthermore, the state-of-the-art in age estimation will not be achieved without further investigation into novel machine learning approaches and the optimization of model architectures and hyperparameters.

As a result, even if the existing models and datasets have established the groundwork for age estimate, improving the performance of the models, feature extraction, and dataset variety will be essential to creating systems that are more precise and broadly applicable.

RESEARCH METHOD

Even if it is complex, age prediction from facial features is important in scientific and face recognition applications. Automated techniques are crucial since the human brain finds it challenging to determine age accurately (Gupta, Rishi & Ajay Khunteta, 2012; Yohanie et al., 2023; Fitriana & Waswa, 2024; Zakiyah, Boonma, & Collado, 2024). Age is indicated by several aspects, such as wrinkles on the face. Classification and regression algorithms are the two main approaches for estimating age (Bekhouché & Salah Eddine, 2015).

Face Aging Database

The tests in this work are conducted using five distinct face databases: Adience (Hussner, 2015), FGNET Fu (2014), AAF Chakraborty (2019), APPA-REAL (Agustsson, 2017), and UTKFace (Zang, 2017). Images are taken under both controlled and uncontrolled circumstances.

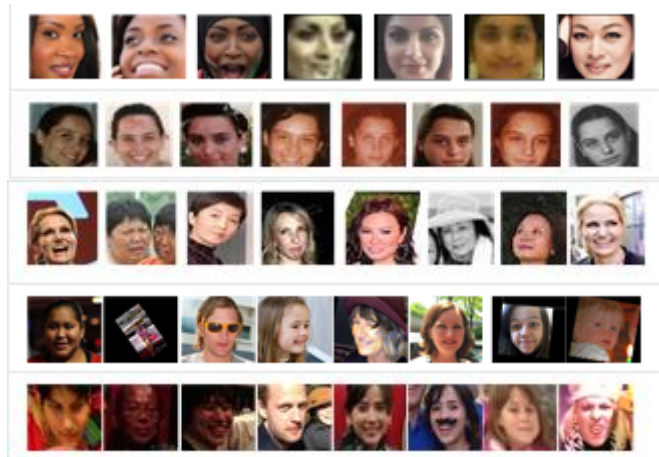


Figure 1 Sample face images from publically available datasets

In Figure.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. Age prediction algorithms are complicated because of other factors such object distance from the camera, the number of objects in the image, image size, and other ambient factors. Examining obstacles is crucial when creating and assessing models since they have an immediate effect on how well the models perform and generalize. It is evident that there is an uneven distribution of data samples across all age categories in the available samples. Although most datasets contain a sizable proportion of samples in the 25–35 age range, it is clear that the age distribution differs greatly across the datasets.

Preproposing Steps

According to the literature, pre-trained models perform better while requiring less complexity. Age estimation using regression and classification models was the subject of numerous studies.

Bilateral Filter

Images are smoothed and noise is reduced with a bilateral filter that maintains edges. The bilateral filter preserves edges during smoothing by accounting for the value difference with the neighbors. The fundamental principle of the bilateral filter is that a pixel must have a similar value to another pixel in addition to being in close proximity for it to affect it. The equation is shown in eq. (1)

$$BF[I_p] = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(I_p - I_q) I_q \tag{1}$$

W_p is normalization factor, G_{σ_s} range kernel (Gaussian function), G_{σ_r} spatial or domain kernel, p & q original input image pixels for filtering, I_p and I_q are the pixel coordinates

Locate Face-Haar-Cascade fontal face features

Each sub-window of the image is computed at varied scales and positions using distinct Haar-like features. The Adaboost algorithm is used to select the main features. Each sub-window undergoes face detection through a cascade of classifiers. Figure 2 shows sample Haar-like filters.

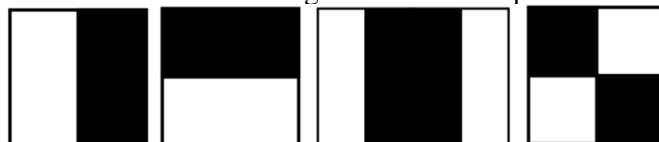


Figure 2. A sample Haar-like features filters

Resize the Image

Resampling technique is used to resize the face image by interpolation rather than crop to preserve the integrity of the image. The resizing process is calculated using the linear interpolation formula as given in eq. (2).

$$y = y_1 + (x - x_1) \frac{(y_2 - y_1)}{(x_2 - x_1)} \tag{2}$$

Where (x_1, y_1) , (x_2, y_2) and (x, y) are the original image size, resized image size and predicted pixel coordinates, respectively.

Grayscale Conversion

When converting an RGB image to grayscale, each pixel's RGB values are combined to produce a single brightness value for output. Considering the human perception that the green component largely determines the perceived brightness, a suitable approach is to apply a weighted average of RGB values is as given in eq. (3):

$$P = 0.3R + 0.59G + 0.11B \tag{3}$$

Where P is the pixel intensity in grayscaled image and (R, G, B) are the pixel intensity values in color image.

Proposed Model

As seen in Figure 3, we have suggested a customized age estimation approach in our study. The steps followed for the experiments are: applied bilateral filters to reduce the noise and preserve the edge, locate the face from the image, resize the face image and convert it to grayscale image. The resulting image is passed to Neural Network layers, i.e. Before feeding the suggested model with the input, the image is pre-processed to extract the face using the HAAR cascade and then scaled.

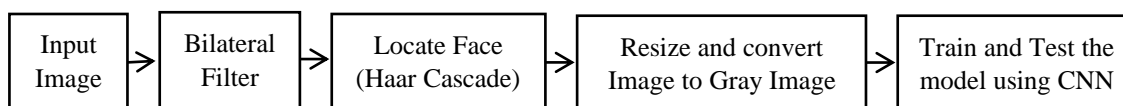


Figure 3. Proposed age estimation model

Convolution, BatchNormalization, and MaxPooling layers make up the first three layers of the model. These layers are repeated five times, and then three dense layers with a 0.4 dropout rate are added to the model to combat over-fitting during training. Setting the hyper-parameter settings for the best classifier and regression performance, respectively, as indicated in table 1 takes an average of 80 epochs to train the model. There are 674,049 total parameters in the proposed regression model, with 672,769 trainable parameters, while the classification model has 13,182,594 total parameters with 13,179,842 trainable parameters. Because pre-trained models save time and money, they are the subject of the literature reviews. In this work, we examined the CNN model's performance in relation to the training time across five distinct datasets. With the least amount of computing effort and resources, the suggested model achieves competitive outcomes when compared to pre-trained models found in the literature.

Table 1. 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

RESULTS AND DISCUSSION

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. The average absolute error between estimated age and the chronological age of a person is the Mean Absolute Error (Rothe, 2015). The ideal value of MAE is 'Zero' but in real time it is not possible but a better model shows MAE near to 'Zero'. The MAE is evaluate using eq. (4).

$$MAE = \frac{1}{m} \sum_{i=1}^m |x_i - y_i| \tag{4}$$

where m is the number of data points, x_i and y_i 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 model is the age estimation model is trained on average for 80 epochs for each individual dataset and evaluated in terms of overall loss, MAE for regression and Accuracy for classification. The detailed results are as shown in figure 4, figure 5, figure 6, figure 7, figure 8 and figure 9 are Regression Model Training Loss, Regression Model Validation Loss, Regression Model Training results measured as MAE, Regression Model Validation results measured as MAE, Classification Model Training results measured in terms of Accuracy and Classification Model Validation results measured in terms of Accuracy, respectively.

From figure 4, figure 5, figure 6 and figure 7, we observe that the models performance is a smooth curve for the datasets collected under uncontrolled environment whereas curve is zig-zag for the datasets collected under controlled environment i.e. for FGNET. At the same time, 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. The Regression and classification observations of age estimation are tabulated in Table 2.

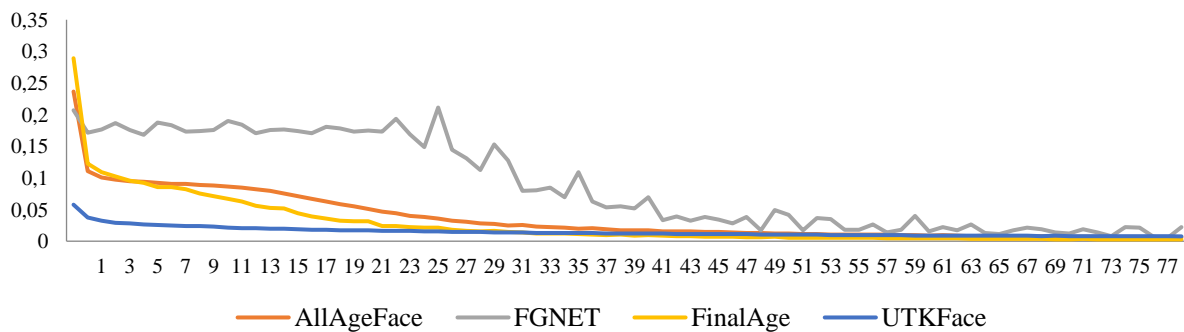


Figure 4. Regression Model Training Loss

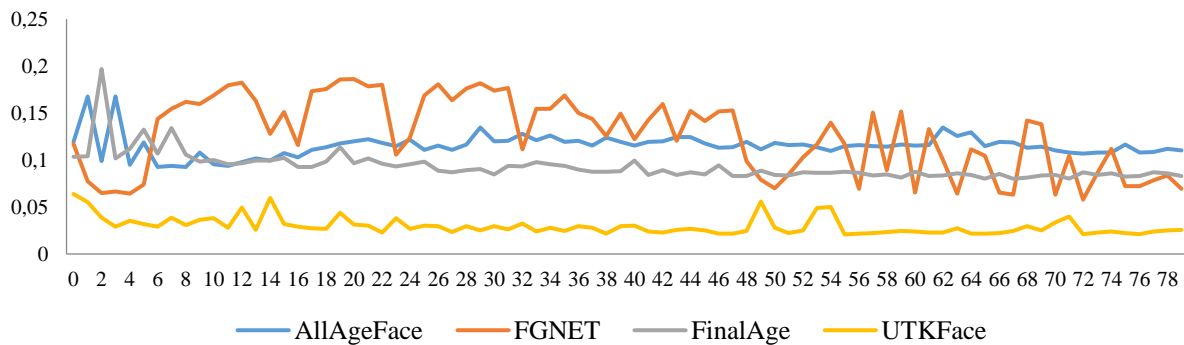


Figure 5 Regression Model Validation Loss

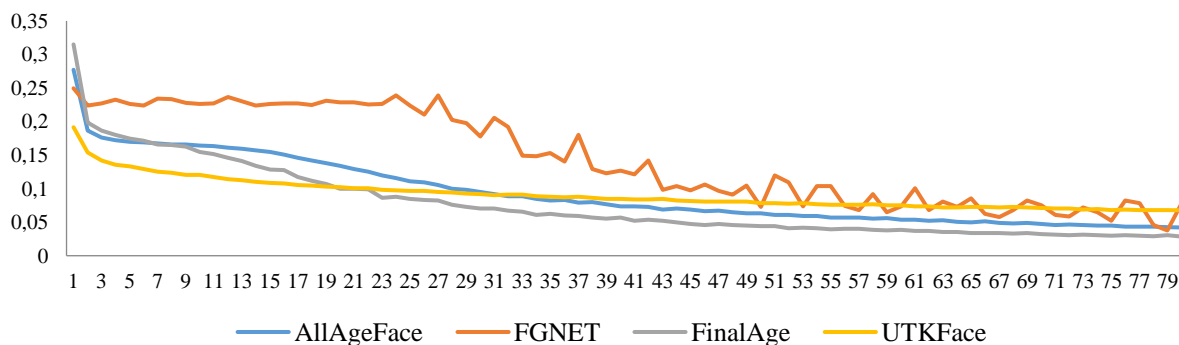


Figure 6 Regression Model Training results measured as MAE

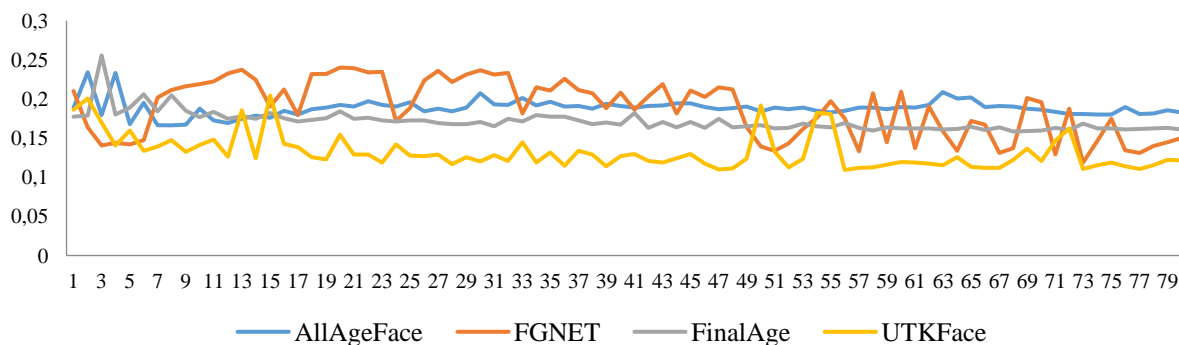


Figure 7 Regression Model Validation results measured as MAE

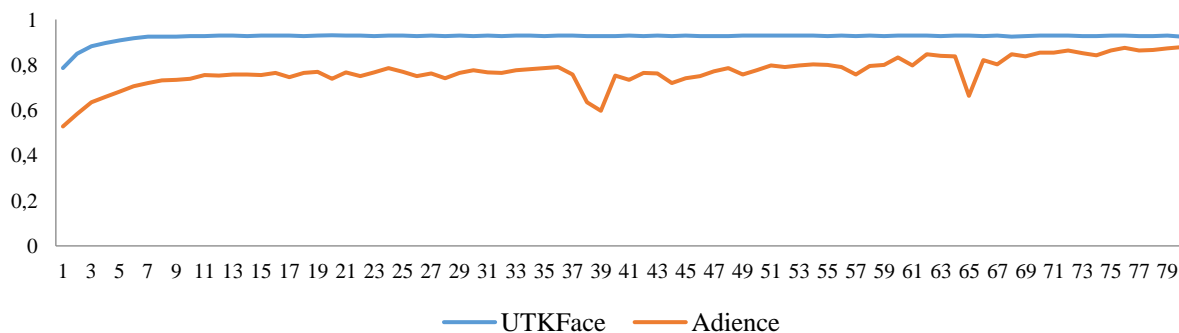


Figure 8 Classification Model Training results measured in terms of Accuracy

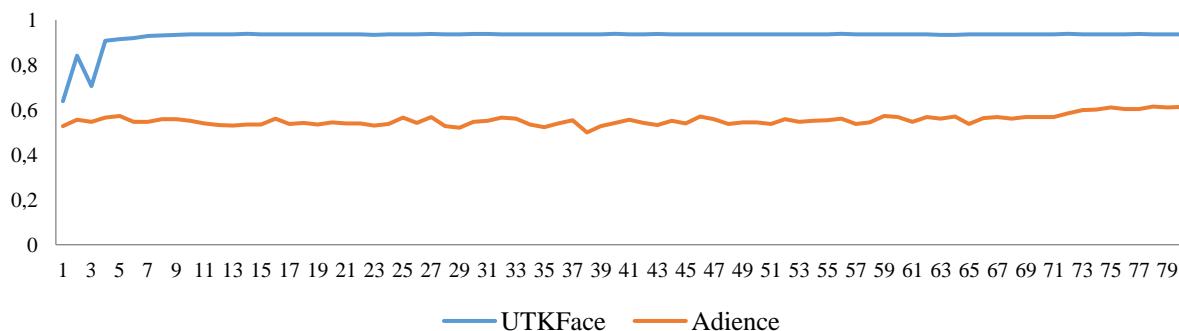


Figure 9 Classification Model Validation results measured in terms of Accuracy

Table 2. Regression and classification observations of age estimation are shown above and below tables.

Dataset	loss	mae	val_loss	val_mae	Time taken (sec)
APPA-REAL	0.277	2.853	8.006	15.840	6.21
FGNET	0.484	3.767	5.784	11.886	7.33
UTKFace	0.763	6.769	2.087	10.937	5.89
AllAgeFace	0.600	4.210	9.264	16.636	8.79

Dataset	Accuracy	Testing Accuracy	Time taken (sec)
Adience	93.844	62.458	1.20
UTKFace	93.025	93.733	2.34

The performance of the suggested model is contrasted with that of the pre-trained models currently in use, which are indicated in Table 3. Using the UTKFace dataset, the authors (Meghana, 2020) employed pre-trained ResNetV2 and ResNet50 models to attain a 60% accuracy rate with five class labels. In a different study, the accuracy was 61.7% when ANN and the Covnet pre-trained model were employed (Ghildiyal, 2020); it was 79.12% when VGG16, ResNet50, and SENet50 pre-trained models were used (Sheoran, 2021). And we achieved 93.7% of accuracy with provided model utilizing UTKFace with 8 class labels (0-3, 4-7, 8-14, 15-24, 25-37, 38-47, 48-59, 60+). Comparable outcomes are noted for the Adience dataset. (Lapuschkin, 2017) obtained an accuracy of 59.7% by comparing the layer-wise outcome using four different DNN models. On the other hand, (Benkaddour, 2021) developed a model that requires 40,000–80,000 epochs of training to get an accuracy of 91.75%. The maximum accuracy attained by our suggested model was 93.8%.

Table 3 presents the findings of the regression models that were employed in the literature. These models were pre-trained. To obtain an MAE of 5.49, the authors (Sheoran, 2021) employed VGG16, ResNet50, and SENet50. Using WideResNet and FaceNet pre-trained models, (Puc, 2020) obtained MAE of 7.25, 6.33, and 7.03 for UTKFace, FGNET, and APPA-REAL dataset. The authors summarized the findings based on Gender and Race.

Table 3. Evaluating the proposed model's effectiveness against existing models

Data set	UTKFace	Adience	FGNET	APPA-REAL	AAF
Year	Classification	Regression	Classification	Regression	Regression
2016	50.2 (Ekmekji, 2016)			4.5 (Pontes, 2016)	
2017		50.7 (Levi, 2017)		4.13 (Chen, 2017)	
		53.6 (Lapuschkin, 2017)			
		59.9 (Qawaqneh, 2017)			
		66.49 (Duan, 2017)			
2018				5.39 (Ng, 2018)	
2019				3.9 (Sawant, 2019)	
				3.05 (Taheri, 2019)	

Data set	UTKFace		Adience		FGNET	APPA-REAL	AAF
2020	60 (Meghana, 2020)	7.25 (Puc, 2020)	91.75 (Benkaddour, 2020)	3.14 (Xie, 2020)			
2021	61.7 (Ghildiyal, 2020)	79.12 (Sheoran, 2021)			6.33 (Puc, 2021)	7.03 (Puc, 2021)	
2022	80.76 (Raman, 2022)				66.5 (Raman, 2022)		
2023			60 (Lu, 2023)				
2024	93.7	4.2	93.8		3.76	2.85	4.21

The researchers from (Xie, 2020) to (Pontes, 2016) used FGNET dataset and measured the model performance in terms of MAE as shown in table 4. (Xie, 2020) used ResNet model with ensemble learning approach for training and achieved a MAE of 3.14. (Taheri, 2019) 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. The authors of (Sawant, 2019) used local direction and moment pattern features to train age estimation model and their model’s enhanced performance was 3.9 MAE. (Ng, 2018) 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, 2016) 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 (Xie, 2020), (Taheri, 2019) and (Sawant, 2019).

Table 4. Classification models performance with the number of class labels.

Dataset	UTKFace		Adience	
No. of classes	5	8	6	8
Age group range	0-14, 14-25, 25-40, 40-60, 60+	0-3, 4-7, 8-14, 15-24, 25-37, 38-47, 48-59, 60+	0-6, 8-20, 25-32, 38-43, 48-53, 60+	0-3, 4-7, 8-14, 15-24, 25-37, 38-47, 48-59, 60+
Accuracy (%)	61.7 (Meghana, 2020)	93.7 (Our model)	91.75 (Benkaddour, 2021)	93.84 (Our model)

From table 4, we observe that the classification model performance has improved by increasing the number of class groups as compared with the training models used in the literature. 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 (Meghana, 2020) and (Benkaddour, 2021). Further, our models performance is effective as compared to the pretrained models from the literature as it reduces the computation time and space with minimum number of nodes and hidden layers.

The prediction time taken by age classification model is less compared to that of regression model because the output of regression is an exact value whereas classification gives a range of values under on label.

CONCLUSION

Automatic age prediction from images of faces is becoming more popular due to its potential benefits in security, law enforcement, and Human-Computer Interaction (HCI). Age assessment remains challenging despite significant advancements due to the influence of multiple factors such as genetics, environment, lifestyle, and facial expressions. Those who are the same age appear considerably

different from one other because of the variance in facial aging brought on by these factors. To address these challenges, in our work, we employed CNNs for automated age prediction. FGNET, Adience, APPA-REAL, UTKFace, and All-Age-Face are some of the publicly available datasets that we used to estimate age using our model, which we defined as a combination classification and regression problem. We assessed and compared the performance of the current pretrained models with our proposed CNN model. Our model performed comparably to the pretrained models in age prediction tasks, as evidenced by the classification and regression results. The results show that our CNN-based method, which offers competitive accuracy and potentially higher flexibility and adaptability with minimal computational complexity, is a good replacement for pre-trained models. Furthermore, the classification model took less time because of minimum number of class labels as compared to that of regression model. A robust model that can be functionally effective across variety of dataset in real-time application can be created by merging facial features with age, gender and texture features. Additionally, the model's adaptability and flexibility can be improved by collecting multivariant featured dataset.

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AUTHOR CONTRIBUTIONS

All the three authors have conceptualized the work. B. Patil worked on methodology, carried out the experiments and prepared the original draft. M. Hangarge reviewed and edited by supervising the work. All authors provided critical feedback and helped shape the research, analysis and manuscript.

CONFLICTS OF INTEREST

The author(s) declare no conflict of interest.

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