Age Group Classification and Gender Prediction using Facial Skin Texture Analysis

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ABSTRACT
In today's rapidly evolving world, facial recognition technology plays a pivotal role. The extraction of human attributes such as gender and age from biometric data has gained significant attention in recent years. Despite advances in computer vision, accurately predicting age and gender from unprocessed, live facial images remains a challenge in commercial and real-world applications. Current age classification methods rely on texture and shape information, often without considering filtered facial features. This research uses Convolutional Neural Network for age group and gender estimation using filtered images, which may affect perceived age. By comparing original and filtered images, the true age of individuals can be determined while maintaining their identity. Age groups are dynamically categorized based on the number of groups using a deep convolutional neural network. Experimental results demonstrate high accuracy in both age and gender prediction, outperforming existing techniques and contributing to a more robust security system.

Keywords
Convolution Neural Network, Facial Skin Texture, Age Categorization, Gender Prediction.

1. INTRODUCTION
In recent years, the computer vision community has shown considerable interest in facial analysis. The facial individuality of a human being are unique and necessary in identifying their individuality, age, gender, feelings, and cultural background. Age and gender classification be a great significance in a wide range of practical applications, including security and video examination, electronic client connection management, biometrics, electronic vending machines, human-computer interaction, entertainment, cosmetology, and forensic art. Nevertheless, accurately classifying age and gender still poses numerous challenges, which persist as unresolved issues. Despite the ongoing progress in computer vision methods, accurately predicting age and gender for unprocessed live faces still falls short of the requests for marketable and real-world use. However, through the use of depth sensors to capture wrinkles and facial features in a 3D model, one can ascertain identity and age accurately, even when someone is wearing heavy makeup, except in cases of skin stretching. Moreover, depth sensors possess the ability to capture and identify faces even in total darkness [1] [2].

2. LITERATURE SURVEY
2.1 Inference Analysis on Age Group
Age has perpetually held significance as a defining characteristic. Determining an exact age solely from a single image proves to be a challenging task due to various factors such as makeup, lighting, obstructions, and facial expressions. Consequently, this endeavor to estimate the age range associated with a particular image [6] [13].

2.2 Inference Analysis on Gender
The difficulty arises from the fact that the average faces of females and males are highly alike. Additional difficulties arise in uncontrolled environments where factors such as lighting, facial expressions, and ethnicity can cause confusion. Most face gender estimation algorithms consist of two stages after face detection: feature extraction and classification [9] [11].

2.3 Skin Texture Analysis
Human complexion refers to the inherent color, texture, and overall look of the skin, particularly on the face. It is a genetic characteristic influenced by melanin, a group of biological pigments. Melanocytes distribute melanin granules, known as melanosomes, to the skin cells in the epidermis. These melanosomes shield the DNA in the cell nucleus from sun-induced mutations. The body has mechanisms to defend against external threats, and historically, complexion was believed to reflect one's personality traits [8] [12].

3. PROPOSED METHODOLOGY
The proposed framework requires an underlying phase of image preprocessing, which includes face recognition, landmark discovery, and face alignment. This preprocessing phase reads the face images before they are taken care of in the future network. Accordingly this research work is organized into three fundamental stages: image preprocessing, features learning, and the network arrangement interaction itself. The proposed work flow is given in Figure 1.

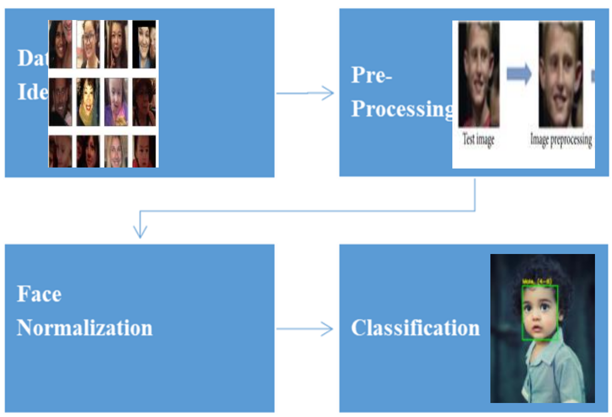


Figure 1: Age and Gender Prediction Work Flow

3.2 Image Preprocessing

Complex age and gender classifiers are intended to deal with the grouping task in unfiltered certifiable situations. A large number of these facial pictures are not as expected, non-front facing, and show different degrees of posture, appearance, lighting, and foundation contrasts. Thus, these face pictures caught in normal settings should go through identification, arrangement, and resulting use as contributions for the classifiers.

3.3 Image Face Detection

The underlying move toward image preprocessing includes distinguishing faces. To distinguish a face, each input image is turned inside the scope of - 90° to 90° points, with a 5° augmentation. In this manner, the identifier picks the input image that yields the most reliable face identification result. If the face image is not known in any of the transformed input images, the first information image is expanded and the face recognition process is repeated until the face is effectively recognized [4].

3.3 Face Normalization Process

During the normalization interaction, the model first trims the rectangular face region that has been recognized. Accordingly, it continues to distinguish the eye pair, mouth, nose, and jawline. These outcomes in acquiring distinct images of the left eye, right eye, left eyebrow, right eyebrow, and mouth, which incorporate the image of the lips. Moreover, the model identifies the jaw hairline part of the face picture and gives a picture of the nose too [7].

3.4. Proposed Network Architecture

The proposed architecture is a compact and efficient convolutional neural network (CNN) designed with three convolutional layers and three fully connected layers. The design prioritizes a smaller system structure to mitigate over fitting risks and address specific challenges of the task. This network processes input images across all three color channels. Initially, images are resized to 256×256 and a cropped 227×227 segment is fed as input.The first convolutional layer applies 96 filters of size 3×7×7, followed by a rectified linear unit (ReLU) activation function. Max-pooling is performed over 3×3 regions with a stride of 2, reducing spatial dimensions, and a local response normalization layer is applied. The second convolutional layer receives an output tensor of 96×28×28 and employs 256 filters of size 5×55. Similar operations—ReLU, max-pooling, and local response normalization—are applied with tuned hyper parameters. The third convolutional layer operates on a 256×14×14 tensor and utilizes 384 filters of 3×3, followed by ReLU and max-pooling. The fully connected layers transition the network to higher-level feature extraction. The first fully connected layer maps the flattened input to a 512-dimensional vector, followed by ReLU activation. The second fully connected layer retains the 512-dimensional structure, with a dropout mechanism introduced to improve generalization.

Finally, the third fully connected layer outputs a vector representing class probabilities, determined by a soft max activation. Predictions are based on the class with the highest probability, enabling effective classification tasks such as age or gender determination. This architecture exemplifies a well-balanced trade-off between simplicity, computational efficiency, and task-specific accuracy. This complete work flow is illustrated in Figure 2.

3.6 Network Training of Proposed Work

Carry out two extra procedures to additionally limit the risk of over fitting. First and foremost, present dropout regularization by randomly deactivating the result of network neurons. Incorporate two dropout layers with a dropout pace of 0.5 (half the likelihood of setting a neuron's result to nothing).

Then, information expansion by randomly choosing a harvest of 227 × 227 pixels from the 256 × 256 information picture and flipping it during each training iteration. This technique looks like the different crop and mirror varieties utilized. Training is directed utilizing stochastic gradient descent with a batch size of fifty images. The initial learning rate is set to e −3, and it is decreased to e −4 after 10K cycles as shown in Figure 2.

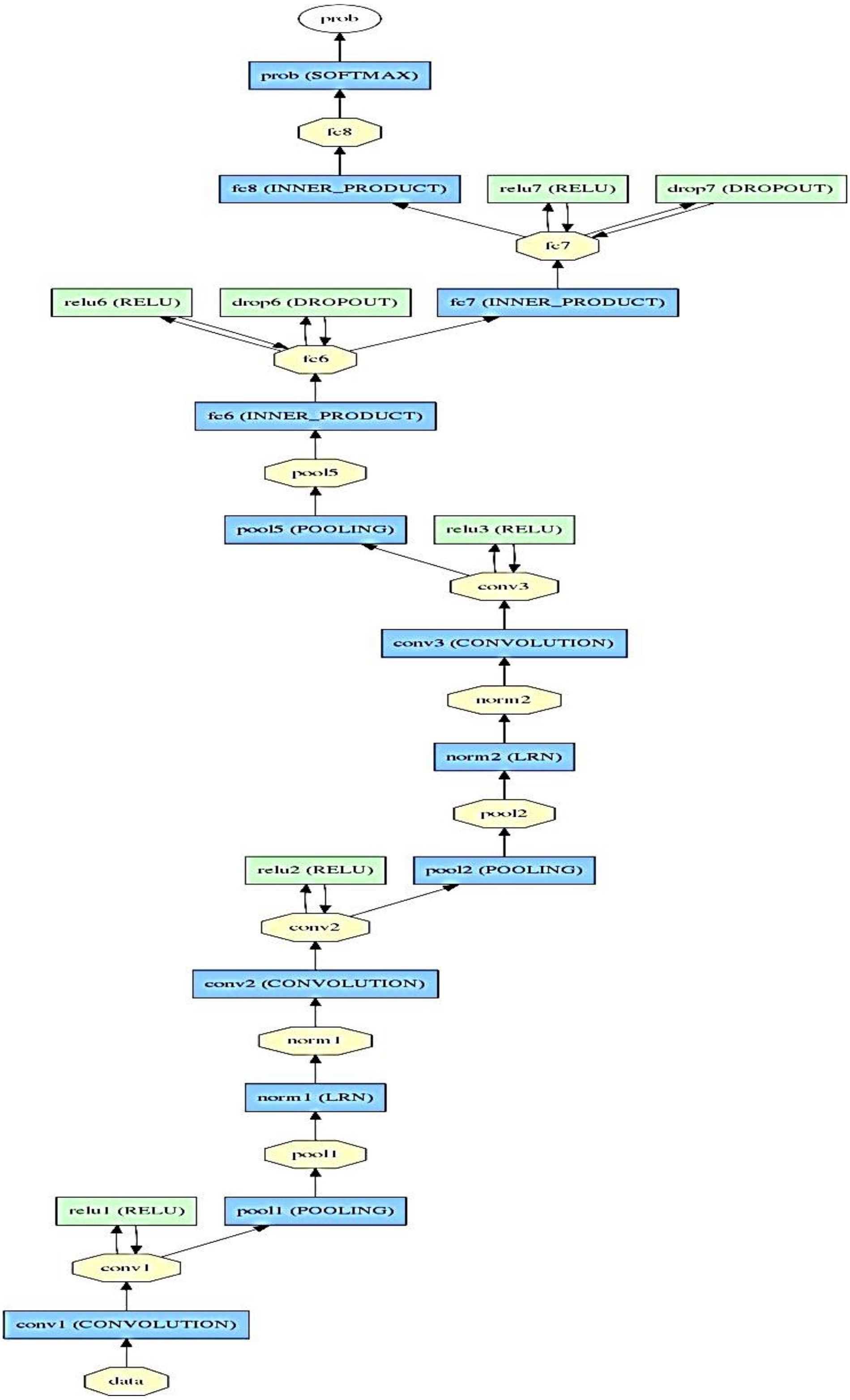


Figure 1: Proposed Network Architecture for Age Group Classification and Gender Prediction using Facial Skin Texture4

3.7 Prediction Performance Analysis

The work conducted tests on two approaches for utilizing the network in order to generate age and gender predictions for unfamiliar faces.

- **Center Crop:** Providing the network with a face image that has been cropped to 227 × 227 pixels around the center of the face.
- **Over-sampling**: In the oversampling process, get five clipping regions of size 227 × 227 pixels. Four of these regions are extracted from the corners of a 256 × 256 face image, while one crop region is taken from the center of the face. All five images, including their horizontal reflections, are

then offered online. The final prediction of the network is determined by calculating the average prediction value of all these variants.

The proposed work have noticed that small changes in audience images due to various image issues (e.g., occlusions, motion amounts, etc.) can significantly affect the quality of the results.

This alternative approach, called oversampling, aims to correct these small deviations by providing the mesh with multiple inverted versions of the same surface, eliminating the need to improve alignment accuracy [8].

4. EXPERTIMENTAL RESULT AND PERFORMANCE ANALYSIS

4.1 Age and Gender Prediction in Multiple Face Image

Figure 3: Multi-Face Image Prediction

4.2 Age and Gender Prediction in Single Face Image

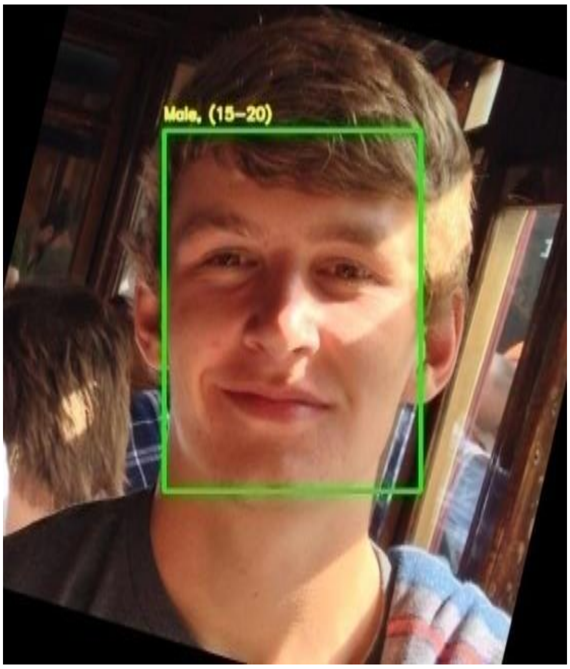


Figure 4: Single Face Image Prediction

4.3 Skin Texture Comparison

Figure 5: Age Comparison between the same person without and with makeup

4.4 Estimated Accuracy Analysis

Accuracy for Age

Total Images	:	10142
Correctly Detected Images	:	9659
Age Accuracy	:	95.23 %

Accuracy for Gender

Total Image	:	10142

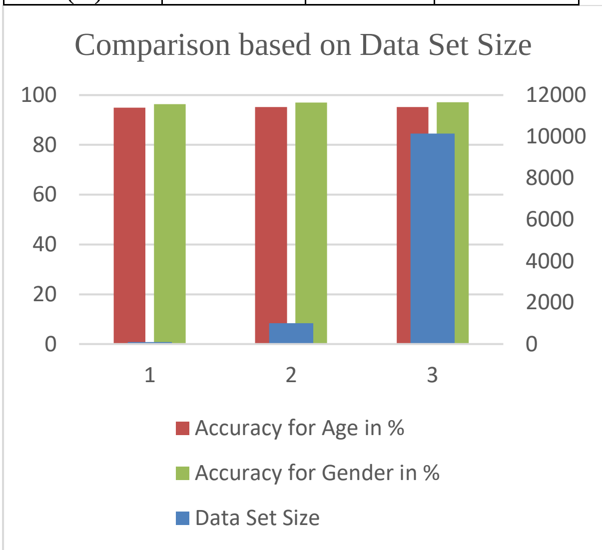
Correctly Detected Images	:	9846
Gender Accuracy	:	97.08 %

4.5 Accuracy Comparison based on Dataset Size

The accuracy doesn't get affected even though the dataset size get increased. The difference in the accuracy is at mostly close to one other to obtain a better accuracy level for age and gender is given in Table 1. The proposed research works efficiently produce a good accuracy for age and gender with gradual increase in dataset size is plotted in the Graph 1.

Table 1: Accuracy Comparison

No of images in Dataset	**100**	**1000**	**10142**
Accuracy for age (%)	94.92	95.2	95.23
Accuracy for gender (%)	96.37	97	97.08



Graph 1: Age and Gender Accuracy Comparison with different Data Set Size

4.5 Estimated Gender Validation

As far as gender grouping, there are just two possible results. The model assigns out a certainty worth to the input image ranging from 0 to 1, with values near 1 showing a male portrayal and values close to 0 demonstrating a female portrayal. Consequently, the gender characterization limit is set at 0.5. With a similar test dataset, gender classification accomplished an exactness of around 97%, which is exceptionally palatable for pragmatic applications. This leads to derive that age classification represents a more prominent test contrasted with gender classification, possibly requiring further approval moves toward improve its exactness [10] [11] [14].

4.6 Estimated Age Validation

The usage of age group classes, instead of explicit mathematical ages, offers a few benefits. To oblige this, the changes are made in the picked model to deliver an age class as a result. In particular, the research work consolidated an extra system to translate the exact age demonstrated by the first model into the assigned scope of age group classes. By carrying out this arrangement, the model accomplished a noteworthy accuracy rate of 95%.The proposed framework created by the model was custom-fitted for every one of the classes.

For example, consider the 16-24 age group. Every one of the examples having a place with this class was gathered from the approval dataset. For each image expectation, determine the level of models that were accurately anticipated inside this class. This data permits to decide the extent of information that was precisely anticipated inside the 16-24 age group, as well as the extent that was mistakenly anticipated inside different classes. Subsequently, the work can presume that examples inside the 16-24 age group were erroneously delegated having a place with the 25-40 age group as shown in Figure 6., [15] [16]

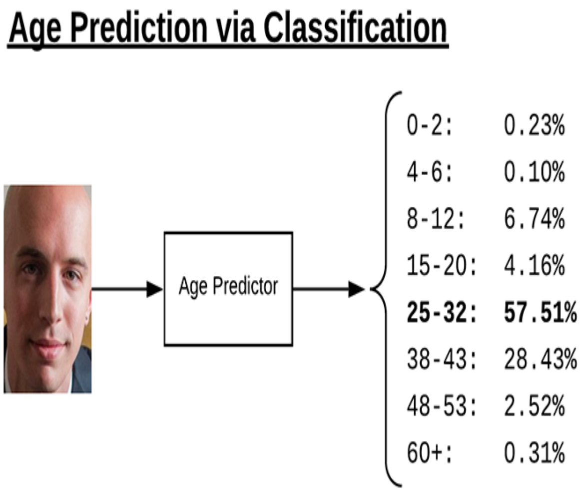


Figure 6: Age Categorization

4.7 Analysis of Skin Texture Difference

The purpose of cosmetics for older individuals is to conceal the effects of aging. The more pronounced these effects are, the more reliant the user becomes on cosmetics to effectively combat them. In the present context, the utilization of cosmetics and cosmetic products is not unexpected.

Nowadays, people place great importance on enhancing their well-being and appearance. They are mindful of their health and have also experienced changes in their lifestyle. They find it difficult to resist this behavior and consequently turn to activities like aerobics and health clubs. Moreover, they utilize cosmetics to enhance their social acceptance by presenting themselves well, which in turn contributes to their self-confidence and contentment. The growing acceptance of cosmetics and their usage in society can be attributed to the harmonious combination of demographic factors such as age and gender [3[[5].

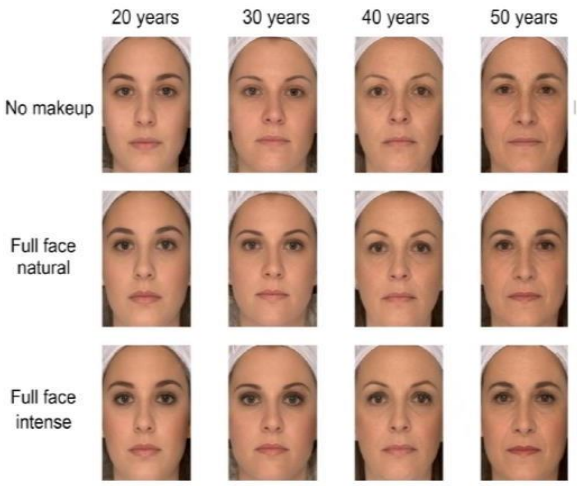


Figure 7: Difference in Comparison of Skin Texture

By comparing the image with makeup and without makeup the difference in their age are easily seen. When the face has the complexion the actual age of a person is been decreased and shows the incorrect age of a person. The comparison of the image with and without makeup are shown in Figure 7, [17] [18].

5. CONCLUSION

The proposed CNN-based model demonstrates exceptional performance in age categorization and gender prediction, achieving an impressive age prediction accuracy of 95.23% and gender prediction accuracy of 97.08% on a dataset comprising 10,142 images. The architecture integrates key preprocessing steps, including normalization, and supports multiple image formats such as JPG, JPEG, and PNG. Notably, the model excels in unique scenarios, such as predicting attributes for cartoon characters and comparing images with and without makeup, while delivering significant improvements in processing speed. Future research could focus on extending the model's capabilities to predict age and gender for individuals wearing masks, enabling real-time applications. Moreover, advancements in robust image processing techniques to analyze filtered images and facial expressions with enhanced accuracy present a promising avenue for further exploration and development.

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