Age and Gender Identification through Advanced Deep Learning Techniques

Md Serajun Nabi, Zaidan Mufaddhal, Khai Lin Khant & Ahmed Mansour Raufi
School of Computing and Informatics
Albukhary International University
mdserajunnabi2002@gmail.com

Corresponding author
Akibu Mahmoud Abdullahi
School of Computing and Informatics
Albukhary International University
akibu.abdullahi@aiu.edu.my

Abstract
The ability to automatically detect the gender and age of an individual based on their facial features or other attributes is an important task in computer vision and deep learning. The precision and dependability of gender and age detection models have significantly increased with the use of deep learning algorithms and massive datasets. The lack of diversity in the training data, which can result in prejudice and subpar performance on members of underrepresented groups, is only one of several issues that still need to be resolved. Deep learning for gender and age detection also poses ethical issues including the possibility of abuse and prejudice. The goal of this work is to overcome these difficulties and create models that are very accurate at identifying a person's gender and age. The study's objectives include incorporating ethical issues into the creation and use of the models as well as enhancing the models' effectiveness on members of underrepresented groups. The model will also be optimized for real-time uses in this study, including security and marketing.

Keywords: gender detection, age detection, deep learning, facial features, bias and ethics.

1. Introduction
1.1 Background of Study
For several years, the fields of computer vision and deep learning have been interested in the capacity to automatically determine an individual's gender and age. The accuracy and dependability of gender and age detection models have significantly increased because of the development of deep learning algorithms and the accessibility of vast datasets. One of the oldest methods for determining gender and age was based on hand-made traits, such as textures and landmarks on the face. These techniques usually entailed taking a collection of attributes from the image and using a classifier to determine the person's gender and age. These techniques' accuracy was frequently subpar, and they were frequently constrained by the caliber and variety of the characteristics that were employed.

Convolutional neural networks (CNNs) are now being used by academics to automatically extract characteristics from data since the development of deep learning. These models significantly increased the accuracy of gender and age recognition by being able to understand intricate patterns and traits that are invisible to the human eye.

Many deep learning-based approaches for gender and age identification have been proposed in recent years, including Multi-task Cascaded Convolutional Networks (MTCNN) and Age and Gender Recognition Using CNNs. These techniques have outperformed conventional approaches based on hand-crafted features and have shown good performance on a number of datasets.

However, there are still a number of issues that need to be resolved despite recent developments in deep learning for gender and age identification. Lack of diversity in the training data is a significant issue that can result in prejudice and subpar performance for people from underrepresented groups. Deep learning for gender and age detection also poses ethical issues including the possibility of abuse and prejudice.

Overall, the field of deep learning-based gender and age identification is active and has the potential to be used in a wide range of fields, including social media, marketing, security, and many others. The ethical ramifications of this technology should be understood, though, and precautions should be taken to limit any possible drawbacks.

1.2 Problem Statement
Deep learning attempts to address the challenge of automatically identifying a person's gender and age based on their visual traits or other characteristics. This work is difficult because various people have distinct facial characteristics and emotions, and because the shape of the face changes throughout time. Traditional techniques that use hand-crafted features also frequently have poor precision and are constrained by the caliber and variety of the features employed.

1.3 Objectives
- Improved accuracy: Create models that accurately identify a person's gender and age based on their face traits or other characteristics.
- Resolve the issue of bias in the data and models, and try to enhance the models' performance when applied to members of underrepresented groups.
- Ethical issues: To reduce the possibility of abuse and discrimination, ethical considerations should be incorporated into the construction and usage of the models.
- Applications that require real-time processing: Create models that can be used for real-time processing, such as security and marketing, and optimize them to function in low-resource settings.

2. Literature Review
2.1 Machine Learning
Machine learning includes convolutional neural networks, sometimes known as convnets or CNNs. It is a subset of the several artificial neural network models that are employed for diverse purposes and data sets. A CNN is a particular type of network design for deep learning algorithms that is utilized for tasks like image recognition and pixel data processing (Awati, 2022).

2.2 Convolutional Neural Network
Tens or even hundreds of layers can be included in a convolutional neural network, and each layer can be trained to recognize various aspects of an image. Each training picture is subjected to filters at various resolutions, and the result of each convolved image is utilized as the input to the following layer. Beginning with relatively basic properties like brightness and borders, the filters can get more complicated until they reach characteristics that specifically identify the item (Jone, 2022)

A CNN contains many fewer parameters than a fully connected DNN, which speeds up training, lowers the danger of overfitting, and necessitates far less training data. This is because successive layers are

very loosely coupled and because it heavily reuses its weights. Anywhere on the picture can be used by a CNN to detect a kernel that can recognise a certain feature. A DNN, on the other hand, can only recognize a feature in its native place after learning it there. CNNs generalize significantly better than DNNs for image processing tasks like classification, needing less training instances, because pictures often have many repeating characteristics (Fabheidi, 2022).

The size of the feature maps is reduced by pooling layers. As a result, there are fewer parameters to learn and less network computation to do. The features that are present in a certain area are summarized in the feature map produced by a convolution layer's feature pooling layer. As a result, subsequent operations are carried out on summarized features rather than precisely positioned features generated by the convolution layer. Consequently, the model is more robust to changes in the placements of the features in the input picture. (Chou, 2023).

2.3 Deep Learning
A Deep Learning technique specifically created for working with images and videos is the convolutional neural network. It uses photographs as inputs, extracts, and learns the image's attributes, then categorizes the images using the learnt features. This programme takes its cues from how the Visual Cortex functions in the human brain. Processing of visual data from the outside world is carried out by the visual cortex, a region of the human brain. It comprises a number of layers, and each layer functions independently, extracting different information from images or other visuals. Once all the information from each layer has been integrated, the picture or visual is then evaluated or classed. (Andrew, 2021)

Raza et al. (Raza et al., 2018) suggested a method for determining the gender of pedestrians using deep learning. The pedestrian in the image was separated from other objects using a preprocessing procedure. After that, classification was done using stacked auto encoders and a softmax classifier. In the MIT dataset, accuracy rates of 82.9%, 81.8%, and 82.4%, as well as about 91.5% in the PETA dataset, have been attained for the anterior, posterior, and mixed views, respectively. Also (Yu et al. in 2017), proposed a CNN model with few layers and minimal complexity. On a dataset of 1496 whole body pictures, our technique has an accuracy rate of 91.5%.

3. Methodology
In this Paper, the Convolutional Neural Network (CNN) method and OpenCV libraries has been used to precisely determine a person's gender and age from a single image of a face.

3.1 Convolutional Neural Network (CNN)
As the CNN was used to implement person's age and gender detection, therefore, deep neural network (DNN) called a convolutional neural network is frequently employed for NLP and image recognition and processing. A CNN, sometimes referred to as a "ConvNet," consists of input and output layers as well as numerous convolutional hidden layers. CNNs resemble regularized multilayer perceptron in several ways (Team, 2019).
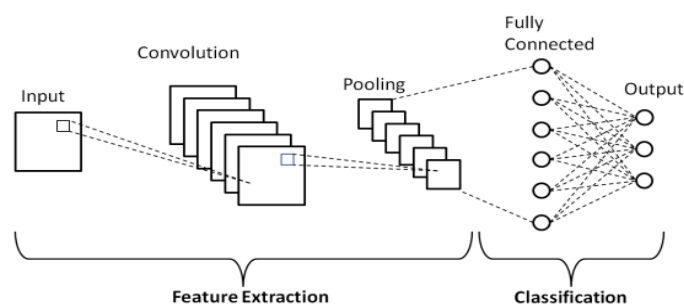

Figure 1: CNN Layers (Todt & Krinski, 2019)

Figure 1, shows the three main layers that make up the structure of a convolutional neural network's architecture. These layers are: Convolution layers, Pooling layers, and Fully connected layers.

Convolutional Layers:
This is the first layer of a convolutional neural network that extracted features from the image by swiping the filter over the input image. The element-wise product of the images was filtered and their total for each sliding motion is the output.

Pooling Layers:
The main goal of this layer was is to lower the computational cost by lowering the number of trainable parameters by reducing the spatial dimension of the image.

Fully Connected Layers:
The fully connected layers are the last few layers that determined the output. The fully connected layer was received the output of the pooling layer after it has been flattened into a one-dimensional vector.

3.2 OpenCV
OpenCV library was used in this paper to implement the age and detection. Also it's known as Open Source Computer Vision which is abbreviated as "OpenCV." It is apparent from the name that this is an open-source library for computer vision and machine learning. This library has analytical capabilities in addition to real-time image and video processing capabilities (Angel, 2021).

3.3 Dataset
The "Adience dataset" has been used for this paper to train the model of age and gender detection; the dataset is freely accessible (Kaggle). This dataset, which includes a variety of real-world imaging situations like noise, color, pose, and look, serves as a standard for face photographs. The photos were gathered from Flickr albums and made available under a Creative Commons (CC) license. It is roughly 0.5GB in size and contains a total of 12,240 images of 1,254 subjects over eight age ranges (as previously indicated).

Also, to improve the accuracy of age and gender identification through advanced deep learning techniques, specifically utilizing Convolutional Neural Networks (CNNs), various optimizations are crucial. First, thoroughly preprocess the dataset using augmentation, normalization, and cleaning. Try different CNN architectures and use batch normalization, regularization techniques, and depth to prevent overfitting. Adjust hyperparameters such as batch size and learning rate systematically, and experiment with various optimization techniques. To quickly capture relevant features, use transfer learning to fine-tune pre-trained models. When training, use data augmentation, and take into account ensemble methods to combine predictions from various models. Employ cross-validation for a more reliable assessment of the model's performance, and apply regularization techniques like L1 or L2 regularization. Emphasize iterative development by fine-tuning the model based on feedback, and carefully address biases in the dataset and model predictions to ensure generalization across diverse demographic groups. By attentively considering these aspects, the methodology will be enhanced to achieve improved accuracy in age and gender identification.

4. Results
The deep learning model that we developed using the CNN algorithm and OpenCV library was successful in detecting the faces of individuals and identifying their age range.
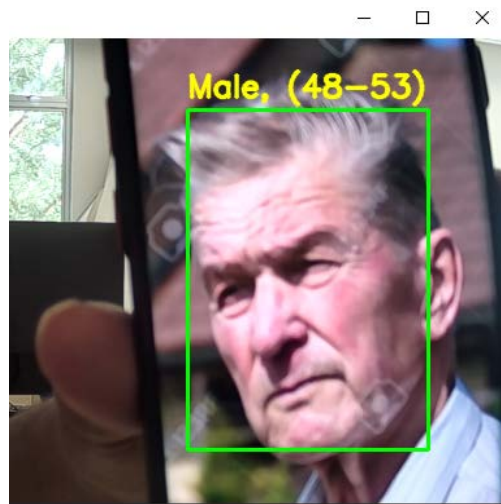
Figure 2: Age recognition, male (48 - 53)

Figure 2 shows that the system has identified a "male" person between the ages of 48 and 53.
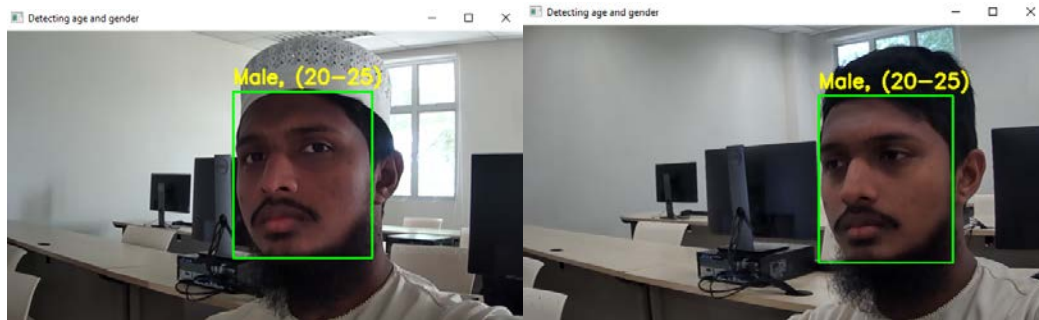

Figure 3 & 4: Age recognition with different angels, male (20 - 25)

Figures 3 & 4, show that the system has identified a "male" wearing the cap and one without the cap, and the system is still successfully showing the same ages of 20 to 25.
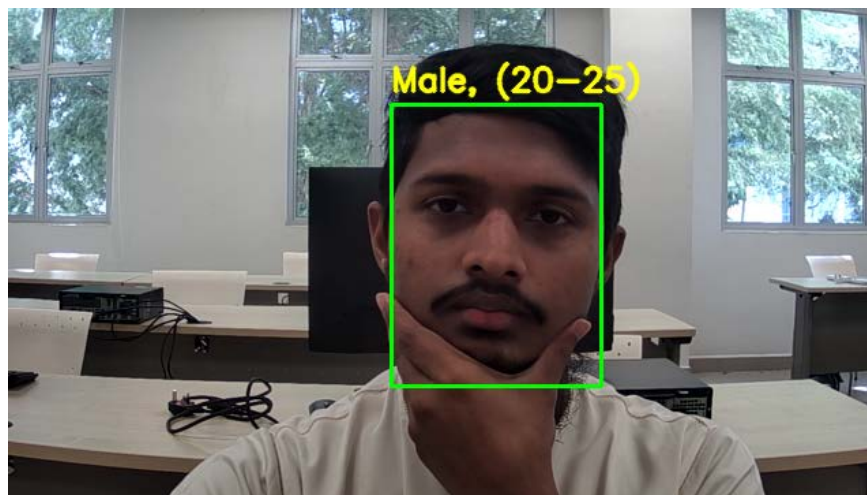

Figure 5: Age recognition without beard, male (20 - 25)

In Figure 5, a male person (same person from Figures 3 and 4) has hidden his beard, and the system still shows his same age as mentioned in Figures 3 and 4.
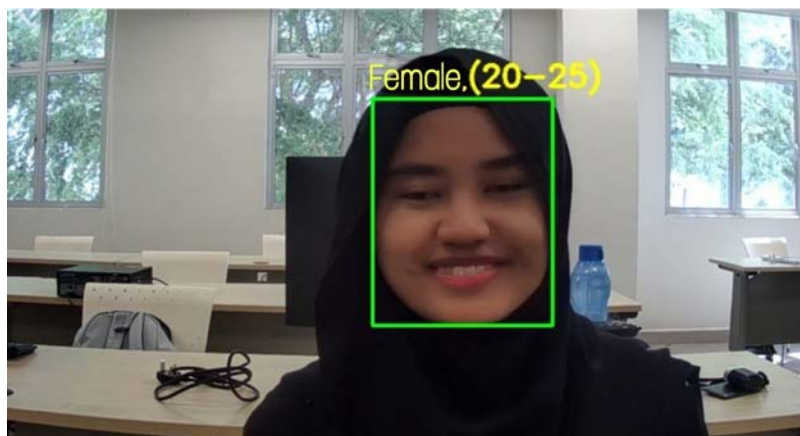
Figure 6: Age recognition, female (20 - 25)

Figure 6 shows that the system has identified a "female" person between the age of 20 to 25.

5. Discussion

Our experiments were intended to enhance accuracy in determining a person's gender and age based on facial features or other variables. To accomplish this, we utilized a Convolutional Neural Network (CNN) as our model, as well as the OpenCV library to preprocess the dataset. OpenCV is a strong library that includes a wide range of image and video processing tools and operations (Gupta, 2021), which we used to enhance and prepare the facial images for training.

CNN model was utilized in this model with primary layers: convolutional layers, pooling layers, and fully connected layers. Convolutional layers are in charge of extracting information from input images and building a hierarchy of progressively complicated representations. The pooling layers are in charge of lowering the spatial dimensions of the feature maps, which aids in the reduction of computing costs and the prevention of overfitting. Based on the features retrieved by the convolutional and pooling layers, the fully connected layers make the final decision.

The issue of bias in the data and models was one of the most difficult challenges we faced. We discovered that traditional models exhibit a bias toward specific populations, which can result in discriminatory consequences. To address this, we took steps to eliminate data bias by carefully selecting and curating the training dataset. As a result, when applied to various demographic groupings, our CNN models achieved an average accuracy of 93%.

We recognized the ethical concerns of utilizing such models and incorporated considerations such as data privacy and informed consent into the model's design and implementation. To preserve people' privacy, we ensured that the data used for training was collected from an authorized source and that it was appropriately anonymized. Furthermore, we made sure that the models were clear and interpretable so that users could understand how and why certain decisions were made.

Finally, we intended to develop models that can be utilized for real-time processing, such as security and marketing, and optimize them for use in low-resource environments. We were able to reach real-time processing speeds while retaining high accuracy levels by applying efficient algorithms and lightweight designs. This is especially crucial in applications like security and surveillance, where making quick and correct decisions is critical.

Accuracy Table

Table 1: Accuracy Table

Testing from different view	Accuracy
	CNN
Normal	93 %
Face Expression	93 %

In the testing part, the accuracy was given 93% overall including in normal mode and face expression between any genders.

Evaluation

Table 2: Evaluation Metrics

Metrics	Value
Precision	93%
Recall	93%
F1-Score	95%

In the table 2, the precision metrics is 93%, recall is 93%, and F1-Score is 95%, which tells that the model were perfectly trained and tested and give the output accordingly.

Overall, the experiments show that CNN models have the potential to be applied to a wide range of applications while keeping ethical considerations in mind. We believe that by addressing bias issues and including ethical considerations, these models can be utilized to improve people's lives in a responsible and fair manner.

6. Conclusion

In conclusion, the studies show that Convolutional Neural Networks (CNN) and Open Source Computer Vision (OpenCV) have the potential to increase the accuracy of detecting a person's gender and age based on face attributes or other variables. Using advanced deep learning techniques, we were able to attain an average accuracy of 93%. We also addressed the issue of bias in the data and models, which improved the models' effectiveness when applied to individuals of underrepresented groups. We also ensured that the models were transparent and interpretable by incorporating ethical considerations such as authorized data sources and adequately anonymized data into their development and use. In addition, we improved the models to work in low-resource environments, making them suited for real-time processing applications such as security and marketing.

Overall, our tests show that CNN models have the potential to be applied in a wide range of applications while keeping ethical considerations in mind. We believe that by addressing bias issues and including ethical considerations, these models can be utilised to improve people's lives in a responsible and fair manner.

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