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# GENDER-BASED AGE RECOGNITION USING IMAGE PROCESSING WITH RCNN AGE BASED

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## ABSTRACT

The human race has progressed to the point that the twenty-first century represents the commencement of inconceivable achievements. The aforementioned technologies can be used to determine a person's age and gender just by looking at them through a camera, image, or video. The study will examine the various approaches available, as well as which one is the most accurate and how they all fit together. It will also emphasis its significance and how it can be put into practice to improve our daily lives. Furthermore, by overcoming the difficulty of accuracy and time, to obtain the most effective predictions and results. Furthermore, the map for how this technology might be used to societal benefit looks at a wide range of applications, including security services, CCTV surveillance and policing, and dating applications.

## INTRODUCTION

Facial recognition (FR) is utilized for the most part for wellbeing purposes, despite the fact that enthusiasm for different territories of utilization is developing [1]. In all actuality, FR innovation has gotten noteworthy consideration as it has the potential for a wide scope of law authorization and different business applications [2]. It has been generally utilized in numerous spaces, for example, ATM, social insurance framework, driving permit framework, train reservation framework, observing assistance, and identification verification. How it functions is the product for facial acknowledgment peruses the face's geometry. The hole between the ears and the good ways from the front to the jaw are key variables [3]. The code distinguishes facial highlights that are crucial to your face separation and produce your facial mark. Because of deep learning techniques, there have been critical advances in FR [4]. In the early stages, exploring the interest, for the most part, focused on FR with a deep system of

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significant light or picture faces. Stephen [5] given a brief review of the techniques of deep learning and face-to-face learning and compares some of the basic neural formulas based on common convolution neural networks (CNNs). The deep networks used in FR, such as deep belief network (DBN), convolutional neural network (CNN, autoencoder (AE), and others are analyzed for architecture [6]. Mandal [7] assessed a significant measure of profound learning strategies.

Age and gender information are very important for various realworld applications, such as social understanding, biometrics, identity verification, video surveillance, human-computer interaction, electronic customer, crowd behavior analysis, online advertisement, item recommendation, and many more. Despite their huge applications, being able to automatically predicting age and gender from face images is a very hard problem, mainly due to the various sources of intra-class variations on the facial images of people, which makes the use of these models in real world applications limited. There are numerous works proposed for age and gender prediction in the past several years. The earlier works were mainly based on hand-crafted features extracted facial images followed by a classifier. But with the great success of deep learning models in various computer vision problems in the past decade [1][5], the more recent works on age and gender predictions are mostly shifted toward deep neural networks based models.

In this work, we propose a deep learning framework to jointly predict the age and gender from face images. Given the intuition that some local regions of the face have more clear signals about the age and gender of an individual (such as beard and mustache for male, and wrinkles around eyes and mouth for age), we use an attentional convolutional network. As one of our backbone models, to better attend to the salient and informative part of the face. Figure 1 provide three sample images, and the corresponding attention map outputs of two different layers of our model for these images. As we can see, the model outputs are mostly sensitive to the edge patterns
around facial parts, as well as wrinkles, which are important for age and gender prediction.

As predicting age and gender from faces are very related, we use a single model with multi-task learning approach to jointly predict both gender and age bucket. Also, given that knowing the gender of someone, we can better estimate her/his age, we augment the feature

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of the age-prediction branch with the predicted gender output. Through experimental results, we show that adding the predicted gender information to the Age prediction branch, improves the model performance. To further improve the prediction accuracy of our model, we combine the prediction of attentional network with the residual network, and use their ensemble model as the final predictor.

Facial analysis has gained much recognition in the computer vision community in the recent past [1–4]. Human's face contains features that determine identity, age, gender, emotions, and the ethnicity of people [5, 6]. Among these features, age and gender classification can be especially helpful in several real-world applications including security and video surveillance, electronic customer relationship
management, biometrics, electronic vending machines, human-computer interaction, entertainment, cosmetology, and forensic art [7–9]. However, several issues in age and gender classification are still open problems. Age and gender predictions of unfiltered real-life faces are yet to meet the requirements of commercial and real-world applications in spite of the progress computer vision community keeps making with the continuous improvement of the new techniques that improve the state of the art [10–12]. Over the past years, a lot of methods have been proposed to solve the classifications problem. Many of those methods are handcrafted which perform unsatisfactorily on the age and gender predictions of unconstrained in-the-wild images [2,13] else conventional hand-engineered methods relied on the differences in dimensions of facial features and face descriptors [14–20] which do not have the ability to handle
the varying degrees of variation observed in these challenging unconstrained imaging conditions. ,e images in these categories have some variations in appearance, noise, pose, and lighting which may affect the ability of those manually designed computer vision methods to accurately classify the age and gender of the images. Recently, deep learning-based methods [21–28] have shown encouraging performance in this field especially on the age and gender classification of unfiltered face images.
As technology increases, the applications that combine the advanced fields of pattern recognition and image processing are used to find age and gender. In today's world, age plays a prominent role, when you appear for an interview, health check-ups. The information of age is used in many government, private and advertising sector organization to find the culprits, employee eligible for the job, audience be targeted for their publicity of product respectively.

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However, it's not that easy to find the age of a person, and there are constraints that restrict us from seeing the correct age among the set of images.

RELATED WORK

**1 Base Paper**

Felix Anda, David Lillis, and others who were part of the forensic and security research group have led their research towards the evaluation of the state of art behavior of different cloud-based biometric services (CBBS). The Model-View-Controller (MVC) is used to collect the data according to the criteria provided. The unnecessary and wrong images are removed at the manual filtering step. The
mechanism used for evaluation to find the least mean square error (MAE) among different CBBS and pre-trained models is an empirical evaluation based on observation. Here the Caffe model is used in sensing the age and gender [1].

Md. Harif Rahman, Md. Abul Bashar has identified the age and gender by converting the RBG (red, blue, green) image to (luminance, chrominance blue, and red) format as it is used in video compression. The primary usage of this format is to find the skin-tone. The lighting compensation (LC) algorithm is used in the pre-processing phase to enhance the image and restore natural color. Gabor filter is used for feature extraction from the pre-processed image and classified using the logistic regression [2].

In this paper, curvature changes in non-uniform Rational B-Splines (NURBS) deformations are used to detect the variation in age and gender-related surface patterns of MR images. By this, the changes in brain development corresponding to the age and gender are found [3]. A wide range of algorithms is used and compared at different stages in distinguishing age and gender. As a pre-processing
technique, population pyramids scaling is used, which is then classified for gender detection according to the accuracy score between linear SVM and logistic regression. The age prediction is made in 2 methods, either using node attributes with the multinomial logistic process (MN Logistic) or by using network topology with a communication network structure and reaction-diffusion algorithm [4].

The spotting of age and gender is done by using a deep residual learning network with connections that contains a gender estimation network and a gender-specific age network where the output from gender network was used as weights for estimating the outputs of the

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two age networks. The specified model used regression for estimation of age [5]. The database FG-net has the predefined columns that specify the correct location of eyes, nose, and lips, etc. such that they can be identified from the set of images easily. This paper includes the usage of SVM for the classification of gender and age [6].

In order to the categorization of age and gender from the dataset, predefined information regarding the gender and age levels between 17 to 80. The three different feature vectors are considered, namely duration of fixation, density, arcs, which are considered while implementing the protocols to categorize the male and female from the given dataset and then an ADA-boost protocol in the pre-processing. The final methodology used is the gaze analysis technique for human identification (GANT) for prediction [7]. [8] Considers a dataset with different gender and age groups, where the personality, age, and gender labels are considered as a corbora. The open SMILE is used to extract features from an emotional challenge competition in 2009. These features are them split, and shared presentation between the corpora is found by the shared-hidden-layer auto-encoder (SHLA). A support vector machine with a linear kernel is being used for classification, and later the cross-validation is done uses the WC-CNN (integral component CNN), which is characterized into two types of neural networks, the whole face network, and the facial component network. The entire face network is used as the primary classifier, and the resulting classification is evaluated by the confidence analysis. Finally, the global and local network's outputs are joined to achieve the desired partitioning of age and gender. Usage of deep networks VGG-16 architecture for feature extraction, and the age estimation is done using the fully connected layers (fc6). To train the dataset, structured output SVM (SO-SVM) is used. The RBF kernel is the key to gender and smile classification [10].

Face is one of the most popular biometrics (along with fingerprint, iris, and palmprint [6][11]), and face recognition and facial attributes/characteristics prediction have attracted a lot of attention in the past few decades [12][14]. Age and gender prediction from face images, as a specific face analysis problem have also drawn attention in the recent years, and there have been several previous works for age and gender prediction from face images. Here we provide an overview of some of the most promising works.

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In this section, we briefly review the age and gender classification literature and describe both the early methods and those that are most related to our proposed method, focusing on age and gender classification of face images from unconstrained real-world environments. Almost all of the early methods in age and gender classifications were handcrafted, focusing on manually engineering the facial features from the face.

**PYTHON**

**Python** is a programming language, which means it's a language both people and computers can understand. Python was developed by a Dutch software engineer named Guido van Rossum, who created the language to solve some problems he saw in computer languages of the time.

**Python** is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, and a syntax that allows programmers to express concepts in fewer lines of code, notably using significant whitespace. It provides constructs that enable clear programming on both small and large scales.

Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library.

Python interpreters are available for many operating systems. C Python, the reference implementation of Python, is opensource software and has a community-based development model, as do nearly all of its variant implementations. C Python is managed by the non-profit Python Software Foundation.

**You Can Use Python for Pretty Much Anything**

One significant advantage of learning Python is that it's a general-purpose language that can be applied in a large variety of projects. Below are just some of the most common fields where Python has found its use:

- Data science
- Scientific and mathematical computing
- Web development
- Computer graphics
- Basic game development

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- Mapping and geography (GIS software)

**Python Is Widely Used in Data Science**

Python's ecosystem is growing over the years and it's more and more capable of the statistical analysis.

It's the best compromise between scale and sophistication (in terms od data processing).

Python emphasizes productivity and readability.

Python is used by programmers that want to delve into data analysis or apply statistical techniques (and by dev that turn to data science)

There are plenty of Python scientific packages for data visualization, machine learning, natural language processing, complex data analysis and more. All of these factors make Python a great tool for scientific computing and a solid alternative for commercial packages such as MatLab. The most popular libraries and tools for data science are:

**Pandas**: a library for data manipulation and analysis. The library provides data structures and operations for manipulating numerical tables and time series.

**NumPy**: the fundamental package for scientific computing with Python, adding support for large, multi-dimensional arrays and matrices, along with a large library of high-level mathematical functions to operate on these arrays.

**SciPy**: a library used by scientists, analysts, and engineers doing scientific computing and technical computing.

Being a free, cross-platform, general-purpose and high-level programming language, Python has been widely adopted by the scientific community. Scientists value Python for its precise and efficient syntax, relatively flat learning curve and the fact that it integrates well with other languages (e.g. C/C++).

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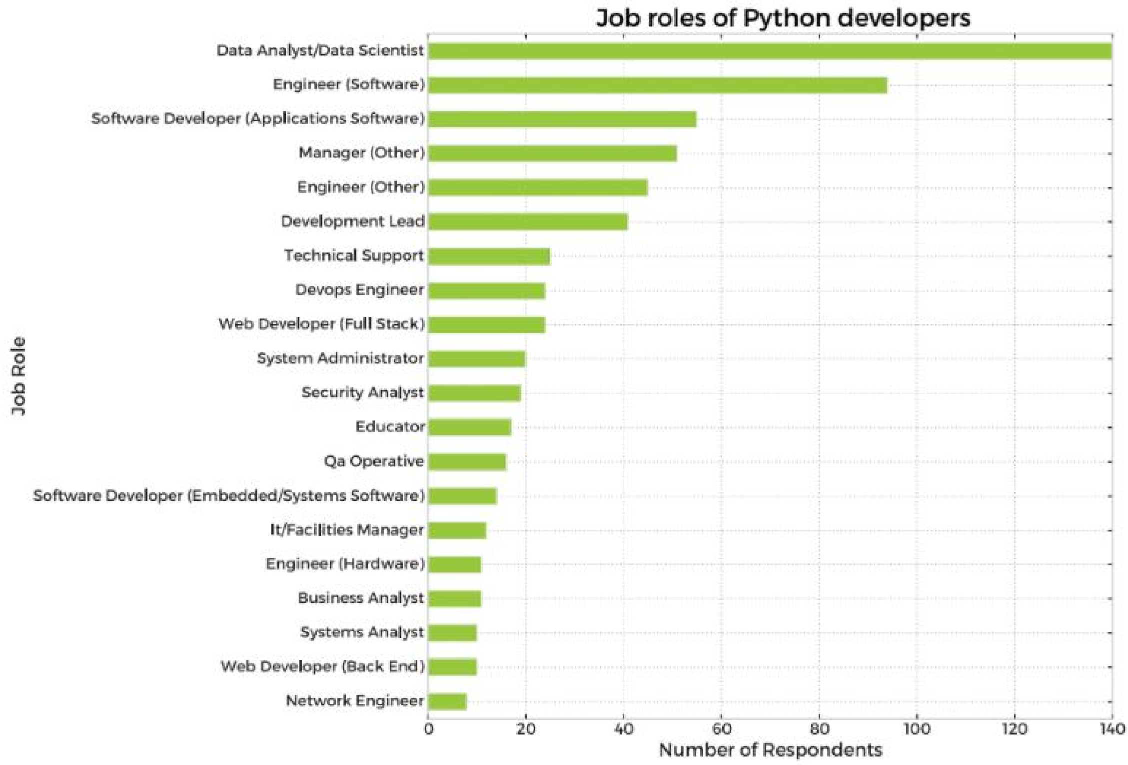


# METHODOLOGY

Open cv

At this stage, all the images in the dataset are inspected to find out if there is an image file without the label in the format of its representation. If any such image file is found, then it is either removed/any estimated values are assigned. Since we have the cropped images along with the data set else, this process of cropping can be categorized under the pre-processing phase.

Recognition Window

In the UTK Face dataset, the cropped images don't have any borders or margins around the face, which is called as tightly crop. There is a need to be tightly crop [15] the images in the main images folder, which is accessed in the python program. To align and crop, we arrange the margin argument to 0 when the dataset is trained by taking the weights into consideration. Model For the sensing of age and gender through images, we used a neural network model called the ResNet50, which is a CNN. A single CNN [16] is used to find the age and gender. In this only CNN, both the assumptions are simultaneously predicted, such that there is no need to run two different models for different attributes. By the various stages of CNN, the input images are first convoluted according to the filter, and later the required features are

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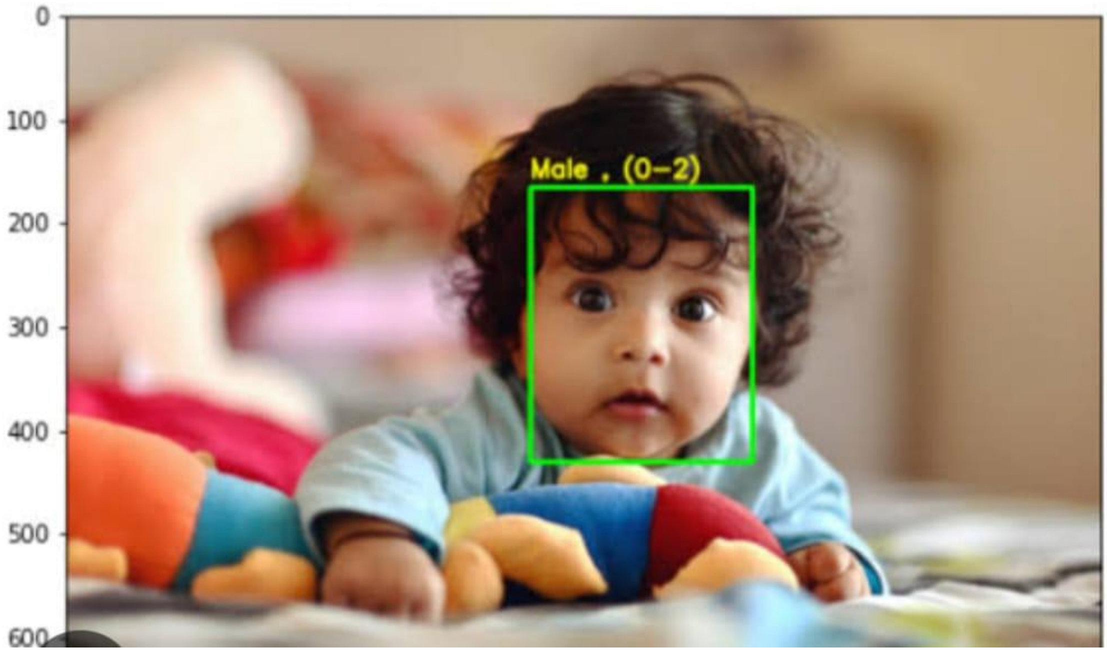
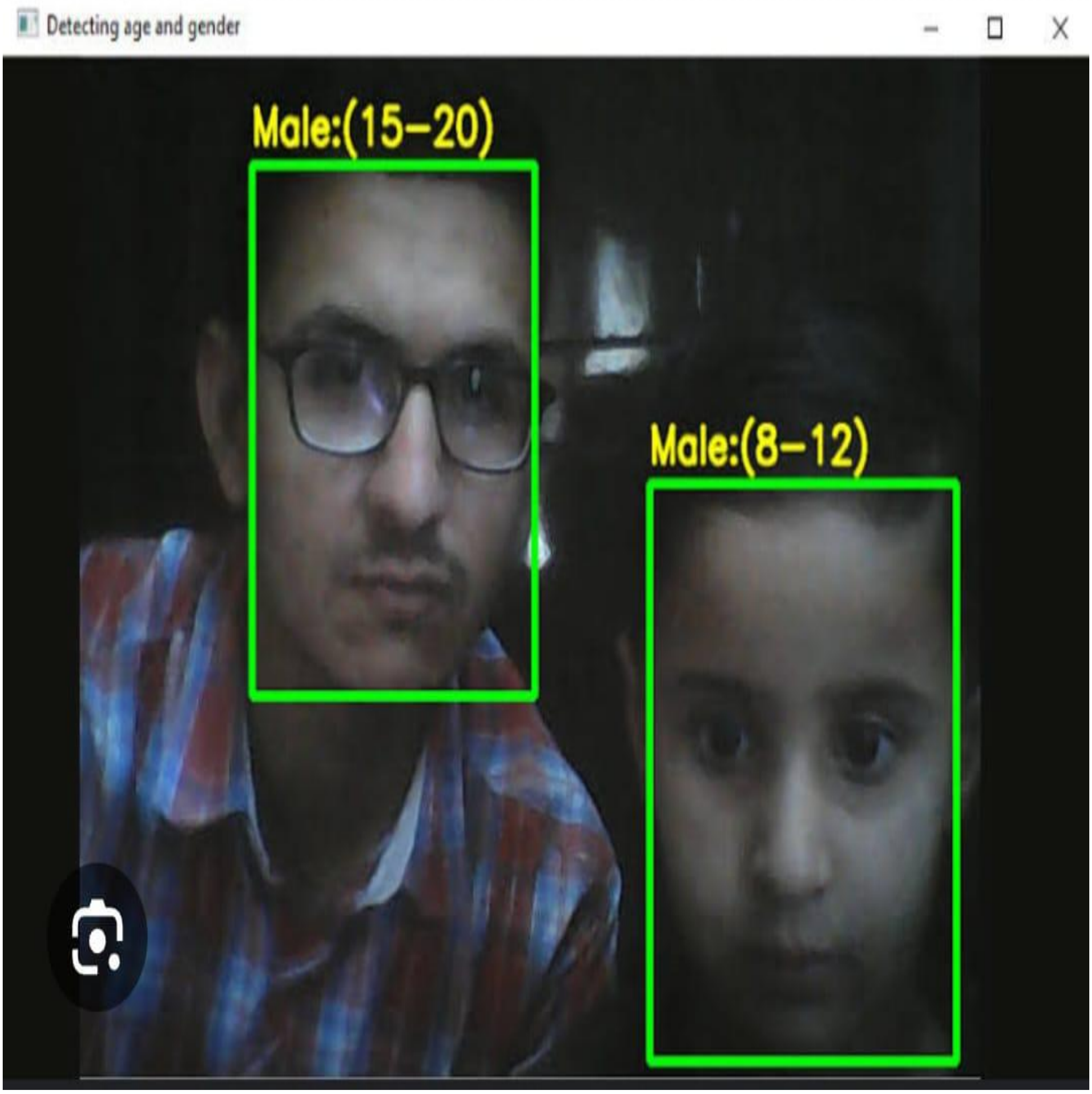
pooled out, and finally, by fully connected layer, the features and weights are mapped such that we could estimate the age and gender of the person.

. 4RESULTS

```
show_results("image4.jpeg")
```

```
Gender : Male, conf = 0.962
Age : (0-2), conf = 0.991
```




Detecting age and gender
Male:(15–20)
Male:(8–12)

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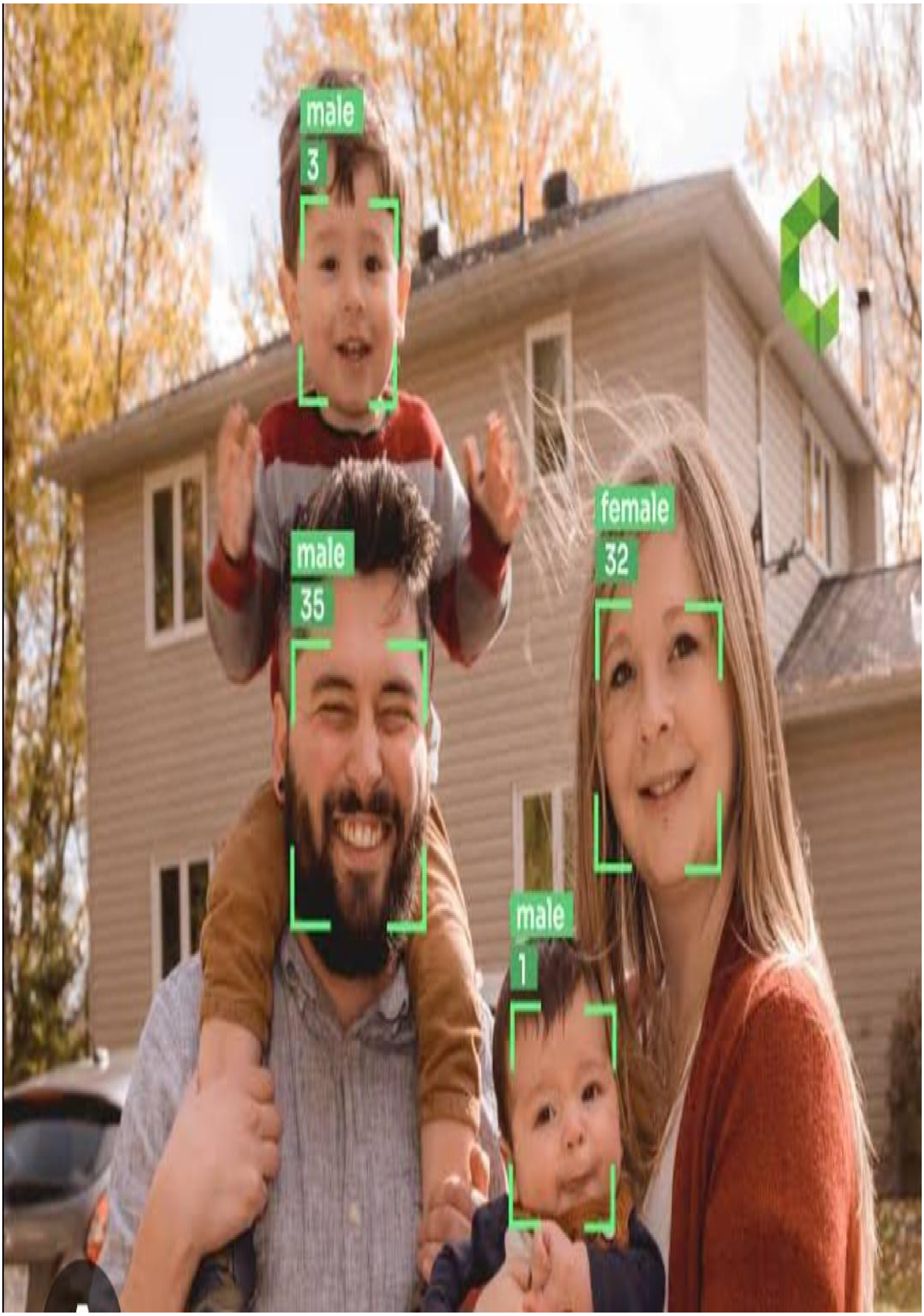

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## CONCLUSION

For a wide range of applications, age and gender are critical factors. The scientific community has been more interested in estimating age and gender through facial photographs. This research offers a revolutionary nutrition recommendation system depending on age and gender detection from a facial image. Most of the existing nutrition recommendation system

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provides nutritional advice based on the information entered by the user manually or using the pathological reports. In this context, the current paper presents a recommender system which automatically captures the face and classifies the age and gender of an individual without any physical communication. Based on the classification results, nutritional recommendation is listed to the users. This paper incorporates DCNN, HPSO, and classification. Experiments reveal that the proposed system's age and gender recognition approaches exceed existing methods on the basis of accuracy and computational efficiency. In future, it is planned to develop group recommendation system for a group of users in public places.

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