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Age and Gender prediction for better Marketing strategies.

P.R.Tanay vel[1],D.Sasi kiran[2],Manoj kumar[3], and P.Ramya vani[4]

[1,2,3,4]Department of Electronics and Computer Engineering,
Sreenidhi Institute of Science and Technology, Hyderabad

veltanay@gmail.com[1], genesysfreak@gmail.com[2] ,surnammanoj123@gmail.com[3] and ramyavanip@sreenidhi.edu.in[4]

Abstract. This paper examines the latest research in age and gender prediction and explores the potential implications for businesses to improve their marketing strategies. We deployed a Convolutional neural network (CNN) using deep learning technologies and algorithms that fit together for gender classification and age detection. We aim to improve customer–business interface in two common marketing areas i.e. E-Commerce and Brick -n- Mortar retail stores. The prime objective is to use deep learning to develop a gender and age prediction of a human face in an image, using this data the system recommends to the shopper the list of merchandise that matches his choice.

Keywords: Age, Gender, CNN, Marketing

1 Introduction

In recent years, marketing has evolved from traditional mass advertising to personalized, data-driven campaigns. The advancements in technology and data analytics have provided businesses with opportunities to understand the customer better and customize their marketing plans. Age and gender are two significant factors in this direction. Understanding these factors is essential for businesses to design effective marketing campaigns that can influence customer buying decisions. However, identifying age and gender accurately is a challenging task, especially in the digital world where privacy concerns are high. This paper explores the latest research in age and gender prediction using machine learning algorithms and its potential implications on selling.

Gender and age play a significant role in interpersonal interactions among people who live in communities. The use of smart gadgets has expanded as technology has progressed, and social media has begun to draw everyone's attention (smart gadgets have widely penetrated society, and Social media is shaping the mindset of people).

OpenCV, an open-source computer vision library, provides powerful tools for image processing and analysis. One of its applications is age and gender detection, which is finding utility in the areas of marketing, and healthcare. Age and gender detection using OpenCV are based on Convolutional Neural Networks (CNN.

We can use the features of the image that is extracted to recommend to the customer to connect to their preferences faster, like in a physical retail store.

2 Literature Survey

Marketing is growingly depending on Convolutional Neural Networks (CNNs) to target advertising and promotional materials linked to different demographics. In particular, understanding the effects of age and gender on consumer behavior has been study. Thus we decide to employ CNN for this grand purpose of aiding businesses to have better interfaces with costumers,

Age and Gender Detection with CNN:

One of the most popular applications of CNNs in marketing research has been in age and gender detection. Researchers have used CNNs to analyze images of consumers and estimate their age and gender. In a study by Chen et al. (2019), a CNN model was trained to predict age and gender based on facial images. The model achieved an accuracy of 91.4% for gender detection and an error of 5.61 years for age prediction. Another study by Hsu et al. (2020) used a CNN model to analyse social media profile pictures to predict age and gender. The study found that the model achieved an accuracy of 82.8% for gender detection and an error of 3.2 years for age prediction. The authors suggested that their model could be used to target social media ads to specific demographic groups.

Impact on Marketing Strategies:

Several studies have investigated the impact of age and gender detection on marketing strategies. For example, a study by Yan et al. (2018) used a CNN model to predict the age and gender of online shoppers. They found that age and gender were significant predictors of purchase behaviour and that targeting ads to specific demographics improved click-through rates.

Similarly, in a study by Bapna et al. (2019), a CNN model was used to analyze consumer images and predict their age and gender. The study found that targeting ads to specific demographics based on the model's predictions led to significant improvements in click-through rates and conversion rates.

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3 Proposed Methodology

The proposed work aims to develop a model that can assist VIPs by providing face and object recognition and offering real-time navigation. The objective of this model is to identify objects including indoor and outdoor, for example, cars, bikes, buses, sofas, pens, pencils, phones, etc. It is also trained to recognize facial emotions neutral, angry, sad, happy, and surprised. It also offers navigation support on demand in form of longitude and latitude. The proposed model consists of the following modules:

A. Face recognition use the [11] OpenCV library to capture video frames from the camera and perform face detection. It then uses Keras to load a pre-trained CNN (Convolutional Neural Network) model for age and gender prediction. The model takes the ROI extracted from the video frame and predicts the probability of Age and Gender.

B. The Proposed Model, detects Age and Gender of the User and it recommends the user a list of preferences he could choose from using the history of purchase of a certain group of people according to the Age and sex.

2.1 Face Recognition

A convolutional neural network (CNN) is a type of artificial neural network used for image recognition and other tasks involving pixel data. It is a core element of deep learning algorithms and is highly suitable for computer vision tasks, such as object recognition and pattern recognition. The architecture of a CNN is analogous to the connectivity pattern of the human brain, with neurons arranged in a way similar to the brain's frontal lobe. A CNN consists of three layers: a convolutional layer, a pooling layer, and a fully connected layer. The convolutional layer is the core building block, where computations happen and features are identified. The pooling layer reduces the number of parameters in the input, while the fully connected layer performs image classification based on the extracted features.

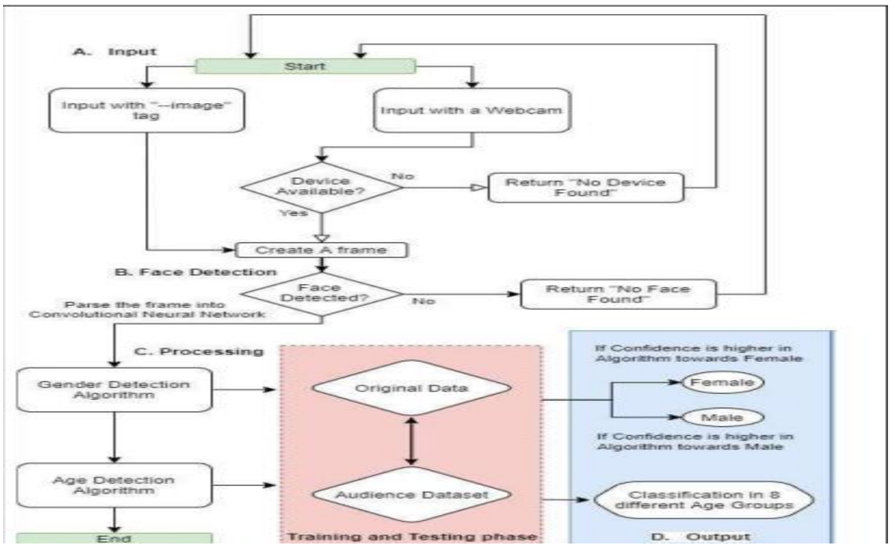

Fig.3. CNN Algorithm

This algorithm implements a facial Age and gender system that uses OpenCV . It detects faces in real-time video frames using a pre-trained Haar Cascade classifier and extracts a region of interest to classify emotions using a pre-trained CNN model. It uses OpenCV to capture video frames. The CNN model predicts the probability of seven emotions. The script displays the video stream with the predicted emotion label and a bar graph showing the probability of each emotion. The system runs until the user presses the 'q' key to quit

2.2 Age and Gender prediction

Age and gender detection using Convolutional Neural Networks (CNN) involves the use of several layers that perform feature extraction and classification. The CNN layers are designed to learn and extract relevant features from the images, which are then used to make age and gender predictions.

The first layer in the CNN is the input layer, which takes in the preprocessed image data. The input layer is followed by several convolutional layers, which perform feature extraction by applying a set of filters to the input image. Each filter learns to detect specific features, such as edges, textures, and shapes, by convolving with the input image. The output of the convolutional layers is a set of feature maps that represent the learned features at different spatial locations in the input image.

The output of the convolutional layers is then passed through a non-linear activation function, such as ReLU (Rectified Linear Unit), which helps to introduce non-linearity into the model and make it more expressive.

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The ReLU function sets all negative values in the feature maps to zero, while retaining positive values.

After the activation function, the output of the convolutional layers is then passed through a pooling layer. The pooling layer performs downsampling by reducing the spatial dimensions of the feature maps while retaining the most important features. The most commonly used pooling operation is max pooling, which takes the maximum value within a local region of the feature map and retains it in the pooled output.

The output of the pooling layer is then passed through another set of convolutional layers, activation functions, and pooling layers, which continue to extract and refine the learned features. This process is repeated for several layers, with each layer learning more complex and abstract features.

The final layers in the CNN are the fully connected layers, which perform classification. The output of the convolutional and pooling layers is flattened into a one-dimensional vector and fed into the fully connected layers. The fully connected layers use this vector to make age and gender predictions by learning a mapping between the input features and the output labels. The final output of the CNN is a probability distribution over the possible age and gender labels.

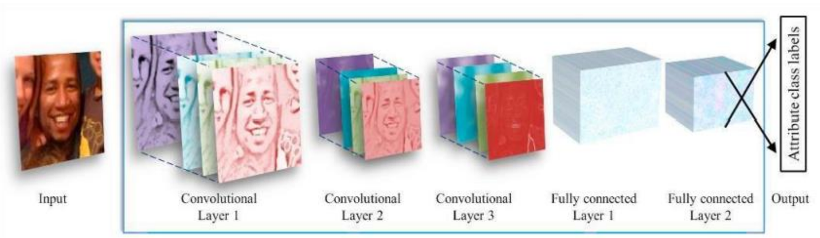

Fig.1. Working of CNN with images for Gender recognition

1. Obtain the age and gender of the user.

- This can be done through a user input form or by using an age and gender detection algorithm to automatically detect the user's age and gender from an image or video feed.

2. Use the age and gender to select a relevant dataset of clothing items.

- Similarly, separate datasets could be used for male and female users.

3. Use machine learning algorithms to predict which clothing items are most likely to be preferred by the user based on their age and gender.

4. Display the recommended clothing items to the user, along with any relevant details such as size, color, price, and availability.

- This could be done through a web or mobile app interface that shows the recommended clothing items in a visually appealing and user-friendly way

5. Allow the user to select and purchase the recommended clothing items if they choose to do so.

- This could be done through a checkout process integrated with an online retailer, where the user can purchase the recommended items directly from the app interface.

- Alternatively, the user could be redirected to a retailer's website or physical store to make their purchase.

3 Comparision

Model	Architecture	Accuracy (Gender)	MAE (Age)
VGG-Face	16-layer CNN	97.3%	4.0 years
ResNet	Deep CNN with residual connections	95.6%	4.2 years
Inception-ResNet-v2	Hybrid of Inception and ResNet	95.2%	4.5 years
MobileNet	Lightweight CNN	92.7%	6.2 years

[14] Total Score = (sum of all feature values / total number of features) + 2

Total Score = $\sum_{k=1}^{N}\frac{Vk}{N}$ ---(1)

Fig.8. Comparison between existing models

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Classification report :

              precision    recall  f1-score   support

           0       0.90      0.91      0.90      2487
           1       0.90      0.88      0.89      2254

    accuracy                           0.90      4741
   macro avg       0.90      0.90      0.90      4741
weighted avg       0.90      0.90      0.90      4741
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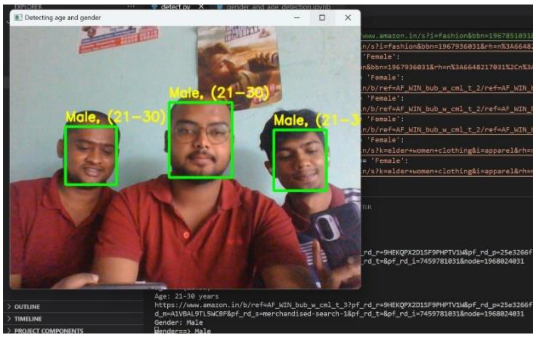
Fig . Classification report

4 Results

The following figures show how seamlessly the customer is finding his preferences and is happy to save time and energy.

(i) Age and Gender detection



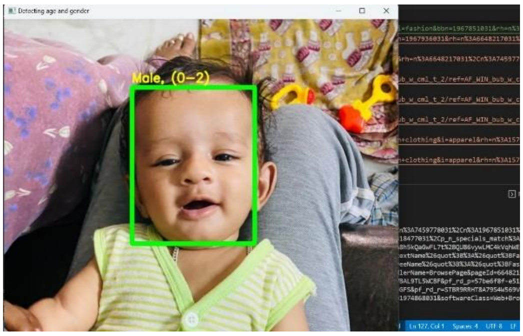


Fig.1. Results for Age and gender detection

(ii) User preferences recommendation

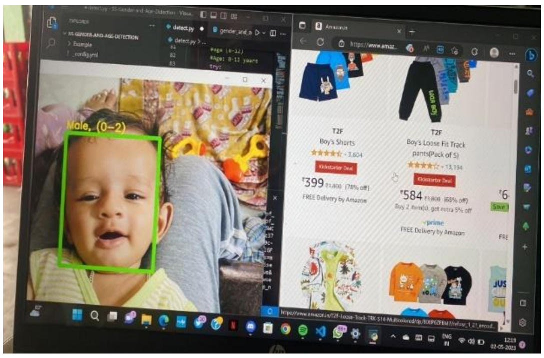


Fig.11. Results for User preferences recomendation

5. Conclusion and Future scope

Age and gender prediction using machine learning algorithms has the potential to revolutionize the way businesses design their marketing strategies. Understanding the age and gender of customers can help businesses design targeted and personalized campaigns that appeal to specific audiences. For example, a clothing retailer can use age and gender prediction to recommend clothes that are popular among the age and gender group of the customer. Similarly, a food delivery service can use age and gender prediction to recommend food that is popular among the age and gender group of the customer. The corporate can use the user's data to plan their production for Research & Development to introduce compatible products to the market.

However, privacy concerns are high in the digital world, and businesses need to ensure that customer data is collected and used ethically. The government should rationalize the collection and use of personal data for ethical purposes/marketing purposes, with the intent to make a win-win situation for businesses and customers.

Future research should improvise algorithms more robust and accurate in predicting age and gender. Entering deep into the arena of this work, we found that if that software is rightly embedded with the hardware using Raspberry Pi, that will have a wider scope and the efficient use of AI will give better results in understanding and predicting customer choices.

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