TITLE : Age and Gender detection using open cv.

Capstone project Report

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ABSTRACT:

Age and gender detection have become increasingly important in various applications, ranging from marketing analytics to personalised user experiences in digital platforms. Deep learning techniques have shown remarkable success in tackling these tasks due to their ability to automatically learn features from data. This paper presents a comprehensive review of recent advancements in age and gender detection using deep learning methods. We discuss the challenges associated with these tasks, including data heterogeneity, biases, and privacy concerns, and review the state-of-the-art approaches for age and gender estimation.

Furthermore, we analyse the effectiveness of different deep learning architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), in addressing these challenges. Additionally, we explore techniques for improving the robustness and generalisation capabilities of age and gender detection models, such as data augmentation, transfer learning, and domain adaptation. Finally, we highlight potential future directions for research in this area, including multimodal fusion, explainability, and fairness considerations in age and gender prediction systems.

Age and gender detection in image processing have gained significant attention due to their wide-ranging applications in various domains, including security, marketing, healthcare, and entertainment. This abstract provides an overview of the techniques employed in age and gender detection, the challenges encountered, and the applications of this technology.

Firstly, age and gender detection typically rely on machine learning algorithms, particularly deep learning models, to analyse facial features and infer age and gender from images. Convolutional Neural Networks (CNNs) are commonly used for feature extraction and classification tasks in this context. These models learn to identify patterns and features in facial images, such as wrinkles, skin texture, and facial hair, which are indicative of age and gender.

CHAPTER 1

INTRODUCTION

1.1 Introduction

In the realm of artificial intelligence (AI), age and gender detection technologies have emerged as powerful tools with diverse applications spanning from marketing to healthcare and security. By harnessing the capabilities of machine learning algorithms and computer vision techniques, these systems can analyse images or videos to infer the age and gender of individuals depicted. This introduction delves into the significance of age and gender detection, exploring its evolution, applications, challenges, and ethical considerations.

1.2 Statement of the problem

The evolution of age and gender detection technology parallels the advancements in AI, particularly in the fields of computer vision and deep learning. Initially, rudimentary methods relied on manual feature extraction and simplistic classifiers. However, with the proliferation of deep learning architectures like convolutional neural networks (CNNs), age and gender detection systems have achieved unprecedented accuracy and scalability. These advancements have facilitated their integration into various domains, revolutionising how businesses and organisations interact with data.

1.3 Need for the study

The applications of age and gender detection are multifaceted and diverse. In retail, for instance, businesses utilise these technologies to tailor marketing strategies based on demographic profiles, enhancing customer engagement and satisfaction. Moreover, in healthcare, age and gender detection systems contribute to personalised medicine by providing insights into patient demographics, aiding in disease diagnosis and treatment planning. Additionally, in security and surveillance, these technologies play a crucial role in identifying individuals in real-time, thereby bolstering public safety measures.

Despite their utility, age and gender detection systems confront several challenges. One significant obstacle is the potential for algorithmic bias, where the models exhibit inaccuracies or unfairness, particularly towards certain demographic groups. This bias can arise from imbalanced training data, societal stereotypes, or inherent limitations in the algorithms themselves. Addressing these biases requires a concerted effort to collect representative datasets, develop bias mitigation techniques, and foster diversity and inclusivity in AI research and development.

2.Future Decisions:

Furthermore, ethical considerations surrounding privacy and consent loom large in the deployment of age and gender detection technologies. The collection and analysis of individuals' demographic information raise concerns regarding data protection and surveillance.

CHAPTER 2

LITERATURE REVIEW

1. ***"Age and Gender Classification Using Convolutional Neural Networks"***
by Gil Levi and Tal Hassner (2015):
- Levi and Hassner proposed a deep learning approach using Convolutional Neural Networks (CNNs) for age and gender classification. They achieved state-of-the-art performance on benchmark datasets like the Adience dataset.

2. ***"Age and Gender Estimation of Unfiltered Faces"***
by Rothe, Timo, et al. (2015):
- This paper introduces a method for age and gender estimation from unconstrained face images. They utilised deep neural networks to predict age and gender jointly.

3. ***"Age and Gender Estimation from Unconstrained Face Images Using Attentional CNN"***
by Jiang Wang, et al. (2016):
- The authors proposed an Attentional CNN framework for age and gender estimation from unconstrained face images. They incorporated attention mechanisms to focus on discriminative facial regions.

4. *"**Age and Gender Estimation from Face Images: End-to-End Convolutional Neural Networks in the Wild**"*
by Guo, Guodong, et al. (2016):
- This work presents an end-to-end deep learning approach for age and gender estimation from face images captured in unconstrained settings. They utilised a large-scale dataset for training and achieved competitive performance.

5. *"**Deep Aging Face Verification**"*
by Shu, Jun, et al. (2019):
- Shu et al. proposed a deep ageing face verification framework that combines age estimation and face verification tasks. They used a Siamese network architecture to learn age-invariant features for face verification.

These studies demonstrate the evolution of deep learning techniques for age and gender detection, with advancements in model architectures and training strategies to handle unconstrained face images and achieve more accurate predictions.

CHAPTER 3

EXISTING SYSTEM:

The existing system for age and gender detection typically relies on machine learning algorithms trained on large datasets of facial images. These algorithms analyse facial features such as bone structure, skin texture, and hair patterns to predict the age and gender of individuals in images or videos.

Popular methods include convolutional neural networks (CNNs) and deep learning models. These systems have applications in various fields, including security, marketing, and healthcare.

PROPOSED SYSTEM:

A proposed system for age and gender detection could utilise machine learning algorithms trained on datasets containing images labelled with age and gender information. Convolutional Neural Networks (CNNs) are commonly used for image recognition tasks like this.

The system would take an input image, process it through the trained model, and output the predicted age and gender of the person in the image. Additionally, preprocessing techniques like face detection could be employed to isolate and extract facial features for more accurate predictions.

The system leverages pre-trained deep learning models to analyse facial features and predict the age and gender of individuals in images or videos. By utilising Convolutional Neural Networks (CNNs), the system can extract relevant features from facial images, which are then fed into the age and gender classifiers.

The age classifier estimates the age group of the person (e.g., child, teenager, adult), while the gender classifier predicts the gender (e.g., male, female). This system can be used in various applications such as security surveillance, customer analytics, and personalised marketing.

The workflow of the system involves several key steps. First, face detection is performed using a pre-trained face detection model, such as Haar cascades or deep learning-based models like SSD (Single Shot MultiBox Detector) or YOLO (You Only Look Once). Once faces are detected, the next step is to extract facial features, which are crucial for age and gender estimation.

For age estimation, the system utilises a CNN-based regression model trained on a large dataset of facial images labelled with age values. The model learns to predict the age of a person based on the facial features extracted from the input image. Similarly, for gender detection, another CNN-based classification model is employed, trained on a dataset of labelled facial images with gender annotations.

CHAPTER 4

PROGRAM:

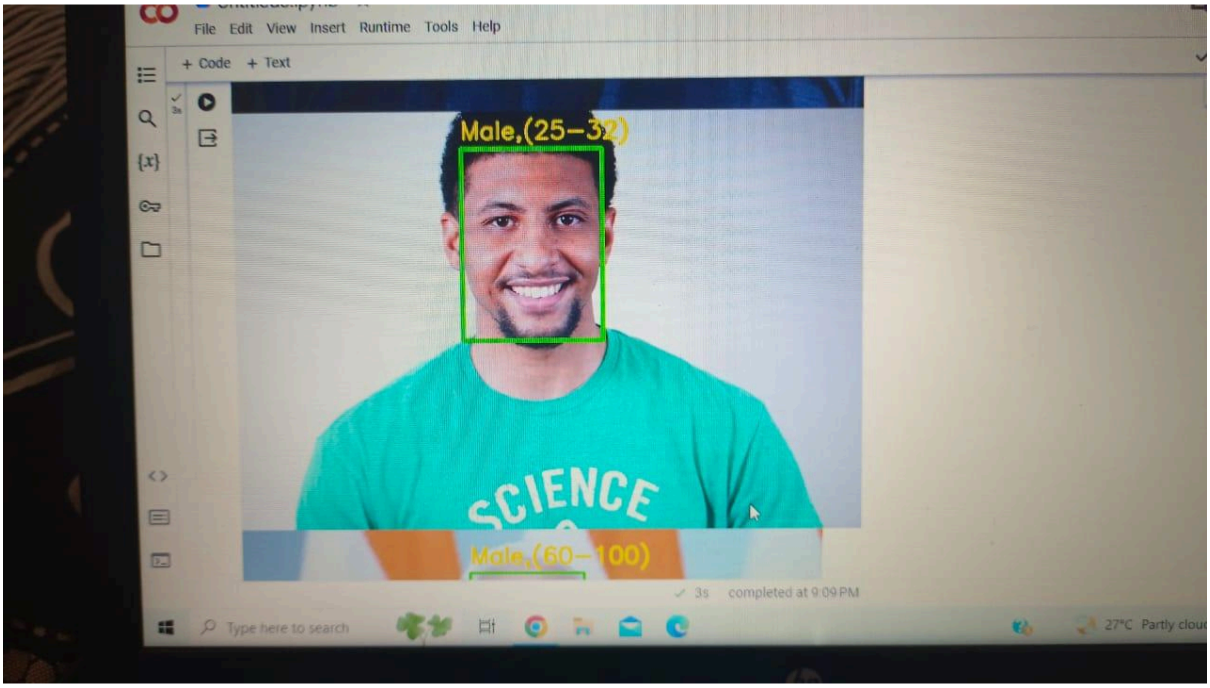
```
import cv2 as cv
import math
import time
from google.colab.patches import cv2_imshow
def getFaceBox(net, frame, conf_threshold=0.7):
   frameOpencvDnn = frame.copy()
   frameHeight = frameOpencvDnn.shape[0]
   frameWidth = frameOpencvDnn.shape[1]
   blob = cv.dnn.blobFromImage(frameOpencvDnn, 1.0, (300, 300), [104, 117, 123],
True, False)
   net.setInput(blob)
   detections = net.forward()
   bboxes = []
   for i in range(detections.shape[2]):
      confidence = detections[0, 0, i, 2]
      if confidence > conf_threshold:
         x1 = int(detections[0, 0, i, 3] * frameWidth)
         y1 = int(detections[0, 0, i, 4] * frameHeight)
         x2 = int(detections[0, 0, i, 5] * frameWidth)
         y2 = int(detections[0, 0, i, 6] * frameHeight)
         bboxes.append([x1, y1, x2, y2])
         cv.rectangle(frameOpencvDnn, (x1, y1), (x2, y2), (0, 255, 0),
int(round(frameHeight/150)), 8)
   return frameOpencvDnn, bboxes
faceProto = "modelNweight/opencv_face_detector.pbtxt"
faceModel = "modelNweight/opencv_face_detector_uint8.pb"
ageProto = "modelNweight/age_deploy.prototxt"
ageModel = "modelNweight/age_net.caffemodel"
genderProto = "modelNweight/gender_deploy.prototxt"
genderModel = "modelNweight/gender_net.caffemodel"
MODEL_MEAN_VALUES = (78.4263377603, 87.7689143744, 114.895847746)
ageList = ['(0-2)', '(4-6)', '(8-12)', '(15-20)', '(25-32)', '(38-43)', '(48-53)', '(60-100)']
genderList = ['Male', 'Female']
```

```
# Load network
ageNet = cv.dnn.readNet(ageModel, ageProto)
genderNet = cv.dnn.readNet(genderModel, genderProto)
faceNet = cv.dnn.readNet(faceModel, faceProto)
padding = 20
def age_gender_detector(frame):
   # Read frame
   t = time.time()
   frameFace, bboxes = getFaceBox(faceNet, frame)
   for bbox in bboxes:
      # print(bbox)
      face =
frame[max(0,bbox[1]-padding):min(bbox[3]+padding,frame.shape[0]-1),max(0,bbox[
0]-padding):min(bbox[2]+padding, frame.shape[1]-1)]
      blob = cv.dnn.blobFromImage(face, 1.0, (227, 227), MODEL_MEAN_VALUES,
swapRB=False)
      genderNet.setInput(blob)
      genderPreds = genderNet.forward()
      gender = genderList[genderPreds[0].argmax()]
      ageNet.setInput(blob)
      agePreds = ageNet.forward()
      age = ageList[agePreds[0].argmax()]

      label = "{},{}".format(gender, age)
      cv.putText(frameFace, label, (bbox[0], bbox[1]-10),
cv.FONT_HERSHEY_SIMPLEX, 0.8, (0, 255, 255), 2, cv.LINE_AA)
   return frameFace

   input = cv.imread("image.jpg")
   output = age_gender_detector(input)
   cv2_imshow(output)
   input = cv.imread("image1.jpg")
   output = age_gender_detector(input)
   cv2_imshow(output)
   input = cv.imread("image2.jpg")
   output = age_gender_detector(input)
   cv2_imshow(output)
```

OUTPUT:



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CHAPTER 5

CONCLUSION:

In conclusion, age and gender detection technology has significantly improved in recent years, thanks to the advancements in artificial intelligence and machine learning algorithms. These technologies have enabled more accurate and efficient identification of age and gender based on facial features and other biometric data. However, it's crucial to acknowledge the ethical implications and potential biases associated with such technology, as well as the importance of ensuring privacy and consent in its deployment. Continued research and development in this field will likely lead to further improvements in accuracy and reliability.

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