International Journal of Engineering Sciences & Research Technology

(A Peer Reviewed Online Journal)
Impact Factor: 5.164

IJESRT

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

IJESRT
INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

REAL TIME HUMAN FACE DETECTION, TRACKING OF AGE AND GENDER USING CNN ON RASPBERRY PI

Rishna V[*1] & Arunlal C.K[2]
[*1&2]Digital Signal Processing, KMCT College of Engineering, Calicut, India

DOI: 10.5281/zenodo.2629169

ABSTRACT

Human face detection and face feature classification lead to many applications. In fact, a person can posses face in many ways to classify the facial features by its identity, gender, emotions, age etc. Here we use the age and gender features of a human. By finding the face landmark features we track the age and gender of the human. Tracking of human gender and age is significant because people respond differently according to gender and age. It leads in various applications in the field of authentication, security and surveillance systems, social platforms and social media. Here this paper proposes a cost-effective method for real-time human age and gender tracking from the facial features. This is achieved by Convolutional neural network which first used for face-detection and then facial features classification and regression methods. Using soft stage wise regression and comparing with the input data set in which we have various levels of age group face images. By using regression this method proposes a compact size model for estimation of age and gender. In this proposed paper the age and gender tracking are implemented into the hardware domain which is a simple and efficient system. This is done to increase the processing speed which is sufficient for the real-time application. The hardware domain is successfully implemented in the Raspberry Pi, which is a credit card sized minicomputer. For achieving various challenging facial features here uses IMDB-WIKI database.

KEYWORDS: FACE DETECTION, CONVOLUTIONAL NEURAL NETWORK, RASPBERRY PI, PYTHON.

1. INTRODUCTION

Nowadays computers are being trained to work just like as human eye. Were human eye senses a moving image, normally as colored image and also in three dimensional in daylight. So now the computer vision technology trained the computer such a way that to sense the image taken the image feature and identify its peculiarity. The computer vision technology can simply defined as the science and technology of the machines which are able to collect and analyze images or videos with the aim of extracting image from the processed visual information and anxious with the speculation behind computer science system. In recent years camera plays a major role in the daily life of an individual [1]. it can possess in the mobile devices. Computer vision technology plays a major role in various fields like social media platforms, industrial purpose, medical image analysis, security and surveillance. Human machine interaction put forward much development in the whole life and it make easier for many things.

The age and gender detection applications are widely spread in many fields. The Applications of age and gender detection can play an important role including human-computer interaction (HCI), that is by a smart system detect the age of a nearby person or an advertisement board adapting its offer for young, adult, or elderly people and the next one is access control, that is restricting the access of minors from certain products like alcohol from vending machines or to events with adult content, and also the law enforcement, that is automatic scanning of video record for suspects with an age estimation can help during investigations and also in surveillance, like automatic detection of unattended children at unusual hours and place, and the other one is perceived age, that is there is a large interest of the general public in the perceived age also relevant when assessing plastic surgery, facial beauty product development, theater and movie role casting, or human resources

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

help for public age specific role employment. These are the some of the application can be done by the age and gender detection.

Here this works involves Google cloud vision technology by compute the content by machine learning process [2]. Google cloud vision technology helps in image labeling, face and land mark detection, optical character recognition through the machine learning technology. To communicate with Google cloud vision, REST API [3][4] is an easy way. So thus it's known as Google cloud vision API. Where this is a method to incorporate an embedded system with Google cloud vision. So here we used this to fulfill the gap of age and gender detection for Google cloud vision technology. That is real time human face detection and tracking of age and gender using CNN on raspberry pi 3 model where the raspberry pi itself is an minicomputer which is about a ATM card size. The raspberry pi is programmed using the software tool python. For the machine learning process we have to train and test the data set to get proper age and gender detection. A recently introduced IMDB-WIKI data set benchmark face database is to be taken for training and testing purpose. Propose this by learning representation through the use of convolutional neural network (CNN).Here we compare of different data set to evaluate it with IMDB-WIKI data set[5]. Since the publicly available face image data sets are often of small to medium size, rarely exceeding tens of thousands of images, and often without age information we decided to collect a large data set of celebrities. Here we take IMDB, WIKI and MORPH2 data set for training and testing split and also evaluates its age distribution.

In this proposed method it makes use of real time images for the extraction features. The images are captured using camera and feed into the programmed raspberry pi module it will evaluate the age and gender of the image from the facial features. The gender estimation in simple by CNN classification for age estimation we have to consider a novel CNN model called soft stage wise regression (SSR-Net)[6].the model is efficient with 0.32MB memory and achieves best results. We have to consider the age estimation problem as a regression problem because age is continues value not a set of discrete classes.

2. RELATED WORKS

There are several works are done on facial gender and age detection .In this section we make a review the state-of-the-art gender and age estimation methods. That are mainly based on the basis of face feature extraction, analysis of the extracted images, methods used for the estimation of ages, the data set to be taken. By deciding these parameters the age and gender detection process will takes place. the age and gender detection works are carried out for years. and new methodes are implemented in every works.

A work based on the facial global feature distance measure as a pre-cursor to perform the support vector machine based classification technique to improve the performance results. This approach is contributed by H. D. Vankayalapati [7] and it seems to be promising with the test performed on the front pose images of GTAV database of AT&T by using the MATLAB. This method can be further evaluated in future by using different databases with various poses other than the frontal pose. Used Support Vector Machine (SVM) algorithm for feature classification using MATLAB. Facial edge has carried out using Laplace of Gaussian filter to determine the landmarks positions. To eliminate this limitation of race and ethnicity Elham Arianasab [8] presented his work using Neural Network-based classification algorithm for gender diagnosis and reliability is mainly based on pixel value and geometric facial features. ANN based algorithm has been used on full face images which is main idea derived from Leonardo davincci principle. For the robustness of this system, training and testing on whole dataset is presented to classify them into male and female using Neural Network.

The classification accuracy was also affected by resizing the face images before and after alignment [9]. Erno Makinen and Roope Raisamo [9] have proposed four fundamental different gender detection method like SVM [7], LBP, Adaboost and Neural Network with their classification rate and sensitivity analysis for classifiers by varying rotation, scale, and translation of the face images by using IMM face database as well as FERET data base. The age estimation problem is a regression problem. Rothe et al. [10] fed CNN features to support vector regression [11] for age estimation. Agustsson [12] proposed Anchored Regression Network (ARN) which combines multiple linear regression over soft assignments to anchor points As pointed out by previous studies[13][14], regression-based approaches often suffer from over fitting because of randomness in the aging process and ambiguous mapping. DEX performs age estimation by carrying out multi-class classification and

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

then calculating the expected value as the age estimation [14][15].Liu et al. used regression and classification simultaneously for age estimation[16]. Malli et al. used age groups and their age-shifted groupings for training an ensemble of deep learning models [17].

Gil Levi [18] presented the Convolutional Neural Network (CNN) for different face positions, pixel resolutions and size which shows noticeable increase in performance of gender classification rate. The adience face dataset has been used for training and testing the particular dataset. Finally, for the real-time application purpose most preferable and reliable board for gender detection system, Raspberry Pi 3 Model B+ board and camera module has been used by Davide Mulfari [19] for making an assistive technology system by using Google Cloud Vision platform's REST API to process images as well as facial features extraction in form of JSON response.

3. PROPOSED WORK

This paper is a real time application for the gender and age detection using raspberry pi 3 board with a camera module. Here the real time face of the human being are detected by the camera module and the images are fed into the CNN architecture which contains several layers to extract the features and classify the images based on the training and testing[1]

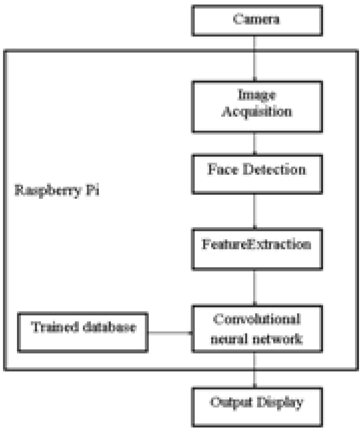

Fig.1.Block Diagram of proposed method

Here we calculate the age and gender. Since age values are continuous we have to generate regression problem then we have to solve it to estimate the age. So here uses SSR Net for the age estimation. Figure1 shows the block diagram for the proposed method the image detection, feature extraction training the data set whole will takes place on the raspberry pi3 module. The Raspberry Pi is a low cost, credit-card sized computer that plugs into a computer monitor or TV, and uses a standard keyboard and mouse. Here we use a mobile camera as the camera unit it can be connected with the processor by the app IP camera in the mobile through a shared network. Then the displays as a computer monitor itself. Raspberry pi is connected with computer through a Raspbian platform the programming of the raspberry is done through python 3.

Embedded System

The Raspberry Pi 3 Model B+ (Raspberry Pi 3 Model B Plus) is the latest version of the Raspberry Pi, a tiny credit card size Computer. This has 40 GPIO pin to add a keyboard, mouse, display, power supply, micro SD card with installed Linux Distribution and have a full- fledged computer that can run applications from word processors and spreadsheets to games.

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

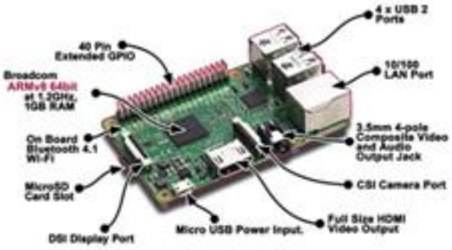

Fig.2.Raspberry Pi Module

This module has following hardware specification:

1) Chip:
    2) Broadcom BCM2837B0
    3) 64bit
    4) ARMv8
    5) Quad Core Cortex A53
        1.2 GHz
6) Memory: 1GB LPDDR2 SDRAM
7) Connections:
    8) Four USB 2.0 ports (up to 480 megabits per second)
    9) HDMI port
    10) 3.5mm 4-pole Composite Video and Audio jack
    11) Micro USB Power Input
    12) DSI Display Port
    13) CSI Camera Port
    14) Micro SD card Sold
        40-pin GPIO
15) Communication:
    16) 802.11ac Wi-Fi wireless Networking;IEEE 802.11.b/g/n/ac compatible
    17) Bluetooth 4.2 wireless technology with BLE
    18) 10/100/1000BASE-T Ethernet limited to 300Mbps

Raspbian Linux distribution software is used to load this raspberry pi module.

Network Structure

In this paper we used Multi-task Cascaded Convolutional Network (MTCNN)[20] model for face detection. This model has three convolutional networks (P-Net, R-Net, and O-Net) and is able to outperform many face-detection benchmarks while retaining real-time performance. The first thing is to pass an image to the program. In this model, create an image pyramid, in order to detect faces of all different sizes. In other words, creates different copies of the same image in different sizes to search for different sized faces within the image. In the P-Net, for each scaled image, a 12x12 kernel runs through the image, searching for a face. Within each of these 12x12 kernels, 3 convolutions are run through with 3x3 kernels. Convolution 4–1 outputs the probability of a face being in each bounding box, and convolution 4–2 outputs the coordinates of the bounding boxes. R-Net has a similar structure, but with even more layers. It takes the P-Net bounding boxes as its inputs, and refines its coordinates. The output of the P-net is given to O-Net where O-Net splits into 3 layers in the end, giving out 3 different outputs: the probability of a face being in the box, the coordinates of the bounding box, and the coordinates of the facial landmarks (locations of the eyes, nose, and mouth).

Figure 3(a) shows the detailed network structure of the proposed SSR-Net. This structure is designed from the complementary 2-stream structure proposed by Yang et al. [21], It is a 2-stream structure, which contains a 3x3 convolution, batch normalization, on linear activation and 2x2 pooling but the activation function and pooling is taken different for both the stream to make it heterogeneous. This is done because to get different features and their fusion could improve the performance. Features from different levels are taken or different stages. For each stage, features from both streams at some level are fed into a fusion block which is Illustrated in Figure .3(b).

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

The fusion block generates stage wise outputs, the distribution the offset vector and the scale factor for the k-th stage. In the fusion block, features from both streams passes through1 × 1 convolution, activation and pooling for having more compact features. For obtaining the two obtained N feature maps are fused by element wise multiplication the product then goes through a Fully- connected layer and then a Tan h function for obtaining a

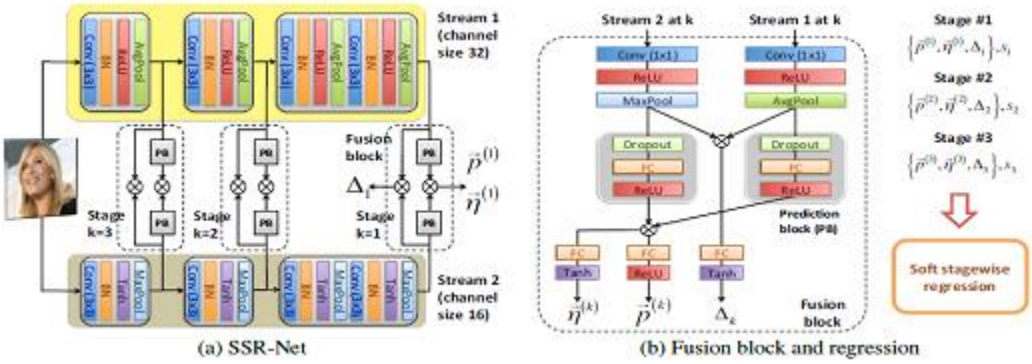

Fig.3. (a) The structure of the proposed Soft Stage wise Regression Network (b) the detailed structure of the fusion block in SSR-Net and the structure of the prediction block(PB).

. value in [−1, 1] as both end, are vectors and more complex
Thus, the features go through an additional prediction block before taking element-wise multiplication, FC layer and activation. Since presents a distribution, ReLU is used as its activation for obtaining positive values. On the other hand, Tan h is used to allow shift on both positive and negative sides.To reduce the model size without sacrificing much accuracy, we propose to use a coarse-to-fine strategy with multi-stage prediction. Assume that there are K stages and there are sk bins for the k-th stage. For each stage, we train a network at generates the distribution (or that stage. The age is predicted by the following formula for stage wise regression, SSR-Net gives the outputs (or an input image x and the numbers of bins the predicted age ỹ for x is calculated as

$$y = \sum_{k=1}^{K}\sum_{i=0}^{s_k-1} p_i^{(k)} \cdot \bar{i}\left(\frac{V}{\prod_{j=1}^{k}\bar{s}_j}\right) \qquad (1)$$

Where ī is the shifted bin index defined as in equation (2) is adjusted bin number.

$$\bar{i} = i + \eta_i^{(k)} \qquad (2)$$

Equation (1) is considered as soft stage wise regression because the bins are adjusted by fractional numbers. Softness is or the k-th stage and i is the bin index. It is easier to walking through a solid example.

Consider that estimating age within the range of 0-90 years old (V=90).So here there is two stages (K=2) and also three bins for each stage (s1=s2=3). Here we consider both classification and regression stages. In classification point of view, stage #1 classifies the image as 3 stages like youth (0-30),middle age(30-60) and old age(60-90). For stage #2 by considering the bins and it will get s2=3 bins, thus the width of the bins become 10 in stage #2.thus the classifier classify the images as relatively younger (0-10), in the middle (10-20)or relatively older(20-30) within the age group assigned in the stage#1. Note that there is only one classifier at stage #2, shared by all age groups of stage #1. Stage #1 predicts the age with a coarse granularity while stage #2 refines it with a finer granularity.

The advantage of stage wise regression is that the number of classes is small at each stage, leading to much fewer parameters and a more compact model.With the predicted age ỹ, obtained the SSR-Net model for age estimation.

Experiments
On this section describes pre-processing, experimental settings, and competing methods. Next, report the experiments on IMDB-WIKI and MORPH2 datasets. Then at last the paper implemented into the raspberry pi module and the output will displayed on the computer screen where the real time camera work is done by the mobile camera using the app IP Camera.

Pre-processing: The experiments is conducted on different datasets for age estimation, including the IMDB-WIKI [14] [15], and MORPH2 [22]. Following the procedure suggested by previous work [23],for pre-processing consider all the face images and they are aligned using facial landmarks such as eyes, mouth and the

nose. After the alignment the resolution of face images are set into 64x64 by cropping and resizing the image. By lowering the resolution it would be better for mobile and embedded devices. The program was implemented with Keras in python 3. The custom layer for soft stage wise regression is powered by Keras' automatic differentiation. For training, common data augmentation tricks including zooming, shifting, shearing, and flipping were randomly activated the batch size is 128 for the IMDB dataset and 50 for other datasets. The training time for SSR-Net is around 4 hours including pre-training.

Competing methods and Dataset: *By considering compact model it will consider reduced memory and also would sacrifice over the accuracy for memory and speed. The age and gender estimation model are less in this method. Mobile Net [24] replaces standard convolution with depth wise separable convolution for reducing parameters and computation overhead. Dense Net [25] connects each layer to every other layer in a feed-forward fashion and can achieve.*

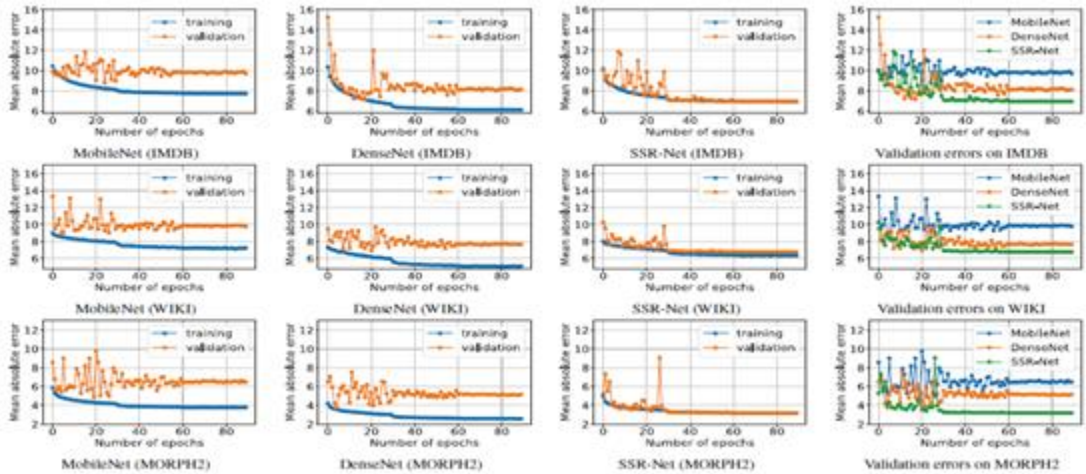

Fig.4. Comparisons of the training progression for Mobile Net, Dense Net, SSR-Net (from left to right), and their validation comparisons on IMDB, WIKI and MORPH2 (from top to bottom).

good performance with fewer parameters. Both Mobile Net and Dense Net are general-purpose network models with tunable parameters. We chose the parameters so that their model sizes are roughly 1 MB for fair comparison with SSR-Net. In the comparison of training progression considered 80% of the dataset are taken for training and the other 20% is taken as validation set.

On the first three columns, blue curves represent the progression of the training errors in MAE while orange curves are for the validation errors. If the two curves are close, it means that the model obtained from the training data can be better applied to the validation data. The models with this property suffer less from over fitting. From this point of view, SSR-Net outperforms the other two methods on all *datasets. The last column shows that SSR-Net outperforms the others in every validation set.*

TABLE.1.COMPARISONS OF METHODS ON THE MORPH2 DATASET

	Compact model		
Methods	SSR-Net	MobileNet	Dense Net
imageNet	-	-	-
IMDB-WIKI	√	√	√
Input size	64x64x3		

ISSN: 2277-9655
Impact Factor: 5.164
CODEN: IJESS7

Model size	**0.32MB**	1.0MB	1.1MB
Infernce time on GPU/CPU(c)	0.17/2.69	0.10/1.07	0.75/28.8
MAE	**3.16**	6.50	5.05

The IMDB-WIKI dataset is the largest face image dataset with age labels. It contains 523,051 face images of 20,284 celebrities. Among them, 460,723 images were collected from IMDB and the remaining 62,328 were from Wikipedia. Figure 4 compares the progression of the training Processes for Mobile-Net, Dense-Net and the proposed SSR-Net on the IMDB, WIKI and MORPH2 datasets. The blue curves show the progression of the training error while the orange ones for the validation set. It is clear that the blue and orange curves of SSR-Net are closer than other two methods. It means that our model trained on the training set can be more successfully. The divergence between the training errors and the validation error shows that Mobile Net and Dense Net suffer more fom over fitting.

From Table 1 where given a comparison of method on the MORPH2 dataset. Where in the table image net and IMDB are preprocessing stage work.MORPH2 is the most popular benchmark dataset for age estimation. It has around 55,000 face images of 13,000 people. Their ages range from 16 to 77 years old. Similar to previous work [23], we randomly divided the dataset into independent training (80%) and testing (20%) sets For reducing memory footprint, compact models usually take lower-resolution images as inputs (64 × 64 × 3) and contains much fewer parameters.

The proposed SSR-Net is very compact and only consumes 0.32 MB of memory while Mobile-Net and Dense-Net take roughly 1MDB. Before training with MORPH2, we used the IMDB-WIKI dataset for pre-training. SSR-Net achieves 3.16 MAE, the best among compact models. It even surpasses several bulky models despite that it consumes less than 1/1500 of their model sizes. With the extremely compact SSR-Net is suitable to be adopted on mobile and embedded platforms. The last row of Figure 2 shows the training/validation curves for Mobile Net, Dense- Net and SSR-Net on MORPH2. Again, SSR-Net suffers less from over fitting compared to the other two compact models.

Experiment Prototype: *The proposed work is implemented on Raspberry Pi board for the real-time application which can be shown in Fig. 5 as our system prototype. It shows the system arrangement for perfect face and gender detection.The display is used here as the computer monitor. The age and the gender with real time image are obtained. The age and gender is displayed in the box as 34, M.*

Fig.5. Prototype for age and gender detection

4. CONCLUSION

This paper introduced a real time age and gender detection process. This has been implemented by a Raspberry pi module. This helps to close the gap of Google cloud vision technology which has given the facial features only, where Google has introduced the REST API, which extracts information from visual data. In this work we use the facial feature to detect the age and gender of a human. This used by CNN which is a novel method for age and gender estimation using Soft Stage wise regression Network (SSR-Net). It is efficient method than existing method like Mobile-Net and DenseNet.it also make good performance on multiple age estimation data sets where SSR-Net reduces the number of neurons and it suit to compact model which is suitable for the mobile and embedded devices. Here another contribution is the IMDB-WIKI data set which is the largest public face dataset which provides age and gender details. Here we used raspberry pi module to implement the idea which is a credit card size minicomputer which works in python.

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