

Age and Gender Prediction and Validation Through Single User Images Using CNN

Abdullah M. Abu Nada¹, Eman Alajrami², Ahemd A. Al-Saqqa³, Samy S. Abu-Naser⁴

^{1,3} IT Unite, University of Palestine, Gaza, Palestine

² IT Department, University of Palestine, Gaza, Palestine

⁴ IT Department, Al-Azhar University, Gaza, Palestine

Email: e.alajrami@up.edu.ps¹, a.abunada@up.edu.ps², ah.saqqa @up.edu.ps³, abunaser@alazhar.edu.ps⁴

Abstract— Recently, the user's gender and age range are very important for organizations to understand their customers' needs and develop their strategies to provide more enhanced services to them. These organizations mostly rely on their enterprise systems to collect data from users, which forms play an important role in it. This data should be correct and accurate and sometimes must be within a specific format. So, the application form validators and rules were proposed. When we have a look at the related works form validators, we found that their methods work well with the different types of data. But unfortunately, there is a lack of auto detection of the user's age and gender. In addition, they neither detect nor validate the real user's age range that reflects from his/her photo. For example, the ID photo must reflect the person's age range. In this paper, we suggest a new approach to validate the user's gender and age range that is reflected from his photo correctly. Also, adding a double-check layer validator by linking between user photo, gender, and date of birth form inputs based on the Deep Learning approach, by detecting the gender and estimate the age from a single person's photo using a Convolutional Neural Network (CNN or ConvNets). Then, on top of that, a web service to make the validation process is implemented. Finally, we evaluated this solution using the University of Palestine students' photos, and show it has achieved a good result in gender prediction and has challenges in age prediction.

Keywords— Gender recognition, Age Recognition, Face Identification, Form Validator

I. INTRODUCTION

In enterprise systems, the forms play an important role to collect data from users, and the form validators support it to collect accurate data by validating the entered data and reducing the user's input errors.

Gender and age range reflected by the user photo validation process highly depends on face, age and gender detector algorithms. So, let us review the most important algorithms that we will deal with in this study. Face detection is an important step in the gender and age detection process. It detects the human faces from other objects in an image [1]. There are several algorithms to achieve this task such as Haar Cascade, Deep neural Networks DNN, Histogram of Oriented Gradients HoG, and Convolutional Neural Network CNN, each of them has its own usage, advantages, and disadvantages. Convolutional neural network CNN is one of the main algorithms for deep learning in which it can learn to do classification tasks directly from images [2]. This algorithm will be very useful in our case by assuming the gender and the age range prediction as a classification problem with two classes Male and Female for gender and multiple classes for the age ranges.

In this paper, we attempt to propose a form validator to validate a gender and age range that's reflected from user photo, based on an automatic age and gender classification using CNN and evaluate it using real persons photos dataset.

II. RELATED WORKS

Researchers have been working on gender and age recognition and estimation for years. They used several deep learning algorithms to do so, and they worked hard to enhance the accuracy and precision of age and gender estimation from a person's photo. Many deep learning

algorithms were used in face detection, face recognition, age estimation, gender recognition and identification.

A. Face Detection

Several algorithms were proposed for face detection such as Viola and Jones algorithms [3]. Viola and Jones applied rectangular boxes for the face. Another algorithm is the Haar Cascade classifier which has been used for human detection and face detection [4-6]. It was given by Open Source Computer Vision (OpenCV) libraries. Other algorithms commonly used in face detection by OpenCV are HOG, Linear SVM, Single Shot Detectors (SSDs) [5]. In 2019, Alajrami et al. used the Haar Cascade classifier in human and face detection to improve surveillance systems' efficiency, and it gave good results [7]. Jhili Bhattacharya et al. used real-time DNN-based face identification for visually impaired persons [8].

B. Age And Gender Classification

Not only deep learning algorithms work well only in face recognition, but also in age and gender prediction through user's images. Regarding the OpenCV, age and gender prediction depends on analyzing the image of a person. Thus face detection is a pre-step for predicting age and gender. Then, the face Region of Interest (ROI) is extracted and the age detector algorithm is applied [6]. Zakariya Qawaqneh et al. used Deep CNN for age estimation based on the VGG-Face model, and they proved that a CNN model can be utilized for age estimation to improve performance [9]. Hlaing Htake Khaung Tin used Principal Component Analysis (PCA) to predict age of face images [10]. Nagesh Singh Chauhan used CNN and OpenCV to predict the age and gender of human faces that appear in any video, and the accuracy of his prediction is excellent [10]. Haibin Liao et al. used CNN and Divide-and-Rule strategy for age estimation of face images. They used CNN to extract robust features

from the images, then age-based and sequential study of rank-based age estimation learning methods is utilized and then a divide-and-rule face age estimator is proposed [11]. They proved that the performance of divide-and-rule estimators is much better than classical SVM and SVR. Unicar, Michal, et al. proposed structured SVM classifier to predict age, gender and smile from a single face image by deep features [12]. Olatunbosun Agbo-Ajala and Serestina Viriri proposed a novel CNN model to extract features from unconstrained real-life face images and classified them to age and gender groups. They achieved classification accuracy of 84.8% on age group and 89.7% on gender [13].

Proposed solution attempt to validate age, gender and the recency of personal photo user inputs by prediction the age and gender from photo and comparing it with other inputs.

III. MATERIAL AND METODS

The main goal of this paper is an attempt to propose a form validation role that can be linking between gender, DOB, and user photo inputs and validate each of them based on their relationship. For example, the gender entered by the user will be checked with the detected gender from the user photo. Also, the real age range reflected by the user photo will be validated according to the DOB entered by the user, etc. This task can be achieved based on the flowing steps:

A. Face detection

DNN model was selected according to its superiority over other algorithms like (Haar Cascade, HoG, and CNN) in accuracy, speed, running at real-time on CPU, and detect faces in various scales and orientations [14]. By converting the user photo to blob and passing it through the network layers, then will have a 4D matrix as output detections, which the 3rd dimension represents the number of detected faces in the photo and the 4th dimension contains information about the score of the face (percentage of detected face features) and bounding box. Finally, to get the correct detected face bounding box on the user photo, the bounding box has normalized between [0,1] and multiplied by the height and width of the original photo.

B. Gender Prediction

The gender prediction is assumed as a classification problem and the output layer of this network is a SoftMax with 2 nodes, which represents Male and Female classes. Using the model in [15] It is a network that uses 3 layers, two of them are fully connected layers and the last one is an output layer. By loading this model into memory and passing the output of the face detection process (detected face) through the gender prediction network, then we will have the predicted values for both classes as an output from the network. now we can take the maximum value of the output and use it as a predicted gender.

C. Age Prediction

Due to the difficulty of assuming age prediction as a regression problem because the humans in the same age may look very different based on each person's genetics and it's very hard for humans to predict accurate age on just looking at the person, but it will be reasonable when predicting the range of age. So, we assumed it as a classification problem by using Adience dataset [15-17] the ages grouped as a

following (0–2), (4–6), (8–12), (15–20), (25–32), (38–43), (48–53), (60–100). Like gender prediction Using the model in [4] as a network that uses 9 layers, eight of them are fully connected layers and the last one is an output layer. By loading this model into memory and passing the output of the face detection process (detected face) through the age prediction network, then we will have the predicted values for all classes as an output from the network. now we can take the maximum value of the output and use it as a predicted age group.

D. Web Service

To provide a suitable interface for gender and age range validator, a RESTFUL API was selected to serve the model. Also, the most of required libraries for Machine Learning (ML) and face detection are available on Python. So, the Flask framework has been chosen for web service implementation. As Figure 1 web service contains four endpoints, the first one takes the user input (user photo, gender, and date of birth), then calls the second and third endpoints that responsible for age and gender detection by sending the user photo to it. Then these services call the face detection endpoint to extract the face from the image and did their own tasks on it.

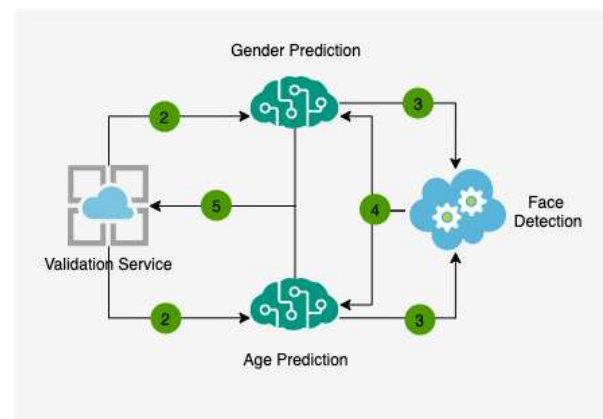


Fig. 1. Shows a web service architecture and the endpoints communication

Finally, after age and gender prediction, the validation service checks the gender predicted from user photo is the same as entered one and checks the age range that predicts from user photo is close to the real age entered by the user.

IV. EXPERIMENTS AND RESULTS

Our proposed solution was implemented using the latest OpenCV library using the Caffe deep learning framework to predict user age and gender. A subset of the University of Palestine (UP) students' photos were selected to be testing data. This subset is divided into two categories according to students' gender (Male and Female) and used for testing and evaluating the student's age and gender prediction.

A. Datasets

The UP students' dataset was used in our research. The dataset contains both gender categories (Male and Female). It contains about 430 students' photos which have 233 Males and 195 Females and age range between 20-55.

B. Evaluation of proposed solution

Regarding our experiments on the evaluation of the proposed solution using the UP students' dataset, the proposed solution has a good result for gender prediction, but unfortunately, it suffered in age estimation. As Table 1 we have noticed the gender prediction accuracy overall for both genders was about 82%. Also, we noticed the model has better results by predicting male's faces photos and it was about 89%, and 74% for females. After analyzing the images in which the model did not succeed in gender prediction, we extracted several reasons for that. The main reason Sometimes the difference between the features of the female and male faces within specific ages is not as clear as it should be. Also, in female photos, Hijab hides some face features. Finally, there is a weakness in the used model, it did not give the mustache enough weight in gender prediction.

Table 1 SHOWS THE GENDER PREDICTION CONFUSION MATRIX RESULT

Predicted	Actual		
		Male	Female
		Male	Female
	Male	207	26
	Female	50	145
	Accuracy	0.8224299	

Regarding the age prediction results in Table 2 we disappointed from prediction accuracy it was about 57% as overall for both genders. But to be honest this is a challenging problem because it depends on several factors. For example, according to the human race taxonomy, many people look very different at the same age. Also, the nature of the human psyche drives him to conceal his true age using many ways.

Table 2 SHOWS THE AGE PREDICTION CONFUSION MATRIX RESULT

Predicted	Actual		
		Male	Female
		Male	Female
	Male	132	101
	Female	81	114
	Accuracy	0.57	

V. CONCLUSION

Recently, age, gender, and the recency of personal photos have become important information for several organizations and governments for business, identification, security and, etc usage. Also, this data collected from persons through the enterprise system, so the form validators were proposed to reduce the user data entry errors. In this paper, we attempt to propose a new solution to validate these data by predicting age and gender from a single person photo and comparing it with entered gender and date-of-birth. Then, after evaluation, we found it has good results in gender prediction, but it still suffers in age prediction.

VI. FUTURE WORKS

This approach can be improved to enhance the weakness points in age and gender prediction in many ways. First, by using the large and complex model in [18] that trained on more than 500K of person photos then evaluating the estimation accuracy and performance speed and did not

consume a lot of resources and optimize it to be usable in the application forms. Also, regarding low accuracy results in age and gender prediction from female photos, due to several problems we discussed before, it's reasonable to train a new model through CNN using a large UP students' dataset that contains more than 15000 photos and a lot of photos for females that are wearing Hijab, then evaluating it using the testing dataset.

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