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CNN Model for Analyzing Masked Facial RGB Images Using Cloud Computing

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Abstract: The world invasion of dangerous virus diseases such as Covid 19, in the last few years, force people to wear masks as precaution. Although this prudence reduces the risk of infection and viruses' spread, it adds difficulty to distinguishing or identifying a person. This paper proposes a method to analyze images of masked persons for classifying their gender, in addition to identifying the colors of their skin and their eyes. We apply residual learning using the convolutional neural network (CNN) based on the visible part of the face. Cloud computing resources have been used as a convenient environment of substantial computing ability. Also, new database of RGB face images was created for testing. Experiments have been operated on the constructed database beside other datasets of facial images after cropping. The proposed model gives 96% gender classification accuracy and 100% skin/eye color identification.

Keywords: *Cloud computing, Convolution neural networks, Eye color, Gender classification, Masked faces, Skin color.*

1. Introduction

Although wearing masks is an effective way to avoid infection with sever diseases as Covid-19, the mask significantly weakens the performance of face recognition and discrimination systems. Since masks cover a large part of the face, thus the characteristics that help the systems in revealing the identity of the person. Resulting in the necessity to find a quick solution to support the work of recognition systems in the presence of this pandemic. Recent masked facial recognition systems focus on the exposed areas like eyes, eyebrows, and forehead, trying to extract many characteristics as possible.

With the field of computer vision and the development of deep learning systems, the recognition problem becomes solvable, but it needs more adequate techniques for identifying characteristics accurately, [1].

In addition to masks, many things may be worn that cover several parts of face such as scarfs, sunglasses, hats, etc. It is obvious that wearing these things leads to difficulty in distinguishing and may be used in many cases to hide or camouflage. Therefore, it is also necessary to support recognition systems for the purpose of overcoming these challenges. Despite, using techniques such as support vector machine (SVM), principle component analysis (PCA), Gobar wavelet and local binary patterns (LBP) showed good results, [2], the combination of CNN and deep learning recently has established motivating strength. Cloud computing is a growing field of research in computer science nowadays. It aims at enabling full support for user tasks. Its main principle is making computing appear anytime and everywhere by utilizing daily used user devices. It plays a great role in many application fields such as healthcare and military intelligence data fusion. Cloud customers rent the usage from a third-party provider to use resources as a service. They can access these services using a web browser, [3].

This paper presents a deep learning residual network model that distinguishes the gender and detects the skin and eye color of masked or undercover persons from their images based on CNNs. Proposed model has been implemented on the Cloud system using the Google Colab, Google drive and Gmail to perform classification tasks. Experimentally, new RGB face images dataset has been constructed from masked faces and other unmasked faces using cropping. For our dataset, the proposal identifies the faces, and extracts the needed characteristics including eye color, skin color, and gender from the upper face region.

2. Related Work

Despite of the existence of large number of facial recognition applications, they are not enough adequate. Most of them suffer from variant types of physical/digital attacks and become inefficient due to inclination, [4]. Although, recent studies concentrate on real difficulties including different angles, intensity of illumination, facial

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expressions, different in age, and others. However, the biggest challenge is distinguishing covered faces because many of the features that are used to distinguish are covered, and this requires many attempts to exploit the visible characteristics.

2.1 Gender Classification

Recent research spotlights the impact of gender classification. The prediction method in [5] fuses result of classification of heads with another classification for the whole body. Fadhlan restricts his attention to hand-crafted images to reduce the CNN complexity and lower memory consumption by decreasing the training parameters, [6]. Others concentrates on classifying pedestrian, and use ACS technique to produce an optimized set of features, [7]. While authors, in previous work, focus their concern to utilize thermal images, [8].

Face detection may be deemed as mandatory phase in any recognition system. In this phase, a box is placed around the selected face and cropped from the image or frame. The mechanism used in the selection must be strong and unaffected by the lighting or noise in the image, [9]. Deep learning recently improved the performance of object detection, which produced an effective deep learning-based face detector. RetinaFace has been used in [1] as a quick efficient encoder. It is a hybrid self-supervised and extra-supervised multi-task learning face detector that can handle various scales of faces.

Several researchers suggested smart glasses to detect and recognize face depending on a stored database. These glasses assist security and law enforcement controls in discovering and apprehending suspects and wanted persons in several locations such as airports, and main road controls. Haar-like features has been used as a pre-step for face detection, [10]. To discover the highly variable patterns in faces, a hybrid method has been proposed that depending on CNN as it extracts a large number of features from its successive layers, [11]. On the other hand, CNNs were used to detect facial expressions and gestures, not only the main features of the face, as these networks can overcome imaging problems such as the intensity of lighting, [12].

For masked faces, research [13] decomposes the recognition problem that have random partial occlusions into three stages. First, the system used the PDSN to capture the correspondence between corrupted feature elements and occluded facial blocks. Then, it established a mask dictionary from the learned mask generators. In testing, it merges the feature discarding mask (FDM) of random partial occlusions from dictionary, which is then multiplied with the original feature to delete the effect of partial occlusions.

Some studies of masked images' analysis discovered that triplet loss is not applicable to the datasets, because the results of online triplet selection contain fewer mask changes, making it difficult for the model to learn the relationship between mask occlusion and feature mapping. In [14], authors designed an Att-inception module that combines convolutional block attention module, and the Inception-Resnet module, in order to get the system more attention to the uncovered area.

2.2 Viola-Jones Algorithm

This algorithm was proposed by Paul Viola and Michael Jones in 2001. It is a famous detection algorithm that provides a competitive detection rate in real-time. This detector has become popular due to its open-source code. In 2015, Gupta presented a modified version for face detection. It gives high accurate rates in finding specified region of unknown size in an image, [15]. The system training phase, splits input images into two sets. Positive image set including face images, and negative image set for others. In addition, the system collected and stored all face images features in specific file. While in the testing phase, it classified each input image is it facial or not from stored features. If the image passes all the threshold, then it is classified as facial.

Viola-jones algorithm performance, for face detection, has been analyzed in [16]. It was implemented for different purposes, such as identifying persons, [17].
The algorithm consists mainly of the following four stages.

Stage 1 (Haar Feature Selection): it is used to extract rectangle features called Haar features. It computes the difference $\sum BP - \sum WP$, where BP is the Black pixel area, and WP is the White pixel area. Different types of features are extracted like in figure 1. Each extracted feature is connected with a unique location of sub window.

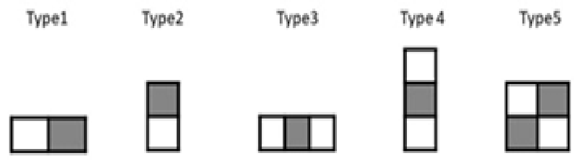


Fig. 1 Sample types of Haar features

Stage 2 (Integral image): it converts the input image into an integral image. Each pixel's equivalent is created by the total summation of all pixels above and to the left of current pixel, see Figure 2. The values of the pixels are corresponded with the rectangle corners in the input image.

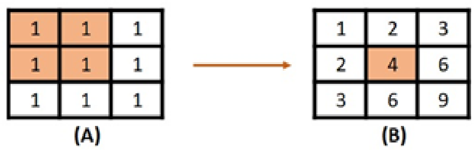


Fig. 2 Integral Image

Stage 3 (Adaboost): it is considered as a machine-learning method. It identifies relevant and irrelevant features. Then it assigns a weight to all of them. It constructs a strong classifier as a linear combination of weak classifiers whose weights are evaluated as follows:

$$Weak\ classifier = \begin{cases} 1\ ; idenified\ a\ feature \\ 0\ ; Not\ idenified\ any\ feature \end{cases}$$

Stage 4 (Cascade classifier): it is used for combining many features efficiently. As a final classifier, it consists of several simpler classifiers, applied subsequently. In every phase, it verifies whether a window is a face or not. A non-face window is discarded, otherwise, it is passed to next stage.

Viola-Jones algorithm are also used for eye detection. It shows good performance in recognizing driver's drowsy, [18]. It depends on the hypothesis that eyes' part is darker than other parts of the face. It also discards regions corresponding to eyebrows.

2.3 Deep Residual Learning

Lately, deep networks have been presented to find accurate solutions for AI and ML dilemmas. CNN are adapted for image processing. Although deep CNN has pivotal impact on image classification, experiments rival the difficulty of training and optimization. This leads to presenting residual learning models to facilitate the process, while increasing accuracy, [19]. Residual neural network (ResNet) is an evolved CNN with deeper layers and more sensible computations that overcomes vanishing gradient problem. It has accomplished progress in cancer prediction and malware detection, [20]. Also, it achieves high accurate rate in sensor signal recognition for daily sports activity, [21].

In our previous work [8], we adopted deep CNN for recognizing gender from infrared thermal images. Experiments concludes that adding new layers makes the back-propagation steps become difficult, but it is necessary for big databases.

3. Proposed System

In this paper, we propose a deep learning system for analyzing masked facial RGB images. It consists of three phases. Phase I recognizes gender, phase II identifies eye color, and phase III predicts skin color. We concentrated on extracting features from the upper part of a given face. The proposal aims to operate dynamically on the Cloud for any picked picture during surveillance monitoring. Therefore, it additionally considers having pictures with unmasked faces. Viola-Jones algorithm has been modified to extract eyes and forehead region from masked/unmasked faces.

3.1 Phase I: Gender

Phase I adapts our model presented in [8]. The proposed ResNet model consisted of 50 layers. Every layer contains two convolution filters stacked together. Then, after two layers a skipping connection is added. Moreover, we have added a max pooling in first layer and an average pooling in last layer. Yet, fully connected network is applied at the end of layers.

This model has been implemented with different number of layers, for RGB images. All versions compress several primary layers that are labeled by convolution layers, batch normalization layer, and rectified linear unit layer. They are differentiated according to a specified number, as listed in Table 1.

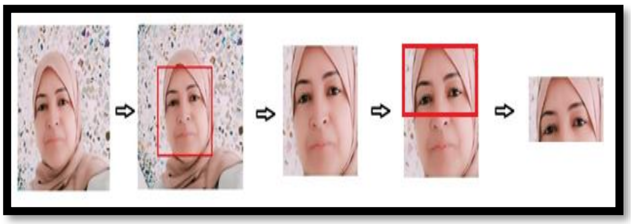
The input is an RGB image resulted after preprocessing and excluding only the region of eyes and forehead from faces. The output of the final fully connected stage is two primary binary outputs to classify the person gender as Man (M) or Woman (W).

Table 1 Types of Residual Networks

Layer Name	**Output Size**	**50-Layer**	**101-Layer**
Conv1	112 x 112	7 x 7 , 64 , stride 2	
Conv2-x	56 x 56	$\begin{bmatrix} 1\text{ x }1 , 64 \\ 3\text{ x }3 , 64 \\ 1\text{ x }1 , 256 \end{bmatrix}$	$\begin{bmatrix} 1\text{ x }1 , 64 \\ 3\text{ x }3 , 64 \\ 1\text{ x }1 , 256 \end{bmatrix}$
Conv3-x	28 x 28	$\begin{bmatrix} 1\text{ x }1 , 128 \\ 3\text{ x }3 , 128 \\ 1\text{ x }1 , 512 \end{bmatrix}$	$\begin{bmatrix} 1\text{ x }1 , 128 \\ 3\text{ x }3 , 128 \\ 1\text{ x }1 , 512 \end{bmatrix}$
Conv4-x	14 x 14	$\begin{bmatrix} 1\text{ x }1 , 256 \\ 3\text{ x }3 , 256 \\ 1\text{ x }1 , 1024 \end{bmatrix}$	$\begin{bmatrix} 1\text{ x }1 , 256 \\ 3\text{ x }3 , 256 \\ 1\text{ x }1 , 1024 \end{bmatrix}$
Conv5-x	7 x 7	$\begin{bmatrix} 1\text{ x }1 , 512 \\ 3\text{ x }3 , 512 \\ 1\text{ x }1 , 2048 \end{bmatrix}$	$\begin{bmatrix} 1\text{ x }1 , 512 \\ 3\text{ x }3 , 512 \\ 1\text{ x }1 , 2048 \end{bmatrix}$
	1 x 1	Average pool, 1000-d fc, softmax	
FLOPS		3.8×10^9	7.6×10^9

In preprocessing, if the input includes a masked face, we explore that it is sufficient to crop unmasked part directly, like example in Figure 3(a). Otherwise, the proposal first detects the face then apply cropping, such as in Figure 3(b).

(a)



(b)

Fig. 3 Results of detecting eyes and forehead region

3.2 Phase II: Skin

To detect Human's skin, we must recognize appropriate regions and skin-colored pixels in an input image. Skin color is usually exercised in human skin detection because it has rapid processing and doesn't change to orientation or size, [22, 23]. Although there are variant statistics of colors, but they are not accurate enough.

Based on our experiments, new classification for human skin detection is suggested in this paper. We have categorized skin colors into five categories (*Dark*, *Brown*, *Medium*, *Fair*, *Light*) illustrated in Figure 4. The main parameters used to recognize a skin pixel are Red, Green, and Blue (RGB). Using color harmony program, the result of classification is based on Table 2.

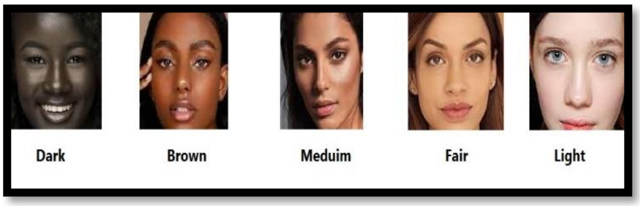


Fig. 4 Skin Color Degrees

Table 2 Classification of Skin color

Skin	Red	Green	Blue
Dark	0 - 158	0 - 102	0 - 88
Brown	135 - 172	94 - 120	35 - 80
Medium	132 - 162	90 - 138	81 - 135
Fair	163 - 210	80 - 195	50 - 199
Light	210 - 255	109 - 255	75 - 255

3.3 Phase III: Eyes

Despite of the clearness of eyes color, it was difficult to be determined exactly because each color has many degrees. Studies emphasized that the detection of eyes colors is very critical, since this region is small (approximately 11 mm) and it is very sensitive toward illumination, [24, 25].

Figure 5 shows samples of citizens of different nationalities augmenting studied eye colors in this research. Table 3 categorizes these color degrees according to the proposed ranges. We have deduced these values upon results of practical tests.

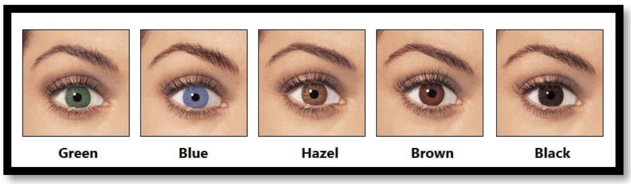


Fig. 5 Eyes color degrees

Table 3 Classification of eyes color

Eyes Color	Red	Green	Blue
Black	0-60	0-60	0-60
Brown	28-160	0-97	0-80
Hazel	84-218	45-154	0-81
Blue	0-150	0-175	80-255
Green	0-200	80-255	0-255

4. Experimental Results

In this work, we constructed a dataset from masked and unmasked facial RGB images, to assess the proposal. The dataset size was 13029 images, 9260 for Males and 3769 for Females, collected from different resources. One resource is the Caltech 101 dataset [26], the other is the CelebFaces Attributes (CelebA) dataset [27], in addition to Internet public photos of celebrities, and images of authors' acquaintances. For each image, we extracted the acquired region (as shown in Figure 3) and labeled it. Then, all images were resized, and their pixel value was normalized to [0, 255].

The RGB_ResNet network models for proposed system were implemented, using online Python Version 3.8.15 (default, 12 Oct. 2022) [GCC 7.5.0], on Google Colab Pro, then trained. 10% of the dataset images were excluded for the recognition phase, and the rest of the images were divided into 40% for training and 60% for testing. The training time of these models were recorded for each one separately. Resnet50 expended 28000 seconds, where Resnet 101 exhausted 31000 seconds.

Figure 6 shows the accuracy and loss for both networks during Epoch. It is worse mentioning that enlarging the size of the training data did not enhance the accuracy of the proposed model further.

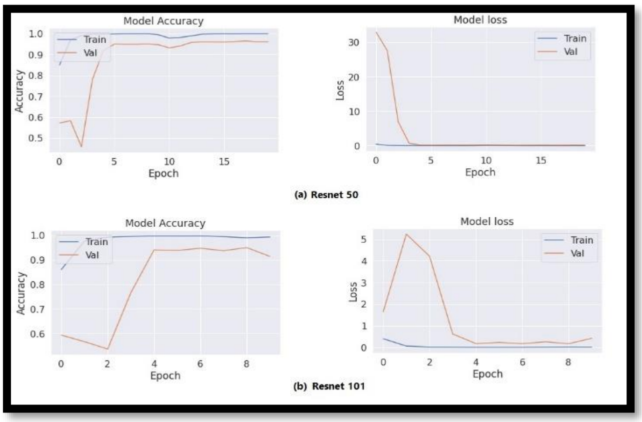


Fig. 6 Accuracy and loss for the networks

Furthermore, four other classification performance metrics labeled precision rate (P), recall rate (R), F1-score (F), and overall accuracy (A), have been applied. They are evaluated from the resulted confusion matrix recording true positives (*T_P*), false positives (*F_P*), false negatives (*F_N*) and true negatives (*T_N*), by the formulas:

$$P = \frac{T\_P}{T\_P + F\_P} \quad (1)$$

$$R = \frac{T\_P}{T\_P+F\_N} \quad (2)$$

$$F = 2\left(\frac{P.R}{P + R}\right) \quad (3)$$

$$A = \frac{T\_P+T\_N}{T\_P+F\_P+T\_N+F\_N} \quad (4)$$

Table 4 below, presents the results of these metrics using RGB_ResNet 50, and 101, respectively. For comparison, the table also includes computed values of experimenting our previous model [8] (implemented using MATLAB 2020) on the new RGB dataset. In addition, performance ratios of other experiments for other researchers are summarized in Table 5, against the average discrimination rate (ADR) of our gender classifiers.

For eye color and skin color, the system has recognized them 100% correctly. Bright eye colors were rear. The large percentage of humans' eyes were in range of *Brown* to *Black*. Likewise, the highest ratios of skin color were *Fair* and *Medium*. These results match real-world genetic factors affection.

Table 4 Performance measures of proposed Network with our previous research

Networks / Training Model	Resnet 50				Resnet 101			
	P	R	F	A	P	R	F	A
[8]	83.8%	93%	88%	87.6%	84.9%	91.5%	88.08%	87.6%
Proposal	94.9%	92%	93%	94.6%	96.2%	93%	94.6%	95.6%

5. Conclusion

In this paper, a masked face analysis system has been proposed to classify gender, eyes, and skin. Two deep residual network models with different numbers of layers (50 and 101) have been implemented using Cloud. These models differ in the number of convolutional filters. A new database has been built up and utilized to train the models. Both models have shown the best gender classification ADR (100%), for the dataset of size 13029. Resnet 101 accomplishes precision rate (96.2%), recall rate (93%), F1-score (84.6%), and overall accuracy (95.6%). Although there are improvements in performance metrics of Resnet 101 than Resnet 50. These improvements are small compared with the time needed to train and validates, but it is necessary to use more layers when the data are huge. As well, the system classifies the eye and skin colors with 100% precision. We concluded that the number of data must be commensurate with the type of network. Furthermore, the color of Arabs' eyes and skin are very alike, but they can be easily differentiated from Americans, European and Caucasian people. The system performance promotes its adaptation for person identification, in the future, to be employed in security and surveillance applications.

Table 5 Performance measures of proposal with previous work

Ref	Method	Metrics Ratio %		Photo Type	Region
[5]	VGG19	A: 94.02		RGB	Face & body
	Resnet50	A: 94.91			
	Resnet101	A: 93.88			
[6]	Custom CNN	A: 0.94	A: 0.95	Gray / RGB	Face
	GoogleNet	A: 0.95	A: 0.96		
	AlexNet	A: 0.89	A: 0.90		
[12]	2 Proposel CNN	A: 99.5		RGB	Face
		A: 85.13			

[14]	CBAM_Reduction	LFW_m: 99.08 CF_m: 96.78 MFR2: 98.00	RGB	Masked Face
	CBAM_All	LFW_m: 99.18 CF_m: 97.17 MFR2: 98.00		
	Att-Inception	LFW_m: 99.33 CF_m: 97.03 MFR2: 98.50		
[8]	Resnet50	ADR: 97	IRT	Face
	Resnet101	ADR: 98		
Proposal	Resnet50	ADR: 100	RGB	Masked Face
	Resnet101	ADR: 100		

Author contributions

Alyaa Jalil: Software, Field study, Writing-Reviewing and Editing, Data curation, Writing-Original draft preparation, Validation, Visualization, Investigation **Essam El-Seidy** : Field study**,** Writing-Reviewing and Editing **Sameh Daoud:** Conceptualization**,** Methodology**,** Field study**,** Writing-Reviewing and Editing **Naglaa M. Reda:** Methodology**,** Data curation, Writing-Reviewing and Editing, Validation., Field study, Visualization, Investigation.

Conflicts of interest

The authors declare no conflicts of interest.

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