Mask Scan Entry System

Atish Peshattiwar[1], Saloni Paunikar[2], Radhika Meshram[3],

Shivam Mohta[4], Shrirang Joshi[5] Somesh Viswakarma[6]

[1]*Electronicss&Yeshwantrao chavan college of Engineering*
[2]*Electronicss&Yeshwantrao chavan college of Engineering*
[3]*Electronicss&Yeshwantrao chavan college of Engineering*
[4]*Electronicss&Yeshwantrao chavan college of Engineering*
[5]*Electronicss&Yeshwantrao chavan college of Engineering*
[6]*Electronicss&Yeshwantrao chavan college of Engineering*

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Abstract - Rapid worldwide spread of Coronavirus Disease 2019 (COVID-19) has resulted in a global pandemic. Correct facemask-wearing is valuable in infectious disease control, but the effectiveness of facemasks has been diminished mostly due to improper wearing. However, there have not been any published reports on the automatic identification of facemask wearing conditions. In this study, we developed a new facemask-wearing condition identification method in combination with image super-resolution with classification network (SRCNet), which quantified a three categories classification problem based on unconstrained 2D facial image images. The proposed algorithm contained four main steps: image pre-processing, face detection and crop, image super-resolution, and facemask wearing conditions identification. Our method was trained and evaluated on public dataset Medical Masks Dataset containing 100 images with 67 images of no facemask-wearing, 34 images of incorrect facemask-wearing, and 30 images of correct facemask-wearing. Finally, the proposed SRCNet achieved 98.70% accuracy and outperformed traditional endto-end image classification methods using deep learning without image super-resolution by over 1.5% in kappa. Our findings indicate that the proposed SRCNet could achieve high accuracy identification in facemask-wearing conditions, which have potential application in epidemic prevention involving COVID-19. Keywords: automatic identication, facemask, condition identication method, image super resolution with classication network, SRCNet

.***Key Words***: facial recognition; convolutional neural network; image super-resolution; facemask-wearing condition; deep learning; SRCNet; COVID-19

1.INTRODUCTION

The spread of COVID-19 Pandemic Disease has created a most crucial global health crisis of the planet. In December, 2019, Wuhan, Hubei province, China, became the center of a pandemic of pneumonia of unknown cause, which raised intense attention in China as well as internationally [1]. Deadly coronaviruses have previously induced respiratory infections especially Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS). The prevalent symptoms of COVID - 19 are fever, tiredness, dry cough, anosmia, sore throat, headache, etc. Its arrival has stopped the world due to its severity and adverse effects on humans. For a person having mild symptoms, it takes a fort-night for getting recovered. The recovery period for patients having critical symptoms depends on the severity. It is advisable for a person to stay quarantined or to be in self-isolation if affected by coronavirus. Reverse transcription-polymerase chain reaction (RTPCR) is a standard method that is currently being implemented to detect the presence of the virus in an individual's body. Putting on a face mask can restrict the spread of the virus. In many cases, coronavirus can be asymptomatic too. Wearing face masks and following safe social distancing are two of the improved safety protocols got to be followed publicly places so as to stop the spread of the virus. Till now there is no clinically approved antiviral medicine and no specific vaccines that are effective against COVID-19. Everyone must be aware of the challenges and concern that are brought by this pandemic to our world. Every effort should incline to know and control the disease, and therefore the time to act is now. Therefore, face mask detection has become an important computer vision task to assist the society. This paper describes approach to stop the spread of the pandemic by monitoring in real time if person is wearing face masks in public places. WHO stresses on prioritizing medical masks and respirators for health care assistants.

2. Body of Paper

Figure 1 offers the diagram of the proposed algorithm, which contains three main steps: Image pre-processing, facial detection and cropping, and SRCNet for SR and facemask-wearing condition identification. After the pre-processing of raw images, all facial areas of images are detected using a multitask cascaded convolutional neural network [12]. The facial areas are then cropped, where the sizes of the cropped images vary. All cropped images are then sent to SRCNet for facemask-wearing condition identification. In SRCNet, all images are judged for the need of SR. As the size of the input images for the facemask-wearing condition identification network is 224 × 224, cropped images with a size no larger than 150 × 150 (i.e., width or length no more than 150) are sent to the SR network, and then for facemask-wearing condition identification. Otherwise, the cropped images are then directly sent for facemask-wearing condition identification. The output is the probabilities of the input images with respect to the three categories: NFW, IFW, and CFW. After passing through the classifier, the pipeline outputs the final facemask-wearing condition results.

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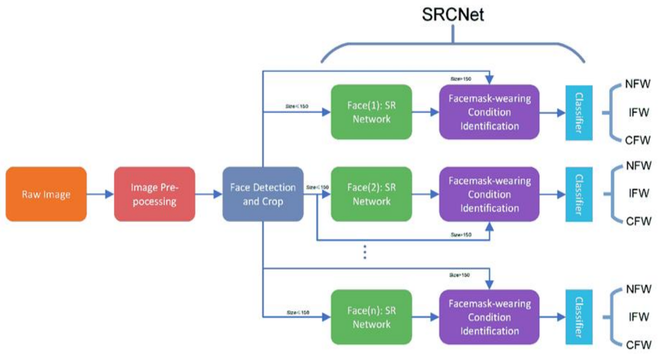

Figure 1. Diagram of the proposed algorithm.

Image Pre-processing

The goal of image pre-processing was to improve the accuracy in following face detection and facemask-wearing condition identification. The SRCNet was designed to be applied in public for classification, which took uncontrolled 2D RGB images as input. As the raw images taken in real life had a considerable variance in exposure and contrast, image pre-processing was needed for the accuracy of face detection and facemask-wearing condition identification. The raw images were adjusted using MATLAB image processing toolbox by mapping the values of the input intensity image to the new value, in which 1% of the values were saturated at low and high intensities of the input data.

Face Detection and Crop

As the SRCNet need to concentrate on the information from faces rather than the background to improve accuracy, a face detector was needed for the detection of faces and crop face areas. The uncontrolled 2D images had differences in face size, expression, and background. Hence a robust and high accurate face detector was needed. The multitask cascaded convolutional neural network was adopted for face detection, which performed well in getting face areas in real environments. After getting the position of the face, the faces were then cropped from the pre-processed image as the inputs of SR network or facemask-wearing condition identification network depend on image sizes**.**

SR Network

The first stage of SRCNet was SR network. The cropped face images had a huge variance in size, which could possibly damage the final identification accuracy of SRCNet. Hence, SR was applied before classification. The structure of SR network was inspired by RED14, which used convolutional layers as auto-encoder and deconvolutional layers for image up-sample. The symmetric skip connections were also applied for preservative of image details. The detailed architectural information of SR network was shown in Fig. 2.

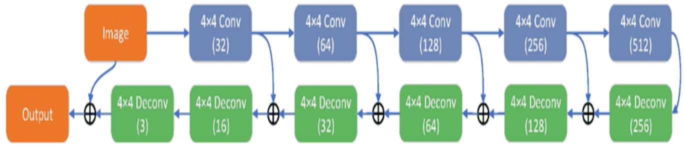

Figure 2. Structure of SR Network.

Training Details The training of SRCNet contained two main steps: SR network training and facemask-wearing condition identification network training. The first step of facemask wearing condition identification network training was initialization. The network was trained using the ImageNet dataset, with the training parameters proposed in . The second step was to form a general facial recognition model. The output classes were modified to match with the class numbers (10,562). For initialization, the weight and bias in the final modified fully connected layer were initialized using a normal distribution with 0 mean and 0.01 standard deviation. The network was trained for 50 epochs, with the training data set shuffled in every epoch. To increase the training speed, the learning rate drop was 0.9 for every 6 epochs with an initial learning rate of 10−4, which eliminated the problem of the loss becoming stable. The network was trained using Adam as the optimizer, with $\beta1 = 0.8$, $\beta2 = 0.998$, = 10−8, and 10−4 weight decay for L2 regularization, in order to avoid overfitting . Data augmentation can reduce the overfitting problem and contribute to the final accuracy of the network . To train the general facial recognition network, the training dataset was randomly rotated in a range of 10◦ (in a normal distribution), shifted vertically and horizontally in a range of Sensors 2020, 20, 5236 11 of 238 pixels, and horizontally flipped in every epoch. During the fine-tuning stage, the augmentation was mild, with rotation within 6◦ (in normal distribution), shifting by up to 4 pixels (vertically and horizontally), and with a random horizontal flip in every epoch. SRCNet was implemented by MATLAB with the deep learning and image processing Toolboxes for network training and image processing. A single Nvidia graphics processing unit (GPU) with the Nvidia CUDA deep neural network library (cuDNN) and compute unified device architecture (CUDA) was applied to implement SRCNet. Experiment Results For SR networks, the most widely used full-reference quality metrics are peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) . The PSNR was used as the metric for quantitatively evaluating image restoration quality, while SSIM compared local patterns of pixel intensities for luminance and contrast.Comparisons with previous state-of-the-art methods, including RED , SRCNN , VDSR, Lanczos , and bicubic, were made to illustrate the performance of the proposed SR network. For testing with different kernel sizes of Gaussian filters, the testing set was first filtered with Gaussian filters with kernel sizes of 3 × 3, 5 × 5, 7 × 7, and 9 × 9, and a standard deviation of 10, then downsampled to 112 × 112 for evaluation. For testing with different image resolutions, the testing set was first filtered with a Gaussian filter with a kernel size of 5 × 5 and a standard deviation of 10, then down-sampled to 64 × 64, 96 × 96, 112 × 112, and 150 × 150 for evaluation. The sizes of input images were the same as the outputs of the SR network. For evaluation of the effect of the SR network on the facemask-wearing condition identification network, which takes 224 × 224 images as input, all down-sampled testing sets were up-sampled to 224 × 224 as the input of the SR network. The evaluation results are shown in Tables 2–4. Compared to previous state-of-the-art methods, the proposed SR network performed better, especially in terms of SSIM.

Down Sample	Proposed SR network	RED	SRCNN	Bicubic
64×64	25.7461	25.7343	25.9489	27.1157
96×96	27.6264	27.6412	27.8157	27.4728
112×112	29.1508	28.8447	28.1890	27.4700

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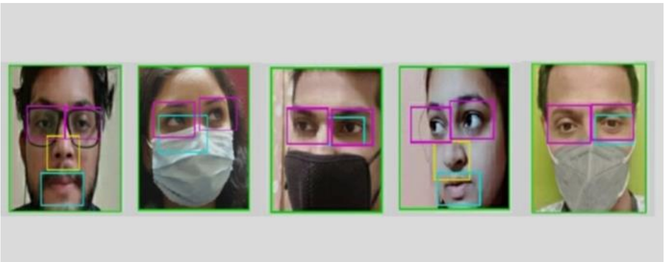
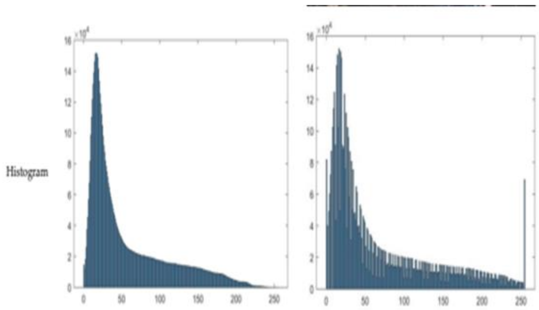
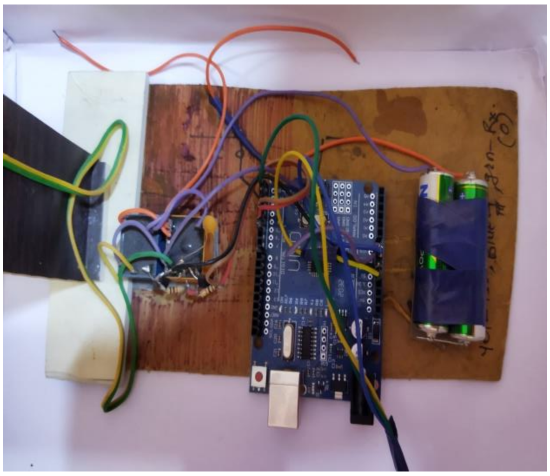


Fig -1: Results



3. CONCLUSIONS

The new facemask-wearing condition identification method was proposed, which combines an SR network with a classification network (SRCNet) for facial image classification. To identify facemask-wearing condition, the input images were processed with image pre-processing, -facial detection and cropping, SR, and facemask-wearing condition identification. Finally, SRCNet achieved a 98.70% accuracy and outperformed traditional end-to-end image classification methods by over 1.5% in kappa. Our findings indicate that the proposed SRCNet can achieve high accuracy in facemask-wearing condition identification, which is meaningful for the prevention of epidemic diseases including COVID-19 in public. There are a few limitations to our study. Firstly, the Medical Masks Dataset we used for facemask-wearing condition identification is relatively small, where it cannot cover all postures or environments. In addition, the dataset does not contain video, where the identification result on a video stream cannot be tested. As for the proposed algorithm, the identification time for a single image is a little long, where an average of 10 images can be identified in a second, which does not meet the basic video frame rate of 24 frames per second (fps). In future studies, a more extensive facemask-wearing data set including images and videos will be collected and labelled with more details, in order to improve the performance of SRCNet. The data set shall contain faces with different postures, environments, and lighting conditions. In addition, SRCNet will be improved, based on either single image or video with IoT technologies, and a more efficient and accurate algorithm will be explored, which can contribute to the practical application of identifying facemask-wearing condition.



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