Facial Mask Detection Using Boosted CNN in Smart City Network

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Abstract

This research the establishment of a "Safety system for mask detection during the current COVID-19 pandemic." Since the extraordinary COVID-19 global epidemic, which has mandated the wearing of masks in public places, face mask detection has experienced tremendous advancement in the fields of computer vision and deep learning, among other areas of research. For this reason, machine-learning experts have developed a number of methods and strategies for identifying unmasked individuals utilising a variety of mask detection models in order to combat the scenario. In order to offer Facial Mask Detection Using Boosted CNN in Smart City Network in Smart City Network Several existing technologies, such as face detection, biometric authentication, and facial expression detection, can be integrated into this user-friendly architecture to enable additional developments in the future.

Keywords

Facial Mask Detection , CNN , COVID-19.

Introduction

In the discipline of biometrics, facial modelling and analysis has always been a significant area of investigation[1]. Recent years have seen a rapid increase in the development of related study areas such as face detection, face recognition, facial attribute classification, head pose classification or estimate, among others. However, for several types of research, the use of high-quality photographs is an obligatory requirement[2]. As a result, facial photos with a tiny amount of head deflection tend to be more popular than others. The purpose of this paper is to investigate the topic of head posture categorization, which has the potential to improve the performance of many algorithms that deal with faces. Furthermore, this discovery has significant implications for a wide range of applications, including human attention monitoring, driver tiredness monitoring, and interaction-based face liveness identification, among others. In 2020, the COVID-19[3] virus will have spread over the world [4], and it can be propagated by contact]. As a result, identity authentication systems that rely on passwords or fingerprints are dangerous. During the COVID-19 coronavirus epidemic,[5] the vast majority of people are required to wear a mask. As a result, the performance of numerous algorithms that deal with faces is being tested. These algorithms must be improved in order to be effective in solving the challenge. As a result, the classification problem for head poses examined in this study is for people who are wearing masks. Despite the fact that the approaches described above have yielded positive results in head position categorization, every performance is negatively impacted when photographs of the face are taken while wearing a mask. This is due to the fact that masks obscure a great deal of information from the face. Furthermore, in order to obtain reliable results from the algorithm of head posture categorization, sufficient information must be provided[6]. Pose estimation and facial landmark detection, in particular, require clear and high-quality face photos taken without the use of a mask. In order to solve the problem of head position categorization with masks, we pay close attention to the colour texture of the images. Our attention is drawn to the parts of the face that contain information that is useful for determining head position classification. As an added bonus, our method does not rely on facial landmark detection and instead extracts features using CNN.

Related work

G. H. Minariet al.[7] The goal of this research was to design a system that could detect anomalies in images recorded on a city street by surveillance video cameras. In order to find faces in pictures, we'll use the Mask R-CNN detection method. A binary mask is used to identify abnormalities in the individuals' behaviour. To minimise false positives, we utilised Facial Landmarks to make sure the system can distinguish individuals and authorised persons.

The study by I. M. Revina et al. [8] The facial expressions required to teach expressions including disgust, melancholy, a grin, and surprise are trained using the Convolutional Neural Network (CNN). On the CNN channel, you will see four types of face expressions: disgust, grief, a grin, and astonishment. A considerable improvement to the accuracy of recognition is offered by the proposed technique. This technique is suited for any requirements that may develop in the future.

The researchers M. A. K. and colleagues conducted the research. [9] The Gabor wavelet and deep transfer learning were used to study face and veil recognition. Using Gabor wavelet features in addition to deep learning CNN features to provide a more robust feature vector that may help in recognising the face more accurately. In this case, it was proven to have an average recognition accuracy of 97 percent.

S. Ge et al.[10] By enhancing face movements and expressions, lost facial signals can be partially restored. Noise-induced facial cues can be considerably decreased as a result of this method. Finally, the Verification module is put in place to find face areas and refine their placements by using a unified CNN architecture, which simultaneously executes classification and regression processes in parallel.

P. Mittal et al. [11] This research aims to create an unique lightweight Convolutional Neural Network-based method for tackling this challenge. In contrast to other models that have been constructed in the past, the suggested model is slightly more accurate. This methodology also aims to provide a stable system that complies with COVID-19 requirements in the actual world.

This is written by R. B. Hadiprakoso et al. [12] This technique combines two modules: an eye-opening/lip movement analysis module (the blinking eye module) and a CCN classifier module (the CCN classifier module). Our CNN classification system is trained using datasets derived from openly accessible data. This face recognition programme was developed by assembling these two components sequentially and integrating them on the Android operating system. The module's capability to recognise various forms of face spoof assaults such as those carried out with posters, masks, or cellphonesis proven in the tests' findings.

Using binary image masks generated from the positions of facial landmarks, the work of S. Jaiswal et al. [13] describes a novel technique of storing form characteristics. Dynamic CNN features work effectively when representing temporal information when combined with Bi-directional Long Short-Term Memory.

Proposed Methodology

While it is known that handmade methods for spoof detection have excellent accuracy, theoretical studies have proven that using multilayer techniques for feature extraction is important for systems dealing with complex tasks such as photo analysis [14]. convolutional neural networks, or CNNs, are deep learning architectures that include several layers of neurons and use multiple filters (convolution and sampling) (initially two-dimensional images). At the top of neural networks, high-level and durable representations of the provided input signal are produced. We proposed a width-extended CNN (MCNN) in this article by using an algorithm inspired by [15] called PatchNet to a smaller CNN referred to as PatchNet. This is a simplified picture of PatchNet, shown in Fig. 2. On the bottom are two layers, with 5 5 and 2 2-sized kernels and strides of 1 and 2 pixels for convolution and pooling, respectively. In order to help interpret and draw general conclusions about the maximum values of the input feature maps, the pooling procedures sample their maximum values, along with an additional layer of 931 neurons with ReLU (Rectified Linear Unit) activations and a separate, higher-dimensional layer with 2 neurons are also present in the network's top. confronting the enemy Face recognition procedures are described here. Before an alert can be sent, preprocessing, face detection, and recognition are all necessary steps. If recognition determines that a face is present, an alarm is sent to the proper authorities.

Algorithm:

The first step 1 is to use the image database as the input to the system.

The Face detection algorithm in this step will inspect the video input.

Step 2: To find out who someone is or who is in a given image, look for a face or many faces using camera input, or find traits such as a nose, lips, and so on.

Step 3: After being shrunk in the previous step, the image obtained in this step will be outputted at a certain size. When lighting conditions are not adjustable, images feature uneven contrast with higher intensity levels concentrated in certain areas. The Histogram equalisation approach can equalise these levels.

Step 4: Next, we utilise feature extraction to extract certain useful features from the image, and then we use these features to create an image feature vector. We recommend that you utilise the Eigen face-based approach and the discrete cosine transform method in this stage.

Once the retrieved characteristics have been matched with the stored features in the datacenter, Step 5 can begin. In the event of a match, the code sequence 6 will be run. In Step 6, an alarm message will be issued to or the nearest police station or other concerned authorities if a match is identified in the previous step.

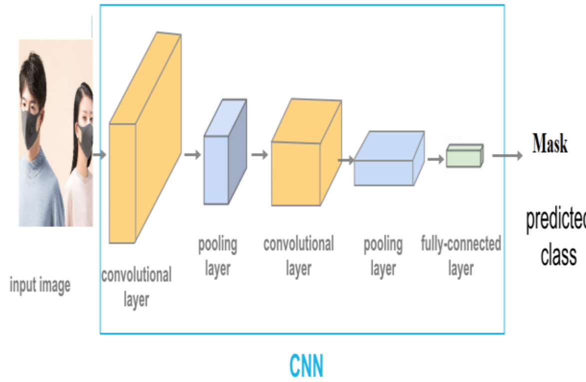

Figure 1: Modified CNN process for mask detection

Results analysis

To estimate the computational demands of the proposed mCNN in order to identify face spoofing, we compared its performance with two state-of-the-art CNNs: well-referenced face spoofing detection CNN Fine-Tuned[18] VGG-Face [19] and a recently proposed CNN[20] built on random patches, which has yet to be benchmarked. Instead of just telling you how long the CNNs on the input side of the face recognition performed each of the multiplication operations in the forward pass, we provide the multiplication operations required by the adopted CNNs in the forward pass of each face image (or patches). This parameter is unrelated to the hardware being used. To be an active learner and try new computer environments Python as well as the computing environment. A machine learning library has been implemented using Python in order to categorise facemask data. One of Jupiter's major purposes is for processing and storing databases. included the i3-2.8GHz CPU and 8GB of RAM used for Jupiter Notebook instals was utilised for implementing a python application. To meet these needs, a GPU will be utilised to swiftly manipulate and modify memory to fast alter pictures in a frame buffer to provide the desired output for a display device.

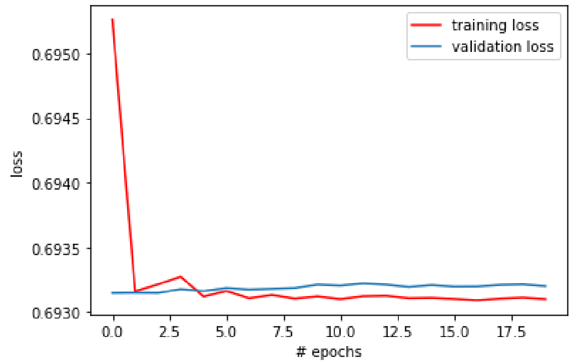

Figure 2: Training loss and validation loss

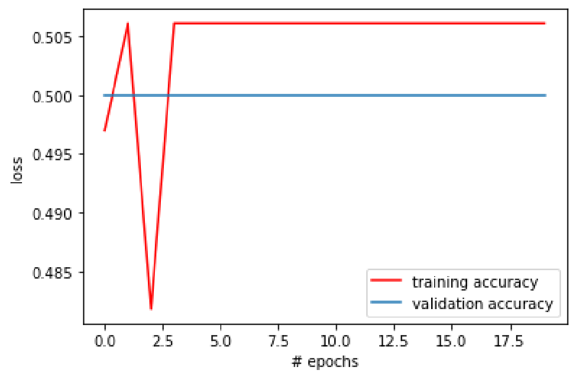

Figure 3: Training Accuracy and validation accuracy

Conclusion and Future Work

The suggested project assists in identifying criminals and retrieving people's faces, which are both found in the datacenter. The face information is provided to officials, who have access to the Database. It is also feasible to keep a suspect's face in the datacenter, and use it to search in public areas in the future for speedier trials. A unique application of the technique may be used to locate a missing individual. This approach can help in reducing the crime and easing the workload of police officers by helping to reduce societal imbalance. In light of the current Covid-19 issues, it is also done on the system when individuals are required to wear masks in public areas. In this area, encouraging results were reached as well. The system is now in place and has been thoroughly verified on campus. With cloud architecture, it will be possible to build a huge network of this system by linking multiple cameras to it and tracing criminals wherever and whenever. We aim to examine the CNN's capabilities in several picture domains, such as representations of textures for face spoofing detection in other colour spaces, and to determine the capability of learning local features for face spoofing detection in other colour spaces.

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