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Implementation of ai based protective mask detector

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ABSTRACT

The global impact of the corona virus disease is significant. Firmly stop the corona virus from spreading. A single-shot detector (SSD)-based object identification technique that focuses on accurate, real-time face mask detection in densely populated settings such as communities and workplaces where there are a lot of people is described. On the basis of two methodologies, we suggest a system in this project. Single-shot multi-box recognition, often known as SSD, is a technique for identifying people wearing face masks in an image in a single attempt. By removing the area recommendation network, which causes an accuracy loss, SSD is employed to accelerate the cycle. Implementing our application in closed-circuit television (CCTV) surveillance systems. It will identify who is wearing the mask and who is not by using mobilenetV2 and machine learning techniques. With the aid of the single shot detection technique, it can filter photographs on the spot and distinguish between them. The data collected during this process, such as image capture, is kept in the cloud to ensure that the application functions properly.

Keywords: *MobilenetV2, Single Shot Detection, Mask, Detection, Dataset, Virus, and Data Sets.*

1. INTRODUCTION

The newest virus that has swept the globe in only a few months is the coronavirus (COVID-19). The World Health Organization labeled this virus a global pandemic on March 11, 2020, although it first appeared at the beginning of December 2019 close to Wuhan City in Hubei Province, China (WHO). More than 2 million fatalities have been documented globally, and the World Health Organization estimates that many millions of individuals have been infected with the virus up to this point. Fever, a dry cough, and exhaustion are among the most typical symptoms of a coronavirus. Close physical contact with those who have been exposed to the virus through coughs, sneezes, or exhales makes it easy to spread. Throughout the world, the WHO had issued a state of emergency and programme for detecting face masks that can be utilized in a variety of settings, including business offices, malls, theatres, and other venues where there are plenty of people. We utilised the historical object detection model MobilenetV2 to create this application. We frequently use them. In the Kaggle face mask detection dataset, which is openly accessible.
A 224*224 pixel starting network resolution is used to train this model. Higher detection will be achieved with higher resolution. "Validating the usage and detection of the mask using machine learning" is used to determine whether or not someone is using a face mask. People who work in big groups, those who have moderate symptoms, and those who are caring for others who are ill have all been advised by medical professionals to wear masks. The system is tailored to MobilenetV2[6] technology, the Voila Jones algorithmic programme, and a Single-shot detection tool depending on the requirements in order to make our work easier. It may also determine what percentage of people are wearing masks and what percentage are not. The result produced by this model is accurate and cost-effective.

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The many methods used to create face detection and face recognition systems, as well as the use of face masks from various papers, will all be covered in this essay. This essay has been divided into several sections in order to examine the methods now in use and determine which strategy is practical and effective enough to apply to the situation of society today. The optimum methods will then be determined by taking into account the limitations and drawbacks of each approach. There are as many classes as candidates, and recognition must classify a particular face. Therefore, many face detection techniques and face recognition algorithms have many characteristics. Four categories are used to group methods. Since these categories may overlap, an algorithm may fall under two or more of them.

Knowledge-based methods

Approaches based on rules that encrypt our understanding of human faces. Methods with feature invariance. algorithms that search for a face's invariant features no matter the angle or position. The issue with this strategy is that it is challenging to transform human knowledge into clear rules. If these constraints are too severe, they can miss faces that don't fit the criteria. On the other side, if the guidelines are overly broad, there can be a lot of false positives. Methods for template matching These algorithms contrast the input photos with previously saved faces or feature patterns.

Appearance-based methods

A template matching technique that uses a learnt pattern database. By the end of 2020, the coronavirus disease 2019 (COVID-19) will have killed more than 1.7 million people, according to the World Health Organization (WHO) [1]. In the fight against COVID19, a number of computer-assisted strategies have been developed, including automatic detection of COVID-19 instances based on X-ray or pictures from computed tomography (CT) [2], [3], trend analysis of COVID-19 [4], and study of how people responded to COVID-19 [5]. However, it is more important than ever for people to take precautions against the COVID-19 virus. Thankfully, the study [6] showed that surgical face masks can aid in reducing coronavirus spread. The WHO currently advises using a face mask if you have respiratory symptoms or are taking care of someone who does [7]. Several public service providers also mandate that customers only utilise their services while donning masks [8].

Traditional object detectors are often constructed using manually created feature extractors. While earlier research used a number of feature extractors, including the histogram of oriented gradients (HOG), the scale-invariant feature transform (SIFT), and others [12], the Viola Jones detector used the Haar feature in conjunction with the integral picture approach [11].

Deep learning-based object detectors recently shown higher performance and have dominated the creation of new object detectors. Deep learning can learn the features from beginning to end without relying on existing information to build feature extractors [13]. One-stage and two-stage detectors are the two categories of deep learning-based object detectors. One-stage detectors, such as SSD and YOLO (you only look once) [14]. The benefit of SSD is that it uses multiscale feature maps to detect things. Contrarily, two-stage detectors, like region-based convolutional neural network (R-CNN) and faster R-CNN, used two networks to carry out a coarse-to-fine detection. A feature pyramid network (FPN) was utilised by RetinaFace [18], a specialised face mask detector, to combine high-level and low-level semantic information to improve detection efficiency. RetinaFace used a multi-scale detection architecture similar to SSD. Numerous methods were also developed to research face mask detection. The chronology shows that Retina Face Mask was this project's first iteration.

In numerous nations around the world since December 2019, the COVID-19 epidemic has had a long-lasting effect. It was developed in Wuhan, China. As of March 11, 2020, 114 countries were badly afflicted, according to the World Health Organization (WHO), which classified it as a fatal sickness that has spread over the world. To combat this dangerous disease, all medical professionals, healthcare organisations, medical practitioners, and researchers are working to develop the right vaccinations and medications (Megahed & Ghoneim, 2020). However, no significant advancements have been made to date. When a person with the virus sneezes, coughs, or speaks to another person, water droplets from their mouth or nose travel through the air and infect nearby individuals (Kumar et al., 2020).

Face with the Covid-19 outbreak forcing people to wear face masks, maintain social distance, and wash their hands with hand sanitizer, mask detection has become a popular application. Face mask detection has not yet received the attention it needs, despite other issues with social isolation and sanitization receiving attention up to this point. The most important precaution to do in situations when maintaining social distance is difficult is to wear a mask during this epidemic (Rahmani & Mirmahaleh, 2020).
It is imperative to use a mask, especially for those who are more likely to experience severe COVID-19 disease-related sickness. According to research, COVID-19 spreads most readily among individuals who are in close proximity to one another (within a distance of roughly 6 feet). People who are infected but do not exhibit any symptoms can also transfer the disease (Ge et al., 2020). As a result, the Centers for Disease Control and Prevention (CDC)1 advised everyone 2 years of age and older to wear a mask in

public, especially when other social distancing (Sun & Zhai, 2020) precautions are challenging to maintain. Thus, by lowering the possibility that an infected individual may pass this lethal virus to a healthy. A mask must be worn at all times, especially by those who are more susceptible to developing serious COVID-19 disease-related illnesses. It has been discovered that COVID-19 is primarily spread among those who are in close proximity to one another (almost 6 feet), and that it can also be disseminated by those who are infected but do not exhibit any symptoms (Ge et al., 2020). Therefore, the Centers for Disease Control and Prevention (CDC)1 advised everyone aged 2 and older to wear a mask in public, particularly when other social distancing (Sun & Zhai, 2020) strategies are challenging to maintain.

In the field of image processing and computer vision, face mask detection has shown to be an astounding challenge. Face detection can be used for a variety of purposes, from face identification to capturing facial gestures, the latter of which requires that the face be exposed with extreme precision. as a result of the quick advancement in the field of machines.

Existing system

Viola Jones Algorithm: The Viola Jones Algorithm, upon which the current method is based, is primarily unsuccessful when the image is turned upside down. We have included the detection of face masks in this study because masks are typically not the focal focus in techniques of identifying threats. Additionally, lightning conditions are not compatible with the current technology. The current approach employs computer-generated images to detect face masks, however it does so slowly. The detection of face masks may be flawed by data set problems in the current system.

2. PROPOSED SYSTEM

Single shot detection algorithm

Vector machines, one of the leading candidates, are supported by the suggested system. Additionally, the Viola-Jones algorithm is employed. This system employs Mobilenetv2 technology, which produces extremely high and precise face identification and filtering rates. Single-shot detection using SSD technology involves finishing the picture capture procedure in a single shot. It produces a successful method of taking pictures. It also consists of numerous intricate procedures, including face and feature extraction. Even with less effective webcams, we can complete all these intricate tasks. The logs of things can be quickly found. The rate of processing has increased. A high processing rate will produce an effective outcome.

Feasibility Study

To determine whether the project is feasible and to evaluate the advantages and disadvantages of the suggested system, a feasibility study is conducted. It is examined how well the use of masks in crowded places works. There are three ways to do the feasibility study.

Economic Feasibility

The proposed system does not require any high-cost equipment. This project can be developed within the available software.

Technical Feasibility

The suggested system is a machine learning model in its entirety. Visual studio, Kaggle data sets, Jupyter Notebook, and Anaconda prompt are the primary technologies utilized in this project. Moreover, Python is the language used to carry out the operation. The tools mentioned above can be used without cost and only require basic technological knowledge. We can infer from this that the project is technically possible.

Social Feasibility

The social feasibility of a proposal determines whether it will be accepted or not. There are no social difficulties with our project, and it is environmentally friendly. Instead of feeling frightened by the system, our project must recognise its necessity. Since everyone in the community may use our project to protect the environment and society, it is important. System acceptability is at a very high degree and is influenced by the methods used in the system. Our system is really accustomed to the culture.

3. LITERATURE SURVEY

Dr. Vandana S. Bhat, et al. Review on Literature Survey of Human Recog-nition with Face Mask,2021.

Face detection is a process with numerous uses, including position estimation, compression, and face tracking. Face detection is a two-class problem that requires us to determine whether or not a face is present in a photograph. This method can be thought of as a condensed version of the face recognition issue. Adaboost is an approach for creating a linear combination of a "strong" classifier. The machine learning algorithm Adaboost, often known as adaptive boosting, was developed. It is a meta algorithm that can enhance the performance of numerous other learning algorithms by working in tandem with them. Adaboost is adaptive in that it modifies newly constructed classifiers in favour of examples that were incorrectly classified by earlier classifiers. Adaboost is an approach for creating a linear combination of a "strong" classifier. The machine learning algorithm Adaboost, often known as adaptive boosting, was developed.

It is a meta-algorithm that can enhance the performance of numerous other learning algorithms by working in tandem with them. Adaboost is adaptive in that it modifies newly constructed classifiers in favour of examples that were incorrectly classified by earlier classifiers. Each round of a sequence of rounds is called by and a new weak classifier is generated by Adaboost. from a collection of training pictures. Both face detection and face localization can be accomplished with this technique. A typical face, such as frontal, might be utilised in this way.

Mingjie Jiang, et al. RETINAFACEMASK: A FACE MASK DETECTOR,8:

We developed a new dataset called MAsked FAces for Face Mask Detection by reannotating the existing Masked FAces (MAFA) dataset used for masked face analysis (MAFA-FMD). We suggested an unique context attention module that concentrate on learning discriminating features related with face mask wearing states (CAM). The module can focus on context features that are crucial for face mask wearing states and extract more useful context features from them. We employed transfer learning (TL) to transfer the knowledge learnt from face detection tasks, which was inspired by how humans improve their skills by utilising knowledge obtained from previous activities. Through experiments, we showed that face detection and face mask detection have a strong correlation, and the feature discovered during the former task is helpful for the latter. Studies on ablation demonstrated the usefulness of the CAM and TL because they can significantly increase the mean average precision (mAP).

ZhongyuanWang, etal.Maskedface Recognition Dataset and Application,2020:

Finally, three experts utilised LabelImg to re-label any new faces as well as manually update all reference box locations and class annotations. We recognised the following masks as genuine masks when recognising them: disposable medical masks, medical surgical masks, medical protective masks, dusk masks, gas masks, and respirators. Additionally, fabric masks were also accepted as legitimate options because the CDC (Centers for Disease Control and Prevention) also recommends them [22]. Some masks that don't fully encompass the mouth and nose have been ruled invalid. For instance, despite the fact that they resemble some types of masks, people who wear traditional Chinese veils were not deemed cases of mask wearers. The main distinctions between the MAFA-FMD and the original MAFA are enumerated.

The revised annotation covers three separate mask-wearing states: not wearing a mask, wearing a mask properly, and wearing a mask incorrectly. This is more accurate in terms of protecting the public's health. There are about 56,000 annotations in MAFA-FMD. MAFA-FMD has 56,084 annotated faces, which is roughly 16,000 more than MAFA, and 39,485 annotated faces altogether, which is what MAFA contains. Although MAFAFMD contains both masked and unmasked faces, MAFA does not annotate faces without any masks for face types. Additionally, the classification of mask types has been changed to include three categories: "no mask wearing," "proper masking wearing," and "incorrect mask wearing," with corresponding numbers of 26,463, 28,233, and 1,388 for each category. For this dataset collected in the field, the unbalanced label distribution demonstrates a long-tailed issue. Additionally, MAFA-FMD incorporates blurred faces that were absent from the original MAFA annotation. From roughly 1,000 in MAFA, there are now more low resolution (lower than 32 32 resolution) annotations. Various Face Mask Detection system [5]–[10] implementations appeared when the world began to take precautions against the Coronavirus. Along with the Masked Face Detection Dataset (MFDD) built-in data, which consists of 24,771 masked facial photos, Wang et al. [11] presented three different classifications of masked face datasets. The Simulated Masked Face Recognition Dataset (SMFRD) covers 500,000 facial photographs of 10,000 people while the Real-world Masked Face Recognition Dataset (RMFRD) has 5,000 images of 525 persons wearing masks and 90,000 images of the same 525 participants without masks. RMFRD is the most widely used masked face dataset in the modern era out of these, according to the best judgement of the researchers. A variety of applications using masked face photos can be created based on the fact that all such datasets are publicly available to academia and business. The proposed model for multigranular masked face image identification has a 95% accuracy rate, improving the results created by the industrial sector. For the identification of masked faces, Hariri et al. [12] proposed a quantization-based method and a deep learning strategy. The suggested technique might also be expanded to better application domains like video surveillance and the retrieval of violent footage. The first task, in the writers' opinion, was to take the mask off of the face. Afterward, use Pre-Trained Deep Convolutional Neural Nets (CNNs) to implement the chosen area's finest characteristics (mostly eyes and forehead area).

Preethi Nagrath, et al. A real time DNN-based face mask detection system using single shot multibox detector and MobileNetV2 ,2021:

This is a sizable real-world mask dataset, together with a no mask dataset and a "Stimulated Mask Face Recognition Dataset" (SMFRD). On earlier public face datasets in this collection, face masks have been used. Additionally, this library contains 500,000 facial photographs of 1000 different people. Shiming Ge et al. [12] introduced the MAFA dataset to address the face detection issue. The MAFA dataset includes more than 35,000 face-masked photos and over 36,000 online face images. Different levels of occlusion are present in the images in this collection, and masks and orientations have at least partially overfilled each face. LLE-CNNs feature three main modules that have also been shown to be effective for face mask identification. In the first module, two CNNs are combined and trained to combine facial features from input images with appropriate descriptors. These characteristics vectors are then transformed into matching-based attributes using the Local Linear Embedding (LLE) technique. To further identify the candidate's face areas using a single CNN, the verification module integrates classification and regression tasks. Surprisingly, the MAFA dataset performs at least 15.6% better than six other states using our suggested method. Jiankang Deng and others (9) RetinaFace is a single stage face detector that uses extra supervised and self-supervised multi-task learning while doing pixel-by-pixel face detection.

T.Poggio et al. A project for an intelligent system: Vision and Learning,vol.42, 2017:

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The geometric landmarks on the face were located using the anthropometric concept, and they evolved with age. Additionally, as variations in facial expression occur, the face muscles adapt. A successful method for facial ageing was presented after collecting human hair and taking into account all factors. The suggested methodology is sufficiently time-complex. Table 1 below contains a review of prior studies in the topic of face mask detection.

4. GENERAL ARCHITECTURE

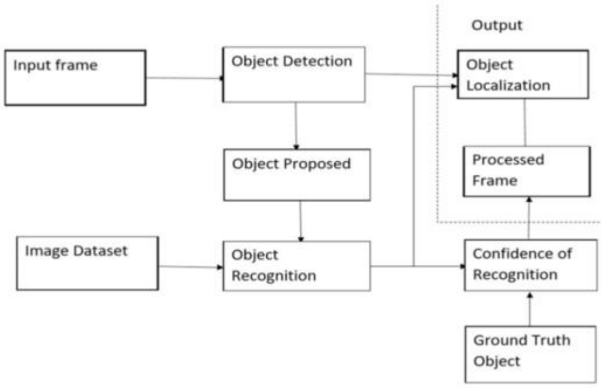


Figure 1. Object Detection Model

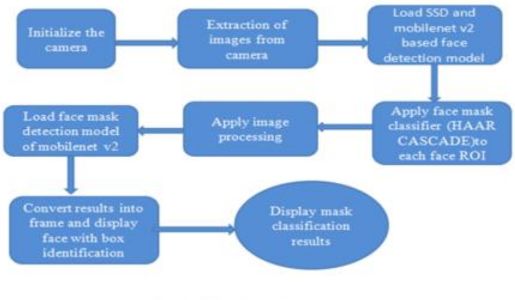


Figure 2. SSD Architecture Design

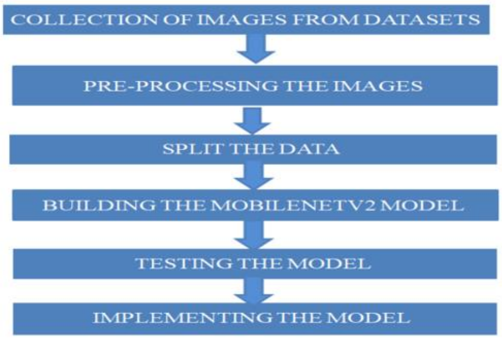
The project's architecture diagram is shown in Figure 2. First, the camera's input is used, and the algorithm is taught using sets of data that serve as training data. The photographs that were captured will be extracted using the camera's data. Following that, the photos are sent to the SSD model, and MobileNetV2 is added to the detection model. The image is then processed using image processing techniques, and whether or not the subject is wearing a mask is determined.

Design Phase

The flow of the processing methods used in the suggested model is represented by the design phase. The design process integrates all the steps into one and results in a desirable product.

Data Flow Diagram

The suggested system's flow diagram is shown in Figure 3. Data sets from Kaggle are utilized to compile information on those who wear masks and those who do not. As part of the preprocessing process, the image is resized to fit system requirements, pushed into the array, processed using the MobilenetV2 model, and hot encoded labels. To satisfy the model's requirements, the data is divided into two portions of 75% and 25%. 25% is allotted for testing the data, while 75% is allotted for training. The model is then built in the following stage, which is done by utilizing MBV2. Testing is carried out to see whether the project is viable. By combining all of these steps, the model is finally put into practice.



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Sequence Diagram

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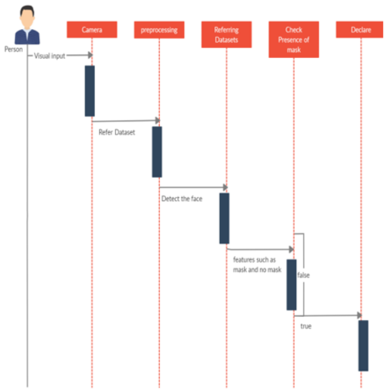

Figure 3. Sequence Diagram

Module Description

Data collection and training of data

Data Collection and training using Machine Learning Algorithms. Data collection consists of collecting samples of data sets and categorizing them as masked and unmasked.

Sample Dataset

Step:1 Data collection

Geometric factors that distinguish between the young and the old have been studied.

Step:2 Processing of data

The development of the Face Mask Recognition model begins with collecting is the data. The data set trains data on people who use masks and who do not.

Step:3 Segmentation the Data

Before preparing and testing the data, a pre-processing portion would show up. Four processes make up a pre-processing step: resizing the image's size, arrayizing it, utilising MobileNetV2 to pre-process data, and hot encoding labels.

Step:4 Building the Model

The model building process comes next. Building a model involves six steps: creating a training picture generator for augmentation, using MobileNetV2 as a base model, adding model parameters, collecting the model, coaching the model, and finally, saving the model for the long-term prediction technique.

Step:5 Testing the Model

There are procedures for testing the model to ensure that it can predict data accurately. Making predictions about the testing set is the first stage.

Step:6 Implementing the model

In the video, the model is upheld. The image pans from border to border.

5. CONCLUSIONS AND FUTURE WORKS

Conclusion

Therefore, we can stop the spread of the Corona virus in communities by validating the use and detection of masks using machine learning approaches. Both the training and testing datasets are correctly identified as being masked or unmasked in the proposed mask detection effort. Images are classified as having masked faces or having unmasked faces using the MobilenetV2 image classifiers. This is a crucial stage in the execution. The proposed model's accuracy was satisfactory, and it can be used at any time. The approach can be used to stop the transmission of viruses in any institution, including a school, office, mall, and densely inhabited places.

Future Work

Therefore, we can stop the spread of the Coronavirus in communities by validating the use and detection of masks using machine learning approaches. Both the training and testing datasets are correctly identified as being masked or unmasked in the proposed mask detection effort. Images are classified as having masked faces or having unmasked faces using the MobilenetV2 image classifiers. This is a crucial stage in the execution. The proposed model's accuracy was satisfactory, and it can be used at any time. The approach can be used to stop the transmission of viruses in any institution, including a school, office, mall, and densely inhabited places

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