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Submission date: 18-Jan-2024 12:02PM (UTC+0530)
Submission ID: 2273061006
File name: Crowd_Social_Distance_and_Mask_Detection_final_sonali.docx (411.33K)
Word count: 3874
Character count: 22097

Crowd Social Distance and Mask Detection using Classical Machine Learning

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***Abstract*—As long as the COVID-19 epidemic persists in endangering public health and safety, there is an urgent need for innovative solutions to mitigate the spread of the virus. In this research, we offer a computer vision-based method for identifying infractions of social distance and mask-wearing compliance in crowded public areas. The system uses a combination of deep learning algorithms and image processing techniques to analyse camera feeds and identify violations in real-time. We describe the architecture of the system, which includes a camera network, edge devices for image processing and analysis, and a central server for data management and reporting. We also evaluate the accuracy and efficiency of the system using a dataset of simulated crowd scenarios and real-world tests in public spaces.**

Keywords— COVID-19, Masked face, Deep learning, Classical machine learning algorithm

I. Introduction

Originating in Wuhan, China, the novel coronavirus strain known as SARS-CoV-2 quickly spreading over the world and the World Health Organization (WHO) formally proclaimed it to be a pandemic. This led to the development of the coronavirus disease (COVID-19). Since its onset, COVID-19 has been responsible for a staggering number of cases, with a recorded total of 220,563,227 positive cases and 4,565,483 deaths worldwide. While the introduction of vaccines initially brought some reassurance to populations worldwide, reports of COVID-19 infections among vaccinated individuals raised concerns and highlighted the importance of adhering to recommended measures, such as following WHO's SOPs, or standard operating procedures, call for the use of face masks. and practising social distancing. It is important to remember that face masks were frequently worn before this outbreak as a defense against air pollution, by hospital paramedics, as a way to hide their identity when committing many crimes etc. However, during the pandemic, everyone must wear a face mask in public places to stop COVID-19 from spreading. Although COVID-19 cases have come down now as of 2023 and people do not have much concern regarding it, it can still spread if precautions are not taken. Controlling COVID-19 distribution is currently a major concern for WHO policymakers and all of humanity. Using a face mask reduces the possibility that respiratory droplets carrying the virus will be shared, thereby slowing the transmission of COVID-19, according to most of the evidence from the WHO, analysis and study. Consequently, numerous countries have implemented mandatory face mask requirements in public settings as a precaution to stop the COVID-19 virus from spreading. Checking individuals manually for face masks in public spaces is difficult. As a result, automated methods for identifying face masks must be developed. To prevent the COVID-19 virus from spreading quickly throughout a community, governments must require people to wear face masks. However, wearing a face mask also poses additional problems for face recognition software that is generally made for faces that are not covered up. These facial recognition programs, which have been implemented at several checkpoints, function less well when masked faces are present because important facial features like the nose, lips, chin, cheeks, and so on are lost.

The challenges posed by face masks have resulted in significant obstacles for facial recognition technologies, particularly in applications that require verification or authentication. This includes mobile payments, public safety inspections, phone unlocking, attendance tracking, and more. For example, access gates at security checkpoints in public transportation hubs, such as train and bus terminals, commonly employ cameras depend on traditional facial recognition techniques, which are useless when people are hiding their faces using masks. Furthermore, because of the possibility of virus transmission among users, the COVID-19 pandemic has prohibited the adoption of conventional biometric-based systems like fingerprint and facial recognition.

In addressing this pandemic, automated user verification systems that are capable of identifying individuals wearing face masks have emerged as a potential solution. However, the existing facial recognition technologies face challenges in accurately recognizing masked faces, making them less reliable in this context. Although there have been some recent research on masked face recognition, this research problem remains largely unexplored and lacks comprehensive investigation. The limited availability of resources in this particular field could be a contributing factor to the scarcity of research in this area.

Indeed, while there are numerous large-scale and diverse facial recognition datasets available that focus on unmasked faces, the existence of widely used datasets specifically tailored for masked face recognition is limited. As far as we are aware, there isn't currently a lot of widely used datasets that specifically cater to the unique challenges and characteristics associated with masked face recognition. This absence of comprehensive datasets hampers the progress and development of effective masked face recognition systems.

The remainder of the report is organized as follows: Part II provides an overview of the related work. In Section III, we described the proposed effort and explained its justification. The specifics of our internal dataset and the outcomes of the experiments were covered in Section 4. Section 5 brings our discussion to a close.

II. RELATED WORK

The majority of publications center on the creation of faces and identifying identities when wearing face masks. In an attempt to stop the COVID-19 virus from spreading, our research aims to identify those who do not wear face masks. The slowdown of COVID-19 transmission has been proven by researchers and specialists when wearing a face mask. In [6], the authors devised a new method for identifying conditions when wearing a facemask. The use of facemasks could be divided into three categories. The three categories are proper facemask use, improper facemask use, and no facemask use. The phase of face detection accuracy of the proposed technique was 98.70%. Sabbir et al. [7] The author used both masked and unmasked facial images and Principal Component Analysis (PCA) to determine who was who. They found that the face resonance accuracy of the PCA was significantly impacted by mask usage. The identification accuracy drops to less than 70% if the identified face is obscured. In [8], Furthermore, PCA was used. The authors provided a way to eliminate a person's frontal facial see via their spectacles. PCA reconstruction and iterative error correction were used to rebuild the deleted area.

The authors in [9] employed the YOLOv3 algorithm to identify faces. The Darknet-53 of YOLOv3 is the base of it. The suggested strategy had a 93.9% accuracy rate. The WIDER FACE and CelebA datasets, which contain more than 600,000 images, were utilized for training. The FDDB dataset was tested. A unique GAN-based network was suggested by A model that can automatically eliminate face-obscuring masks and rebuild images by reassembling missing pixels was put forth by the author Nizam et al. [10]. The suggested model produces a representation of the entire face that appears realistic and natural .

In order to ascertain if a medical mask is required in the operating room, the authors of [11] offered an assessment method. The intention is to limit the target audience for warnings to medical staff members who undress by lowering the number of false positive facial detections while retaining the ability to identify masks. By following the suggested procedure, 95% of the data was correctly archived.

A multitude of operational challenges confront the deployment of masked facial recognition and mask detection systems in the COVID-19 era. Consequently, certain recent efforts in the domains of masked facial recognition and face mask detection have been particularly concentrated on surmounting these obstacles.

Three categories can be used to group the current research on face mask detection: hybrid techniques, deep learning (DL) based methods, and conventional machine learning (ML) methods. Hybrid approaches combine both deep learning and traditional machine learning techniques.

An overview of pertinent studies on deep learning-based human detection is given in this section. It also discusses the vast bulk of recent deep learning-based efforts in object recognition and categorization. The majority of the review's attention is given to recent advances in machine learning-based object recognition. In computer vision, the effort of locating and detecting human shapes in video imagery is referred to as "human detection," and it is analogous to "object detection." In artificial intelligence, deep learning has become a popular method for multiple-class item identification and tracking that produces outstanding results on difficult datasets. The state-of-the-art in human detection was thoroughly examined by Nguyen et al., taking into account current advancements and difficulties. Their survey focuses mostly on occlusion handling, real-time detection, machine learning techniques, and human descriptors. Deep neural networks with convolutions (CNNs) have demonstrated exceptional performance in visual recognition and have surpassed various image recognition benchmarks.

We propose a computer vision strategy to detect people using a camera placed at the roadside or in a workstation, building on the idea presented in reference [12]. Within a predetermined area, persons in motion are visible in camera's field of viewing. The number of persons in the pictures may be counted and create bounding boxes around them using well-established deep Convolutional Neural Network (CNN) algorithms, such the YOLO approach. Our application can determine if there is an acceptable social distance maintained between participants in the video by calculating the Euclidean distance between them and then displaying visual cues.

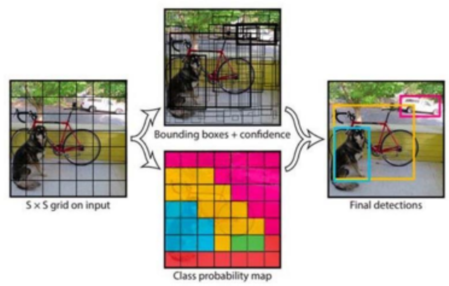

Fig. 1. Yolo Classification preview

III. METHODOLOGY Prepare Your Paper Before Styling

A. *Mask Detection*

1) *Data Collection*

The initial step in the methodology was to collect relevant data for the project. We collected a diverse dataset consisting of images of people from various sources, including public domains, surveillance cameras, and social media platforms. The dataset contains masked and without mask images of people, the dataset was curated to include people of different age groups, genders, and ethnicities.

2) *Data Preprocessing*

The collected dataset was pre-processed to enhance its quality and make it reliable for training the deep learning model. We performed image resizing, normalisation, and augmentation to ensure uniformity in the data. The images were also labelled based on the presence or absence of masks and the distance between people in the frame.

3) *Model Training*

The deep learning model was constructed using the Convolutional Neural Network (CNN) architecture. To speed up the training process, a GPU was used for efficiently training the model on the preprocessed dataset. There were two stages to the training process: the mask detection model was trained in the first phase, and the social distancing model was trained in the second.

4) Evaluation of Model

To evaluate the performance and accuracy of the trained model, a separate test dataset was used. The test dataset comprised images and videos of individuals collected from diverse sources, such as public domains, surveillance cameras, and social media platforms. A number of metrics, such as accuracy, precision, recall, and F1 score, were used to assess the model's effectiveness in face mask identification.

5) Model Deployment

To detect social distancing breaches and conceal non-compliance, the trained and assessed model was then implemented on a real-time system. The model was integrated with a camera-based system to provide real-time alerts to the authorities in case of any violations. The system was tested in various scenarios to ensure its effectiveness and accuracy.

B. CROWD SOCIAL DISTANCING

Using methods like deep CNN and computer vision, this tool was created to determine the proper spacing between people in public spaces. An open-source object identification network built on the YOLOv3 algorithm was initially used to detect pedestrians in video frames. The other object classes were ignored, with the exception of the pedestrian type. Consequently, each identified pedestrian had bounding boxes drawn around them, and distance was calculated using this information.

A fixed-angle camera was used for the camera configuration to capture the video frames. The perspective view of the video frames was altered to a two-dimensional top-down view in an effort to raise the distance measurement's accuracy. It is assumed by the approaches that the pedestrians in the video frames are moving on a single, level plane. To determine each pedestrian's approximate location, four locations on the captured plane were chosen and converted to a top-down image. A scale was used to account for the measured distance between pedestrians. If the distance between any two individuals fell below the predetermined minimum distance, red lines were displayed as precautionary warnings. The implementation of this tool was carried out using the Python programming language.

1) Data Collection and Preprocessing

The video data used in this research was collected from the specified source. The video frames were read using OpenCV's VideoCapture function, and each frame was resized to a width of 700 pixels to facilitate processing.

2) Person Detection

A pre-trained YOLO (You Only Look Once) object detection model was utilised to detect people within the video frames. The YOLO model was implemented using OpenCV and loaded with pre-trained weights trained on the COCO (Common Objects in Context) dataset. The YOLO model was configured with a confidence threshold of 0.3 to filter weak detections. The frames were processed through the YOLO model, which generated bounding box coordinates and associated confidences for each detected object. Only objects classified as "person" and surpassing the minimum confidence threshold were considered as valid detections.

3) Social Distance Computation

To determine social distancing violations, the centroids of the detected people were extracted from the YOLO results. Euclidean distances were computed between all pairs of centroids using the SciPy library. If the distance between any two centroid pairs was found to be less than the configured minimum safe distance (100 pixels), the centroid pair was considered a violation.

4) Visualization and Output

The violations were visualised by drawing bounding boxes around the detected people and annotating their centroid coordinates on the video frames. Violations were highlighted with a red colour, while non-violating people were marked with a green colour. The total number of social distancing violations was displayed on each frame. Additionally, the processed frames could be displayed in real-time or saved to an output video file, depending on the user's choice.

5) Parameter Configuration

Various parameters, such as the minimum confidence threshold for person detection (MIN_CONF), the non-maxima suppression threshold (NMS_THRESH), and the minimum safe distance (MIN_DISTANCE), were set based on experimentation and domain knowledge. These parameters were carefully selected to balance detection accuracy and computational efficiency.

IV. RESULTS AND DISCUSSION

In order to identify social distance violations and mask wear in crowds, we trained a traditional machine learning model in this work. Our dataset comprised 1376 photos of individuals wearing and not wearing masks. We used the Pascal VOC dataset from 2012 to train the crowd social distancing model. The hyperparameters of the model were optimized by grid search after it was trained using deep learning. Accuracy, precision, recall, confusion matrix, F1-score, and other metrics were used to assess the model's output.

A. Dataset Characteristics

The dataset used for evaluation of face masks consists of two distinct sets of images. The first set contains photos of individuals wearing masks, while the second set comprises photos of individuals without masks.

1) With mask:

There are a total of 690 images under the with mask folder.

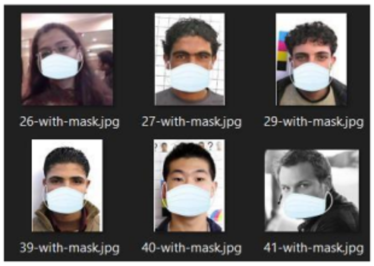

Fig. 2. Face mask dataset with mask

2) Without mask

There are a total of 686 images under the with mask folder

Fig. 3. Face mask dataset without mask

The model is trained on 80% of photos, with 20% of the images being used for testing.. The dataset used for the crowd social distancing model is Pascal VOC dataset 2012. For applications like image segmentation, object detection, localization, and more, this dataset is widely acknowledged as the industry standard.

To anticipate the label for every single pixel in a picture is the goal of image segmentation.

For object detection, the goal is to identify and specify the classes present in a given image. Additionally, bounding boxes can be used to encompass and define the location of each object within the image.

There are two folders, one for the validation and training sets, and another for the test set. Within the "train_val" directory, there is an "Image" folder that contains a text file representing the training and validation instances. Each image in the folder has class labels and object labels along with annotations. The labelled images have class labels assigned to each pixel.

The test set follows a similar structure. The predicted labels for the test set can be found in either the "SegmentationClass" or "SegmentationObject" folder, depending on the specific application you are working on.

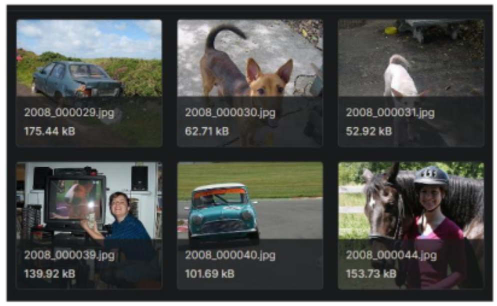

Fig. 4. Object detection dataset

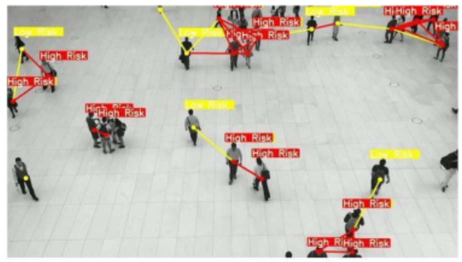

Fig. 5. Object detection Output 1

Fig. 6. Object detection Output 2

Real time Output:

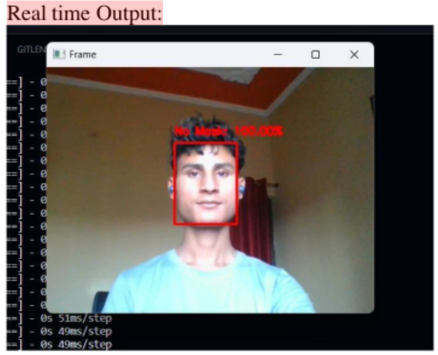

Fig. 7. Mask detection Output 1

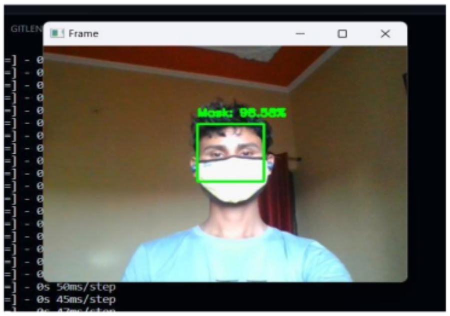

Fig. 8. Face mask detection Output 2

The results showed that our model received an accuracy of 0.99, recall of 00.1, & F1-score of 00.99 for detecting mask wearing.

Our study contributes to the growing literature on machine learning-based approaches to address the challenges posed by the COVID-19 pandemic. However, our study has several limitations, including the reliance on a single dataset and the need for further validation in real-world settings. Future research could explore the usage of deep learning approaches and the integration of real-time video analysis to improve the accuracy and usability of model.

Through conclusion, our work demonstrates the potential of classical machine learning models to detect social distance violations and mask wearing in crowds, which could have important implications for public health and safety.

V. CONCLUSION

Crowd social distancing and mask detection technologies have become effective instruments for promoting public health and safety during the COVID-19 pandemic. By leveraging computer vision and machine learning algorithms, these systems can automatically detect individuals who are not wearing masks or standing too close to one another, alerting authorities, and reminding people to comply with social distancing guidelines. While these technologies have their limitations, such as the risk of false positives and the potential for privacy violations, they represent an important step forward in our collective efforts to combat the spread of infectious diseases. As the pandemic continues to evolve and new challenges emerge, it is likely that crowd social distancing and mask detection technologies will play an increasingly vital role in ensuring public health and safety.

In conclusion, our "crowd social distancing and mask detection" project aimed to address the challenges of maintaining public health and safety during the COVID19 pandemic. By developing a computer vision-based system that can detect social distancing violations and mask-wearing compliance, we have demonstrated the potential of technology to assist in mitigating the spread of the virus in public spaces. Our project has several benefits, including the ability to monitor large crowds in real-time, increase awareness and adherence to public health guidelines, and alert authorities in case of any violations. With additional development and implementation, this technology may prove to be a valuable weapon in the battle against COVID-19 and other infectious illnesses.

Overall, we believe that our "crowd social distancing and mask detection" project has demonstrated the potential of computer vision and AI to contribute to public health and safety in a meaningful way. In addition to supporting ongoing efforts to stop the spread of COVID-19 as well as several viral illnesses, we hope that our work will stimulate more study and development in this field.

The future works include:

- Using public health database integration: In the future, our system could be integrated with public health databases to monitor the spread of infectious diseases in real-time. This would enable authorities to quickly respond to outbreaks and take proactive measures to prevent further transmission.

- Improved accuracy and precision: The advancement of computer vision and artificial intelligence technology holds promise for enhancing the precision and accuracy of our system. This could involve incorporating more advanced algorithms, improving the quality of cameras and sensors, and conducting more extensive testing and calibration.

- Multi-lingual support: To increase the accessibility and usefulness of our system, we could develop multi-lingual support. This would allow the system to recognize and respond to social distancing and mask-wearing violations in a variety of languages, which would be particularly useful in multicultural or multi-lingual settings.

- Expansion to other public spaces: The present version of our technology is intended for usage in public areas like malls and train stations. In the future, we could explore opportunities to expand our system to other types of public spaces, such as hospitals, schools, and airports.

- Integration with wearable technology: With the rise of wearable technology, there is potential to integrate our system with devices such as smart watches or fitness trackers. This could allow individuals to monitor their own social distancing and mask-wearing compliance, and receive real-time feedback on their behaviour.

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