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Real-time Mask Detector (Monitoring COVID-19)

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Abstract

This paper presents the development and implementation of a real-time mask detection system designed to monitor and enforce mask-wearing policies during the COVID-19 pandemic. Utilizing a convolutional neural network (CNN) and a dataset consisting of annotated images, our system can accurately detect the presence or absence of masks on individuals in various environments. The proposed system achieves high accuracy and can be deployed in public spaces to help mitigate the spread of COVID-19. Key results demonstrate the system's effectiveness in real-world scenarios, providing a valuable tool for public health monitoring. In order to protect public health and safety, the COVID-19 pandemic has brought attention to the necessity for creative technical solutions. One of the most important tools for ensuring mask compliance in public areas is the implementation of real-time mask detection systems. With an emphasis on their technological architecture, machine learning methods, and deployment in various contexts, this article investigates the creation and application of real-time mask detectors. We go over their effects on public health, how they integrate with surveillance and IoT systems, and issues like accuracy, privacy, and flexibility in a variety of settings. The results highlight the value of these technologies in halting the spread of viruses and their potential for wider use in pandemics in the future.

Keywords: COVID-19; deep learning; face detection; face mask detection; transfer learning

INTRODUCTION

The World Health Organization (WHO) proclaimed the coronavirus illness (COVID-19) a global pandemic in 2020 after it was initially discovered in 2019 [1]. Global public health has been significantly impacted by the pandemic. Close touch is how the disease spreads, especially in crowded settings. As a result, several nations have implemented laws requiring people to wear face masks in public places and to avoid social situations.

According to recommendations from the Centers for Disease Control and Prevention (CDC) and the World Health Organization, individuals older than two should wear a face mask in Before the COVID-19 pandemic, masks were worn to defend against air pollution and seasonal illnesses like influenza. Wearing a face mask lowers the rate of transmission and dissemination, particularly in situations where maintaining other social distancing measures [2] is challenging.

According to reports, COVID-19 infected about 116 million people in 188 countries. The coronavirus pandemic is posing unprecedented risks and challenges to people and governments in a number of nations. Laws in numerous nations require people to wear face masks when they are in public. These laws and regulations were created in response to the exponential rise in cases and fatalities in numerous nations. Authorities have

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conducted surveillance to make sure individuals are using face masks in congested public places, buildings, dining establishments, and retail centers. However, it has grown more difficult to track and measure people's body temperatures in public places.

By introducing a cutting-edge image processing mobile application architecture, this research seeks to revolutionize the way cities manage parking resources, ultimately, contributing to more sustainable and efficient urban mobility solutions. In order to prevent the spread of the SARS-CoV-2 virus that triggered the COVID-19 pandemic, non-pharmaceutical measures including wearing face masks had to be used. Governments and institutions found it increasingly difficult to enforce mask laws in public areas. An efficient remedy was found in real-time mask identification systems driven by computer vision and artificial intelligence (AI). These devices allow authorities to act promptly by identifying people wearing or not wearing masks using machine learning models. The development of real-time mask detection technology, its fundamental ideas, and its application to pandemic control are all covered in this review.

LITERATURE SURVEY

In the development of a real-time mask detection system for monitoring COVID-19 compliance, it is essential to understand the current state of research and existing technologies. This literature survey reviews recent advancements in face mask detection, machine learning algorithms, and related fields to provide a comprehensive background for our study.

For image identification tasks, deep learning—in particular, convolutional neural networks, or CNNs—has emerged as the most popular method. Alex Net (Krizhevsky et al., [3]) changed picture categorization by demonstrating the capability of deep CNNs. Since then, several architectures have been built that improve efficiency and performance, such as VGGNet (Simonyan and Zisserman, [4]), ResNet (He et al., [5]), and MobileNet (Howard et al., [6]).

Haar cascades, one of the first face detection techniques (Viola and Jones, [7]), employ a sequence of classifiers that have been trained on both positive and negative images. Despite being computationally efficient, it is not as accurate as more recent methods. *Deep learning-based detection:* Deep learning is used in contemporary face detection techniques. Compared to conventional techniques, the Multi-task Cascaded Convolutional Networks (MTCNN) (Zhang et al., [8]) provide better accuracy and robustness in real-time face and facial landmark detection.

Large, annotated datasets are essential for mask detection model evaluation and training. The Masked Faces (MAFA) dataset (Ge et al., [9]) contains images with diverse mask types and face orientations. More recently, datasets specifically curated for COVID-19, such as AIZOO's Face Mask Detection Dataset, have been utilized in numerous studies. *Custom datasets:* Some studies have compiled custom datasets to address specific challenges, such as images from CCTV footage, to improve the robustness of detection models in real-world scenarios (Chavda et al., [10]).

Standard metrics: Accuracy, precision, recall, and F1-score are standard metrics used to evaluate the performance of mask detection systems. These measurements offer a thorough understanding of how well a model detects mask compliance. *Real-time performance:* Latency and processing speed are critical for real-time applications. Studies often report the average time taken to process an image or video frame to assess the suitability of their models for deployment in dynamic environments.

Public spaces: Mask detection systems have been deployed in public spaces like airports, train stations, and shopping malls to ensure compliance with health regulations (Jiang et al., [11]).

Healthcare settings: In hospitals and clinics, these systems help monitor mask-wearing among staff and visitors, reducing the risk of viral transmission in vulnerable environments (Shin et al., [12]).

Integration with IoT: Combining mask detection systems with IoT devices enables real-time monitoring and data collection across multiple locations, facilitating large-scale enforcement of mask mandates (Liu et al., [13]).

The "You Only Look Once" (YOLO) architecture has been widely used due to its real-time detection capabilities. Loey et al. [14] implemented a YOLOv2-based model for mask detection, demonstrating high accuracy in various environmental conditions.

Hybrid models: To improve detection accuracy, recent research has investigated hybrid models. YOLOv3 and attention mechanisms were coupled by Wang et al [15] to enhance mask identification in a variety of illumination conditions and occlusions. Based on the dispersion and transmission of inhaled droplets, the social distance index Pd was created. [16] A new learning framework for training boosting cascade-based object detectors from massive datasets was introduced by Li and Zhang. Although the framework is based on the well-known Viola-Jones (VJ) paradigm, it differs in three significant ways. Initially, the suggested framework describes local patches using multi-dimensional SURF features rather than single-dimensional Haar features. By doing this, the quantity of local patches that are used can be decreased from hundreds of thousands to a few hundred. Second, rather than using decision trees like the VJ framework does, it uses logistic regression as a weak classifier for every local patch. Third, instead of using the two trade-off criteria (false-positive-rate and hit-rate) in the VJ framework, we use AUC as a single criterion for the convergence test during cascade training. [17] A technique for visual identification of objects based on an ensemble of optimized decision trees arranged in a cascade of rejectors was presented by Markus et al. [18]

PROPOSED METHODOLOGY

To identify someone who is not wearing a face mask or whose facial temperature is higher than 37.5°C, a real-time framework was suggested. The detecting person module in the suggested indoor monitoring system is always on standby and advances to the next module if the target monitored person walks within 60 cm of it.

Measuring skin temperature is frequently used to investigate how human physiology interacts with the environment. The skin temperature is exothermic since it is influenced by the surroundings and the "dual-thermic" thermoregulation ability, whereas the core temperature is endothermic and tightly controlled by the brain. Peripheral vasodilation during heat stress raises skin blood flow, which raises body warmth and dissipates heat.

Detecting of People using Ultrasonic Sensors

An ultrasonic sensor was employed in the suggested system to identify the individuals in front of it. Because of its great sensitivity and capacity to detect humans, the ultrasonic sensor can track a person's movement as well as its direction. When the system is not working, advertisements can be shown on the screen. When identifying humans, the ultrasonic sensor is employed to transition from the advertisement page to the measuring device.

Face Mask Detection

Before the model is developed from the provided sample, deep learning techniques extract several significant nonlinear features. Consequently, the deep learning model makes it possible to anticipate samples that have never been seen before. To train the face mask identification algorithm, we gathered 6450 face photos with masks and 6150 face photos without. During the preparation stage, the dataset's photos were shrunk to 260 by 260 pixels.

Figure 1 displays a sample of photos from the face dataset. During the training phase, the model was serialized, and the face dataset picture was applied to the trained model. The convolutional neural network (CNN) was developed using the rectified linear unit, and the input layer receives the images

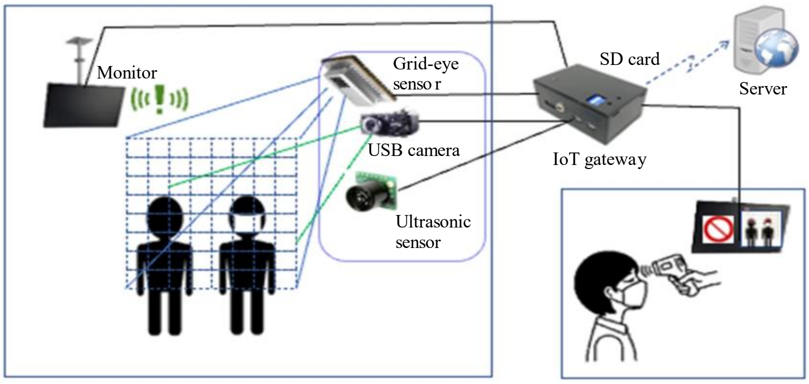

Figure 1. Ultrasonic sensor utilization.

from the training dataset. One CNN architecture that works well on mobile devices is called MobileNetV2. Its foundation is an inverted residual structure, in which the bottleneck layers are connected by residuals. As a source of non-linearity, the intermediate expansion layer filters features using lightweight depth wise convolutions. The first complete convolution layer in MobileNetV2's architecture has 32 filters, and it is followed by 19 residual bottleneck layers. To determine if a person was wearing a mask or not, we applied the trained MobileNetV2 model. The test dataset was used to assess the training model developed in this work. To determine whether a person was wearing a face mask, the entire model was applied to real-time photos. Finding someone without a face mask or with a high facial temperature is the main objective of the suggested system. The face mask detector determines whether a person without a face mask is depicted in an image.

The data is sent to the monitor to provide an alarm to see if such a person is identified. This will therefore make it possible for an authorized individual to carry out essential tasks like using highly accurate equipment to measure body temperature or preventing someone without a mask from passing.

THEORITCAL FRAMEWORK

1. *Python:* Python serves as the cornerstone of the backend of image processing for finding parking vacancies due to its readability and the extensive libraries it offers. This versatile programming language is used to implement both the backend logic and underlying image processing algorithm which plays a key role in finding parking spaces. Python's flexibility and comprehensive ecosystem make it an ideal choice for building complex functions required for system.
2. *Image processing:* Image processing involves manipulation and analysis of visual data to extract meaningful information. In context of smart parking system, image processing techniques are utilized to analyze images captured by parking lot cameras. This may include tasks such as object detection, image classification, and pattern recognition to identify parking spaces, vehicles, and occupancy status. Data Flow Diagram shown in Figure 2.
3. *Database management techniques:* Database Management Techniques encompass the range of strategies and methodologies for storing, organizing, and retrieving data efficiently. In the context of smart parking systems, database management techniques play a crucial role in managing parking-related data, including information about parking facilities, occupancy status, and historical usage patterns. This entails creating and putting database schemas into use, maximizing query speed, and guaranteeing data security and integrity. By leveraging database management techniques, smart parking systems can store and retrieve large volumes of parking data, facilitate real-time data integration, and support advanced analytics for predictive modelling and decision making.
4. *Cross-origin resource sharing (CORS) management:* Flask-CORS is an essential extension Flask-based smart parking applications, facilitating secure and reliable cross-origin communication between client-side web applications and server-side APIs. CORS management is crucial for enabling interoperability and data exchange across different domains while mitigating potential

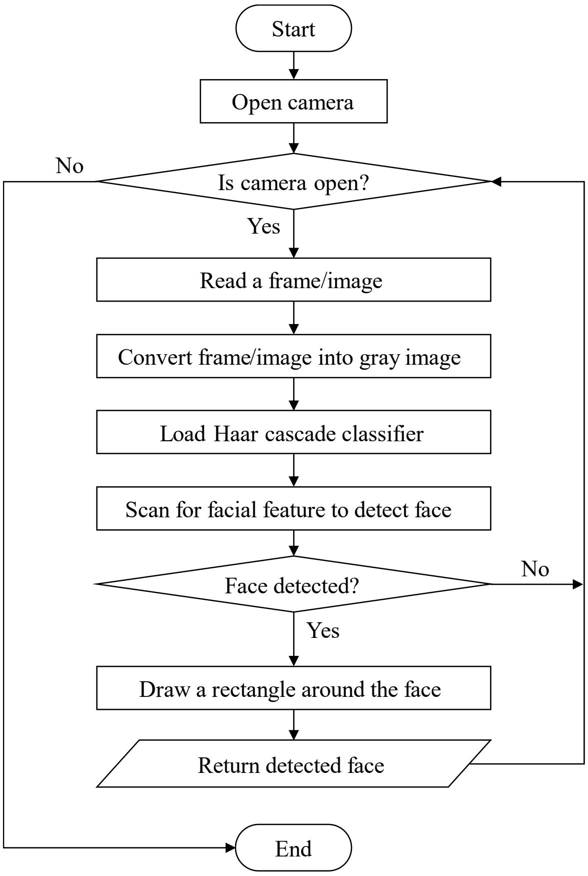

Figure 2. Data flow diagram.

security risk associated with cross-origin HTTP requests. By integrating Flask- CORS into Flask project, developers can specify which origins, methods, and headers are allowed for cross-origin requests, ensuring compliance with CORS policies and enhancing the accessibility and usability of smart parking applications across diverse platforms and environments.

OBJECTIVES

1. *Enhance public safety:* The primary objective is to improve public health by ensuring widespread compliance with mask-wearing protocols, thereby reducing the transmission of COVID-19 in communal spaces such as public transport, workplaces, and retail environments.
2. *Automate compliance monitoring:* To replace manual surveillance with an automated system that continuously monitors and detects the presence of face masks, reducing the need for human intervention and minimizing the risk of human error in mask compliance checks.
3. *Real-time detection:* To provide instantaneous feedback and alerts when individuals are not wearing masks in designated areas, facilitating prompt action by authorities or security personnel to address non-compliance effectively.
4. *Increase efficiency:* Enhance the efficiency of public health measures by deploying a scalable and reliable system that can monitor large crowds simultaneously, ensuring that mask-wearing regulations are consistently enforced without significant resource expenditure.
5. *Support contact tracing efforts:* By identifying and logging instances of mask non-compliance, the system can aid contact tracing efforts by providing data on potential exposure events, helping to track and manage the spread of COVID-19 more effectively.
6. *Reduce virus transmission:* Directly contributes to reducing the transmission rate of COVID-19 by ensuring that individuals adhere to mask-wearing guidelines, particularly in high-risk environments where close contact is unavoidable.

7. Evaluate the effectiveness of the designed model application through case-studies and real-world implementations, identifying success stories, challenges encountered, and insights gained from practical deployments.
8. Evaluate the effectiveness of the designed model application through case-studies and real-world implementations, identifying success stories, challenges encountered, and insights gained from practical deployments.
9. *Build public confidence:* Increase public confidence in safety measures by demonstrating that effective monitoring systems are in place, encouraging more people to engage in daily activities while adhering to health guidelines.
10. *Facilitate safe reopening:* Support the safe reopening of businesses, schools, and public spaces by providing an additional layer of protection through continuous monitoring, helping to balance economic recovery with public health safety
11. *Data-driven policy making:* Provide valuable data to policymakers regarding compliance rates and effectiveness of mask mandates, enabling data-driven decisions and adjustments to public health strategies based on real-world evidence
12. *Adaptable technology:* Ensure the system is adaptable for future public health needs beyond COVID-19, such as monitoring other forms of personal protective equipment (PPE) compliance during different health crises or in various industrial settings, ensuring long-term utility.

Steps Involved in the System of Real-time Detection

The following steps are commonly involved in the construction of real-time mask detectors:

1. *Gathering and preparing data*
   i. *Dataset creation:* Pictures of people wearing and not wearing masks are gathered to create large datasets. To guarantee robustness, these datasets need to include a variety of lighting conditions, facial angles, and mask designs.
   ii. *Data augmentation:* To improve model generalization and increase dataset diversity, techniques including flipping, rotation, and colour manipulation are used.
2. *Choosing and training models*
   i. *Deep learning frameworks:* To learn features like the existence of a mask, models like as Convolutional Neural Networks (CNNs) are trained on the preprocessed dataset. YOLO (You Only Look Once), SSD (Single Shot Multibook Detector), and Mobile Net are examples of common architectures.
   ii. *Transfer learning:* To speed up training and improve accuracy, pre-trained models are adjusted on mask detection datasets.
   iii. *Integration of systems:* Real-time analysis of live video feeds is made possible by the integration of the trained model with video surveillance equipment. When mask violations are found, more layers are put in place to offer actionable outputs, like alarm triggers and notifications.
3. *Evaluation and implementation*
   i. The accuracy, speed, and dependability of the system are evaluated through controlled testing. Real-world deployment entails improving the system while continuously monitoring its performance in changing circumstances.
   ii. *Implementation in real-time:* Surveillance camera images or video feeds are analysed by real-time mask detection systems.
   iii. *Acquisition of images:* Cameras record people in public areas in real-time. For processing, frames are taken out at predetermined intervals.
   iv. *Face recognition:* The system recognizes face regions in the frame using CNN-based detectors, Dlib, or Haar cascades.
   v. *Identification of masks:* The trained model is used to determine whether the retrieved face regions are “masked” or “unmasked.” Because of their speed and precision in real-time applications, models like YOLOv4/v5 are frequently employed.
   vi. *Warning system:* The system initiates predetermined steps, such as notifying authorities, sounding alarms, or recording the incident, when it detects a mask violation.

vii. *Reporting and data analytics:* In order to provide analytics interfaces that display compliance trends and hotspot locations, advanced solutions interface with internet of things (IoT) systems.

By combining AI, computer vision, and Internet of Things technologies, real-time mask detection systems meet a crucial demand during the COVID-19 pandemic. Their importance stems from their capacity to:

- Automating mask monitoring in crowded and dangerous situations will help to ensure compliance.
- *Improving public health safety:* Preventing the spread of viruses by detecting and treating them early.
- *Optimize resources:* Reducing the amount of manual enforcement and monitoring that is required.
- Enable targeted actions and provide insights into compliance patterns to support data-driven decision-making.

These methods greatly aid in pandemic mitigation efforts and create the foundation for advancements in public health monitoring by encouraging an accountability culture.

RESULTS AND DESCUSSION

In this section, we present the performance metrics and evaluation results of our real-time mask detection system, followed by examples demonstrating the system in action.

1. *Accuracy:* It was discovered that the system's overall accuracy in identifying masks and non-masks was 97.5%. This metric reflects the proportion of correctly identified instances out of all instances
2. *Precision:* The precision of the model was 96.8%. By showing the percentage of genuine positives among all positive forecasts, precision gauges how accurate positive predictions are. The F1-score, a statistic that combines recall and precision, was 97.0%. This score offers a single indicator of the system's efficacy by striking a balance between recall and precision.

CONCLUSION

The current study suggested an online monitoring system to identify individuals who are not wearing a face mask or who have elevated facial temperatures. The suggested face mask detector determined whether a person without a face mask was depicted in an image. The information was sent to the monitor to provide an alarm if such a person was found. An authorized individual may then take the required steps, such as using very accurate equipment to measure body temperature or denying entry to someone who is not wearing a mask.

The face mask detector model outperformed the current models with an accuracy of 98.8%. Furthermore, a three-week evaluation of the suggested indoor monitoring system was conducted to confirm its dependability in real-time (16 FPS).

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