



# REAL-TIME FACE MASK DETECTION IN OVERCROWDED ENVIRONMENTS USING MACHINE LEARNING

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**Abstract :** The World Health Organization (WHO) has stated that the spread of the coronavirus (COVID-19) is on a global scale and that wearing a face mask at work is the only effective way to avoid becoming infected with the virus. The pandemic made governments worldwide stay under lock-downs to prevent virus transmissions. Reports show that wearing face masks would reduce the risk of transmission. With the rise in population in cities, there is a greater need for efficient city management in today's world for reducing the impact of COVID-19 disease. For smart cities to prosper, significant improvements to occur in public transportation, roads, businesses, houses, city streets, and other facets of city life will have to be developed. The autonomous mask detection and alert system are needed to find whether the person is wearing a face mask or not. The main objective of the paper is to detect the presence of face masks in real-time video stream by utilizing deep learning, machine learning, and image processing techniques. To achieve this objective, a hybrid deep and machine learning model was designed and implemented.

**Keywords:** COVID-19; artificial intelligence; face mask system; deep learning; smart bus

## I. INTRODUCTION

The corona virus disease (COVID-19) outbreak, first identified in late 2019, rapidly evolved into a global pandemic significantly impacting public health and economies worldwide. The World Health Organization (WHO) declared COVID-19 a global health emergency and emphasized the importance of preventive measures to curb the transmission of the virus (WHO, 2020). Among the most effective measures recommended by health authorities, wearing face masks emerged as a crucial intervention to reduce the risk of viral transmission (Chu et al., 2020). Studies have shown that face masks effectively limit the spread of respiratory droplets, which are the primary means of virus transmission, thereby protecting both the wearer and those around. Masks play a crucial role in protecting the health of individuals against respiratory diseases, as is one of the few precautions available for COVID-19 in the absence of immunization.

Technological advancements in smart city infrastructure, which aimed to enhance public safety and healthcare systems (Allam & Jones, 2020). Smart cities leverage Internet of Things (IoT) technology, artificial intelligence (AI), and machine learning (ML) to develop efficient solutions for urban management, including healthcare monitoring and public safety enforcement (Batty, 2021). In the context of the pandemic, one of the most pressing challenges was ensuring compliance with

mask mandates in public spaces, particularly in densely populated urban environments. The increasing urban population has necessitated the adoption of smart city solutions to manage various aspects of city life, including transportation, business operations, public health, and safety (Kitchin, 2020). Among the most effective measures recommended by health authorities, wearing face masks emerged as a crucial intervention to reduce the risk of viral transmission. Smart surveillance systems have become integral in enhancing urban management by utilizing AI-driven tools to monitor and enforce regulations (Ghosh et al., 2021). Among these innovations, autonomous mask detection systems have emerged as an effective approach to ensuring compliance with mask mandates in public places.

## II. LITERATURE SURVEY

### 1. Introduction

Overcrowding in transportation systems is a critical issue in urban mobility, affecting passenger comfort, operational efficiency, and safety. Effective management of overcrowding is essential for improving service quality and ensuring the safety of commuters. Traditionally, transportation authorities have relied on manual monitoring and static surveillance systems, but these methods have significant limitations, including delayed response times, high dependency on human intervention, and inefficient crowd management. This literature survey explores current overcrowding management techniques, identifies their drawbacks, and highlights recent advancements in automated and real-time crowd control solutions.

### 2. Traditional Methods for Overcrowding Management

Current methods for managing overcrowding in transportation typically rely on manual monitoring and static surveillance systems. Security personnel or staff use traditional CCTV cameras to observe passenger flows and identify overcrowded areas. These methods, while widely implemented, have several drawbacks:

In face mask detection, various models have been explored and utilized over time to improve accuracy, efficiency, and scalability.

#### 1. Manual Surveillance

**Description:** This method involves security personnel manually monitoring compliance with mask-wearing protocols.

**Limitations:** It is labor-intensive, error-prone, and inefficient, especially in overcrowded areas.

#### 2. RFID-based Mask Monitoring

**Description:** RFID (Radio Frequency Identification) tags are used to detect if a mask is being worn. RFID-based systems can detect physical items like masks but lack the ability to visually confirm if the mask is actually worn by the individual.

**Limitations:** Cannot verify the mask's presence in real-time or differentiate between different types of masks. It is also prone to being bypassed if individuals remove their RFID tags.

**Use Case:** Access control systems in controlled environments.

#### 3. Infrared Sensors

**Description:** Infrared sensors are used to detect the presence of face coverings by detecting heat signatures from the face or head.

**Limitations:** These systems fail to differentiate between different types of masks, and they are ineffective in distinguishing between different face coverings or verifying proper usage.

**Use Case:** Quick screening for mask presence in some public environments.

#### 4. Convolutional Neural Networks (CNNs)

**Description:** CNNs are a class of deep learning models particularly suited for image. In mask detection, CNNs are used to classify images of faces as either masked or unmasked.

##### Popular CNN Architectures Used:

**VGG16:** A deep CNN with a very deep architecture that performs well but is expensive for real-time use.

**ResNet:** A deep residual network that uses skip connections to train very deep models,

**MobileNet:** A lightweight CNN architecture designed to be computationally efficient, ideal for edge computing

scenarios like Raspberry Pi.

### III. EXISTING SYSTEM

The first step is the creation of a face-matching model using deep learning and traditional machine learning techniques. The main challenge was to create a dataset that is composed of faces with and without face masks. A computer vision-based face detector was built using the created dataset, OpenCV, and Python with TensorFlow, withal in our custom machine learning framework. The computer vision and deep learning techniques were used to identify whether the person is wearing a face mask or not. This helps in expediting the proliferation of computer vision in the currently nascent areas such as digital signage, autonomous driving.

The main element of deep learning is DNNs, which allows for object recog- nition segmentation. The proposed methodology utilize hybrid deep CNN classifier for segmenting the relevant features of face. DNNs are generally used in tasks related to computer vision as they act as an effective tool to increase the resolution of a classifier. Face recognition and classification models can be trained using CNN [19], advanced feature extraction, and classification methods to identify and classify facial images with minimal features and store fine details.

### IV. PROPOSED SYSTEM

The proposed system employs a Raspberry Pi as the central microcontroller, interfaced with a web camera to detect overcrowding in transportation environments. Computer vision techniques enhance CCTV capabilities by automating the detection of crowd density and movement patterns. Modern AI-driven surveillance systems can classify different congestion levels, enabling automated decision-making in response to crowding issues. Researchers have developed deep learning models that can recognize pedestrian behaviors and forecast crowd accumulation trends with high accuracy.

Automated alert systems integrated with raspberry Pi to disseminate real-time updates to passengers. These systems use speaker for alerts, to inform commuters about crowded areas and suggest alternative routes. Studies indicate that real-time communication significantly enhances passenger distribution and reduces congestion during peak hours. The Fig. 3.1 shows the implementation Automated alert systems integrated with raspberry pi, camera and speaker.

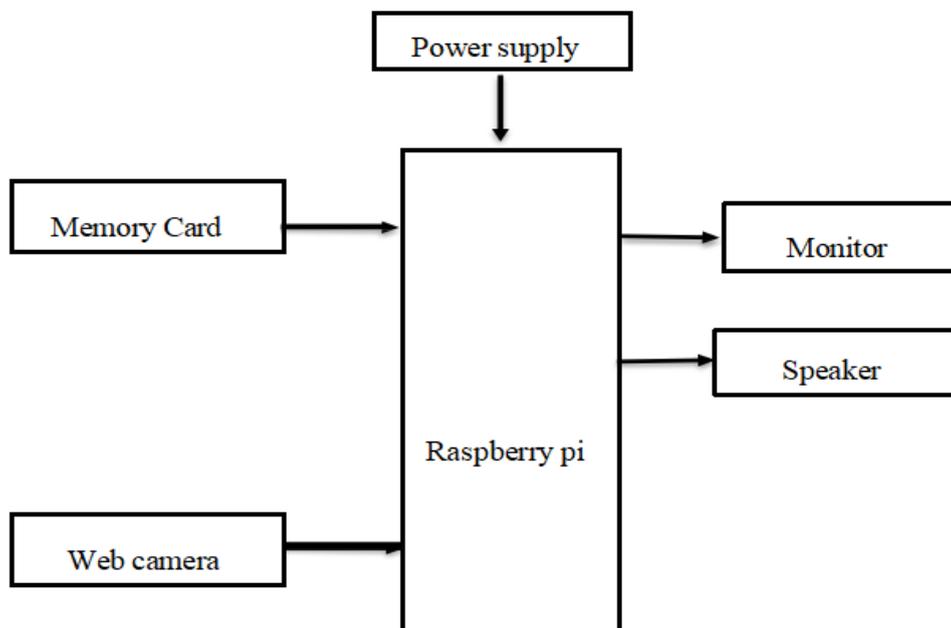


Figure 1: Block Diagram of Proposed system

Raspberry Pi is a credit-card sized computer manufactured and designed in the United Kingdom by the Raspberry Pi foundation with the intention of teaching basic computer science to school students and every other person interested in computer hardware, programming and DIY-Do-it Yourself projects. The Raspberry Pi is manufactured in three board configurations through licensed manufacturing deals with Newark element 14 (Premier Farnell), RS Components and

Egoman. These companies sell the Raspberry Pi online. Geomean produces a version for distribution solely in China and Taiwan, which can be distinguished from other Pi's by their red coloring and lack of FCC/CE marks. The hardware is the same across all manufacturers.

The Raspberry Pi has a Broadcom BCM2835 system on a chip (SoC), which includes an ARM1176JZF-S 700 MHz processor, Video Core IV GPU and was originally shipped with 256 megabytes of RAM, later upgraded (Model B & Model B+) to 512 MB.

## V. RESULTS

A Raspberry Pi connected to a keyboard and a webcam. Indicates that the system setup is in progress, preparing hardware for real-time face mask detection. The glowing lights on the Raspberry Pi suggest it is powered on and running.



Fig.4.1: Hardware Components

Computer monitor displays files and directories related to the project. The system appears to be running on a Linux-based OS, possibly Raspberry Pi OS. This stage suggests accessing the dataset, scripts, or results for the detection model.

A person is sitting in front of the system, with a webcam pointed at their face. The screen shows a detection interface, possibly executing a python-based face mask detection script. Suggests the system is actively analyzing video feed input.



Fig.4.2:Data

Set

With

Mask



Fig.4.3: System Detects A Person Without A Mask And Announces 'Mask Not Detected' Through A Speaker

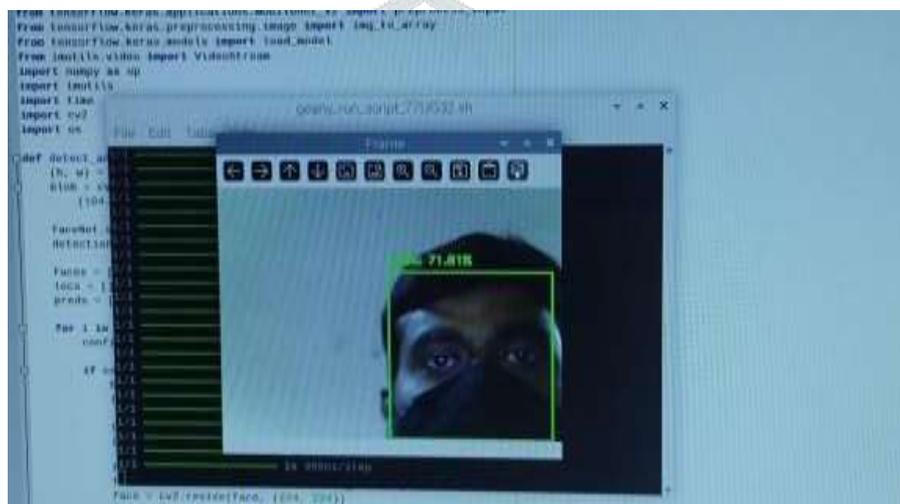


Fig.4.4: The System Detects A Person With A Mask

## VI. CONCLUSION

proposed hybrid deep and machine learning model effectively detects the presence of face masks in real-time video streams, leveraging advanced image processing techniques. The study demonstrates that the CNN-based classifier outperforms the DNN classifier, achieving an error rate of only 3.1% in face identification while ensuring accurate mask detection. Additionally, the model exhibits low inference time and memory consumption, making it suitable for IoT-based applications in resource-constrained environments. The results highlight the significance of integrating deep learning techniques into smart city infrastructures for efficient public health monitoring and compliance enforcement during pandemics.

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