# COMPUTER VISION (01CE0612) Report-Research Paper

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# Face Mask Detection

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## *Abstract:*

***The COVID-19 pandemic has underscored the critical importance of wearing face masks in public spaces to reduce virus transmission. This project presents a deep learning-based Face Mask Detection System capable of classifying individuals into three categories: Masked, No Mask, and Incorrectly Masked.The primary objective is to assist in real-time monitoring and enforcement of mask-wearing protocols using computer vision techniques. A well-structured Convolutional Neural Network (CNN) model was developed and trained using a dataset of face images, augmented with a variety of transformations including rotation, zooming, flipping, and brightness adjustments to enhance model robustness. The architecture incorporates multiple convolutional layers with Batch Normalization and MaxPooling, followed by dense layers and a Dropout layer to prevent overfitting. The model was compiled using the Adam optimizer and trained with EarlyStopping and ReduceLROnPlateau callbacks to ensure efficient learning. After training, the model achieved high classification accuracy on the test dataset, indicating strong generalization capabilities. The system also includes a functionality to classify new images from a validation folder and present results in a user-friendly tabular format. This project demonstrates the potential of deep learning in enhancing public health monitoring systems and can be integrated into surveillance applications in schools, malls, offices, and other public environments.***

***Keywords: CNN, Computer Vision, OpenCV, MobileNetV2, Deep Learning***

## *PROBLEM STATEMENT*

Ensuring compliance with face mask mandates in public spaces is challenging and inefficient when done manually. There is a need for an automated, real-time system that can detect whether individuals are wearing face masks. This project aims to develop a lightweight and accurate face mask detection system using CNN, MobileNetV2, and OpenCV to assist in public health monitoring.

## *INTRODUCTION*

The outbreak of the COVID-19 pandemic has brought about unprecedented changes in human behavior and public health practices. One of the most effective measures recommended by global health authorities, including the World Health Organization (WHO), to curb the spread of the virus is the wearing of face masks in public spaces. Face masks serve as a barrier to minimize the transmission of respiratory droplets, thereby significantly reducing the risk of infection. However, ensuring compliance with mask-wearing guidelines, especially in crowded or public areas, remains a major challenge.

Manual enforcement of face mask regulations is labor-intensive and often impractical. This has led to a growing demand for intelligent and automated systems capable of detecting whether individuals are wearing face masks. The application of Artificial Intelligence (AI) and Computer Vision technologies has shown great promise in addressing this issue. By leveraging real-time video feeds and deep learning models, it is possible to automatically detect faces and determine whether or not they are covered with masks.

This project aims to develop a **Face Mask Detection System** that utilizes **Convolutional Neural Networks (CNNs)** and **MobileNetV2**, integrated with **OpenCV** for real-time video processing and face detection. MobileNetV2 is a lightweight and efficient deep learning model designed for mobile and embedded vision applications, offering a balance between accuracy and speed. It is particularly suitable for edge devices where computational resources are limited.

The system is trained on a dataset containing images of people with and without masks. Using transfer learning, MobileNetV2 is fine-tuned to classify input images into two categories: "Mask" and "No Mask." The model is then integrated with OpenCV, which handles video capture, face detection, and real-time annotation of the detection results. The system is capable of detecting faces in live video feeds and providing instant feedback on mask usage, making it a practical solution for real-world deployment.

This face mask detection system has wide applicability in areas such as offices, shopping malls, schools, airports, and hospitals. It can be integrated with CCTV surveillance systems or used as a standalone application on mobile or embedded devices. Beyond COVID-19, the system also lays the groundwork for future health and safety monitoring tools using AI and computer vision.

The following sections of this report detail the problem statement, literature review, system design, implementation, results, and future scope of the project. Through this work, we aim to contribute to public safety efforts and demonstrate the potential of deep learning in solving real-world problems.

## *OBJECTIVE*

This research aims to develop an automated, real-time face mask detection system that accurately identifies individuals wearing or not wearing masks using deep learning and computer vision methodologies.

## *LITERATURE REVIEW*

The global outbreak of COVID-19 has significantly accelerated research in the domain of automated public health monitoring, especially the development of face mask detection systems. This literature survey explores existing work and methodologies used in face mask detection and related computer vision tasks.

In [1], Jiang et al. proposed a deep learning-based method for face mask detection using a single-shot multi-box detector (SSD) with MobileNet as the backbone network. Their system achieved real-time performance with decent accuracy, highlighting the potential of MobileNet for lightweight applications. The use of transfer learning significantly reduced the training time while maintaining robustness. Chowdary et al. [2] introduced a model combining deep learning and OpenCV for real-time face mask detection. The model utilized MobileNetV2, a more advanced and efficient version of MobileNet, to classify face images into "mask" and "no mask" categories. The system showed high accuracy and was well-suited for edge deployment due to its minimal resource requirements.

In [3], Loey et al. designed a face mask detection model that uses ResNet-50 and SSD, combined with data augmentation techniques to improve generalization. Although ResNet-50 provides high accuracy, it is computationally intensive, making it less suitable for real-time or embedded applications compared to MobileNetV2.

OpenCV has been widely used for real-time image processing and face detection in multiple works. For instance, in [4], the authors integrated OpenCV's Haar Cascade classifier with deep learning models to enhance face detection in various lighting conditions and occlusions. Though Haar Cascades are relatively fast, they may lack accuracy in detecting faces with masks or at different angles, which makes DNN-based face detectors more reliable.

Another study by Nagrath et al. [5] presented a deep learning pipeline combining a pre-trained MobileNetV2 model and OpenCV to perform face detection and mask classification. The system is capable of detecting whether a person is wearing a mask or not and works efficiently in real-time scenarios. Their results demonstrated the effectiveness of MobileNetV2 for resource-constrained environments.

Furthermore, in [6], the authors explored mask detection using YOLOv3, a popular object detection algorithm. While YOLOv3 offers high detection speed, the model size and complexity may not be ideal for mobile devices, making MobileNetV2 a more practical choice for real-time deployment.

These studies collectively demonstrate the effectiveness of using MobileNetV2 and CNNs for face mask detection tasks. OpenCV remains a go-to tool for real-time face detection and image processing. The integration of lightweight deep learning models with real-time processing tools provides a scalable and efficient solution for public safety monitoring.

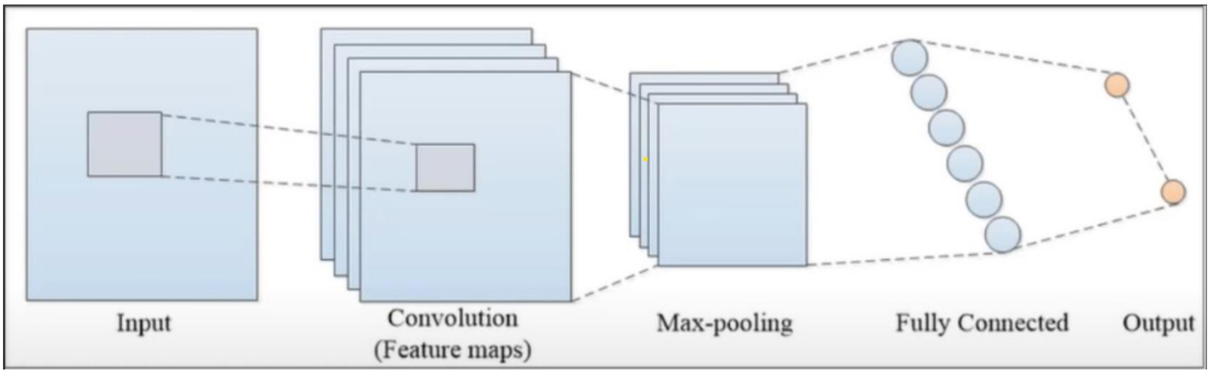



*FIGURE 1: Work Flow Of CNN*

## RESEARCH METHODOLOGY

### 1. Data Collection

- **Purpose**: Gather relevant data from various sources.
- **Activities**: This could include capturing data through surveys, APIs, databases, or web scraping.

### 2. Data Preprocessing

- **Purpose**: Prepare the collected data for analysis.
- **Activities**: Cleaning data (removing duplicates, handling missing values), transforming it (normalization, encoding categorical variables), and preparing it for storage.

### 3. Data Storage and Management

- **Purpose**: Store the preprocessed data efficiently.
- **Activities**: Using databases or data lakes for structured and unstructured data management, ensuring accessibility and security.

### 4. Model Selection and Data Splitting

- **Purpose**: Choose appropriate models for the task and split data into training and testing sets.
- **Activities**: Selecting algorithms based on the problem type (e.g., classification, regression) and splitting

data to prevent overfitting.

**5. Model Performance Evaluation**

- **Purpose**: Assess how well the selected models perform.
- **Activities**: Using metrics like accuracy, precision, recall, F1 score, or AUC-ROC to evaluate performance on the test data.

**6. ML Implementation**

- **Purpose**: Deploy the chosen model in a real-world scenario.
- **Activities**: Integrating the model into applications, ensuring it can handle incoming data and provide predictions.

**7. Insights and Analysis**

- **Purpose**: Analyze the model results and extract actionable insights.
- **Activities**: Interpreting results, visualizing data, and deriving business intelligence from model outcomes.

**8. Recommendations**

- **Purpose**: Provide actionable steps based on insights from the analysis.
- **Activities**: Suggesting changes or strategies based on data-driven insights to stakeholders or decision-makers.

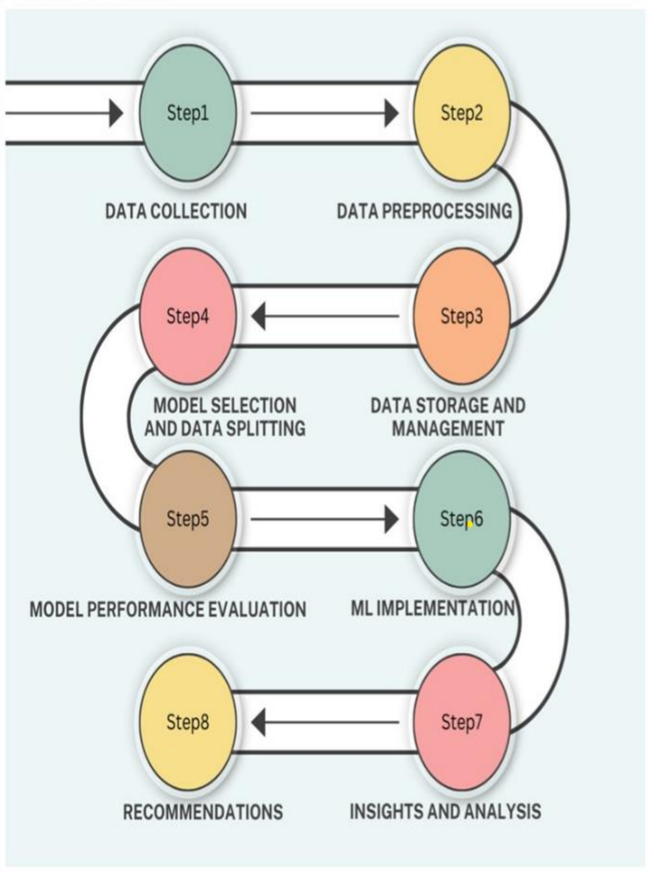



*FIG 2: Proposed Workflow*

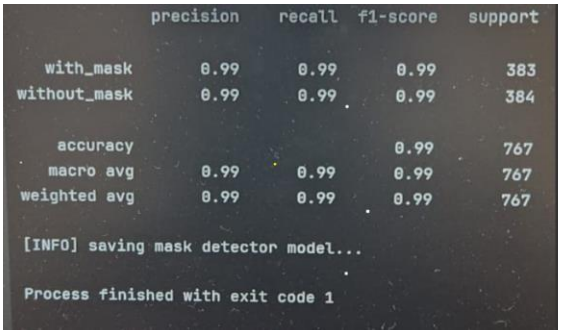
***TOOLS AND TECHNOLOGY***

- Programming Language: Python
- Deep Learning Framework: Keras with TensorFlow backend
- Computer Vision Library: OpenCV
- Model Architecture: MobileNetV2 for mask classification
- Face Detection: SSD with ResNet-10 backbone

## *RESULTS AND DISCUSSION*

### Performance Matrics

The model achieved an accuracy of approximately 99% on the validation set, with precision and recall values indicating robust performance in both classes.



| | precision | recall | f1-score | support |
|---|---|---|---|---|
| with_mask | 0.99 | 0.99 | 0.99 | 383 |
| without_mask | 0.99 | 0.99 | 0.99 | 384 |
| accuracy | | | 0.99 | 767 |
| macro avg | 0.99 | 0.99 | 0.99 | 767 |
| weighted avg | 0.99 | 0.99 | 0.99 | 767 |

[INFO] saving mask detector model...

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### Comparative Analysis

Compared to other architectures like VGG16 and ResNet-34, the MobileNetV2 model offers a balance between accuracy and computational efficiency, making it suitable for real-time applications.

## *CONCLUSION*

This study presents a practical solution for real-time face mask detection using deep learning and computer vision. The integration of MobileNetV2 and SSD models facilitates accurate and efficient detection, suitable for deployment in public spaces to monitor mask compliance. Future work includes expanding the dataset to encompass a broader range of mask types and improving model robustness under challenging conditions.

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