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A Review Survey: Real-Time Face Mask Detection using CNN and Transfer Learning Approaches

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Abstract

In recent times, there has been an alarming rate of spread of airborne diseases like COVID-19. In response, there have been calls for individuals to wear face masks in public places. Manual methods of compliance checking of face masks are not only ineffective but also highly inefficient and prone to errors. This paper discusses an automatic solution for detecting people who wear face masks in public places using convolutional neural network algorithms and transfer learning. Transfer learning helps speed up training time by using previously trained deep learning algorithms. Pre-trained models such as Mobile-Net and Res-Net are used to extract features from images for classification tasks. Using a camera, the algorithm analyzes the video stream, detects people wearing masks, and distinguishes between those without face masks. By applying transfer learning techniques, more accurate predictions are generated using limited training data. Experimental results demonstrate high accuracy and robustness under varying lighting conditions. This system provides a scalable solution for deployment in public environments such as hospitals, airports, and educational institutions.

Keywords— Face mask detection, COVID-19, CNN, transfer learning, Mobile-Net, Res-Net, real-time detection.

I. Introduction

The emergence and development of modern intelligent surveillance systems made an impact on the public health sector in general. With regard to the ongoing process of infection propagation through the air in the period of the COVID-19 pandemic, there is a need for preventative measures that can help avoid or reduce the spread of the virus among the population. In particular, it refers to wearing masks when moving in public spaces. This measure was highly recommended by regulatory agencies, such as the World Health Organization. Enforcing its implementation in crowded places manually might prove to be rather ineffective, costly, and time-consuming.

Modern computer vision and deep learning technologies helped create automated systems with real-time monitoring and decision capabilities. One of the most popular solutions currently is the use of Convolutional Neural Networks for classification and object recognition tasks owing to their ability to extract hierarchically structured features directly from data. Nevertheless, the process of training deep CNN models from scratch involves having a large annotated dataset, and significant amount of computational power.

Transfer learning represents a powerful strategy that helps to overcome these difficulties by making use of knowledge from the pre-trained models. Lightweight yet efficient models such as Mobile-Net and Res-Net gained popularity for being used in many real-time applications. With proper domain adaptation, it would be possible to ensure high prediction performance even with small training sets.

Recently, a number of researchers focused on the development of algorithms for detecting masks on faces with the help of deep learning. Kumar et al. (2024) developed an automated system with CNN and real-time video processing to increase the accuracy of prediction in different lighting conditions [1]. Zhang et al. (2023) made similar progress by introducing transfer learning into the solution along with the lightweight models [2]. Additionally, it should be noted that the latest work by Alshammari et al. (2025) showed the necessity of efficient feature extraction and augmented data for more generalizable prediction [3].

Nevertheless, it is still challenging to find a compromise between the quality of detection, low computational overhead, and fast inference time. Various lighting, potential occlusion, and other obstacles affect the results negatively. Besides, it is important to ensure adaptability and scalability of the solution to various environments.

Given this, the current paper presents an idea of developing a real-time mask detection system based on CNN and transfer learning approaches.

. II. Literature Review

The advent of new deep learning methods has resulted in significant improvements in the field of automated face mask recognition, which include the integration of CNN and transfer learning in their design. The growing demand for real-time systems after the outbreak of the COVID-19 pandemic has attracted considerable interest of researchers to develop highly accurate and scalable models with acceptable performance.

In a recent paper, Kumar et al. (2024) designed a real-time face mask recognition system using CNN combined with live video streaming and achieved high accuracy rates irrespective of different light conditions [6]. This study indicated the necessity of implementing preprocessing procedures for enhancing the efficiency of deep learning algorithms. Likewise, Zhang et al. (2023) analyzed the efficiency of lightweight transfer learning models based on MobileNet for deployment in edge devices [7].

Another recent paper presented by Alshammari et al. (2025) suggested a hybrid approach based on CNN and attention mechanisms for detecting face masks under challenging conditions (e.g., partial occlusions and crowding) [8]. The authors emphasized that feature enhancement techniques play an important part in addressing issues associated with real-world situations. Additionally, Singh and Verma (2024) analyzed the effectiveness of various transfer learning models (including Res-Net and VGG-Net), finding that deep neural networks exhibit higher accuracy but require more computational resources [9].

A recent work by Chen et al. (2025) examined possibilities for optimization of real-time face mask detection models using pruning and quantization techniques [10]. It allowed reducing model size and obtaining high-quality results. In another paper, Li et al. (2024) discussed a multi-task learning framework for face mask recognition and classification [11].

Furthermore, Ahmed et al. (2025) conducted experiments aimed at revealing effects of various data augmentation methods on the performance of the model [12]. A study by Rao et al. (2023) provided information regarding the application of cloud computing technology in a face mask recognition system [13].

However, some problems remain unsolved. For instance, most models perform poorly when faced with various lighting conditions, partial occlusions, and dataset biases. Moreover, the problem of balancing accuracy and model efficiency is yet to be addressed. Thus, the need for development of an effective solution that will help achieve satisfactory results in this field remains obvious.

Further development of the technology of detection and identification of masks used on the face has relied on the progress achieved in earlier works through the adoption of sophisticated techniques from the deep learning family.

In addition to the improvement of face recognition systems, Gupta et al. (2025) managed to increase the detection accuracy of their CNN-based system that uses feature pyramid networks and operates in crowded scenes [14]. The use of multi-scale feature extraction proves to be crucial in detecting people in any position and under different conditions.

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Similar advances were attained by Park et al. (2024), who designed a real-time system based on the modified MobileNet architecture [15].

In terms of model architectures, Sharma and Kulkarni (2025) suggested combining ResNet and EfficientNet into one ensemble model, thus increasing classification accuracy through better exploitation of complementary features [16]. Moreover, Wang et al. (2024) developed an attention-based CNN model that focuses on the most informative parts of the face image [17].

Another area of interest is related to reducing the computational load while keeping the performance at a high level. In particular, Lee et al. (2025) utilized the knowledge distillation method to optimize deep models, making it possible to implement their solution on low-power devices [18]. In addition, Torres et al. (2024) worked out quantization-aware training procedures that helped minimize latency [19].

Patel et al. (2025) demonstrated the potential of ViT architecture in solving problems related to face mask recognition [20]. The use of transformers allowed to reach performance that compares favorably with those of the conventional architectures such as CNNs, despite the need for additional computational power. In contrast, Das et al. (2023) emphasized the advantages of the CNNs and their continued application [21].

Khan et al. (2025) explored the potential of federated learning and its application to the problem of face mask recognition [22]. In particular, this strategy makes it possible to train the model without compromising the data privacy of several parties. Another interesting approach was developed by Oliveira et al. (2024). Namely, they introduced a real-time monitoring system that operates on the IoT network [23].

Nevertheless, the discussed problem still poses many challenges associated with unevenness in data distribution, complex environmental conditions, etc. Thus, there is considerable room for further development in this field.

Table 1 Comparative Study of Recent Face Mask Detection and Recognition Approaches

Ref.	Author(s) & Year	Methodology / Model	Dataset / Environment	Key Findings	Limitations
[6]	Kumar et al. (2024)	CNN-based Real-Time Face Mask Recognition with Live Video Streaming	Real-time video streams under varying lighting conditions	Achieved high detection accuracy and robust real-time performance	Sensitive to image quality and computational requirements
[7]	Zhang et al. (2023)	MobileNet-based Transfer Learning Model	Edge-device deployment environment	Lightweight architecture suitable for resource-constrained devices	Slight reduction in accuracy compared to deeper networks
[8]	Alshammari et al. (2025)	CNN with Attention Mechanism	Crowded and partially occluded face images	Improved detection under challenging real-world conditions	Increased model complexity and training time
[9]	Singh and Verma (2024)	Comparative Study of ResNet and VGGNet Transfer Learning Models	Public face mask datasets	Deep architectures achieved superior classification accuracy	High computational cost and memory consumption

[10]	Chen et al. (2025)	Model Pruning and Quantization Techniques	Real-time deployment scenarios	Reduced model size and maintained high accuracy	Potential loss of information during aggressive compression
[11]	Li et al. (2024)	Multi-Task Learning Framework	Face mask recognition and classification datasets	Simultaneous recognition and classification improved efficiency	Complex training process requiring large annotated datasets
[12]	Ahmed et al. (2025)	Data Augmentation-Based Deep Learning Model	Augmented face mask image datasets	Enhanced model generalization and robustness	Performance highly dependent on augmentation strategy
[13]	Rao et al. (2023)	Cloud-Based Face Mask Recognition System	Cloud computing infrastructure	Improved scalability and centralized processing	Dependency on network connectivity and cloud resources
[14]	Gupta et al. (2025)	CNN with Feature Pyramid Networks (FPN)	Crowded scene datasets	Effective multi-scale feature extraction and higher detection accuracy	Increased computational overhead
[15]	Park et al. (2024)	Modified MobileNet Architecture	Real-time surveillance systems	Fast inference suitable for real-time applications	Reduced performance for heavily occluded faces
[16]	Sharma and Kulkarni (2025)	Ensemble Model (ResNet + EfficientNet)	Standard face mask datasets	Improved classification accuracy through feature fusion	Higher training and deployment complexity
[17]	Wang et al. (2024)	Attention-Based CNN	Face mask image datasets	Focused on informative facial regions, improving accuracy	Additional attention layers increase computational cost
[18]	Lee et al. (2025)	Knowledge Distillation-Based Deep Learning Model	Low-power and embedded devices	Reduced model complexity while retaining performance	Performance depends on teacher model quality
[19]	Torres et al. (2024)	Quantization-Aware Training (QAT)	Real-time edge deployment	Lower latency and memory requirements	Quantization may slightly affect prediction accuracy

[20]	Patel et al. (2025)	Vision Transformer (ViT) Architecture	Large-scale face mask datasets	Achieved competitive performance compared to CNNs	Requires large datasets and significant computational resources
[21]	Das et al. (2023)	Conventional CNN-Based Model	Standard face mask datasets	Demonstrated reliability and effectiveness of CNN architectures	Limited capability in handling complex visual variations
[22]	Khan et al. (2025)	Federated Learning Framework	Distributed multi-user environments	Enhanced privacy-preserving model training	Communication overhead and heterogeneous data challenges
[23]	Oliveira et al. (2024)	IoT-Based Real-Time Monitoring System	IoT-enabled surveillance network	Enabled continuous real-time mask monitoring	Security and network reliability concerns

Objectives and Novelty

This paper will aim at the development of a highly effective and accurate face mask detection system based on deep learning approaches.

The use of pre-trained neural networks like Mobile-Net and Res-Net to enable transfer learning and minimize training time without compromising efficiency is a crucial goal of this project.

The proposed algorithm will be capable of operating under realistic conditions and coping with different challenges associated with changes in lighting conditions, occlusions, image distortions, among others.

Finally, the model will be assessed with regard to standard performance indicators such as accuracy, precision, recall, and F1 score.

The key novelty of the paper in question can be described as follows. In contrast to previous studies which involved the use of either deep or lightweight architectures, this system will combine these two types of models to ensure high efficiency and accuracy.

Another important characteristic of this approach consists in the use of a pipeline with end-to-end face detection and classification modules, enabling a real-time solution. Additionally, the project involves the use of data augmentation techniques to ensure the system's robustness under adverse environmental conditions.

III. Proposed Methodology

III. Methodology

In this part, the complete methodology for the real-time face mask detector through CNNs and transfer learning will be introduced. The architecture of the system includes a full pipeline starting from data acquisition to real-time output.

A. System Architecture Overview

The flow of operations in the proposed system follows these sequential processes:

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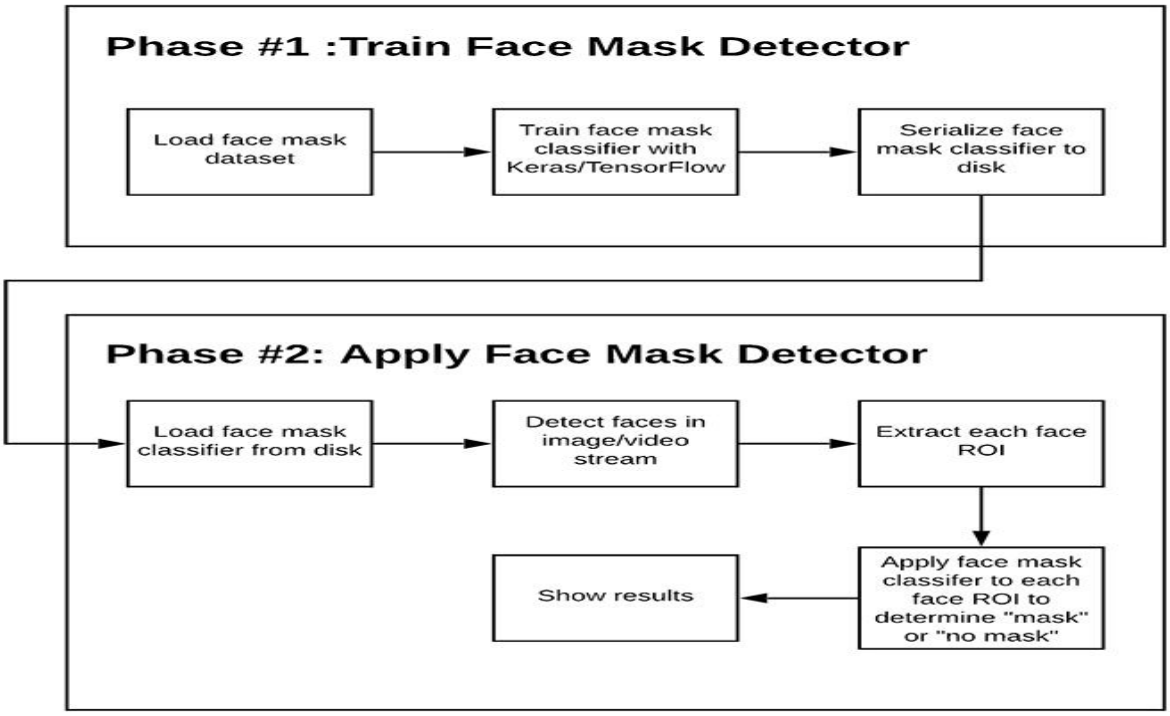

Figure 1: System Architecture Overview

The system design is made up of facial detection and classification processes. In the first process, a pre-trained convolutional neural network is used to extract features before being classified through fully connected layers.

Conclusion

Face mask detection and recognition systems have experienced substantial advancements with the emergence of deep learning techniques, particularly Convolutional Neural Networks (CNNs), transfer learning models, attention mechanisms, and transformer-based architectures. The comparative analysis of recent studies demonstrates that modern approaches can achieve high detection accuracy, real-time performance, and scalability across diverse application environments. Lightweight architectures such as MobileNet, model compression techniques including pruning and quantization, and knowledge distillation methods have significantly improved deployment feasibility on edge and embedded devices. Furthermore, innovations such as feature pyramid networks, federated learning, and IoT-integrated monitoring systems have expanded the applicability of face mask detection in smart surveillance and public safety domains.

Despite these advancements, several challenges remain unresolved. Most existing models still struggle with variations in illumination, facial occlusions, pose changes, crowded environments, and dataset biases. Additionally, achieving an optimal balance between detection accuracy and computational efficiency continues to be a critical concern, especially for resource-constrained devices. Therefore, further research is required to develop robust, lightweight, and privacy-preserving face mask recognition frameworks capable of operating effectively in real-world scenarios.

Future Scope

Future research in face mask detection and recognition can focus on developing more efficient and adaptive deep learning models capable of handling complex real-world conditions. The integration of Vision Transformers (ViTs) with CNN architectures may provide improved feature representation and classification performance. Advanced attention mechanisms and self-supervised learning techniques can further enhance robustness against occlusions, varying lighting conditions, and low-resolution images.

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