Face Mask Detection Using Deep Learning and Computer Vision

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***Abstract*— Automated monitoring of face mask compliance has become essential in public health, especially since the COVID-19 pandemic. Manual enforcement is inefficient in crowded places. This paper proposes a real-time face mask detection system based on deep learning and computer vision. A convolutional neural network (CNN) is trained on a diverse dataset to distinguish between masked and unmasked faces in images and video streams. The system achieved a test accuracy of 97.3% and remained robust under diverse lighting, angles, and partial occlusions. Designed for efficiency, the solution operates in real-time on standard hardware, making it suitable for public health surveillance, access control, and smart monitoring. The implementation is open-source and accessible at GitHub.**

Keywords—Face Mask Detection, Deep Learning, Computer Vision, CNN, COVID-19, Real-time Monitoring

1.INTRODUCTION

The COVID-19 pandemic has made face masks a daily necessity to limit viral spread. Enforcing mask mandates at scale is challenging, especially in high-traffic environments. Automated face mask detection systems can help authorities ensure compliance, reduce manual intervention, and provide actionable data for public health policies. This research presents a deep learning-based face mask detection system that leverages computer vision for real-time performance. By combining a lightweight CNN with robust data augmentation, the system achieves high accuracy and is deployable in various environments. The solution integrates easily with existing surveillance infrastructure and is distributed as open-source software for community use.

The deployment of such an automated face mask detection system can significantly enhance public health safety by ensuring compliance with mask mandates in high-traffic areas such as airports, public transportation, shopping malls, and schools. By leveraging deep learning and computer vision technologies, the system can accurately identify individuals wearing face masks in real-time, enabling authorities to take prompt action in case of non-compliance.

2.REVIEW OF LITERATURE

Recent advancements in face mask detection have focused on improving detection accuracy, efficiency, and privacy. Researchers have made notable contributions, such as Zhang et al. (2025), who introduced a transformer-based model tailored for edge devices, achieving high accuracy and low latency for real-time surveillance. Kumar and Singh (2024) enhanced YOLOv5 for mask detection in crowded settings,

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improving resilience to occlusions and mask variations. Rahman et al. (2024) proposed a federated learning approach, allowing collaborative model training across organizations without sharing sensitive data. Additionally, Alam et al. (2023) developed a hybrid CNN-SVM system, emphasizing adaptability to different mask types and user demographics, while Jin et al. (2023) reviewed computer vision applications for COVID-19, highlighting the importance of scalable, privacy-aware detection systems. Despite these advances, balancing accuracy and computational efficiency remains a challenge. Our work builds on these efforts, focusing on practical deployment and open accessibility to create a robust face mask detection system that can be widely adopted and contribute to public health safety.Recent advancements in face mask detection have focused on improving detection accuracy, efficiency, and privacy, with researchers making notable contributions to address the challenges posed by the COVID-19 pandemic. For instance, Zhang et al. (2025) introduced a transformer-based model tailored for edge devices, achieving high accuracy and low latency for real-time surveillance, which is crucial for deployment in high-traffic areas. Similarly, Kumar and Singh (2024) enhanced YOLOv5 for mask detection in crowded settings, improving resilience to occlusions and mask variations, thereby enhancing the system's ability to handle complex scenarios. Rahman et al. (2024) proposed a federated learning approach, allowing collaborative model training across organizations without sharing sensitive data, which addresses growing concerns about data privacy and security. Additionally, Alam et al. (2023) developed a hybrid CNN-SVM system, emphasizing adaptability to different mask types and user demographics, ensuring the system's effectiveness across diverse populations. Jin et al. (2023) reviewed computer vision applications for COVID-19, highlighting the importance of scalable, privacy-aware detection systems that can be integrated into existing infrastructure. Despite these advances, balancing accuracy and computational efficiency remains a challenge, particularly in resource-constrained environments. Our work builds on these efforts, focusing on practical deployment and open accessibility to create a robust face mask detection system that can be widely adopted and contribute to public health safety, while also ensuring scalability, adaptability, and privacy awareness. By leveraging these advancements and addressing the existing challenges, our system aims to provide a reliable and efficient solution for face mask detection in various settings.

3. PROPOSED METHODOLOGY

A. Dataset Preparation

Our dataset was compiled from sources including Kaggle, the Real-world Masked Face Dataset (RMFD), Bing Search API, and original photographs. It consists of 2,165 images of masked faces and 1,930 images of unmasked faces, representing various ages, ethnicities, lighting conditions, and mask types. Data augmentation (flipping, rotation, brightness adjustment, noise) was used to improve generalization.

B. Model Architecture

The detection pipeline includes two main components:

1. Face Detection: OpenCV's Haar Cascade classifier is used for efficient face localization.
2. Mask Classification: A custom CNN with three convolutional layers, max pooling, dropout, and dense layers classifies each detected face as "masked" or "unmasked."

CNN Structure:

- Conv2D (32 filters, 3×3), ReLU, MaxPooling
- Conv2D (64 filters, 3×3), ReLU, MaxPooling
- Conv2D (128 filters, 3×3), ReLU, MaxPooling
- Dropout (0.25)
- Flatten
- Dense (128, ReLU), Dropout (0.5)
- Output (2, Softmax)

C. Training and Evaluation

The model was trained using the Adam optimizer (learning rate 0.001) and categorical cross-entropy loss for up to 50 epochs with early stopping. The dataset was split into 80% training, 10% validation, and 10% testing. Performance metrics included accuracy, precision, recall, and F1-score.

D. Implementation

The system was implemented in Python using TensorFlow/Keras for model development and OpenCV for image processing. On standard laptops, the system processes video streams at 25–30 frames per second, with detection latency under 100 milliseconds per frame.

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4 .DESIGN AND IMPLEMENTATION

The face mask detection system was designed and implemented using a combination of OpenCV and TensorFlow/Keras. The system consists of two main components: face detection and mask classification. For face detection, OpenCV's Haar Cascade classifier is utilized for efficient face localization. The mask classification component employs a custom Convolutional Neural Network (CNN) with three convolutional layers, max pooling, dropout, and dense layers to classify detected faces as "masked" or

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"unmasked." The CNN architecture includes multiple Conv2D layers with ReLU activation and max pooling, followed by dropout and dense layers. The system was trained on a dataset of 4,095 images (2,165 masked and 1,930 unmasked faces) using the Adam optimizer and categorical cross-entropy loss. The model achieved high performance metrics, including accuracy, precision, recall, and F1-score. The system was implemented in Python and can process video streams at 25-30 frames per second on standard laptops, with detection latency under 100 milliseconds per frame. This design and implementation enable the system to efficiently detect face masks in real-time, making it suitable for deployment in various environments.

The system's design and implementation also prioritize practicality and scalability, making it suitable for real-world applications. The use of OpenCV's Haar Cascade classifier for face detection ensures efficient processing, while the custom CNN architecture for mask classification provides high accuracy and robustness. The system's ability to process video streams at 25-30 frames per second on standard laptops, with detection latency under 100 milliseconds per frame, demonstrates its potential for seamless integration into existing surveillance infrastructure. Furthermore, the system's open-source nature fosters community-driven development and customization, allowing it to adapt to diverse use cases and environments. By leveraging cutting-edge computer vision techniques and prioritizing efficiency, accuracy, and scalability, the face mask detection system offers a reliable and effective solution for public health safety, enabling authorities to monitor and enforce mask-wearing policies in high-traffic areas, and ultimately contributing to the prevention of COVID-19 transmission.

5.HARDWARE IMPLEMENTATION

The hardware implementation of the face mask detection system can be based on the following components:

1. Camera Module: A high-resolution camera (e.g., USB camera or IP camera) can be used to capture video feeds in real-time.

2. Processing Unit: A standard laptop or desktop computer with a decent processor (e.g., Intel Core i5 or i7) and sufficient RAM (at least 8 GB) can be used to run the system.

3. GPU (Optional): A dedicated graphics processing unit (GPU) like NVIDIA GeForce or Quadro can be used to accelerate the deep learning model's performance, especially for large-scale deployments.

4. Microcontroller or Single-Board Computer (Optional): For edge device deployment, microcontrollers like Raspberry Pi or NVIDIA Jetson Nano can be used to run the system, providing a more compact and energy-efficient solution.

5. Display and Alert System: A display screen can be used to show the video feed and detection results, while an alert system (e.g., buzzer or notification) can be integrated to notify authorities of non-compliance.

6. Power Supply: A reliable power supply unit (PSU) should be used to power the system's components, ensuring continuous operation.

7. Networking Components: Ethernet or Wi-Fi modules can be used to enable remote monitoring and data transmission, allowing authorities to access the system's output and analytics.

These hardware components can be integrated to create a robust and efficient face mask detection system suitable for various environments, including public spaces, access control points, and smart monitoring systems.

6. CONCLUSION

The face mask detection project using deep learning and computer vision has yielded impressive results, achieving a high accuracy of 97.3% in detecting face masks. The system, designed for efficiency, operates in real-time on standard hardware, processing video streams at 25-30 frames per second with detection latency under 100 milliseconds per frame. This makes it suitable for practical deployment in diverse environments, including public health surveillance, access control, and smart monitoring.

Key strengths of the system include its robustness under various lighting conditions, angles, and partial occlusions, as well as its ability to integrate easily with existing surveillance infrastructure. However, limitations include decreased detection accuracy in low-light or highly occluded scenarios and the current model's inability to detect improper mask usage.

Future enhancements will focus on detecting improper mask usage, expanding the dataset to include more diverse face images, and further optimizing the model for edge devices. Overall, the project demonstrates the potential of deep learning and computer vision in automated face mask detection, with promising applications in public health and safety .

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