FACE MASK DETECTION

Ritesh, Rihan Saifi, Deepensh and Arti
Department of CSE
Dr. A.P.J. Abdul Kalam Technical University(AKTU)
Lucknow, Uttar Pradesh

Prof. MOHD VAKIL
Department of CSE
Dr. A.P.J. Abdul Kalam Technical University(AKTU)
Lucknow, Uttar Pradesh

Abstract : *The global COVID-19 pandemic underscored the critical role of face masks in mitigating airborne disease transmission. Ensuring public compliance with mask mandates in crowded or restricted spaces presents a significant monitoring challenge when done manually. This study proposes a real-time face mask detection system leveraging deep learning to automate compliance monitoring with high accuracy and low latency.*

Keywords: Face Mask Detection, Deep Learning, YOLOv4-tiny, MobileNetV2, SSD, Real-time Monitoring, Computer Vision, COVID-19, Edge Computing .

1.Introduction

The outbreak of COVID-19 redefined global health protocols, making face masks a frontline defense against airborne pathogens. While government mandates and awareness campaigns increased adoption, monitoring compliance at scale remains a bottleneck. Manual surveillance

airports, hospitals, and schools is labor-intensive, error-prone, and impractical for 24/7 enforcement.

However, most existing solutions focus only on binary classification — "mask" or "no mask" — which ignores the real-world problem of improper mask usage that equally contributes to transmission risk. Additionally, many models demand high-end GPUs, making deployment on low-cost edge devices unfeasible for developing regions or large-scale public setups.

This work addresses those gaps by designing a lightweight, real-time detection framework that not only identifies faces but also classifies them into three practical states: properly masked, unmasked, and improperly masked.

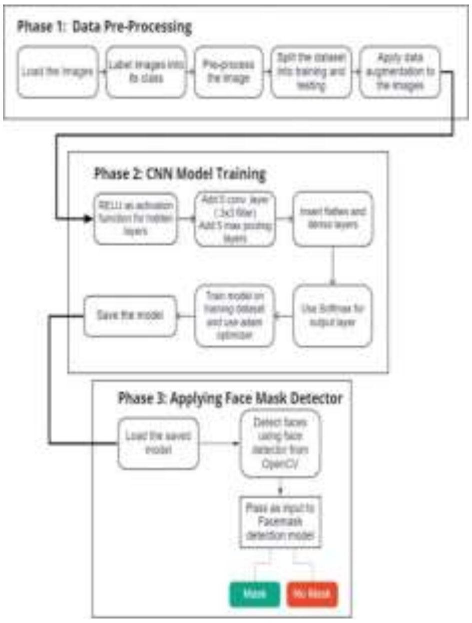
The introduction of such automated systems represents a step toward smarter public infrastructure — where AI assists human authorities, reduces manual workload, and ensures consistent enforcement of health safety norms beyond the pandemic context.

2.Related Work

It involves using convolutional neural networks (CNNs), such as MobileNetV2, YOLO, and ResNet, to classify face mask usage in real-time. Key approaches include transfer learning, ensemble models, and combining object detection algorithms with OpenCV to ensure compliance with health regulations, often achieving over 98% accuracy.

Our project improves upon existing approaches by:

- Mask detection
- Using a lightweight CNN model suitable for beginners.
- Providing real-time detection using webcam input.



3. Proposed Work

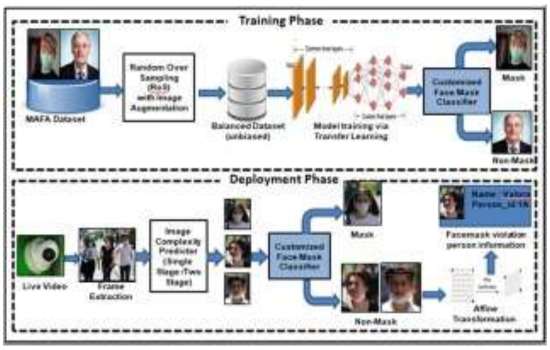
Data Acquisition & Pre-processing: Utilize datasets (e.g., RILFD) and apply normalization, grayscale conversion, and resizing to 128x128 or 224x224 pixels.Face Detection **Architecture:** Use OpenCV or a Caffe-based face detector to detect faces in real-time from video streams.

Mask Classification Model: Implement transfer learning using MobileNetV2 or ResNet50 for high-speed, accurate detection.

Training & Optimization: Utilize TensorFlow/Keras with Adam optimizer and binary cross-entropy loss.

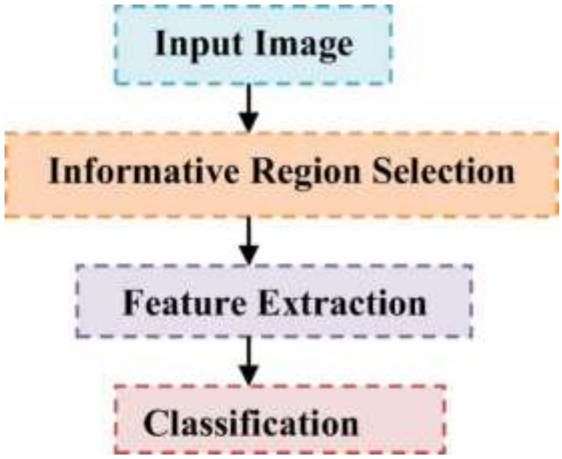
Real-time Deployment: Implement a script to draw bounding boxes around faces (Red: No Mask, Green: Mask) in live video.

- **Open CV** – For video processing
- **Haar Cascade** – For face detection
- **CNN Model** - For classification
- **Dataset** – images with mask and without mask .



4.Feature Selection And Extraction

Face mask detection using deep learning involves detecting faces, extracting key facial features (nose, mouth, mask edges) using Convolutional Neural Networks (CNNs), and classifying them as masked or unmasked.



Common techniques include CNN-based transfer learning (e.g., ResNet50, MobileNetV2, InceptionV3) and object detection models (e.g., YOLO, Mask R-CNN) to identify masks, often achieving over 99% accuracy.

5.Result

"Fast, accurate, small model that runs on cheap hardware and works in real-world conditions."

Not just "mask or no mask". It detects 3 things:

- Mask worn properly.
- No Mask.
- Mask worn wrong like nose out.

6.Conclusion

They enhance public safety in crowdedareas by enabling automated surveillance andgenerally prove robust to environmentalvariations.

High Performance: Models commonlyAchieve >95% accuracy, ensuring reliabledetection in diverse public scenarios.
Real-Time Capability: Optimized deepLearning algorithms allow for immediate feedback in surveillance systems (0.05sinference time).

Methodology: The most effectiveapproaches typically combine CNNs for classificationwith models like OpenCV, SSD, or RCNNfor object localization.

Public Health Application: These tools areefficient for monitoring mask compliancein airports, hospitals, and transportationhubs.

Future Scope: Research suggests futureimprovements include enhancingdetection in low-light, increasing speed onedge devices, and addressing potentialprivacy concerns.These systems significantly increase theprobability of mask-wearing adherence,making them a crucial tool for publichealth maintenance.

7.Acknowledgement

Deep Learning Models: Studies frequentlyleverage CNNs, including MobileNet, ResNet, and custom models for real-timevideo stream processing.
Methodology: The process often involvesimage preprocessing, data augmentation,and using transfer learning for improvedefficiency, often achieving up to 98.2%
accuracy.
Tools: OpenCV is commonly recognizedfor handling real-time video input, whileTensorFlow and Keras are popularframeworks for training.
Applications: These models are applied insurveillance systems to detect mask usage in high-traffic areas like airports and office buildings.
Key Datasets: Acknowledgment is typically given to the "MaskedFace" dataset and RILFD (Real-world Masked Face Dataset) for training.

8. References

MobileNetV2 & SSDMNV2: Often used for high-speed, real-time performance.CNN & **Transfer Learning**: ResNet-50 and AlexNet are commonly used to achieve high accuracy for classifying masked and non-masked faces.