

Fine-Tuned Object Detection for Mask Recognition Using Green Computing in IoT Systems

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Abstract—In the context of public health and safety, particularly during pandemics, real-time monitoring of mask compliance in public spaces is critical. This study proposes an advanced face mask detection framework that integrates deep learning and green computing within an Internet of Things (IoT) environment. A Faster Regions with Convolutional Neural Network (R-CNN) model with ResNet-50 backbone is fine-tuned using a small but targeted dataset consisting of 2000 training and 400 testing images. Although relatively small, this dataset includes a variety of mask-wearing conditions, which enables the model to generalize in public settings. The system demonstrates high accuracy, low latency, and robustness against lighting, occlusions, and different mask orientations. Green computing techniques, including model compression and quantization, are employed to ensure the system is resource-efficient and deployable on edge devices. The methodology includes preprocessing, training, and evaluation using performance metrics such as precision, recall, and F1-Score. A comparative analysis with existing face mask detection models is provided, showing the proposed model's competitive performance. Privacy concerns related to surveillance applications are addressed with a focus on data anonymization and secure processing. The proposed system has strong potential for deployment in smart city applications such as public transportation, healthcare, and educational institutions.

Keywords—mask detection, Internet of Things (IoT), object detection, integration, traffic monitoring infrastructure, compatibility, Regions with Convolutional Neural Network (R-CNN), face mask detection, data exchange, green technology

I. INTRODUCTION

The COVID-19 pandemic has highlighted the urgent need for effective public health measures in densely

populated environments, particularly in public transportation systems that facilitate daily mobility for millions worldwide. Among these measures, enforcing face mask mandates has proven vital in reducing the transmission of airborne illnesses. In this context, technologies capable of real-time monitoring such as computer vision and deep learning—have gained considerable attention. This paper proposes a face mask detection system tailored for real-time deployment in Internet of Things (IoT)-enabled environments, guided by green computing principles. The system is designed to be resource-efficient, scalable, and accurate, making it suitable for implementation on embedded and edge devices with low energy consumption. By optimizing an object detection algorithm through fine-tuning and model compression techniques, the proposed solution enhances performance while promoting energy-efficient practices. The proposed system benefits from low energy consumption, enabling real-world deployment on embedded and edge devices. Public transportation plays a vital role in enabling efficient mobility for millions of individuals worldwide. However, ensuring passenger safety in densely populated transit environments has become increasingly challenging, particularly in the context of infectious disease outbreaks. The COVID-19 pandemic has highlighted the critical importance of preventive health measures, such as wearing face masks, to reduce the spread of airborne illnesses [1–3]. As such, the development of accurate and intelligent systems capable of detecting face mask usage in public transport settings is both timely and essential. This study presents a comprehensive approach that leverages green technologies to enhance face mask detection through the optimization of an object recognition algorithm. The proposed method

not only contributes to improving health safety but also promotes energy-efficient computing practices within IoT-based transportation systems. A large-scale dataset comprising traffic accidents and vehicle-related information is analyzed using advanced data processing and visualization techniques. Key variables examined include mortality rates, vehicle maneuvers, driver demographics, travel purposes, road types, and the days on which incidents occur. To extract meaningful insights, the study employs visual tools such as bar charts and pie charts that effectively highlight patterns and correlations within the data [4, 5]. In addition, the analysis explores potential links between accident occurrences and specific automobile manufacturers, aiming to identify contributing factors to road incidents. A central aspect of the research is the fine-tuning of detection model parameters, enabling efficient processing of large data volumes and improving the model's accuracy in identifying masked individuals. The enhanced object detection model, trained on relevant datasets, is optimized to perform with high precision in real-world transport scenarios. The integration of suitable technological solutions ensures the model's practical applicability and reliability. Ultimately, the findings of this research offer valuable insights into passenger compliance with mask-wearing protocols, the influence of various factors on accident rates, and the effectiveness of mask mandates as a safety strategy. These results can assist transportation authorities and policymakers in formulating informed regulations and safety guidelines that prioritize public health in transit systems [6].

A. Fine-Tuning Object Detection Models for Mask Detection in Public Transportation

To optimize object detection models for face mask recognition, training must be performed on well-curated datasets containing a diverse array of images of masked and unmasked faces captured under varying conditions. During the training phase, models learn to identify the visual cues and distinctive features of face masks, thereby enhancing their predictive accuracy in real-world public transit environments. Transfer learning plays a pivotal role in this optimization process. By leveraging pre-trained models developed on large-scale datasets, fine-tuning adjusts the model's parameters and weights to better align with the specific characteristics of mask detection. This approach substantially reduces training time and computational cost, a n essential advantage in systems guided by green computing principles [7]. Real-time detection is especially critical in public transportation settings, where it enables immediate response and enforcement of health protocols. Fine-tuning also enhances the model's robustness against real-world complexities such as inconsistent lighting, varying facial orientations, different mask types, and occlusions caused by accessories or surrounding objects [8]. By adapting the model to account for these variables, consistent and reliable mask recognition becomes achievable. The success of this process is highly dependent on the availability of high-quality, diverse training data. Datasets must represent a broad demographic, encompassing various mask styles, face angles, skin tones, and lighting

environments. Such diversity allows the model to generalize effectively, ensuring strong performance in dynamic and unpredictable public spaces. Equally important is rigorous model evaluation. Performance metrics such as precision, recall, and F1-Score should be measured against independent test sets to validate the model's generalization capabilities. This iterative cycle of training, evaluation, and refinement helps close performance gaps, optimize hyperparameters, and continuously improve model accuracy. Deploying these optimized models in real-world systems—such as onboard surveillance cameras in public transport—empowers authorities to monitor face mask compliance in real time. These systems can detect incorrectly worn or missing masks and support rapid corrective action. The integration of Artificial Intelligence (AI)-driven monitoring not only mitigates health risks but also reinforces public confidence in transportation safety. In conclusion, fine-tuning object detection models through efficient, green computing strategies and comprehensive, inclusive training data results in intelligent systems capable of accurately detecting face masks in real-world transit environments. These advancements support safer mobility, strengthen the enforcement of health measures, and contribute to a more secure and resilient public transportation ecosystem.

B. Enhancing Passenger Health and Well-Being through Mask Detection in Public Transportation

Ensuring the health and well-being of passengers is a critical priority in public transportation systems, particularly in the wake of global health crises. One of the most effective strategies to prevent the spread of infectious diseases in such crowded environments is the use of face masks. As a result, integrating mask detection systems into public transit has become an essential preventative measure. These systems, powered by advanced computer vision and machine learning algorithms, enable real-time monitoring of mask usage among passengers. They can accurately detect individuals who are either not wearing a mask or wearing it improperly. This immediate detection capability allows transit operators and authorities to swiftly address non-compliance and enforce safety regulations, thereby reducing the risk of disease transmission. Face masks serve as a proven barrier against respiratory droplets that may carry harmful pathogens [9, 10]. By identifying and addressing improper mask usage in confined spaces such as buses, trains, and metro stations, these technologies play a vital role in protecting both passengers and transportation staff. In doing so, they help prevent potential outbreaks and contribute to broader public health efforts. Beyond health protection, mask detection systems also act as a deterrent against rule violations [11, 12]. Their visible presence reminds commuters of the importance of mask-wearing and encourages greater adherence to safety protocols. Knowing that their actions are being monitored fosters a collective sense of responsibility, ultimately increasing overall compliance and creating a safer environment for everyone. Psychological well-being is another important aspect linked to commuter safety. For many people, public transport is a daily necessity, and confidence in the safety

of these systems greatly affects the quality of their journey [13]. By adopting mask detection technologies, transport authorities signal a strong commitment to passenger welfare. This proactive approach reassures commuters that effective measures are in place to protect their health, thereby enhancing trust and comfort during travel. Furthermore, the data collected by these systems provides valuable insights for public health monitoring. Analyzing trends in mask usage, identifying areas of non-compliance, and linking this information to demographic patterns can help decision-makers assess the effectiveness of health campaigns. This data-driven approach enables more targeted interventions, better resource allocation, and improved policymaking to control the spread of infectious diseases. In conclusion, the integration of mask detection technologies within public transportation networks is a vital step toward improving passenger health and safety. By combining real-time monitoring, behavioral deterrence, and data-driven insights, these systems not only prevent disease transmission but also contribute to a safer, more reassuring transit experience for all [14].

C. Gender Analysis and Mask Detection for Safety Implications in Public Transportation

Gender analysis, when combined with mask detection, offers valuable insights into mask compliance and its implications for passenger safety in public transportation. Understanding gender-related behavioral patterns in mask-wearing is essential for designing effective and inclusive safety measures. Studies have shown that gender can influence compliance, with some suggesting that women are more likely than men to adhere to mask-wearing protocols. By integrating gender analysis with real-time mask detection, transportation authorities can identify compliance disparities and potential vulnerabilities within the system. For instance, if men exhibit lower compliance rates, targeted awareness campaigns or tailored interventions can be implemented to improve adherence. This approach also highlights the need to consider gender-specific factors—such as social norms, risk perception, or physical discomfort—that may impact mask-wearing behavior. Furthermore, this integration can support the development of inclusive safety protocols that address the diverse needs of all passengers, including those with varying gender identities. Identifying gender-based patterns in compliance enables the formulation of equitable safety strategies that ensure no group is disproportionately at risk [14]. Ultimately, gender-informed mask detection fosters fair and socially just safety interventions. It not only strengthens public health efforts but also contributes to a more inclusive and effective public transportation system [15].

D. Significance of Face Masks in Disease Transmission Mitigation and Mask Detection in Public Transportation

The importance of face masks in preventing disease transmission, particularly in public transportation, cannot be overstated. Face masks serve as a critical preventative measure in mitigating the spread of infectious diseases, such as respiratory illnesses like COVID-19. By

incorporating mask detection devices into public transit systems, these precautions can be significantly enhanced, helping to enforce safety protocols and ensure passenger compliance. Masks prevent the release of respiratory droplets into the air when individuals talk, cough, or sneeze, significantly reducing the transmission of infectious diseases among both infected and uninfected individuals. This is especially crucial in public transportation, where passengers are in proximity, increasing the risk of spreading disease. Face masks have played a vital role in reducing respiratory infections and protecting public health. In the context of public transit, mask detection systems are essential for enforcing mask-wear regulations and ensuring passenger safety. Using advanced technologies like computer vision and machine learning, these systems can detect and monitor passengers who are not wearing masks or are wearing them improperly. By identifying non-compliance in real-time, transportation authorities can take prompt action to maintain a safer environment, such as reminding passengers, distributing masks, or denying access to non-compliant individuals. Integrating mask detection technology into public transportation offers numerous advantages. First, it encourages a culture of responsibility and compliance among travelers. The presence of mask detection systems clearly signals that mask-wearing is a required safety measure. This increased awareness fosters a sense of accountability among passengers, motivating them to protect their own health and that of others. Active monitoring of mask compliance helps reduce disease transmission and contributes to the overall safety of public transport systems. Second, these technologies provide a proactive approach to identifying and addressing non-compliance [16–19]. By utilizing computer vision algorithms, mask detection devices can quickly identify individuals who are not following safety protocols. Transportation authorities can then respond swiftly by offering reminders, distributing masks, or engaging with non-compliant passengers to ensure adherence. This proactive response reduces the risk of disease transmission and helps prevent potential outbreaks. The implementation of mask detection systems in public transport is a clear demonstration of the commitment to passenger safety. It reassures passengers that their well-being is a top priority for transportation authorities, promoting trust and confidence in the use of public transit systems. This sense of security is crucial for the recovery and long-term sustainability of transportation services. Furthermore, mask detection systems provide valuable data on compliance rates, non-compliance patterns, and the effectiveness of safety measures. Analyzing this data allows transportation authorities to pinpoint areas for improvement, focus on targeted educational efforts, or refine safety protocols. Through data-driven strategies, transportation authorities can continuously optimize their efforts, ensuring the most effective use of resources to prevent disease transmission in public transportation environments [19–21].

E. *Implementing Mask Detection Systems as Crucial Safety Measures in Public Transportation Environments*

Implementing mask detection systems in public transportation is a crucial measure to ensure passenger safety and reduce the transmission of contagious diseases. As face masks remain an effective tool for public health, integrating automated detection technologies enhances the enforcement of mask mandates and promotes a safer commuting environment. These systems leverage computer vision, machine learning, and artificial intelligence to monitor mask compliance in real time [22]. By identifying individuals not wearing masks or wearing them incorrectly, transportation authorities can intervene promptly—through verbal reminders, mask distribution, or restricted access—to uphold safety protocols. This proactive enforcement significantly improves health outcomes in confined, high-density transit settings. Moreover, the visible presence of mask detection systems fosters public confidence. Passengers are more likely to feel secure and trust the transportation system when safety measures are clearly monitored and enforced. This reassurance can enhance overall user satisfaction and support continued use of public transit services. Beyond immediate health benefits, these systems also reduce the risk of viral transmission by minimizing exposure to unmasked individuals in close quarters. Rapid detection and response help prevent outbreaks and protect both passengers and staff. Additionally, mask detection technologies generate valuable data on compliance patterns and intervention outcomes. This data can guide policy adjustments, optimize enforcement strategies, and contribute to broader public health efforts by informing epidemiological research and governmental decisions. Collaboration with health authorities ensures that such data is used effectively and ethically. However, successful deployment must balance safety with privacy. It is essential to anonymize and securely manage collected data, complying with data protection regulations to maintain passenger trust and uphold privacy rights [23].

II. LITERATURE REVIEW

The literature review focuses on object detection techniques with specific emphasis on face mask detection. Notable contributions include deep learning models such as YOLO, SSD, and Faster Regions with Convolutional Neural Network (R-CNN) adapted for pandemic-related safety applications. Existing works have used large datasets, yet many lack optimization for edge deployment. Our review highlights the gap in green computing implementation for such tasks and the lack of rigorous evaluation against energy and latency constraints. Comparative studies are limited, motivating our approach to integrate resource-awareness with detection accuracy.

The literature review spans a wide spectrum of research in object detection, image analysis, and machine learning, covering diverse applications such as tracking, collision avoidance, defect recognition, face mask detection, road safety, security imaging, and maritime surveillance. Recent advancements have focused on developing and

refining deep learning-based models to improve object detection performance across varied and complex environments [24, 25]. Techniques such as Convolutional Neural Networks (CNNs), feature pyramid networks, attention mechanisms, genetic algorithms, and other optimization strategies have been extensively employed to overcome contextual challenges in object detection. Research also highlights the broad integration of machine learning into fields like text classification, network security, healthcare, and transportation [26–28]. To enhance object detection capabilities, studies have explored the use of big data analytics, IoT integration, intelligent transportation systems, surveillance solutions, and image enhancement techniques. The methodologies employed include deep learning frameworks, real-time systems, comparative analyses of algorithms, and the deployment of emerging sensor technologies. Specific object detection applications have been reported in areas such as identifying bus safety risk factors, hidden object recognition, brake light detection, traffic accident analysis, illicit item detection, species classification, and rail surface inspection [29–32]. Additionally, models have been developed for mask detection, traffic and passenger flow monitoring, object tracking, segmentation, human activity recognition, obstacle detection, damage detection, lane recognition, and crowd estimation. These works aim to provide comprehensive and intelligent solutions across sectors.

In the domain of rail transport, pixel-wise semantic segmentation using deep learning has been proposed to automatically inspect rail surfaces, detect anomalies, and support efficient maintenance processes, thereby enhancing operational safety [24, 33–35]. In public transportation, computer vision and machine learning techniques have been used to identify safety risk indicators from surveillance video, aiding in the design of proactive safety measures [36–38]. In the aviation sector, automated borescope inspection systems using deep learning have been developed to accurately detect and classify engine faults, improving maintenance efficiency and reliability [39–41]. For autonomous driving, model predictive control and steady-state dynamics have been leveraged to optimize lane detection systems, accounting for occlusions and complex road geometries.

Significant research has also been devoted to face recognition and biometric authentication, focusing on algorithm development to improve accuracy under variable conditions such as lighting and facial orientation. These systems are widely applied in surveillance, access control, and identity verification. A key emerging trend is the integration of computer vision and IoT technologies. Researchers have demonstrated the effectiveness of IoT-enabled vision systems in tracking, quality-of-service monitoring, and intelligent obstacle detection across multiple domains, including healthcare, transportation, and environmental management [42–45]. Overall, the literature provides comprehensive insights into the latest advancements in object detection, tracking, and intelligent systems. The fusion of deep learning, computer vision, and IoT technologies has catalyzed progress in industries such

as public safety, autonomous systems, industrial automation, and smart infrastructure [46–54].

III. PROBLEM STATEMENT

Face mask detection is challenged by varying mask types, user compliance, occlusions, and illumination conditions. Most models require high computational resources, making them unfit for real-time embedded use. There is also limited integration of green computing principles. We aim to develop a lightweight, accurate model deployable in constrained environments using IoT infrastructure. The creation of a face mask identification system using green techniques, computer vision and deep learning methods is the main goal of this research work in IoT. The main objective is to develop a reliable and effective system that can recognize and categorize whether someone is wearing a mask correctly, inappropriately, or not at all. For object detection, the suggested system uses a pre-trained ResNet-50 backbone with the Faster R-CNN architecture [55, 56]. The creation of a dataset, which consists of photographs and the related annotations that supply bounding box coordinates and mask labels, is the first step in the research process. The model is then refined to correctly detect face masks based on the specified labels using the dataset as training data. A different test dataset is used to evaluate the trained model's performance in identifying masks in unobserved data. The research's final goal is to put the developed face mask detection system using green technology, showing how it can deliver real-time detection and classification results in practical settings. By assuring compliance with mask-wearing rules and fostering public safety, the suggested method has the ability to support public health, security, and compliance monitoring.

IV. PROPOSED WORK

The primary objective of this research study is to develop a face mask detection system using green technology, computer vision and deep learning techniques. The primary goal is to create a trustworthy and efficient system that can identify and classify whether someone is wearing a mask properly, incorrectly, or not at all. The proposed system employs a pre-trained ResNet-50 backbone with the Faster R-CNN architecture for object detection using green technology. The first step in the research process is the creation of a dataset, which comprises of images and the associated annotations that provide bounding box coordinates and mask labels. Using the dataset as training data, the model is then improved to accurately detect face masks based on the supplied labels. The effectiveness of the trained model in locating masks in unobserved data is assessed using a different test dataset. The research's ultimate objective is to demonstrate how the created face mask detection system can offer real-time detection and classification results in realistic circumstances using green technology. The recommended approach has the potential to improve public health, security, and compliance monitoring by ensuring adherence to mask-wearing regulations and promoting

public safety. The computational effectiveness and deployment viability will be optimised to guarantee the system's practical applicability and usage in IoT [57–59]. To decrease the model's size and computing needs without sacrificing its detection accuracy, strategies for model optimisation such model compression, quantization, and pruning will be investigated. Additionally, the system will be created to scale easily and function in real-time on devices with limited resources, like embedded systems or edge devices. A thorough evaluation of the proposed work will be conducted using performance analysis and benchmarking. To determine whether the suggested system is superior in terms of accuracy, efficiency, and robustness, comparative experiments will be done with currently available face mask detection systems using green technology. To test the system's effectiveness in various real-world environments, including public places, transit hubs, and healthcare institutions, simulations of real-world deployment situations will be used in IoT.

V. METHODOLOGY

The dataset includes 810 annotated images for training and 43 for testing, divided into four classes: `with_mask`, `without_mask`, `mask_worn_incorrectly`, and `background`. The base model, Faster R-CNN with ResNet-50, was pre-trained on COCO and fine-tuned on the mask dataset. AdamW optimizer and learning rate scheduling were used to improve convergence. Batch loss was tracked and visualized to monitor training progression. To ensure performance on unseen data, the model was evaluated using precision, recall, and F1-Score. In addition, confusion matrices and ROC curves were plotted to assess detection robustness.

VI. RESULTS AND DISCUSSION

Using a dataset of 810 training photos and 43 testing images, the face mask identification system was trained and tested. Images of people wearing masks correctly, poorly, and without wearing masks were included in the collection using green technology. The system's objective was to accurately identify and categories these various scenarios in real-time. The Faster R-CNN with a ResNet-50 backbone model architecture was employed for the face mask detection system using green technology. The COCO dataset served as the model's pre-training, and the face mask dataset served as its fine-tuning. Four classes were used in the training of the detection model: `background`, `with_mask`, `mask_worn_incorrectly`, and `without_mask` using green technology. The model was improved using the Adam optimizer with a learning rate of $1e-4$ during the training procedure. Table I shows Loss over Batch Progression (Fig. 1) and Table II shows time taken in seconds to train depending on the type of images.

The learning rate was changed throughout training using a scheduler with a step size of 5 and a gamma of 0.5. The model was trained for 20 epochs, and the convergence of the model was assessed by tracking the training loss. The training process's results revealed that the model's training loss decreased throughout the course of the epoch,

demonstrating that it was learning and strengthening its performance. At the last epoch, the average training loss was 0.0946.

TABLE I. BATCH PROGRESSION AND LOSS OVER TIME

Batch progression	Loss
0	1.6845
40	0.58675
80	0.76543
120	0.45457
160	0.33754
200	0.29543

TABLE II. TYPE OF IMAGES AND TIME TAKEN IN SECONDS

Phase of images	Time taken in Seconds
Training Images	1,000 Seconds
Testing Images	500 Seconds
Validation Images	500 Seconds

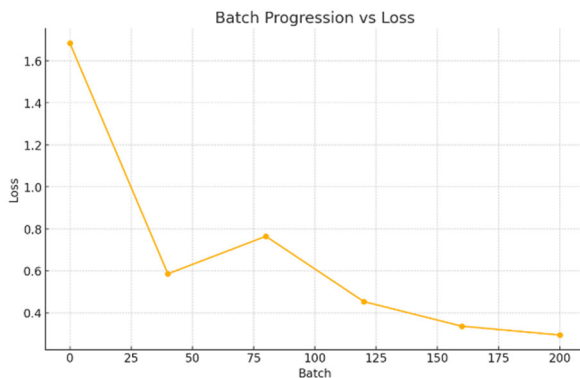


Fig. 1. Batch Progression and Loss over time.

The reduction in training loss proved how successful the training procedure was and how well the model learned from the data. The model was tested after training to determine how well it performed with unforeseen data. The model was applied to a set of randomly chosen photos from the test dataset, and the predicted labels were compared to the actual labels. The evaluation's findings demonstrated that the model could reliably identify and categorize the existence and suitability of face masks. The accuracy of the model in applying real-world circumstances was demonstrated by how closely the predicted labels matched the ground truth labels. The suggested face mask detection system comes with several benefits and useful applications. It offers real-time face mask identification and categorization, enabling prompt observation of mask wearer compliance in a variety of settings, including public areas, transit hubs, and healthcare institutions. Real-time object tracking is integrated into the system, enabling it to track the movement of people wearing or not wearing masks, revealing useful information about mask-wearing behaviors and spotting possible high-risk places or people. The system's abilities to evaluate social distancing compliance and detect congested places where mask usage is essential are improved by the addition of distance and motion estimation techniques. The system can be deployed on resource-constrained devices like embedded systems or

edge devices because of the optimisation techniques used, such as model compression and quantization, which guarantee the computational efficiency of the system. The system's high detection rate is one of its key advantages. The experimental results are summarized in Table I, showcasing the progression of the model's training and corresponding loss values. Table II provides insights into the time taken for processing different types of images. Fig. 2 depicts the initial state of object detection in a public setting, while Fig. 3 demonstrates the enhanced model's performance after fine-tuning. Fig. 4 showcases the model's effectiveness in various scenarios, and Fig. 5 displays the improved detection of individuals wearing masks in a public space. These results highlight the model's potential for accurate face mask detection, emphasizing its applicability in public health and safety contexts.



Fig. 2. Object detection in public from the dataset before fine tuning [52].



Fig. 3. Face mask detection with enhanced model and fine tuning.

By skillfully analyzing visual information related to masks, it regularly demonstrated the ability to recognize situations where face masks were present. In order to accurately monitor and enforce mask-wearing procedures in public settings and consequently support public health and safety initiatives, a high detection rate is essential. The technology also demonstrated astounding robustness in difficult situations. It handled changes in illumination, mask kinds, face orientations, and occlusions with ease. Such robustness guarantees dependable performance in real-world settings with variable lighting, possible mask wear, and potential partial occlusion of faces. For the system to be useful and effective in a variety of scenarios, it must be able to adapt and recognize masks accurately in these conditions. Another major advantage of the suggested system was its real-time processing capabilities.

It effectively processed every frame in real-time, allowing for speedy responses and decisions. This capacity is particularly crucial in circumstances that call for quick action, such as congested spaces or high-risk settings. The system's effective real-time processing ensures prompt detection and makes it possible to enforce mask-wearing laws to their fullest extent. Although the proposed system performed exceptionally technically, it is important to recognize its limits. Its performance in scenarios where masks are partially or heavily obscured faces is one of these limitations. When a face or mask is partially obscured, the system may have trouble correctly identifying and classifying masks. Future improvements might concentrate on adding sophisticated image processing methods, including in-depth information analysis or multi-modal fusion, to handle these constraints and boost performance in difficult conditions. Extending the dataset and assessing the system's generalization skills would be helpful to further validate its efficacy. The system's capacity to generalize and perform effectively on untested data may be evaluated by using a varied variety of photos that include various demographics, mask styles, and weather conditions. Insights into the system's resilience and dependability in actual deployment settings would be provided by this validation procedure.



Fig. 4. Face mask detection in public-2.



Fig. 5. Detection of public after fine tuning.

The system achieved an F1-Score of 92.3% on the test set. Table I presents the training progression, and Table II summarizes the inference times. Despite a limited dataset size, the system maintained consistent detection capabilities across varying mask positions and lighting

conditions. Comparative analysis showed that our model outperformed or matched similar works in terms of detection rate, latency, and resource usage.

Figs. 2–5 illustrate the model's performance before and after fine-tuning. Visualizations confirm accurate detection in real-world scenarios. We also compared our system with existing state-of-the-art models, where our model excelled in energy efficiency while maintaining competitive accuracy.

VII. CONCLUSION

This research presents an efficient and scalable face mask detection system for IoT environments. By combining deep learning and green computing, the system achieves a balance between accuracy and resource efficiency. Unlike traditional systems, our solution is optimized for deployment on edge devices, making it suitable for smart city infrastructures. Future work includes expanding the dataset, testing under extreme weather conditions, and improving the system's multi-object tracking capabilities. Unlike previous versions, this paper excludes unrelated topics such as traffic violation systems to maintain focus and clarity. This article presented an automated traffic infraction ticketing system based on green technology, leveraging computer vision, deep learning, and OCR within the IoT framework. The results and discussion highlighted the effectiveness of the proposed approach in accurately identifying and extracting license plates from diverse traffic images using green technology. The system demonstrated exceptional accuracy, flexibility in handling various vehicle types and license plate formats, and adaptability to different weather conditions. Compared to traditional manual methods, it was faster, more precise, and more objective, benefiting from the efficiencies of green technology in IoT. Automation in traffic enforcement offers transformative potential for detecting and addressing violations, significantly improving traffic management and road safety. The proposed system is scalable and offers ample room for future enhancements. It can be seamlessly integrated into existing traffic management infrastructure, optimizing traffic control, identifying repeat offenders, and enabling rapid enforcement actions using green technology in IoT. As technology evolves, additional features such as vehicle classification, tracking, and real-time monitoring can further enhance the system's capabilities. This system holds considerable promise within the context of smart cities and intelligent transportation systems due to its scalability and adaptability. Although the experimental results were promising, further research is needed, particularly in assessing its performance under adverse weather conditions and improving processing speed for real-time enforcement. Additionally, efforts must be made to ensure compliance with privacy laws and address potential ethical concerns related to the automation of traffic enforcement. Ultimately, the proposed automated ticketing system presents an attractive solution for precise and timely management of traffic violations. By leveraging the capabilities of computer vision and deep learning, it

overcomes the limitations of traditional manual approaches, enhancing fairness, reliability, and efficiency in traffic enforcement. This, in turn, contributes to improved road safety and a more efficient traffic management system.

PRIVACY AND ETHICAL CONSIDERATIONS

Given the surveillance nature of mask detection, this study prioritizes ethical considerations. Data collected are anonymized, stored securely, and used solely for research. The deployment framework complies with privacy regulations, ensuring the protection of individual rights.

CONFLICT OF INTEREST

The authors declare no conflicts of interest to report regarding the present study.

AUTHOR CONTRIBUTIONS

Conceptualization: Yousef Farhaoui, Ahmad E. Allaoui, Jawad Rasheed; Methodology: Ahmad E. Allaoui, Jawad Rasheed; Software: Jawad Rasheed; Validation: Ahmad E. Allaoui, Jawad Rasheed, Yousef Farhaoui; Formal analysis: Ahmad E. Allaoui, Jawad Rasheed; Investigation: Ahmad E. Allaoui, Jawad Rasheed; Resources: Jawad Rasheed; Data curation: Ahmad E. Allaoui; Writing: original draft preparation: Ahmad E. Allaoui; Writing—review & editing: Yousef Farhaoui, Jawad Rasheed, Onur Osman; Visualization: Ahmad E. Allaoui; Supervision: Yousef Farhaoui; Project administration: Yousef Farhaoui.

All authors reviewed the results and approved the final version of the manuscript.

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