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Implementation of Mask Use Detection With SVM and Haar Cascade in OpenCV

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ABSTRACT — Despite a decline in global COVID-19 cases, the persisting threat of SARS-CoV-2 coupled with waning public awareness of the virus threat has raised concerns. A notable number of individuals disregard mask usage or do so incorrectly. It is particularly concerning given that COVID-19 has high transmissibility, especially in crowded areas like shopping centers. Enforcement officers often face challenges in identifying those wearing masks improperly. Herein lies the significance of automated mask detection to aid enforcement officers in containing the spread of the virus. Hence, this paper aims to highlight the importance of automated mask detection in combatting COVID-19 transmission. Previous mask detection algorithms were intricate because they relied heavily on resource-intensive machine learning algorithms and libraries. These algorithms, however, failed to address the problem of incorrect mask usage adequately. Therefore, despite the apparent usage of masks, the virus managed to find transmission pathways. In contrast, this research focuses on creating algorithms that pinpoint improper mask usage and optimize resource utilization without compromising detection quality. The Haar cascade algorithm was utilized to detect faces and the support vector machine (SVM) was used to train the dataset. The model attained an average accuracy of 95.8%, precision of 99.7%, recall of 92.3%, and F1-score of 93.7%. The metrics aligned with prior studies, affirming their reliability. Nevertheless, limitations exist as the model faces challenges in detecting obscured facial features, requiring further research to enhance its detection capabilities. This research contributes to ongoing efforts to improve mask detection technology for more effective virus containment.

KEYWORDS — Image Processing, Video Processing, OpenCV, Haar Cascade Classifier, Face Mask Detection.

I. INTRODUCTION

Coronavirus disease, more commonly known as COVID-19, emerged and spread rapidly since 2019, with Wuhan, China being identified as the initial epicenter. This disease gained global attention due to its highly transmissible nature. People with COVID-19 can have mild to severe symptoms. For some patients, mild symptoms may later develop into severe conditions [1]. In many cases, individuals can be silent carriers as they mistake the symptoms of COVID-19 for common flu during the virus' 14-day incubation period, resulting in rapid spread of the virus. As countermeasures, many countries implemented border closures and imposed lockdowns to control the escalating number of COVID-19 cases, which led to profound global economic devastation [2].

The significant increase in COVID-19 cases that occurred in 2020 caught many countries off guard and prompted the implementation of stricter containment measures. Not only did the outbreak have a profound impact in Asia, but it also impacted Europe and the United States of America as millions of cases were reported. By early 2022, the World Health Organization (WHO) recorded 23 million cases globally and reached 40 million cases later that year. Neglecting COVID-19 safety protocols, such as mask usage and social distancing, contributed to this surge of COVID-19 cases. Nevertheless, wearing face masks does not guarantee immunity against COVID-19, as the effectiveness of masks varies in indoor environments [3]. This result indicates people wearing masks are still at risk of contracting the virus, not to mention those who do not wear masks or wear masks improperly. The ability of SARS-CoV-2 virus, which cause COVID-19, to mutate rapidly further exacerbated the outbreak [4]. The severe shortage of medical supplies and availability of medical personnel to handle the escalating number of COVID-19 patients which continues to grow due to the lack of preparation and, sometimes, many citizens' reluctance to comply with safety protocols issued from their governments, have bolstered the number of patients being admitted to hospitals [5]. Numerous early warning systems have been implemented in several countries, such as South Korea; yet some are ineffective in containing the transmission of COVID-19. Studies have been conducted to address and improve the effectiveness of these early warning systems [6].

The growing number of confirmed cases has also been also attributed to cultural or religious traditions, such as those celebrated in India. During the steady decline of confirmed cases of the COVID-19, thousands of religious devotees gathered by the Ganges River in northern India on 14 January 2022 in order to take the holy dip of the Makar Sankranti festival. This festival involves people bathing in the river to cleanse their sins. Despite the government warning, thousands of people still performed this holy ritual, thereby contributing to the further spread of the virus which its confirmed cases had increased since a month prior. This event led to a massive surge in COVID-19 cases just a few weeks later and became the pinnacle of COVID-19 cases in 2022 in India. It was of great concern given that India managed to suppress the number of confirmed cases in prior months, such as in late 2021 following the devastating surge in May 2021. Events like these are referred to as superspreader events [7].

By March 2023, a remarkable transformation swept across the global landscape, which was the result of extensive vaccination campaigns and a refined comprehension of the COVID-19 through intensive research endeavors. This concerted effort resulted in a palpable decline in the once widespread COVID-19 cases, heralding a newfound hope in the battle against the outbreak. A notable cornerstone in this progress is the comprehensive investigation of classification models designed to effectively identify patients infected with the virus, as elaborated in a previous pivotal study [8]. In a parallel avenue of preventive measures, the deployment of cutting-edge deep learning algorithms gained attention for their real-time capacity to detect face mask compliance. However, adopting such algorithms was challenging, particularly due to the high demand for substantial computational resources. Although deep neural network training is highly effective, it requires significant processing power and time allocation [9]. This juxtaposition thus underscores the intricate dynamics of steering a course between revolutionary technological solutions and the pragmatic constraints posed by resource limitations.

This research paper focuses on the implementation of a trained model with a simpler algorithm to achieve a more accurate detection of both proper and improper mask usage while minimizing computational resources. Prior studies failed to account for improper mask usage as they primarily focused on the identification of individuals who wore masks and those who did not. The proposed model in this research aims to identify both proper and improper mask usage without relying on complex algorithms, namely using OpenCV instead of deep learning methods.

II. FACE MASK RECOGNITION

Face mask recognition involves identifying instances of mask usage, specifically in relation to the COVID-19 pandemic. It aims to detect mask usage in an effort to combat the transmission of COVID-19, which is airborne and commonly transmitted via entry points such as the nose and mouth. Various studies conducted between 2020 and 2022 have primarily focused on training models to distinguish between individuals who properly wear masks and those not wearing them. Unfortunately, these approaches failed to address the crucial aspect of identifying improperly worn masks, thereby significantly contributing to the potential transmission of COVID-19 within immediate environments [10], [11].

Another significant study conducted in 2022 managed to attain a value of 100% for accuracy, precision, recall, and F1-score for their proposed model [12]. However, similar to previous studies, this model also failed to recognize instances of improperly worn masks. Prominent techniques employed in training face mask detection models involve leveraging pretrained convolutional neural network (CNN) models such as MobileNetV2 or InceptionV3, or even a strategic fusion of both [13].

In a distinct trajectory, a study in 2021 proposed a model that harnessed the synergy of the single shot multibox technique as a proficient face detector and the lightweight MobilenetV2 architecture as the backbone of the classifier [14]. This unique fusion, called SSDMNV2, could obtain an accuracy of 92.64%, precision of 94%, recall of 93%, and F1-score of 93%. Nonetheless, akin to its predecessors, this model is not able to discern the instances of improper mask usage, limiting its comprehensive effectiveness in real-world scenarios.

III. METHODOLOGY

This research chose open-source computer vision (OpenCV) for its proven reliability in image processing. OpenCV served as a robust framework that met the requirements of this research, offering a versatile toolkit for detecting complexities in mask usage.

The Haar cascade classifier was selected as the core component of the model's design due to its suitability for discerning facial attributes that signified the correct or incorrect ways of wearing masks. The Haar cascade classifier, renowned for its efficiency and effectiveness in object detection tasks, is also aligned with the objective of identifying nuanced facial configurations.

The Haar cascade classifier derives its name from its underlying concept of Haar-like features, which are akin to pattern templates used to recognize specific attributes in the visual landscape. In this research, these features served as templates to distinguish essential indicators such as facial contours and proportions, allowing this research to ascertain the correctness of mask usage.

By utilizing the Haar cascade classifier within the OpenCV framework, the model capitalizes on the synergy of image processing capabilities and intelligent feature-based analysis. The integration of these two tools facilitates an examination of facial compositions, enabling the model to effectively distinguish between the diverse scenarios of proper and improper mask utilization. In essence, the choice of OpenCV as the foundation and the Haar cascade classifier as the guiding mechanism represents a fusion of advanced technology and astute methodology. OpenCV and Haar cascade classifier are employed to find and extract data for precise mask usage detection.

The paper focuses on an optimization-oriented approach to evaluate the performance metrics. The support vector machine (SVM) was utilized because of its efficient and accurate assessment of the trained model. SVM excels in classification tasks, making it the ideal algorithm used to achieve the objective of gauging the model's performance with precision in detecting proper and improper ways of wearing a mask by identifying the optimal hyperplane that maximizes the margin between these classes, thereby yielding a classification model capable of distinguish subtle details. In terms of capacity, SVM offers the capacity to handle high-dimensional data, making it suitable to handle visual data like mask usage detection. SVM also optimizes its discrimination capabilities by transforming the data into a higher-dimensional space.

In terms of efficiency, SVM is the optimal choice in line with the objective of this research in assessing the trained model performance. This efficiency is particularly pronounced when the kernel trick is employed, enabling SVM to efficiently process data even in cases of nonlinear separability.

The selection of SVM as for training and performance evaluation underscores the need to achieve precision, efficiency, and robustness. Through the utilization of SVM's distinctive attributes, this paper strives to deliver a comprehensive analysis of the trained model's effectiveness in identifying proper and improper mask usage. By employing this method, this paper intends to contribute a nuanced understanding of the model's performance, fostering advancements in the mask usage detection.

The research methodology incorporates a well-structured bifurcation of operations, encompassing two distinct stages. These stages are designed to synergistically achieve the overarching objective of the study: the accurate detection of face mask usage.

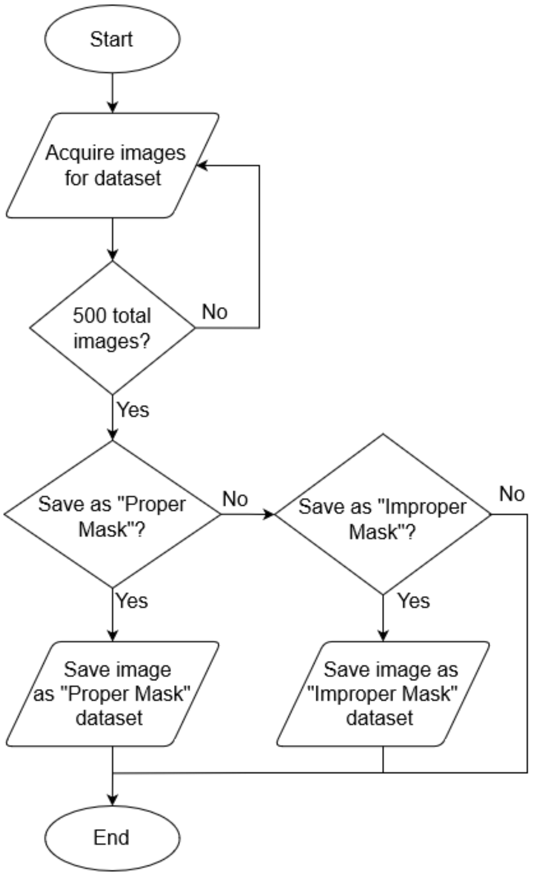


Figure 1. Training program's flowchart.

In the initial stage, this research embarked on the crucial task of data collection, a foundational step that lays the groundwork for subsequent analyses. This endeavor was undertaken through the utilization of one of two purpose-built programs, each crafted to gather pertinent data for the dataset. These programs act as data collection agents, systematically sourcing facial images that encapsulate the diverse spectrum of mask usage scenarios, especially proper to improper way of wearing masks.

In Figure 1, the core functionality of the training program lay in its process of gathering a dataset comprising a total of 500 images. This program categorized the images based on their content, segregating them into two specific datasets: one representing images with proper mask usage and the other indicating instances of improper mask adherence.

In Figure 2, the primary objective of the main program was to utilize or load preexisting datasets of both proper and improper mask usage. It merged these datasets into a single unit and conducted training on this combined dataset. Afterwards, the program applied the newly merged dataset to the video camera feed, allowing the camera to identify and detect the usage of face masks.

In Figure 3, the entire system was designed to load image datasets processed within the training program and subsequently integrate the newly processed datasets into the main program. This integration facilitates their utilization in tandem with a video camera for real-time face mask detection.

Transitioning from dataset collection, the research progresses to its second stage, focusing on the core of the face mask detection process. Utilizing the curated dataset, a purpose-built program was built. This program can distinguish between proper and improper mask usage within acquired facial images.

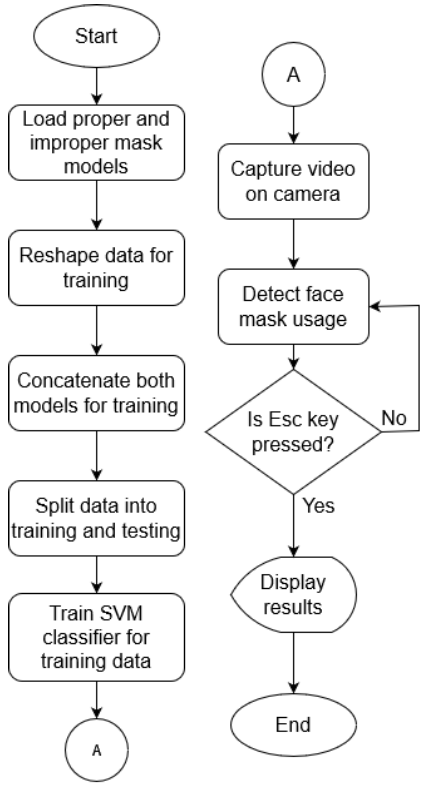


Figure 2. Main program's flowchart.

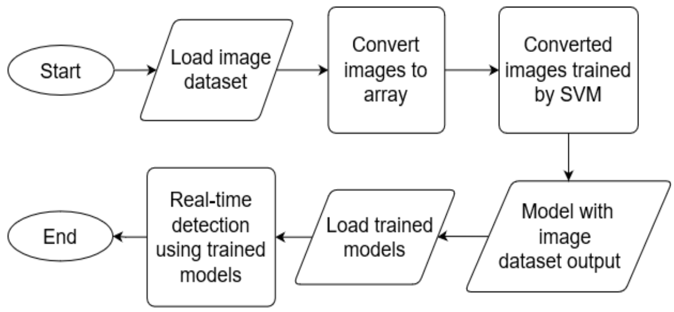


Figure 3. System's block diagram.

The two-stage framework shows the research design, methodical execution, and scientific rigor. Differentiating between data collection and detection stages ensures both accuracy in achieving research objectives. This structured method unravels face mask detection intricacies while maintaining a purpose-driven investigative process.

The subsequent research stage commenced with testing and result acquisition. Using the collected dataset, this stage evaluated the trained model's ability to recognize proper and improper face mask usage across diverse real-world scenarios.

The testing phase assessed the model's ability to detect face masks across diverse scenarios, utilizing a comprehensive dataset representing varied mask usage instances. Each facial image within the dataset served as a test case, where the predictive accuracy of the model in identifying mask usage was evaluated. To ensure robust results, this research evaluated 30 test subjects with diverse facial features and accessories like eyeglasses. This diversification aims to validate the model's performance across a broad range of real-world situations.

This comprehensive evaluation, performed in real-world diversity, provides this paper with a thorough understanding of the model's effectiveness in face mask detection. Through this evaluation, this paper aims to uncover the model's genuine potential and its ability to implement its performance broadly across various practical scenarios.

This reserach utilized a set of established metrics in order to systematically evaluate the trained model's performance. These metrics included accuracy, precision, recall, and F1-score. Accuracy served as the primary metric. It quantifies how well the model's predictions match the ground truth. A higher accuracy score signifies the model's consistent and correct predictions.

Precision assesses the model's ability to minimize false positives. This research investigated the precision with which the model classifies instances as proper or improper mask usage. The higher the precision score, the fewer instances of false positives, indicating the model's precision in detecting improper mask usage.

Recall focuses on the model's capability to identify all instances of a particular class. Recall was used in this research to determine how well the model detected both proper and improper mask usage. A higher recall score indicates a greater ability to detect improper mask usage.

Moreover, the F1-score amalgamates precision and recall, offering a consolidated measure of a model's effectiveness. This score encapsulates the trade-off between precision and recall, thereby providing a balanced metric that underscores the model's overall performance.

A. OPENCV

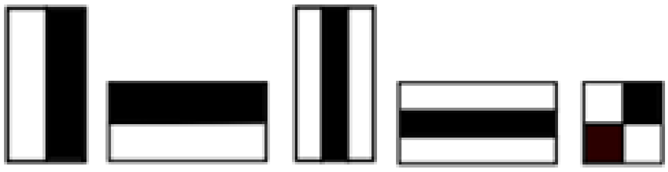
The OpenCV library is a robust and freely accessible resource specifically designed for real-time dynamic image processing. It encompasses an extensive array of computer vision functions and offers a versatile application programming interface (API) catering to both high-level and low-level image processing. This multifaceted framework is essential for optimizing real-time applications through its comprehensive features and functionalities.

For professionals engaged in the domain of computer vision, OpenCV emerges as a paramount choice. Its capabilities mirror those of human visual processing, making it an ideal toolkit for developers to build dependable applications [15]. OpenCV significantly converges with the artificial intelligence (AI), leading to simplified execution of complicated tasks such as object detection [16], augmented reality implementation [17], and interactive computer games development [18]. Among its myriad applications, one of its standout functions is mask detection. Frequently combined with other libraries such as TensorFlow, OpenCV serves as the cornerstone for building robust and accurate face mask detection models [19].

B. HAAR CASCADE CLASSIFIER

The Haar cascade classifier is an efficient algorithm utilized for human face detection. It demonstrates superior performance in face detection due to its speed being dependent on the number of pixels in the image [20]. Additionally, the Haar cascade classifier has been successfully combined with CNN for enhanced face detection [21]. This algorithm employs a technique called Haar-like features, which are trained to build a decision tree known as a cascade classifier. The Haar cascade classifier was then utilized to determine the presence of an object in each processed frame.

Figure 4 exhibits the Haar-like feature. This feature encompasses a diverse range of feature orientations: (a) left-right, (b) top-bottom, (c) vertical-middle, (d) horizontal-middle, and (e) diagonal. Each of these orientations plays a distinct role in detecting and recognizing faces using the Haar-like feature methodology.



(a) (b) (c) (d) (e)

Figure 4. Haar-like feature types.

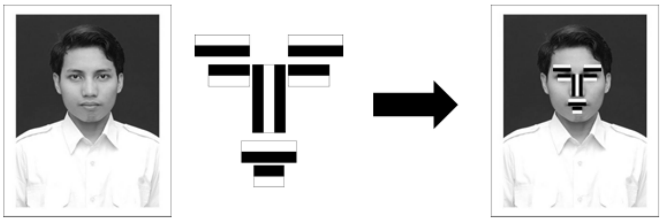


Figure 5. How Haar cascade classifies a person's face.

To initiate this process, the input image underwent a transformative step, which involved a transition from its original composition to grayscale representation. This transformation maintained the intrinsic facial features while homogenizing the color information so that the foundation for subsequent processing steps was formed. Following this step, the algorithm manipulated the image's contrast, thereby enhancing the discernibility of the facial structure. This dynamic contrast enhancement sharpened the image's contours to effectively highlight the contours that define a face.

With the groundwork laid, the algorithm integrated Haar-like features into the image canvas. These features were designed to capture specific visual characteristics inherent to facial structures. By detecting variations in pixel intensities within the detected image where the face was located, the Haar algorithm was able to discover and detect distinct patterns corresponding to eyes, nose, mouth, and eyebrows. The Haar-like features would then assign rectangular areas within the image, each positioned to encapsulate facial attributes as previously mentioned.

In Figure 5, the Haar algorithm performed a classification process to detect distinct facial features such as eyebrows, eyes, nose, and mouth within the frame of an image. The algorithm used a cascade classifier that sequentially processes the image throughout a series of stages with each stage progressively refined the detection process that would be used to filter out nonface regions within the image.

The Haar algorithm navigates through the myriad features that characterize a face. The algorithm's analysis spans from the forehead and eyebrows to the eyes and the distinct contours of the cheeks. It traverses the upper lip to the defining contours of the chin. Each of these elements constitutes a piece of the larger puzzle, and the algorithm's classification process integrated them to construct a comprehensive facial profile.

IV. RESULTS AND DISCUSSION

An extensive dataset was compiled to obtain an effective mask detection. This dataset encompassed a total of 500 facial images showing individuals adhering protocols of properly wearing mask and 500 additional images portraying individuals who were not in compliance with recommended

TABLE I
PERFORMANCE OF THE MODELS COMBINED INTO ONE DATASET

Performance Metrics			
Accuracy	*Precision*	*Recall*	*F1-Score*
95.8%	99.7%	92.3%	93.7%

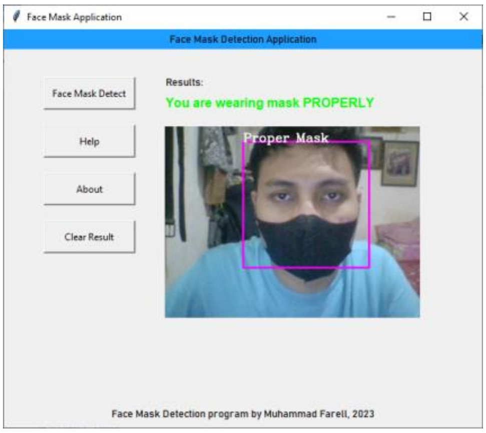


Figure 6. Program integrated with the trained model successfully detects proper mask usage.

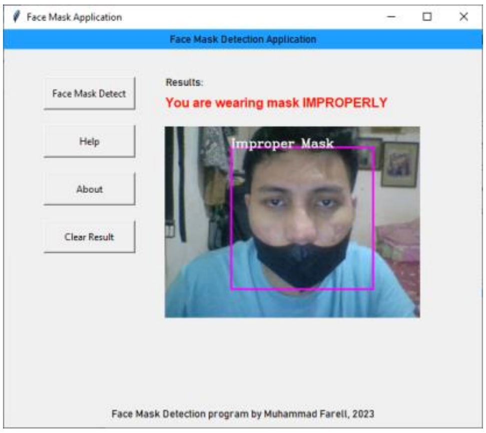


Figure 7. Program integrated with the trained model successfully detects improper mask usage.

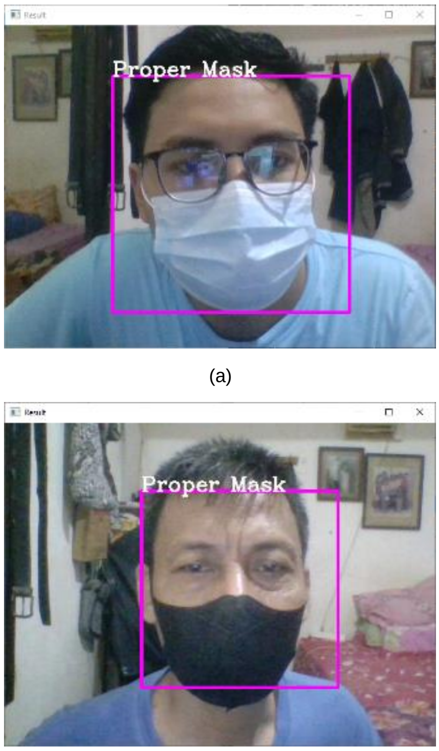
mask usage practices. The combination of these images yielded a comprehensive repository of 1,000 facial images, which served as the foundation of the model's learning process. By averaging 50 measurements of a dataset containing 1,000 images, the concatenation of both proper and improper mask models' performance is presented in Table I.

A division of the dataset was conducted to ensure a robust and unbiased model. This division distinguished the dataset into two distinct segments: a substantial 75% portion earmarked for training and a reserved 25% segment designated for subsequent testing. This allocation enabled the model to be exposed to various scenarios during its training phase while retaining a diverse set of untouched images for validation during the testing phase. This dataset partitioning is pivotal in refining the model's performance, guaranteeing its adaptability to new and unseen data.

In Figure 6 and Figure 7, the program was integrated with the trained model and was used to detect face mask usage. The program with the trained model successfully distinguished proper and improper mask usage when presented with an image of face wearing mask.

In Figure 8 and Figure 9, the program demonstrates its capability to distinguish between individuals wearing masks correctly and those not adhering to proper mask usage. It accomplishes this feat even when various types of masks are being worn and whether the subject is wearing glasses or not.

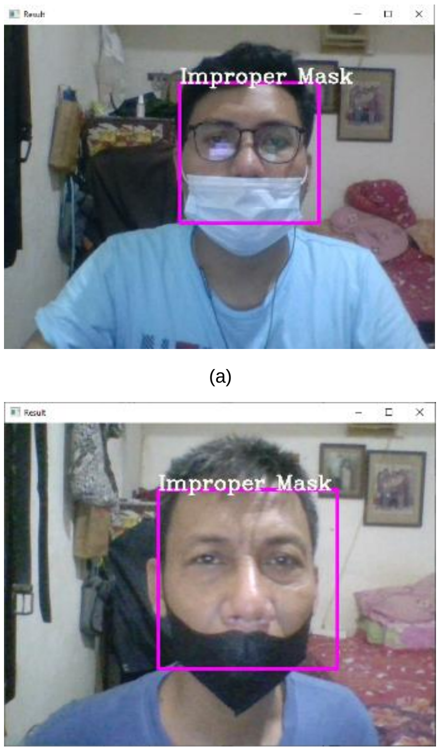
In Figure 10, the program, equipped with the model, exceled in detecting facial features on individuals with distinct facial features. For instance, it successfully identified facial features such as eyes and eyebrows, even when they exhibit a grayish appearance.



(a)

(b)

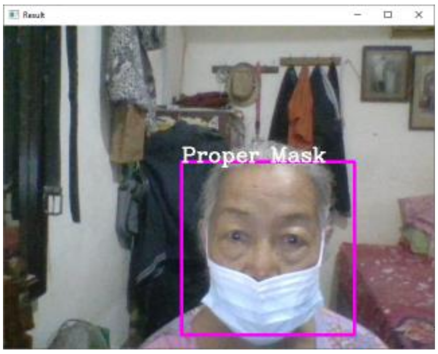
Figure 8. Program successfully detects faces wearing masks properly with (a) glasses and (b) without glasses.



(a)

(b)

Figure 9. Program successfully detects faces wearing masks improperly with (a) glasses and (b) without glasses.



(a)

(b)

Figure 10. Program correctly detects, (a) proper and (b) improper face mask use on someone with narrow eyes and lightly colored eyebrows.

(a)

(b)

Figure 11. Program correctly detects, (a) proper and (b) improper face mask usage on someone using a mask initially not trained to detect.

Figure 11 shows the program's ability to detect face mask usage in individuals wearing different types of masks, even when the initial model was not specifically trained for these particular masks. Furthermore, the program could detect mask usage when only two prominent facial features, such as eyes and eyebrows, were visible, despite the majority of facial features being concealed by the mask.

TABLE II
RESULT OF THIS PAPER MODEL AGAINST PREVIOUS RESEARCH

Objects	Performance Metrics			
	Accuracy	*Precision*	*Recall*	*F1-Score*
This Paper	95.8%	99.7%	92.3%	93.7%
I Made Dwi P. A *et al* [10]	97%	100%	94%	-
MDMFR [12]	100%	100%	100%	100%
SSDMN V2 [14]	92.64%	94%	93%	93%

In Table II, the mask detection model with face recognition (MDMFR) achieved a 100% score across all vital performance metrics: accuracy, precision, recall, and F1-score [12]. However, like other research papers, it focuses solely on detecting properly worn masks and cannot identify improper usage.

This research's model expanded its detection capabilities to cover both proper and improper mask usage, even when glasses were worn. Its design ensured efficient execution with minimal code and optimized resource utilization. The trained model consistently yielded favorable outcomes by employing the Haar cascade classifier for facial feature detection and integrating OpenCV for camera functionality.

Based on the analysis of 30 diverse test subject, the model demonstrated a high degree of accuracy in discerning between proper and improper mask usage, aligning with past iterations in mask recognition. The metrics resulted in 95.8% of accuracy, 99.7% of precision, 92.3% of recall, and 93.7% of F1-score.

Furthermore, the trained model surpassed their initial expected performance benchmarks by proficiently identifying both proper and improper mask usage across various mask types. However, it is essential to acknowledge that the model experienced difficulties when detecting individuals with subtle facial features such as thin or light-colored eyebrows. Furthermore, it also encountered difficulties in detecting facial features that were obstructed by objects such as hair, thereby reducing the visibility of eyebrows or eyes. Individuals with narrower eyes were also hard to detect by the model. These limitations arise due to the model's lack of specific training to address these scenarios.

V. CONCLUSION

The trained model achieves good accuracy in distinguishing between proper and improper mask usage, with an average accuracy rate of 95.8%, precision score of 99.7%, recall score of 92.3%, and F1-score of 93.7% during testing on 30 subjects. These metrics closely matched earlier benchmarks, thereby confirming the model's robustness. An intriguing aspect is the model could surpass the initial expectations. It could identify proper and improper use of masks, encompassing various mask types. Despite not being specifically trained for such variations, the model effectively detected mask variations which held potential real-world implications.

Nonetheless, it is important to recognize the model's shortcomings. Difficulties arose during the process of face detection, particularly when long hair obscured key facial features like eyes, nose, mouth, and eyebrows. In addition, accuracy decreased when these features were occluded or barely visible due to light-colored or thin eyebrows and narrow eyes.

Stringent measures ensured a controlled testing environment, minimizing false positives. Future iterations can refine the model's precision by differentiating between true and false positives. Besides that, a model recognizing mask-less faces can enhance the capabilities of the system.

In conclusion, the trained model exhibited commendable capability in identifying mask usage. Its metrics and adaptability signify significance in combating COVID-19. Continuous advancement opportunities exist to improve efficacy and versatility through refined features and targeted enhancements.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

AUTHORS' CONTRIBUTIONS

Conceptualization, Muhammad Farell; methodology, Muhammad Farell; software, Muhammad Farell; validation, Hustinawaty; investigation, Muhammad Farell; resources, Muhammad Farell; data curation, Muhammad Farell; writing—original draft preparation, Muhammad Farell; writing—review and editing, Hustinawaty; visualization, Muhammad Farell; supervision, Hustinawaty; project administration, Hustinawaty; funding acquisition, Muhammad Farell

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