Precision Face Mask Detection in Crowded Environment using Machine Vision

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***Abstract*—In the face of rampant global disease transmission, effective preventive strategies are imperative. This study tackles the challenge of ensuring compliance in crowded settings by developing a sophisticated face mask detection system. Utilizing MATLAB and the Cascade Object detector, the system focuses on detecting white surgical masks in frontal images. Training the system is critical for accuracy; therefore, cross-validation is employed due to limited data. The results reveal accuracies of 76.67% for initial training, 67.50% for a 9:11 cropping ratio, and 89.17% for a 9:4:7 cropping ratio, highlighting the system's remarkable precision in mask detection. Looking ahead, the system's adaptability can be further expanded to include various mask colors and types, extending its effectiveness beyond COVID-19 to combat a range of respiratory illnesses. This research represents a significant advancement in reinforcing preventive measures against future disease outbreaks, especially in densely populated environments, contributing significantly to global public health and safety initiatives.**

Keywords—Face mask detection; machine vision; cascade object detector; cross-validation

I. Introduction

The persistent threat of infectious diseases underscores the critical importance of preventive measures in halting the spread of viruses. Among these, the act of wearing masks has proven highly effective, forming a crucial line of defense against respiratory particles that can carry diseases [1]. However, ensuring widespread adherence to mask-wearing mandates remains a challenge, particularly in densely populated areas where viruses can quickly find new hosts. Governments worldwide have responded to this challenge by enforcing stringent measures, urging the public to wear masks in all public spaces. This practice, reinforced by global health authorities, emphasizes the significance of maintaining a safe physical distance, wearing well-fitted masks, and adhering strictly to hand hygiene practices [2], [3], [4].

In this pivotal moment, the convergence of innovative technology and public health expertise has ushered in a promising era. Advances in machine vision, where artificial intelligence meets visual sensory processing, have paved the way for transformative solutions [5]. Within this context, we embark on a groundbreaking initiative – the development of a sophisticated face mask detection system. This system, empowered by the capabilities of machine vision, discerns with acute precision whether individuals are wearing masks, irrespective of the disease at hand. The implications of this cutting-edge technology are vast, extending from bustling shops to crowded public transport hubs and even the sterile corridors of hospitals. This face mask detection system stands as a guardian of public health, prepared to combat a spectrum of infectious diseases in any future scenario [6], [7].

This endeavor is not undertaken merely as an academic pursuit; it is signified as a vital stride in the fortification of our technological defenses against potential pandemics. While existing methods are demonstrated to be efficacious, they are often burdened with limitations that hinder their full potential. In the forthcoming sections, the methodology underpinning our face mask detection system will be meticulously dissected, and its accuracy will be rigorously analyzed. This research allows us to save manpower, money and time. Compared to other experiments, we train the system with the smallest number of samples and use the least amount of effort to achieve the greatest effect.

Through this comprehensive and meticulous exploration, significant contributions are being made to the scientific domain. This is not just an academic exercise; it is a proactive engagement in a global mission that seeks to lessen the severe and lasting impact that infectious diseases have on societies across the planet. These diseases, which have plagued humanity for centuries, continue to present complex challenges that require innovative solutions and international cooperation. Our research actively participates in this mission by providing new insights and tools that can be used to detect, prevent, and treat these diseases. It stands as a beacon of hope, a testament to human ingenuity and perseverance. As we illuminate the path forward with our findings, we join hands with fellow researchers and healthcare professionals in our collective endeavor to prepare for and overcome the challenges posed by future pandemics.

This work, therefore, is not just about the present; it is about ensuring a safer and healthier future for all. By pushing the boundaries of what is known, we pave the way for new strategies and interventions that could save millions of lives. In essence, this research embodies the spirit of discovery and the unwavering commitment to public health that characterizes the best of scientific pursuits.

The structure of this paper unfolds as follows: Section II provides an overview of the study's background. Subsequently, Section III delineates the system's implementation and testing process. Section IV and Section V delves into the results and discussion respectively and finally Section VI concludes the paper.

II. Background of the Study

Amidst the persisting COVID-19 pandemic, the significance of precise face mask detection cannot be emphasized enough. Researchers, in a concerted effort to bolster public health protocols and minimize viral spread, have delved into various methodologies for automating the identification of mask-wearing individuals. Numerous pioneering studies have significantly advanced this area. In particular, the utilization of deep models for object identification [8] has showcased remarkable progress in image recognition over recent years (see Table VI).

Stephanie Anderson et al. [9] developed an automatic face mask detection model using Deep Learning. Their model, trained on a diverse dataset comprising Mask, No Mask, and Incorrect Mask classes, achieved a commendable 96% accuracy. The study showcased the potential of Convolutional Neural Networks (CNNs) to discern subtle nuances in mask-wearing, although the challenge of hand-covered faces remained [10], [11].

Anderson et al. [9] developed a deep learning model for face mask detection with a 96% accuracy rate, demonstrating CNNs' capability to identify proper mask usage [10], [11]. Singh et al.'s study [12] utilized IoT for COVID-19 patient monitoring, focusing on device interconnectivity for cluster detection [13]. Prajwal C Hegade et al. [14] introduced a system combining facial recognition with temperature sensing for comprehensive health monitoring. These studies underscore the effectiveness of deep learning and IoT in enhancing mask detection and public health safety [15]. Additionally, point feature detection algorithms like SIFT, SURF, Harris Corner, and FAST are pivotal in object recognition within images [16]. Chhabra and Verma's research [17] on SURF highlighted its robustness in object detection, adapting to scale and rotation changes, which is crucial for accurate mask-wearing assessment. Notably, the proposed approach excels in detecting objects despite scale changes or in-plane rotations, exhibiting robustness to out-of-plane rotations and limited occlusions [18].

Feature-based detectors, which include algorithms such as the Cascade Object detector, Barcode detector, and April Tag detector, provide an alternative approach for object detection and classification [19].

Chowdhury et al. [20] present a cascaded object detection and classification methodology. The model's training, encompassing 50 positive images, employs Cascade Trainer Graphical User Interface (GUI), while MATLAB facilitates testing. The utilization of MATLAB (R2018b) expedites object identification, minimizing code complexity. The approach benefits from GPU acceleration, enhancing training efficiency. The resulting .xml file generated by Cascade Trainer is read by MATLAB to detect objects, subsequently outlined with rectangles and labeled. This approach enhances the accuracy of object detection and labeling, addressing limitations in prior methods while maintaining minimal incorrect refusals [21].

Continuing to build upon the foundations established by these studies, our research aims to develop a face mask detection system using machine vision that effectively identifies whether a person is wearing a mask, achieved through training a Cascade object detector on a limited dataset and utilizing cross-validation due to data constraints. By incorporating the strengths of these approaches and addressing their limitations, we aspire to propel the field of face mask detection further, enhancing its reliability and practicality [22].

According to MATLAB's help center [23], understanding the concept of a Region of Interest (ROI) is fundamental in image analysis. It is depicted as a binary mask image, indicating specific areas of significance within the image, an ROI defines the portion of an image where specific filtering or operations are applied. The toolbox of MATLAB offers versatile methods for defining ROIs and generating binary masks. Shapes such as circles, ellipses, polygons, rectangles, and hand-drawn forms can serve as ROIs, each allowing for modification of shape, appearance, position, and behavior. Alternatively, MATLAB's image processing toolbox enables the creation of ROIs by specifying locations or sizes. This adaptable approach to ROIs, illustrated in Fig. 1, underpins the precision and flexibility of our face mask detection system [24].

As per the documentation provided by MATLAB's help center [25], the trainCascadeObjectDetector function is capable of utilizing three different types of features: Histograms of oriented gradients (HOG) Local binary patterns (LBP), and Haar features. Haar and LBP features are particularly renowned for their ability to precisely capture intricate textures, contributing to the function's effectiveness in object detection [26], making them particularly well-suited for human face detection. On the contrary, HOG features find common application in detecting objects like people and cars. The cascade classifier is organized into stages, where each stage comprises an ensemble of weak learners. These basic learners, known as decision stumps, act as elementary classifiers within the cascade. Fig. 2 illustrates the process flow for training the cascade detector.

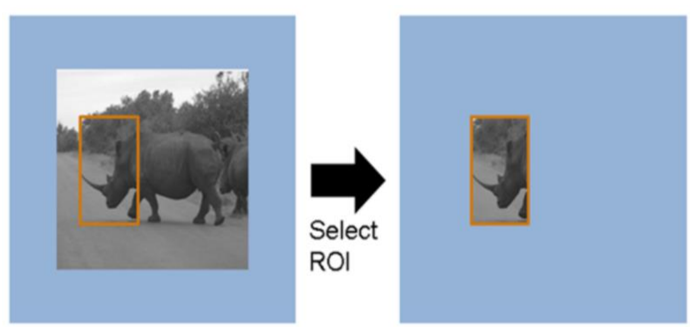

Fig. 1. Front view of people's face.

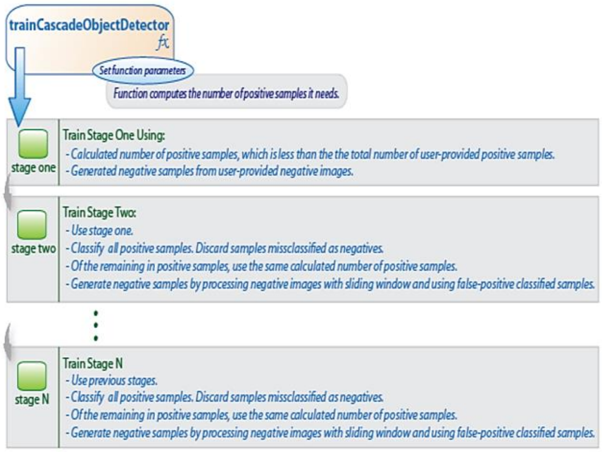

Fig. 2. Illustrates the process flow for training the cascade detector.

The boosting technique is employed at each step to train a classifier that achieves high accuracy. This is accomplished by calculating a weighted average of the decisions made by weak learners [27], [28]. During each stage of the classifier, the current location identified by the sliding window is assigned a positive or negative label. A positive label signifies the presence of an object, whereas a negative label indicates the absence of an object. When negative labels are assigned, the classification process concludes, and the detector proceeds to shift the window to the next position. On the other hand, if a positive label is assigned, the region is subjected to further examination [29], [30]. The detector progresses through phases, swiftly discarding the negative samples, assuming that the object of interest is absent in most windows. Only when the detector confirms the presence of an object in the current window location after the final step does it report the detection of the object [31].

Nevertheless, true positive outcomes are infrequent and demand thorough validation. For efficient functioning, every stage of the cascade must uphold a low false negative rate [32], [33]. If a stage wrongly identifies an object as negative, the classification process stops, and the error remains uncorrected. On the other hand, each stage usually demonstrates a notable false positive rate. Even if the detector mistakenly identifies a non-object as positive, these errors can be corrected in the following stages [34]. Achieving a balance between the number of stages and the false positive rate at each step involves a trade-off, having fewer stages with a lower false positive rate increases complexity, often requiring a larger portion of less skilled learners [35]. Conversely, stages with a higher false positive rate consist of fewer weak learners [36].

Generally, a higher number of foundational stages is favored as it decreases the overall false positive rate with each additional level. For instance, if the false positive rate at each stage is 50%, the overall false positive rate for a two-stage cascade classifier drops to 25%. This percentage further decreases to 12.5% after three stages, and continues to decrease with additional stages. However, with the increase in the number of stages, the classifier requires more extensive training data. Moreover, raising the number of stages amplifies the risk of false negatives, potentially resulting in the unintentional rejection of a positive sample. Modifications to both the false alarm rate and the number of stages can be implemented to attain the intended overall false alarm rate [37], [38], [39].

A. Utilizing Deep Learning for Automated Face Mask Detection

A facial mask detection system was created employing Deep Learning methods. The main objective of this research was to develop a model capable of automatically discerning if a person is wearing a face mask correctly, wearing it incorrectly, or not wearing one at all. For this study, a dataset comprising 3,515 images was utilized, categorized into three classes: Mask, No Mask, and Incorrect Mask. These photos were collected by amalgamating different Kaggle datasets and were stored in JPEG format [40]. Furthermore, Google images were incorporated, and researchers supplemented the dataset with personal photos of themselves, family, and friends to enhance its diversity. The dataset was divided into two segments: 80% for training neural networks and 20% for testing purposes.

Convolutional Neural Networks were selected due to their capability to independently learn multiple filters simultaneously, customized to a particular training dataset and the complexities of a specific predictive modeling problem [41], [42]. In this deep learning algorithm, input images are analyzed, and weights and biases are assigned to different elements or objects within the image, enabling effective distinction between them. CNNs are especially proficient in image detection and recognition owing to their high accuracy [43], [44].

Consequently, the face mask detection model attained an accuracy rate of 96%. Nonetheless, it is crucial to highlight that if an individual covers their face with their hand, the model might misclassify it as either wearing a face mask or wearing it incorrectly [45].

B. Detecting Face Masks Utilizing MobileNet and Global Pooling Block

Moreover, Venkateswarlu et al. [46] have created a face mask detection system employing MobileNet and the Global Pooling Block. They evaluated their model using two publicly accessible datasets. Dataset 1 comprises 1918 images without masks and 1915 images with masks, while Dataset 2 consists of 824 images without masks and 826 images with masks. To augment the data, rotation-based techniques were employed. Fig. 3 depicts the suggested methodology, which initially leverages a pre-trained MobileNet without the output layer to process incoming photos and build a feature map [47]. The global pooling block transforms the multi-dimensional feature map into a one-dimensional vector containing 64 features. Subsequently, a softmax layer with two neurons performs binary classification using these 64 features. The model demonstrated an accuracy of 99% on DS1 and 100% on DS2.

C. System Utilizing Facial Recognition for Non-Contact Temperature Detection, Face Mask Detection, and Attendance Management

In a study conducted by Hegade et al. [14], a system was introduced for non-contact temperature detection, face mask recognition, and attendance management. The setup utilized a Raspberry Pi as the controller, coupled with an ultrasonic sensor to measure the person's distance from the device [48]. The MLX90614 Infrared temperature sensor was utilized for measuring body temperature without direct contact [49]. Attendance updates and mask detection were performed using the HOG facial recognition technique. To establish the system, a database comprising candidate images was created [50]. All images were placed in a single folder, and the file paths were included in the Python source code. Each image was tag with the corresponding candidate's name. The classifier was trained using the HOG algorithm, enabling employee identification during scans. The face detection achieved an efficiency rate of 96.67%.

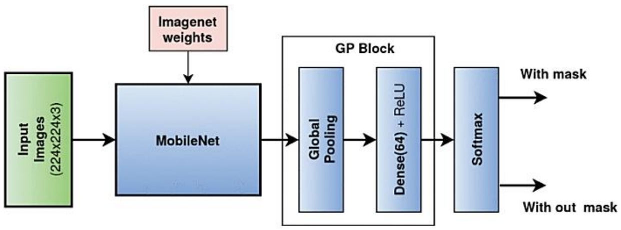

Fig. 3. Illustrates the MobileNet and global pooling architecture [34].

III. The System Implementation and Testing

A. System Architecture

The development and implementation of the face mask detection system involve a coherent architectural framework that encompasses data preprocessing, feature extraction, classification, and result visualization. The integration of these components culminates in a comprehensive solution capable of accurately detecting face masks. The system architecture encompasses a series of integral steps: Data Preprocessing, involving noise reduction, image resizing, and normalization to optimize raw input images; Feature Extraction, utilizing Histograms of Oriented Gradients (HOG) features to extract essential visual attributes from preprocessed images, enabling accurate differentiation between masked and unmasked individuals; Classifier Training, which employs HOG features and labeled training data to iteratively train a Cascade object detector, leveraging an ensemble of weak learners for effective face mask detection; Testing and Evaluation, where the trained Cascade object detector undergoes comprehensive testing using an independent dataset, yielding percentage metrics such as accuracy, precision, and F1-score to quantitatively assess system efficacy; and Result Visualization, highlighting detected face masks within images to visually convey the system's detection capabilities, facilitating performance interpretation and potential enhancement identification.

B. Testing Methodology

The system's testing methodology comprises the subsequent steps: Dataset Compilation, involving the assembly of a diverse dataset containing positive and negative images, enabling the assessment of the system's performance; Feature Extraction, where HOG features are extracted from both positive and negative images, forming the foundation for training the Cascade object detector; Classifier Training, which entails feeding the extracted HOG features into the Cascade object detector training process, enabling the system to differentiate between masked and unmasked individuals based on these discriminative features; and Evaluation, wherein the trained detector undergoes scrutiny using an independent test dataset, resulting in the computation of performance metrics such as accuracy, precision, recall, and F1-score, providing a quantitative gauge of the system's adeptness in detecting face masks. The system's performance evaluation yields insightful results that highlight its capabilities and limitations. The achieved accuracy of 89.17% underscores its efficacy in detecting face masks. While this accuracy may appear lower compared to some prior studies, it's important to note that our system's success is demonstrated with a considerably smaller dataset.

C. Training and Testing Processes

Fig. 4 illustrates the training process flow. Sample images are input and resized during training. Histograms of oriented gradients features are extracted during the Cascade training process. Adaboost algorithm is employed for classification and classifier updates, iterated for every input image.

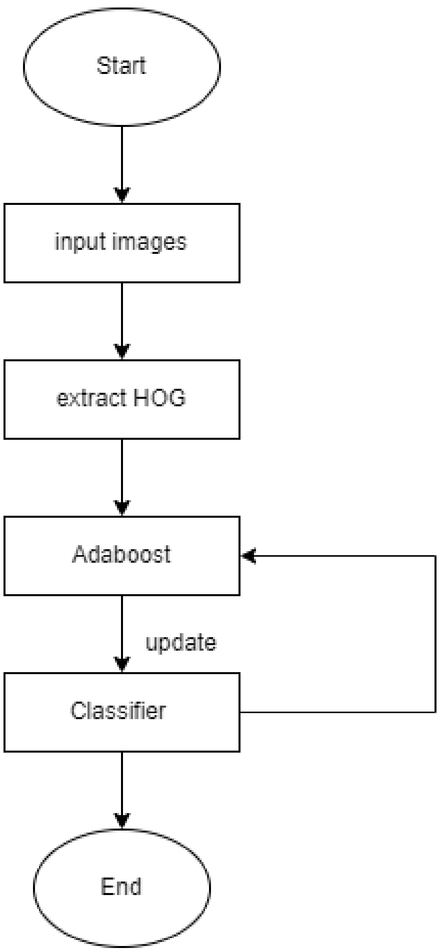

Fig. 4. Training process flow.

Fig. 5 demonstrates the testing procedure flow. A set of test images, containing both positive and negative samples, is used as input data. MATLAB's built-in Cascade detector, employing the Viola-Jones algorithm, is utilized to detect the nose in these images. When the nose is detected, the image is labeled as "no mask." In instances where the nose is not detected, the image undergoes classification using the trained classifier. If the system identifies a mask, the image is labeled as "with mask." On the contrary, if no mask is detected, the image is marked as "no mask."

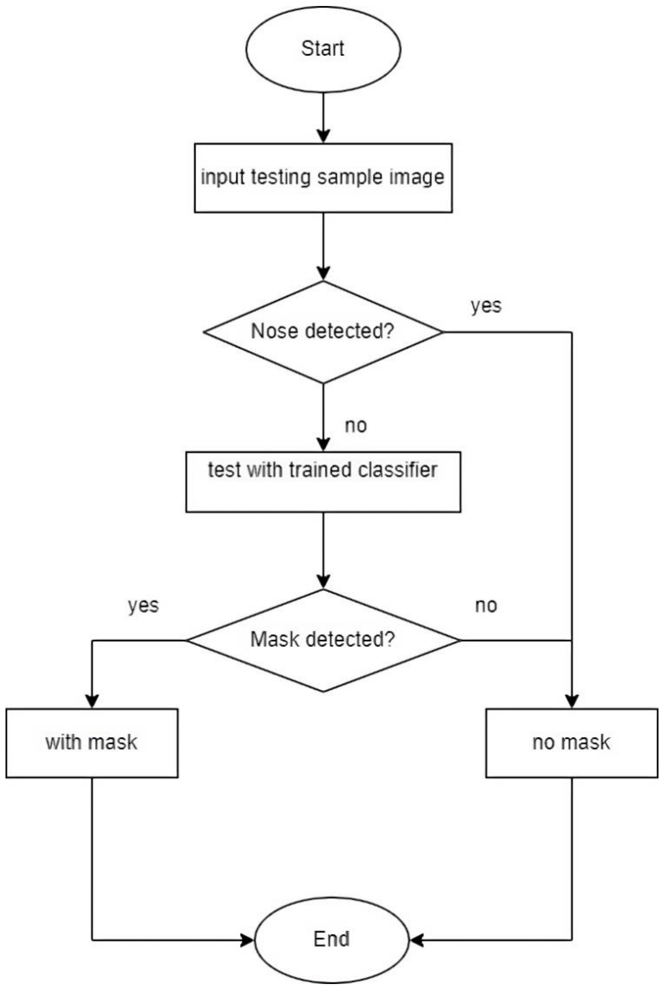

Fig. 5. Testing process flow.

In summary, the Cascade object detector is trained, enabling its application for testing input data images. The final output reveals the detection results, confirming the presence or absence of face masks.

D. Dataset Compilation

A diverse dataset comprising positive and negative images is curated to evaluate the system's performance. Positive images depict individuals wearing masks, while negative images represent unmasked individuals. The dataset includes 60 positive images of individuals wearing white surgical masks with their front view of the face facing the camera. Additionally, 360 negative images of individuals without masks are incorporated for training and testing the Cascade object detector. Refer to Fig. 6 for the positive dataset and Fig. 7 for the negative dataset. Table I shows distribution of data training model.

E. Cross-validation Method

Given the limited number of positive mask images, cross-validation is adopted to enhance the reliability of the system. Cross-validation involves resampling the data to train and test the model across different iterations. Fig. 8 illustrates the cross-validation methodology employed in the system.

TABLE I. DISTRIBUTION OF DATA FOR TRAINING AND TESTING

Testing		Training	
Images depicting a positive context	Images depicting a negative context	Images depicting a positive context	Images depicting a negative context
Image 1-10	Image 301-310	Image 11-60	Image 1-300
Image 11-20	Image 311-320	Image 1-10 & Image 21-60	Image 1-300
Image 21-30	Image 321-330	Image 1-20 & Image 31-60	Image 1-300
Image 31-40	Image 331-340	Image 1-30 & Image 41-60	Image 1-300
Image 41-50	Image 341-350	Image 1-40 & Image 51-60	Image 1-300
Image 51-60	Image 351-360	Image 1-50	Image 1-300

Fig. 6. Positive dataset- people with mask.

Fig. 7. Negative dataset- people without mask.

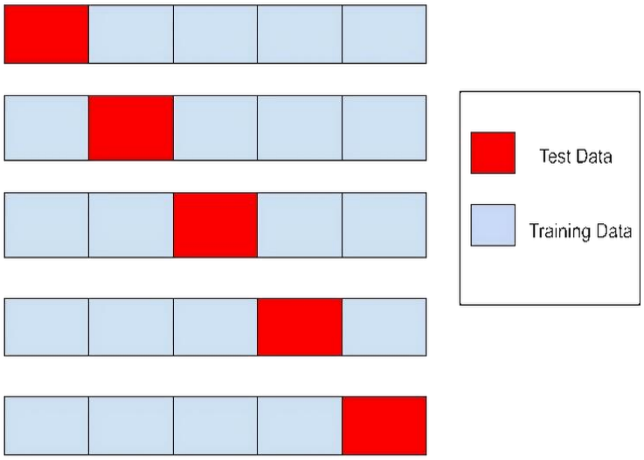

Fig. 8. Cross-validation technique.

F. Result Calculation

The effectiveness of the trained detector is assessed using a separate test dataset. Various performance metrics, such as accuracy, precision, recall, and F1-score, are computed to quantitatively evaluate the system's ability to detect face masks. Accuracy is determined using the following formula:

$$True\ positive\ rate = \frac{True\ positive(TP)}{Positive\ sample(P)} = 1 - False\ Negative\ Rate \quad (1)$$

$$True\ negative\ rate = \frac{True\ negative(TN)}{Negative\ sample(N)} = 1 - False\ Positive\ Rate \quad (2)$$

$$Overall\ accuracy = \frac{True\ negative + True\ Positive}{Total\ number\ of\ sample} \quad (3)$$

In this context, TP signifies the number of accurately detected face mask images, P represents the total count of positive test images, TN indicates the correctly identified images without face masks, and N denotes the total number of negative test images.

IV. Result

A. Results and Discussion of Original Image Dataset

The initial phase of the face mask detection system's evaluation involves the examination of results obtained from the original image dataset. Fig. 9 provides a glimpse into some of the training images, while Fig. 10 showcases a selection of output images generated during this training phase. The outcomes of this training are detailed in Table II, revealing an overall accuracy of 76.67%. While this accuracy represents a significant achievement, it also motivates the pursuit of further experiments to enhance system performance.

$$True\ positive\ rate = \frac{34}{60} = 56.67\% \quad (4)$$

$$True\ negative\ rate = \frac{58}{60} = 96.67\% \quad (5)$$

$$Overall\ accuracy = \frac{92}{120} = 76.67\% \quad (6)$$

TABLE II. Training Outcomes Using Original Images

Set	Quantity of detected positive images	Quantity of detected negative images
1	5	10
2	3	9
3	7	9
4	6	10
5	5	10
6	8	10

Fig. 9. Images in their original dimensions.

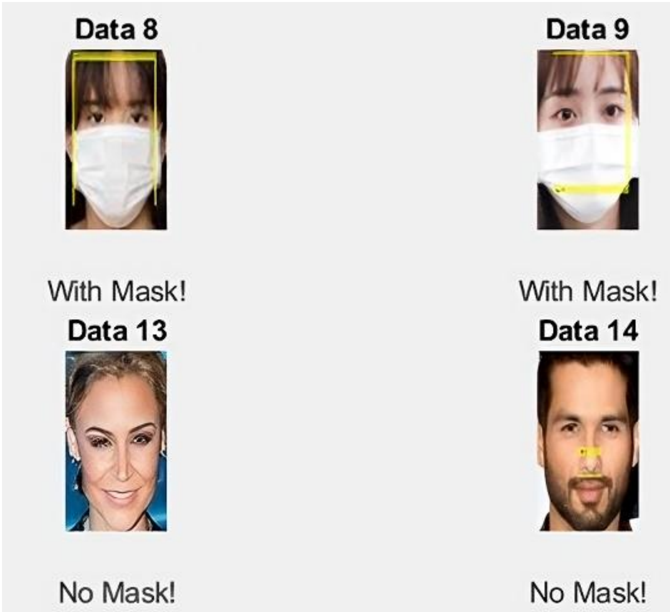

Fig. 10. Results from training with original images.

B. Findings and Discussion of Dataset Cropped with 9:11 Ratio

An iterative training process is carried out to enhance the system's accuracy. This endeavor involves training the system with cropped images that focus on the lower part of the face—specifically, the mask region. Given its critical role in classification and detection, this lower section is deemed a region of interest (ROI). With a cropping ratio of 9:11, as illustrated in Fig. 11, the training dataset is optimized for mask detection. However, despite these efforts, the results presented in Fig. 12 and Table III indicates a reduction in overall accuracy to 67.50%. This outcome prompts further investigation and refinement.

C. Results and Discussion of 9:4:7 Ratio Cropped Image Dataset

An additional challenge surfaces when certain instances yield mask detection failure due to the absence of the lower mask portion in the images. Table V shows the result of different ratios of image trained. The corresponding observations, exemplified by false negative samples like those depicted in Fig. 13, reveal the importance of retaining this critical region.

$$True\ positive\ rate = \frac{21}{60} = 35\% \tag{7}$$

$$True\ negative\ rate = \frac{60}{60} = 100\% \tag{8}$$

$$Overall\ accuracy = \frac{81}{120} = 67.50\% \tag{9}$$

TABLE III. TRAINING OUTCOMES CONDUCTED WITH CROPPED IMAGES USING A 9:11 RATIO

Set	Quantity of detected positive data	Quantity of detected negative data
1	4	10
2	3	10
3	5	10
4	3	10
5	3	10
6	3	10

Fig. 11. Displays cropped images with a ratio of 9:11.

Fig. 12. Illustrates the results obtained from the training process with cropped images using a 9:11 ratio.

Fig. 13. Output of mask cannot be detected.

To address this, a novel training approach is employed, concentrating solely on the upper mask region. The image cropping ratio is set at 9:4:7, as shown in Fig. 14, to ensure the preservation of the mask edge (see Table IV). Fig. 15 presents outputs derived from this training methodology. Remarkably, this strategy yields an overall accuracy of 89.17%, signifying a substantial advancement in the system's performance.

$$True\ positive\ rate = \frac{48}{60} = 80\% \tag{10}$$

$$True\ negative\ rate = \frac{59}{60} = 98.33\% \tag{11}$$

$$Overall\ accuracy = \frac{107}{120} = 89.17\% \tag{12}$$

TABLE IV. OUTCOMES FROM TRAINING USING 9:4:7 CROPPED IMAGES

Set	Number of Identified Negative Images	Number of Identified Positive Images
1	10	7
2	9	8
3	10	9
4	10	7
5	10	8
6	10	9

TABLE V. RESULT OF DIFFERENT RATIO OF IMAGE TRAINED

Picture Ratio	True positive rate	True negative rate	Overall rate
original	56.67%	96.67%	76.67%
9:11	35%	100%	67.50%
9:4:7	80%	98.33%	89.17%

Fig. 14. Displays a cropped image with a ratio of 9:4:7.

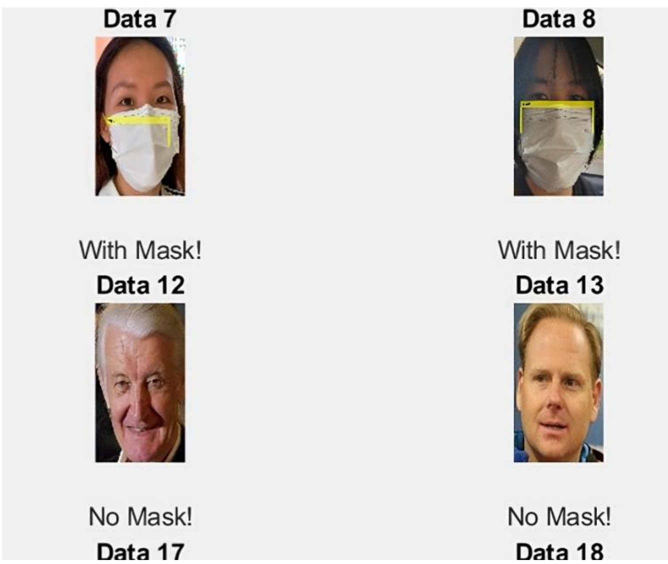

Fig. 15. Illustrates the results obtained from the training process with cropped images using a 9:4:7 ratio.

V. Discussion

To enhance the system's accuracy, a subsequent training iteration was initiated after the initial result yielded only 76.67%. This new experiment involved training the system with cropped images from the training dataset, specifically focusing on the lower part of the image, which constitutes the mask region and is crucial for accurate detection. This region, termed the region of interest (ROI), was cropped using a ratio of 9:11. However, the overall accuracy of this training process was found to be 67.50%. Given this reduced accuracy, additional training sessions were carried out in an attempt to improve the results.

Upon analyzing the output, it was observed that the mask detection occasionally failed when the lowest section of the mask was excluded from the image. Consequently, the decision was made to crop out the lowest part of the mask from the images, potentially impacting the detection process. In this experiment, solely the upper portion of the mask was employed to train the Cascade detector. Consequently, the images were cropped using a ratio of 9:4:7, focusing specifically on the mask's edge section.

The culmination of these diverse training processes contributes to a comprehensive understanding of the system's capabilities. The initial training with original-sized images achieves a commendable accuracy of 76.67%. However, recognizing the potential for enhancement, subsequent training phases are undertaken. The experimentation involving a 9:11 cropped image dataset achieves an accuracy of 67.50%. The apex of this exploration is the training process with a 9:4:7 cropped image dataset, yielding an impressive accuracy of 89.17%. These iterative experiments underscore the system's adaptability and potential for accurate mask detection across various training approaches.

TABLE VI. COMPARISON WITH STUDY STATED ABOVE IN BACKGROUND STUDY

	Study 1 [40]	Study 2 [46]	Study 3 [14]	This study
Sample image	3515	3833	No stated	360
Accuracy	96%	99%	96.67%	89.17%

VI. Conclusion

In summary, this study introduces a face mask detection system utilizing machine vision techniques. The methodology effectively addresses the task of discerning whether an individual is wearing a face mask. The system successfully achieves its primary objective of verifying mask usage, attaining an accuracy rate of 89.17%. Employing a training approach centered on the Cascade object detector, and utilizing cross-validation due to the limited dataset size, this work significantly contributes to the realm of face mask detection. The utilization of a dataset comprised of 60 positive images underscores the challenge posed by limited data availability, distinguishing this study from the broader literature that often leverages more extensive datasets. In summary, this research represents a substantial scientific contribution, addressing the urgent need for accurate face mask detection in crowded environments. By achieving a high accuracy rate and considering the limitations of the dataset, this study showcases the system's potential and sets the stage for future developments in the field of preventive technologies against infectious diseases.

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