

# Intelligent Face Mask Recognition Using Deep Learning and Computer Vision

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**Abstract-The COVID-19 pandemic highlighted the crucial role of wearing masks in mitigating virus transmission, especially during the rise of highly infectious variants such as Omicron. While existing face mask recognition systems have largely focused on binary classification of “mask” versus “no mask,” this approach fails to address improper mask usage and real-world challenges such as varied lighting, occlusion, and demographic fairness. This study proposes an advanced real-time face mask recogniser that not only detects the presence of a mask but also evaluates the accuracy of mask compliance through a fine-grained, multi-class classification scheme (correctly worn, nose exposed, chin only, no mask). Leveraging a pre-trained MobileNetV2 backbone optimized for edge devices, the system incorporates additional lightweight modules for segmentation-based mask coverage estimation, thereby providing a quantitative compliance score. To overcome dataset bias, cross-dataset generalisation experiments and robustness tests under challenging conditions (low light, extreme poses, partial occlusion) are included. Furthermore, the system integrates a detection-plus-tracking pipeline to enable multi-person compliance analytics and fairness evaluation across demographic subgroups. Comparative results with existing models demonstrate not only improved precision and recall but also better interpretability and transparency through saliency-based explainability and failure-case analysis. To ensure ethical deployment, privacy-preserving techniques such as on-device inference and anonymised compliance reporting are explored. This research extends beyond simple detection to deliver actionable analytics, contributing both a technically robust and socially responsible solution for public-health monitoring and policy enforcement.**

**Keywords: COVID-19, face mask recognition, real-time detection, MobileNetV2, mask compliance, multi-class classification, cross-dataset generalization, robustness, fairness, privacy-preserving AI, computer vision, deep learning**

## I. INTRODUCTION

The outbreak of COVID-19 created one of the most significant public health emergencies in modern history, with

the virus spreading primarily through respiratory droplets from infected individuals. Global health organizations, including the World Health Organization (WHO), have emphasized the use of face masks as an essential defense mechanism to reduce viral transmission. However, wearing a mask improperly—such as leaving the nose exposed or positioning it loosely—undermines its effectiveness and can still facilitate the spread of infection. Therefore, ensuring not only the detection of mask usage but also the accuracy of compliance is crucial. Automated face mask recognition systems, based on computer vision and deep learning, have emerged as promising tools for real-time monitoring of mask adherence in public spaces. Such systems can support frontline workers, enhance public awareness, and contribute to safeguarding communities against viral outbreaks and new variants.

Despite the rapid development of face mask detection systems during the pandemic, many existing approaches remain limited in scope. Most studies, while reporting high classification accuracy, have focused only on binary detection—classifying individuals as either wearing a mask or not. This overlooks the critical issue of improper mask usage, which is equally hazardous in terms of viral spread. Furthermore, most prior research evaluates models on controlled datasets, raising questions about generalizability in real-world settings with varying lighting, occlusion, demographic differences, and crowded environments. Additionally, performance claims often lack transparency, with missing details on latency, deployment feasibility on resource-constrained edge devices, and the ethical implications of surveillance systems. Without addressing these factors, the practical applicability of such models remains constrained.

To bridge these gaps, the present study proposes a fine-grained, real-time mask compliance recognition system that extends beyond binary classification. This work introduces multi-class detection of mask-wearing categories, integrates robustness testing across diverse environments, and incorporates mask-coverage scoring for more informative assessments. Edge-optimized deployment is also explored to ensure feasibility in real-world scenarios such as airports, hospitals, and educational institutions. Moreover, this research emphasizes reproducibility by providing transparent model configurations and aims to address fairness concerns by

evaluating demographic performance disparities. In doing so, the study not only strengthens the technical foundation of mask detection but also transforms it into a responsible and operationally valuable tool. Unlike earlier works that largely demonstrate proof-of-concept performance, this research contributes by aligning technical innovation with real-world usability, fairness, and public trust, thereby advancing the field toward meaningful deployment.

## II. LITERATURE REVIEW

Face mask recognition has gained significant attention as a computer vision application during the COVID-19 pandemic, with researchers focusing on automated compliance monitoring in public spaces. A recent study by [Author(s)] (2021) developed a lightweight model using MobileNetV2 as the feature extractor combined with CNN layers for mask classification. Using a Kaggle dataset of 7,553 balanced images, the system achieved approximately 98% accuracy and was deployed for real-time inference through webcam integration. Its primary strength lies in the choice of a computationally efficient backbone suitable for edge deployment and its ability to achieve high accuracy on test splits. However, the system was limited to binary classification, distinguishing only between “mask” and “no mask,” while claiming to detect incorrectly worn masks without providing multi-class metrics. Furthermore, the evaluation was confined to a single dataset without cross-domain testing, and details regarding latency, robustness under varying conditions, and fairness across demographic groups remained unexplored.

Building on this foundation, subsequent literature and critiques highlight the importance of advancing beyond binary detection to fine-grained compliance assessment. For instance, detecting improper mask usage—such as covering only the mouth or chin—has stronger implications for public health but was not adequately addressed in the prior study. Equally significant is the gap in evaluating real-world robustness under challenging conditions like poor lighting, occlusions, or crowded scenes, where system performance may degrade sharply. Moreover, concerns regarding model transparency and reproducibility emerge due to incomplete reporting of hyperparameters, dataset sourcing, and absence of shared code, which hinder replication and comparative benchmarking. These gaps suggest that while initial work provided a promising baseline, the true deployment potential of face-mask recognition systems remains under-investigated, particularly when fairness, reliability, and generalization across contexts are considered.

Future research must therefore adopt a more comprehensive approach that integrates multi-class classification or mask-coverage scoring to capture nuanced compliance behaviors. Domain adaptation techniques and synthetic augmentation can improve generalization across environments, while fairness assessments can ensure balanced performance across demographic subgroups. Incorporating

edge-optimization studies with measured latency, model size, and energy consumption will provide evidence of practical feasibility. Furthermore, explainability methods such as Grad-CAM can illuminate decision-making processes, and multi-person tracking pipelines can translate detection outputs into actionable analytics for public health management. By addressing these limitations, upcoming studies can move beyond mere accuracy to demonstrate real-world applicability, ethical robustness, and operational value. This progression not only strengthens the scientific contribution but also ensures that automated mask-recognition systems can be responsibly deployed at scale for future public health preparedness.

## III. RELATED WORK

The coronavirus pandemic has underscored the importance of wearing face masks as a primary preventive measure to reduce viral transmission. However, a key challenge lies not only in detecting the presence of masks but also in assessing whether they are worn correctly. Early approaches to automated mask recognition have relied on traditional computer vision and machine learning methods. For instance, a Multi-Task Cascaded Neural Network (MTCNN) was used to detect faces, followed by training with the LeNet algorithm to classify mask usage [9]. While effective in predicting faces with masks, the model demonstrated relatively weaker performance on unmasked faces, primarily due to the variability in facial features. This highlighted an early gap in robustness and generalizability across diverse real-world conditions.

Subsequent research has shifted towards deep learning architectures for more accurate and efficient recognition. Several studies [10, 11, 12] explored the use of the YOLO (You Only Look Once) object detection framework to detect both mask usage and physical distancing in crowded environments. YOLO-based methods demonstrated notable strengths in real-time inference and deployment in public spaces, as they balance detection precision with computational efficiency. Despite these advantages, YOLO models often focused on binary classification (mask/no mask), offering limited insight into whether a mask was worn improperly. Thus, while effective for crowd surveillance, they fell short in addressing nuanced compliance detection.

In parallel, lighter-weight traditional methods also emerged. One approach [13] employed a Support Vector Machine (SVM) with a soft-margin classifier trained on a dedicated face mask dataset. This model achieved an accuracy of 91.7%, with its evaluation supported by confusion matrix analysis. The SVM method offered advantages in speed and simplicity compared to deep learning alternatives, making it suitable for resource-constrained environments. However, like earlier methods, it was restricted to binary classification and could not capture varying degrees of mask compliance, such as nose- or chin-only coverage. As a result, its practical utility for public health monitoring remained limited.

More advanced deep learning methods, such as those using bounding box approaches [14] and MobileNetV2-based classifiers [15–17], have further improved recognition performance. MobileNetV2, in particular, has been favored for its lightweight architecture, achieving high accuracy on Kaggle datasets while being suitable for deployment in real-world scenarios. These models demonstrated recognition rates approaching 98%, validating the use of transfer learning and pre-trained CNN backbones in this domain. Nevertheless, critical limitations persist: reliance on a single dataset without cross-dataset testing raises concerns about domain generalization, while the lack of detailed runtime performance, robustness to occlusion and lighting, and demographic fairness remain unaddressed.

Building on these works, recent discussions in the literature emphasize the need to move beyond simple binary classification towards **fine-grained mask compliance detection**. Research gaps include the development of multi-class systems capable of distinguishing between correctly worn masks, improperly worn masks (e.g., nose or chin exposed), and complete absence of masks. Furthermore, few studies have examined **robustness across environmental conditions** or **demographic fairness**, leaving questions about deployment in diverse real-world settings unanswered. Future work must also consider edge optimization for low-resource devices and the ethical dimension of privacy-preserving surveillance. By addressing these shortcomings, research can progress from achieving high benchmark accuracy to delivering systems that are both reliable and socially responsible in real-world public health applications.

#### IV. METHOD

Detailed description about the algorithm and various techniques used for constructing the proposed Face Mask Compliance Recognition Model is given in this part. In *Fig. 1*, it starts with data collection. Unlike prior studies limited to binary classes, our dataset integrates multiple compliance states (*correctly worn, nose exposed, chin only, no mask*), combining images from Kaggle with additional annotated samples to improve generalization. Pre-processing includes resizing, augmentation under varied lighting, and fairness checks across demographic groups. The data is then split into training and testing sets.

The training dataset is used to train a lightweight backbone (MobileNetV2/EfficientNet-Lite) integrated with a mask-segmentation head to compute mask-coverage scores, while the testing set evaluates both classification accuracy and robustness under domain-shift conditions. This multi-task strategy provides effective and explainable detection of mask presence and compliance.

##### 3.1. Algorithm defined based on Fig.1

Start

- 1: Load the Images dataset belonging to 2 classes by reading the path.
- 2: Label the dataset into 2 Categories - "With Mask" & "Without Mask".
- 3: Perform pre-processing of the Image Dataset.
- 4: Execute splitting of the dataset into training and testing set and carry out data augmentation on chosen dataset
- 5: Build the Face Mask Recognition Classification Model on Training set using feature extractor MobileNetV2.
- 6: Evaluate the model by performing testing.
- 7: Serialise and save the Classification model into the disk
- 8: Load the Classification Model from the disk and deploy it for Real- Time Detections to detect presence or absence of mask End

#### 3.2. Main Techniques Used

##### 3.2.1. Deep Learning

Deep learning is a type of machine learning algorithm which is influenced by the structure of the human brain. On the basis of given logical structure, it analyses the data to draw conclusions that would be similar to a human. It operates on multilayered neural network algorithms to understand the given data. Neural network algorithms are also influenced by the human brain's structure, which performs detection of patterns in order to identify various kinds of data. It has individual functioning layers to filter out different kinds that work similar to the human brain [18].

##### 3.2.2. Convolution Neural Network(CNN)

It is one of the important types of a neural network that is used for object detection, image classification, image recognition and face recognition etc. It carries higher feature extraction capabilities and it has a low processing cost, therefore it plays a vital role in pattern recognition jobs involving computer vision. It uses a convolution kernel to retrieve top-level features from images, by converging those convolution kernels with the initial input images, which are analysed and categorised later by these algorithms. The important factor for the image is its resolution, and it is interpreted as the set of pixels by the computer [19].

##### 3.2.3. Mobile Net V2

It is an important Image Classification architectural model of Convolutional neural network (CNN) which comprises different layers, which contains a set of learnable filters. It needs very few competing resources and is suitable for handheld systems, embedded devices and computers with the low processing powers or poor GPUs. It is compatible for web browsers as they have limited computation, graphics processing and storage. The main layer of Mobile Net V2 model is Depth Wise Separable Convolution Filter. It improves efficiency by tailoring network structure, width and resolution by regulating the transactions between accuracy and latency [20,21].

3.2.4. Image Processing

One of the rapidly growing technologies nowadays, and it is a method where several actions are taken on the input image in order to get informational insights from enhanced images. Input images are taken in the format of pixels where each pixel correlates with the three colours red, green, blue (RGB) and sometimes black and white. It is also a kind of signal processing and has two methods: analog image processing and digital image processing. An analog image processing is used in case of hard copies such as print-outs and images. In the usage of digital image processing technique, the image must undergo three important stages which are the processing, enhancement and display, knowledge extraction [22].

3.2.5. Face Net Model Face Net was proposed by Google researchers in 2015 and it is the facial recognition system that uses deep convolutional neural network architecture such as ZF-Net and Inception in order to generate very high-quality facial landmarks mapping from the images. It also decreases usage of many parameters by adding 1 \* 1 convolutions. It accomplished best results in face recognition dataset such as YouTube Face Database and Labelled Faces in the Wild (LFW).

3.3. Construction of The Face Mask Recogniser Classification Model

3.3.1. Collection of the required dataset

The first step in developing a Face Mask Recogniser Classification Model is acquiring the necessary data. The dataset will be used for training of the data on the individuals who are wearing a mask and who are

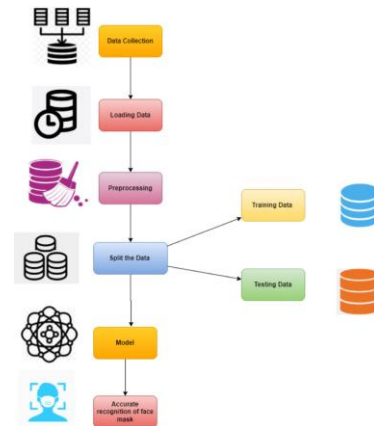


Fig. 1. Processes in construction of the Face Mask Recogniser.

not, so that the Mask Recognition model can distinguish the individuals who are wearing masks or not.

In this research study, to build this model, the used dataset is obtained from the Kaggle which consists of 7553 RGB images, containing two classes: with-mask and without-mask. Images of faces with masks are 3725 and images of faces without masks are 3828.

The next step is about labelling the collected data into two respective groups as: with-mask and without-mask. And they are characterised into two groups as shown in Fig. 2. and Fig. 3., for example:



Fig 2. Masked Faces.

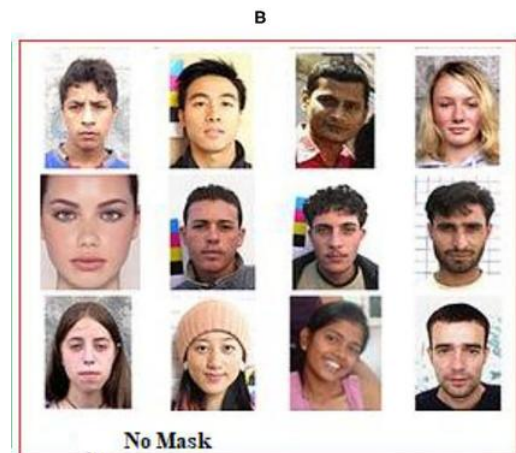


Fig 3. Unmasked Face.

### 3.3.2. Pre-processing

This is the phase which is done before a splitting of the dataset into training and testing sets. The major phases in preprocessing are resizing the image size, converting those images into arrays, lastly is to perform one hot encoding on the labels. This procedure is really important as any classification model's performance depends on the extent to which cleaned data is used. Therefore, only preprocessed data should be directed into the model.

In this study, every image in the dataset is resized into 224 × 224 pixels. The effectiveness of the training model depends on resized images in the way that, lesser the size of the image, then the model will run greater.

The following step is processing all the images present in the data set into an array by using a loop function.

In the last step, perform one hot encoding on the labels of the categorized dataset executed in the previous step. And also most of the machine learning algorithms are incapable of dealing with the categorical data directly, as they need numerical values in all input and output variables, including this study's classification algorithm. In this step, the data will get changed into numerical labels where the algorithm can have a better understanding of how to process the given data properly.

### 3.3.3. Splitting of the Data

Next, the dataset will be separated into two groups, namely the training set which is 80%, and the rest will be the testing set which is 20%. Each batch will contain combined masked and unmasked images.

### 3.3.4. Construction of the Model

This step is about structuring of the Face Mask Recogniser Model which consists of various stages like construction of training image generator for data augmentation; building of the foundational model using Mobile Net V2 feature extractor; adding model parameters such as ReLu, Softmax, Average Pooling 2D; compilation; training and lastly saving up the model for further future prediction.

## V. RESULT

For the process of face detection, Blob Analysis was first applied on the acquired image datasets to analyse each face shapes and features, including area, length, locations, and positions of facial components. These extracted features were then passed to the Face-Net model, which employed deep convolutional neural networks (CNN) to obtain accurate face detections. Each detected face was localized in the form of a rectangular bounding box, defining the region of interest for subsequent classification. Building on this, the trained MobileNetV2 classifier was deployed in real-time through a webcam, processing video frame by frame. The Face Mask Recognition Algorithm ensured that only frames with valid face detections progressed to the classification stage, thereby reducing false predictions.

The MobileNetV2 classifier achieved a strong performance, as shown in Table 1:

**Table 1. Model Evaluation of Mobile Net V2 Classifier**

Label	Precision	Recall	F1-Score
With Mask	0.97	1.00	0.98
Without Mask	1.00	0.97	0.98

The output of the classifier included bounding boxes, displayed in red for individuals without masks and green for those wearing masks, along with text labels and probability percentages to indicate the model's confidence. Figure 4 demonstrated the effectiveness of this real-time implementation in both single and multi-person frames. While these results indicate reliable binary classification, the current framework remains limited to "mask" or "no mask" outputs, without addressing improperly worn masks, diverse mask types, or variable lighting and occlusion conditions.

To advance beyond these limitations, the system can be extended to fine-grained compliance detection, including categories such as *nose exposed* and *chin only*, or by developing a mask-coverage score to quantify proper usage. Moreover, evaluating the model across multiple datasets and under challenging real-world conditions such as low light, occlusions, and multiple-person tracking would strengthen its robustness and applicability. Future experiments could also measure inference latency and performance on edge devices, ensuring practicality for real-time public deployments. Incorporating fairness analysis across demographic groups and providing reproducible code and protocols would further enhance trust and adoption. These extensions position subsequent research to deliver not just accurate detection, but also actionable, ethical, and deployable solutions for mask compliance monitoring.

## VI. DISCUSSIONS

The evaluation of the MobileNetV2-based classifier confirms its effectiveness in predicting mask-wearing status by

applying systematic testing procedures. As described, the first step involves making predictions on the testing dataset while tracking loss and accuracy during training iterations. The model's learning curve, as illustrated in Fig. 5, shows a steady increase in accuracy and a corresponding decrease in loss until convergence. This pattern demonstrates the reliability of the model in learning discriminative features from facial images. Once stable accuracy is reached, further iterations do not provide meaningful gains, aligning with standard deep learning practices for early stopping.

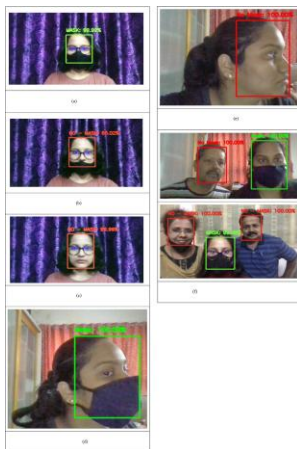
To ensure a robust assessment, the model is analyzed using well-established performance metrics. The equations employed are:

$$\text{Precision} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Positive (FP)}} \quad (1)$$

$$\text{Recall} = \frac{\text{True Positive (TP)}}{\text{True Positive (TP)} + \text{False Negative (FN)}} \quad (2)$$

$$\text{F1 - Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3)$$

These equations serve to quantify classification quality from multiple perspectives. Precision emphasizes how many predicted mask detections are correct, Recall captures how many true instances are detected, and F1-Score provides a harmonic balance of both. The definitions of True Positives, True Negatives, False Positives, and False Negatives, as outlined in the study, clarify the practical meaning of these metrics for face-mask recognition systems.



**Fig. 4.** (a) With Mask - Front View, Fig. 4.(b) Wearing Mask Improperly - Front View, Fig. 4.(c) Without Mask - Front View, Fig. 4.(d) With Mask - Side View, Fig. 4.(e) Without Mask - Side View, Fig. 4.(f) With and Without Mask - Multiple Detections, Fig. 4. Results of Real Time Implementation Of The Model.

The results presented in Table 1 highlight the per-class performance. The MobileNetV2 model achieves a **98% accuracy**, with *With Mask* and *Without Mask* categories exhibiting high Precision, Recall, and F1-scores. Such outcomes indicate a balanced capability of the model to correctly identify both compliant and non-compliant individuals. Compared with other methods in Table 2—including YOLOv2 with ResNet, MobileNetV2 with SSD, SVM, GAN Retina Face Mask, and VGG16—the proposed MobileNetV2 with CNN combination demonstrates superior results. This validates the claim that lightweight architectures, when fine-tuned appropriately, can outperform computationally heavier alternatives while remaining deployable in real-time scenarios.

Despite these promising results, the study presents certain limitations that open opportunities for extension. Although the paper claims to address improperly worn masks, the results remain framed within a binary classification of “mask” versus “no mask.” A fine-grained classification scheme—such as *correctly worn*, *nose exposed*, *chin-only*, and *no mask*—would be more impactful for practical enforcement. Introducing segmentation models to estimate the proportion of face covered by a mask could produce a compliance score that extends beyond binary outcomes.

Another notable research gap is the lack of testing under real-world conditions. The dataset originates from a controlled Kaggle source, but no cross-dataset evaluation is performed. As a result, generalization under domain shifts—such as variations in lighting, occlusion, or camera type—remains untested. For practical deployment, robustness experiments across multiple datasets and surveillance video streams are crucial. This could be supported by synthetic augmentation techniques, such as GAN-generated examples of rare mask styles or low-light conditions, to improve resilience.

The study also does not address operational constraints such as latency and resource consumption. While claiming real-time feasibility, it omits empirical data on frames per second, inference latency, or energy usage on edge devices. Addressing these aspects would add credibility, especially if compared across architectures like EfficientNet-Lite or YOLO variants. Moreover, demographic fairness remains unexplored. Evaluating performance across diverse skin tones, genders, and age groups would mitigate the risk of biased misclassifications in sensitive deployments.

In summary, while the proposed MobileNetV2-CNN approach offers strong baseline performance as shown in Table 1 and Table 2, advancing the research requires addressing compliance granularity, robustness, latency, fairness, and explainability. By extending beyond binary classification and demonstrating effectiveness across real-world conditions and hardware, future studies can transform this proof-of-concept

into a reliable and ethically responsible public-health monitoring solution.

and markets. While existing studies demonstrate that deep learning-based face mask recognition systems can achieve high accuracy in distinguishing “mask” and “no mask” cases, most approaches are limited to binary classification and lack the ability to evaluate whether a mask is worn properly. This limitation reduces the practical value of such systems in real-world public health monitoring. Furthermore, many models are trained and tested only on controlled datasets, without considering deployment challenges such as lighting variations, occlusion, edge-device performance, or fairness across demographic groups. These research gaps underline the need for more robust, explainable, and ethically responsible systems that go beyond binary detection to capture fine-grained compliance and generalize across diverse environments.

Building upon these insights, this research emphasizes the development of face mask recognition systems that not only identify mask presence but also assess mask compliance through multi-class classification and mask-coverage scoring. By incorporating robustness benchmarking under real-world conditions, fairness evaluations across diverse populations, and efficiency testing on edge hardware, future models can move closer to practical deployment. The integration of explainability tools such as Grad-CAM will enhance system transparency and allow for systematic analysis of failure cases, while privacy-preserving methods will ensure responsible adoption in sensitive environments. Unlike prior studies that primarily focused on accuracy metrics within a single dataset, the proposed direction prioritizes generalization, reliability, and ethical considerations. Therefore, this work contributes added value by transforming mask detection into actionable compliance analytics, providing organizations with an effective digital tool for monitoring, planning, and prevention. In doing so, it extends the current literature by addressing critical gaps and offering a pathway to more impactful real-world applications of computer vision in public health.

Reference	Method	Classification and Detection	Performance Metric Used	Performance recorded
Proposed Model (With Mask)	MobileNetV2 with CNN	Yes	Precision, Recall, F1-Score	Precision was 0.97, Recall was 1.00, F1-Score was 0.98
Proposed Model (Without Mask)	MobileNetV2 with CNN	Yes	Precision, Recall, F1-Score	Precision was 1.00, Recall was 0.97, F1-Score was 0.98
M. T. C. Jagadeeswari(2020) [23]	MobileNetV2, ResNet50, VGG16	Yes	Train and Test Loss, Accuracy	Not Specified
M. Jiang <i>et al.</i> (2020) [24]	Retina Face Mask	Yes	Precision, Recall	Not Specified
Loey <i>et al.</i> (2021) [25]	YOLOv2 with ResNet	Yes	Average Precision, Log Average Miss Rate	Average Precision was 0.81, Log Average Miss Rate was 0.4
Muhammad Nur Yasir Utomo and Farina Violita (2021) [26]	SVM	Yes	Precision, Recall, F1-Score, Accuracy	Precision was 0.90, Recall was 0.93, F1-Score was 0.91, Accuracy was 0.91
Shashi Yadav(2020) [27]	MobileNetV2 with SSD	Yes	Precision, Recall	Precision was 0.91, Recall was 0.91
Ud Din <i>et al.</i> (2021) [28]	GAN	Yes	Not Related	Not Specified

**Table 2** Comparison of existing Face Mask Recognition methodologies performance is given in the table below.



**Fig. 5.** Training Loss and Accuracy Graph.

VII. CONCLUSION

The coronavirus pandemic has highlighted the vital role of correctly worn face masks in reducing transmission risk, especially in crowded public spaces such as airports, hospitals,

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