I.J. Image, Graphics and Signal Processing, **2024, 5, 25-35**
Published Online on October 8, 2024 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijigsp.2024.05.03

Enhanced Surgical Mask Recognition Using EfficientNet Architecture

Galib Muhammad Shahriar Himel*
School of Computer Sciences, Universiti Sains Malaysia, 11800 USM Penang, Malaysia
E-mail: galib.muhammad.shahriar@gmail.com
ORCID iD: https://orcid.org/0000-0002-2257-6751
*Corresponding Author

Md. Masudul Islam
Department of Computer Science and Engineering, Jahangirnagar University, Dhaka, Bangladesh
Email: masudulislam11@gmail.com
ORCID iD: https://orcid.org/0000-0001-7643-5420

Received: 23 January, 2024; Revised: 14 February, 2024; Accepted: 17 March, 2024; Published: 08 October, 2024

Abstract: The research article presents a robust solution to detect surgical masks using a combination of deep learning techniques. The proposed method utilizes the SAM to detect the presence of masks in images, while EfficientNet is employed for feature extraction and classification of mask type. The compound scaling method is used to distinguish between surgical and normal masks in the data set of 2000 facial photos, divided into 60% training, 20% validation, and 20% testing sets. The machine learning model is trained on the data set to learn the discriminative characteristics of each class and achieve high accuracy in mask detection. To handle the variability of mask types, the study applies various versions of EfficientNet, and the highest accuracy of 97.5% is achieved using EfficientNetV2L, demonstrating the effectiveness of the proposed method in detecting masks of different complexities and designs.

Index Terms: Surgical mask detection, EfficientNet, face mask recognition, face mask detection, surgical mask recognition, machine learning, image processing, COVID-19, Segment Anything Model, Transfer learning.

1. Introduction

The COVID-19 pandemic has expanded rapidly around the world. This has impacted many companies around the world to think about the precautions to avoid health issues related to COVID-19. Many countries have developed particular measures to limit the transmission of coronaviruses, such as social distancing combined with the wear of masks to protect the mouth and nose, to reduce infection. Alongside the health-related requirements, many companies also changed their skill requirement policies to avoid appointing unskilled employees [1]. It is observed that not every nation has made face masks mandatory, a recent study by the World Health Organization suggests that wearing one can be quite effective in preventing the spread of COVID-19 [2].

In the field of computer vision and image processing face mask detection is a minimal subset of the field. To get a better understanding of how to improve classification model-related literature [3,4,5,6,7,8,9] is to be investigated alongside the subset.

In this context, various studies on mask detection have been published in recent years. There has been a significant amount of research conducted on the topic of detecting and recognizing faces [11]. A comprehensive strategic review is conducted by Vibhuti et al. Al. [10] where the pros and cons of each method have been analyzed, and sources to multiple datasets are mentioned. Rodrguez et al. Al. [12] developed a technique to identify medical masks worn in an operating room. By utilizing two separate detectors, one for detecting faces and the other for identifying medical masks, their approach significantly improved the model's accuracy. Specifically, the method achieved a 95% accuracy rate in detecting faces that were wearing surgical masks. Zekun et al. Al. [13] achieved an accuracy of 89% and developed a web application for user access.

Sanjaya & Rakhmawan [14] developed a machine learning model MobileNetV2 which can detect people who wear a face mask and do not wear it with an accuracy of 96.85%. Arjya, Mohammad, and Rohini [15] proposed a method that detects the face in the image correctly and then identifies whether it has a mask on it or not, and achieves accuracy up to 95.77% and 94.58%, respectively, on two different datasets. Loey et al. [16] introduced a framework that employs machine learning to identify face masks using a collection of high-quality images of faces that resemble those captured at conferences. Their model demonstrated remarkable precision, with an accuracy rate of 99.64% to 100% when identifying face masks. Nevertheless, these images were captured when the face was facing a computer camera situated just a few inches away, and as such, it is not suitable for real-world scenarios where individuals could be walking around at varying distances and angles, resulting in only a partial view of their faces and masks. Qin & Li [17] presented a technique to evaluate the suitability of wearing a mask by analyzing where it is placed. Their method categorizes each scenario into three groups: proper mask placement, incorrect mask placement, and no mask present. The method was successful in identifying face masks and their positions with a 98.7% accuracy rate. Shay & Ghaith [18] used three components: The resNet-50 model, multitask convolutional neural networks (MT-CNN), and CNN classifier to detect face masks. Furthermore, they implemented their technique on a mobile robot called 'Thor' and achieved an accuracy of 81.3%. Eashan & Brian [19] experimented with a huge dataset of 653,997 real-world webcam images and implemented some of the object detection algorithms to understand their effectiveness in such a real-world application. A model based on InceptionV3 was used by G. Jignesh Chowdary et al. Al. [20] to achieve a 99.9% accuracy on the Simulated Masked Face Dataset (SMFD). Amit et al. Al. [21] presents a two-stage face mask detector: RetinaFace model, Dlib & MTCNN. They selected the NASNetMobile-based model to classify face mask detection and achieved 99.23% accuracy. Shilpa et al. Al. [22] proposed a method that combines one-stage and two-stage detectors to achieve low inference time and high accuracy and achieved high accuracy (98.2%) when implemented with ResNet50. Ruchi & Manish [23] proposed a system that has achieved an accuracy of 98% in the synthesized benchmark datasets. The researchers utilized a face detection model called "Single Shot Multibox Detector" and an advanced architecture called "Deep Inception V3" (abbreviated as SSDIV3) to identify important image characteristics and classify them as either "with mask" or "without a mask." Muhammad et al. Al. [24] developed a deep-wise separable convolutional neural network model that achieved 93.14% accuracy. Balaji et al. [25] employed a VGG-16 CNN model that was created in Keras/TensorFlow and OpenCV to detect individuals who did not adhere to the mandatory face mask policy at government workplaces. Sufia et al. Al. [26] experimented on two sets of the dataset and achieved 98.96% accuracy by MobileNetV2, which outperformed VGG19 achieving an accuracy of 99.55%. Sadeddin [27] used a pre-trained ResNet-50 model on an image dataset of approximately 12,000 face mask images and achieved a 99% validation accuracy on 800 of those images. Dostdar et al. Al. [28] evaluated their experiment on two datasets and used the MobileNetV2 & DCNN models. The experiment showed that MobileNetV2 had a higher precision than DCNN on two different datasets. MobileNetV2 had 98% accuracy on dataset 1 and 99% accuracy on dataset 2, while DCNN had 97% accuracy on both datasets. Oumina et al. Al. [29] created a system that combines pre-trained deep learning models (Xception, MobileNetV2, and VGG19) to extract features from input images. They then used different machine learning classifiers, such as SVM and k-NN, to classify these extracted features into two classes (with mask and without mask) using a total of 1376 images. Their experimental results show that the combination of MobileNetV2 with SVM achieved the highest precision of 97.11%. Burhan et al. Al. [30] built a dataset of 14,535 images, including 5000 with incorrect masks, 4789 with masks, and 4746 without masks. They also developed a face mask detection system that can detect all three classes accurately with an average accuracy of 97.81%. In 2021, Afsana et al. conducted a comprehensive and meta-analytic review [31] on facemask detection techniques was done by Afsana et al.

All of these studies have primarily identified surgical and nonsurgical masks as face masks, thus detecting any type of mask, resulting in no in-depth research focusing on the detection of surgical masks that can effectively prevent COVID-19 transmission. The problem was to enforce the mask laws without mentioning any specific mask recommendations. During that time many people wore different types of masks, mostly nonsurgical. That is why this law helped very little to control the spread of the virus. A surgical mask prevents the coronavirus from entering through the mouth and nose, but other masks perform very poorly in this case. The capacity to prevent viruses is approximately 50% in the case of surgical masks, whereas the normal mask has only a 10% chance of prevention or even below.

Some research was published on facemask detection as mentioned above, but no publications were done to develop a complete surgical mask detection model for real-world application effectively. Therefore, in this paper detection of surgical masks is being emphasized to solve the problem.

2. Proposed Method

Various research initiatives are ongoing to utilize AI-driven methods to classify categories from different datasets [32,33,34,35]. Through completed and ongoing research, several observations can be made regarding the effectiveness of different methods on specific types of datasets. Judging from the previous literature we have decided to apply SAM [36] for segmentation and EfficientNet for feature extraction. Pre-trained models such as ResNet50, VGG16, Xception, and EfficientNet were used for feature extraction during classification. These pre-trained models were originally trained on a large image dataset called 'ImageNet' [37]. However, we found that the ResNet50, VGG16, and Xception models work well for classifying facemasks with less challenging conditions. The feature extraction approach in these models relies on color-based pixel information, which is ineffective in identifying surgical masks from a dataset of only masked faces.

To overcome this challenge, we turned to the compound scale-based feature extraction method used by the EfficientNet model. EfficientNet [38] is another pre-trained model based on ImageNet that uses a compound scale approach for feature extraction. Consequently, in this study, EfficientNet was used to detect surgical masks and classify them into various types of masks. Fig. 1 shows a diagram representing our proposed method.

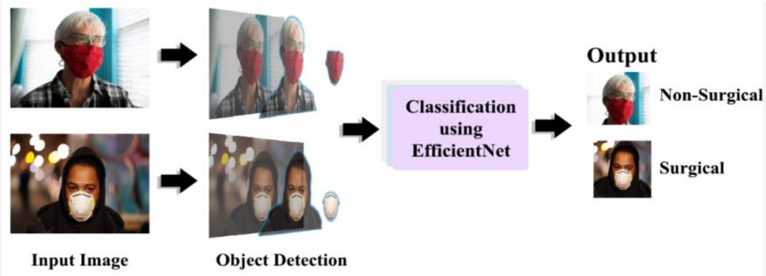


Fig. 1. Proposed model for surgical mask identification

2.1 Dataset

For this experiment, a data set containing 2000 images is used. The dataset has two categories: surgical masks and non-surgical masks. The dataset contains images of various resolutions. Every category contains 1000 images. 1200 images are used for training (600 images from each category). 400 images are used for validation (200 images from each category) and 400 images for separate testing (200 images for each category). The main image data set is from the Face Mask Detection Data Set [39] from 'Kaggle' and we have modified the data set by filtering them into two categories for our research. Because these images are variable in size, we reduced them to a standard resolution of 224 × 224 pixels.

2.2 Experimental Procedure

First of all, the images of the dataset are categorized into two categories, those are surgical and nonsurgical masks. The machine cannot understand the pure colors, so using the 'Numpy Arrays' function, the information from the RGB channel is converted to matrices. This is a part of data preprocessing. After data pre-processing is done, the arrays

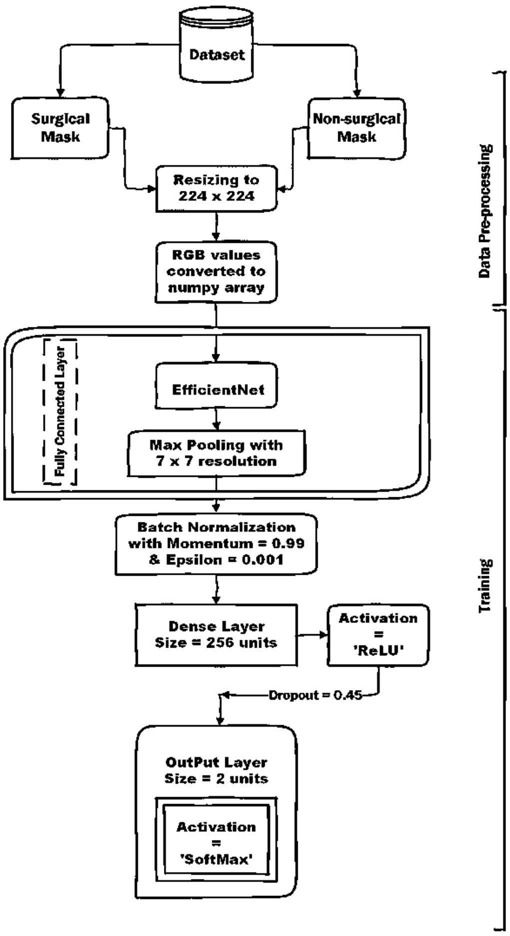


Fig. 2. EfficientNet Model Flow Chart

containing image information are pipelined through SAM to 'Efficient Network'. EfficientNet reduces the dimensions to 7×7 using the 'max pool' function. This output is further given as input to the dense layer of size 256 units. In the dense layer, the activation function 'ReLU' is being used to accelerate. The output layer, using the activation function 'SoftMax', creates two neurons for the probability calculation, as the probable outputs are two. The process uses the concept of 'transfer learning'. The following Fig. 2 describes the whole process in brief using a flowchart.

2.3 Feature Extraction

Generally, CNN models extract features mostly using color-pixel-based factors. This is quite an effective method. But in our case, the color-pixel-based decision is not helpful as both mask categories contain masks of the same/different color, making the model incapable of identifying the masks properly. 'EfficientNet' uses a method that scales the models using a simple yet effective approach called the compound coefficient, which scales the dimensionalities of each portion keeping uniformity by using a predetermined set of scaling coefficients rather than randomly scaling with resolution, width, and depth. The compound scaling approach is based on the principle of scaling with a constant ratio so that the model can maintain balance among the resolution, width, and depth dimensionalities. The following equations demonstrate how it is done mathematically:

$$\text{Depth } d = \alpha^{\phi}, \text{ Width } w = \beta^{\phi}, \text{ Resolution} = \gamma^{\phi}$$
$$\text{Such that } \alpha.\ \beta^2.\ \gamma^2 \approx 2 \text{ and } \alpha \geq 1, \beta \geq 1, \gamma \geq 1 \ \dots \dots \dots \quad (1)$$

If the input image is larger, the network's understanding is that it requires additional layers to expand the receptive field and more channels to capture more fine-grained patterns on the larger image, thus finding better-defining features from images.

2.4 Experimental setup

During the experiment, in the training period, we used the 'Adamax' optimizer, as it is faster and more helpful for sparse data. We used 'categorical cross entropy' as a loss function. 50 epochs were used to train the model. The batch size was set to 30. The learning rate was primarily set at 0.001. But if in any epoch, the loss is greater than the previous epoch, the learning rate is automatically cut off by half. Accuracy matrices were defined to calculate the result. The whole experiment was carried out using a powerful computer that had a core i7 processor, 32 GB of RAM, and 8 GB of GPU memory. The GPU model is NVIDIA GeForce GTX 1070. To manage the CUDA cores [40] of the GPU, CUDA Toolkit version 11.4 and CuDNN [41] version 8.2.2 were used. To run the whole experiment, 'Jupyter-Lab' was used along with an anaconda navigator. Python version 3.8.3, Keras [42], Tensorflow [43] version 2.7, and the Scikit-Learn library were used to manage the machine learning functions.

3. Results

3.1 Training-Validation and Test-Accuracy

In this research, we have used EfficientNetB0', EfficientNetB1', 'EfficientNetB2', 'EfficientNetB3', 'EfficientNetB4', 'EfficientNetB5', 'EfficientNetB6', 'EfficientNetB7', 'EfficientNetV2M' and 'EfficientNetV2L'. In all cases, the training took approximately 10-12 minutes. The following graphs describe the accuracy and loss of the highest and lowest accuracy obtained from the training. In the case of 'EfficientNetB5,' the lowest validation accuracy is 89.75% and the test accuracy is 91%, which is achieved in the 33rd epoch as shown in **Fig. 3**.

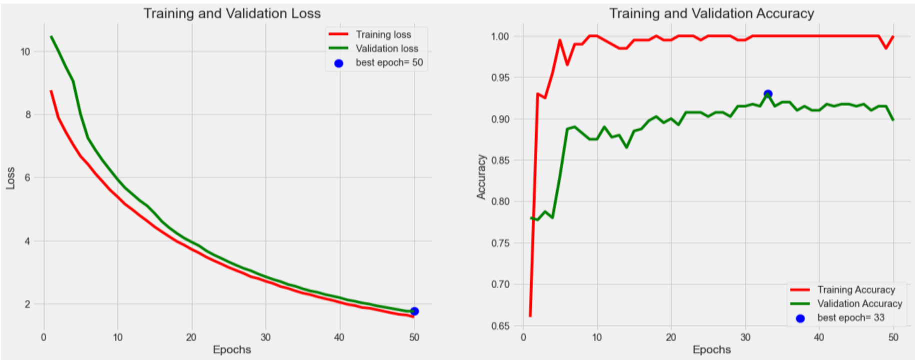


Fig. 3. EfficientNetB5 training curve

In the case of 'EfficientNetV2L', the highest validation precision is 96.75% and the test precision is 97.5%, which is achieved at the 33rd epoch as shown in Figure 4.

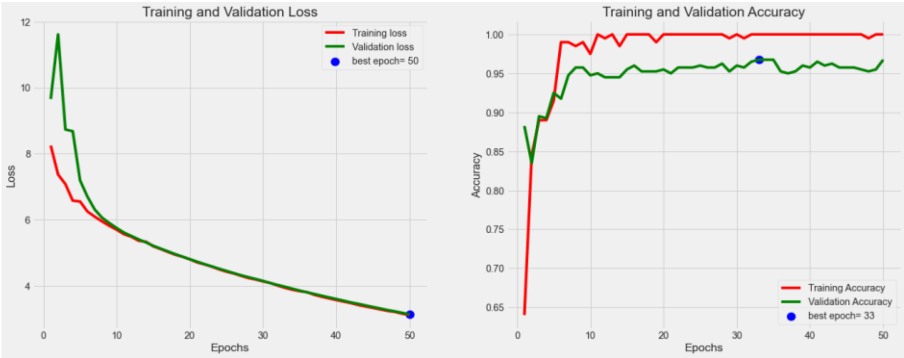
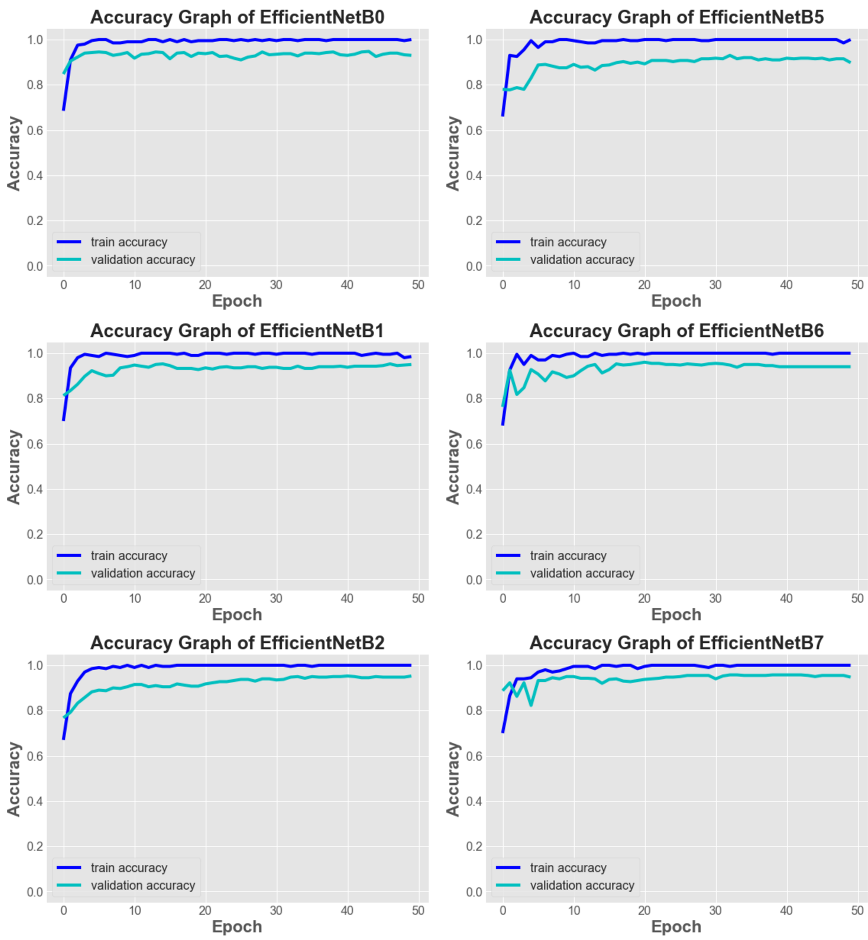


Fig. 4. EfficientNetV2L training curve

The training curve for all the models is demonstrated in Fig. 5 and the detailed result is shown in Table 1 below.

Table 1. Accuracy and Loss Scores

Model	Training Loss	Training Accuracy (%)	Validation Loss	Validation Accuracy (%)	Test Accuracy (%)
EfficientNetB0	1.632	100	1.75581	93	94
EfficientNetB1	1.452	98.5	1.51858	95	95.75
EfficientNetB2	1.544	100	1.63089	95.25	93.75
EfficientNetB3	2.914	100	3.04204	94.5	94.25
EfficientNetB4	1.432	100	1.53435	93.75	93.25
EfficientNetB5	1.577	100	1.75885	89.75	91
EfficientNetB6	1.797	100	1.86337	94	95.75
EfficientNetB7	3.105	100	3.18348	94.75	94.5
EfficientNetV2M	1.332	100	1.38311	95.25	94.75
EfficientNetV2L	3.114	100	3.13626	96.75	**97.5**



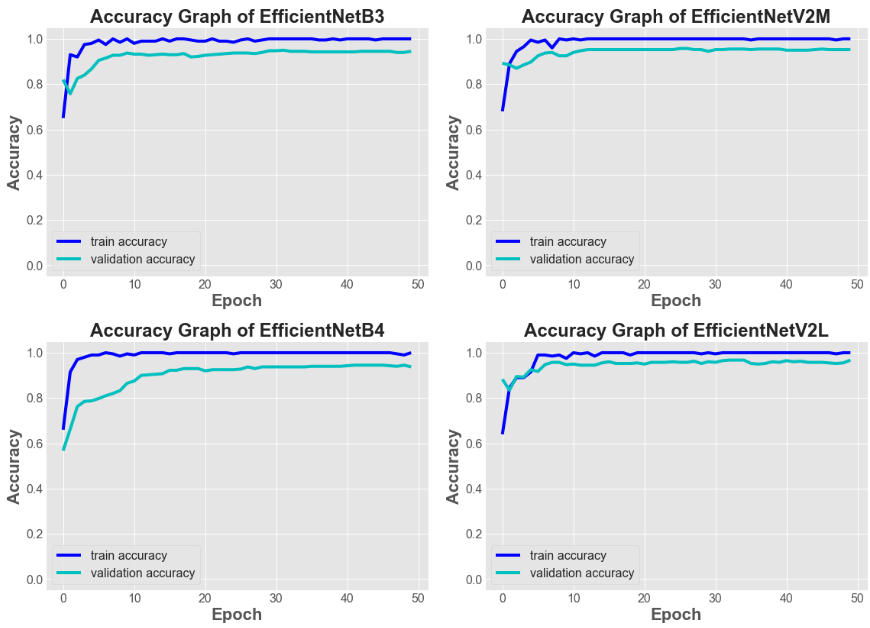


Fig. 5. Accuracy Curves of all EfficientNet Models

Fig. 6 represents the test accuracy comparison for various EfficientNet models.

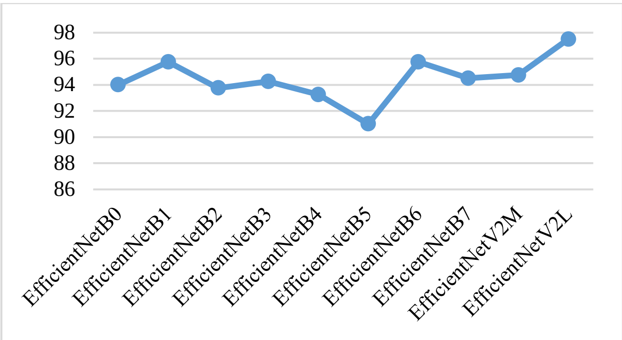


Fig. 6. Test accuracy comparison for all models

3.2 *Confusion Matrices*

The confusion matrices demonstrate which data was actually a nonsurgical mask and are also identified as a nonsurgical mask. And which data was a surgical mask but identified as a non-surgical mask. The same applies to surgical masks. The confusion matrices of all models are shown in Fig. 7.

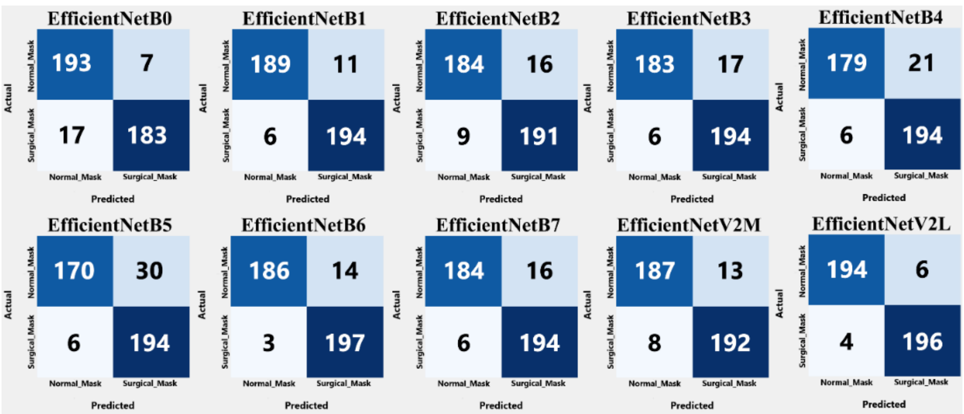


Fig. 7. Confusion Matrices

3.3 Classification Report

In Table 2, the precision, recall, and f1 scores of the models are presented.

Table 2. Classification Report

Model		**Precision**	**Recall**	**f1-score**	**Model**		**Precision**	**Recall**	**f1-score**
Efficient NetB0	Normal	0.92	0.96	0.94	**Efficient NetB5**	Normal	0.97	0.85	0.9
	Surgical	0.96	0.92	0.94		Surgical	0.87	0.97	0.92
	Accuracy			0.94		**Accuracy**			0.91
	Macro Avg.	0.94	0.94	0.94		**Macro Avg.**	0.92	0.91	0.91
	Weighted Avg.	0.94	0.94	0.94		**Weighted Avg.**	0.92	0.91	0.91
Efficient NetB1	Normal	0.97	0.94	0.96	**Efficient NetB6**	Normal	0.98	0.93	0.96
	Surgical	0.95	0.97	0.96		Surgical	0.93	0.98	0.96
	Accuracy			0.96		**Accuracy**			0.96
	Macro Avg.	0.96	0.96	0.96		**Macro Avg.**	0.96	0.96	0.96
	Weighted Avg.	0.96	0.96	0.96		**Weighted Avg.**	0.96	0.96	0.96
Efficient NetB2	Normal	0.95	0.92	0.94	**Efficient NetB7**	Normal	0.97	0.92	0.94
	Surgical	0.92	0.95	0.94		Surgical	0.92	0.97	0.95
	Accuracy			0.94		**Accuracy**			0.94
	Macro Avg.	0.94	0.94	0.94		**Macro Avg.**	0.95	0.95	0.94
	Weighted Avg.	0.94	0.94	0.94		**Weighted Avg.**	0.95	0.94	0.94
Efficient NetB3	Normal	0.97	0.92	0.94	**Efficient NetV2M**	Normal	0.96	0.94	0.95
	Surgical	0.92	0.97	0.94		Surgical	0.94	0.96	0.95
	Accuracy			0.94		**Accuracy**			0.95
	Macro Avg.	0.94	0.94	0.94		**Macro Avg.**	0.95	0.95	0.95
	Weighted Avg.	0.94	0.94	0.94		**Weighted Avg.**	0.95	0.95	0.95
Efficient NetB4	Normal	0.97	0.9	0.93	**Efficient NetV2L**	Normal	0.98	0.97	0.97
	Surgical	0.9	0.97	0.93		Surgical	0.97	0.98	0.98
	Accuracy			0.93		**Accuracy**			0.97
	Macro Avg.	0.93	0.93	0.93		**Macro Avg.**	0.98	0.97	0.97
	Weighted Avg.	0.93	0.93	0.93		**Weighted Avg.**	0.98	0.97	0.97

3.4 Receiver Operating Characteristics

ROC stands for Receiver Operating Characteristic. It is a curve that is commonly used to evaluate the performance of a binary classifier, which is a model that predicts binary outcomes (e.g., yes or no, positive or negative) based on some input features. The ROC curve is a graphical representation of the trade-off between the true positive rate (TPR) and the false positive rate (FPR) of the classifier, as the classification threshold is varied. The true positive rate is the proportion of positive instances that are correctly identified by the classifier, whereas the false positive rate is the proportion of negative instances that are incorrectly classified as positive. **Fig. 8** illustrates the ROC comparison for all EfficientNet models.

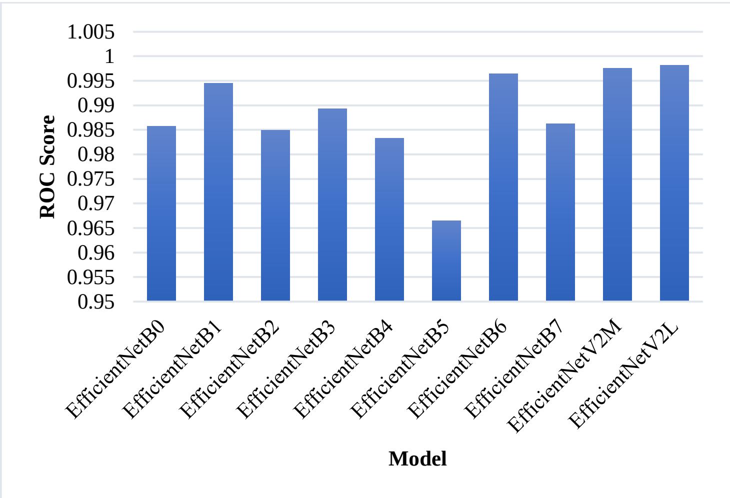


Fig. 8. ROC comparison

Fig. 9 illustrates the ROC curves for all EfficientNet models.

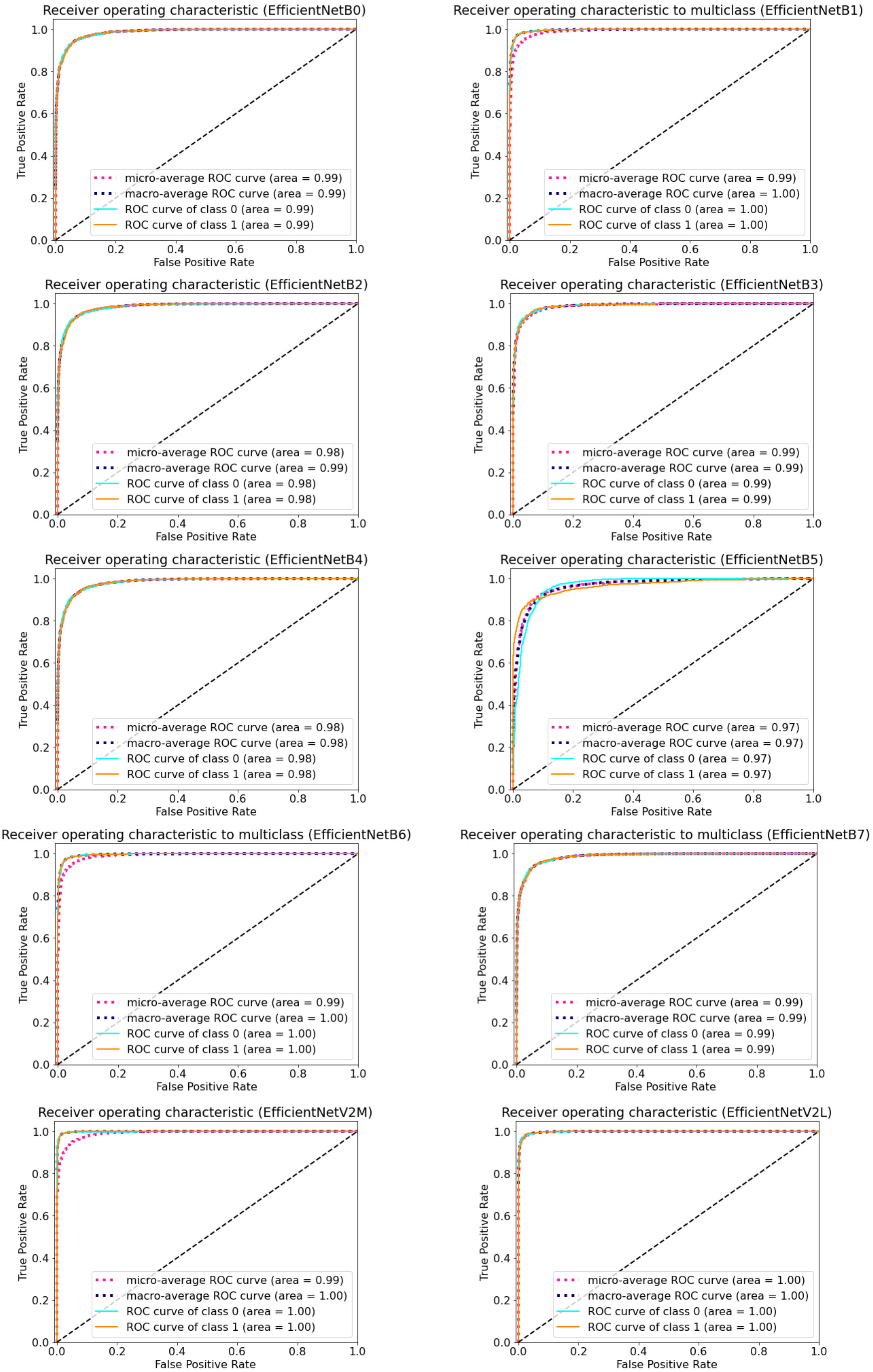


Fig. 9. ROC curve

4. Discussion

During the period of COVID-19, the prevalence of face masks has increased. Wearing face masks has become mandatory in various institutions and public gatherings. But wearing face masks only for the sake of covering the face is not enough to prevent covid-19 certain categories of face masks, especially surgical or medical face masks, wearing can significantly reduce the transmission of COVID-19.

Initially, various institutions emphasized wearing only face masks rather than surgical or medical masks. For this purpose, various types of research have been conducted for automatic face mask detection, some of which have been applied successfully. Some such research datasets are available on online platforms. However, since there is no research and data set specifically on surgical mask identification, we had to prepare our data set for this research, which is why our data set had to be created entirely by ourselves, which took some time. Also, our dataset contains only 2000 images which is somewhat less.

Another challenge of our research is that we have to differentiate two categories which are both images of people wearing masks. Previous research studies have used various methods to detect images of people with and without masks. On the other hand, we had to detect surgical face mask images from masked images. For this, the process of feature extraction was quite complicated, and it was very difficult to get more accuracy in this work.

In our proposed method, we applied scale-based feature extraction instead of color-based feature extraction. For this reason, our machine learning model did not randomly identify all masks that match the color of the surgical mask as a surgical mask and used features other than the color that is only present in the surgical mask as defining features. As a result, our proposed model was able to successfully distinguish surgical masks from normal ones in our prepared surgical mask dataset.

5. Conclusions

In conclusion, the proposed method of surgical mask segmentation and recognition using deep learning techniques presents a robust solution for detecting the presence of surgical masks in images, with high accuracy. The study utilized the Segment Anything Model (SAM) to detect masks and EfficientNet to extract features and classify mask types. The study was motivated by the global epidemic of Covid-19 and the proposed method can be useful in enforcing mask-wearing laws in public places. We compared our proposed method with existing literature on face mask detection and surgical mask detection and found that no research projects were carried out to develop a surgical mask detection model. Therefore, the study fills a significant literature gap by developing a surgical mask detection model and provides a valuable contribution to the field. The proposed method can be useful in real-world applications such as airports, hospitals, and other public places where masks are mandatory. We used various versions of EfficientNet to handle the variability of mask types and designs, and the high precision of 97.5% demonstrates the effectiveness of the proposed method in detecting masks of different complexities and designs. Future research can expand on this study to develop a more comprehensive system that can recognize masks in videos and real-time settings. Overall, this research is a significant step toward making our society safer and healthier.

References

[1] Rahaman, M., Islam, M., Rahman, M. (2023). An Empirical Analysis of IT-Software Job Skill Requirements During COVID-19 Pandemic Period in Bangladesh. In: Hossain, M.S., Majumder, S.P., Siddique, N., Hossain, M.S. (eds) The Fourth Industrial Revolution and Beyond. Lecture Notes in Electrical Engineering, vol 980. Springer, Singapore. https://doi.org/10.1007/978-981-19-8032-9_4

[2] World Health Organization (2021) Advice for Public. In: Who. int. https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public

[3] M. S. Hossain et al., "Tissue Artifact Segmentation and Severity Assessment for Automatic Analysis Using WSI," in IEEE Access, vol. 11, pp. 21977-21991, 2023, doi: 10.1109/ACCESS.2023.3250556.

[4] Hossain, M.S., Shahriar, G.M., Syeed, M.M.M., et al. Region of interest (ROI) selection using vision transformer for automatic analysis using whole slide images. Sci Rep 13, 11314 (2023). https://doi.org/10.1038/s41598-023-38109-6

[5] Galib Muhammad Shahriar Himel, Md. Masudul Islam, Kh. Abdullah Al-Aff, Shams Ibne Karim, Md. Kabir Uddin Sikder, "Skin Cancer Segmentation and Classification Using Vision Transformer for Automatic Analysis in Dermatoscopy-Based Noninvasive Digital System", International Journal of Biomedical Imaging, vol. 2024, Article ID 3022192, 18 pages, 2024. https://doi.org/10.1155/2024/3022192

[6] Galib Muhammad Shahriar Himel, Md. Masudul Islam, Mijanur Rahaman, Vision Intelligence for Smart Sheep Farming: Applying Ensemble Learning to Detect Sheep Breeds, Artificial Intelligence in Agriculture, Volume 11, 2024, Pages 1-12, ISSN 2589-7217, https://doi.org/10.1016/j.aiia.2023.11.002

[7] Saket S. Chaturvedi, Jitendra V. Tembhurne, and Tausif Diwan. 2020. “A Multi-Class Skin Cancer Classification Using Deep Convolutional Neural Networks.” Multimedia Tools and Applications, August. https://doi.org/10.1007/s11042-020-09388-2

[8] Breno Krohling, Pedro B. C. Castro, Andre G. C. Pacheco, and Renato A. Krohling. 2021. “A Smartphone Based Application for Skin Cancer Classification Using Deep Learning with Clinical Images and Lesion Information.” ArXiv:2104.14353 [Cs, Eess], April. https://arxiv.org/abs/2104.14353

[9] Nabeela Kausar, Abdul Hameed, Mohsin Sattar, Ramiza Ashraf, Ali Shariq Imran, Muhammad Zain ul Abidin, and Ammara Ali. 2021. "Multiclass Skin Cancer Classification Using Ensemble of Fine-Tuned Deep Learning Models." Applied Sciences 11 (22): 10593. https://doi.org/10.3390/app112210593

[10] Schroff F, Kalenichenko D, Philbin J (2015) FaceNet: A unified embedding for face recognition and clustering - IEEE Conference Publication. In: Ieee.org. https://ieeexplore.ieee.org/document/7298682

[11] Vibhuti, Jindal, N., Singh, H., et al. Face mask detection in COVID-19: a strategic review. Multimed Tools Appl 81, 40013–40042 (2022). https://doi.org/10.1007/s11042-022-12999-6

[12] Nieto-Rodríguez, A., Mucientes, M., Brea, V.M. (2015). System for Medical Mask Detection in the Operating Room Through Facial Attributes. In: Paredes, R., Cardoso, J., Pardo, X. (eds) Pattern Recognition and Image Analysis. IbPRIA 2015. Lecture Notes in Computer Science(), vol 9117. Springer, Cham. https://doi.org/10.1007/978-3-319-19390-8_16

[13] Wang Z, Wang P, Louis PC, et al (2021) WearMask: Fast In-browser Face Mask Detection with Serverless Edge Computing for COVID-19. arXiv:210100784 [cs, eess]

[14] Sanjaya SA, Adi Rakhmawan S (2020) Face Mask Detection Using MobileNetV2 in The Era of COVID-19 Pandemic. In: IEEE Xplore. https://ieeexplore.ieee.org/abstract/document/9325631

[15] Das A, Wasif Ansari M, Basak R (2020) Covid-19 Face Mask Detection Using TensorFlow, Keras, and OpenCV. 2020 IEEE 17th India Council International Conference (INDICON). https://doi.org/10.1109/indicon49873.2020.9342585

[16] Loey M, Manogaran G, Taha MHN, Khalifa NEM (2021) A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic. Measurement 167:108288. https://doi.org/10.1016/j.measurement.2020.108288

[17] Qin B, Li D (2020) Identifying Facemask-Wearing Condition Using Image Super-Resolution with Classification Network to Prevent COVID-19. Sensors 20:5236. https://doi.org/10.3390/s20185236

[18] Snyder SE, Husari G (2021) Thor: A Deep Learning Approach for Face Mask Detection to Prevent the COVID-19 Pandemic. In: IEEE Xplore. https://ieeexplore.ieee.org/document/9401874. Accessed 8 May 2023

[19] Adhikari E, Davison BD (2021) Face Mask Detection on Real-World Webcam Images. Proceedings of the Conference on Information Technology for Social Good. https://doi.org/10.1145/3462203.3475903

[20] Jignesh Chowdary G, Punn NS, Sonbhadra SK, Agarwal S (2020) Face Mask Detection Using Transfer Learning of InceptionV3. Big Data Analytics 81–90. https://doi.org/10.1007/978-3-030-66665-1_6

[21] Chavda A, Dsouza J, Badgujar S, Damani A (2021) Multi-Stage CNN Architecture for Face Mask Detection. 2021 6th International Conference for Convergence in Technology (I2CT). https://doi.org/10.1109/i2ct51068.2021.9418207

[22] Sethi S, Kathuria M, Kaushik T (2021) Face mask detection using deep learning: An approach to reduce risk of Coronavirus spread. Journal of Biomedical Informatics 120:103848. https://doi.org/10.1016/j.jbi.2021.103848

[23] Jayaswal R, Dixit M (2022) AI-based face mask detection system: a straightforward proposition to fight with Covid-19 situation. Multimedia Tools and Applications. https://doi.org/10.1007/s11042-022-13697-z

[24] Asghar MZ, Albogamy FR, Al-Rakhami MS, et al (2022) Facial Mask Detection Using Depthwise Separable Convolutional Neural Network Model During COVID-19 Pandemic. Frontiers in Public Health 10: https://doi.org/10.3389/fpubh.2022.855254

[25] Balaji S, Balamurugan B, Kumar TA, et al (2021) A Brief Survey on AI-Based Face Mask Detection System for Public Places. In: papers.ssrn.com. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3814341

[26] Azian SJBS, Ng H, Yap TTV, et al (2022) Face Mask Detection Using Deep Learning. In: www.atlantis-press.com. https://www.atlantis-press.com/proceedings/citic-22/125980651. Accessed 8 May 2023

[27] Face mask detection trained on ResNet - 50. In: Wolfram Cloud. https://www.wolframcloud.com/objects/notebookarchive/submissions/2020-12-6z8vw5z/2020-12-6z8vw5z.nb. Accessed 8 May 2023

[28] Hussain D, Ismail M, Hussain I, et al (2022) Face Mask Detection Using Deep Convolutional Neural Network and MobileNetV2-Based Transfer Learning. Wireless Communications and Mobile Computing 2022:1–10. https://doi.org/10.1155/2022/1536318

[29] Oumina A, El Makhfi N, Hamdi M (2020) Control The COVID-19 Pandemic: Face Mask Detection Using Transfer Learning. 2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS). https://doi.org/10.1109/icecocs50124.2020.9314511

[30] Sheikh B ul Haque, Zafar A (2023) RRFMDS: Rapid Real-Time Face Mask Detection System for Effective COVID-19 Monitoring. SN Computer Science 4: https://doi.org/10.1007/s42979-023-01738-9

[31] Nowrin A, Afroz S, Rahman MdS, et al (2021) Comprehensive Review on Facemask Detection Techniques in the Context of Covid-19. IEEE Access 9:106839–106864. https://doi.org/10.1109/access.2021.3100070

[32] Galib Muhammad Shahriar Himel, Md Masudul Islam, GalliformeSpectra: A hen breed dataset, Data in Brief, Volume 52, 2024, 109996, ISSN 2352-3409, https://doi.org/10.1016/j.dib.2023.109996

[33] Md Ripon Sheikh, Md. Masudul Islam, Galib Muhammad Shahriar Himel, LuffaFolio: A multidimensional image dataset of smooth Luffa, Data in Brief, 2024, 110149, ISSN 2352-3409, https://doi.org/10.1016/j.dib.2024.110149

[34] Philipp Tschandl, Cliff Rosendahl, and Harald Kittler. 2018. "The HAM10000 Dataset, a Large Collection of Multi-Source Dermatoscopic Images of Common Pigmented Skin Lesions." Scientific Data 5 (1). https://doi.org/10.1038/sdata.2018.161.

[35] Patil, K., Yogesh Suryawanshi, Amit Dhoka and Prawit Chumchu (2024). Plumbago Zeylanica (Chitrak) Leaf Image Dataset: A Comprehensive Collection for Botanical Studies, Herbal Medicine Research, and Environmental Analyses. Data in Brief, 52, pp.109929–109929. doi:https://doi.org/10.1016/j.dib.2023.109929.

[36] Kirillov A, Mintun E, Ravi N, et al (2023) Segment Anything. arXiv:230402643 [cs]

[37] ImageNet. In: www.image-net.org. https://www.image-net.org/about.php

[38] Tan M, Le QV (2019) EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. In: arXiv.org. https://arxiv.org/abs/1905.11946

[39] Face Mask Detection ~12K Images Dataset. In: www.kaggle.com. https://www.kaggle.com/datasets/ashishjangra27/face-mask-12k-images-dataset

[40] (2013) CUDA Toolkit. In: NVIDIA Developer. https://developer.nvidia.com/cuda-toolkit

[41] Chetlur S, Woolley C, Vandermersch P, et al (2014) cuDNN: Efficient Primitives for Deep Learning. arXiv:14100759 [cs]

[42] Team K Keras documentation: Keras Applications. In: keras.io. https://keras.io/api/applications/#available-models
[43] Abadi M, Barham P, Chen J, et al (2016) TensorFlow: A system for large-scale machine learning. In: Google Research. https://research.google/pubs/pub45381/

Authors' Profiles

Galib Muhammad Shahriar Himel received his 1st BSc degree in Computer Science & Engineering from Ahsanullah University of Science and Technology (AUST) in the year 2016. Then he received his 1st MSc degree in Computer Science & Engineering from United International University (UIU) in the year 2018. Then he received his 2nd BSc degree in Computing from the University of Greenwich (UoG), UK in 2021. After that, he received his 2nd MSc degree in Computer Science specializing in Intelligent Systems from American International University-Bangladesh (AIUB) in the year 2022. He has completed his 3rd MSc degree in Applied Physics and Electronics from Jahangirnagar University (JU) in the year 2023. He has worked as a researcher at the Bangladesh University of Business and Technology (BUBT) and also as a part-time researcher at the Independent University, of Bangladesh (IUB). He is also involved in several types of research related to Bio-medical image processing using machine learning. His research interest includes Artificial Intelligence, Machine Learning, Bioinformatics, Bio-medical image analysis & Computer Vision. Currently, He is pursuing his PhD degree at Universiti Sains Malaysia.

Md. Masudul Islam, an Academician, Researcher & former In-House Web Developer from Bangladesh. He has been working as a teacher at Bangladesh University of Business & Technology (BUBT) in the department of CSE from 2013 till now. At present, he is continuing as Assistant Professor, Dept. of CSE in BUBT. He is doing Ph.D. in the Department of CSE, at Jahangirnagar University. He loves everything that has to do with Teaching, technology, Data Science, Web Programming, Astronomy, Database, Quantum Computing, History, Religion, and System Analysis. He has a true devotion to teaching and research.

How to cite this paper: Galib Muhammad Shahriar Himel, Md. Masudul Islam, "Enhanced Surgical Mask Recognition Using EfficientNet Architecture", International Journal of Image, Graphics and Signal Processing(IJIGSP), Vol.16, No.5, pp. 25-35, 2024. DOI:10.5815/ijigsp.2024.05.03