Incorrect facemask-wearing detection using image processing and deep learning

Zeyad Qasim Habeeb[1], Imad Al-Zaydi[2]
[1]Department of Biomedical Engineering, University of Technology-Iraq, Baghdad, Iraq
[2]College of Medical Informatics, University of Information Technology and Communications, Baghdad, Iraq

Article Info

Article history:

Received Sep 14, 2022
Revised Dec 28, 2022
Accepted Jan 20, 2023

Keywords:

COVID-19
Deep learning
Face mask
Image processing
MobileNetV2

ABSTRACT

Now and in the future, a face mask is a very important strategy to protect people when a new contagious life threatens disease spread through the air appears. Currently, there is a serious health emergency because of the coronavirus disease 2019 (COVID-19) epidemic. The negative consequences of this pandemic need to be protected in public areas. Numerous methods are advised by the World Health Organization (WHO) to reduce infection rates and prevent depleting the available medical resources in the absence of efficient antivirals. Wearing masks is a non-pharmaceutical strategy to lessen the susceptibility to COVID-19 infection. This research aims to create a face mask identification system that is efficient and uses deep learning, which has proven to be beneficial in many real-world applications. This system has also used a transfer learning method with the MobileNetV2 model to classify people who wear face masks properly, wear face masks improperly, and are without masks. The results demonstrate that the proposed system has an accuracy of 99.4% which is higher than current systems.

Corresponding Author:

Zeyad Qasim Habeeb
Department of Biomedical Engineering, University of Technology-Iraq
Baghdad, Iraq
Email: zeyad.q.habeeb@uotechnology.edu.iq

1. INTRODUCTION

A contagious disease called coronavirus disease 2019 (COVID-19) is still easily transmissible and the number of patients who have died or become sick is innumerable [1]. The most frequent symptoms of COVID-19 include muscle or body aches, tiredness, diarrhea, vomiting, congested or runny nose, sore throat, headache, cough, and fever [2]. No clinically licensed antiviral medication against COVID-19 has been reported as of yet. The entire human population is facing significant health, economic, environmental, and societal issues as a result of this disease [3]. People cannot isolate themselves from society and stay unconnected to the world [4]. It is challenging to manually check people in public places for face masks. Therefore, it is necessary to develop automated techniques for identifying face masks [5]. Since the COVID-19 pandemic's appearance, The fields of computer vision have made major advancements in face mask detection [6]. However, many face mask detection technologies still struggle with limited accuracy or detecting improperly worn masks.

The following are the primary contributions of this research: the MobileNetv2 model, a cutting-edge object detector that uses a convolution neural network, is the base of the proposed system for detecting face masks. MobileNetv2 has been proven of performing typical object detection tasks, but its evaluation for incorrect facemask-wearing detection is insufficient. Second, a transfer learning technique has been applied to the MobileNetv2 detector, which enhanced the performance and led to superior outcomes when compared to cutting-edge techniques. Third, the proposed system is capable of detecting improperly worn masks as well as properly worn masks and no masks. Fourth, the Haar cascade classifier [2] has been used in this research to extract frontal face photos in the masked faces (MAFA) dataset. This classifier has been used because the MAFA dataset has noisy data so we need to isolate frontal face images from the noisy photos using the Haar wavelet approach. Training the proposed system with unnoisy data can lead to better performance. A more formal explanation of our research is given in Figure 1.

The article is structured as follows: section 2 provides information on earlier studies on face mask detection. Section 3 contains information regarding convolutional neural network (CNN) architectures that were utilized. Additionally, this part explains how to train and evaluate CNN models for face mask recognition as well as transfer learning instructions. In section 4, the datasets, evaluation metrics and results of this research are explained. Section 5 outlines the conclusions and recommendations for future work.

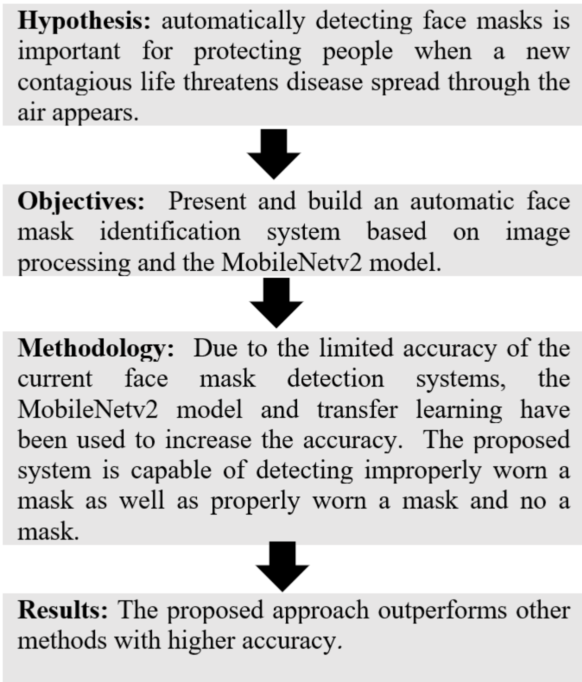

Figure 1. Hypothesis, main objective, method, and result

2. LITERATURE SURVEY

Wearing masks is a crucial way to avoid COVID-19 infection [7]. Recent research employs deep learning for face mask detection [8]. Many cutting-edge, pre-trained deep learning models, including you only look once (YOLO) and faster regions with convolutional neural networks (R-CNN) were utilized for transfer learning on new datasets [9]. In addition, It may also use visual geometry group (VGG), residual network (ResNet), and deep layer aggregation (DLA) [10].

Research by Qin and Li [11] developed a novel face mask identification technique. It divides the use of facemasks into three groups. The categories include not donning a face mask, donning one incorrectly, and appropriately donning a face mask. The suggested algorithm's face detection accuracy is 98.70%. The best model for recognizing face masks was determined by comparing three classifiers; MobileNet, support vector machine (SVM) and k-nearest neighbour (k-NN) [12]. The outcomes demonstrated that MobileNet outperforms SVM and k-NN in term of accuracy. Research by Militante and Dionisio [13] deep learning has been used and it demonstrated its effectiveness in computer vision detection. Deep learning techniques have been employed for recognizing faces and face masks. The trained model performs with a 96% accuracy rate on the dataset that was collected. The system develops a face mask recognition system connected to the raspberry Pi that notifies and it captures facial images if the individual being monitored is not wearing a mask. Based on deep learning, Loey *et al.* [14] introduced a hybrid approach for classifying face masks. To check whether or not face masks are present in images, the authors integrated the ResNet-50 feature extraction network and applied the transfer learning method. The hybrid model used by the authors to evaluate the suggested technique produced a classification accuracy of 99.6%. Reseacrh by Nieto-Rodríguez *et al.* [15] presented a system for determining if the required medical mask is not worn. It aimed to decrease the rate of false positives (FP) of face detections while maintaining the ability to recognize masks. The suggested system had a 95% accuracy rate. Research by Sadhukhan and Bhattacharya [16] proposed a hybrid face mask detection system. It has used traditional methods, deep learning and handcrafted feature extractors. Considering the small amount of data, robust features were extracted using both manual and deep learning techniques (CNN, local binary patterns, hue moments, and textural Harlick feature). Then, features were chosen using the principal component analysis (PCA). Research by Chen *et al.* [17] provide a mobile phone-based method to detect face masks. They have used face mask micro photos of the gray-level co-occurrence matrix (GLCM) to extract several properties.

The k-NN algorithm has been used in the next step to develop a three-result detection system. The system can obtain an accuracy of 82.87% according to validation results. Saravanan *et al*. [18] suggested a system based on the pre-trained deep learning model called Vgg16. The suggested method trains only the final layer of the Vgg16 which cuts down on training time and effort. To train and evaluate the proposed approach, two datasets are used. During testing with a small dataset, the suggested strategy provides an accuracy of 96.50% and 91% with a medium dataset. Research by Meivel *et al*. [19] proposed a method for complex images in the dataset, this paper discusses how to use MATLAB to detect masks. For mask detection, the faster R-CNN technique and dataset allotment were specified by MATLAB. In this paper, complicated images are managed by a facial recognition system. This system has achieved high results. Research by Ieamsaard *et al.* [20] investigate a face mask identification technique that works well by utilizing the "YOLOV5" deep learning model. A comparative model was trained using different epochs (there are 20 to 500 epochs in the range.). The deep learning model that performed best in the tests had 300 epochs and 96.5% accuracy. In order to more effectively deploy face mask identification in the real world, especially when monitoring mask dress-up in public areas, research by Yang *et al.* [21] suggest replacing manual face mask detection with a (YOLOV5) method. The experimental findings demonstrate that the proposed algorithm in this research can successfully identify face masks in public areas. For mini YOLO v4, Kumar *et al*. [8] suggested YOLO v4 with a revised and enhanced prediction network. By incorporating a modified-dense spatial pyramid pooling (SPP) that helps to improve the accurate prediction. They also used an activation function (Mish), with additional detection layers and modified anchor boxes to improve the mini YOLO v4 backbone architecture. High accuracy was attained with the suggested method.

3. METHOD

CNN architectures of the MobileNet model have been described in subsection 3.1. The transfer learning has been explained in subsection 3.2. Figure 2 shows the flow diagram of the proposed system. The diagram consists of a pre-processing stage using the Haar wavelet approach which is followed by splitting data into: training data and testing data. The MobileNetv2 model is then used in the proposed system.

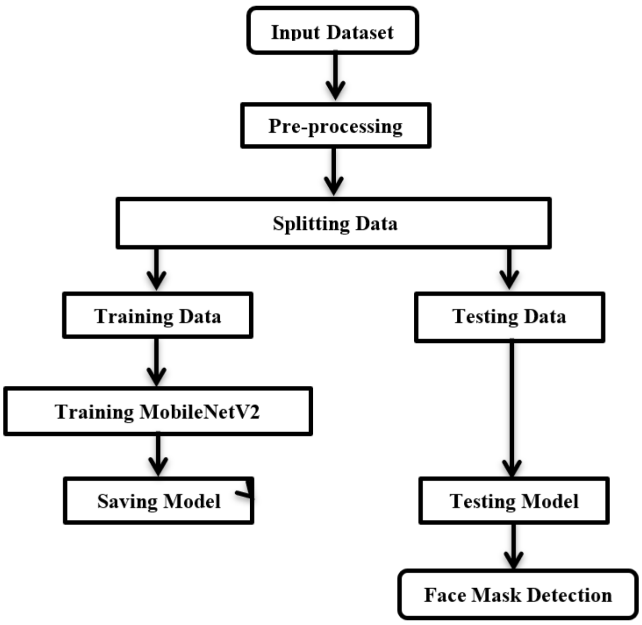

Figure 2. General flow diagram of the proposed system

3.1. MobileNetV2 model

A CNN with 53 layers called MobileNet-v2 [22] is used in this research. The ImageNet database has been used to train this model. This network can categorize images into more than a thousand different object categories. The network can accept images up to 224 by 224 pixels. MobileNetV2 refers to the MobileNet models' second generation. The number of parameters in this version is substantially lower. As a result, deep neural networks become thinner. It functions best in embedded and mobile systems because of its lightweight. Since MobileNetV2 is more lightweight than MobilenetV1, it can also be used with web browsers because browsers have lower storage, computation power and graphic processing capabilities.

The shortcut connections are located between the thin bottleneck layers in an inverted residual structure on which it is based. To retain representational power, it also eliminates nonlinearities in the narrow layers. In terms of semantic segmentation, object detection, and classification, MobileNetV2 overcomes the latest technologies for mobile visual recognition. It is a major improvement over MobileNetV1. The ability of the model to switch between higher-level descriptors, such as image categories, and lower-level descriptors, such as pixels, is contained in the inner layer, the intermediary inputs and outputs of the model are encoded by the bottlenecks. Finally, shortcuts allow for quicker training and improved accuracy, much like with conventional residual connections. Figure 3 shows the MobileNetv2 block diagram. This diagram with layers and functions of the MobileNetV2 are explained [6]:

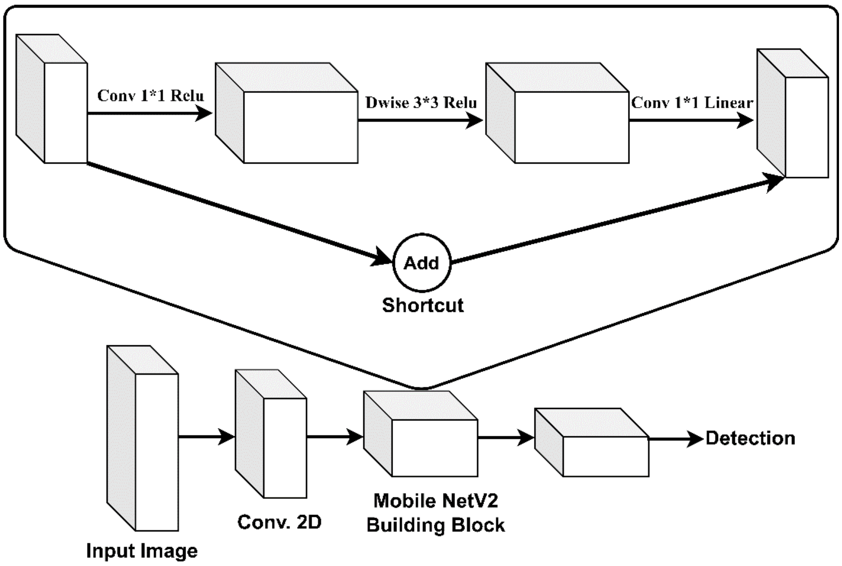

Figure 3. Architecture of MobileNetV2 [23]

3.1.1. Convolutional layer

Convolutional layers serve as the main building components. The method of using a filter with input to create an activation is known as convolution. Employing the same filter continuously to input results is used to create a feature map, which displays the locations and degree of a recognized feature in input, such as an image. CNNs are innovative in that they have the ability to automatically use a lot of parallel filters that are fitted to a training dataset while adhering to a specific predictive modeling problem, such as image categorization. The outcome is a set of very precise features that are present throughout the input images.

3.1.2. Fully-connected layer

These layers have complete links to the activation layers and are added to the model. The multi-class or binary categorization of the provided photos is made possible with the aid of these layers. One activation function utilized in these layers is called SoftMax, which gives the likelihood of the result of projected output classes.

3.1.3. Non-linear layer

An activation layer that is not linear in a neural network is what gives the network its nonlinear characteristic. It indicates that MobileNetv2 can successfully approximate functions that are nonlinear or it can correctly predict the subclass of a function that is separated by a nonlinear decision boundary. Typically, these layers are placed after the convolutional layers.

3.1.4. Linear bottlenecks

It reverses the traditional bottleneck architecture. It significantly increases performance and optimizes the model complexity. The inverted residual block has been commonly used in later mobile network designs due to its excellent efficiency. The final convolution of a residual block with linear output, before it is applied to the start activations, is the linear bottleneck.

3.2. Transfer learning

It appears that knowledge transfer between tasks comes naturally to human learners. In other words, we recognize and use the relevant information from earlier learning experiences when confronted with new situations. The easier it is for us to learn a new task, the more it matches our previous experience. On the other hand, traditional machine learning algorithms emphasize distinct tasks. Transfer learning aims to alter this by creating strategies to leverage knowledge learned from previous activities to improve learning in a target activity. A step to enabling machine learning as efficiently as human learning is the advancement of knowledge transfer techniques. Transfer methods are typically straightforward extensions of machine learning that were employed to learn the objectives, and thus depend heavily on those algorithms. Some of the approaches employed in transfer learning include well-known classification and inference techniques like markov logic networks, markov logic networks and neural networks.

There are three typical ways that transfer might enhance learning. First, as compared to an uninformed agent's beginning performance in the target task, the initial performance achieved using simply the transferred knowledge is superior. The second issue is the variance between the highest performance that can be attained in the target with transfer learning and the performance achieved without it. The third is the speedup level of using the transferred information instead of starting from scratch. The system that is suggested makes use of deep neural networks. However, training requires a lot of processing time and computing resources. To overcome these challenges, transfer learning is used in this case to train the network.

In this research, the output layer must contain only three nodes corresponding to the proper mask class, improper mask class and non-mask class. TensorFlow was used to load ImageNet's pre-trained weights. To prevent the impairment of previously learned features, the base layers of the MobleNetv2 model are then frozen. Then, the other layers are trained with the gathered MAFA dataset to determine the features required to identify features needed to distinguish between a face that is correctly wearing a mask, one that is not, and one that is not wearing a mask at all.

4. EXPERIMENTAL RESULTS

The first step is to train the model with the appropriate dataset to predict face mask status. Subsection 4.1 describes the datasets and the pre-processing. The evaluation metrics are described in sub section 4.2. Finally, subsection 4.2 shows the results of the proposed system and compression with current methods.

4.1. Dataset

There was a significant amount of noise in the masked face recognition dataset, and the images had a significant amount of repetition. Since a robust dataset impacts how accurate a model would be after being training stage, the used dataset is processed in two steps. First, the repeats were manually deleted once they had been detected. Second, the inaccurate images that were discovered in the above dataset are also removed manually. Different datasets can be used for face mask detection such as the Kaggle dataset for face mask detection [24] and the MAFA dataset [25]. The MAFA dataset has been selected to evaluate the proposed system because different orientations and levels of occlusion are present in the faces in this dataset. Therefore, a practical and robust proposed system must be proposed and implemented to achieve high performance with this dataset. MAFA dataset is also a very large dataset and includes different types of face masks so it can be utilized to offer a comprehensive baseline of all types of MAFA for face mask detection systems. In this dataset, a set of facial photos from the Internet are first collected. During this procedure, more than 300,000 photos with faces are retrieved from social networks using keywords like "face," "mask," "occlusion," and "cover." They only save pictures that have a side length of at least 80 pixels. Images with only faces and no occlusion are then manually eliminated. At least one face is hidden in each of the final 30, 811 photos that they collect. Different orientations and levels of occlusion are present in the faces in the dataset. Six key characteristics of each masked face are listed for each image throughout the annotation process which includes the positions of mask type, face, occlusion degree, face orientation, eyes, and the positions of masks. Feature extraction was carried out using the Haar Wavelet approach with a 24×24 window size utilizing the Haar cascade classifier. Only 10,000 face images from the MAFA dataset have been chosen and it has been divided into 8,300 images for training and 1,700 images for testing.

4.2. The evaluation metrics

Several performance criteria are employed to assess the proposed system. They are presented in (1)-(4). These metrics are based on four variables. First, true positives (TP) are positive tuples that are accurately classified as positives by the classifier. Second, true negatives (TN) are negative tuples that are successfully classified as negative by the classifier. Third, FP are negative tuples that the classifier misinterpreted as positive. Fourth, false negatives (FN) are negative tuples that have been incorrectly categorized as negative by the classifier.

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$F1-score = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (4)$$

4.3. The results

We used the Adam optimization method to train our model, setting the learning rate for updating network weights to 0.0001, the number of iterations equal to 100 for each epoch, and the batch size equal to 32. The accuracy, precision, recall and f1-score are 99.4%, 99.4%, 98.6%, and 99.2%, respectively. Table 1 shows that the suggested system achieves greater accuracy than RetinaFaceMask and comparative results with results in [26]. In particular, when compared to RetinaFaceMask, the proposed model provides 6% greater precision in mask identification. The recall has increased by 5.1%. When compared to the results of [26], the proposed model provides 0.48% greater precision in mask identification. The recall has increased by 0.36%. Table 2 shows the results of the proposed system using different learning rates. Figures 4-6 show samples of various test results for identifying people wearing masks properly, wearing masks improperly and no mask exist. They show the accuracy of the prediction of the proposed system on some images from the MAFA dataset. The red boxes in Figure 4 represent the outcome of the detection of people who do not put a mask. Figure 5 shows the results of the proposed system with four samples for people who wear a face mask properly (blue boxes). Finally, the results of the proposed system with four samples of individuals who improperly don face masks are shown in Figure 6 (yellow boxes).

In comparison with the cutting-edge methods, the proposed system has been compared with RetinaFaceMask public baseline results and the results of the face mask detection system have been presented by the authors in [26]. Precision and recall for face mask identification are used to evaluate RetinaFaceMask's effectiveness after training with the MAFA dataset, therefore the performance of the proposed system is also measured in the same setting for comparison purposes. We used precision and recall, two common criteria, to compare the performance of these systems.

Table 1. Comparison of the proposed system with current methods

Model	Precision (%)	Recall (%)
RetinaFaceMask based on ResNet	93.4	94.5
Sethi *et al.* [26]	98.92	98.24
Ge *et al.* [25]	76.40	-
The proposed system	99.40	98.60

Table 2. The performance of the proposed system with different learning rate

Learning rate	Precision (%)	Recall (%)
0.00001	95.7	95.9
0.00005	96.1	96.5
0.0001(best)	99.40	98.60
0.0005	95.3	96.1
0.001	94.1	94.9

Figure 4. The results of people who do not put a mask

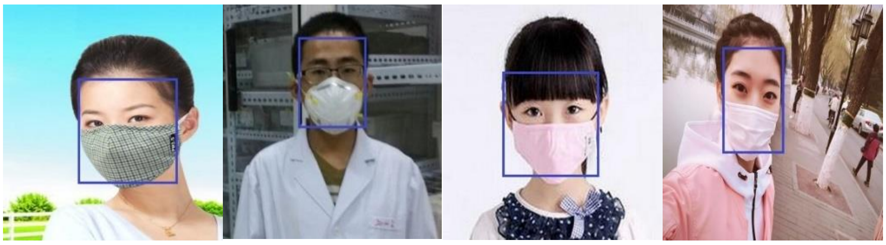

Figure 5. The results of wearing a face mask properly

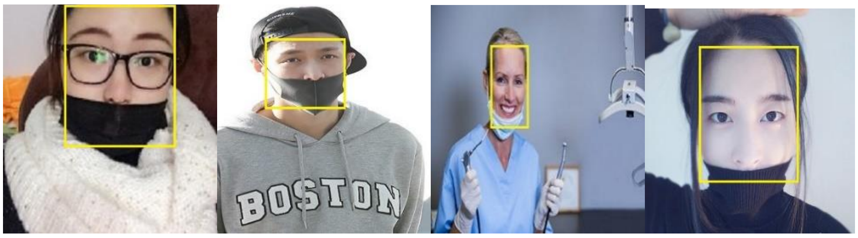

Figure 6. The results of wearing a face mask improperly

5. CONCLUSION

COVID-19 is a pandemic that spreads by both directly and indirectly human contact. The proposed system is capable of classifying people into three groups based on whether they are wearing face masks. This system has used a pre-trained deep learning called MobileNetv2 and image processing to detect face masks. Moreover, a highly reliable and cost-effective solution was introduced by applying transfer learning to the MobileNetv2 model and considerable experimentation over a large dataset has been implemented. The MAFA dataset has been used to train and test the proposed system. Since the MAFA dataset has incorrect images, they have been manually deleted to increase the precision of the detection and improve inaccurate predictions in the proposed system. The proposed system has achieved very impressive results with an accuracy equal to 99%. The proposed method will be tested in real-time circumstances in upcoming work. Additionally, a face mask can be utilized in conjunction with the proposed method to identify facial landmarks for biometric functions.

REFERENCES

[1] World Health Organization, "WHO coronavirus disease (COVID-19) dashboard," *World Health Organization*, 2020. https://www.who.int/covid-19 (accessed Jun. 06, 2022).

[2] S. Hussain *et al.*, "IoT and deep learning based approach for rapid screening and face mask detection for infection spread control of COVID-19," *Applied Sciences*, vol. 11, no. 8, pp. 1–27, Apr. 2021, doi: 10.3390/app11083495.

[3] S. Yadav, "Deep learning based safe social distancing and face mask detection in public areas for covid-19 safety guidelines adherence," *International Journal for Research in Applied Science and Engineering Technology*, vol. 8, no. 7, pp. 1368–1375, Jul. 2020, doi: 10.22214/ijraset.2020.30560.

[4] C. Z. Basha, B. N. L. Pravallika, and E. B. Shankar, "An efficient face mask detector with pytorch and deep learning," *EAI Endorsed Transactions on Pervasive Health and Technology*, vol. 7, no. 25, pp. 1–8, Jan. 2021, doi: 10.4108/eai.8-1-2021.167843.

[5] N. Ullah, A. Javed, M. A. Ghazanfar, A. Alsufyani, and S. Bourouis, "A novel DeepMaskNet model for face mask detection and masked facial recognition," *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 10, pp. 9905–9914, Nov. 2022, doi: 10.1016/j.jksuci.2021.12.017.

[6] P. Nagrath, R. Jain, A. Madan, R. Arora, P. Kataria, and J. Hemanth, "SSDMNV2: A real time DNN-based face mask detection

system using single shot multibox detector and MobileNetV2," *Sustainable Cities and Society*, vol. 66, pp. 1–11, Mar. 2021, doi: 10.1016/j.scs.2020.102692.
[7] J. W. Tang, T. J. Liebner, B. A. Craven, and G. S. Settles, "A schlieren optical study of the human cough with and without wearing masks for aerosol infection control," *Journal of The Royal Society Interface*, vol. 6, no. 6, pp. 727–736, Dec. 2009, doi: 10.1098/rsif.2009.0295.focus.
[8] A. Kumar, A. Kalia, and A. Kalia, "ETL-YOLO v4: A face mask detection algorithm in era of COVID-19 pandemic," *Optik*, vol. 259, pp. 1–13, Jun. 2022, doi: 10.1016/j.ijleo.2022.169051.
[9] N. Ottakath *et al.*, "ViDMASK dataset for face mask detection with social distance measurement," *Displays*, vol. 73, pp. 1–13, Jul. 2022, doi: 10.1016/j.displa.2022.102235.
[10] P. Wu, H. Li, N. Zeng, and F. Li, "FMD-Yolo: An efficient face mask detection method for COVID-19 prevention and control in public," *Image and Vision Computing*, vol. 117, pp. 1–10, Jan. 2022, doi: 10.1016/j.imavis.2021.104341.
[11] B. Qin and D. Li, "Identifying facemask-wearing condition using image super-resolution with classification network to prevent COVID-19," *Sensors*, vol. 20, no. 18, pp. 1–23, Sep. 2020, doi: 10.3390/s20185236.
[12] W. Vijitkunsawat and P. Chantngarm, "Study of the performance of machine learning algorithms for face mask detection," in *2020 - 5th International Conference on Information Technology (InCIT)*, Oct. 2020, no. 1, pp. 39–43, doi: 10.1109/InCIT50588.2020.9310963.
[13] S. V. Militante and N. V. Dionisio, "Real-time facemask recognition with alarm system using deep learning," in *2020 11th IEEE Control and System Graduate Research Colloquium (ICSGRC)*, Aug. 2020, pp. 106–110, doi: 10.1109/ICSGRC49013.2020.9232610.
[14] M. Loey, G. Manogaran, M. H. N. Taha, and N. E. M. Khalifa, "A hybrid deep transfer learning model with machine learning methods for face mask detection in the era of the COVID-19 pandemic," *Measurement*, vol. 167, pp. 1–11, Jan. 2021, doi: 10.1016/j.measurement.2020.108288.
[15] A. Nieto-Rodríguez, M. Mucientes, and V. M. Brea, "System for medical mask detection in the operating room through facial attributes," in *Iberian Conference on Pattern Recognition and Image Analysis*, 2015, pp. 138–145, doi: 10.1007/978-3-319-19390-8_16.
[16] M. Sadhukhan and I. Bhattacharya, "HybridFaceMaskNet : A novel face-mask detection framework using hybrid approach," *Research Square*, pp. 1–17, 2021, doi: 10.21203/rs.3.rs-476241/v1.
[17] Y. Chen *et al.*, "Face mask assistant: Detection of face mask service stage based on mobile phone," *IEEE Sensors Journal*, vol. 21, no. 9, pp. 11084–11093, May 2021, doi: 10.1109/JSEN.2021.3061178.
[18] T. M. Saravanan, K. Karthiha, R. Kavinkumar, S. Gokul, and J. P. Mishra, "A novel machine learning scheme for face mask detection using pretrained convolutional neural network," in *Materials Today: Proceedings*, 2022, pp. 150–156, doi: 10.1016/j.matpr.2022.01.165.
[19] S. Meivel, K. I. Devi, S. U. Maheswari, and J. V. Menaka, "WITHDRAWN: Real time data analysis of face mask detection and social distance measurement using Matlab," in *Materials Today: Proceedings*, Feb. 2021, pp. 1–7, doi: 10.1016/j.matpr.2020.12.1042.
[20] J. Ieamsaard, S. N. Charoensook, and S. Yammen, "Deep learning-based face mask detection using YoloV5," in *2021 9th International Electrical Engineering Congress (iEECON)*, Mar. 2021, pp. 428–431, doi: 10.1109/iEECON51072.2021.9440346.
[21] G. Yang *et al.*, "Garbage classification system with YOLOV5 based on image recognition," in *2021 IEEE 6th International Conference on Signal and Image Processing (ICSIP)*, Oct. 2021, pp. 11–18, doi: 10.1109/ICSIP52628.2021.9688725.
[22] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L.-C. Chen, "MobileNetV2: Inverted residuals and linear bottlenecks," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Jun. 2018, pp. 4510–4520, doi: 10.1109/CVPR.2018.00474.
[23] J. S. Talahua, J. Buele, P. Calvopiña, and J. Varela-Aldás, "Facial recognition system for people with and without face mask in times of the covid-19 pandemic," *Sustainability*, vol. 13, no. 12, pp. 1–19, Jun. 2021, doi: 10.3390/su13126900.
[24] Kaggle, "Kaggle dataset. Face mask detection," *Kaggle*, 2020. https://www.kaggle.com/datasets/andrewmvd/face-mask-detection (accesed Oct. 17, 2022).
[25] S. Ge, J. Li, Q. Ye, and Z. Luo, "Detecting masked faces in the wild with LLE-CNNs," in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jul. 2017, pp. 426–434, doi: 10.1109/CVPR.2017.53.
[26] S. Sethi, M. Kathuria, and T. Kaushik, "Face mask detection using deep learning: An approach to reduce risk of Coronavirus spread," *Journal of Biomedical Informatics*, vol. 120, pp. 1–12, Aug. 2021, doi: 10.1016/j.jbi.2021.103848.

BIOGRAPHIES OF AUTHORS

Zeyad Qasim Habeeb was born in Baghdad, Iraq in 1979. He received his B.S. in Computer Engineering, from the University of Technology-Iraq, Iraq in 2003. He received his M.S. in Computer Engineering from the University of Baghdad, Iraq in 2012. He graduated with a Ph.D. in Computer Engineering from the University of Portsmouth, the UK in 2018. He has been involved in teaching in the area of Image processing, Bioimaging systems, and Medical informatics. His research interests are in the areas of image processing, bioimaging systems, computer vision, image representation, pattern recognition, artificial intelligence, people detection, and crowd counting. He can be contacted at email: zeyad.q.habeeb@uotechnology.edu.iq.

Imad Al-Zaydi is a lecturer in the Medical Informatics College, University of Information Technology and Communications, Iraq. He received his B.S. in computer and control engineering, from the University of Technology, Iraq. He received his Ph.D. and M.Sc degree in information technology from the University Utara Malaysia, Malaysia. His research interests are in optical character recognition, automatic speech recognition, image processing, medical images, computer vision, natural language processing, and strings alignment. He can be contacted at email: emadkassam@uoitc.edu.iq.