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Intelligent Control and Monitoring of Infectious Viral Diseases Based on Deep Learning

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Abstract

Every year, many deaths occur due to various strains of viral diseases, especially during the Arbaeen procession, numerous crowds in blessed places, and the beginning of the academic year of schools and universities in the country. The spread of compliance with health protocols was considered the best solution to stop this disease, and each individual's commitment to these protocols played a crucial role. Since manually monitoring compliance with health protocols is time-consuming, laborious, and error-prone, using an intelligent monitoring system to check people's mask coverage and identify symptomatic people regardless of quarantine regulations is strongly required in public environments. This article proposes an automatic hardware/software system based on artificial intelligence to identify people's mask cover and measure body temperature, which performs face recognition, mask cover detection and body temperature measurement, respectively, using the Viola Jones algorithm, convolutional neural network and temperature sensor. The Viola Jones converts a gray-level image to face area detected of the image. CNN model that optimized through transfer learning for classifying images is the ResNet type. If a person has not used a mask or the person's body temperature is higher than 37.5 degrees, the system will issue a warning. The proposed model was obtained accuracies of 99% and 98% for the training and validation sets at Epoch 18. In the field evaluation, this system was able to achieve 96% accuracy in face recognition and 100% accuracy in mask cover detection. This smart system can be used to monitor compliance with health protocols in public centers.

Keywords: Viral Infection Identification; Facial Recognition; Body Temperature Measurement; Mask Detection; Convolutional Neural Network; Deep Learning.

1. Introduction

Today's world is witnessing the spread of new epidemics, the latest of which was Covid-19, which led to the death of many people and damage to a wide range of jobs and businesses [1]. In addition, pilgrimages involving mass processions and large gatherings at religious sites always pose a threat of intensifying waves of viral diseases in society [1]. Despite the many advances in the field of medicine and engineering technologies, the control and treatment of these pandemics are facing many challenges. Unfortunately, due to the occurrence of mild symptoms in some patients, the follow-up of treatment issues is not followed seriously until the occurrence of severe symptoms, which can lead to serious problems such as pneumonia, not receiving enough oxygen, and even death in the elderly and people with underlying problems [2-3]. Researchers are not optimistic about the definitive treatment of this disease, despite numerous efforts to develop vaccines and effective drugs, due to its high contagiousness and the emergence of different strains of it, at least in the short term, on this basis, experts still believe that the best solution is to follow health protocols from all members of society know [4]. Based on this, wearing a mask and complying with quarantine regulations is the main preventive measure that can significantly limit the spread of many infectious viral diseases [4]. As a result, many organizations and institutions have encouraged people to follow quarantine rules in case of suspicious symptoms and wear masks in public environments. Some governments have even made it mandatory, and non-compliance is subject to heavy fines. It seems that the most effective way to overcome the epidemic of this disease is to observe health protocols by all members of the society so that the epidemic chain of this disease can be broken as much as possible. Unfortunately, many people in society have not followed these protocols to deal with the spread of the disease, and without paying attention to them, they travel without masks in the public areas of cities, blessed places, and the entry-exit crossings of the country's borders. For this reason, the existence of an intelligent automatic monitoring system to check the masks of people and identify suspected people with diseases in public environments is highly necessary. Due to the large number of public places, the implementation of this process in a manual way, while time-consuming, depends on the condition of the person inspecting. If it is carried out while imposing high costs, it will not be immune from human errors. In addition, due to the lack of an intelligent system, information monitoring will be time-consuming and impose a massive financial burden on the healthcare centers. Based on this, an automatic intelligent system to check the mask cover and identify people suspected of having a disease who violate the quarantine rules is necessary. Various researches have been done so far in the field of automatic identification of people with or without masks [5-11]. For example, Chawda and his colleagues introduced a method of identifying people with and without masks using facial images based on convolutional neural networks [12]. The Convolutional neural network (CNN) presented in this research consists of two convolutional sub-networks. The first sub-network is responsible for identifying the face area, and the second sub-network is responsible for classifying the face into two classes: masked and unmasked [12]. In another study, Loui and his colleagues presented a method for distinguishing people wearing masks from people without a mask based on a combination of transfer learning, deep learning models, and classical machine learning methods [13]. In this method, a pre-trained CNN model was used as a feature extractor, and a decision tree model was used as a classifier [13]. In a different study, Chen and his colleagues presented an automatic method for determining mask quality using mobile phone cameras to prevent virus transmission based on image processing [14]. In this method based on classical machine learning, co-occurrence features were extracted from the image and the k-nearest neighbor model was used to perform classification operations [15-16]. Also, in 2022, Wu and his colleagues introduced a new method to analyze people's mask coverage based on deep learning in wide-view images [17]. The method presented in this research was based on the development of a local CNN based on the Yolo model, which could identify the faces of people in the images and classify each face into three classes: masked, unmasked, and wrongly masked [18]. Table 1 shows a summary of these studies. However, these methods have a high computational load can only be implemented on powerful computer systems, and practically cannot be implemented in embedded systems. As a result, these methods are only suitable for use in closed-circuit cameras and do not have the ability to prevent people without masks and suspected of respiratory diseases from entering public places. Also, body temperature is one of the most significant parameters in respiratory diseases, colds, influenza, Sars, and COVID-19, but previous studies have not considered it.

Table 1. A summary of the research conducted in the field of mask recognition of people in images and video frames

Published year	Method type	Reference
2021	Two-layer convolutional neural network	[12]
2021	A hybrid model of classical machine learning and transfer learning deep CNN model	[13]
2021	A method based on co-occurrence and k-nearest neighbor feature extraction for use in mobile phones	[14]
2022	A local CNN based on YOLO model to identify masked and unmasked people in wide field of view images	[17]

By exploiting growth of the express logistics industry, millions express bills images must be recognized. Automatic detecting express bills must be acquired by developing new algorithm. Semantic fusion rotated object detector was proposed by Zhang et.al [19]. As mentioned above, face recognition systems play a crucial role in many access control and automatic identification systems. However, these systems still have shortcomings that reduce their performance efficiency. As a result, the main goal of this study is to provide an inexpensive hardware/software system to detect the mask cover and measure people's body temperature with a light algorithm that can be implemented on embedded systems. It was used to prevent people without masks and suspected of respiratory diseases from entering public centers. In this article, the Viola Jones algorithm is used for converting the gray-level image to face area of detected image. CNN model is optimized through ResNet type transfer learning for classifying face images with and without a mask. This article is configured in five sections, which are followed by a brief introduction of each chapter. The second chapter, Materials and Methods, introduces and describes the database and all the methods used in the proposed system. The third chapter explains the details of the proposed system and its parts, and the fourth chapter reports the system's results. At the end, the proposed system will be discussed, and a general conclusion of the research will be presented.

2. Materials and Methods

In order to implement a model that recognizes people without a mask and with a mask, a data set of face images without a mask and with a mask is needed. In this research, a public database of face images without mask and with mask was used, which contains 4095 images [20]. Out of these 4095 images, 2165 images belong to the class without mask and the remaining images, i.e. 1930 images, belong to the class with mask. Also, 25 people, 19 men and 6 woman, volunteered to participate in the evaluating of the proposed system. Fig. 1 shows an example of some images of this database [20].

2-1. Viola Jones Algorithm

In 2001, Viola Jones algorithm was introduced as the first real-time full-face face recognition system by Jones et al. [21]. This method uses three sequential processes for its performance. Basically, this method creates a new representation of the image called a cumulative image, which allows it to extract features faster. Then they extracted the features of Harr from the cumulative image. These features are actually rectangles that describe different parts of the face. They are placed on the photos in a repetitive process. Then, by using a modified version of the boosting learning algorithm called Adabost, classification is done in this proposed algorithm while extracting features. By providing a flow structure that quickly passes through the background areas of the image in the initial layers of the cascade and can focus calculations more on the face areas, the calculation speed can be increased. The Viola Jones algorithm is used in real-time applications due to its high accuracy and fast performance [21]. Due to the acceptable performance of the Viola Jones algorithm in terms of speed and accuracy, this algorithm has been used for face recognition in this research.

Fig. 1. Examples of database images used to implement and evaluate the mask recognition model [9]

2-2. Convolutional Neural Network (CNN)

CNN is one of the conventional techniques of deep learning, which is modeled after the biological neurobiological model of the visual cortex of the brain [22]. Researchers claim that through different nerves in the visual cortex area, different maps of the visual field of the human eye are created that these maps become smaller and deeper under the influence of some biochemical processes during movement in the frontal region of the brain [22]. Based on this, the proposed CNN is designed in ways that can simulate the mentioned process in the visual cortex of the brain. In other words, the CNN technique can receive a multi-dimensional input such as image and signal, create different maps of it along the network select the best ones at the end of the network, and perform the final operation [23]. Fig. 2 shows the general structure of a CNN model. It shows that after extracting the maps of lower perceptual levels, the maps of higher perceptual levels are determined by increasing the length of the network.

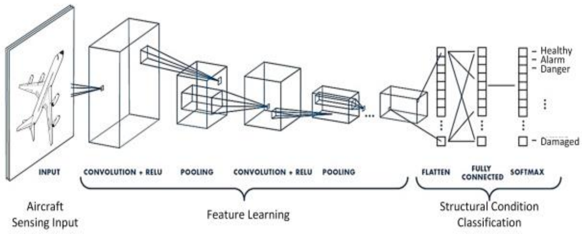

Fig. 2. An example of the structure of a CNN [1]

The configuration of CNNs models comprise of several layers such as convolutional layers, pooling layers, fully connected layers, activation layers, and Softmax layers. The convolutional layer, which is the core of CNN models, is responsible for generating different maps from the input data [24]. These layers allow the implementation of functions such as creating different maps from the input data, sampling the created maps, decision making functions, flattening of the volume map and multiplying adjustable weights on the flatted maps. In other words, by generating these maps, these layers extract different features from the input data in of low, medium and high level of understanding of the input data [22-24]. The convolutional layer consists of several trainable spatial filters, each of which participates in the convolution operation with the input data. During the network learning process, the weight and bias values of the filters (which are not fixed) are adjusted to achieve optimal performance for the network under training. By reducing the dimensions (width and height) of the input mapping, the pooling layers reduce the number of trainable parameters and the computational load of the network [22-24]. In other words, these layers perform the sampling operation of the input mapping in the direction of width and height. This layer slides a window with a fixed height and width along the width and height of the input mapping of each band. This layer reports the results of the analysis in the form of an output map by applying a predetermined statistical analysis on the values of the input mapping located in the sliding window area at each sliding time [25]. Based on the type of statistical analysis, the integration layers are defined in different ways, the most common of which are the maximum integration layer and the average integration layer. The maximum integration layer selects the maximum value of the input mapping values located in the sliding window area, and the average integration layer puts the average value of the input mapping values enclosed in the sliding window area into the output mapping. The activation layer consists of a non-linear function that is applied to each input mapping layer. From a biological point of view, this layer somewhat simulates the way the action potential occurs in nerve cells. This layer can use non-linear functions such as absolute values, sigmoids, hyperbolic tangents, etc [25]. The most common nonlinear function used in CNN models is the Rectified Linear Unit function [24]. Various studies have shown that using this function while increasing the speed of network training can avoid categories such as discontinuities and the impossibility of derivation during network training [24-26]. Like a filter, this function passes values greater than zero and replaces values smaller than or equal to zero. After the function of Rectified Linear Unit was introduced, a generalized type of it was introduced under the title of function of Leaky Rectified Linear Activation. In this idea, instead of zeroing values smaller than zero, they were replaced and displayed with a coefficient generally smaller than one [25-27]. After receiving the volumetric mapping, fully connected layer multiplies it into a column and then into a weight and bias vector whose values are variable and can be trained, and provides the result of this operation to the next layer. The way to determine these parameters is achieved through an iterative training process until the desired result is achieved for the network under training for each input. Usually, at the end of CNN model architectures, by using several fully-connected layers while selecting the best features, the desired output is produced and presented [27] At the end of networks based on deep learning architecture, which is designed for the purpose of data classification, there is generally a layer called Softmax layer. This layer receives the output of the last all-connected layer for each number of available classes, for each input data after calculating the probability function, assigns the input data to the corresponding class with the highest probability [25]. One of the methods to reduce overfitting in all deep learning structures is to use dropout layer. In this way, during network training, this layer randomly sets some of the trainable weights to zero (either in the convolutional layer or in the fully-connected layer) [24]. This process forces the network weights to be optimally optimized during training. On the other hand, this process prevents the correlation of weights and prevents overfitting. It should be noted that the presence of this layer is not mandatory in CNN architectures.

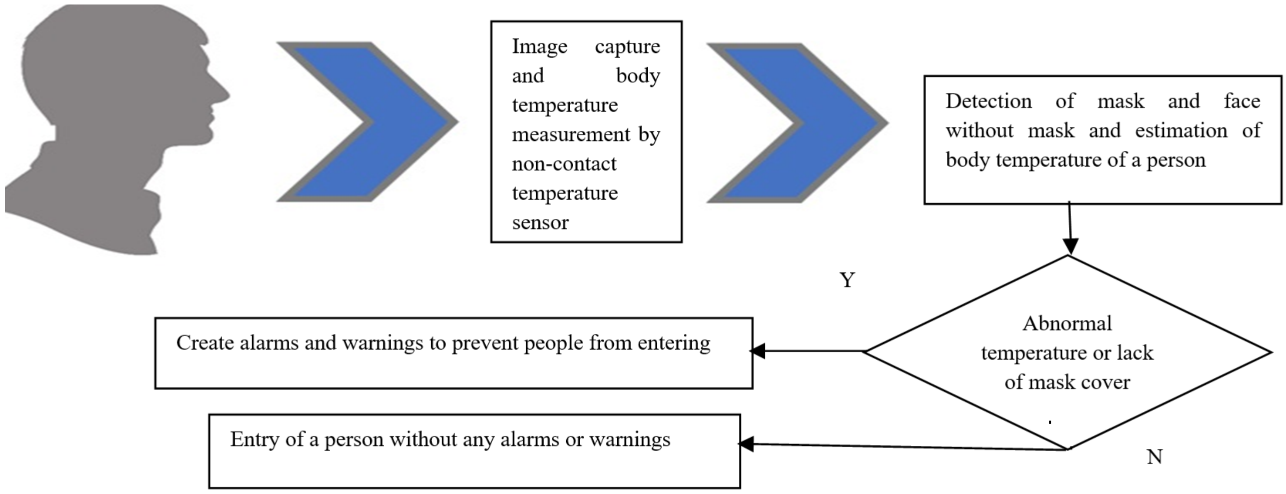

Fig. 3. General flow chart of proposed system performance

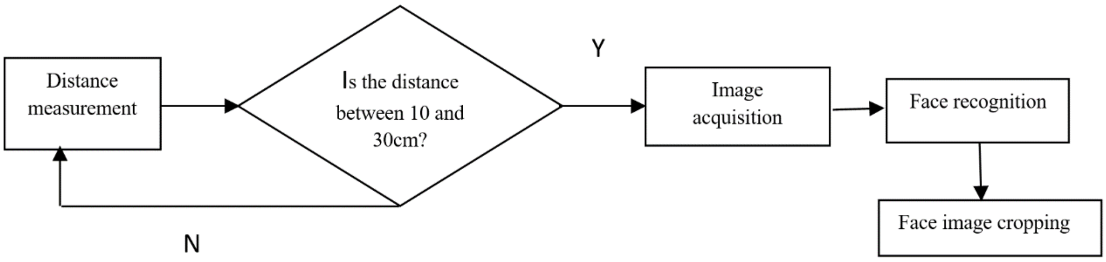

Fig. 4. Flowchart of face recognition part in the proposed system

3. Proposed System

The flowchart of the hardware/software system of the proposed design for detecting people's mask cover and measuring body temperature in this article is shown in Fig. 3. As the person approaches the proposed hardware-software system, imaging starts, and a picture of the person's face is taken. After identifying the face region using Viola Jones algorithm, the identified face image is separated from the original image. By applying the face image to a CNN model, it is classified into classes with and without a mask. In the next step, the person's temperature is measured through a non-contact temperature sensor. If the person wears a mask and his body temperature is less than 37.5 degrees, the person is placed in the permitted class, and no warning is issued. However, if the above two situations occur, the system alert will be activated while placing the person in an unauthorized class. It should be noted that all information, including the condition of the mask cover, body temperature and detected face, are shown on the system screen after the image is recorded and the temperature is measured. All components of this system, which respectively include face recognition, mask recognition, body temperature measurement, and person measurement in terms of being allowed and not allowed, are explained below.

3-1. Face Recognition

The flowchart of automatic face recognition taken from Fig. 4 consists of a distance sensor (ultrasound sensor HC-SR05) and a camera (5-megapixel regular Raspberry Pi camera). The main core of the software, which is based on Viola Jones algorithm, is responsible for face recognition. The proposed system uses a distance sensor to measure the distance at any moment and if a person is within 10 to 30cm, it activates the camera and takes a picture of the person in front of the system. In other words, the minimum distance and the maximum distance for the device to start working are 10 and 30cm, respectively. After converting the image into a gray-level image and applying the Viola Jones algorithm to it, the output shows the detected face area of the image.

3-2. Mask Detection

The second part of the proposed system, based on the CNN model, performs the task of identifying mask coverage. The input of this section is the face image and its output is the result of classifying the isolated face image into one of the mask and nonmask classes. The previously trained CNN model is of the ResNet type and is optimized based on transfer learning for classifying face images with and without a mask. For the transfer learning of this model, the database introduced in sections 1-2 is used. Thus, 80% of the data set was used for model training, and 20% was used for model validation. After training, this model will be able to classify the received facial image into two classes: with and without a mask. The error function of the proposed model and its optimizer for training the model is the binary entropy-intersectional function and Adam's optimizer, respectively. The learning rate of the model is selected as 0.0003, which remains constant during the training of the model. Also, the number of epochs and batch size for training the model were chosen as 18 and 32, respectively. In order to implement this model, Cross library has been used in the Python programming environment. The training and testing of this model has also been done in the free cloud space of Google Colab, which uses an NVIDIA Tesla k80 GPU for training and testing networks. It should be noted that after the training, this model is saved in the form of a file and installed on the hardware system.

3-2-1. Body Temperature Measurement

After identifying the mask cover, the body temperature is measured through the system's microcomputer processor (Raspberry Pi 4 RAM 2 GB), connected to the MLX90614 non-contact infrared temperature sensor through the I2C protocol. When the user's forehead is close to the device, the sensor sends an infrared ray and records the return ray from the forehead surface, processes it and sends it to the processor.

3-3. Measuring the Authorized or Unauthorized Person

In the final part of the proposed system, the mask cover and the measured temperature determine whether a person's measurement is authorized or unauthorized. If the mask is not used or the body temperature is higher than 37.5 degrees, while the person is in an unauthorized class, the gate guards will prevent the suspicious person from entering by activating the alarm system. Otherwise, the system will not issue any warning while the target person is in the authorized class.

4. Results

In this part, after describing the proposed system, the method of evaluating the mask recognition model, which is the core of the system, is explained, and then the evaluation criteria used are explained in detail. After that, the results obtained from the evaluation of the mask recognition model as well as the field evaluation are presented in a quantitative and qualitative manner.

4-1. Criteria and Method of Evaluation

To evaluate the artificial intelligence model of mask recognition, by allocating 80% of the database to the training set, the training model is created, and with the remaining 20% to the validation set, the model is evaluated. The evaluation of the model is estimated by the validation set using the accuracy and error indicators mentioned in relations 1-4 and 2-4.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{1}$$

$$Loss = 1 - Accuracy, \tag{2}$$

In these relations, TP and TN are respectively equal to the number of masked and unmasked items correctly recognized by the system. Subsequently, FP and FN are the number of masked and unmasked cases that were wrongly recognized by the system. Also, to measure the face recognition algorithm, the criterion of correct identification rate (CIR) is used according to equation 4-3.

$$CIR = \frac{N_{CI}}{M}, \tag{3}$$

In Equation (3), N_{CI} shows the number of correct faces identified by the algorithm and M is the total number of faces.

4-2. Results of the Mask Recognition Model

Fig. 5 shows the accuracy and error diagram of the mask recognition model during the training of the model for the training and validation datasets. According to Fig. 5, the model in the 18th Epoch was able to obtain the highest accuracy and the lowest error for the training and validation data set. In this Epoch, the accuracy and error of the model for the training and validation datasets are the closest to each other. This issue, along with the high level of accuracy and low level of error, shows the optimal training of the model in this Epoch, which indicates the absence of overfitting and under fitting. As a result, the model's training has been stopped in this Epoch, the 18th Epoch. Quantitatively, the proposed model was able to obtain accuracies of 99% and 98% for the training and validation sets in the last Epoch, i.e. Epoch 18 based on Equation (1). The error value of the model was obtained in the last Epoch for training and validation sets equal to 2% and 4%, respectively based on Equation (2). These results show that the mask recognition model can classify face images without a mask and with a mask with very high accuracy.

Fig. 5. The accuracy and error of the mask detector model for training and validation data sets

4-3. Field Evaluation

In order to evaluate the final system in the field and to check its performance, 25 people including 19 men and 6 women were used, each of them standing in front of the proposed system once with a mask and once without a mask. Fig. 6 shows examples of the results of the proposed system in the field evaluation.

Fig. 6. Examples of the output of the proposed system

The face recognition algorithm of the proposed system was able to correctly identify the faces of 24 candidates and failed to identify the person's face in only one case. Based on these results, the CIR obtained in this evaluation was 96%, which is a relatively good result based on Equation (3) and Table 2. Confusion matrix that presented at Table 2, described classification model performance by comparing predicted values against actual values.

Table 2. Confusion matrix in mask cover detection between 25 people including 19 men and 6 women.

Predicted / Actual	no-Mask	Mask
no-Mask	TP=13	FN=0
Mask	FP=1	TN=11

However, in ideal conditions, the face recognition algorithm should work more accurately than in the current state because if it is not done correctly, the subsequent parts of the system will also suffer errors. In detecting whether a person is wearing a mask or not, the system correctly recognized all 24 identified faces, which shows the high accuracy and good performance of the mask recognition department. In the field of temperature detection, the system was able to detect the temperature of people in the range between 35 and 36 degrees, which is very close to the reference temperature of healthy people, and these results show the optimal performance of the body temperature measurement section in the proposed system.

5. Conclusion

This research presents an intelligent hardware-software system for detecting people's mask cover and measuring body temperature. This system includes image recording by camera, distance measurement, and temperature measurement using infrared non-contact temperature sensor, while its software part includes face recognition and mask recognition. Face recognition using the Viola Jones algorithm and mask cover detection using a CNN model of ResNet type, which is based on transfer learning for the classification of face images without a mask and with an optimized mask. Compared to previous studies that tried to provide face mask detection methods, this study introduces a hardware/software system with an algorithm that can be installed on embedded hardware. In other words, previous studies only focused on providing methods based on closed-circuit camera images, all of which required powerful computer systems to run [23-25]. In addition, in this study, the body temperature factor is considered as an important factor in identifying suspected people with viral and respiratory diseases. The innovative idea of using the Viola Jones algorithm and the use of the distance sensor led to the software being lightened and the execution speed of the proposed algorithm being reduced. The use of the distance sensor is effective because it performs face recognition and mask recognition only if a person is in front of the device, thus preventing the processing of consecutive frames. Therefore, it can be claimed that this article has presented an inexpensive and quick intelligent system to control compliance with health protocols based on mask detection and body temperature measurement. However, this system is a little weak in terms of face recognition performance and in some situations, such as a shadow falling on the face, it cannot identify the face well. To solve this problem, other facial recognition algorithms such as MTCNN [28], Face Net [29] and DBC Face [30] can be used instead of the Viola Jones algorithm. However, the use of the two mentioned algorithms requires the use of a more powerful hardware platform than Raspberry Pi 4. On the other hand, the non-contact temperature sensor used in the system does not have a large optimal range, and the person must bring his forehead to the device at a distance of 10 to 30cm to correctly measure the person's temperature.

6. Discussion

The proposed system can be used in many organizations and public places, such as government offices and agencies, shopping malls, schools and universities, construction complexes, hotels, shrines, and Arbaeen walks, etc. in crowded conditions. This accurate and fast-acting system based on artificial intelligence reduces the need of human resources of organizations and organizations to control health protocols. The results of the evaluation of the proposed system show high accuracy in the classification of face images without a mask and with a mask. Temperature measurement at longer distances (a distance of one meter or more) can be realized through more expensive temperature sensors and thermal cameras such as MLX90640. In the following, future works are provided to improve this topic in future research by adding new capabilities. One of the most important things in the transmission and spread of diseases is not using the mask properly. By upgrading the algorithm, the software part can be equipped with the ability to detect whether wearing a mask is correct or incorrect. In this way, the system, while recognizing the correctness of the use of the mask by the person, gives a warning to the person if it is not used correctly. In addition, it is possible to add the ability to count people along with information such as the status of the mask cover, the measured temperature, and the recorded time to the system, and by saving it in the form of a text file, it can be transferred through the USB port. After analyzing the mask and body temperature, the person can be asked to remove the mask, in this way, by adding the face recognition feature to the proposed system, the authentication feature can also be screened. Also, by monitoring the information obtained from the proposed system, it is possible to provide information such as the number of people following health protocols to estimate the occurrence of future peaks and provide it to crisis control and passive defense management organizations.

References

[1] Fauci, A. S., Lane, H. C., & Redfield, R. R. (2020). Covid-19—navigating the uncharted. *New England Journal of Medicine*, *382*(13), 1268-1269.

[2] Yang, L., Liu, S., Liu, J., Zhang, Z., Wan, X., Huang, B., & Zhang, Y. (2020). COVID-19: immunopathogenesis and Immunotherapeutics. *Signal transduction and targeted therapy*, *5*(1), 128.

[3] Velavan, T. P., & Meyer, C. G. (2020). The COVID-19 epidemic. *Tropical medicine & international health*, *25*(3), 278.

[4] Khanna, R. C., Cicinelli, M. V., Gilbert, S. S., Honavar, S. G., & Murthy, G. V. (2020). COVID-19 pandemic: Lessons learned and future directions. *Indian journal of ophthalmology*, *68*(5), 703-710.

[5] Shatnawi, M., Alhanaee, K., Alhammadi, M., & Almenhali, N. (2023). Advancements in Machine Learning-Based Face Mask Detection: A Review of Methods and Challenges. *International Journal of Electrical and Electronics Research*, *11*(3), 844-850.

[6] Zhang, H., Tang, J., Wu, P., Li, H., & Zeng, N. (2023). A novel attention-based enhancement framework for face mask detection in complicated scenarios. *Signal Processing: Image Communication*, *116*, 116985.

[7] Liu, Y., & Qu, Y. (2024). Construction of a smart face recognition model for university libraries based on FaceNet-MMAR algorithm. *Plos one*, *19*(1), e0296656.

[8] Singh, N., & Tripathi, P. (2024). An efficient model for detecting real-time facemask based on different Classification Algorithms. *Multimedia Tools and Applications*, *83*(18), 55175-55198.

[9] Hosny, K. M., Ibrahim, N. A., Mohamed, E. R., & Hamza, H. M. (2024). Artificial intelligence-based masked face detection: A survey. Intelligent Systems with Applications, 22, 200391.

[10] S. Wani, "Face mask detection and alarming system using machine learning," IJAEM, vol.5, no.1, pp.914-919, 2024.

[11] Ak, Ö. B., Kuruöz, E., & Ak, A. (2024). Determining the Reliability of Personal Masks with Convolutional Neural Networks. *Afet ve Risk Dergisi*, *7*(1), 71-85.

[12] Chavda, A., Dsouza, J., Badgujar, S., & Damani, A. (2021, April). Multi-stage CNN architecture for face mask detection. In *2021 6th International Conference for Convergence in Technology (i2ct)* (pp. 1-8). IEEE.

[13] Loey, M., Manogaran, G., Taha, M. H. N., & Khalifa, N. E. M. (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.

[14] Chen, Y., Hu, M., Hua, C., Zhai, G., Zhang, J., Li, Q., & Yang, S. X. (2021). Face mask assistant: Detection of face mask service stage based on mobile phone. *IEEE Sensors Journal*, *21*(9), 11084-11093.

[15] Al-Nabulsi, J., Turab, N., Owida, H. A., Al-Naami, B., De Fazio, R., & Visconti, P. (2023). Iot solutions and ai-based frameworks for masked-face and face recognition to fight the COVID-19 pandemic. *Sensors*, *23*(16), 7193.

[16] Rusia, M. K., & Singh, D. K. (2024). An improved deep transfer learning approach to identify the human face mask in real-time considering the COVID-19 pandemic. *Multimedia Tools and Applications*, *83*(7), 21695-21743.

[17] Wu, P., Li, H., Zeng, N., & Li, F. (2022). FMD-Yolo: An efficient face mask detection method for COVID-19 prevention and control in public. *Image and vision computing*, *117*, 104341.

[18] Mostafa, S. A., Ravi, S., Zebari, N. A., Mohammed, M. A., Nedoma, J., ... & Ding, W. (2024). A YOLO-based deep learning model for Real-Time face mask detection via drone surveillance in public spaces. *Information Sciences*, 120865.

[19] Zhang, L., Peng, J., Liu, W., Yuan, H., Tan, S., Wang, L., & Yi, F. (2023). A semantic fusion based approach for express bill detection in complex scenes. *Image and Vision Computing*, *135*, 104708.

[20] Deb, D. B. C., & Patil, S. (2021, May 14). Face mask detection. GitHub. Retrieved August 11, 2025, from https://github.com/chandrikadeb7/Face-Mask-Detection

[21] Viola, P., & Jones, M. (2001, December). Rapid object detection using a boosted cascade of simple features. In *Proceedings of the 2001 IEEE computer society conference on computer vision and pattern recognition. CVPR 2001* (Vol. 1, pp. I-I). Ieee.

[22] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.

[23] O'Mahony, N., Campbell, S., Carvalho, A., Harapanahalli, S., Hernandez, G. V., Krpalkova, L., & Walsh, J. (2020). Deep learning vs. traditional computer vision. In *Advances in Computer Vision: Proceedings of the 2019 Computer Vision Conference (CVC), Volume 1 1* (pp. 128-144). Springer International Publishing.

[24] Tabian, I., Fu, H., & Sharif Khodaei, Z. (2019). A convolutional neural network for impact detection and characterization of complex composite structures. *Sensors*, *19*(22), 4933.

[25] O'Shea, K. (2015). An introduction to convolutional neural networks. *arXiv preprint arXiv:1511.08458*.

[26] Pouyanfar, S., Sadiq, S., Yan, Y., Tian, H., Tao, Y., Reyes, M. P., … & Iyengar, S. S. (2018). A survey on deep learning: Algorithms, techniques, and applications. *ACM computing surveys (CSUR)*, *51*(5), 1-36.

[27] Albawi, S., Mohammed, T. A., & Al-Zawi, S. (2017). Understanding of a convolutional neural network. 2017 International Conference on Engineering and Technology (ICET), Antalya, Turkey, 1–6.

[28] Yin, X., & Liu, X. (2017). Multi-task convolutional neural network for pose-invariant face recognition. *IEEE Transactions on Image Processing*, *27*(2), 964-975.

[29] Schroff, F., Kalenichenko, D., & Philbin, J. (2015). Facenet: A unified embedding for face recognition and clustering. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 815-823).

[30] Li, X., Lai, S., & Qian, X. (2021). Dbcface: Towards pure convolutional neural network face detection. *IEEE Transactions on Circuits and Systems for Video Technology*, *32*(4), 1792-1804.

Biography

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