Bulletin of Electrical Engineering and Informatics
Vol. 11, No. 2, April 2022, pp. 1047~1055
ISSN: 2302-9285, DOI: 10.11591/eei.v11i2.3369

Surveillance system of mask detection with infrared temperature sensor on Jetson Nano Kit

Noor Faleh Abdul Hassan, Ali A. Abed, Turki Y. Abdalla
Department of Computer Engineering, College of Engineering, Basrah University, Basrah, Iraq

Article Info

Article history:

Received Nov 12, 2021
Revised Feb 12, 2022
Accepted Mar 14, 2022

Keywords:

AMG8833 sensor
COVID-19
Deep learning
MobileNetV2
NVIDIA Jetson Nano

ABSTRACT

Coronavirus desease-19 (COVID-19) has made it mandatory for people to cover their faces in public areas since the right use of a mask is effective at protecting people from viral infection. It has been also shown that body temperature may indicate an individual's health state. Deep learning is being used in this work to construct an actual strategy to meet the current demand for mask-wearing status and facial temperature detection before entering a public venue. For the mask detection service provider, a surveillance system is constructed utilizing a deep learning technique employing a Jetson Nano. The alert is triggered by an infrared temperature sensor and a buzzer. AMG8833 and C920e camera are used to take input images and measure a person's body temperature at the same time. A warning sound is produced when the temperature of a person's face exceeds the normal range for human beings during these tests, which result in a live video showing the right information on whether the individual is wearing a mask correctly and how hot his or her face is. The model is light and fast, with a 99% accuracy rate for training and a 100% accuracy rate while testing.

This is an open access article under the CC BY-SA license.

Corresponding Author:

Noor Faleh Abdul Hassan
Department of Computer Engineering, College of Engineering, Basrah University
GRCR+5JJ, Basrah, Iraq
Email: pgs2341@uobasrah.edu.iq, dr.noorfaleh@gmail.com

1. INTRODUCTION

Coronavirus desease-19 (COVID-19), which was originally found in Wuhan, China, is a virus-borne disease caused by the severe acute respiratory syndrome-coronavirus-2 (SARS-CoV-2) viral that causes acute respiratory infections in humans. It has spread to several nations globally since December 12, 2019 [1]–[3]. The illness has spread to at least 221 countries, with over 130.3 million cases reported and almost 2.8 million deaths. COVID-19 individuals infected with SARS-CoV-2 exhibit typical flu symptoms, including fatigue, fever, dry cough, runny nose, sore throat, and body aches. COVID-19's fast spread prompted the World Health Organization (WHO) to proclaim it a "pandemic" on March 11, 2020 [4]. At the present, the WHO advises that persons using face masks do so if they have respiratory symptoms or are caring for someone who does. Additionally, several public service providers restrict clients from using their services unless they are wearing masks. As a result, face mask identification has become a critical area of research for assisting the worldwide community, yet research in this area is restricted [5], [6]. Previous research has shown that wearing a facemask is beneficial in avoiding the transmission of respiratory infections. For example, N95 and surgical masks are 91% and 68% effective in preventing the spread of SARS, respectively [7]. Although much research has been conducted on the use of covered face identification algorithms in ATM surveillance, many of these studies failed to consider the acquired ATM surveillance scene (camera view and camera–user distance), as well as face-covering accessories [8], [9].

This paper determines if a mask may be worn by using the NVIDIA Jetson development Kit series and a webcam. Additionally, the surface temperature of the human body may be monitored concurrently by attaching an infrared (IR) array sensor device named AMG8833. Following that, if the human body temperature exceeds the threshold value, a buzzer alert will sound to notify. The operating environment may be run in a docker container that includes TensorFlow2, Keras, and the MobileNet model. Since COVID-19, the significance of mask use and temperature monitoring has grown globally. However, the present situation is that specialized camera equipment is prohibitively costly and does not reach those in need. This work aims to contribute to the democratization of artificial intelligence by offering solutions that use low-cost, high-performance artificial intelligence (AI) edge devices such as the NVIDIA Jetson Nano. The rest of the article is structured is being as: the second section discusses previous studies. In section 3, describe the methodology and the recommended strategy fully. Section 4 analyzed the observed measurements. Finally, section 5, concludes with a discussion.

2. RELATED WORKS

This section discusses several past approaches for face mask identification systems that make use of convolutional neural networks (CNNs). Research by Sethi *et al.* [10] three commonly used baseline models, deep residual networks-50 (ResNet50), Alexnet, and MobileNet were employed in the experiment. When integrating these models with the proposed model, they examined the potential of obtaining highly accurate results with a decreased inference time. With ResNet50, it was found that the recommended technique had a high degree of precision (98.2%). It also has accuracy and recall of 11.07 and 6.44%, respectively, compared to a previously published public baseline model known as RetinaFaceMask detector. For video surveillance systems, the model proposed was a good choice. Research by Jagadeeswari and Theja [11] individuals who don't use masks were highlighted by using learning algorithms. To ensure that the System was able to correctly identify if a person was wearing a mask, it was trained. An alert should be triggered if the algorithm recognizes a person without a mask, so that the community or the necessary authorities may be informed and take appropriate action. Classifiers with different optimizers must be considered to build an efficient system that can be used on large scales. ResNet50, VGG16, and MobileNetV2 were compared against adaptive moment estimation (ADAM), adaptive gradient algorithm (ADAGRAD), and stochastic gradient descent (SGD) as optimizers. Oumina *et al.* [12] evaluated the use of several deep CNNs to extract deep characteristics from photos of faces. The collected characteristics were processed using a variety of machine learning classifiers, including the support vector machine (SVM) and the K-nearest neighbors (K-NN) were utilized and studied to assess the performance of all models using a variety of different measures, such as accuracy and precision. The best classification rate obtained was 97.1%, which was attained with the combination of SVM and the MobileNetV2 model. Das *et al.* [13] offered a simplified technique that makes use of certain fundamental machine learning libraries such as TensorFlow, Keras, OpenCV, and scikit-learn. The suggested approach properly spotted the face in the picture and determined whether it wore a mask. Additionally, as a surveillance job performer, that could detect a face and a mask in motion. On two distinct datasets, the approach achieved an accuracy of 95.77% and 94.58%, respectively. Research by Rao *et al.* [14] the idea of a facial recognition system that could be used to identify a person who was wearing a mask by detecting others who weren't wearing masks was put forward. The fine amount was delivered to that person's cell phone and address once that data was merged with a public identity database. A CNN model was used to distinguish between those wearing masks and those who were not. To build the model, they employed two convolutional layers each with 100 filters, dropped out 0.5%, and activated the hidden and fully connected layers, respectively, using Relu and SoftMax activation functions. As the loss function, cross-entropy was utilized; the model's optimization was done using Adam. A cascade classifier was used to categorize faces based on approximately 1500 photos, both with and without masks. It had a precision of 91.21%. Research by Aljumah [15] decision tables, neural networks, SVMs, oneRs, K-NNs, dense neural networks (DNNs), and long short-term memory (LSTM) were utilized to detect coronavirus cases from time-sensitive data. Simulated COVID-19 data was used to test the eight algorithms after selecting the suitable symptoms. According to the statistics, five of these eight algorithms had a success rate of more than 90%. Suresh *et al.* [16] addressed facemask detection and notification more thoroughly. The suggested system/model was trained and evaluated using Kaggle datasets. The system was performed in real-time and detected if an individual's face was covered by a facemask. If not, the individual was notified individually through text message. The mask was created using real-time public faces and placed into a CNN as an input. Vinitha and Velantina [17] utilized a live camera feed and generated an alarm sound (buzzer) when someone was not wearing a mask. The objective was to determine whether the individual in an image/video stream is wearing a face mask using computer vision and deep learning. Sen and Sawant [18] proposed a mask detection system capable of detecting any form of mask and masks of varying shapes in video streams to comply with the government's standards. For mask identification from images/video streams, a deep learning algorithm was utilized, and the Python PyTorch package was used. The suggested system was capable of distinguishing between those who wore masks and those who did not. Mundial *et al.* [19] used a combination of supervised learning and DNN-based facial traits to recognize masked faces. A dataset of masked faces was used to train the SVM classifier on the state-of-the-art facial recognition feature vector. The recommended technique yields up to 97% accuracy when using masked faces. Research by Nagrath *et al.* [20] the single shot multibox detector was utilized as a face detector, and the MobilenetV2 architecture served as a framework for the classifier, which was very lightweight and could be used in embedded devices for real-time mask identification. Accuracy of 0.9264 and an F1 of 0.93.

3. METHOD

Since COVID-19, the significance of mask use and temperature monitoring has grown globally. However, the present situation is that specialized camera equipment is prohibitively costly and does not reach those in need. The system aims to contribute to the democratization of artificial intelligence by offering solutions that use low-cost, high-performance AI edge devices such as the NVIDIA Jetson Nano. In this paper, the surveillance system of mask detection through the pre-trained CNNs model provided with AMG8833 sensor and a buzzer to alert are investigated.

3.1. MobileNetV2

Face mask recognition in this study is accomplished via the use of MobileNetV2, a machine learning technique, rather than the visual classifier. Improved computational speed and efficiency are used in this model [21]. In both high and low-computing environments, it may be used. A new version of MobileNetV2 builds on the principles of the first version [22]. A two-tiered structure underpins the MobileNetV1 network. This is known as depthwise convolution, and each input port receives a convolution filter for light filtering. Layers are convolutions of 1×1 known as pointwise convolutions, which employ linear combinations of input channels to build new feature sets. ReLU6 serves as the benchmark in this case. As a result of its excellent statistical properties when utilized with low-precision computing, ReLU6 is often deployed. It is possible to categorize blocks in MobileNetV2 into two kinds [23]. Residual blocks have a stride of one and the initial block is one of these. A declining block must have a two-step stride to be successful. There are two types of blocks in the stratum with a 1×1 convolution pool, the initial step is to activate the ReLU. A deeper convolution layer is the second layer, as previously stated. Third layer convolution is done again, but no non-linearity is introduced to this convolution. When ReLU is used, deeper networks have the capacity to classifiers based on non-zero outputs generated. The MobileNetV2 network has a single convolution layer and 19 bottlenecks [24]. Figure 1 is a MobileNet illustration.

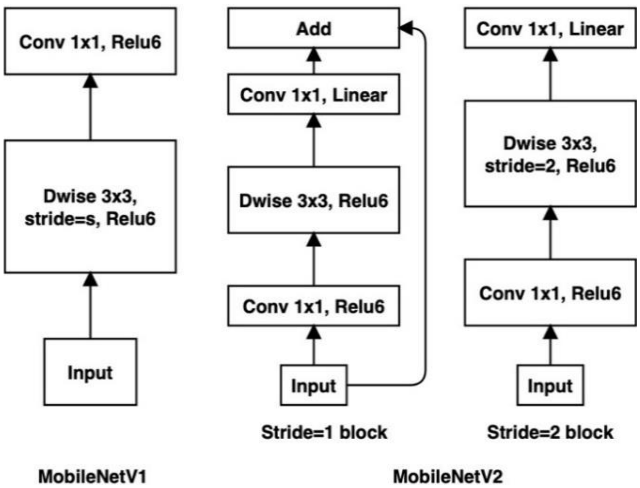


Figure 1. MobileNet architecture

3.2. Dataset

Gathering data is the first step in constructing a face-mask recognition model. Mask wearers and non-mask wearers are included in the dataset, which is derived from a mask-related dataset [25], [26]. Photos of data masked combined with unmasked photographs were used to create this dataset, which includes 2,165 images and 1,930 images. The item's face is all that is visible in this cropped image. To separate the data that has a mask from the rest, it must first be labeled. It is divided into two distinct categories once the data has been tagged. The pre-processing of data is necessary before training and testing can begin. Downsizing the image, turning the image into an array, using MobileNetV2 to preprocess the input, and finally performing hot encoding on the labels are the four processes of pre-processing. In computer vision, pre-processing such as scaling is required since training models are so powerful. In many cases, models perform better if their pictures are decreased in size. This research found that the images tested were 224x224 pixels. To utilize the loop function, the data is first transformed into an array. The MobileNet model will be used for pre-processing. To complete this step, labeled data must be performed through hot encoding since learning algorithms cannot handle labeled data directly. To put it another way, instead of a numerical input and output, any variable is required. Because of this, the technique is also assigned an arbitrary numerical value. Training data accounts for 75% of the entire data while testing data accounts for the remaining 25%. It includes all the masks in this collection. Some masks, on the other hand, and aren't.

3.3. Building and testing the model

Training image generator, basic model using MobileNetV2, model parameter addition, compilation, and model training on MacBook M1 processor with Jetson Nano Kit are all included in this work. Model storage for future predictions on the Jetson Nano Kit is also included on a new Apple M1 computer, 16 GB of random acces memory (RAM) and an 8-core central processing unit (CPU) dan graphics processing unit (GPU) are used for testing. The Python 3.8 [27] is used to conduct several experiments. Mathematical formulas for evaluating the MobileNetV2 model are presented in the following (1)-(4) based on [28].

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

$$Precision = \frac{[TP]}{[TP+FP]} \tag{2}$$

$$Recall = \frac{[TP]}{[TP+FN]} \tag{3}$$

$$F1 - Score = 2 \times \frac{[\,Precision \times Recall\,]}{[\,Precision + Recall\,]} \tag{4}$$

These abbreviations FN symbolizes false negative, TP symbolizes true positive, FP symbolizes false positive, and TN symbolizes true negative [29]. True positive values in the previous equations refer to pictures that have been labeled as true and produced a true result as predicted by the model. Similarly, true negative pictures are those that have been categorized as true but generated an incorrect outcome because of prediction. False-positive images have been categorized as false yet produced false positives because of prediction. False-negative images are those that are categorized as false yet turn out to be accurate, resulting, and in false negatives. Precision is a metric that indicates the number of expected positive values. The recall statistic quantified a classifier's ability to identify all positive cases, while the F1-score quantified test accuracy. These evaluation measures have been selected because they provide the most accurate findings through a balanced dataset. Model testing is divided into stages to verify that it can make accurate predictions. Predictions are made about the testing set's first stage.

3.4. Hardware components

3.4.1. Jetson Nano and secure digital card

A new NVIDIA Kit makes it possible to run modern AI workloads at previously unheard-of scalability, power, and price [30]. Figure 2 illustrates as AI frameworks and models may now be used by developers, educators, and makers to construct applications for classification tasks, object recognition, categorization, and speech processing, among other things. General-purpose input/output (GPIO) to camera serial interface (CSI) I/Os are all included in this Kit, which is powered by micro-universal serial bus (micro-USB). This makes it easier to link a wide variety of new detectors to allow for a variety of AI applications. It consumes just 5 watts of power, making it very energy efficient [31]. SD, or secure digital, is a detachable memory card format that is used to read and write large quantities of data in a variety of mobile gadgets, cameras, and smart devices.

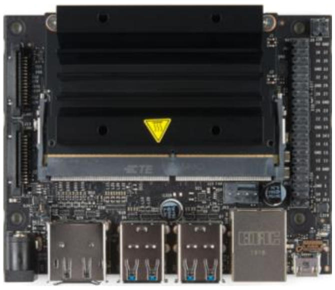


Figure 2. Jetson Nano

3.4.2. AMG8833 sensor and C920e webcam

As shown in Figure 3 Panasonic developed the AMG8833 64-pixel temperature sensor as part of their grid-EYE product line. The sensor is composed of an 8x8 array of infrared thermopiles that detect the infrared radiation emitted by emissive bodies to determine the temperature. Grid-EYE communicates with Jetson Nano through the inter-integrated circuit (I^2C) interface. The AMG8833 has a lens that limits the viewing angle of the sensor to 60 degrees, resulting in a sensing area appropriate for objects in the mid-field (as opposed to far-field or near-field). Additionally, it operates between 3.3 and 5 volts, with a sample rate of 1 Hz – 10 Hz and temperature accuracy of about 0.25°C throughout the temperature range of 0°C to 80°C. The AMG8833 is ideally suited for non-contact temperature measurement applications such as thermal imaging, heat transfer analysis, human temperature monitoring, heating, and air conditioning management, and industrial control. C920e with numerous resolutions, including 1080 p (Full HD) at 30 frames per second and 720 p (HD) at 30 frames per second, are supported.

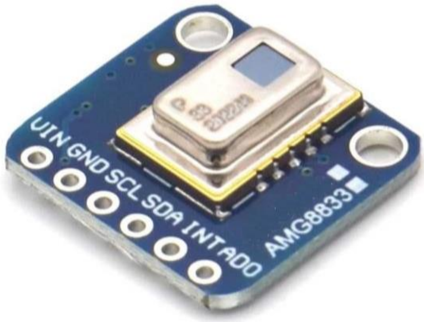


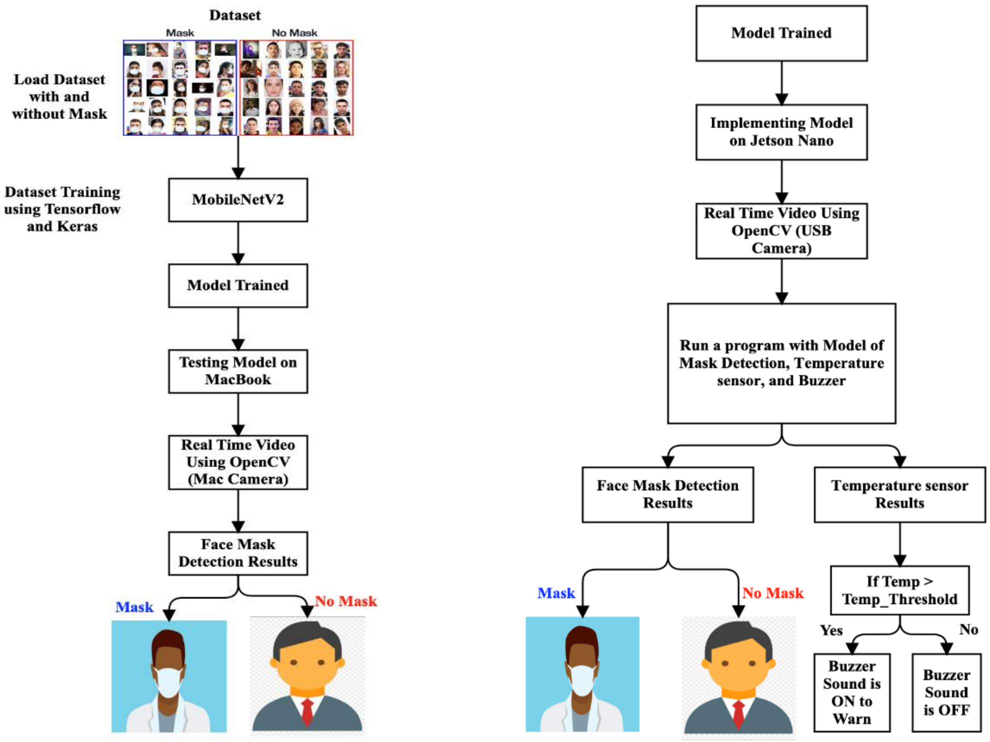
Figure 3. AMG8833

3.4.3. Power supply, screen, HDMI cable, breadboard, wired jumper cables, relay, and buzzer with battery 9 V

The power supply is 110 V – 220 V alternating current (AC) input and 5 V direct current (DC) output up to 4 A. The screen connects via high-definition multimedia interface (HDMI) cable to the Jetson Nano. The jumper wire is ideal for connecting pins of a Nano Kit to the 830 solderless tie-point prototype breadboard. Buzzer with battery is wired to JQC-3FF-S-Z 5 V relay from tongling factory.

3.5. The final setup

Data for mask detection is first loaded into the model's dataset. Data preparation involves the usage of dynamically loaded (DL) libraries. The MobileNetV2 classifier is trained using TensorFlow, Keras, and OpenCV. A MacBook M1 with fast CPU and GPU capabilities is used to train and test a model using the mask detection approach, resulting in an accuracy of 99% during training and 100% during testing. A low-cost development Kit called the Jetson Nano is used to implement the model learned on the Jetson Nano. A Nano Kit and a logitech USB camera C920e are used to capture real-time video. After developing a face mask classification model, faces may be recovered from images and video streams as needed. In certain cases, mask detection can tell whether a person has been wearing a mask at all. An additional sensor, the AMG8833, is used to measure body temperature, and a buzzer sounds if a person's body temperature exceeds a certain threshold. As depicted in Figures 4(a) and (b), the suggested system's flowchart.



(a) (b)

Figure 4. Flow chart of proposed system (a) training and testing the model and (b) implementing the model

4. EXPERIMENTS AND RESULTS

The system determines if a mask may be worn by using the NVIDIA Jetson Development Kit series and a Webcam. Additionally, the surface temperature of the human body may be monitored concurrently by attaching an IR array sensor device named AMG8833. Following that, if the human body temperature exceeds the threshold value has been set to 37°C, a buzzer alert will sound to notify. The operating environment may be run in a docker container that includes TensorFlow2, Keras, and the MobileNet model.

4.1. Training the model

The model's loss and accuracy were evaluated twenty times during training on the MacBook M1 chip, as shown in Figure 5. With the start of the second phase, accuracy increases while loss reduces, as seen in Figure 5. The model's accuracy may be improved without more iterations if the accuracy stays stable. Table 1 shows the results of the evaluation of the model in the next stage. Macro average (MA) function calculates F1 for each label and delivers the average without taking the fraction of each label in the dataset into consideration. The weighted average (WA) function takes into consideration the fraction of each label in the dataset while calculating F1 for each label. When applied to a MacBook's M1 chip, a simulation is depicted in Figure 6.

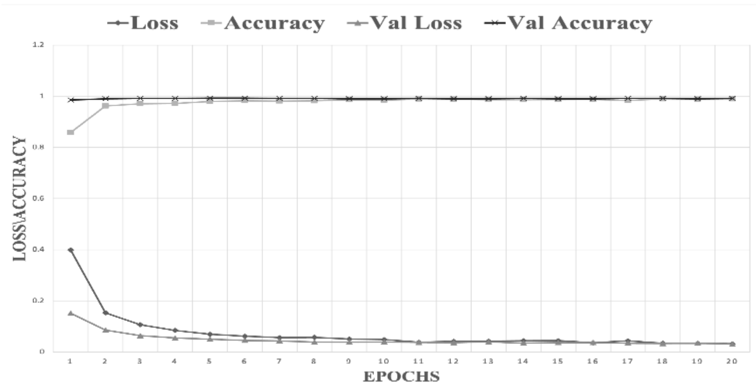


Figure 5. Training model

Table 1. Evaluation of the model

	Support	Recall	F1-score	Precision
Mask	433	100%	99%	99%
No mask	386	98%	99%	100%
Accuracy	819		99%	
MA	819	99%	99%	99%
WA	819	99%	99%	99%

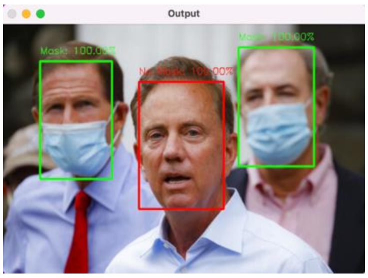


Figure 6. Predicting on MacBook M1

4.2. Implementing the model

After training and testing the model on a MacBook M1, the model is implemented on the Jetson Nano, and the pins of a Nano Kit are connected to the AMG8833 sensor. The following diagram illustrates the relationship between AMG8833, relay, buzzer, battery, and Jetson. Figure 7 depicts the final setup. The results of the surveillance proposed system on the NVIDIA Jetson Nano GPU development board are shown in Figure 8.

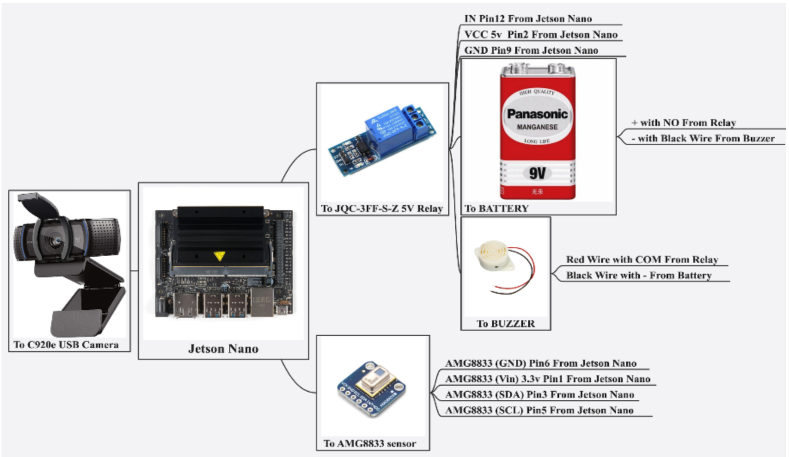


Figure 7. The final setup

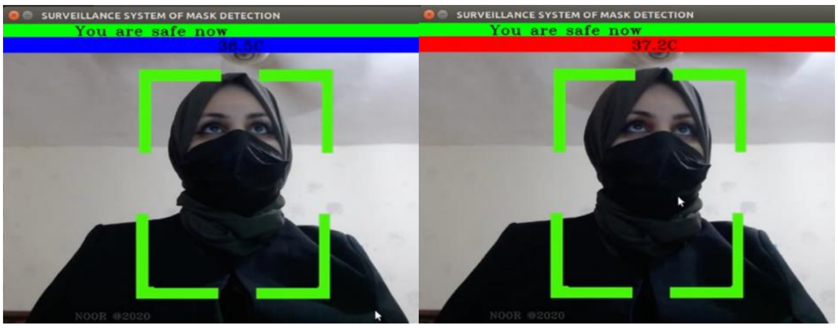


Figure 8. Surveillance proposed system on Jetson Nano

5. CONCLUSION

The COVID-19 disease can no longer spread due to the NVIDIA Jetson Nano and the MobileNetV2 lightweight model. As a rule, face-mask detection should be used in high-traffic areas, such as retail malls, public transit stations, and office buildings. When the system is installed in any area, it may be configured to gather either an on-the-fly live stream or an archived video feed. These kinds of real-time detection models might be quite useful in surveillance systems with edge applications that can recognize little elements like masks, masked faces, human temperature, and buzzer sounds when they are over a specific threshold of temperature testing indicated that the MacBook M1 has a 99% accuracy rate for training the model and a 100% accuracy rate for testing.

REFERENCES

[1] H. Li, Shang-Ming Liu, Xiao-Hua Yu, Shi-Lin Tang, and Chao-Ke Tang, "Coronavirus disease 2019 (COVID-19): current status and future perspectives," *International Journal of Antimicrobial Agents*, vol. 55, no. 5, p. 105951, May 2020, doi: 10.1016/j.ijantimicag.2020.105951.

[2] X. Xu *et al*., "Evolution of the novel coronavirus from the ongoing Wuhan outbreak and modeling of its spike protein for risk of human transmission," *Science China Life Sciences*, vol. 63, no. 3, pp. 457–460, January 2020. doi: 10.1007/s11427-020-1637-5.

[3] O. Karaman, A. Alhudhaif, and K. Polat, "Development of smart camera systems based on artificial intelligence network for social distance detection to fight against COVID-19," *Applied Soft Computing*, vol. 110, October 2021, doi: 10.1016/j.asoc.2021.107610.

[4] E. R. Ghomi *et al*., "A collection of the novel coronavirus (COVID-19) detection assays, issues, and challenges," *Heliyon*, vol. 7, no. 6, p. E07247, June 2021, doi: 10.1016/j.heliyon.2021.e07247.

[5] Y. Fang, Y. Nie, and M. Penny, "Transmission dynamics of the COVID-19 outbreak and effectiveness of government interventions: A data-driven analysis," *Journal of Medical Virology*, vol. 92, no. 6, pp. 645–659, March 2020, doi: 10.1002/jmv.25750.

[6] S. Feng, C. Shen, N. Xia, W. Song, M. Fan, and B. J. Cowling, "Rational use of face masks in the COVID-19 pandemic," *The Lancet Respiratory Medicine*, vol. 8, no. 5, pp. 434–436, May 2020. doi: 10.1016/S2213-2600(20)30134-X.

[7] 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, p. 5236, September 2020, doi: 10.3390/s20185236.

[8] T. Sikandar, K. H. Ghazali, and M. F. Rabbi, "ATM crime detection using image processing integrated video surveillance: a systematic review," *Multimedia Systems*, vol. 25, no. 3, pp. 229–251, December 2018, doi: 10.1007/s00530-018-0599-4.

[9] T. Sikandar, W. N. A. W. Samsudin, M. F. Rabbi, and K. H. Ghazali, "An Efficient Method for Detecting Covered Face Scenarios in ATM Surveillance Camera," *SN Computer Science*, vol. 1, no. 3, pp. 1–11, May 2020, doi: 10.1007/s42979-020-00163-6.

[10] 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, p. 103848, August 2021, doi: 10.1016/j.jbi.2021.103848.

[11] C. Jagadeeswari and M. U. Theja, "Performance Evaluation of Intelligent Face Mask Detection System with various Deep Learning Classifiers," *International Journal of Advanced Science and Technology*, vol. 29, no. 11s, pp. 3074–3082, 2020.

[12] A. Oumina, N. El Makhfi, and M. Hamdi, "Control The COVID–19 Pandemic: Face Mask Detection Using Transfer Learning," *2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS)*, 2020, pp. 1–5, doi: 10.1109/ICECOCS50124.2020.9314511.

[13] A. Das, M. W. Ansari, and R. Basak, "Covid–19 Face Mask Detection Using TensorFlow, Keras and OpenCV," *2020 IEEE 17th India Council International Conference (INDICON)*, 2020, pp. 1–5, doi: 10.1109/INDICON49873.2020.9342585.

[14] T. S. Rao, S. A. Devi, P. Dileep, and M. S. Ram, "A Novel Approach to Detect Face Mask to Control Covid Using Deep Learning," *European Journal of Molecular and Clinical Medicine*, vol. 7, no. 6, pp. 658–668, 2020.

[15] A. Aljumah, "Assessment of machine learning techniques in IoT-based architecture for the monitoring and prediction of COVID-19," *Electronics*, vol. 10, no. 15, p. 1834, July 2021, doi: 10.3390/electronics10151834.

[16] K. Suresh, M. Palangappa, and S. Bhuvan, "Face Mask Detection by using Optimistic Convolutional Neural Network," *2021 6th International Conference on Inventive Computation Technologies (ICICT)*, 2021, pp. 1084–1089, doi: 10.1109/ICICT50816.2021.9358653.

[17] V. Vinitha and V. Velantina, "COVID-19 Facemask Detection with Deep Learning and Computer Vision," *International Research Journal of Engineering and Technology*, vol. 7, no. 8, pp. 3127–3132, August 2020. [Online]. Available: https://www.irjet.net/archives/V7/i8/IRJET-V7I8530.pdf.

[18] S. Sen and K. Sawant, "Face mask detection for covid_19 pandemic using pytorch in deep learning," *IOP Conference Series: Materials Science and Engineering*, vol. 1070, no. 1, p. 012061, February 2021, doi: 10.1088/1757-899x/1070/1/012061.

[19] I. Q. Mundial, M. S. Ul Hassan, M. I. Tiwana, W. S. Qureshi, and E. Alanazi, "Towards Facial Recognition Problem in COVID-19 Pandemic," *2020 4rd International Conference on Electrical, Telecommunication and Computer Engineering (ELTICOM)*, 2020, pp. 210–214, doi: 10.1109/ELTICOM50775.2020.9230504.

[20] 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, p. 102692, March 2021, doi: 10.1016/j.scs.2020.102692.

[21] S. A. Sanjaya and S. A. Rakhmawan, "Face Mask Detection Using MobileNetV2 in The Era of COVID-19 Pandemic," *2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI)*, 2020, pp. 1–5, doi: 10.1109/ICDABI51230.2020.9325631.

[22] A. G. Howard *et al*., "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," *arXiv preprint arXiv:1704.04861*, April 2017, doi: 10.48550/arXiv.1704.04861.

[23] T. Ghosh *et al*., "Bangla handwritten character recognition using mobilenet v1 architecture," *Bulletin of Electrical Engineering and Informatics*, vol. 9, no. 6, pp. 2547–2554, December 2020, doi: 10.11591/eei.v9i6.2234.

[24] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 4510–4520, doi: 10.1109/CVPR.2018.00474.

[25] D. Matthias, C. Managwu, and O. Olumide, “Face mask detection application and dataset,” *Journal of Computer Science and Its Application*, vol. 27, no. 2, 2020, doi: 10.4314/jcsia.v27i2.5.

[26] A. Cabani, K. Hammoudi, H. Benhabiles, and M. Melkemi, “MaskedFace-Net–A dataset of correctly/incorrectly masked face images in the context of COVID-19,” *Smart Health*, vol. 19, March 2021, doi: 10.1016/j.smhl.2020.100144.

[27] A. A. Abed and S. A. Rahman, “Python-based Raspberry Pi for Hand Gesture Recognition,” *International Journal of Computer Applications*, vol. 173, no. 4, pp. 18–24, September 2017, doi: 10.5120/ijca2017915285.

[28] S. Saypadith and S. Aramvith, "Real-Time Multiple Face Recognition using Deep Learning on Embedded GPU System," *2018 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, 2018, pp. 1318–1324, doi: 10.23919/APSIPA.2018.8659751.

[29] A. Al Mamun, P. P. Em, and J. Hossen, “Lane marking detection using simple encode decode deep learning technique: SegNet,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 4, pp. 3032–3039, August 2021, doi: 10.11591/ijece.v11i4.pp3032-3039.

[30] S. Saponara, A. Elhanashi, and A. Gagliardi, “Implementing a real-time, AI-based, people detection and social distancing measuring system for Covid-19,” *Journal of Real-Time Image Processing*, vol 18, no. 6, pp. 1937–1947, January 2021, doi: 10.1007/s11554-021-01070-6.

[31] S. U. Rehman, M. R. Razzaq, and M. H. Hussian, “Training of SSD (Single Shot Detector) for Facial Detection using Nvidia Jetson Nano,” *arXiv preprint arXiv:2105.13906*, May 2021, doi: 10.48550/arXiv.2105.13906.

BIOGRAPHIES OF AUTHORS

Noor Faleh Abdul Hassan M.Sc. student at the Department of Computer Engineering-Basrah University-Iraq. Received the B.Sc. degree in Computer Engineering in 2015. Her field of interest is computer vision, embedded systems, and robotics. She is currently a group researcher working in developing deep learning models and algorithms in Python. She can be contacted at email: pgs2341@uobasrah.edu.iq and dr.noorfaleh@gmail.com.

Ali A. Abed Assistant Professor at Basrah University's Department of Computer Engineering in Iraq. Received the B.Sc. & M.Sc. degrees in Electrical Engineering in 1996 & 1998 respectively. He received a Ph.D. in Computer & Control Engineering in 2012. His field of interest is robotics, computer vision, and IoT. He is IEEE senior member, IEEE member in Robotics & Automation Society, IEEE member in IoT Community, member ACM. He is currently supervising a group of researchers working with developing deep learning models for computer vision applications. He can be contacted at email: ali.abed@uobasrah.edu.iq.

Turki Y. Abdalla is a Professor at the University of Basrah, College of Engineering. Received a Ph.D. in Electrical Engineering from the College of Engineering at the University of Basrah, Iraq. Robot control, multiple mobile robots, intelligent control, soft computing, and image processing are his research interests. He is an IEEE Senior Member. He can be contacted at email: turki.abdalla@uobasrah.edu.iq.