Computer Vision-Based IoT Architecture for Post COVID-19 Preventive Measures

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***Abstract*—The COVID-19 pandemic has wreaked havoc on people all across the world. Even though the number of verified COVID-19 cases is steadily decreasing, the danger persists. Only societal awareness and preventative measures can assist to minimize the number of impacted patients in the work environment. People often forget to wear masks before entering the work premises or are not careful enough to wear masks correctly. Keeping this in mind, this paper proposes an IoT-based architecture for taking all essential steps to combat the COVID-19 pandemic. The proposed low-cost architecture is divided into three components: one to detect face masks by using deep learning technologies, another to monitor contactless body temperature and the other to dispense disinfectants to the visitors. At first, we review all the existing state-of-the-art technologies, then we design and develop a working prototype. Here, we present our results with the accuracy of 97.43% using a deep Convolutional Neural Network (CNN) and 99.88% accuracy using MobileNetV2 deep learning architecture for automatic face mask detection.**

***Keywords*—Artificial Intelligence (AI), Convolutional Neural Network (CNN), Deep Learning (DL), Computer Vision, Intelligent Automation (IA), MobileNetV2**

I. INTRODUCTION

Coronavirus disease (COVID-19) is a highly contagious viral illness caused by the SARS-CoV-2 virus [1]. With its continuous evolution into diverse variations across countries, this virus has brought human life globally to a halt. It has negatively impacted several countries in multiple waves. The greatest approach to preventing and reducing the spread of the COVID-19 virus is to educate everyone on the virus, the sickness it causes, and how it spreads. Because the COVID-19 virus is mostly transmitted by droplets of saliva or nasal discharge when an infected person coughs or sneezes, proper respiratory etiquette and the use of a mask are essential. To stop the virus from spreading, several developing and developed countries had to shut down their whole country. Even though vaccination has already been initiated, the daily confirmed cases worldwide are still not that much negligible [2]. However, the daily COVID-19 new confirmed cases are shown in Fig. 1. The government of different countries has already taken different initiatives such as self-isolation, country lockdown, social distance, canceling events, postponed economic projects, etc. for protecting against the spreading of Coronavirus. However, these non-pharmaceutical interventions have an impact on the country's economic disruptions as well as individuals' physical [3] and mental health [4]. Therefore, to control COVID-19 spreading with the lowest possible effects on our daily lives and society, an intellectual and systematic way of executing the mentioned non-pharmaceutical interventions is highly desirable.

Even though the different types of vaccines are available on the market now, new virus strains are coming due to transformations. Although the perfect way of preventing pandemics is to bring everyone under the vaccine, still, many countries' healthcare systems do not have advanced to vaccinate everyone. Many overpopulated and underdeveloped nations are still failing to combat this pandemic, despite their best efforts. However, in many populated countries, the COVID-19 waves are coming back over and over. On the other hand, the World Health Organization (WHO) already published several guidelines for protection against the spreading of COVID-19 and advised everyone to wear a face mask in public zones since most positive cases are found in overcrowded places [5]. So it is highly required to ensure wearing a face mask in all areas especially educational institutes, libraries, hospitals, shopping malls, markets, superstores, offices, courts, etc. But manually monitoring and identifying individuals with masks and no masks is a very challenging task. The Internet of Things (IoT), Machine learning, and Deep learning-based AI algorithms can be utilized to ensure that all visitors are wearing masks, to prevent COVID-19 transmission [6].

IoT devices collect and transfer data with little human interaction utilizing different transfer protocols and are widely used in healthcare, educational institutes, offices, etc. to monitor and analyze user activities and health conditions, vital signs, etc. The data generated in IoT

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platform is used to develop a prediction model using big data analytics and machine/deep learning-based AI algorithms. On the other hand, Artificial Intelligence (AI) is an area of research in which machines can do tasks that would typically need human intelligence. There is also the concept of machine learning, in which computers may learn from experience and gain abilities without human participation, which is part of this. Deep learning is a technique in which AI-based algorithms inspired by the human brain are utilized to learn from massive amounts of data (DL) [7]. To improve the existing condition of COVID, many AI-based algorithms have been employed in the past to diagnose or monitor preventative actions which are described below.

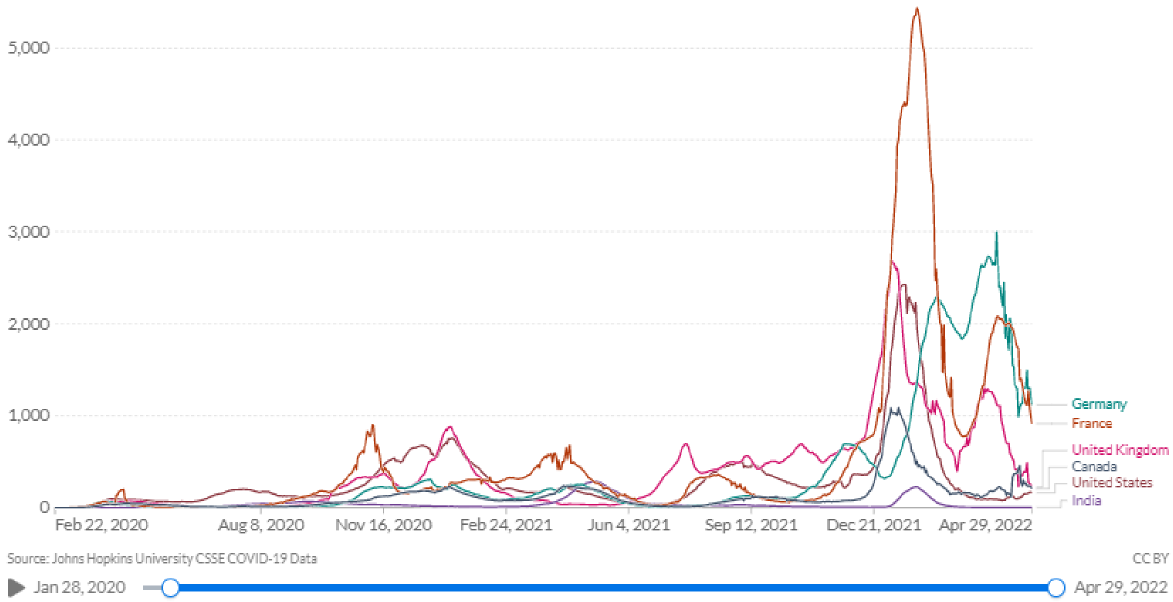


Figure 1. Daily new confirmed COVID-19 cases per million people [2].

II. MOTIVATION

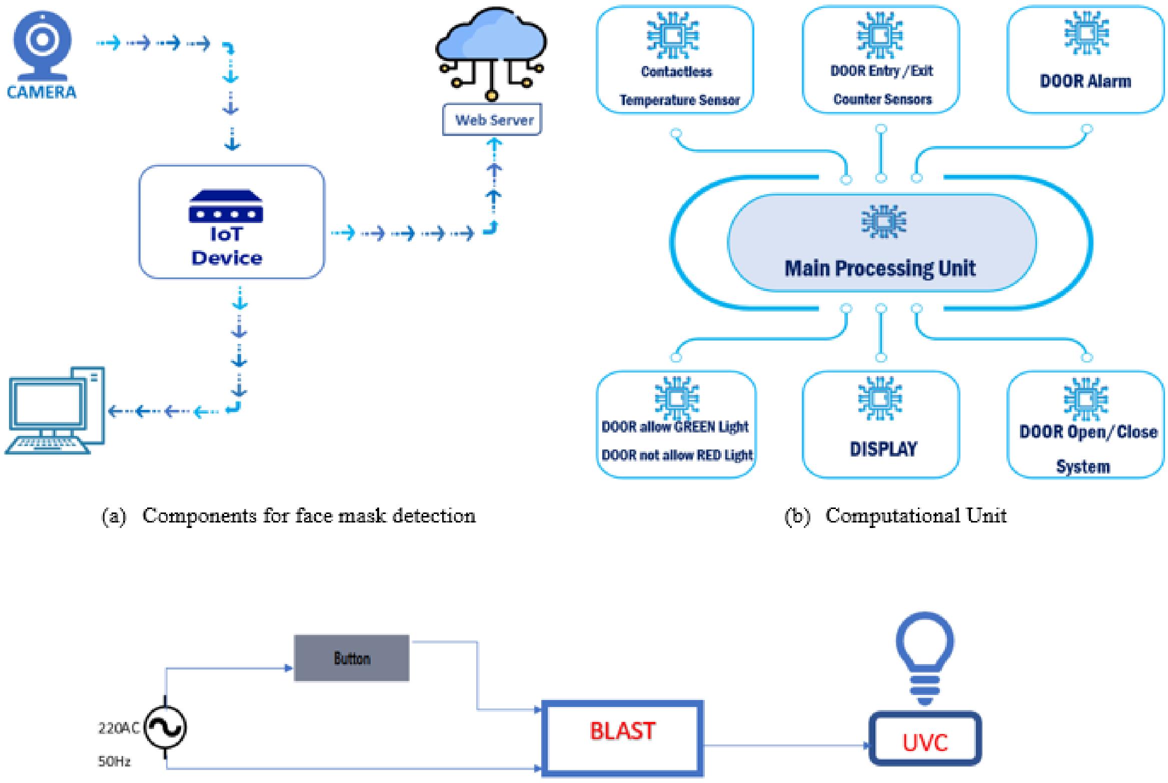
SARS-CoV-2 has spread to 213 countries, resulting in approximately 88 million instances of COVID-19 disease as of January 2021. The COVID-19 pandemic scenario is currently unfavorable due to several reasons, including poor vaccination rates in many countries and a lack of accessible COVID-19 pharmacological therapy [8]. The longevity of SARS-CoV-2 immunity is yet unknown, and additional longitudinal research is needed to find out. According to a Harvard Public Health School forecast, if SARS-CoV-2 protection is not durable, COVID-19 outbreaks will occur regularly. The interventions, such as prolonged self-isolation and complete city lockdown, have impacts on people's both physical [9] and mental health [10]. It is thus highly desirable to build a more intelligent and systematic implementation of nonpharmaceutical interventions to ensure effective COVID-19 control with minimal possible impacts on our lives and society. The Internet of Things (IoT) can be utilized for remote health monitoring, such as linking older citizens with chronic illnesses to physicians and hospital services [11].

In this paper, computer vision-based IoT architecture is proposed for preventive measures of Post-Covid-19 at different workplaces. Although few mask detection systems can detect faces with a mask or without a mask, however, incorrect mask detection has not been explored in earlier research works (Fig. 2). Identifying the incorrect mask wearing is also very important as people often forget to put on a mask correctly before entering a populated place like an office, shopping mall, university, etc. At the time of writing this paper, a new variant is found called omicron after the deadly delta variant. Our proposed inexpensive system (Fig. 3) can automatically monitor and warn about symptomatic COVID patients before entering the institution premises. The overall contributions of this paper are summarized as follows:

- Computer vision-based IoT architecture for post-COVID-19 preventive measures in different workplaces such as educational institutions, hospitals, shopping malls, banks, etc.
- The MobileNetV2 architecture has been fine-tuned for mask detection.
- The performance of the proposed fine-tuned architectures has been measured through a rigorous simulation and compared with existing deep CNN mask detection methods.

The rest of the paper is organized as follows: Section II explains the inspiration behind this study, the literature review is described in Section III, Section IV explains the comparative study between the MobileNetV2 architecture and traditional convolutional neural networks, Section V covers the proposed system, Section VI presents the experimental setup of the proposed prototype system. Finally, Section VII brings the paper to an end.

Figure 2. The three scenarios of face mask detection.



(a) Components for face mask detection

(b) Computational Unit

(c) Disinfection Mechanism using UVC

Figure 3. The architecture of the proposed system components - (a) Hardware components for face detection. (b) The sensors and other peripherals used in the framework for measuring body temperature, alerting and keeping track of the number of people entering and departing. (c) The box equipped with UV ray-based disinfecting mechanism.

III. Literature Review

We conducted an extensive literature review to learn about the recent existing important related work to proceed to develop the proposed system. In this section, we describe the most closely relevant up-to-date literature review as follows.

A. *IoT Based Systems*

Dong *et al*. [12] proposed a fog-cloud-based IoT platform for the systematic and intelligent COVID-19 prevention and control having two components: sensor-based monitoring and data-based prediction. The sensor-based monitoring includes breath, blood, body temperature, and human activity monitoring. And the data-based prediction included the disease outbreak and virus mutation prediction using data analytics rather than machine learning. Sathyaseelan *et al*. [13] proposed a system that uses a Microcontroller Unit (MCU) and a Bluetooth module that collects tags and communications with a database from the COVID RADAR application. The system alerts the users in a particular area for possible COVID risk. Vedaei *et al*. in [14] created a framework called COVID-SAFE which is divided into three parts: An IoT node that tracks various health parameters such as body temperature, cough rate, respiratory rate, and blood oxygen saturation, a smartphone application that collects information from the IoT node and display user's health condition, a fog-based Machine Learning tool that analyses the data. The application also notifies the user about maintaining a distance when there is a risk. Lu and Sun [15] proposed a face recognition-based roll-call system and thermal imager for body temperature monitoring as an initiative of COVID-19 spread in the classroom environment. Baskaran *et al*. [16] proposed an IoT-based framework for a work environment where the system controls access of the employees based on body temperature and face recognition using an IR sensor and camera. However, the system did not implement mask detection. Mohammed *et* *al*. [17] designed a smart helmet equipped with thermal imaging devices for detecting infected people in crowds. The crowd was scanned with an infrared camera, and if a person's body temperature was detected high, the face was captured with a camera with the person's location using GPS. Kumar *et al*. [18] proposed an IoT-based architecture that can be deployed in public toilets, airports, malls, hospitals, offices, etc. The system consists of several sensors and devices such as IR sensors, a smartwatch, an optical camera IP camera for body temperature measurement, heart rate detection, and face recognition of patients respectively to prevent COVID-19 spread.

B. *Face Mask Detection*

Wearing a face mask is an integral part of preventing COVID-19. Snyder *et al*. [19] developed a three-component-based deep learning architecture to identify if a human subject is wearing a mask or not. At the initial stage, they implemented deep residual learning (ResNet-50) with Feature Pyramid Network (FPN) for the detection of human subjects in video feeds. Then a Multi-Task Convolutional Neural Networks (MT-CNN) was utilized to identify and extract human faces from the video feeds. Finally, they constructed and trained a convolutional neural network classifier to detect masked and unmasked persons. All of these were integrated into a mobile robot named Thor. They presented evaluation results with F1 score accuracy of 87.7 % with a recall accuracy of 99.2 %. However, the system did not have any incorrect face mask detection. Singh *et al*. [20] used two state-of-the-art object detection models using YOLOv3 and faster R-CNN for face mask detection. The models were trained with the dataset containing both images of people with masks and without masks. In their work, bounding boxes (red or green) were drawn around the faces of people, indicating the presence of a mask. The YOLOv3 model obtained an average precision of 55 within 0.045 second inference time whereas the faster R-CNN model obtained an average precision of 62 within 0.15 second inference time. The system did not have any incorrect mask detection, though. Batagelj *et al*. [21] conducted an experimental evaluation of several recent face detectors and compared them with their model's performance results for face mask detection. They also investigated the usefulness of multiple off-the-shelf deep learning models for finding the correct face mask placement. Their main focus was on creating a method that can detect proper face mask placement. For the study, the Masked Faces (MAFA) [22] and WIDER FACE datasets [23] were used. The dataset consisted of images both of real-world and simulated face mask placement. All tested models achieved average recognition accuracy of over 97 %. Loey *et al*. [24] implemented a hybrid model deploying deep and classical machine learning for face mask detection that consisted of two parts. First, feature extraction was done using ResNet50 then face mask classification was done utilizing decision trees, Support Vector Machine (SVM), and ensemble algorithm. Real-World Masked Face Dataset (RMFD) [25], the Simulated Masked Face Dataset (SMFD) [25], and Labelled Faces in Wild (LFW) [25] were used for the study. They achieved an accuracy of 99.64 % with SVM in RMFD, and 99.49 % in SMFD while 100 % in LFW.

Negi *et al*. [26] introduced CNN and VGG16-based two deep neural models for detecting masks over the simulated masked face dataset to integrate and enforce AI-based preventive measures and showed that the proposed CNN and VGG16 architectures achieved a testing accuracy of 97.42% and 98.97% respectively. On the other hand, Mashyal *et al*. [27] proposed a system that determines the face mask and send a notification to appropriate staff if a person not wearing a mask is found in any public place. The proposed system captures images using a live feed camera and uses a CNN-based deep model to detect the face masks with an accuracy of 96.54%. In another research, Mahurkar and Gadge used the YOLOv4 model for detecting face masks to restrict the spread of COVID-19 in real-time [28]. The model is experimented with different iterations and from the comparative study, the YOLOv4 model at 3000 iterations is selected as the best model among all with an accuracy of 98%.

C. *Smart Gate*

Longo *et al*. [29] proposed a prototype of a smart gate for monitoring people's movement and occupancy levels and demographic data estimates. However, the solution does not implement the machine learning approach and is not an inexpensive solution. Khayyat and Munshi [30] proposed a SmartGate system implementing the Triz theory principles. The system contains an entering procedure with a social distance of two meters, then measures body temperature through a thermal camera and allows access if only an individual has a normal temperature. The system also sends alert SMS to persons having high temperatures and also suggests some nearby hospitals. The system did not consider detecting face masks which is vital for preventing COVID-19. Putra *et al*. [31] proposed a smart gate system that grants access based on normal body temperature and the presence of a mask implementing Integrated COVID-19 Early Prevention evices (INCEPS). The system also kept a disinfectant spray box to sterilize individuals' cloth and belongings. They also created an INCEPS website to monitor the density of people in the region and made a warning mechanism for when the place becomes crowded. However, the system did not propose any solution if a person is wearing a mask incorrectly or not.

IV. DEEP CNN AND MOBILENETV2

Traditional convolutional neural networks (CNN) is the most typical deep neural network that is commonly used to detect patterns in pictures, but they may also be used for natural language processing, computer vision, signal processing, spatial data analysis, and other applications. To recognize what characteristics, like edges, are present across an image, CNN employ filters (also known as kernels) [32]. However, image data training with CNN is usually computationally high and time-consuming. A standard convolution has the computation cost of (Eq. (1)):

$$D_K.D_K.M.N.D_F.D_F \quad (1)$$

where the computational cost depends multiplicatively on the number of input channels M, the number of output channels N the kernel size $D_K \times D_K$ and the feature map size $D_F \times D_F$ [30].

In contrast, MobileNets are fast and efficient convolutional neural network architectures designed for mobile and embedded vision applications [33]. MobileNet models address each of these above-mentioned terms and their interactions. At First, it uses depth wise separable convolutions to break the interaction between the number of output channels and the size of the kernel. The convolutional layer has two functions: one is to filter the input with a depth wise convolution layer and then a pointwise (1×1) convolution layer merges the filtered values to form new features The depth wise and pointwise convolutions work together to generate a "depth wise separable" convolution block. The main difference between MobileNet architecture and a traditional CNN instead of a single 3×3 convolution layer followed by the batch norm and ReLU. Mobile Nets split the convolution into a 3×3 (depth-wise convolutional layer) and then a 1×1 (pointwise convolutional layer). The combination of the depth-wise convolution and 1×1 (pointwise) convolution is called depth-wise separable convolution whose computational cost is measured as Eq. (2).

$$D_K.D_K.M.D_F\ .D_F + M.N.D_F\ .D_F \quad (2)$$

which is significantly faster than equation (1). According to Howard *et al.*, [33], the MobileNetV2 with k = 3, 3×3 depth-wise separable convolutions resulted in 8 to 9 times smaller computational costs than that of standard convolutions. Two basic global hyperparameters are proposed that efficiently trade off latency and accuracy. Based on the constraints of the issue, these hyper-parameters enable the model builder to select the appropriate model size for their application [33]. This is illustrated in Fig. 4 where DK is the spatial dimension of the kernel assumed to be square and M is the number of input channels and N is the number of output channels. A global average pooling layer is often found at the conclusion of a MobileNet-based classifier, followed by a fully-connected classification layer or an analogous 1×1 convolution, and a softmax.

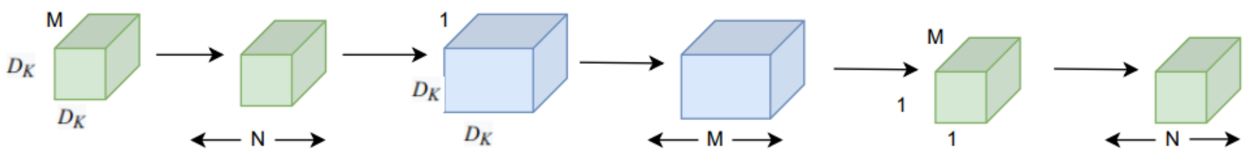


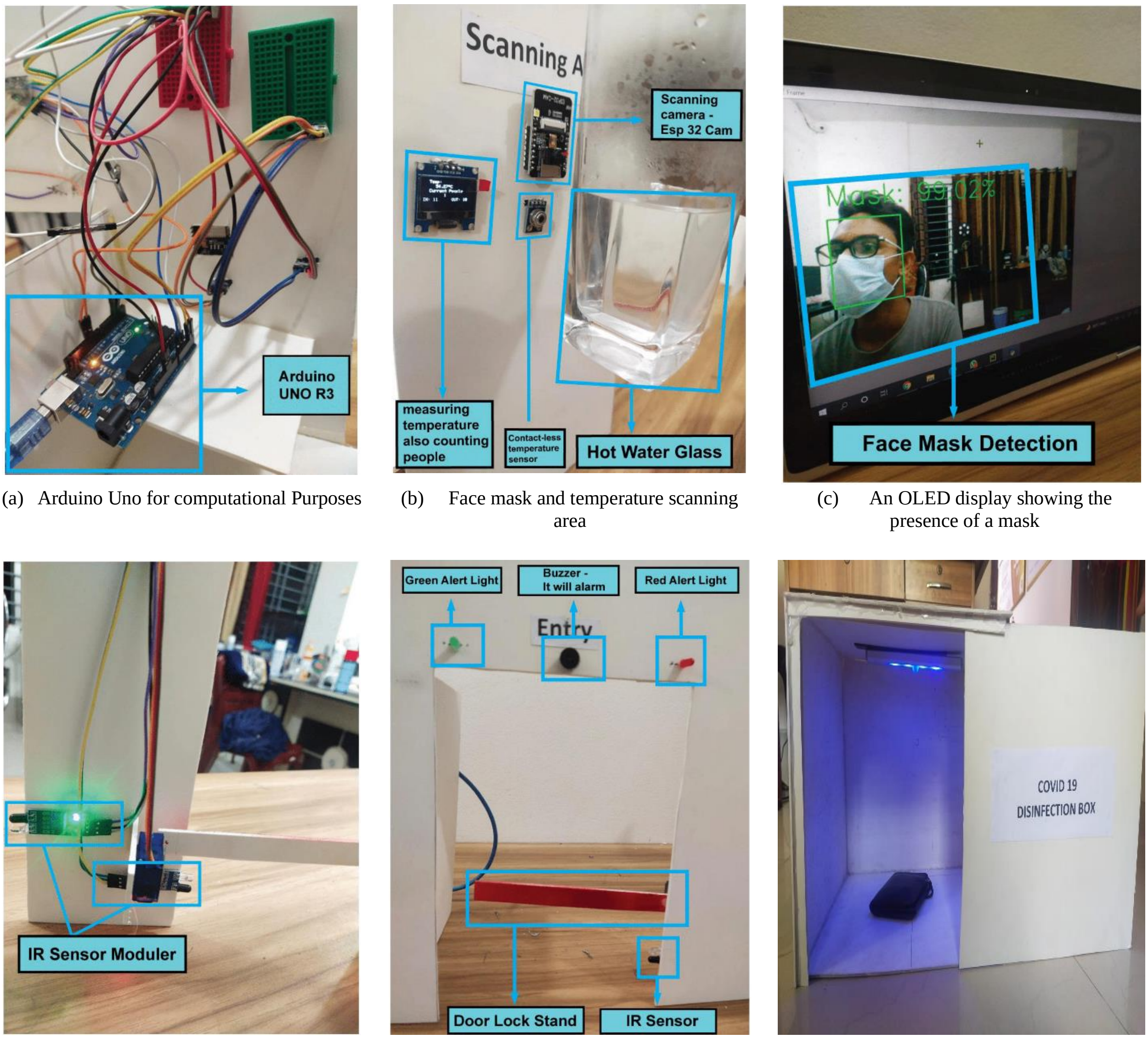
Figure 4. The standard convolutional filters in MobileNetV2 architecture.

MobileNetV2 is an improved version of the previous neural network architecture that is specifically tailored for mobile and resource-constrained environments by paying attention to the reduction of required memory. This improved version can solve problems like classification, detection, and segmentation. It achieves the perfect balance between evaluation results and implementation efficiency on mobile devices. Even though it is very similar to ordinary CNN models but still there exist some differences. The main contribution is a novel layer module: the inverted residual with the linear bottleneck. This module takes as an input a low-dimensional compressed representation which is first expanded to the high-dimension and filtered with a lightweight depth-wise convolution. Features are subsequently projected back to a low-dimensional representation with a linear convolution. The depth-wise separable convolution operation is divided into two phases: first in applying each filter to one of all channels and then in several 1 × 1 filters are applied to all channels of the output of the previous phase. MobileNetV2 combines the pointwise convolution and the bottleneck together and uses pointwise to realize to bottleneck. Using ReLU activation to data after dimensionality reduction causes the loss of lots of information. Thus, linear is used as the activation function in the bottleneck layer to reduce the loss of information. In the inverted residual block, an expansion layer is added at the beginning of the block and then ReLU is used to add some non-linearity to the model. In a nutshell, the input and the output are added together, and a summary of them is used as the output of the whole block to get better propagation of gradients. The advantages of the MobileNetV2 are listed as follows:

(1) Lightweight and less processing intensive
(2) Best suited for embedded system environment
(3) Low memory requirements suitable for embedded hardware and programmable micro-controllers
(4) Fast and accurate for both training and detection

V. The Proposed Architecture

The architecture of the proposed system is presented in Fig. 3, the working components of the proposed architecture's prototype are presented in Fig. 5 and the workflow of the proposed system is presented in Fig. 6. The proposed system works in three stages - 1) Correct, incorrect, and no mask detection, 2) body temperature measurement, and 3) disinfecting belongings using UV box rays.



(a) Arduino Uno for computational Purposes (b) Face mask and temperature scanning area (c) An OLED display showing the presence of a mask

(d) IR sensor module (e) Entry gate (f) Disinfectant box

Figure 5. The prototype of the proposed system - (a) Arduino does for the computations. (b) The scanning area measures the body temperature, scan for face keep track of the people entering or departing. Here, a glass of hot water is used for checking the high temperature. (c) An LED display showing the availability of the mask. (d) The entrance door with alert sensors and devices. (e) The box with UV-ray is used for disinfecting the possessions of the person. (f) The complete system is presented in this figure.

Fever is one of COVID-19's most common symptoms. Checking a person's body temperature before entrance is one of the most used COVID-19 prevention techniques at many institutions. The proposed architecture employed an Infrared (IR) sensor to detect the body temperature of the probable COVID19 symptomatic person's entry permission or not allowing a person to enter. The body temperature can be measured from a short distance without any physical touch with this sensor. Properly Wearing a mask is an effective way of preventing COVID-19 and also spreading COVID-19 to others. Thus, a camera with deep learning (with CNN, and then MobileNetV2) is utilized to determine whether or not a person is wearing a mask or not or wearing mask incorrectly. The algorithm used in MobileNetV2 is presented in Algorithm 1. A door entrance and exit IR sensor counter is also implemented to monitor if the place is getting crowded or not. The two main system conditions to warn are — the body temperature is not normal, and the individual entering is not wearing a mask. When one of these circumstances is met, the system deems it a potential danger and warns by flashing a red signal, playing a buzzer, and blocking that specific individual from entering. If a person meets these criteria, the system will grant him/her access. After entering, a disinfectant spray will be sprayed over the person's body, and his belongings will be disinfected using UV rays. The components that were used for building a prototype of the system are briefly described in this section. The hardware setup is done in 3 stages – face detection, warning mechanism, and finally disinfection of individuals' belongings. All the components with their price are shown in Table I.

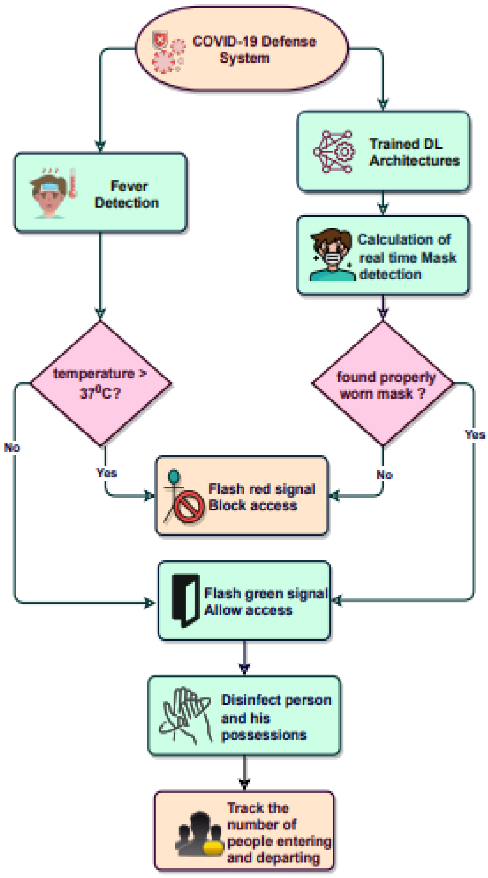


Figure 6. The flowchart of the deep learning-based proposed system.

Algorithm 1: Proposed face mask detection algorithm

Input: Subset of the dataset for training X, Subset of the dataset for testing T, Deep Neural Network (DNN) model for face detection M_1, Pre-trained MobileNetV2 model M^2 , Number of iterations *epochs*, Training batch per iteration *batchSize*, Streaming Video S

Result: Fine-tuned MobileNetV2 model trained on the dataset with updated weights m, Condition of face mask (with mask, without a mask, incorrect mask) f

Initialize the base model M2;
Add GlobalAveragePooling2D, Dropout and Dense layers on the top layer of M2;
iter ← 0;
while *iter* < *epochs* **do**
  initialize a validation set V;
  Rescale the input images X with pixel values in the range [−1, 1];
  b ← 0;
  while *b* < *batchSize* **do**
    Update the weights of M2 by training on X and validating on V ;
  iter = *iter* + 1;
m ← the updated weights of the trained M2;
Evaluate the performance of m on the test set T;
Initiate Video Streaming S;
for *eachframe* ∈ *S* do
  Apply M1 to detect face in frame;
  Generate a bounding box around the detected face;
  Apply m to predict the condition of face mask;
  Predictions *p*[probability of incorrect mask condition, probability of with mask condition, probability of without mask condition];
f ← maximum value in the array *p*[];

TABLE I. HARDWARE COMPONENTS OF THE PROPOSED SYSTEM AND THEIR PRICES EXCLUDING THE DISPLAY UNIT

Components	**Quantity**	**Price in USD**
Arduino Uno	1	10.50
IR Sensor	2	1*2 = 2.00
ESP-32 CAM Module	1	10.50
OLED Display	1	5.00
Buzzer	1	0.5
Servo Motor	1	1.40
LEDs	2	0.05*2 = 0.10
MLX90614 (Contactless Temp. IR Sensor)	1	13.00
9V Battery with connectors	1	0.10
UVC Lamp	1	29.00
Software Component (Open Source Arduino IDE, Python Libraries)	-	0.00
	Total Cost in USD =	**72.10**

For the computational unit, the Arduino development board was used with additional hardware blocks shown in Fig. 3. However, the hardware components used in our system are discussed below.

(1) *Arduino Uno:* The Arduino Uno is used for computational purposes. It is a Microchip ATmega328P-based open-source micro-controller board created by Arduino. cc [34]. The board has several digital and analog input/output (I/O) pins that may be linked to various expansion boards and other systems [35]. The board contains 14 digital I/O pins and 6 analog I/O pins, and it can be programmed using the Arduino IDE (Integrated Development Environment) and a type B USB connector [36]. It is powered by a USB connection or an external 9-volt battery, and it supports voltages ranging from 7 to 20 volts [37].

(2) *ESP32-CAM Module:* At the initial stage, for face detection ESP32-CAM module was used (Fig. 5(b)). The ESP32-CAM is a full-featured micro-controller that also has an integrated video camera and micro SD card socket. A video streaming web server was built with the ESP32-CAM that can access the camera streaming server on the local network. This stream was fed into the preloaded deep learning model for necessary calculation. When the model detects a properly worn mask in the stream, it sends a positive signal otherwise negative.

(3) *Contactless Temperature IR Sensor:* MLX90614: For the second stage, the suggested framework employed an infrared (IR) sensor (Fig. 5(b)) to identify a possible COVID danger in the situation of permitting or not allowing a person to enter. The body temperature can be measured from a short distance without any physical touch with MLX90614. It is an IR Temperature sensor for non-contact temperature measurements. It has an I2C interface to communicate with the micro-controller. It has 0.5 degrees Celsius over a wide range of temperatures.

(4) *IR Sensors:* In this project, another infrared sensor detects interrupt when it detects an obstacle. The pair of IR sensors can detect people

from both directions, i.e. the number of people entering and the number of people exiting.

(5) *Lock:* A solenoid lock works on the electronic mechanical locking mechanism. This type of lock has a slug with a slanted cut and a good mounting bracket. When the power is applied, DC creates a magnetic field that moves the slug inside and keeps the door in the unlocked position. The slug will retain its position until the power is removed. When the power is disconnected the slug moves outside and locks the door (Fig. 5(e)).

(6) *UV-Ray Box:* Finally, UV ray was used to kill germs like COVID-19 and other viruses and bacteria from the possessions of a person before entering the premises. UVC radiation has been successfully deployed worldwide to kill SARS-CoV-2 virus. The destruction ultimately leads to the inactivation of the virus [38]. The UV-Ray Box prototype was created as shown in Fig. 5(f).

(7) *Others:* Some other components like display, buzzer, and LEDs were used to alert when a risk is found. The temperature and the number of people entering or exiting were shown using an OLED display. Green LED was used to show door unlock and red LED was used to show door lock conditions. An additional AC power supply with an adapter also was added for the wall plug.

VI. EXPERIMENTAL SETUP

For the comparison of the experimental results, we first use the traditional 3-layer architecture of deep convolutional neural network (Deep CNN) (Fig. 7) [39] architecture and then use MobileNetV2 [40] architecture (Fig. 8). The rationale behind testing both architectures is to find the best resulting architecture for our proposed system. The experimental tests were performed using a Core i5 processor with an 8GB RAM computer.

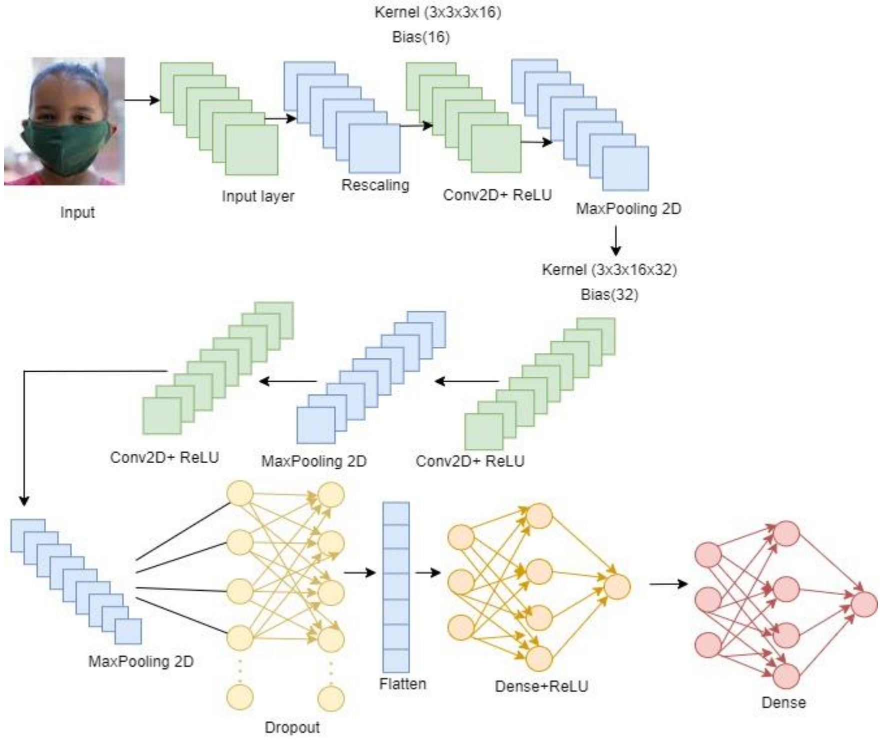


Figure 7. The architecture of the CNN model used in the proposed system.

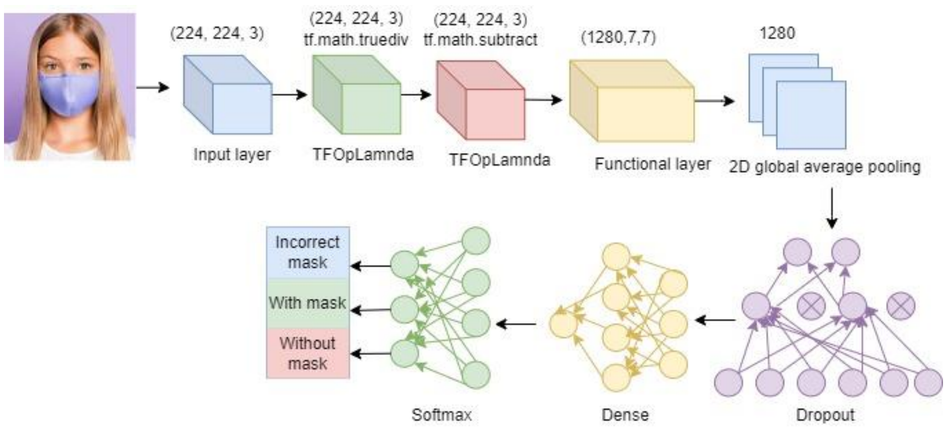


Figure 8. The architecture of the fine-tuned MobileNetV2 used in the proposed system.

A. Dataset

The dataset used in this experiment was acquired from this study [41], which included two primary groups: one group wearing a mask and the other group without any mask. The dataset includes 5521 photographs of people who were appropriately wearing masks and 5521 images of those who were not. Furthermore, 5521 images were gathered from MaskedFace-Net [42, 43] dataset for detecting the case of the incorrect mask. These three classes of face mask detection are depicted in Fig. 2. A total of 16,563 samples was split into 80% train data and 20% test data. The rest of 20% of the training data was used for validation.

B. Deep Learning Models

Google Colab, a Google cloud-based Python programming environment that runs in the browser, was used to develop and train the deep learning models [44]. TensorFlow [45] (version 2.7.0), Keras (version 2.7.0) [46], NumPy [47], and Matplotlib [48] were the main libraries utilized for inference in the Python (version 3.7 12) environment. We first implement the proposed system architecture using the traditional CNN and then using the MobileNetV2. The key details of the implemented CNN and MobileNetV2 models are described as follows.

(1) **Deep CNN Model:** The Deep Convolutional Neural Network (DCNN) architecture had three convolutional layers each with a kernel size of [3×3] with three consecutive max-pooling layers. The full architectural design with the kernel and bias size of the three convolutional layers is portrayed in Fig. 7. The input images had the dimension of [224, 224, 3]. After rescaling, the images were fed into the first convolutional layer. The model was trained for 20 epochs on the training and validation set of with mask, without a mask, and incorrect mask images (detailed in section VI-A) and finally achieved an accuracy of 93% on the test set (Table II). The performance metrics and model accuracy are presented in Fig. 9 and Table III respectively.

(2) **MobileNetV2 Model:** MobileNetV2 is a CNN architecture intended for mobile or embedded devices that can run on limited computation resources. It is based on an inverted residual structure where the residual connections are between the bottleneck layers [40]. Unlike MobileNet, MobileNetV2 uses inverted residual blocks with bottlenecking features and thus improves greater performance. The initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers, uses lightweight depth-wise convolutions to filter features. In our proposed system, for face mask detection, the fine-tuned MobileNetV2 model's output shapes of each layer are shown in Fig. 8 and the algorithm is presented in Algorithm 1. The implementation of the proposed architecture code and data set is uploaded in public github[1]. Since MobileNetV2 is used as the base model and this model requires pixel values ranging [−1, 1], but the input images had pixel values in the range [0, 255], the images were rescaled using *tf.math.truediv* and *tf.math.subtract* functions in the TFOpLambda layer of the architecture. Initially, a MobileNetV2 model was created, which comes pre-loaded with ImageNet-trained weights. The convolutional foundation that was built in the previous stage was frozen to be used as a feature extractor. A classification head with the GlobalAveragePooling2D layer was added to create predictions from the block of features. To turn these features into a single prediction per picture, a dense layer was employed. Then the model was trained for 10 epochs on the training data which were sufficient without overfitting the model. Only a few layers on top of the MobileNetV2 base model were needed to train with our dataset since the model was pre-trained with ImageNet images for the feature extraction. To improve the performance, the model was fine-tuned by training the weights of the top layers of the pre-trained model alongside the training of the classifier. As a result, the base model was left unfrozen. Then the model was trained for another 10 epochs and finally achieved an accuracy of 99.28% on the test set (Table II).

(3) **Model Performance Evaluation Metrics**: The accuracy and loss curves of both models are portrayed in Fig. 9. Four evaluation metrics: accuracy, precision, recall, and f1-score were measured to assess the performance of the models.

i) **Accuracy:** The most basic classification metric is accuracy. It is the percentage of correct outcomes out of the total number of instances evaluated as shown in 3. It is also a good option for evaluating classification issues that are evenly distributed and not skewed, or that has no class imbalance [50]. Eq. (3) is the formula for calculating accuracy.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{3}$$

where, TP = True Positive: A true positive result is one in which the model accurately predicts the positive class (with mask, without mask, incorrect mask); TN = True Negative: A real negative, on the other hand, is a result in which the model accurately predicts the negative class (not with mask, not without mask, not incorrect mask); FP = False Positive: A false positive occurs when the model predicts the positive class (with mask, without mask, incorrect mask) inaccurately, and FN = False Negative: A false negative is when the model predicts the negative class (not with mask, not without mask, not incorrect mask) inaccurately.

[1]https://github.com/JSrabonee/FaceMaskDetection/blob/066eff0263c15b623fa6dda3d21cc9c228c6892b/Face_mask_detection.ipynb

ii) **Precision:** The ratio of properly predicted positive observations to total anticipated positive observations is known as precision [53]. When one wants to be absolutely certain of the predictions, precision is a good statistic to use [50]. The formula for measuring precision is given in Eq. (4):

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

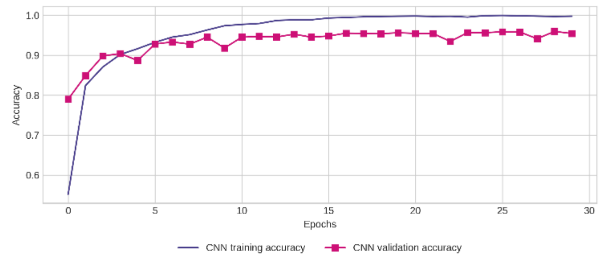
iii) **Recall:** The recall is an indicator of how well the model recognizes the True Positives [54]. When the aim is to collect as many positives as possible, recall is a good choice of evaluation parameter [55]. The formula of recall is given in Eq. (5):

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

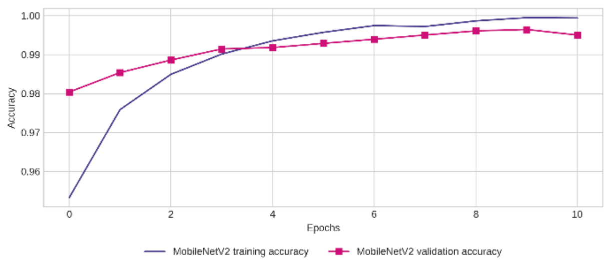
iv) **F1-Score:** Since there is a trade-off between precision and recall, this means that if one increases, the other decreases for which the f1-score plays a good role. The F1 score is the harmonic mean of precision and recalls [54]. The formula is given in Eq. (6):

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \tag{6}$$

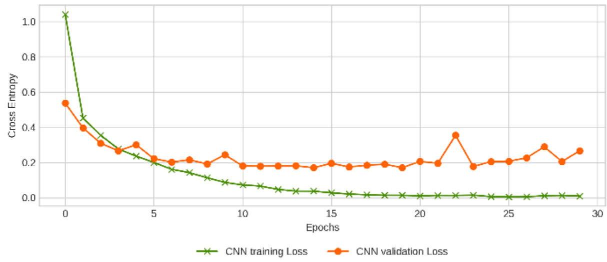
Table III shows the values of these parameters for both the CNN and MobileNetV2 architectures. From the table, it can be observed that the MobileNetV2 architecture performed better than the CNN. So, the proposed system was deployed using MobileNetV2.



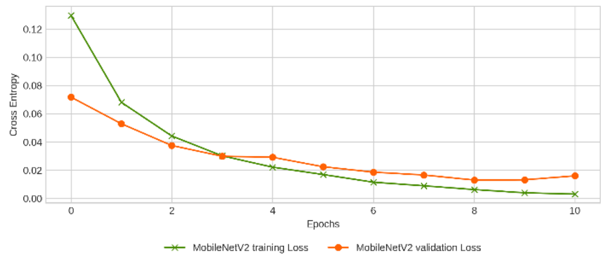
(a) Accuracy curve of the proposed CNN model



(b) Accuracy curve of the MobileNetV2 architecture



(c) Loss curve of the proposed CNN model



(d) Loss curve of the MobileNetV2 architecture

Figure 9. The accuracy and loss curves of both the CNN and MobileNetV2 models.

TABLE II. COMPARISON OF FACE MASK DETECTION METHODS AND ACCURACIES

Sl.	Work Refs., Year	Data Source	Sample Size				Method Used	Evaluation Result
			With mask	**Without Mask**	**Incorrect Mask**	**Total**		
1	Bhuiyan *et al.* [49], 2020	Web-Scrapping	300	300	None	600	YoloV3	Accuracy = 96%
2	Oumina *et al.* [50], 2020	GitHub	690	686	None	1376	MobileNetV2 + SVM	Accuracy = 97.11%
3	Loey *et al.* [51], 2021	Medical Mask Dataset (MMD)	-	-	None	1415	YoloV3 with ResNet50	Average Precision = 81%
		Face Mask Dataset	-	-	None	1570		
4	Loey *et al.* [24], 2021	Real-World Masked Face Dataset (RMFD)	5000	90000	None	95000	SVM	Accuracy = 99.64%
		Simulated Masked Face Dataset (SMFD)	785	785	None	1570		Accuracy = 99.49%
		Labeled Faces in the Wild (LFW)	0	13000	None	13000		Accuracy = 100%
5	Zhang *et al.* [52], 2021	MAFA + Internet	-	-	484	4672	R-CNN	Mean Average Precision = 84%
6	Negi *et al.* [26], 2021	Simulated Masked Face Dataset	826	825	-	1651	CNN	Testing Accuracy = 97.42%
							VGG16	Testing Accuracy = 98.97%
7	Mashyal *et al.* [27], 2021	Face Mask Detection	1380	1371	-	2751	CNN	Accuracy = 96.54%
8	Mahurkar *et al.* [28], 2021	Web	400	400	-	800	YOLOv4	Accuracy = 98%
9	Proposed Method	[41], MaskedFace-Net [42, 43]	5521	5521	5521	16563	CNN	**Accuracy = 97.43%**
							MobileNetV2	**Accuracy = 99.88%**

Figure 10. The user evaluation of the prototype detecting mask, no mask, and incorrect mask.

TABLE III. EVALUATION RESULT OF THE PROPOSED MODELS

Model	Classes	Precision (%)	Recall (%)	F1 Score (%)
CNN	Incorrect mask	99.91	98.91	99.41
	With mask	95.78	96.74	96.26
	Without mask	96.65	96.65	96.65
Fine-tuned MobileNetV2	Incorrect mask	100	100	100
	With mask	99.64	100	99.82
	Without mask	100	99.64	99.82

C. User Evaluation

The proposed system prototype was evaluated with 20 individual volunteers (15 males, 5 females) with consent. The prototype demonstrated 99.25% accuracy for with mask, 100% accuracy for the no mask, and 99.05% for the incorrect mask (Fig. 10). The temperature measurement module and the UV disinfectant worked as expected. For the UV-Ray Box effectiveness, we relied on the accuracy of the UV-Ray specification sheet provided by the hardware manufacturer [56].

VII. CONCLUSION

By automating prevention, the proposed system is able to take the preventive measure for the Post-COVID-19 issue. Almost every organization now has a secure access policy. The proposed architecture aims at eliminating any human error with a machine learning-based approach for the work environment and thus keeps individuals safe from COVID-19 infection. The system is extensively tested not only for the face mask or no face mask detection but also the incorrect mask detection using deep learning with greater accuracy, which is one of the novelties of this research. Our proposed system is fast and accurate in comparison to the traditional CNN having added features such as an automatic disinfectant dispenser and UV Ray disinfectant box. Unlike expensive solutions, this low-cost architecture is ready to be deployed in any organization especially in underdeveloped countries without much effort or cost.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Ahsanul Akib contributed to setting up the experimental hardware setups, and user evaluations of the prototype, Jannatul Ferdous Srabonee contributed to machine learning coding, machine learning tools setup, and algorithm development for the optimum solution and initial paper writing, Suman Saha contributed towards revising and fine-tuning the manuscript, Kamruddin Nur and M. F. Mridha contributed as supervising, validating the research outcome and writing the technical part of the paper. All authors had approved the final version of the paper.

REFERENCES

[1] World Health Organization. Coronavirus. [Online]. Available: https://www.who.int/health-topics/coronavirus

[2] COVID-19 data explorer - Our world in data. [Online]. Available: https://ourworldindata.org/explorers/coronavirus-data explorer?zoomToSelection=true&time=2020-03-01..latest&facet=none&pickerSort=asc&pickerMetric=location&Interval=7day+rolling+average&Relative+to+Population=true&Align+outbreaks=false&country=USA~GBR~CAN~DEU~ITA~IND&Metric= Confirmed+cases

[3] A. J. Pinto, D. W. Dunstan, N. Owen, *et al.*, "Combating physical inactivity during the COVID-19 pandemic," *Nature Rev. Rheumatology*, vol. 16, no. 7, pp. 347-348, 2020.

[4] A. Fiorillo and P. Gorwood, "The consequences of the COVID-19 pandemic on mental health and implications for clinical practice," *Eur. Psychiatry*, vol. 63, no. 1, p. e32, 2020.

[5] J. D. Sachs, R. Horton, J. Bagenal, *et al.*, "The lancet COVID-19 commission," *Lancet*, vol. 396, no. 10249, pp. 454-455, 2020.

[6] S. Agarwal, N. S. Punn, S. K. Sonbhadra, *et al.*, "Unleashing the power of disruptive and emerging technologies amid COVID-19: A detailed review," arXiv 2020, arXiv:2005.11507, 2021.

[7] Forbes. What is deep learning ai? A simple guide with 8 practical examples. [Online]. Available: https://www.forbes.com/sites/bernardmarr/2018/10/01/whatis-deep-learning-ai-a-simple-guide-with-8-practical-examples/?sh=78a097b68d4b

[8] Issue brief: The impact of COVID-19 on us vaccination rates – national foundation for infectious diseases. [Online]. Available: https://www.nfid.org/keep-up-the-rates/ issue-brief-the-impact-of-COVID-19-on-us-vaccination-rates/

[9] A. J. Pinto, D. W. Dunstan, N. Owen, *et al.*, "Combating physical inactivity during the COVID-19 pandemic," *Nature Reviews Rheumatology*, vol. 16, no. 7, pp. 347-348, 2020.

[10] A. Fiorillo and P. Gorwood, "The consequences of the COVID-19 pandemic on mental health and implications for clinical practice," *European Psychiatry*, vol. 63, no. 1, 2020.

[11] Y. Yuehong, Y. Zeng, X. Chen, *et al.*, "The internet of things in healthcare: An overview," *Journal of Industrial Information Integration*, vol. 1, pp. 3-13, 2016.

[12] Y. Dong and Y. D. Yao, "IoT platform for COVID-19 prevention and control: A survey," *IEEE Access*, vol. 9, pp. 49929-49941, 2021.

[13] M. P. Sathyaseelan, M. K. Chakravarthi, A. P. Sathyaseelan, *et al.*, "IoT based COVID de-escalation system using bluetooth low level energy," in *Proc. 6th International Conference on Inventive Computation Technologies*, 2021, pp. 174-177.

[14] S. S. Vedaei, A. Fotovvat, M. R. Mohebbian, *et al.*, "COVID-Safe: An IoT-based system for automated health monitoring and surveillance in post-pandemic life," *IEEE Access*, vol. 8, pp. 188538-188551, 2020.

[15] H. Y. Lu and K. T. Sun, "Classroom system with intelligent epidemic prevention of COVID-19," in *Proc. IEEE Eurasia Conference on IOT, Communication and Engineering*, 2020, pp. 195-198.

[16] K. Baskaran, P. Baskaran, V. Rajaram, *et al.*, "IoT based COVID preventive system for work environment," in *Proc. Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)*, 2020, pp. 65-71.

[17] M. Mohammed, H. Syamsudin, S. Al-Zubaidi, *et al.*, "Novel COVID-19 detection and diagnosis system using IoT based smart helmet," *International Journal of Psychosocial Rehabilitation*, vol. 24, no. 7, pp. 2296-2303, 2020.

[18] K. Kumar, N. Kumar, and R. Shah, "Role of IoT to avoid spreading of COVID-19," *International Journal of Intelligent Networks*, vol. 1, pp. 32-35, 2020.

[19] S. E. Snyder and G. Husari, "Thor: A deep learning approach for face mask detection to prevent the COVID-19 pandemic," in *Proc. SoutheastCon*, 2021, pp. 1-8.

[20] S. Singh, U. Ahuja, M. Kumar, *et al.*, "Face mask detection using YOLOv3 and faster R-CNN models: COVID-19 environment," *Multimedia Tools and Applications*, vol. 80, no. 13, pp. 19753-19768, 2021.

[21] B. Batagelj, P. Peer, V. Struc, *et al.*, "How to correctly detect face-masks for COVID-19 from visual information?" *Applied Sciences*, vol. 11, no. 5, p. 2070, 2021.

[22] MAFA (MAsked FAces) – CKAN. [Online]. Available: http://221.228.208.243/ne/dataset/0b33a2ece1f549b18c7ff725fb50c561

[23] Wider face: A face detection benchmark. [Online]. Available: http://shuoyang1213.me/WIDERFACE/

[24] M. Loey, G. Manogaran, M. H. N. Taha, *et al.*, "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, p. 108288, 2021.

[25] X-zhangyang. Real-World masked face DatasetRMFD. [Online]. Available: https://github.com/X-zhangyang/

[26] A. Negi, K. Kumar, P. Chauhan, *et al.*, "Deep neural architecture for face mask detection on simulated masked face dataset against COVID-19 pandemic," in *Proc. International Conference on Computing, Communication, and Intelligent Systems*, 2021, pp. 595-600.

[27] A. Mashyal, B. Chougula, S. Kobal, *et al.*, "Facial mask detection and alert system," in *Proc. International Conference on Intelligent Technologies*, 2021, pp. 1-5.

[28] R. R. Mahurkar and N. G. Gadge, "Real-Time COVID-19 face mask detection with YOLOv4," in *Proc. Second International Conference on Electronics and Sustainable Communication Systems*, 2021, pp. 1250-1255.

[29] E. Longo, A. E. Redondi, M. Bianchini, *et al.*, "Smart gate: A modular system for occupancy and environmental monitoring of spaces," in *Proc. 5th International Conference on Smart and Sustainable Technologies*, 2020, pp. 1-6.

[30] M. Khayyat and R. Munshi, "Smartgate system: Automating the detection and control of COVID-19," in *Proc. 4th International Conference on Future Networks and Distributed Systems*, 2020, pp. 1-6.

[31] D. D. Putra, M. Febriyanto, M. M. Nadra, *et al.*, "Design of smart-gate based on artificial intelligence possibly for COVID-19 early prevention at public area," in *Proc. 14th International Conference on Telecommunication Systems, Services, and Applications*, 2020, pp. 1-4.

[32] What is a convolutional layer? [Online]. Available: https://databricks.com/glossary/convolutional-layer

[33] A. G. Howard, M. Zhu, B. Chen, *et al.*, "MobileNets: Efficient convolutional neural networks for mobile vision applications," arXiv:1704.04861, Apr. 2017.

[34] Ben. What is an Arduino? - learn.sparkfun.com. [Online]. Available: https://learn.sparkfun.com/tutorials/

[35] Arduino Uno for beginners - Projects, programming and parts (Tutorial). [Online]. Available: https://www.makerspaces.com/arduino-uno-tutorial-beginners/

[36] Wayback machine. [Online]. Available: https://web.archive.org/web/20180403132515

[37] Arduino Uno Rev3. [Online]. Available: https://store-usa.arduino.cc/products/arduino-uno-rev3

[38] M. Buonanno, D. Welch, I. Shuryak, *et al.*, "Far-UVC light (222 nm) efficiently and safely inactivates airborne human coronaviruses," *Scientific Reports*, vol. 10, no. 1, pp. 1-8, 2020.

[39] Image classification | TensorFlow Core. [Online]. Available: https://www.tensorflow.org/tutorials/ images/classification

[40] M. Sandler, A. Howard, M. Zhu, *et al.*, "MobileNetV2: Inverted residuals and linear bottlenecks," arXiv:1801.04381, Mar. 2019.

[41] P. Nagrath, R. Jain, A. Madan, *et al.*, "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, 2021.

[42] A. Cabani, K. Hammoudi, H. Benhabiles, *et al.*, "Maskedface-net – A dataset of correctly/incorrectly masked face images in the context of COVID-19," *Smart Health*, 2020.

[43] K. Hammoudi, A. Cabani, H. Benhabiles, *et al.*, "Validating the correct wearing of protection mask by taking a selfie: Design of a mobile application "CheckYourMask" to limit the spread of COVID-19," *Computer Modeling in Engineering & Sciences*, vol. 124, no. 3, pp. 1049-1059, 2020.

[44] Google colaboratory. [Online]. Available: https://colab.research.google.com

[45] TensorFlow. [Online]. Available: https://www.tensorflow.org/

[46] Module: tf.keras | TensorFlow Core v2.7.0. [Online]. Available: https://www.tensorflow.org/api docs/ python/tf/keras

[47] NumPy. [Online]. Available: https://numpy.org/

[48] Matplotlib: Python plotting — Matplotlib 3.4.3 documentation. [Online]. Available: https://matplotlib.org/

[49] M. R. Bhuiyan, S. A. Khushbu, and M. S. Islam, "A deep learning based assistive system to classify COVID-19 face mask for human safety with YOLOv3," in *Proc. 11th International Conference on Computing, Communication and Networking Technologies*, 2020, pp. 1-5.

[50] A. Oumina, N. E. Makhfi, and M. Hamdi, "Control the COVID-19 pandemic: Face mask detection using transfer learning," in *Proc. IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science*, Dec. 2020, pp. 1-5.

[51] M. Loey, G. Manogaran, M. H. N. Taha, *et al.*, "Fighting against COVID-19: A novel deep learning model based on YOLO-v2 with ResNet-50 for medical face mask detection," *Sustainable Cities and Society*, vol. 65, p. 102600, Feb. 2021.

[52] J. Zhang, F. Han, Y. Chun, *et al.*, "A novel detection framework about conditions of wearing face mask for helping control the spread of COVID-19," *IEEE Access*, vol. 9, pp. 42975-42984, 2021.

[53] What is precision in ml? [Online]. Available: https://askinglot.com/what-is-precision-in-ml

[54] Precision vs recall | Precision and recall machine learning. (Sep. 2020). [Online]. Available: https://www.analyticsvidhya.com/blog/2020/09/precision-recallmachine-learning/

[55] R. Agarwal. (Sep. 2020). The 5 classification evaluation metrics every data scientist must know. [Online]. Available: https://towardsdatascience.com/the5-classification-evaluation-metrics-you-must-know-aa97784ff226

[56] Storrea. T5 UVC ultraviolet light tube-30W. [Online]. Available: https://www.ipcctvbd.com/product/t5-uvc-ultraviolet-light-tube-30w

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