# A New Embedded Surveillance System for Reducing COVID-19 Outbreak in Elderly Based on Deep Learning and IoT

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***Abstract*— As a result of the fast spread of Coronavirus disease (COVID-19) throughout the world, it became urgent to evolve an aided-intelligent system to help healthcare organizations to control and early detect COVID-19 outbreak, especially after massive development in the computing. Artificial Intelligence and Deep Learning methods could introduce real assistance to many healthcare organizations in this global problem by monitoring, detecting, and reporting on infected persons in early-stage. As is well known, the elderly are most vulnerable to the effects of COVID-19, therefore, we aim through this paper is to present the embedded system has the ability to detect and report on the elderly in the endemic areas. An age estimation from a facial image based on deep learning methods and Internet of Things is also applied to send notification to mobile or any other device systems that the application is embedded on it based on IoT. Depending on the experimental results on the proposed system through the Mean Average Error rate, the proposed system gave better or equivalent to the results of the state-of-the-art techniques, and the prediction results of an average accuracy achieved 89.45%. Finally, the proposed system has the capacity to help reduce the intensity of spread COVID-19 by identified older people and prevent them from prohibited in dangerous areas.**

***Keywords*— *Age estimate, Deep Learning, convolutional neural networks, COVID-19, Internet of Things***

## I. INTRODUCTION

With the rapid growth in the number of COVID-19 casualties, the health system of several nations has reached to the collapse point. Several countries have announced the complete closure and invited its people to stay at home and avoid gatherings. In addition to that, some of the countries have issued instructions to prevent the elder from go out home [1].

Aged people above 60 are at higher risk of getting those infectious diseases, and affect them more than teen-agers, and death rate is higher among them because of their suppressed immune system [2], so that to control it we suggest a new smart security system to detect elderly people in public areas such as streets and markets. When any infectious disease develops in any environment, the serious threats are upon aged people (60 years and above).

Deep learning can just play an instrumental in reducing the prevalence of the COVID-19 through the use of their applications in diagnostic, treatment, and monitoring [3].

In the last years, the influence of rapid development in deep learning applications is beginning to appear in the human-life noticeably [4].

Deep Learning is a mixture of different Machine Learning techniques that essentially concentrate on the feature captures and classification of images, while it is successfully applied on many applications such as face recognition, age estimate, object detection, and in medical image analysis, segmentation, and classification [4].

The age estimation is utilized deep learning and machine learning algorithms to identify a person's age depend on features obtained from the face image. As a notable characteristic of the face, age estimation has brought significant attention due to its applications that possibilities of being used in Human-Computer Interaction [5], surveillance monitoring [6], and other applications.

In general, the main stages of the face age estimation system include face detection, face alignment, pre-processing, feature extraction, and estimation as well as to other secondary stages. Features extracted can be considered as one of the most important stages that have a significant influence on the functioning of age estimation systems. Therefore, many age feature extraction techniques have been suggested to describe the shape and the texture feature of the face [7].

Geometric features are sensitive to pose differences and it is not enough for age estimation in adults. Accordingly, appearance models have been suggested to extract the texture features of the face as well as to its geometric [8]. Also, Global and local methods have been applied to represent the texture and shape of the face image [9]. These involve Biologically Inspired Features [10], and Active Appearance Models [11].

Over the past five years, deep convolutional neural networks (CNNs) played impressively in face age estimates.They have exceeded classical classification and regression methods and also, they have even exceeded human performance on some of the factors [12]. Amongst various kinds of deep learning architectures that introduce a solution for machine learning problems depending on using of large datasets, convolutional neural networks (CNN)

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have been shown big success through their proficiency at capturing the important features of images [13].

A number of studies included using deep learning methods in face age estimation application, Gunay et al. [14] introduced a local binary pattern (LBP) method for age estimation and got relatively good results. Zhifeng Li [15] introduced a hierarchical learning model depended on the local pattern selection method to predict the age from the face image. Lanitis et al. [16] suggested Active Appearance Model to face age estimation. It is used AAM features, a quadratic regression function for age estimation. Liu et al. [17] introduced a face age estimation based on a deep feature learning method. Rothe et al. [18] used deep CNNs for age classification. Each of the VGG-16 architecture and IMDBWIKI datasets are used in this work.

The major contributions of this work could be summarized as follows:

1- In this work, we proposed smart embedded system rely on deep learning and internet of things to introduce an intelligent surveillance system to help the health care organization during the COVID-19 pandemic.

2- Pre-trained deep CNN is proposed to resolve the problem of age estimate problems rely on face images and this model improved by using face alignment.

3- This system is connected to the internet, which works by detecting any aged person, then directly the notification will be sent to mobile or any other device systems that the application is embedded on it based on IoT.

This paper is summarized as follows: In Section 1, an introduction in addition to a short survey of related work is presented. In Section 2, the structure of the system, and the suggested approaches are explained. In section 3, the audience benchmark dataset explained. Experimental results are displayed in Section 4. Finally, in Section 5, the paper is concluded with a short discussion.

## II. SYSTEM STRUCTURE

The effective use of deep learning in the computer vision field has enhanced the results significantly, leading to growing interest in the use of deep learning in computer vision and related fields such as Image processing and pattern recognition. The proposed system consists of six stage process.

The stages are summarized as the following: Firstly, face detection is applied to localize faces in the input video streams. Secondly, the face alignment and extract of Interest (ROI) of face Region are applied, and then, the deep learning model age detectors is used to determine the age of the person that detected in the first stage. Finally, the age is estimated depending on the results from stage 2 and stage 3. If a person is equal or more than 60 years old, the warning message will be sent through IoT system. The architecture of the system is displayed in the Fig. 1.

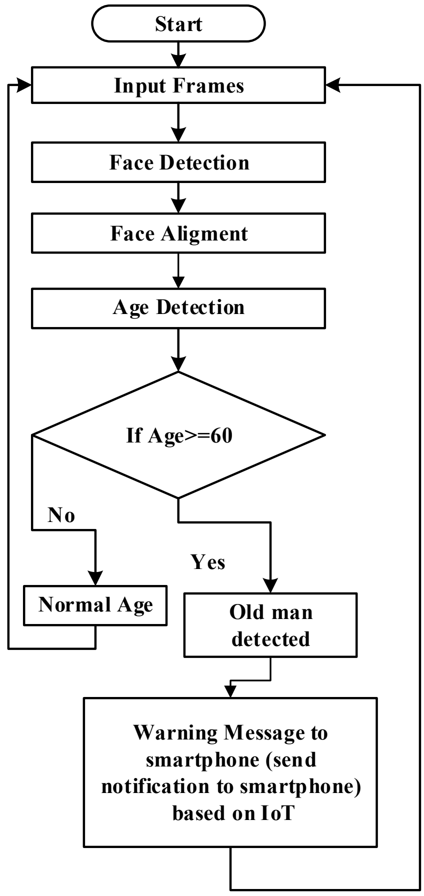


**Fig.1.** The system architecture

### A. *Face Detection*

The first phase of the proposal system is face detection. The early traditional methods of face detection had based on classical machine learning algorithms. One of the successful face detection system method introduced by Viola and Jones.

The original Viola Jones [19] detector utilized Haar-like features. This provided a fast response to detect the face in the image but at the same time, it failed in detecting faces from various angles. With the significant evolution of deep learning, most works in the area of face detection are headed to use a deep learning model.

In this work, deep learning based face detector is used. This model relied on Single Shot Multibox detector [19] and applies ResNet-10 Architecture as the backbone.

The SSD approach relies on a feed-forward convolutional network that generates fixed-size groups of bounding boxes and scores for the presence of object class instances in those boxes, subsequent by a non-maximum suppression stage to generate the last detections. The SSD network architecture is shown in Fig. 2.

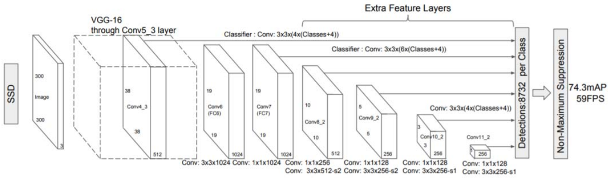


**Fig. 2.** The SSD network architecture[19]

### B. Face Alignment

Facial alignment is the second stage of the system. It is a normalization method, usually applied to enhance the accuracy and achieved better results of the face age estimation system. The aim of this stage is to center and rotate of the image to become the eyes on a horizontal line and scale the resize of the face image to become identical. The Fig. 3 shows an example about face alignment process.

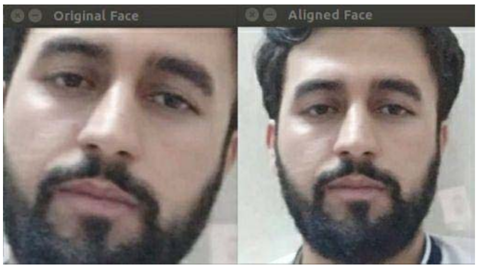


**Fig. 3.** The image before and after face aligning.

Several methods attempt to use a pre-defined 3D model and then implement a transform to the input image so that the feature on the input face agrees with the features on the 3D model. On the other hand, there are methods that use more simple techniques based on the facial features themselves to get a normalized rotation, translation, and scale representation of the face. The Fig. 4 below shows the eyes detector output.

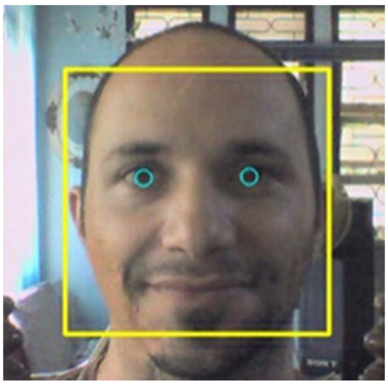

**Fig.4.** Face and Eyes Detector.

In this work, the facial alignment stage is based on determining the coordinates of the eyes. Using eye detection technique as the method for alignment. The face in the image is a practical and helpful way because the eyes of the person in the frontal view are horizontal and on opposite locations of the face and have a somewhat standard location and size within a face, notwithstanding variations in facial expressions, the eye open or close, lighting conditions, camera properties, the distance between the camera and the person in addition to other conditions.

### C. Neural Network Architecture

The network architecture model implemented by [20] is applied in this proposed system. The network is composed of three convolutional layers in addition to two fully-connected layers along accompanied by a small amount of neurons. Fig. 5. Shows the main stages of CNN architecture model for age estimation.

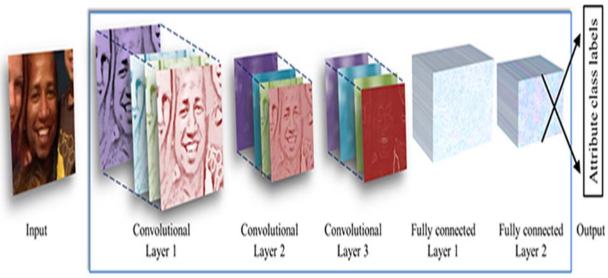


**Fig. 5.** Main stages of CNN architecture model for age estimation [20].

The three-color channels (red, green, and blue) are handled straightway via the network. All input images will be resized to 256 x 256 pixels and cropped to 227 x 227 pixels before fed to the network. After that, the subsequent convolutional layers of the network are made known as follows:

1. In the first layer, the cropped input image will be fed to 96 filters of size 3x7x7 pixels. This step followed by a rectified linear unit and a pooling layer. This consumed by the maximum value of 3 x 3 regions with 2 x 2-pixel strides and a local response normalization layer.
2. In the second layer, 256 filters made up of 96x5x5 pixels are used to process the output image of the first layer. This steep also will be followed by each of ReLU, a pooling layer, and a response normalization layer with the same hyperparameters that used in the first layer.
3. In the final two convolutional layers, 384 filters of size 256x3x3 pixels are used to processed the input image from the previous layer followed by a ReLU and a pooling layer. After that, the convolutional layers are followed by two fully connected layers
4. A first fully connected layer consists of 512 neurons in addition to a dropout layer.
5. The 512- dimensional output of the first fully connected layer, is fed into the second, which is consists of 512 neurons, followed by a ReLU and a dropout layer.
6. Finally, the output of the third fully connected layer, which maps to the final categorizing for age, is received by a softmax layer to assigns a probability for each class.

### D. Telebot API

The Telegram Bot API is an HTTP-based interface made for developers keen on building bots for Telegram. Bots are third party applications that running inside Telegram. A bot may be turned into smart newspaper, any published relevant content will send to the client instantly it's possible. Furthermore, by external services content a bot can enhance Telegram chats easily such as Image Bot, Gif Bot, Music Bot, etc. TeleBots are special accounts at the core that for setting up no telephone number has required ever.

Newbot command can be utilized for creating a new bot. username and name will be asked by the Bot Father, then a mandate token for new bot will be created. In contact details, the name of bot is displayed. The username is a short name; to be utilized as a part of notice and note that the username is saved in database inside the Telegram application, and it is necessary have in no case been utilized before.

Token is a combination of capital and small letters, and numbers for example, token maybe generated like this: 122001443:ABHdqTcdCh1vGWJxfWesfSAs0K4FQLD saw that is needed to approve the bot and send demands to the TeleBot API. Fig. 6 demonstrate the bot has been made and BotFather reveals to you token.

For utilizing a Telegram Bot API with a Jetson TX2 platform only require to install the python TeleBot API library. For doing this we can utilize the command pip install python-telegram-bot from the shell. After this library had installed it can be utilized in our scripts. Telegram bot APIs are being utilized in our system only for that message could be send from Jetson TX2 to our smart phone.

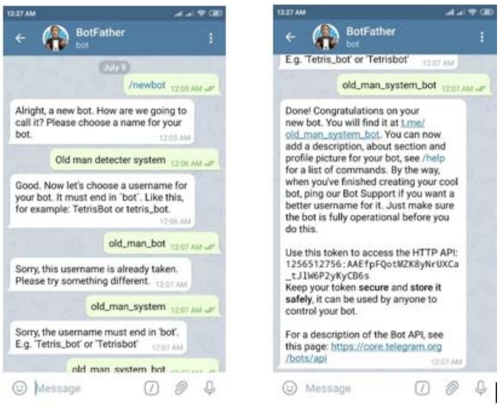


**Fig. 6.** Created boot and display tokens

## III. ADIENCE BENCHMARK DATASET

To evaluate the performance of the proposed system, the dataset Adience Benchmark [21] is used. The dataset contains 26, 000 face images from 2284 individuals. The images of this database captured in a real-life and unconstrained environment. It involves all the differences in appearance, noise, pose, lighting conditions, in addition to other conditions. Fig. 7 show sample of 3 Adience database.

**Fig. 7** Sample of Adience database

The dataset is classified into eight age class: {[0, 2], [4, 6], [8, 13], [15, 20], [25, 32], [38, 43], [48, 53], [60, -]}. Table 1 displays the categorization the database into a collection of age groups.

TABLE I. CATEGORIZATION THE DATASET

| Type | 0-2 | 4-6 | 8-13 | 15-20 | 25-32 | 38-43 | 48-53 | 60- | Total |
|---|---|---|---|---|---|---|---|---|---|
| Male | 745 | 928 | 934 | 734 | 2308 | 1294 | 392 | 442 | 8192 |
| Female | 682 | 1234 | 1360 | 919 | 2589 | 1056 | 433 | 427 | 9411 |
| Both | 1427 | 2162 | 2294 | 1653 | 4897 | 2350 | 825 | 869 | 19487 |

## IV. EXPERIMENTAL RESULTS

The recommended system is prepared for old man detection in real-time by utilizing computer vision and deep learning methods. The python libraries are used to apply the proposed system as a programing language. NVidia Jetson TX2 card was used as an embedded platform for real-time realization of the proposed deep learning algorithm in this study. An experimental environment has been created to make applications on this card. In this experiment environment, a screen, wireless keyboard and mouse are connected to the NVidia Jetson TX2 card. The established real-time system is given in the image in Fig. 8.

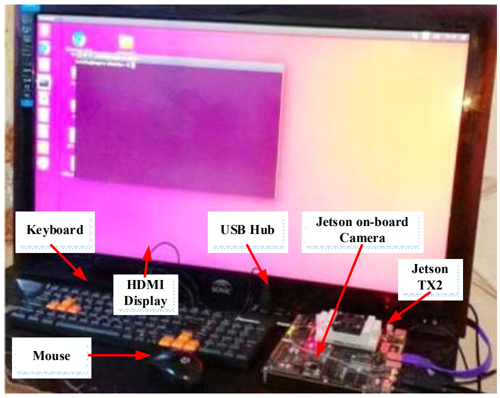


**Fig. 8.** Experimental setup

Smartphone application has been integrated with the existed system to develop a smart security system based on age detection to detect elderly people for a personal area. An embedded platform successfully grab the images when the system detects any old man and send it to smartphone with notifications by using IoT.

The algorithm has been applied to all the frames and the system detects the faces in the grabbed frames. The face detection is done by help of deep learning model and age prediction is done by help of deep learning model.

The proposed system implements four process which are capturing frames, face detection and extract ROI of each faces, face alignment and identify the age of the persons with sending old man images as alert and notifications to the user's smartphone if a person is more than 60 years old. The IoT will be activated only when an old man is detected.

Jetson TX2 has a Wi-Fi wireless that is beneficial to see the activity and show old man pictures promptly on the smartphone application “Telegram” when the system detect an old man as shown in Fig. 9. The output images and notifications that received on the smartphone applications are showed in Fig. 10.


**Fig. 9.** Screenshot of warning messages on the smartphone

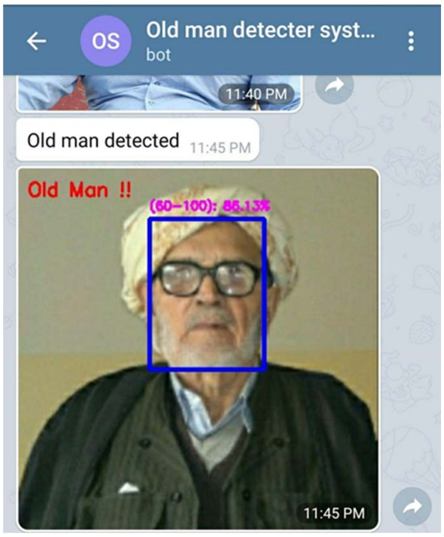


**Fig. 10.** Old man detection image and notification on IoT API

The algorithm detects and predict the age of each faces successfully. If 98 face detects, the system will notify old man detected as appearing in Fig. 9. Furthermore, the algorithm detects and predict age for another face without sending warning message to the smartphone as appeared in Fig. 11.

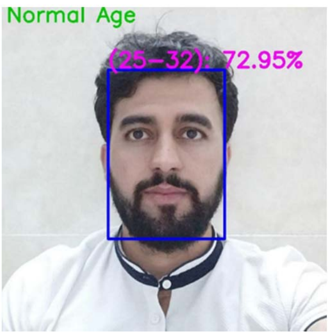


**Fig. 11.** The output of the algorithm for normal face (non-old man)

As shown in the above figure, the proposed system has correctly predicted age to be 25-32 with 72.95 % confidence. The actual age is 28 years old in the above face.

Age detection system isn't always exact, as appeared in Figure 12. In the figure, recommended age detector system is wrong, the given face is 45 years old, making proposed system off by nearly 13 years.

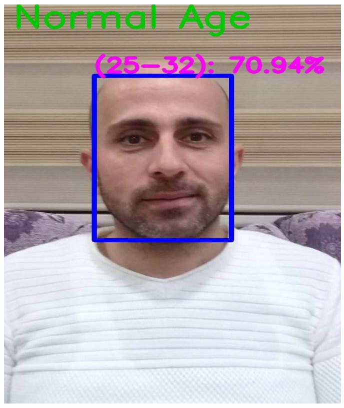


**Fig. 12.** The output of the algorithm for normal face (non-old man)

The process of visual age detection is tough since if we look at the above face, actually look to be approximately 35 years old. Indeed, he doesn't look such a guy in his early 45s. To estimate the age, you cannot trust the actual age of the person. Instead, you should measure the accuracy among the predicted age and the perceived age. Estimating age is a difficult problem. Factors that determine the cause of this, including smoking habits, lifestyle, work and genetics. If a human is struggling to guess exactly someone's age, then definitely a machine will struggle too. These show that many of the errors made by age detection systems are due to extremely challenging seeing above circumstances.

In this paper, a pre-trained deep learning model is used to detect old man people. Furthermore, we improved this age prediction model by using face alignment technique to input frames that can achieve more accuracy. Also, by using a set of input frames, we compared the accuracy of the model without using face alignment algorithm with the proposed system by using face alignment algorithm as appeared in TableII.

TABLE II. ACCURACY COMPARISON FOR PROPOSED METHOD

| Method | Accuracy |
|---|---|
| Pre-Trained Model | 84.7% |
| Proposed Method | 89.45 % |

The proposed system able to automatically predict age with reasonably high accuracy. The face alignment algorithm achieved good results and ensured that better than the pre-trained model. The face alignment technique detects the geometric structure of faces and then tries to observe a canonical alignment of the face based on rotation, scale, and translation. In several situations, face alignment technique can enhance the results of face applications, including age prediction and face recognition. Moreover, we can enhance the accuracy of age detection systems by using additional training data and apply more data augmentation techniques during the training stage.

Since the proposed system is an embedded system, we compared the speed of the system by using Jetson TX2 with Raspberry Pi3. The proposed method consists of loading two deep learning models that face detector and age detector models. Jetson TX2 platform can achieve a reasonable speed that is ~10.4 frames per second (FPS) as appeared in Table III. Conversely, Raspberry Pi3platform can't obtain a reasonable speed to operate the proposed system. As indicated, a Jetson TX2 is 6.5 times faster than Raspberry Pi3.

TABLE III. SPEED COMPARISON OF EMBEDDED PLATFORMS

| Embedded Platform | Frames Per Second (FPS) |
|---|---|
| Jetson TX2 | ~ 10.4 |
| Raspberry Pi3 | ~ 1.6 |

## V. CONCLUSION

In this work, Embedded Surveillance System was presented to help in reducing COVID-19 Outbreak by detecting the elderly which are more affected by this disease, in the endemic areas. An age estimation used to determine the age of the person. An enhancement age estimation method was applied to enhance the results of pre-trained deep networks by utilizing face alignment. Then Internet of Things is used to send a notification to mobile or any other device systems to refer to the presence of the elderly in the area. The proposal system was evaluated using a public database and the obtained results show that the system gave a satisfactory performance. In addition to that, the accuracy of the proposed system is compared using two types of comparisons. In the first one, the enhancement deep learning model rely on face alignment and pre-trained deep networks is implemented. The obtained results showed that the combination of face alignment and pre-trained deep networks proven age estimation performance. Furthermore, the proposal system implemented using two kinds of hardware and comparison between them is done.

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