International Journal of Engineering Trends and Technology Volume 69 Issue 10, 33-37, October, 2021
ISSN: 2231 – 5381 /doi:10.14445/22315381/IJETT-V69I10P205 ©2021 Seventh Sense Research Group®

CNN Applied In Public Transport For The Protection Against The Covid-19 Spread

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Abstract — *With the Coronavirus becoming a huge threat, the world is experiencing a very uncertain situation. In Morocco, especially after confinement, the number of cases has increased dramatically; this sudden increase is due to several factors, including public transport. This is where our project derives its interest, because thanks to the many alternatives it offers, it reduces the risk of contamination, which makes it possible to reduce the cases of illnesses linked to Covid-19 as well as to reduce the rate of accidents. To achieve our goal, the transport will be equipped with new technologies boosted by artificial intelligence and other tools, a passenger so that he can board the bus must be wearing a facial mask detected through an artificial intelligence-based mask detector. Covid-19 not only affects the physical health of the person, but it has a major impact on mental health, especially for drivers who are more involved to be infected by the virus. For this, there is an emotion recognition system based on AI and social intelligence that detects the emotions of the driver and generates actions that correct, regulate and stabilize their emotional state. A deep learning algorithm has been applied, and an accuracy rate of 91.23% was found in CNN with only 300 epochs.*

Keywords — *Covid-19, Artificial Intelligence, Emotional Recognition, Social Intelligence, Deep Learning*.

I. INTRODUCTION

2020 saw a historic upheaval with the onset of the COVID-19 pandemic. On November 17, 2019, the planet experienced the virus's spread caused by the coronavirus-SARS-CoV-2. The beginning of this pandemic was recorded in China to quickly touch all the countries of the world what made stopping this pandemic necessary for the continuity of humanity. This is pushing the researchers of entire nations to start the process of finding solutions, whether medical, psychological, or even technical.

Several researchers have studied artificial intelligence to protect people against the spread of Covid-19. Jamshidi et al. [1] have focused on Emerging Deep Learning Theories and Methods for Diagnosis and Treatment of COVID-19, which leads them to construct an AI-based platform to hasten the diagnosis and treatment of COVID-19 disease. Asad et al. [2] take charge to supervise everyday train passengers between the ages of 16 and 59, as well as those over 60 (vulnerable age groups), with recommendations for specific travel times and routes. In order to protect the people against the spread of covid-19. By classifying mobility prediction of different age groups, this study offered simulation results for daily train travelers in order to get ML-driven classification accuracy, precision, recall, and F-measure scores. With an overall classification accuracy of 86.43 percent and 81.96 percent in the age groups 16-59 years and over 60 years, the SVM classifier surpassed all other five classifiers. Laguarta et al. [3] have examined the construction way of an AI speech processing system that uses acoustic biomarker feature extractors to pre-screen cough recordings for COVID-19 and give a personalized patient saliency map to longitudinally monitor patients in real-time, non-invasively, and at nearly zero variable cost.

Some works have exploited IoT to detect people infected with Covid-19. Ashraf et al. [4] developed a smart edge surveillance system that is effective in remote monitoring, advance warning, and detection of a person's fever, heart rate, cardiac conditions, and some of the radiological features to detect the infected (suspicious) person using wearable smart gadgets using Artificial Intelligence, big data analytics, and the Internet of Things. They have developed a model that can assist detect and track contagious individuals. Edge computing will be used to analyze and make decisions based on the patient's data.

Convolutional Neural Network (CNN) is the current trend for using deep machine learning in Computer-Vision. Other studies have deployed CNN to detect the persons wearing masks in public places [5]. In other aspects, researchers have used CNN to assess people's emotions in social media during Covid-19 [6].

The following is a breakdown of the paper's structure. The first section describes the methodologies and tools used, as well as the experiments that were conducted. The results are presented and discussed in the second section. The findings are summarized, and conclusions are presented in the final section.

II. RESEARCH METHOD

The system englobes two main sub-systems. Each one focuses on a specified type of transport user, and we have the Driver Sub-system that helps the driver cheer up and stabilizes his psychological state depending on each emotion he acquires through time. The other one is the Passenger Sub-system that prevents and minimizes the danger of the spread of COVID-19 in transport by supervising the face mask of each passenger. The system classification is in Figure1.

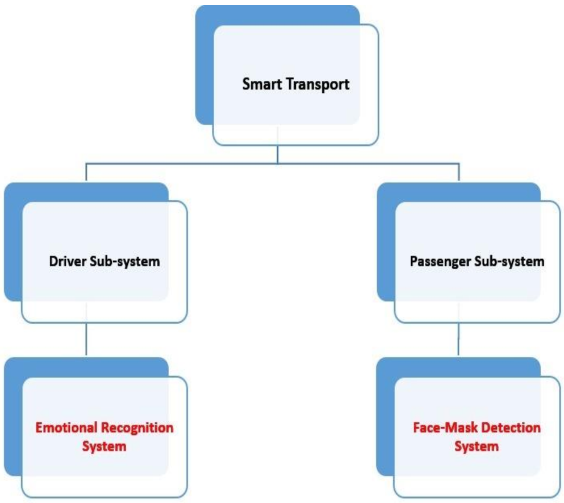

Fig 1: Smart transport

A. Dataset

Most of the images used on this test are taken from the FER2013 database [7], the resolution of the images is stored as 48x48 pixel, the total number of images used are 31 424, tested on 28 910 and validated on 2514 samples as figured in Table 1.

TABLE I. Emotion Dataset

Emotion	Resolution	Tested on	Validated on	Total
Angry	48x48	4564	397	4961
Happy	48x48	8322	724	9046
Sad	48x48	5593	486	6079
Neutral	48x48	5720	497	6217
Fear	48x48	4711	410	5121

The dataset of face mask detector is built of "with mask" and "without mask" images [8], the data consists of 224x224 pixel images, the total number of images used are 1485, tested on 1224 and validated on 261 samples as figured in Table 2.

TABLE II. Mask Dataset

State	Resolution	Tested on	Validated on	Total
With mask	224x224	614	131	745
Without mask	224x224	610	130	740

B. Driver sub-system

The process of this sub-system is the recognition of the most dominant emotion of the driver every 30s (the user can change this value as required); it can be Sadness, Anger, Fear, or Happiness. The choice of these emotions is based on researches done on how COVID-19 shaped the psychological thinking of people. Each of the aforementioned emotions has its own workflow. Figure 2 depicts the whole workflow of the subsystem.

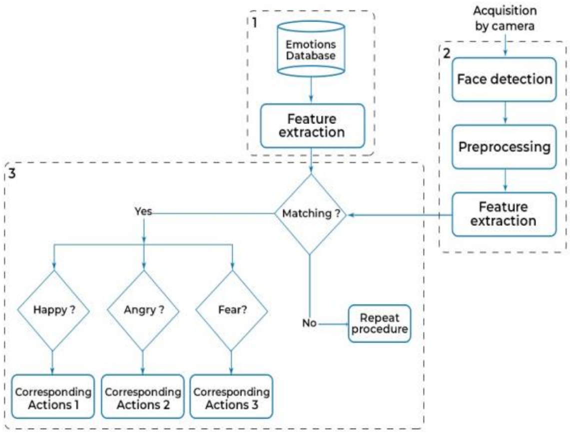

Fig 2: Data flow diagram

The first portion of the diagram illustrates a database in which images of people with various emotions will be sent into feature extraction, from which our algorithm will extract some helpful features to identify emotions.

The second section shows how our camera will be used as an input and delivered to a face identification algorithm to detect the driver's face using the Haarcascade classifier. The image of the captured face will be sent for preprocessing, which will include scaling the image, applying filters, and removing undesired noise. This part's output will be forwarded to feature extraction, which will extract features that will be used to match the features of the emotions in the database

The matching procedure is the third step. The features of the emotions in the camera-captured image of the driver will be compared to features contained in the emotions database. The system will generate a probability of each pre-defined emotion, and the emotion with the highest probability will be the one to apply its actions. If not, then the process will be repeated.

C. Passenger sub-system

The process of this sub-system is the detection of whether the passenger has his mask put on correctly or not. However, we define whether the passenger is allowed to step in the transport or not. Figure 3 depicts the whole workflow of the subsystem.

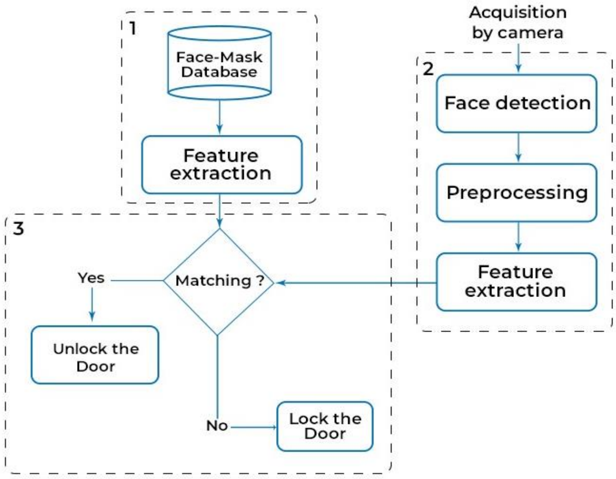

Fig 3: Data flow diagram

The diagram's initial section represents a database where the photos of different people with masks put on and off will be sent into a feature extraction algorithm, which will extract some valuable features used by our algorithm to identify the state of the mask.

The second portion shows how our camera will be used as an input and transmitted to a face detection algorithm, which will use the Haarcascade classifier to recognize the passenger's face. The image of the captured face will be sent for preprocessing, which will include scaling the image, applying filters, and removing undesired noise. This part's output will be sent for feature extraction, which will be used to match the database's features.

The matching procedure is the third step. The features in the image of the passenger captured by the camera will be compared to features in the face-mask database for a match. The system will generate a probability of how correct the mask is put on, and the output with the highest probability will be the one to apply its actions. If not, then the process will be remaining locked.

III. RESULTS AND DISCUSSION

In this section, we will discuss the results of the two proposed models, the first one concerns emotions detection, and the second one concerns the face mask detector. The results discussion will be given in two main sub-chapters.

A. *Emotion Experiment*

To recognize the face expression, we have developed the model shown in figure 4; the data input of the model is the normalized pixels that have been realized by the pixels extracted from the resized image. Our model is composed of three convolution layers of 2 dimensions. Each one is activated by the ReLU function. After that, the number of pixels is reduced by MaxPooling in order to explore the necessary parameters. The second part of our model is the fully connected neural network, which is based on a dense Layer in order to deeply connect all neurons; this layer is activated by the Softmax function to categorize the face expression.

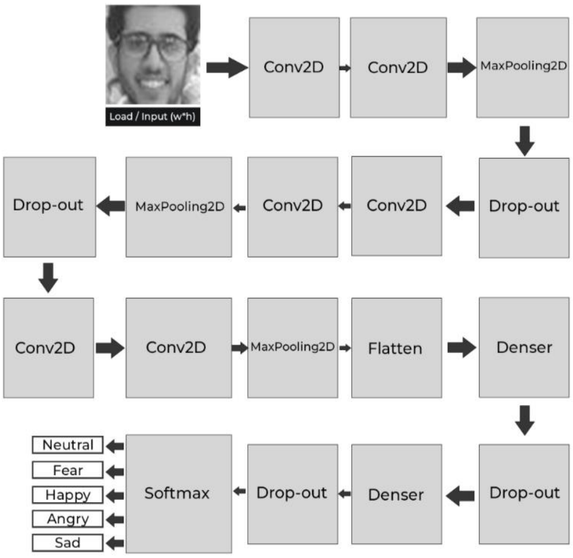

Fig 4: CNN architecture

To obtain the best accuracy of our model, we have changed the value of hyper-parameters and check out if our model increments its accuracy. Table 3 resumes the final hyper-parameters that we have chosen for our model.

TABLE III. Hyper-parameters

Hyper-parameters	Value
Number of filters of the 1st convolution layer	64
Number of filters of the 2nd convolution layer	64
Number of filters of the 3rd convolution layer	128
Number of filters of the fully connected neural networks	1024
Pool size	(2,2)
Optimizer	Adam
Loss function	categorical_crossentropy
Batch size	64
Epochs	300

In the results, we recorded the loss along with accuracy to highlight the model's accuracy for the training data. Figure 5 displays the loss and accuracy of the datasets for 300 epochs. It is observed that the suggested CNNs exhibit good accuracy from 150 epochs. Our model shows good stability and high accuracy, comparing to other works, as mentioned in table 4.

Fig 5: Training Loss and Accuracy in terms of Epoch's size

Emotional recognition algorithms have evolved in these past years, and each model based on Neural Networks and Convolutional Neural Networks gives better accuracy based on the number of emotions in the dataset. Also, based on the parameters guiding the architecture, such as the number of layers, the number of neurons per layer, the number of training iterations, and the list go on. The reason why we proposed a CNN with a huge amount of dataset and with compatible parameters is in order to deliver an accuracy of 91,23%.

TABLE IV. Results and Comparison

Method	Published	Type	Accuracy
Mel frequency cepstral coefficients (MFCC)	Year-2015 [9]	Hidden Markov Model tool kit (HTK)	68%
Neural Networks	Year-2018 [10]	Deep Learning Methods	Sad 78.54% Surprise 93.26% Happy 95.25% Anger 91.22% Disgust 84.32% Fear 82.58%
Convolutional Neural Networks (CNN)	Year-2018 [11]	Deep Learning Methods	60.03%
Convolutional Neural Networks (CNN)	Year-2019 [12]	Deep Learning Methods	70%
Convolutional Neural Networks (CNN)	Year-2019 [13]	Deep Learning Methods	Angry 95% Happy 93% Sad 91% Neutral 85% Surprise 45% Fear 75%
Support Vector Machine (SVM)	Year-2020 [14]	Supervised learning Methods	91%
Convolutional Neural Networks (CNN)	Proposed	Deep Learning Methods	91.23%

B. *Face Mask Experiment*

For this model, we have replaced the classical CNN with a MobileNetV2 architecture to optimize the number of operations so that we can have an efficient model for embedded vision applications. After loading the pixels of the image into the model, we apply an AvegragePooling2D, then come to the Flatten layer that makes the output linear to pass it through the dense layer, and right after that, we apply the Drop-out technique to select neurons randomly and ignore them during training to prevent over-fitting, and finally, comes the Softmax function for the classification of the result into 'mask detected' or 'mask not detected'.

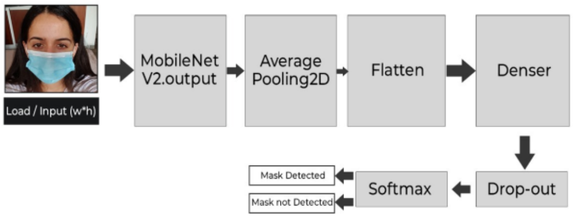

Fig 6: CNN architecture

For this model, we have checked out the value of hyper-parameters that allows having the most excellent accuracy, the final hyper-parameters which help to obtain the finest accuracy are shown in table 5 below.

TABLE V. Hyper-parameters

Hyper-parameter	Value
Number of filters of all convolution layers	32
Pool size	(7,7)
Optimizer	Adam
Loss function	binary_crossentropy
Batch size	32
Epochs	50

In the results, we recorded the loss along with accuracy to highlight the model's accuracy for the training data. Figure 7 displays the loss and accuracy of the datasets for 300 epochs. It is observed that the suggested CNNs exhibit good accuracy from 150 epochs. Our model shows good stability and high accuracy, comparing to other works as mentioned in table 6.

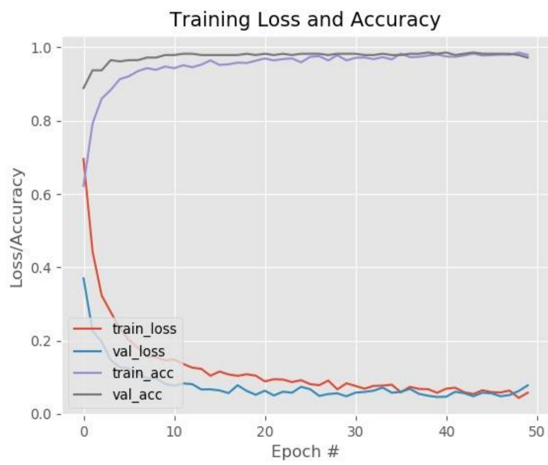

Fig 7: Training Loss and Accuracy in terms of Epoch's size

The methods used in this type of classification are based on Deep Learning methods. As YoloV3 is defined as a clever CNN that is applied for object detection in real-time, and its recognition rate for face-mask detection is estimated to be 96%. CCTV cameras made it even more accurate to detect face-masks with a recognition rate of 98,7%. We proposed a MobileNetV2 model that delivered a recognition rate of 97,96%, close to the CCTV method.

TABLE VI. Results and Comparison

Method	Published	Type	Recognition rate
YOLOv3	15 October 2020 [15]	Deep Learning Mehods	96% (4000 epochs)
Closed-Circuit Television (CCTV) cameras	08 October 2020 [16]	Deep Learning Methods	98.7% (100 epochs)
R-CNN model	29 October 2020 [17]	Deep Learning Methods	96%
The lightweight backbone network for face masks detection based on SSD and spatial separable convolution and Feature Enhancement Module (FEM)	30 November 2020 [18]	Deep Learning Methods	88.7%
RetinaNet Model	09 November 2020 [19]	Deep Learning Methods	81.31%
MTCNN face detection model	03 November 2020 [20]	Deep Learning Methods	81.74%
VGG-16 model	03 November 2020 [21]	Deep Learning Methods	97%
MobileNetV2 model	Proposed	Deep Learning Methods	97.96%

IV. CONCLUSION

In This proposed paper, we have developed two sub-systems to combat the rapid spread of covid-19 in public transport and to make drivers more comfortable by improving their emotions.

An emotional recognition system that detects the driver's most dominant emotion in real-time and the choice of these emotions is based on researches done on how COVID-19 shaped the psychological thinking of people. By using the current trend for deep learning in Computer-Vision, the Convolutional Neural Network (CNN), our system rich an important rate of accuracy (91.23%) with only 300 epochs. For passengers, we have developed a face mask detection system to define whether the passenger is allowed to step in the transport or not. The MobileNetV2 model method based on deep learning gives us an unprecedented recognition rate (97.96%) during 50 epochs.

For future improvement, this work will be enriched by other sub-systems:

• Heartbeat sensor in the steering wheel to analyze the heartbeats of the conductor.

• Speech recognition to define the emotion of the driver by speech treatment.

All these systems will be integrated on FPGA to guarantee a real-time application, hardware acceleration, and parallel data processing.

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