Intelligent and secure real-time auto-stop car system using deep-learning models

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Abstract *– In this study, we introduce an innovative auto-stop car system empowered by deep learning technology, specifically employing two Convolutional Neural Networks (CNNs) for face recognition and travel drowsiness detection. Implemented on a Raspberry Pi 4, our system is designed to cater exclusively to certified drivers, ensuring enhanced safety through intelligent features. The face recognition CNN model accurately identifies authorized drivers, employing deep learning techniques to verify their identity before granting access to vehicle functions. This first model demonstrates a remarkable accuracy rate of 99.1%, surpassing existing solutions in secure driver authentication. Simultaneously, our second CNN focuses on real-time detecting+ of driver drowsiness, monitoring eye movements, and utilizing a touch sensor on the steering wheel. Upon detecting signs of drowsiness, the system issues an immediate alert through a speaker, initiating an emergency park and sending a distress message via Global Positioning System (GPS). The successful implementation of our proposed system on the Raspberry Pi 4, integrated with a real-time monitoring camera, attains an impressive accuracy of 99.1% for both deep learning models. This performance surpasses current industry benchmarks, showcasing the efficacy and reliability of our solution. Our auto-stop car system advances user convenience and establishes unparalleled safety standards, marking a significant stride in autonomous vehicle technology.*

Keywords*: auto-stop car system, CNN, deep learning, drowsiness recognition, face recognition*

1. INTRODUCTION

Many incidents, such as robberies and unexpectedly unwanted entrances, happen now. Security is therefore important in this day and age [1]. People are constantly preoccupied with daily activities in a safe, including private properties, houses, and cars [2, 3]. To access traditional systems, a user needs to identify himself using different ways, such as passwords, and intelligent cards. These security measures have certain flaws; for instance, they are susceptible to forgetfulness and theft by unauthorized parties. As a result, software that ensures a better security level is needed to be developed. Our brain's capacity to solely think in images rather than words is one of its distinctive qualities [4, 5]. You might once forget where you put your car key, but you have never forgotten to bring a face with you. Each individual's face is different and the most essential portion of the body, Thus, it can represent various feelings, including identification and weariness. It also reflects the emotional effects and the sleeping or drowsiness of people. The facial expression can explain the fatigue problem in people as well as the other indicators, including vital parameters. In the driving mode of people, different vital parameters can be measured, such as heart rate, fever, eye activities, and visual activities, such as listening and speaking. Moreover, biometrics are also can be considered. This is done using sensors to measure movement, touch, availability, and so on. These biometric approaches have high detection accuracy, but they need more installation efforts to obtain the necessary measures. As a result, they are more challenging to implement in the real world than contactless methods [6, 7]. Because of this, most research in the field concentrates on non-intrusive detection techniques based on the driver's behavior to identify driver weariness or distraction. These non-intrusive techniques employ embedded sensors in various locations throughout the car to track steering wheel movement, lane deviation, and steering wheel angle. Due to the road, driving conditions are variable, the real-time systems with regular updating are necessary [8].

This paper presents a novel and intelligent car auto-stop system designed to enhance driver safety during vehicle operations. Leveraging state-of-the-art CNN-deep learning algorithms, our system integrates face and drowsiness-based eye recognition models to identify and monitor the driver's identity and alertness in real time. A key innovation of our approach is the seamless combination of these models within the proposed car auto-stop system, which is designed to activate a stop mode when the system detects that the driver is unconscious.

The implementation is carried out on a Raspberry Pi 4, utilizing a camera for efficient face and eye activity detection. Additionally, the system incorporates a touch sensor and a speaker for enhanced interactivity. Notably, the face and drowsiness models are trained on meticulously collected datasets, resulting in impressive testing accuracy rates of 99.1% for both. This high accuracy underscores the robustness and reliability of our proposed system.

By addressing the critical aspects of driver identity verification and real-time drowsiness detection, our work contributes significantly to intelligent transportation systems. The seamless integration of our models into a practical auto-stop system offers a tangible solution to enhance road safety by preventing potential accidents caused by unconscious driving. This paper serves as a valuable resource for researchers, practitioners, and policymakers interested in the intersection of deep learning, computer vision, and automotive safety.

2. RELATED WORK

The studied field was considered by several researchers around the world. In this section, we divided the related studies into two parts for simplicity. The recognition works for people's faces as well as emotional face gestures.

2.1. FACE RECOGNITION

The facial recognition system is a computer vision model designed to match a human face with a digital image or video frame. Facial detection or face verification poses a challenge in computer vision, and various real-time face detection applications exist. Subsequently, research efforts shifted towards developing a model that automatically detects human faces [9, 10].

In [11], the authors propose the Fisher face method, which stands out as one of the most widely used face recognition algorithms. Fisher Face utilizes Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) methods to extract image characteristics and identify faces based on the reduction in face space dimension. Fisher's face also demonstrates resistance to issues such as blurring and noise-induced image problems. The proposed system accuracy is 93%. In [12], the authors suggest that the memory constraints of embedded devices, owing to the complex structure of CNN, can be addressed by employing a Field Programmable Gate Array (FPGA) based accelerator for face feature extraction. This approach facilitates the acceleration of the entire CNN. Neural networks find applications in various fields, including healthcare, aerial picture categorization, and facial recognition. According to [13], the Raspberry Pi, a smart embedded device with a built-in camera capable of capturing images and videos, can detect motion using a motion detector sensor. The information detected can be transmitted to the administrator via the Wireless Fidelity (Wi-Fi) module of this advanced embedded device. The proposed system can detect any security threat with an accuracy of 95.5% and a precision of 91%. In [14], present research frameworks rely on extracting low-level features and representing mid-level features, but recent studies have prioritized utilizing deep learning models. Over the past decade to fifteen years, numerous distinctive algorithms for detecting human faces have been developed, and these algorithms find application in platforms like Facebook, WhatsApp, biometric verification, and autonomous vehicles. The highest accuracy achieved for Virtual Makeup (VMU), face recognition, and 14 celebrity datasets is 98%, 98.24%, 89.39%, and 95.71%, respectively.

2.2. DROWSINESS RECOGNITION

Using feature extraction-based algorithms, efforts in literature have been made to address the challenge of detecting weariness and sleepiness (drowsiness) [15]. The primary focus of these studies has been monitoring the driver's attention deficit. Techniques based on feature extraction, as indicated in [16] and [17], provided faster identification and lower computing complexity. However, they were more dependent on the quality of imaging and lighting. Recently, researchers have shifted their focus to driver face monitoring using deep learning, eliminating explicit feature extraction from raw images. When appropriately trained, machine learning algorithms exhibit high precision and reliability in identifying drowsiness.

In [18], the proposed work establishes a drowsy detection and accident avoidance system based on eye blink duration. Initially, the open and closed states of the eyes are detected using the Eye-Aspect Ratio (EAR). Subsequently, the blink duration or count during transitions from open to closed states is analyzed. The system identifies drowsiness when the blink duration exceeds a certain limit, sending an alert message to the driver through an alarm. The developed system demonstrated an accuracy of approximately 92.5%. In [19], the authors introduced volunteer eye-blinking as a Human-Computer Interaction (HCI), employing an advanced computer vision detector for real-time processing with a generic camera. Eye-blink detection was performed in addition to eye-state identification, involving face recognition, modeling, Region of Interest (ROI) extraction, and eye-state classification. The system included a rotation compensator, an ROI evaluator, and a moving average filter. Two additional datasets, the Youtube Eye-state Classification (YEC) dataset and the Analysis of Biological Data (ABD), were created, achieving an accuracy of 97.44% for the CNN and Support Vector Machine (SVM) on various datasets. In [20], eye-blinking-based drowsiness detection was implemented, analyzing eye-blink patterns. Custom data were used for model training, and real-time fluctuation representations of eye landmarks were measured using deep learning methods. Experimental analysis demonstrated a correlation between yawning and closed eyes, categorized as drowsy, with an overall performance of 95.8% accuracy for drowsy-eye detection and 0.84% for yawning detection. In [21], the authors initiated their work on drowsiness detection by detecting yawning. They proposed a three-step method using the "Face Boxes" face detector to locate the driver's face and a DNN model to classify the face and detect yawning. Deep Neural Networks (DNN) model was trained using a dataset obtained from the developed Drive Safely system, achieving an accuracy of 95.2%. In [22], a deep learning-based approach was presented for detecting driver drowsiness using CNNs. eye and yawning were used for detecting drowsiness, achieving an average accuracy of 96% on the Yawing Detection Dataset (YawDD).

Finally, in [23], a model for evaluating driver fatigue based on eye state and yawning. Utilizing CNN and Visual Geometry Group (Vgg16), the model detected facial sleepiness expressions classified into four categories (open, closed, yawning, and no yawning). Testing on a dataset of 2900 images resulted in high accountability, with the CNN model achieving an accuracy rate of 97%.

3. PROPOSED AUTO-STOP CAR SYSTEM

The proposed auto-stop car system performs two phases of jobs. The first phase identifies the driver, while the second phase monitors the driver's status if entering the drowsiness mode. In this case, the system performs the auto-stop for a car. This section is divided into subsections to ease the structure of the proposed system.

3.1. GENERAL STRUCTURE

This work utilizes two deep-learning models to recognize four individuals and monitor them while driving for the cause of drowsiness. The face images of the four individuals are employed as the input dataset for the first deep learning model in the training phase. This particular model categorizes the images into four distinct groups corresponding to the previously mentioned, individuals, enabling us to identify a specific person. The second deep learning model is designed to identify drowsiness by analyzing the status of the person's eyes, whether open or closed. To accomplish this, we employ facial images of the four individuals, including closed and open-eye instances, as the input dataset for the second deep-learning model. This approach allows us to make a definitive determination regarding their drowsiness status. In the notification of the driver's closed eyes mode, the touch sensor ensures that the driver is catching the driving wheel, while the sound messages are sent to the driver through the speakers to wake up. If there is no response from the driver, the auto-stop car mode is activated. A general block diagram of the proposed system is presented in Fig. 1.

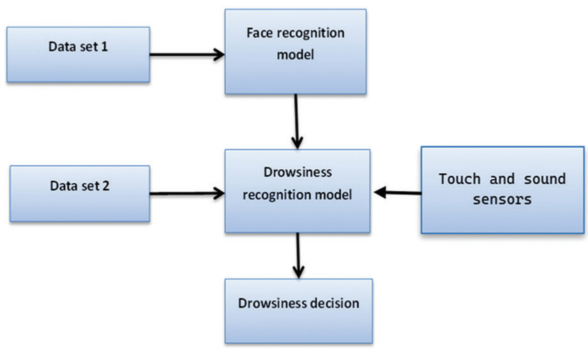
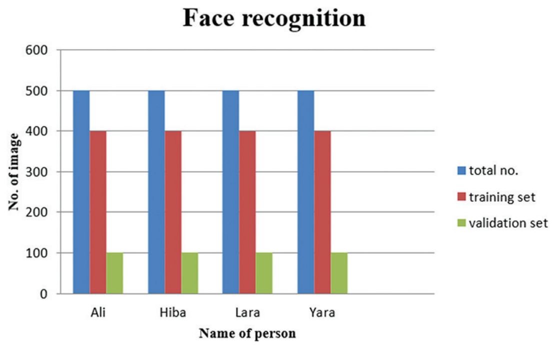


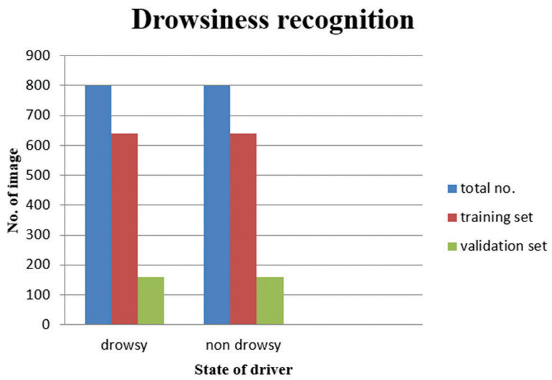
Fig. 1. General structure model

3.2. DATASET

In the proposed system, numerous images are collected to support training the presented deep learning models. In the driver identification model, 2000 images are prepared for the investigated four individuals: Ali, Hiba, Lara, and Yaraa. Each individual, class, is represented by 500 images (400 photos for training, constituting 80%, and 100 photos for validation, constituting 20%), as visually depicted in Fig. 2(a). Subsequently, we conducted an additional set of 1600 photos focusing on the same group of individuals to enable classification for drowsiness(conscious) detection. As illustrated in Fig. 2(b), each individual, or class, is depicted by 800 photos (640 photos allocated for training, which constitutes 80%, and 160 photos designated for validation, which constitutes 20%). This extensive dataset enhances the accuracy of our drowsiness classification process.



(a) Dataset for person face recognition



(b) Dataset for drowsiness recognition

Fig. 2. Dataset allocation for each stage of the proposed deep learning model

Typically, image preprocessing techniques are applied as a preliminary step before the training process of the models including reducing computational complexity and adjusting dimensions to enhance overall performance. In the case of this dataset, the original images are standardized to a resolution of 224 × 224 pixels. The image's pixel values were normalized to manipulate the intensity pixel values within a more manageable range. This normalization process entails transforming the pixel values, which originally fell within the range of (0-255), to a normalized range of (0-1) simplifying subsequent calculations.

3.3. PROPOSED DEEP LEARNING MODELS

The proposed backbone deep learning model for face and drowsiness recognition uses 15 CNN layers. The designed deep learning layers are shown as follows:

- Starting from the first layer, performed as the input layer. It carries out images from the pre-processing stage described in the pre-processing stage section.
- There are three stages of convolution layers; each stage consists of convolution and rectified linear units (Relu), which are the activation function, max-pooling, and dropout ranges (from 25% to 50%) layers.
- One fully connected layer is implemented.
- The dropout layer is adopted with a probability ratio of 50% before the final layer (sigmoid layer). It uses four classes of face images in the CNN model for face recognition. In comparison, the softmax layer uses two classes of face images in the CNN model for drowsiness recognition.

It is important to note that the differences between both proposed deep learning models in terms of sophisticated descriptions of each layer, including output shape and parameters, are illustrated in Tables 1 and 2.

Table 1. CNN's layer of face recognition

Layer (type)	Output Shape	Param #
image_input (InputLayer)	[(None, 224, 224, 3)]	0
layer_1 (Conv2D)	(None, 224, 224, 32)	896
layer_2 (Conv2D)	(None, 224, 224, 64)	18496
layer_3 (MaxPooling2D)	(None, 112, 112, 64)	0
layer_4 (Conv2D)	(None, 112, 112, 64)	36928
layer_5 (MaxPooling2D)	(None, 56, 56, 64)	0
dropout_1 (Dropout)	(None, 56, 56, 64)	0
layer_6 (Conv2D)	(None, 56, 56, 128)	73856
layer_7 (MaxPooling2D)	(None, 28, 28, 128)	0
dropout_2 (Dropout)	(None, 28, 28, 128)	0
fc_1 (Flatten)	(None, 100352)	0
layer_8 (Dense)	(None, 64)	0
dropout_3 (Dropout)	(None, 64)	0
pridictions (Dense)	(None, 2)	130

Table 1. CNN's layer of face recognition

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image_input (InputLayer)	[(None, 224, 224, 3)]	0
layer_1 (Conv2D)	(None, 224, 224, 32)	896
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dropout_1 (Dropout)	(None, 56, 56, 64)	0
layer_6 (Conv2D)	(None, 56, 56, 128)	73856
layer_7 (MaxPooling2D)	(None, 28, 28, 128)	0
dropout_2 (Dropout)	(None, 28, 28, 128)	0
fc_1 (Flatten)	(None, 100352)	0
layer_8 (Dense)	(None, 64)	6422592
dropout_3 (Dropout)	(None, 64)	0
pridictions (Dense)	(None, 4)	260

3.4. Proposed algorithm

Fig. 3 illustrates the proposed algorithm for the auto-stop system as a flowchart. When an image is acquired through the Raspberry Pi camera, the face recognition model determines whether the person is authorized. The authorized drivers can now drive the car, meanwhile; the drowsiness recognition model monitors them focusing on eyes for closure exceeding 3 seconds. If the touch sensor is not activated during this period, the system responds by sending a sound message through the speaker. If the person's eyes remain closed and unresponsive, the system autonomously stops the car and sends a GPS message to assist the driver.

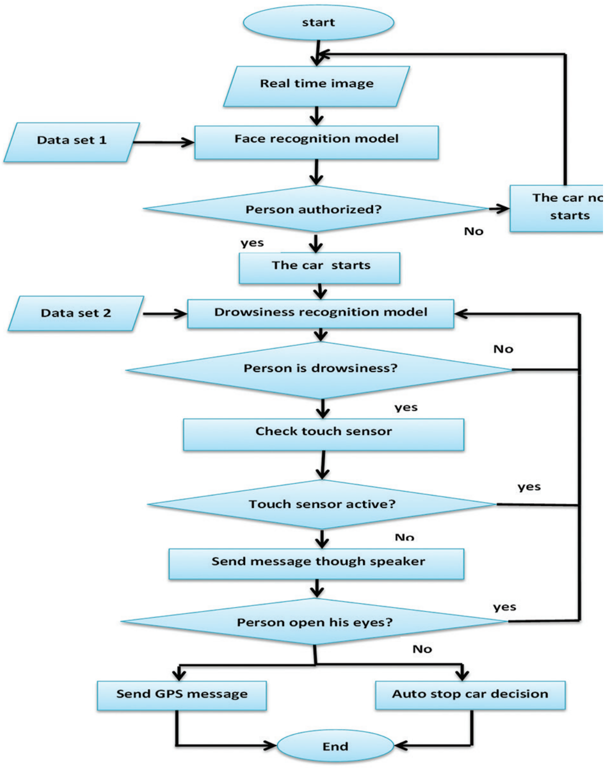


Fig. 3. Proposed algorithm flowchart

3.5. PROPOSED SYSTEM IMPLEMENTATION

The CNN models, proposed in the presented auto-stop car system, are trained using Python within the Anaconda Python 3.7 environment, employing Keras as the backend framework (utilizing Tensor Flow). The training takes place on a Windows 10 laptop equipped with an Intel R Core (TM) i7-6820 HQ CPU, featuring 4 physical and 8 logical cores, 8 GB of RAM.

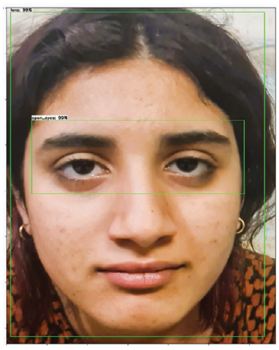


Fig. 4. Test image after converting the model to Tf_light

The weight updates are based on training data, while validation data provides insights into the network's progressive improvements. The hyperparameters that yielded the highest accuracies are optimizer: Adam, learning rate: 0.0001, batch size: 4, and epochs:100, a balance between accuracy and training time. Subsequently, the model is converted to Tensor Flow Lite format, and its performance is evaluated on previously unseen images from the "test" folder. These images are not part of the training data, providing a genuine measure of the model's accuracy. As indicated in Fig. 4, the model demonstrated a remarkable accuracy of 99% in detecting open eyes and recognizing the authorized person, "Lara".

Following the conversion to Tensor Flow Lite and creating a trained .tf _lite model, the next step involves deploying it on a Raspberry Pi. To execute the model, the Tensor Flow Lite Runtime is installed on the Raspberry Pi 4, and the Python environment and directory structure are configured for running the application. Four Python scripts are developed to accommodate various input sources, including images, videos, web streams, or webcam feeds. The proposed model specifically utilized TFLite_detection_webcam.py. The hardware components used in this research are a Raspberry Pi 4 model B (8 GB), a memory card, a Pi-Camera 5MP, a display screen, a speaker, a touch sensor, and LEDs as shown in Fig. 5. The LEDs are used to indicate the actuation performance of the system in different cases. For example, if one of the authorized individuals is recognized for the driver identification phase, a green LED is activated; otherwise, a yellow LED is illuminated. While in the drowsiness phase, An emergency is declared if the driver neglects to grip the sensor while their eyes are closed for more than three seconds, the system responds by activating a speaker to deliver a voice message, confirming the driver's alertness and alerting them to the situation. If the driver's eyes remain closed and unresponsive. The car initiates safety protocols, including activating warning lights, gradually reducing speed, and executing a controlled right turn to bring the vehicle to a stop. All these instructions are represented by a red LED illumination.

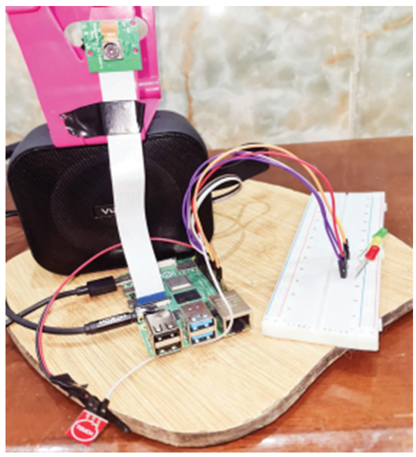
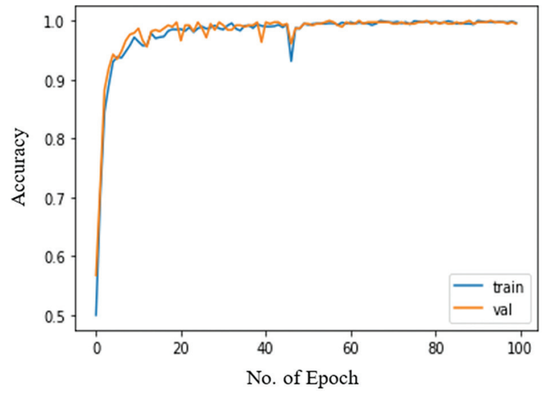


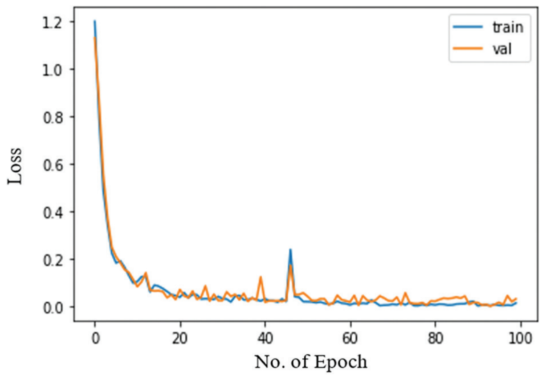
Fig. 5. The proposed system implementation

4. RESULTS

First, the proposed deep learning models are tested by adopting the training and testing accuracy and loss factors. The accuracy and loss for training and validation sets of the proposed face recognition model (driver recognition) are shown in Fig. 6. The accuracy ratio reaches saturation over 99% after 60 epochs in both the training and validation processes. Meanwhile, the losses occurred to be minimal immediately after 60 epochs.

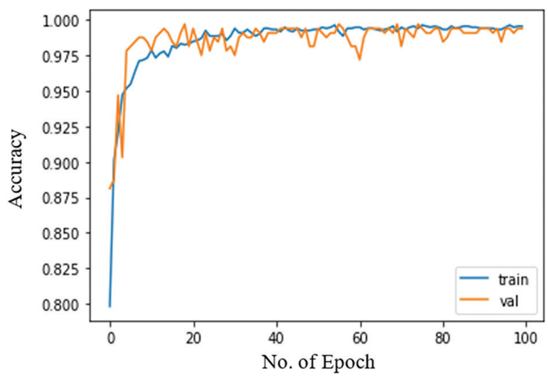


(a) Training and validation accuracy

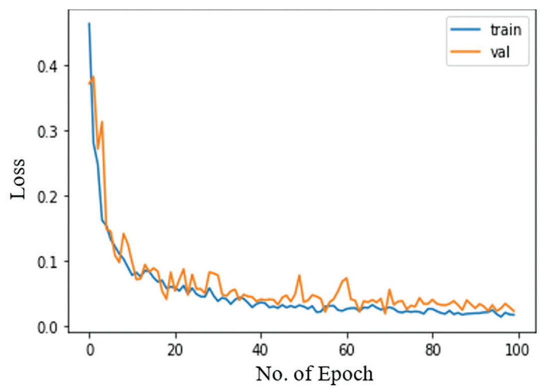


(b) Training and validation loss

Fig. 6. Accuracy and loss in training and validation of Face Recognition Model



(a) Indicating the accuracy



(b) Indicating the loss

Fig. 7. Accuracy and loss in training and validation for drowsiness model

In Fig. 7(a), the accuracy of the proposed model for detecting drowsiness during both training and validation phases is depicted. Meanwhile, Fig. 7(b) illustrates a different aspect: the variation in loss over time. The loss curve exhibits a decline beginning at the 67th epoch, followed by a period of stabilization, and then a gradual deceleration for the subsequent 100 epochs. Remarkably, despite the dataset containing only 800 image samples for each class, the suggested model performs remarkably well, achieving impressive accuracy rates of 99.54% for the training set and 99.37% for the validation set.

To test the performance of the proposed system, different case studies are adopted to simulate the possible situations that might face the proposed auto-stop car system.

4.1. CASE STUDY 1: UNAUTHORIZED DRIVER

If the driver is not an authorized driver (not one of the four authorized individuals), the system does not allow the car to start up. In the proposed system implementation prototype, a yellow LED is turned on to indicate that the driver is not authorized as shown in Fig. 8.

Fig. 8. Unauthorized driver case study

4.2. CASE STUDY 2: AUTHORIZED DRIVER

If the person is an authorized driver, a green LED is turned on to indicate that the proposed system recognizes the driver and the car starts up as shown in Fig. 9. Then, the system performs the drowsiness recognition monitoring mode.

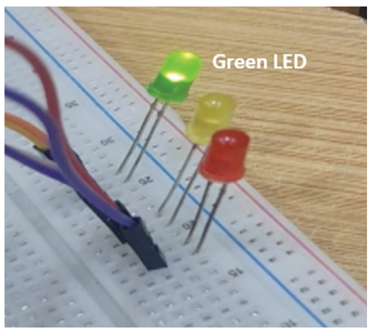


Fig. 9. Authorized driver case study

4.3. CASE STUDY 3: DRIVER TOUCHES SENSOR

While the authorized driver performs the driving, the touch sensor indicates that he/she is in driving mode, yet the system continues to monitor the driver's eyes.

4.4. CASE STUDY 4: DRIVER DOESN'T TOUCH SENSOR (3-SECOND TIMER)

If the authorized driver does not touch the touch sensor on the steering wheel, the system sends a sound message to alert the driver and check the level of drowsiness. If the driver opens his/her eyes within 3 seconds, the system returns to monitoring the driver's eyes.

4.5. CASE STUDY 5: DRIVER DOESN'T OPEN EYES (3-SECONDS TIMER EXPIRES)

If the authorized driver does not open his/her eyes within 3 seconds, the system sends another sound message to alert the driver and check their level of drowsiness. Then if the driver is still in closed eyes mode, a red LED is turned on as an emergency signal in the prototype to represent the auto-stop car mode, where the system sends a message through GPS to request help for the driver. Fig. 10 demonstrates how the detecting system can distinguish between drowsy drivers. A driver-alerting warning is promptly delivered once sleepiness signs are recognized during the real-time detection procedure, which has a 99% accuracy rate.

Fig. 10. Real-time drowsiness detection system

One essential key to evaluating the proposed system's accuracy is finding the accuracy ratio. The accuracy ratio is calculated as follows [24]:

$$A_{cc} = \frac{N_{cc}}{T_S} \times 100\%. \quad (1)$$

Where A_{cc} is the accuracy of classification, N_{cc} is the number of correctly classified images, and T_s is the total number of samples.

The proposed system is tested in real-time mode by considering numerous cases of drivers for both driver recognition and drowsiness recognition models.

This test is performed on the presented prototype to ensure the proposed models work properly. This assessment consisted of two stages: first recognizing the drivers and then determining their emotional states. The face recognition model has been tested with 120 images (30 images per person), yielding an average accuracy of 99.1%, as shown in Table 3. The drowsiness model is tested with 120 images, 30 for each driver, and an accuracy of 99.1% is achieved as shown in Table 4. This proves that the proposed models in the presented auto-stop car system work highly and efficiently.

On the other hand, the proposed drowsiness recognition model is compared with different models in the literature to validate the proposed work as shown in Table 5. This table, it is shows the superiority of the proposed deep learning model amongst the literature works in terms of accuracy to have 99.1% in the hardware implementation prototype not in the simulations as in the literature works.

Table 3. The effectiveness of the proposed CNN model for face recognition

Person name	Total test Images	No. of the correct image in face detection	No. of the incorrect image in face detection	Image percentage for face detection
Ali	30	30	0	100%
Hiba	30	30	0	100%
Lara	30	30	0	100%
Yara	30	29	1	96.6%
Total	120	119	1	99.1

Table 4. The effectiveness of the proposed CNN model for drowsiness recognition

State of recognition image	Total test Images	No. of the correct recognition image	No. of the incorrect recognition image	Image recognition percentage
Drowsy	60	59	1	98.3%
Non-Drowsy	60	60	0	100%
Total	120	118	1	99.1%

Table 5. Accuracy Comparison of drowsiness detection model with literature works.

Reference	Year	Method	Accuracy
[18]	2021	Eye-aspect ratio (EAR).	92.5%
[21]	2021	DNN model	90%
[19]	2022	CNN and SVM	97.44%
[22]	2022	CNN model	96%
[20]	2023	Deep learning methods	95.8%
[23]	2023	CNN and VGG16	97%.
		Our proposed CNN model	99.1%

5. CONCLUSIONS

An intelligent auto-stop car system was presented using deep learning models. The systems adopted two deep learning models with the same backbone design, one for driver recognition and the other for drowsiness recognition while driving. It also considered touch and camera sensors as well as a speaker and microphone for ensuring the driver's status in driving mode. The proposed system was implemented as a prototype in a Raspberry Pi device connected with the utilized sensors and group of LEDs. These LEDs indicate the actuation modes performed after the system makes decisions. The proposed deep learning models are tested in simulation and real-time phases and the obtained results proved the claim of this research in terms of accuracy and efficiency. At the same time, the auto-stop car system was tested in real-time mode with different case studies and the results were promising. The real-time accuracy, achieved using the prototype, was 99.1% for both deep learning models.

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