FatigueAlert: A real-time fatigue detection system using hybrid features and Pre-train mCNN model

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Summary
Several computer-vision based applications are developed to detect of driver fatigue (DDF) and to decrease road accidents in a real-time environment. Those DDF systems were more focused on extracting visual-features. However, it is very much difficult to extract visual-features for defining PERCLOS measure due to different factors such as night-time driving, head is not centered-aligned and occlusion of faces. Due to these reasons, it is very much difficult to detect driver eyes, mouth and ears. As a result, some authors suggested using non-visual features combined with visual features to get accurate results. Accordingly, a hybrid and novel DDF system is developed in this paper by combining both visual and non-visual features through multi-cams stream approach and electrocardiography (ECG) sensors to measure heart rate variability (HRV). Those ECG sensors are mounted on driver's steering. This DDF system is known as FatigueAlert and developed through deep architecture especially transfer-learning method. The proposed FatigueAlert system pre-trained many convolutional neural network (mCNN) models on different driver's eyes, ears and mouths datasets. Three online datasets such as closed eyes in the wild (CEW), yawing dataset (YAWDD) and Columbia gaze dataset (CAVE-DB) were utilized to train and evaluate the proposed FatigueAlert system. On average, the FatigueAlert DDF system achieved 93.4% detection accuracy on different real-time driver's datasets. To perform comparisons, different deep-learning models were used to compare with proposed pre-trained mCNN multi-layer architecture model. The obtained results indicate that the FatigueAlert system is outperformed compared to other state-of-the-art DDF systems.

Key words:
Driver Fatigue, Video sequences, Feature extraction, Head, Transfer Learning, Deep-leering, Conventional neural network

1. Introduction

Driver's fatigue is a vital and primarily roots cause to reduce traffic accidents. Detection of driver fatigue (DDF) is based on behavioral measures through image processing and machine learning techniques [1]. To detect DDF, there are many systems developed in the past. To measure the level of drowsiness, there are many authors used driver faces information to extract visual features. At most, the facial features include eye blinks, head movements and yawing. To develop such the DDF system, it is most challenging tasks and it is very much difficult to achieve promising results. In practice, the development of such DDF system requires accurate and robust methods that can work in a real-time environment. However in the past, there are several DDF systems developed based on deep-learning algorithms to detect and predict driver's drowsiness. The steps to develop DDF systems are visually represented in Fig.1.

Compare to traditional-machine learning approaches, the deep-neural network models (DNNMs) reported higher accuracy for detecting [2] of driver drowsiness. In fact, there are many applications of DNNMs in the context of computer vision, business intelligence and bioinformatics. It is due to the fact that the DNNMs methods do not require domain-expert knowledge about image processing and automatically learn features. There are many variance of deep-learning models utilized in the past but the convolutional neural networks (CNNs) model is type of DNNMs that can automatically learn and predict the driver drowsiness based on eyes, mouth and ears.

Bimodal DNNMs are also used in the past [3] to predict driver drowsiness in a real-time environment. Although, a framework using image-based facial information and a biomedical DNMs were also used to detect fatigue. The authors utilized 65 landmark points on different face regions including eyes, mouth and chin. Those face regions are visually shown in Fig.2. They used a digital camera to detect facial expression based on these landmark points. However, it is very much difficult for single camera to detect facial features due to light illumination; head is not center-aligned and face occlusions.

Many authors used Viola Jones landmark points to detect facial features such as in paper [4]. The authors developed DDF system in three phases. First, they detect facial features by Viola Jones, the eye tracking and then detect yawn condition of the drivers. Afterwards, the authors used DNNMs approach to classify the consecutive frames into fatigue and non-fatigue states. The final decision if fatigue is detected then alarm is generated to alert the driver about falling sleep state. This process is really important to save human lives.

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In the past, the authors were also used two stacked autoencoder DNNMs to train landmark points and texture patterns. Later on, these two DNNMs are combined together by learning a joint layer to construct bimodal DNNMs. These unified models were then used to construct a fuses model to extract landmark points and texture patterns of driver faces. Finally, the authors used a prediction model to classify state of the driver drowsiness.
The rest of the paper is organized as follows. The section 2 introduces literature review and section 3 is used to show training dataset and proposed methodology. The methodology related to detection of face, and locates eye and mouth regions on multi-cams approach. Section 4 introduces the experimental process to evaluate the performance of FatigueAlert system and analyze fatigue state. Finally, in Section 5, the conclusions and future work are expressed.

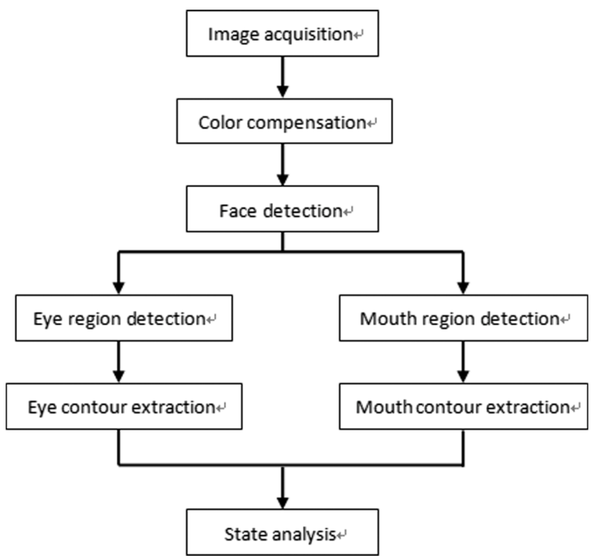

Fig. 1 Example of state-of-the-art driver fatigue prediction systems with different states.

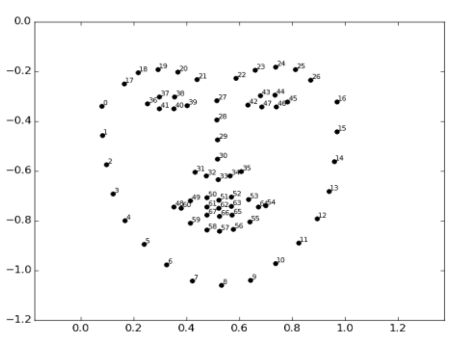

Fig. 2 Define 65 landmark points to extract the eye and yawn regions from a set of facial landmarks

2. Literature Review

Electroencephalography (EEG) [5] signals based driver fatigue classification system was developed by authors. After detecting EEG-based non-visual features, the authors used convolutional neural network (CCNN) architecture was used to recognize EEG signals into drivers fatigue stage. To develop this system, the authors replaced convolutional filters with Restricted Boltzmann Machine (RBM). The authors used 37 subject to test the performance of fatigue detection system. Another driver's inattention or drowsiness system was developed in [6] by deep-learning based approach on a low-cost board. The authors designed DNNMs-learning algorithm to minimize the network structure and obtained 89.5% detection accuracy on 14.0 frames per second.
In [7], another solution for prediction of driver's cognitive states (drowsy or alert) using electrocardiography (ECG) and EEG signals data was developed thorough support vector machines (SVMs). In a driving simulator, the authors utilized 22 subjects for making difference between alert and drowsy states without using visual features. The authors used ECG features such as heart rate (HR) and heart rate variability (HRV). To test the system, they used EEG and ECG features significantly improve the performance. The authors reported that 80% detection accuracy was acceptable to make difference between alert and drowsy states of the drivers. However in paper [8], the authors used only EEG-based driver fatigue with sparse-deep belief network (DBN) classifier. The authors noticed that the sparse-DBN classifier is best to model features in the pre-training layer. By comparing different classification algorithms, the authors reported 90.8% detection sensitivity and 90.5% specificity.
Yawn detection was performed in [9] to detect driver fatigue in a real-time environment. Due to the dynamics in driver's movements and lighting conditions, it is very much difficult to detect driver fatigue. The authors developed many methods to detect yawn through face detector, a nose tracker and a yawing detector. All those visual features are extracted through image processing algorithm and those features are classified through DNNMs approach. Experiments are conducted on real-world driving data, and results show that the CNN model obtained higher detection rate compare to other techniques. Whereas in [10], the authors used a Haar-wavelets to detect face features using a single camera. The authors did not use any non-visual features. They combined Haar features with correlation filter to detect driver fatigue. These features are then classified using DNNMs but implemented on graphical processing unit (GPU)-based platform. On average, the authors got 95%

detection accuracy to categorize methods based on conventional computer vision techniques.

Other DNNMs was developed in [11] to detect driver drowsiness. This paper proposed a deep architecture for learning effective features based on visual features. The authors utilized three DNNMs learning algorithms to extract and learn local facial features and head gestures for reliable detection. The outputs of the three networks are integrated and fed to a softmax classifier for drowsiness detection. The authors achieved 73.06% detection accuracy on NTHU-drowsy benchmark dataset. Similar in [12], the authors used eye-closure, nodding and hawing to detect driver drowsiness. This is the only study that deals with driver face occlusion such as sunglasses or scarf using active appearance model (AAM). The authors used CNN of DNNMs methods to extract features and reported 87.46% detection accuracy.

In [13], the authors developed a hierarchical temporal deep belief network (HTDBN) algorithm was proposed to detect driver drowsiness. The authors used high-level facial and head features to recognize drowsiness related issue. Whereas in [14], the authors used CNN type of DNNMs to recognize driver fatigue. The authors used driver hand position to automatically learn and predict pre-defined driving postures. Based on hand-position, the authors recognize safe/unsafe driver postures. A pre-training step was applied on driver posture dataset. An overall 99.78% detection accuracy was achieved. The ECG-based driver fatigue detection system was developed in [15]. The authors reported 77.36% detection accuracy.

In [16], the authors developed DDF system based on Yawn detection by using single camera and a variant of DNNMs that is recurrent neural network (RNN)-long short term memory (LSTM). The authors also implemented CNN model to extract spatial driver fatigues and then analyze those features using LSTM technique. On average, the authors reported 87% detection accuracy. Another study in [18], the authors used LSTM model with EEG and forehead EOG signals to detect driver drowsiness. The authors suggested that the LSTM model based on EEG and EOG signals provided best vigilance estimation compare to other approaches. A different approach was developed in [19] through RNN-LSTM model and implemented on GS1 IoT-based standard. The authors developed fatigue detection system based on vehicle motion data and model using GS1 standard language. They used an optimal algorithm with RNN-LSTM DNNMs. All the algorithms are implemented through Raspberry Pi.

In [20], the authors used psycho-physical state to determine driver fatigue. In that study, the authors used photoplethysmography (PPG) sensors instead of ECG sensors to measure heart rate variability (HRV) for determining driver fatigue. They analyzed the skin micro-movements and changes in facial color due to blood circulation quite indistinguishable with naked eye in order to extract facial landmarks and to reconstruct PPG signal. In [22], a DDF system was developed by using RNN model along with LSTM. The authors used mainly two parameters such as HRV and PERCLOS to predict driver fatigue. The authors achieved 88% driver fatigue detection accuracy based on RNN-LSTM model.

In [23], the authors developed driver fatigue detection system by multi-index cascade CNN model. It is new DNNMs algorithm to detect driver fatigue by pre-training learning algorithm. The authors reported that they achieved 98.42% of fatigue detection accuracy. Whereas in [17], the authors utilized a pre-trained AlexNet transfer learning mechanism. To develop this system, the authors did modification to the structure of AlexNet pre-trained model. The authors reported 5.5% misclassification rate compare to other approaches. The authors claimed that the pre-trained model is another best method to apply in the domain of fatigue detection in a real-time environment.

Similar in [21], the deep CNN model was developed. In particular, seven common driving activities are identified. Among these activities, the first four are regarded as normal driving tasks, while the rest three are classified into the distraction group. The authors developed this DFD system using low-cost camera and they involved ten drivers to collect data. Also, they used transfer learning approach to reduce training cost and to fine-tune the pre-trained CNN model. They utilized three pre-trained CNN models such as AlexNet, GoogleNet and ResNet50. They achieved 91.4% detection accuracy on this dataset.

3. Proposed Architecture

A hybrid FatigueAlert system is developed in this paper by combining both visual and non-visual features through multi-cams stream approach and electrocardiography (ECG) sensors to measure heart rate variability (HRV). Those ECG sensors are mounted on driver’s steering. This DDF system is known as FatigueAlert and developed through deep architecture especially transfer-learning method. The proposed FatigueAlert system pre-trained many convolutional neural network (CNN) models on different driver’s eyes, ears and mouths datasets. Three online datasets such as CEW, Drowsy and SSS are utilized to train and evaluate the proposed FatigueAlert system. The development steps are explained in the following sub-sections.

3.1 Utilization of Dataset

The datasets for building FatigueAlert system were collected from various online data sources such as closed eyes in the wild (CEW) [24], yawing dataset (YAWDD) [25] and Columbia gaze dataset (CAVE-DB) [26]. These three datasets were used to capture visual features. However in case of non-visual features, two electrocardiography (ECG) sensors were used to capture driver heart variability. These ECG sensors were help to reduce face occlusion problem in case if driver face is not detected properly or head is not center-aligned.

In the CEW datasets, there were total 2423 eyes images were presented including both open and close eyes status. The driver face image is of size (100 x 100) resolution. From CEW dataset, 1800 images were used to train the deep-neural network whereas 623 were left to perform test. From YAWDD dataset, there were total 351 video sequences especially for yawn detection. To train FatigueAlert system, all the video frames are converted into a single image frame. Those image frames contained open or close mouth state for yawn detection. Whereas from CAVE-DB, there were 56 subjects involve gathering on total 5880 image frames on different head poses and gazing directions. From the CAVE-DB, there were total 3000 images were selected to train the classifier. The images in CAVE-DB datasets were different in face orientation, eye closure and wearing big glasses under different light illumination.

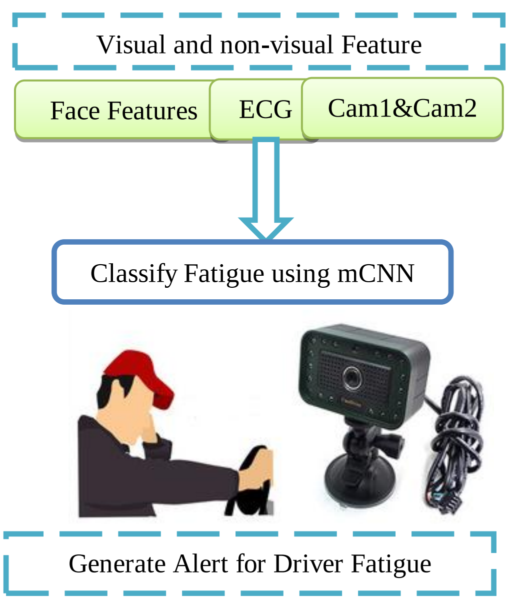

Fig. 3 A systematic flow diagram of proposed Driver Fatigue Alert system.

To gather ECG signals, four subjects are requested to provide a real-time driving data in case of yawn, mouth open/close and sleepy conditions. Two ECG sensors were mounted on steering wheel and low-cost Arduino board was utilized to capture these serial signals. These ECG signals were filtered and the mCNN model was trained to predict the above-mentioned states of the drivers.

3.2 Methodology

Three convolutional neural networks (mCNN) based pre-trained model were built based on eye recognition, yawn analysis and classification of electrocardiography (ECG) signals. The ECG sensor signals were build thorough real-time driver heart rate variability (HRV) measurement during highway driving under different conditions. Figure 3 shows the systematic flow diagram of proposed driver fatigue detection system. Those steps are explained in the subsequent paragraphs.

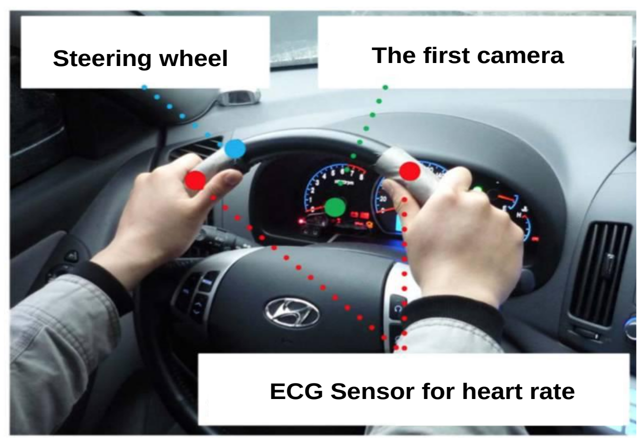

Fig. 4 An example of Driver Fatigue Alert system with ECG sensors and Hybrid features extracted from two-position cameras.

3.2.1 Visual and non-visual features Detection

A multi-task cascade convolutional neural network (MTCNN) [27] was used for mainly extracting of facial visual features of the drivers. In the past, the MTCNN network was used for face detection and key point detection. The MTCNN model was used in this paper to extract five main points defines as the left and right mouth corners, the center of the nose, and the centers of the left and right eyes.

Moreover, the heart rate variability (HRV) is measured thorough two ECG sensors mounted on steering wheel of the car. A visual example to show that how those sensors are mounted on steering is represented in Fig.4. The signals coming from input real-time sensors are not unified and contained noises. Therefore, the pre-train three states CNN model was used to extract meaningful information from heart pulses. This CNN model is known as ECNN.

3.3 Detection of Eye Stage for Drowsiness

After detecting the eye region as mentioned in sub-section (3.2.1), the next step is to judge the eye state. For detection a real-time eye state, a CNN model was constructed known as EyeCNN based on convolutional neural network (CNN) approach. To build FatigueAlert system, a five-layer based CNN model was utilized in this paper. The size of pooling layers is (2x2), and the step size is 2. The 2 size is fixed after doing experiments and it can be used to reduce the image size while obtaining the main features.

After the pooling layer, there are nodes in the full-connection layer that integrates the features extracted from the previous layers that are 512 in total features. Those features then integrate the features extracted from the previous layers. Afterwards, t network then achieves the two-classification task by the Softmax layer that is eyes open or closed.

3.4. Prediction Model for Driver Fatigue

After training eyes and mouth, the next steps is to build driver fatigue prediction model based on different states of the drivers. Yawn counting, blink frequency, closed eyes intervals and HRV measure through ECG sensors are all integrated together to make a final prediction. Among all those features, the eye, ECG signals and mouth state are the three most obvious visual and non-visual features for estimation of driver drowsiness in a real-time environment. The proposed FatigueAlert system can determine the driver's eye and mouth state, ECG signals and then establish a fatigue detection model.

During experiments on datasets, it was observed that the drivers can blink eyes based on 10 times / minute under normal circumstances. If they are blinking more frequently compare to this criteria then it should definitely leads toward driver fatigue. Therefore in this paper, this criterion was setup. Moreover to develop FatigueAlert system, PERCLOS criterion was also utilized to estimate the eye fatigue.

FatigueAlert system generated alert to the driver based on several visual and non-visual features such as driver's eyes and mouth state, PERCLOS measure, output of HRT-ECG sensors and yawn count. According to all those indicators, the final decision is based on a fixed threshold value. This threshold value determined by doing many rapidly experiments on acquired datasets and real-time video frames. Those video frames were acquired different weather conditions and environments. On those acquired datasets, the experimental results indicate that when PERCLOUS measure value (P)>0.25 and the heart rate (BMP) is within range of (75.0 to 85.0) then the driver may be in a fatigued driving state.

4. Experimental Results

Driver FatigueAlert system was implemented and tested on Intel ® Core i7-4300U processor, 8GB RAM and NVidia 2GB GPU. All pre-train CNN models were programmed in Python (an open source platform). This computer has 4 USB serial ports and one VGA port to connect three cameras and one Arduino board for ECG sensors. The PySerial library was utilized to receive input from Arduino board in order to analyze hart rate variability measure. All other CNN models have built in Tensorflow and Keras platforms. Those models are imported to Jupiter environment to make good documentation the code.

Figure 4 is visually displayed the results obtained by the proposed FatigueAlert system. To train the network, the three online data sources are utilized as briefly described in the data acquisition section. All those CNN models, alert generation system and data acquisition from multi-cams approach are implemented using multi-threaded approach. On average, the detection accuracy on a real-time dataset was evaluated that is 93.4%. It is comparable with the state-of-the-art approaches. On these datasets, the miss-classification errors were 0.45%, so it can be further reduced by optimization techniques. Those optimization techniques will be further evaluated in the future.

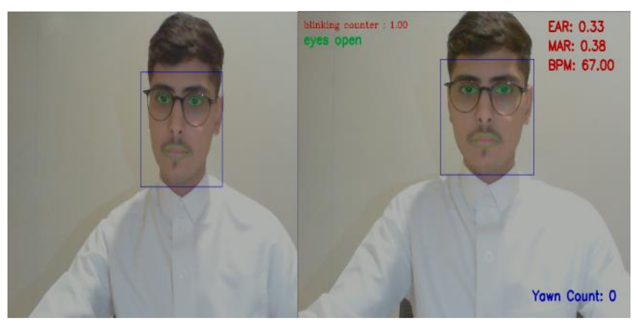

Fig. 5 An example of Driver Fatigue Alert system with ECG sensors and Hybrid features extracted from two-position cameras.

Compare to state-of-the-art approaches, this FatigueAlert system is capable to detect face features by using two-camera compare to a single camera. Also in this FatigueAlert system, multiple ECG sensors were deployed on the steering wheel to detect driver fatigue in a robust manner in case if cameras are unable to detect facial features. It was observed that especially in case of Saudi Arabia (KSA), many drivers including both male/female are doing veil. So, face occlusion is very common among drivers in KSA environment. As a result, it became very much difficult to detect driver fatigue in a real-time environment. As result in this paper, a hybrid approach was used to develop this FatigueAlert system.

Table 1: Fatiguealert Detection System Results Based on Pre-Train Mcnn And Other Deep-Learning Models.

Video ID.	FatigueAlert Performance			
	Duration	aKCNN	Proposed mCNN with pre-train	Standard SCNN
1.	130s	0.831	0. 923	0.725
2.	140s	0.825	0.954	0.623
3.	200s	0.845	0.976	0.61
Accuracy of Fatigue Detection		**83.50 %**	**93.50 %**	**64%**

It is not possible to perform comparisons to other state-of-the-art are driver fatigue detection systems because many systems were deployed in the different environments and unfit to the Saudi Arabia (KSA) weather and conditions. As a result, the comparisons were performed on different variant of deep-learning models. For predicting driver drowsiness, the Table I shows the experimental results obtained by standard CNN and

Table I represents standard single SCNN without pre-training and standard CNN deep-learning algorithms using k parameter (KCNN) shows result through pre-training models. In all these models, visual and non-visual hybrid features are extracted and classified. Also, mCNN model is the proposed model with pre-training strategy. This table shows the performance comparison results that obtained by deep-learning methods developed in this paper. Although, there are several recent algorithms that focused only on employing the deep learning algorithms but none-of-them focused on optimize features through transfer learning. This is the main focused on this FatigueAlert detection algorithm.

Table I shows the comparison results with standard CNN model with softmax classifier and CNN compare to proposed FatigueAlert system by using a pre-train mCNN and CNN models on hybrid features. These driver drowsiness detection (DDD) systems were evaluated on 130 seconds, 140 seconds and 200 seconds videos recorded during real-time driving conditions on KSA highway roads. On average, the proposed FatigueAlert detection system obtained higher 0.923, 0.954 and 0.976 classification detection accuracy on different videos intervals such as (130, 140, and 200) seconds, respectively. This detection accuracy is calculated based on true fatigue detection index and higher the value means the algorithm is outperformed compared to other approaches. Also in this table, the standard SCNN multi-layer model achieved 0.725, 0.623 and 0.61 detection accuracy on different videos intervals such as (130, 140, and 200) seconds, respectively. On average, the SCNN algorithm obtained 64% detection accuracy compare to proposed mCNN model that is 93.50%. Similarly in case of KCNN model, the detection accuracy is 0.831, 0825 and 0.845 when recorded by different videos intervals such as (130, 140, and 200) seconds, respectively. On average, the KCNN model was achieved 83.50 % fatigue detection accuracy compare to the proposed FatigueAlert system that is 93.5%. As a result, the Table II shows that the proposed FatigueAlert detection system is outperformed compare to other multi-layer deep-learning methods.

The work presented in this paper focuses on the high problems of road accidents caused mainly by the driver's sleepiness. The focus of the work is the development of "FatigueAlert" system according to KSA environment. The author specifies that FatigueAlert is based on the integration of visual functionality through PERCLOS measurement and non-visual characteristics by means of heart rate sensors (ECG). It is based on a transfer learning based on several levels using a convolutional neural network (CNN) was used to detect driver fatigue. Those hybrid characteristics in night driving and to be precise results, the ECG sensors were put on the steering by analyzing heart rate signals in case the camera is not enough to get the face. To test of FatigueAlert system, three online data sets were used. The testing of this research undoubtedly has the FatigueAlert system reduces road accidents.

Initial prototype of driver fatigue system is already developed and tested on a real-time environment as shown in Fig.6. In this prototype system, two cameras were used along with heart beat sensors to predict driver drowsiness. However, we are still required to use brain wave sensors to get higher accuracy of driver fatigue. This point-of-view will be addressed in the future. According to our limited knowledge, there is not perfect system that can be used in KSA environment to detect driver drowsiness due to face occlusion and high temperature. As a result, this is first time effort to develop driver fatigue detection through pre-trained mCNN models and visual and non-visual features. In the literature, there is also good trend to detect and predict driver fatigue using cloud and mobile computing environments [28-40]. This point will be also addressed in the upcoming studies.

5. Conclusion

FatigueAlert system has an important factor to save road-side accidents. In this paper, a detection of driver fatigue (DDF) algorithm based on pre-train CNN model is developed and it is known as mCNN architecture. In the past, there are several computer-vision based applications developed to detect of driver fatigue (DDF). Those DDF systems were more focused on extracting visual-features. However, it is very much difficult to extract visual-features for defining PERCLOS measure due to different factors such as night-time driving, head is not centered-aligned and occlusion of faces. To overcome those problems, a novel FatigueAlert system is developed in this paper based on hybrid features.

A hybrid DDF system is developed in this paper by combining both visual and non-visual features through multi-cams stream approach and electrocardiography (ECG) sensors to measure heart rate variability (HRV). Those ECG sensors are mounted on driver's steering. This DDF system is known as FatigueAlert and developed through deep architecture especially transfer-learning method. The proposed FatigueAlert system pre-trained many convolutional neural network (CNN) models on different driver's eyes, ears and mouths datasets. Three online datasets such as CEW, Drowsy and SSS are utilized to train and evaluate the proposed FatigueAlert system. On average, the FatigueAlert DDF system achieved 93.4% detection accuracy on different real-time driver's datasets. To extend this approach in the future, a hardware-based approach will be adopted.

Fig. 6 Prototype Design of Driver Fatigue Simulator using two-view cameras and heart beat sensors.

Moreover, the FatigueAlert will be upgraded in the future to add more computational processing through cloud computing. Also in order to decrease the sensors and camera cost, mobile computing sensors will be used and test the driver fatigue. On future, mobile application and cloud computing resources will be integrated to improve computational power and cost of FatigueAlert system.

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