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Artificial intelligence system for driver distraction by stacked deep learning classification

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ABSTRACT

Increasing efforts in the transportation system have recently improved driver safety and reduced crash rates. Lack of attention and fatigue directly affect the driver's consciousness. Driver distraction is an essential driver-specific factor in the practical applicability of forward collision warning (FCW). However, there are still too many false alarms generated by the existing FCW system to be mitigated. This paper proposes facial detection to identify features and test anomalies' prediction against drivers using stacked convolutional neural network (CNN) layers. The proposed model used overlapping HAAR and stacked CNN features to identify classifications of eye areas, such as open or closed. In addition to the sliding query window's overall intensity information. The conventional HAAR function, which elevates the brightness of nearby regions, is still preferable. This method considers current intelligent transportation system-based solutions to minimize distraction effects by continuously comparing with flexible thresholds. The experimental results are analyzed from accurate driving datasets. At 456 iterations, the results acquired over 80% accuracy, while loss is near zero. The implication of driver's risk tolerance is further explored in this manner. Several risks are connected to driving any type of transportation system.

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1. INTRODUCTION

Reducing road traffic injuries and fatalities have become an excellent global health emphasis. According to the current world health organization (WHO) [1], car accidents are expected to become the eighth major cause of death worldwide by 2030, especially among millennials. A GLOBAL status report on road safety (2018) has shown that this cost increases every year. In Malaysia, approximately 7,152 deaths had occurred in 2016, with 87% of fatalities being males and 13% females [2]. There were 27,613,120 road accidents involving various vehicles. 25,800,679 recorded accidents consisted of 12,677,041 motorized two and three-wheelers, 1,191,310 heavy trucks, 59,977 buses, and 561,154 other vehicles [2]. The number of motorway traffic deaths was estimated using data from the Royal Malaysian Police and the Department of Road Transport [3]. In 2013, there were 6,915 fatal accidents from registered cars, 6,674 in 2014, 6,706 in 2015, 7,152 in 2016, and 6,740 in 2017. These figures exceed the baseline. The fatality rate had slightly reduced in 2017 from 1.42% in 2016 to 1.22%. This data indicates that the Malaysian Road Safety strategy should be more advanced to decrease these numbers. It is significant for all road safety stakeholders to identify the main cause of road traffic fatalities [3].

Given the severe impact of fatalities, the causes of road accidents must be investigated to alleviate concerns. Manufacturing vehicles should enhance traffic condition tracking and monitoring system through intelligent surveillance since cross-functional activities present a challenge for everyone. With the rise of multitasking, distractions can be fatal for drivers, especially on the highway. Three variables are found to contribute to distractions among drivers:

a. Sleepiness or fatigue: sleep deprivation or exhaustion may occur throughout a journey. In this scenario, the driver would not be in the proper state of mind to continue driving [4].
b. Outdoor distractions: the driver may engage in other activities such as texting or listening to loud music, mainly from the audio system [5].
c. Weather: the forecasted weather may become unpredictable and rapidly change. Choosing to drive can be hazardous. Strong thunderstorms or other weather phenomena (such as heavy fog) may significantly increase hazards on the road [6].

By extracting local features from visual data, convolutional layers reduce the number of variables to be studied [7]. Researchers have subsequently highlighted the latest method to address road accidents. With such distracting elements and the possibility for machine learning-based methods to detect driver distraction, these technologies are potentially promising solutions. Ersal *et al*. [8] a neural network (N.N.) model was combined with an overlapping HAAR classification algorithm to identify moments of driver distraction. Normal behaviour was defined as the instances when the driver is not performing any secondary task. Another approach, described by Wollmer *et al*. used general vehicle dynamics and driver head tracking information to model driver distraction based on long short-term memory (LTSM). The researchers created the framework to detect distracted driving behaviour [9]. Driver distraction detection was combined with adaptive safety systems in Iranmanesh *et al*. [10] to reduce false warnings while maintaining necessary ones. It is worth noting that their framework did not include any features related to the driver's eyes or face [10]. Artificial intelligence systems are the best methods for generating safety due to computational vision in handling emergency perspectives. Convolutional neural networks (CNNs) are a significant subset of artificial intelligence, as mentioned in the previous article [11], [12]. The performance accuracy will be higher with visual detection [13] of the driver's condition using CNN as input data in real-time for the forward collision warning (FCW) system. The forward-collision alert system can provide an early warning before collisions with an object in front of the vehicle [14]. Nevertheless, the problem faced by FCW in the vehicle is the issuance of false alerts or the inability to issue current warnings effectively. This situation will automatically lead drivers to turn the system off due to annoying alerts. Each driver has unique characteristics that drastically impact their decisions and reactions in different driving conditions. The particular driver's driving style depends on the instantaneous mental state, road condition, and traffic situation of the vehicle [15]-[17]. The research reveals several challenges and limitations regarding the FCW system. These are a self-learning algorithm [18], eye-tracking recognition and identification, and an adaptive driving assistance system. The key findings of this previous research show limitations regarding the eye closeness detection system such as blurring or high pixels on images [19], [20].

The only way to resolve this issue is to ensure that the driver's assistant system adapts to the driver itself. The system can adjust the control strategy to different driver characteristics. When the system's driver features can be complemented automatically by adding the learning results to the visual technique, the system can assist the driver's behaviours. In the early stages, research into this adaptive behaviour assistance method focuses mainly on the classical algorithm, such as sobel edge detection [21], support vector machine [22], WCN classification [23], CART method [24], standard ada-boost [25], viola-jones algorithm [26] and haar cascade classifier [27]. Advanced research utilizing a revolutionary algorithm detects and identifies driver distractions via the driving system's eye closeness visual feature.

This research proposes a new methodology for developing an artificial intelligence system that determines drowsiness or fatigue among drivers using the stacked CNN framework as feature extraction and combined with overlapping HAAR. Its integration demonstrates the importance of comparing classification techniques for driver distraction while incorporating computer vision such as circumstances and conditions. This paper also focuses on validating the algorithm's ability to compute the system's accuracy and loss. This research further incorporates existing literature to develop a strategy that addresses the factors contributing to road accidents or fatalities from various perspectives, including the driver's eyes, and face. Our distraction detection module broadens the applicability of the proposed framework with reliance on in-vehicle cameras, which has not been previously covered in the literature. This study also investigates potential research that can be considered for planning road safety strategies and reducing false alarms that may trouble drivers.

2. RESEARCH METHOD

2.1. Cascaded object detection

This phase portrays the classification of eye-closeness using a vision cascade object detection algorithm. In the first step, the classification of eye regions such as open or closed is identified using HAAR features and the stacked CNN. HAAR cascade object detection is one of the well-known cascaded object detection algorithms that define the presence of parts like the eye, nose, and mouth, from a frontal face. It has essential functions that compute the face features using integral representation for an image. The critical image can be calculated from an image using a few operations per pixel. At a specified period, the HAAR features are computed at different locations. The two-rectangular feature value is the difference between the pixels of those rectangular regions. It is performed in both vertical and horizontal directions. An aggregate of any rectangle is computed in four array references on the integral image. It is obtained from eight references, and thus the adjacent rectangular sum is calculated from six array references.

2.2. Stacked convolutional neural network

After computing the eye region, the stacked CNN is deployed to classify whether the eye is closed or open. Deep CNN (DCNN) aims to convolute the image with its kernel functions to yield the feature map vectors. The estimated kernel weight is associated with each successor and predecessor layers unit. The weights determined during the training process are done at the convolutional layers. Feature vectors of each frame will be fed to CNN, and hence the training will be carried out. The functionality of CNN can be bifurcated into four key areas i) the HAAR-based eye feature vectors will be fed to the input layer, ii) the convolutional layer takes the features of neurons related to the local regions, and it computes the scalar product among the areas related to the neuron's weight, iii) then, the pooling layer helps to activate the parameters used for the down sampling process, and iv) the fully connected layer will then generate scores for the classes (from the activations) utilized for the classification process. Figure 1 illustrates the drowsiness detection using stacked models to develop eye closeness. The methodology contributes to the literature, that it combines deep neural network models with supervised machine learning to classify the drowsy condition.

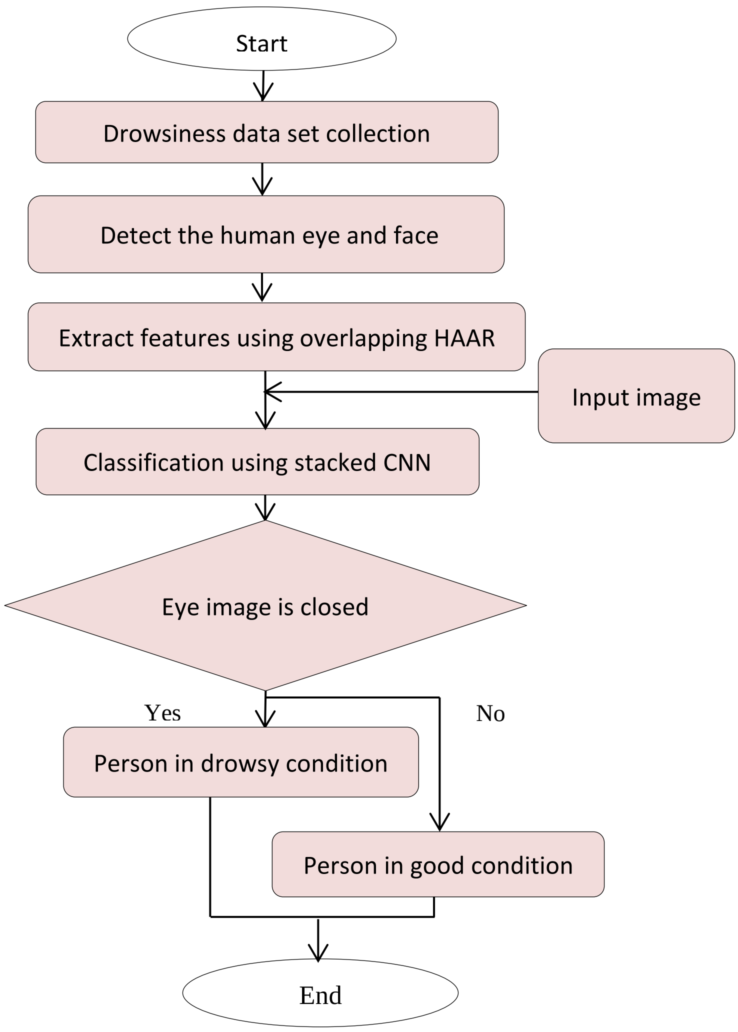

Figure 1. Flowchart of method system design

3. RESULTS AND DISCUSSION

The warning generation process can be individualized by determining the driver's immediate risk tolerance and evaluating it to its standard tolerance for risk. Algorithm 1 represents this reasonable level, which may be the primary parameter of the recommended visual adaptive FCW algorithm. It explains the importance of alert generation based on the likely intensity of the hazard, referred to as the warning triggering threshold (Thwt). Consequently, a warning is generated whenever instantaneous eye image (*EImage*) falls below *Thwt*, signifying that the impact of risk is more significant than the driver's standard tolerance for risk level these days.

Algorithm 1: Visual distraction adaptive-FCW framework (any time instant t)

```
Subsystem for Threshold Improvements:
if eye_image_flag(t) = 1 then
    if warning_flag(t-td) = 1 then
         if
           distracted_condition - warning_triggered then
         end
    else
          if EI_mage (t) < Th_cd   then
           cautious_condition - warning_triggered
          end
     end
else
       if distraction_flag (t) = 1 then
           Do nothing - warning_not_triggered and no_input_image
     else
         if warning_flag (t-td) = 1 then
           Warning_triggered but no_input_image
         end
     end
```

The cautious deceleration threshold is the second threshold (Thcd). From the simulation, the adaptive FCW approach attempts to appropriately tune the Thwt based on the most recent eye image profile by simultaneously considering Thcd. The need for warning generation is confirmed only when the driver's eye threshold is less than Thcd.

The classifier's performance was evaluated according to three dimensions: responsiveness, selectivity, and consistency. Sensitivity quantifies the predicted output in response to an input change. The sensitivity indicates the proportion of clearly recognized true positives. It contrasts with selectivity, quantifying the proportion of successfully predicted true negatives. The relationship between the predicted and actual values is referred to as consistency. It indicates the degree to which the expected value is close to the real deal. The following equations were used to quantify the three factors:

$$Sensitivity\ (\%) = \frac{TruePositives}{TruePositives + FalseNegatives}\ x\ 100$$

$$Specificity\ (\%) = \frac{TrueNegatives}{TrueNegatives + FlasePositives}\ x\ 100$$

$$Accuracy\ (100\%) = \frac{TruePositives + TrueNegatives}{TotalNumberofSamples}\ x\ 100$$

Figure 2 show that the validation of the accuracy and loos of closed eyes detection in real scenarios for all the training datasets is 84.74%. All evaluation training data are presented in the figures below. Figure 3 presents the intercorrelations among the eight dataset measures. It shows that 0.32 of the threshold is set up by the system and provides the warning of closed eyes. Figure 4 illustrates the receiver operating characteristic (ROC) curve by using classification between true positive rates versus false positive rate in the 0.638 area under the curve. The lost validation percentage is near zero, with the maximum iterations of 456. The area under the curve is 0.684211, which is true-positive. True-negative is highly classified for the dataset. On the other hand, accuracy is from the eight dataset groups with 1,000 frames. The allocated data portions for the training and testing phases of CNN model construction are 80% and 20%, respectively.

Figure 5 shows the driver's image underneath the open and closed eyes histogram. The images were adjusted from original to grayscale to obtain low intensity: (A) and (C) are authentic images in the range of 1.5×10^4 to 1.4×10^4 at 178 pixels; (B) and (D) are images after conversion to grayscale at a lower number of pixels with intensity 6664 and 5892, respectively. Results reveal that when images are converted to grayscale, it will decrease the intensity, Zeger *et al*. [28] support this finding. Utilizing modern processors and parallel programming, it is possible to perform simple pixel-by-pixel processing on a megapixel image in milliseconds. Other operations require excessive time, such as facial recognition, image resizing, and mean-shift segmentation. When the processing time is necessary to process an image or extract valuable data, most systems should operate faster.

The performance of all classes in the dataset is depicted in Table 1, which shows the confusion matrix for all classes. The classification gives the effectiveness of models that have been used. Accuracy, precision, and F-score values will be calculated using true negative (TN), true positive (TP), false positive (FP), and false negative (FN) values shown in Table 2. The accuracy value indicates how well the system can correctly categorize the data. In other words, the accuracy value compares the correctly classified data and the entire data set. The precision value is the proportion of correctly classified positive data categories to all positively classified data. As indicated in Table 3, the kappa coefficient is an additional measure of accuracy. A classification's kappa score indicates how close the final score was to the true value, given only the chance of success. It can transform a deal from 0 to 1. There is no similarity between the classified image and the reference image if the kappa coefficient equals 0. If the kappa coefficient equals 1, the image is classified and identical to the ground truth image. Consequently, the classification is more accurate with the higher the kappa coefficient.

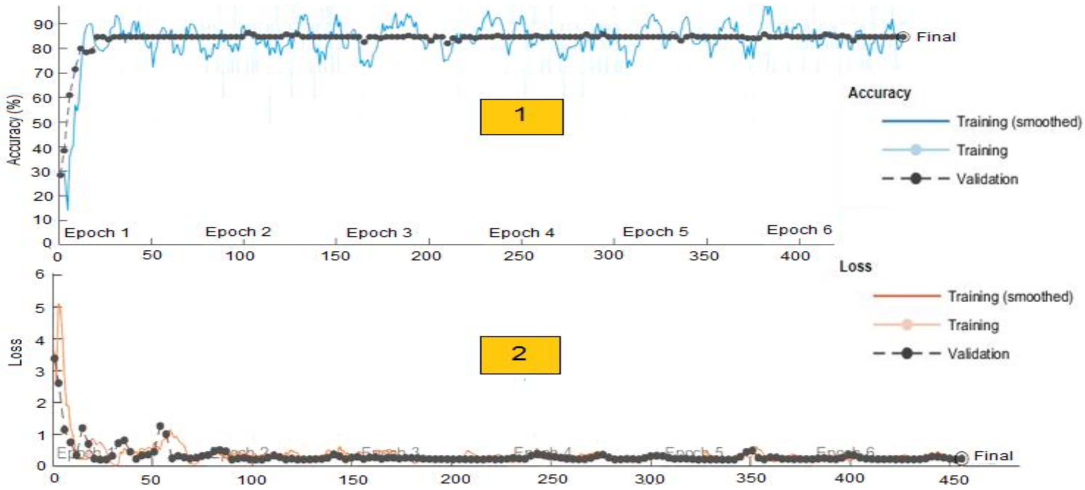

Figure 2. Result of the training progress

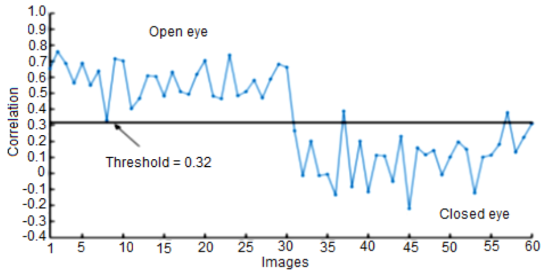

Figure 3. The threshold for triggering a warning in the system

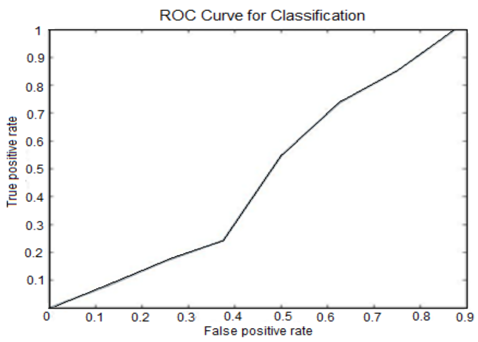

Figure 4. ROC curve for output

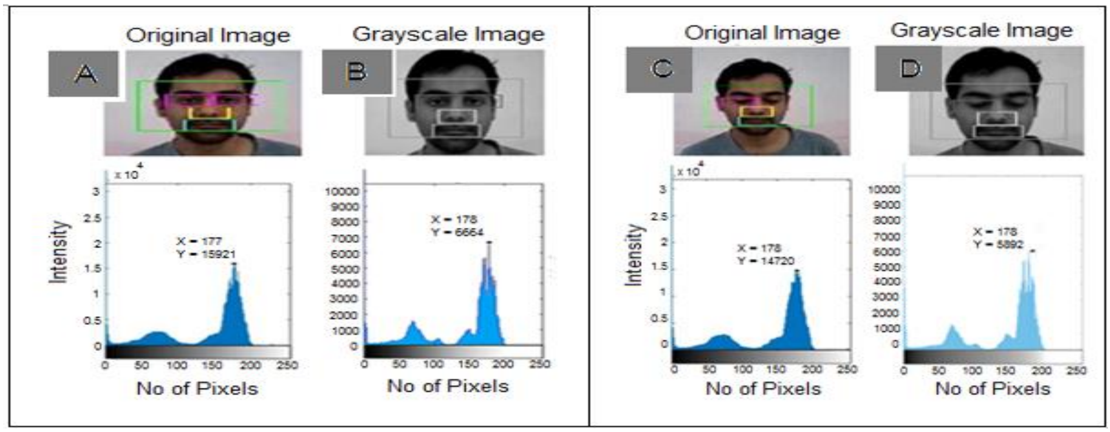

Figure 5. The driver's image in open and closed eyes histogram underneath

Table 1. Confusion matrix for all classes

	predict_ class1	predict_ class2	predict_ class3	predict_ class4	predict_ class5	predict_ class6	predict_ class7	predict_ class8
Actual_class1	76	0	0	0	0	0	0	0
Actual_class2	0	86	0	0	0	0	0	0
Actual_class3	0	0	72	0	0	0	0	0
Actual_class4	0	0	0	32	0	0	0	32
Actual_class5	0	0	0	0	181	0	0	0
Actual_class6	0	0	0	0	0	108	0	0
Actual_class7	0	0	0	0	0	0	142	0
Actual_class8	0	0	0	113	0	0	0	113

Table 2. Multi-class confusion matrix output for TP, FP, FN, and TN

	True positive	False positive	False negative	True negative
Actual_class1	76	0	0	879
Actual_class2	86	0	0	869
Actual_class3	72	0	0	883
Actual_class4	32	113	32	778
Actual_class5	181	0	0	774
Actual_class6	108	0	0	847
Actual_class7	142	0	0	813
Actual_class8	113	32	113	697

Table 3. Multi-class confusion matrix output

Class	Accuracy of single	Error of single	Accuracy in total	Error in total	Sensitivity	Specificity	Precision	False positive rate	F1 score	Matthews correlation coefficient	Kappa
Class 1	1	0	0.07958	0	1	1	1	0	1	1	0.84084
Class 2	1	0	0.09005	0	1	1	1	0	1	1	0.8199
Class 3	1	0	0.07539	0	1	1	1	0	1	1	0.84921
Class 4	0.5	0.5	0.03350	0.11832	0.5	0.87318	0.22069	0.1268	0.306	0.26003	0.79462
Class 5	1	0	0.18953	0	1	1	1	0	1	1	0.62094
Class 6	1	0	0.11309	0	1	1	1	0	1	1	0.77382
Class 7	1	0	0.14869	0	1	1	1	0	1	1	0.70262
Class 8	0.5	0.5	0.11832	0.03350	0.5	0.9561	0.77931	0.0438	0.609	0.5402	0.64089

4. CONCLUSION AND RECOMMENDATION

The paper's primary objective is to identify distraction aspects and technologies that address drivers' distractions on their characteristics and faces. As previously explained, numerous systems are present for image processing. They impressively stacked CNN for classification and overlapping HAAR features as an identifying yielded the highest value for supervised learning. Another significant discovery is that the method used to notice distractions can be further improved regarding classification, identification, and verification to obtain authentic and more prominent images as input datasets. This work proposes an adaptive framework for FCW that is driver distraction-aware. This method will decrease the number of false warnings, which can distract from important notifications. The CNN classification technique relies on a realistic dataset to reveal the driver's distraction status, focusing on the driver's face, eyes, and mouth.

The visual of closed eyes has been used as a proxy for the driver's tolerance for risk, with a threshold set to define when warnings should be generated. The entire entry is adaptively and continuously revised in response to driver distraction. Thus, a driver's perception of dangerous scenarios is captured based on the image profile of the eyes. This article also contributes to the literature by examining the driver's face, eyes, and mouth due to false warnings where the system cannot detect different drivers. Possible FCW innovations to be reviewed to incorporate diverse data sources and improve driver distraction management activities. Due to the significant quality gain achieved at a modest advancement in network specifications, combining methods has demonstrated considerable success in statistical signal training and extraction and classification problems. It is now possible to reduce the number of false alerts encountered in nearly all FCW.

The percentage to reduce false positive and false negative is higher by adding the parameters in the system. Previous research had overlooked both parameters: driver characteristics (such as braking, steering, speedy turns, and signaling) and images from the face while the driver is tired. This combination of inputs will expand the existing system to be more innovative in line with evolving automation in the industry. It is anticipated that additional research into different methods and FCW will offer further data to support the proposed approach.

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