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Intelligent Transportation in The Prevention of Accidents

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ABSTRACT

Information technology has significantly influenced numerous industrial sectors, and its integration into transportation systems has emerged as a promising solution, giving rise to intelligent transportation systems (ITS). Among the key application areas of ITS is the use of computer vision for accident prevention. Specifically, intelligent driver monitoring systems play a crucial role in enhancing vehicle safety by proactively identifying and addressing conditions that may lead to accidents. These systems aim to assist and alert drivers by intelligently recognizing potentially dangerous situations, thereby contributing to a substantial reduction in traffic accidents and related incidents. A major concern within intelligent transportation is driver drowsiness, a critical factor in preventing severe financial and human losses caused by traffic accidents. To address this, intelligent systems are employed to enhance vehicle control by continuously analyzing the driver's physical state and behavioral patterns. Consequently, the development of a system capable of accurately assessing a driver's alertness or fatigue level based on both driver behavior and vehicle status holds great importance. Notably, the proposed system presented in this research demonstrates superior performance compared to existing approaches, achieving 96% accuracy, 94% sensitivity, and 94% specificity in detecting driver drowsiness.

1. INTRODUCTION

Machine Intelligence methods have a wide range of applications [1-6]. Congested cities need transportation networks that can easily maintain them. And due to the ever-increasing expansion of transportation demands and the occurrence of problems caused by the increase in urban traffic, including air pollution, noise pollution, fuel consumption, waste of time and energy and their imposed costs, providing a suitable solution to smooth traffic flow is of particular importance. . Artificial intelligence and smart transportation have tremendous applications in all parts of the supply chain and enable smart cities to easily achieve this goal. Any smart city - or any human habitation - must have three qualities in abundance: livability, efficiency and sustainability. The role of transportation networks and technologies is huge in deciding how livable, efficient and sustainable smart cities can be. Smart transportation

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is the key to creating networks of vehicles in smart cities for this purpose. The more demand transportation companies receive, the more artificial intelligence will be used [7]. Intelligent transportation has many solutions for many problems. Solutions like:

- Resource management
- Predicting fluctuations in global transport volumes before they occur
- Optimizing shipping routes and faster delivery
- Better customer service
- Ability to recognize advanced images that determine the status of products and shipments
- The ability to predict and monitor parameters such as traffic, weather and socio-economic issues for more accurate freight pricing.

Intelligent transportation systems intelligently combine road and vehicle with the aim of improving traffic flow. Possible performance measures in this field are maximum capacity, travel times, safety, fuel consumption, reliability during travel times, resistance, etc. Intelligent transportation systems by using remote information and communication technology show the traffic density and can reduce it. The desired future of intelligent transportation systems is to be able to predict and estimate the traffic conditions in the next moments, in the present time. Due to the lack of awareness and knowledge of the traffic conditions at every moment and the moments after that, having the initiative to drive and control cars is far from expected [8] currently, computer vision can be used in countless different programs in Smart cities used. One of the critical application areas in intelligent transportation is computer vision. Computer vision for accident prevention According to the CDC, about 1.35 million people are victims of motor vehicle accidents every year, and about 3,700 people die in road accidents every day.

They lose themselves. A large number of these deaths involve pedestrians, cyclists and motorcyclists. Such accidents occur due to several factors such as poor visibility, fatigue and sleepiness of the driver, lack of concentration and technical defects and other reasons. Today, dynamic image recording and processing is an important part of vehicles [9]. Vehicles in smart cities need computer vision tools for the safety of passengers and pedestrians. Smart transportation wouldn't exist without computer vision, artificial intelligence, Internet of Things, blockchain, and a few other smart city technologies.

Computer vision is particularly effective in analyzing dynamically captured data and applying it to vehicles and traffic control devices. In this way, it can be said with certainty that computer vision plays its role in building livable, sustainable and more efficient smart cities [10] One of the most important concerns in smart transportation in the smart city infrastructure is to prevent damages. A significant financial and life loss caused by traffic accidents is the sleepiness of drivers. Therefore, due to the increase in travel requests in the transportation system and the increase in vehicle traffic, today, in order to increase safety, reduce accidents and financial costs, Most of today's cars are equipped with various safety and driving control systems [11] and intelligent systems are used to make the control systems of transportation vehicles smarter by analyzing different driver states, so the main goal of this research is to discuss the role of transportation. And intelligent transmission in accidents is early detection and warning of drowsiness so that the necessary measures can be taken as quickly as possible.

1.1. Thematic research literature

So far, many researches have been done on the role of intelligent transportation in accidents to estimate and predict the reaction time of the driver and vehicle system using field tests and driving simulations. In [12], ideas for providing a new model based on input and output modeling and correcting the error in estimating the behavior of the driver of the pursuit vehicle to increase or decrease are presented. Based on this idea, calculating and using the instantaneous reaction time of the driver and the car as an input for system modeling, as well as the appropriate and correct selection of the inputs and outputs of the selected inputs, according to the size of the time delay. That is, considering that the delay of the driver and vehicle system is not a fixed value in consecutive moments, then the selection of the corresponding inputs and outputs, in fact, the right and appropriate stimulation and reaction, should be done according to the momentary delay between each input and output.

This issue reduces the error in modeling and increases the precision and accuracy of the model. It has been shown in [13] that there is a high correlation between the reaction time and the acceleration of the lead car and the relative distance between the lead car and the follower car. In [14], a FIS model for prediction is presented, which has four inputs and one output.

The moments of the driver and the following car (τ), relative speed (ΔV), relative distance (ΔX) and the speed of the following car are the four inputs of this model. The output of the model is equal to the acceleration of the pursuing vehicle (aFV). The training of this model is based on the selection of appropriate inputs and outputs according to the momentary delay of the driver and the car. In this model, a hidden layer with 9 nodes and post-propagation algorithm is used. In [15], the results of the analysis and investigation of the driver's delay time in practical tests showed that this time depends a lot on the driving and test conditions. Also, this time changes quickly in a simple movement with increasing and decreasing acceleration In [16], this idea shows a great dependence between the delay time with the relative speed and the acceleration of the pursuing car in the careful analysis of the real data from the traffic flow to investigate the car chasing behavior. In this idea, the changes in the relative speed and acceleration of the chasing car are similar to the concept of stimulation and reaction.

The method of calculating the momentary delay of the driver and the car is based on the fact that with the change in the direction of the momentary relative speed (occurrence of the minimum and maximum in the curve of the relative speed of two cars or the change in the sign of the relative acceleration), the driver of the pursuing car commands the car to change the acceleration with a delay and The mechanism of applying the driver's command in the car executes the driver's command with a delay and reduces or increases the acceleration. Finally, this driver's command is realized in the form of a change in the direction of the instantaneous acceleration (occurrence of minimum and maximum in the acceleration curve of the following car).

Hence, the instantaneous delay of the system the driver and the car is the time interval between two consecutive changes, two consecutive minimums or two consecutive maximums, in the graph of the relative speed and acceleration of the chasing car. This idea is called the stimulus-reaction idea to estimate and determine the momentary delay of the driver and the car in the behavior of following the car. In the smart car project of MIT University [17] and the advanced safe car project of Toyota Company or ASV, one of the physiological signs obtained from the functioning of human body parts such as the brain and heart and among the most accurate signs for diagnosis Drowsiness is from a long history They are available to diagnose drowsiness in different areas has been used and the driver must wear a special bracelet to measure the heart rate and be examined. Although physiological methods have high accuracy, but to obtain these symptoms, electrodes must be attached to the person's body, which is unpleasant or annoying for the driver. According to this point, these methods cannot be used practically in the car.

2. RESEARCH METHODS

In the topic of intelligent transportation, intelligent driver monitoring systems are among the things that have been taken into consideration in the safety of cars, so that these systems try to help and warn the driver by intelligently diagnosing accident-causing conditions. By using such intelligent systems, driving accidents can be significantly reduced. The most important equipment that has been considered for smart cars so far includes emergency brake assist systems, front crash warning, lane departure warning, driver blind spot detection, smart front lights, and drowsiness detection, among which the drowsiness detection system. The driver is extremely important in preventing accidents and fatal road accidents. There is no specific method or solution to prevent driver drowsiness, but in general, by timely diagnosis, preventive measures are taken to prevent accidents. For this reason, a system that can intelligently detect the driver's level of alertness or sleepiness by controlling the driver's behavior and the condition of the car is important. Such systems warn the driver when he is drowsy and perform a series of precautionary measures. For example, when faced with drowsiness, they can warn the driver by using sound signals, vibration of the seat or steering wheel, or sound alarms and playing loud music, and if necessary, by activating the emergency braking system and the car's air bag.

They have a significant effect in reducing accidents and driving fatalities. During sleepiness, a person's appearance and face undergo noticeable changes, the most important of which are the eyes, head, mouth, and sitting position. Visual signs of drowsiness can be extracted by photographing the driver and using image processing methods. People in the condition of tiredness and sleepiness show some special behaviors which can be easily seen in appearance changes such as eyes, head and face as shown in Fig. 1. Prolonged blinking time, slow movement of eyelids, closeness of eyelids to each other or even closing of eyelids, frequent lowering of the head, yawning, squinting, numbness, hangover and slouching are the most common visual characteristics of a sleepy person.

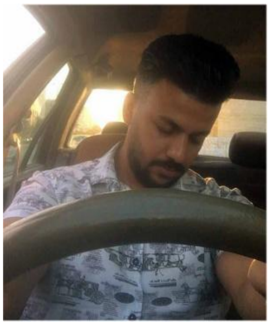

Fig. 1. Appearance changes such as eyes, head and face during sleepiness

Machine vision is a non-intrusive technique to detect the visual signs of a sleepy person. In this method, the person's pictures are taken by the camera that is in front of him and then the desired signs are extracted from it by machine vision and image processing techniques. The eyes focus. The most important of these changes include changes in the amount of blinking, the amount of eye closure, and the direction of eye movement. In this method, by using a color video camera that is placed directly in front of the driver's face, the driver's face is first recognized in the image, and then the driver's eyes are examined to detect the micro-sleeps. The proposed algorithm of this research to detect driver drowsiness includes steps 1- pre-processing 2- face recognition 3- locating eyes 4- determining the state of the eyes when the driver is drowsy. In the pre-processing stage of this algorithm, it is necessary to obtain the information related to the driver's face and separate it from other components inside the car, such as the seat, etc. The video received from the camera is nothing but a long sequence of still images that are updated one after another. And each of these images is just a collection of pixels with different values placed in the corresponding position. Therefore, in the driver's face recognition stage, the pixels taken from each image frame are used using the cascade classification algorithm. Cascade classification or well-known enhanced classification cascades work with Haar-like features and are a special application of ensemble learning, which is called boosting. These tools mainly rely on Adaboost classifiers and other models such as Real Adaboost, Gentle Adaboost or Logitboost. There are some common features that can be observed in all human faces, such as:

1. An area including the eye area that is darker compared to the species.
2. The lighter colour of the nose compared to the eyes
3. The special position of the eyes, mouth and nose, etc.

These characteristics are called Haar characteristics. In this part of driver's face recognition implementation, the main idea is to reject those sub-objects that do not contain a face, and at the same time, the areas that have such characteristics remain protected. Since our task is proper face recognition, we want to reduce the rate of false negative detection, i.e. material that contained a face but was not recognized as such. In Abenda, the image taken from the camera turns into a gray image. This is done to reduce the dimensions of the input image. In fact, instead of two points for each pixel described by red, green, and blue colors, a simple linear transformation is used:

$$Ygray = xR + xG + xB \qquad (1)$$

A series of classifications are then applied to each sub-object. These classifiers are simple decision trees where any negative result at a point leads to the rejection of a sub-object, possibly including a face. The first classifier often reduces the negative examples with low computational cost, and the subsequent classifiers remove the next negative examples with higher cost by using higher computational power. Classifiers are trained using Adaboost and the threshold is set to minimize the false detection rate. Then, for each recognized face, a rectangle is drawn around the face and eyes. Fig. 2.

Fig. 2. Driver's face recognition

Then, in order to identify and follow the pupil for open or closed eyes, three neural networks svm, mlp, and cnn have been used in parallel with the collective voting technique to classify and detect the driver's sleepiness. Fig. 3.

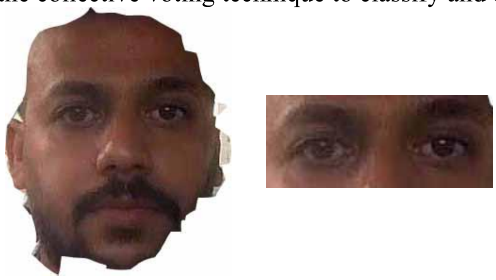

Fig. 3. Detection of open and closed eyes of the driver

If the classifiers do not recognize any candidate as having open eyes, it can be assumed that the driver's eyes are closed. But since every person blinks approximately every six seconds, as soon as the driver's eyes are detected as closed, it is not possible to determine the driver's sleepiness with certainty. Therefore, we also calculate the distance between the opening and closing of the eye, which represents blinking. For this purpose, the following relations were used to calculate the percentage of closed eyes and the rate of blinking:

Eye closed percentage = time the eyes were closed in the last 20 seconds / 20
Blink rate = the number of eye blinks in 20 seconds

If it is detected that the eyes are closed for more than twenty seconds, it is considered one of the most obvious signs of drowsiness, and the diagnostic system predicts and warns the driver in the state of sleep.

3. EVALUATION

The data set used in this research includes 5000 image frames of the information of 35 car drivers, 70% of which are training data, 15% of validation data, and 15% of test data. And the training of algorithms has been done in 100 IPAC. Then, after implementing the proposed algorithm, according to the mentioned explanations and definitions, the classification performance can be checked with the help of the Confusion Matrix table.

Table 1. Confusion Matrix

		Predicted label	
		Positive	**negative**
Known label	negative	TP	**FN**
	Positive	FP	**TN**

- The sample is a member of the positive category and is recognized as a member of the same class (True Positive).
- The class member sample is positive and the class member is recognized as negative (False Negative)

- The sample is a member of the negative class and is recognized as a member of the same class (True Negative).
- And finally, the class member sample is negative and the class member is recognized as positive (False Positive).

FNR2 and FPR1 error rates are used to accurately evaluate the method of extracting the driver's somnolence signs, which are respectively introduced as False Negative and False Positive. The FPR rate shows how many percent of the cases that should not have been detected by the system, and the FNR rate shows how many percent of the cases the system detected.

He failed to reveal what should have been revealed. Based on the tests performed to evaluate the efficiency of the proposed system, the results of Table 2 were obtained.

Table 2. Evaluation of sleepiness symptoms

FNR	FPR	
%13	%1	The rate of eye closure
%10	%3	Blink rate

The efficiency of the model has been evaluated on the training and test data sets, using evaluation criteria, accuracy, precision, and sensitivity. Then the results have been compared with previous articles in Table 4.

Formula 1: Accuracy evaluation criterion, or classification rate: It is a measurement criterion that determines the ability of a model to associate the result with the features of the available information.

$$\mathbf{Acc}\text{uracy} = \frac{\text{Tp} + \text{Tn}}{\text{Tp} + \text{Tn} + \text{Fp} + \text{Fn}} \tag{1}$$

Formula 2: Error rate: The classification error criterion is exactly the opposite of the classification accuracy criterion, the lowest value of which is zero and the highest value is 1, or in other words, when we have the best efficiency, its value is zero.

$$\mathbf{E}\text{ror } \mathbf{R}\text{ate} = \frac{\text{FN} + \text{FP}}{\text{TN} + \text{TP} + \text{FN} + \text{FP}} \tag{2}$$

Formula 3: Correctness evaluation criterion: In fact, it asks when the model predicts a positive result, to what extent is this result correct? As a result, the more correct positive predictions are compared to negative positives, the higher the accuracy of the prediction.

$$\mathbf{P}\text{recision} = \frac{\text{Tp}}{\text{Tp} + \text{Fp}} \tag{3}$$

Formula 4-Sensitivity evaluation criterion: When the negative detection value is high, the sensitivity criterion will be a suitable criterion, that is, if the model has more false diagnoses, the sensitivity value is low.

$$\mathbf{R}\text{ecall} = \frac{\text{Tp}}{\text{Tp} + \text{Fn}} \tag{4}$$

In Table 3 all the stated evaluation criteria are checked and the results are shown.

Table 3. Evaluation of the proposed model

	Accuracy	**Precision**	**Recall**	**ER**
SVM	%90	%91	%89	**%10**
MLP	%89	%85	%88	**%11**
CNN	%93	%94	%91	**%7**
ENSEMBLE	%96	%94	%94	**%4**

Table 4. Comparison of the proposed model

	Accuracy	**Precision**	**Recall**	**ER**
Królak[11]	%95	%96	%98	**%5**
ENSEMBLE	%96	%94	%94	**%4**

4. DISCUSSION AND CONCLUSION

The purpose of this article is to recognize the face and track the driver's eye movements to detect his sleepiness. Therefore, a monitoring system has been provided to detect driver drowsiness. In this system, the driver's lens is first extracted, then the location of the eyes is determined, and two types of signs, the percentage of eye closure and the blinking rate, are extracted from the eye region, and three neural networks are generated by taking into account the percentage of eye closure. It warns the driver of falling asleep. In the qualitative evaluation of the proposed system, it can be said that the presented results are considered very good; but the most important flaw of the proposed system is the face tracking algorithm. It can be said that the main reason for the occurrence of errors in the extraction of features of the eye area was the occurrence of disturbances in face detection and tracking operations. Because if the location of the face is determined inaccurately, the eye detection is not done well, and as a result, it will be difficult to detect the condition of the eyes in terms of whether they are open or closed. Therefore, the signs of driver fatigue are not extracted properly and the efficiency of the system decreases. Among the future goals, we can point out the replacement of a suitable tracking method instead of the current method. The proposed system was tested for people without glasses. Due to the reflection of light from the glasses, the presence of glasses reduces the accuracy of face detection algorithms and extracting signs of fatigue and lack of concentration. So that the suggestion system for people who wear sunglasses is completely disrupted. Of course, the presence of glasses, especially sunglasses, creates major problems in other driver's face monitoring systems.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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