Fuzzy logic-based driver fatigue prediction system for safe and eco-friendly driving

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ABSTRACT

The advancement of intelligent car systems in recent years has been significantly influenced by developments in information technology. Driver fatigue is a dominant problem in car accidents. The goal of advanced driving assistance is to develop an advanced driving assistance system (ADAS) a eco-friendly model which focuses on the detection of drowsy driver, to notify drivers of their fatigued condition to prevent accidents on the roads. With relation to driving, the driver mustn't be distracted by alarms when they are not tired. The answer to this unanswered question is provided by 60-second photograph sequences that were taken when the subject's face was visible. To reduce false positives, two alternative solutions for determining whether the driver is drowsy have been developed. To extract numerical data from photos and feed it into a fuzzy logic-based system, convolutional network is applied initially; later deep learning technique is followed. The fuzzy logic-based solution avoids the false alarm of the system.

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1. INTRODUCTION

To sustain performance over time, driving an automobile is a complicated, diverse, and sometimes dangerous task that calls for the complete mobilization of physiological and cognitive resources. Accidents and other serious repercussions might result from the loss of these resources. Determining the driver's operating status is also made more crucial by the promise of autonomous cars. This has lately led to a significant amount of research, both from a theoretical standpoint and with an eye towards practical applications. The task is difficult: it involves not only seeing but also foreseeing deterioration in the driver's operating status. When operating an automobile, a driver must balance a wide range of psychological and physical factors. As per World Health Organization (WHO) estimates that millions of people suffer injuries and fatalities as a result of motor vehicle collisions each year, with driver inattention and weariness topping the list of contributing factors [1]. According to the American Automobile Association, fatigued drivers are to blame for 21% of fatal traffic accidents and 7% of all collisions [2]. According to US based National Highway Traffic Safety Administration (NHTSA) around 2.2% to 2.6% of all yearly fatal accidents in the United States between 2015 and 2019 were caused by driver drowsiness; these figures exclude accidents that merely resulted in property damage [3]. Over 30,000 injury accidents (5.0% of all injuries), according to sources, occurred in 2009 [4]. According to a 2017 survey by the Foundation for Traffic Safety, 42.4% of drivers drive without at least one or more days of sleep, or less than six hours of sleep, and the majority of drivers (87.9) interpret what they see as undesirable behavior (95.2%) [5]. From this perspective, we present two alternative methods for tackling the fatigue detection issue [6]. During the initial stage, deep learning technique is followed to examine the set of driver picture. deep neural networks-based approaches are used to detect human cognitive parameters such as sleepiness, driver’s age and head posture [7]. Later, deep learning techniques and artificial intelligence (AI) is used to extract significant features from the image, after which the information is fed into a fuzzy inference system to assess the inattention level of the driver [8]. The first suggested method is carried out using a convolutional neural network (CNN), which is a class of neural network that extract features from the data sequences (for instance, using weather data from the last seven days to estimate the weather tomorrow) [9]. The model will be able to forecast whether or not the driver is drowsy since the CNN architecture is able to detect the image pattern and locate trends throughout the sequence of images [10]. The second method, in contrast, uses combined techniques of deep learning and AI to pre-process the driver's photos [11]. The histogram of oriented gradients (HOG) that pinpoint facial elements namely mouth or eyes whereas linear supporting vector machine (SVM) will be used to identify the face [12]. In this study, a combination of HOG and linear SVM was employed to identify the driver's face.

This section provides a summary of the methods and strategies used before to identify tiredness. The first approach is based on driving habits and depends heavily on the characteristics of the car, the condition of the roads, and the driver. It has been utilized before driving patterns should be estimated using deviations from lateral or lane positions or steering wheel movements. Driver assistance system is implemented with a single low-cost camera that is placed inner of the automobile, this solution is non-invasive and does not depend on wearable gadgets [13]. For face recognition, a Haar-cascade approach is employed, and for processing and classification, simple neural network architecture is used [14]. Converting video frames to grayscale is the first step [15]. The Haar-cascade approach is then utilized to trim faces from images in two stages considering that it is a simple, accurate and rapid process of face detection [16]. The validation of the Haar-cascade approach is done by stratified k-fold (STKF) [17]. The output images acquired through the pre-processing and face detection sub-system are separated into five equal halves [18]. Recognizing fatigue based on visual cues. A tried-and-true method for detecting driver drowsiness is to use a video camera to record eyelid movement and gaze. Visual indicators of fatigue include drooping posture, yawning, frequent nodding, slow eyelid movement, a sluggish facial expression, and a decreased degree of eye opening. Numerous studies have been conducted on these strategies. Yet, these methods frequently exhibit sensitivity to outside elements like brightness or the driver's look. In this research, raw data from multiple data sets in the literature is used to identify driver weariness utilizing (multi-task ConNN). In this study, the dlib package is used to recognize and track drivers' faces in the real-time film. The face, mouth, and eye areas were then defined using the dlib technique on these scaled pictures. The mouth and eye are opened or closed, and the opening is designated according to the closed condition, in these defined places. “1” represents open states, while “0” represents closed states. We were able to achieve an 85% accuracy rate overall.

The systems for facial landmark detection, blink detection, and yawn detection were the main topics of this literature review [19]. Among the techniques used to identify sleepiness are deep CNN, computer vision, behavioral measures, and machine learning algorithms, each of which has advantages, drawbacks, and varying degrees of accuracy [20]. Technologies based on eye aspect ratio (EAR) and mouth aspect ratio (MAR) have been investigated for the detection of blinks and yawns [21]. “Computer vision-based drowsiness detection for motorized vehicles with web push notifications,” the title claims. In this work, they describe a computer vision-based system for identifying the drowsiness in cars, complete with alert sounds and web push notifications. The driver will be informed by these messages, enabling them to prevent an accident. To help the driver stay focused, the system can also send out an alert that shows local coffee shops. In light of this, the system successfully identified the driver's sleepiness throughout the trial run. The eyes' openness or closure was determined using the EAR. A buzzer provided an alert, and after that the user. These will be done with an emphasis on speed and reliability, which are necessary for the real-world, challenging application of preventing car accidents and making driving and roads safer. This work intends to put together a system that can assess a driver's state of fatigue based on facial image sequences. The driver-based advanced driving assistance system (ADAS) system for identifying sleepiness is constrained into two key factors. We have developed this work with a part of has two key constraints: early detection and minimizing false positives. To prevent false positives that would annoy the driver and force them to turn off the ADAS without using the remaining features, the system is designed to only alert the driver in actual cases of weariness. It is difficult to determine the frame rate at which the camera and system must exchange data when capturing the driver. Due to the vast count of frames per second (FPS) to be analyze, a high frame rate will overload the system, but a low FPS can have a detrimental effect on system performance. In this field, having sufficient FPS is essential for appreciating image sequence elements with extremely little durations, like blinks. In order to predict driver drowsiness, this research suggests an advanced approach that associates deep learning and AI techniques to take out various features from the photos and then incorporates those features into a fuzzy logic-based system. However, the process structure is depicted in Figure 1, which includes three phases: pre-processing, analysis, and alarm activation.

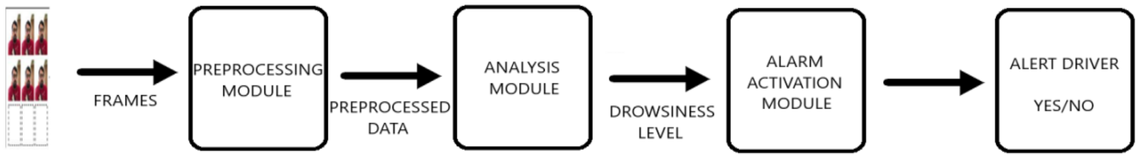

Figure 1. Driver drowsiness estimation modules

2. PROPOSED METHOD

While the driver is behind the wheel, a camera records the driver's face and streams it as video. The software then evaluates the video for signs of fatigue, sleepiness, and drowsiness intensity [22]. The driver's facial tracking, level of exhaustion, and identification of important facial regions based on eye closure and yawning are the essential factors that should be studied for analysis at this point [23]. Finally, any drowsiness is found from the driver, a voice alert is given. The pre-processing module receives these images and is responsible for transforming them into data that the sleepiness detection model may use [24].

The analysis module receives the pre-processed data after which it executes activities related to fatigue detection and determines the driver's level of drowsiness at that moment using data from the preceding 60 seconds [25]. The alarm activation module then receives the calculated level of tiredness and decides whether or not to notify the driver based on past levels of drowsiness [26]. As was previously mentioned, the main objective of alarm activation system is to verify the accuracy of false positives produced by the module (when diver awake give an intimation of drowsiness alerts), false positives can upset the driver and increases the chance that the system will be turned off [27]. This is one of the reasons researchers are experimenting with movies rather than frames and tightening up the testing procedures, as the classification of a 10-minutefilm would be deemed "drowsy" regardless of what is discovered before or after that one alarm is activated. The human-computer interface system in charge of warning the driver via visual and/or auditory cues will receive the system's decision once it has been decided whether or not to inform the driver (a yes/no possible outcome). Figure 2 illustrates the three modules of each possible solution: pre-processing, analysis, and alarm activation.

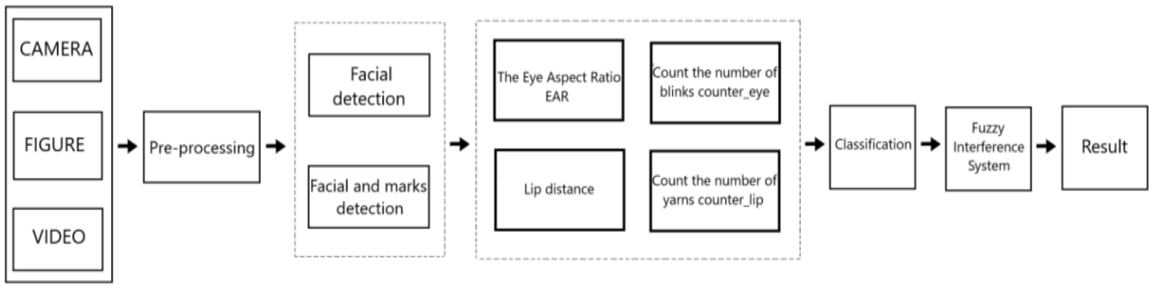

Figure 2. Architecture modules

2.1. Workflow

High-resolution cameras are used to monitor and capture images, with the frames being extracted individually and alerts being provided [28]. Haar cascade classifiers compute the MAR and EAR from each extracted frame, which is then used to reveal the pattern of facial traits. Yawns and blinks are considered when the threshold values go beyond the EAR and MAR values. This value is then sent to the fuzzy inference system, which determines whether or not an alarm should sound after a predetermined number of frames in which the driver's eye blinking rate and yawns have been suspected. The alarm has been activated to awaken the driver, and it will continue to sound until the driver responds.

2.2. Facial features and gesture detection

Frame acquisition: to record the driver's field of view, a top-of-the-line digital camera is mounted in the automobile and is set to close mode. To assess the driver's current condition, real-time video is gathered, and frames are quickly retrieved and analyzed. To position the driver's face in a video, SVM and HOG technique is used. Combining HOG and linear SVM detectors is advised to increase accuracy while lowering false positives. The dlib library file is used to predict the eye and yawn detection process.

2.3. Blink rate calculation

A blink nature is easily identified by measuring the EAR, which is the vertical distance between the upper and lower eyelids fractioned by its horizontal length. Figure 3 shows that the vertical and horizontal distance between the upper and lower eyelids decreases during a blink, but this distance tends to increase following a blink when the eye is open. As a result, the number of times you blink increases while the EAR decreases (towards zero). Subsequently, the driver's actions are suspected when the EAR count drops below the threshold. The formula below can be used to calculate EAR. The periphery of the eye is shown in Figure 3 from P1 to P6. Horizontal edges are indicated by points P1 through P4 and vertical edges by points P2, P6, P3, and P5. The openness values that usually range between 0.20 and 0.40

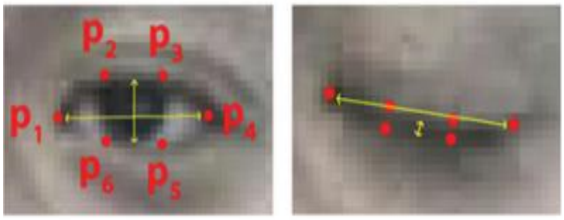

Figure 3. Eye detection

$$EAR = (||P_2 - P_6|| + ||P_3 - P_5||) / (2 * ||P_1 - P_4||) \quad (1)$$

2.4. Yawn counts

The eight coordinates system is used to predict the dlib landmark function from the mouth as shown in Figure 4. The facial landmarks are marked by moving clockwise direction starting from lower left corner of the mouth. It has been found that there is a connection between the horizontal and vertical coordinates. MAR is obtained by dividing the vertical distance between the corners of the upper lips and lower lips by horizontal line between the corners of the lips. Someone's upper and lower lip space gets bigger when they yawn. Horizontal edges are indicated by points P1 through P4 and vertical edges by points P2, P6, P3, and P5.

Figure 4. Yawn detection

$$MAR = (||P_1 - P_5|| + ||P_2 - P_4||) / (2 * ||P_6 - P_3||) \quad (2)$$

To detect sleepiness, a Mamdani fuzzy inference system requires inputs, outputs, and rules to be specified. For each input, there must be a corresponding variable whose range of values is defined by one or more fuzzy sets (for example, the variable “blinks count” receives as integer, fuzzy sets as three different levels “high,” “normal,” and “low”). Each and every fuzzy set (x) function is specified as set A, and for each input x, a degree of membership is determined (x). The membership rate ranges from 0 to 1, with 0 denoting complete falsehood and value x not belonging to the fuzzy set A, and 1 denoting complete truth. Triangular (tri) and trapezoidal (trap) membership functions, depicted in Figure 5, are employed in this investigation. Because they can express the change in values on most fuzzy sets quickly and accurately, in fuzzy logic these membership functions is quite commonly used.

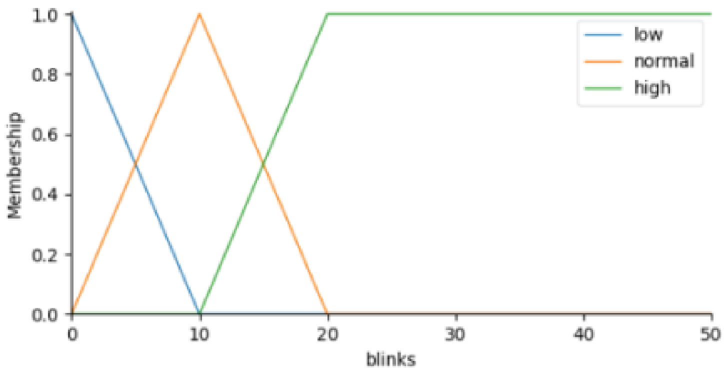

Figure 5. Membership values

Table 1 illustrates how the range of membership values is connected along to fuzzy set guides the selection of a particular membership function over others. Triangular functions have three membership values (0, 1 and 0), while trapezoidal functions have four points (with membership values of 1, 2, and 0). (with membership values 0, 1, 1, and 0).

Table 1. Blinks and yawns using membership values

Variable name	Fuzzy sets	
	Name	Membership function
Quantity of blinks (blinks)	Low	tri (0,0,10)
	Normal	tri (0,10,20)
	High	trap (10,20,50,50)
Average blink period in seconds (avg_link)	Low	trap (0,0,0.10,0.30)
	Normal	trap (0.10,0.30,0.40,0.60)
	High	trap (0.40,0.60,30,30)
Quantity of microsleep (microsleeps)	Low	tri (0,0,2)
	High	trap (0,3,10,10)
Count of yawns (yawns)	Low	tri (0,0,2)
	High	trap (0,2,10,10)
A few minutes of yawning	Low	tri (0,0,10)
(avg_yawn)	High	trap (0,10,30,30)

2.5. Alarm activation

To give alert for the driver the subsequent conditions to be followed: 1) a driver is deemed tired when the analysis module's output over a level known as the drowsiness threshold. This number can be anywhere between 0 and 1. 2) To sound an alarm, the motorist must be considered drowsy many times in the last 60 seconds. How long (in seconds) the driver must be drowsy before being alerted, which determines the time parameter. This number varies from 0 to 60.

When the driver is considered drowsy for a specified amount of time, an alarm is triggered. A second alarm is not triggered if the circumstance that caused the alarm to be sounded persists after the driver has been notified. Instead, if the parameters for notifying the driver are no longer met, a new alarm is triggered, and sleepiness is detected once more. Each video is examined frame by frame to assess the system's effectiveness, with each frame determining the driver's level of sleepiness. The alarm activation module of the ADAS then chooses whether or not to warn the driver. The number of alerts raised during the video is counted, and the accuracy of the system is determined.

3. PERFORMANCE ANALYSIS - SUBJECTS WITH DIFFERENT ETHINITIES

To get the desired findings, a huge number of photographs were shot, and their sleepiness accuracy was assessed using eye and yawn detection. In a suitable real-time driving environment, the proposed system must be able to identify tiredness. The quality of the camera will also influence performance. Both daytime and night-time drivers can use the suggested system because of its well-designed and user-friendly interface. Users can use the interface to accomplish their goals by following it step by step. If the programme crashes unexpectedly, the proposed system must be able to recover and become ready to use again. All of these subjects are recorded in a range of simulated driving scenarios, including standard driving mode, yawning, slow blink rate, conscious laughing, and dizzy napping, in both day and night lighting settings. Hence, an infrared (IR) lamp was used in the experiment to obtain IR pictures for the dataset. The drowsiness detection system's prototype will be built on a microcontroller board with all of the necessary peripheral hardware, and Python 3 will be utilized to create the software capabilities. The significance of appropriate face alignment is demonstrated in Figures 6 to 8. An incorrectly aligned face, as seen in Figure 6, could lead to erroneous detection or processing. On the other hand, a correctly aligned face is shown in Figure 9, guaranteeing maximum accuracy and performance. Furthermore, Figure 7 illustrates a situation in which the person is wearing spectacles, emphasizing possible issues such as occlusions or reflections that may impair system performance.

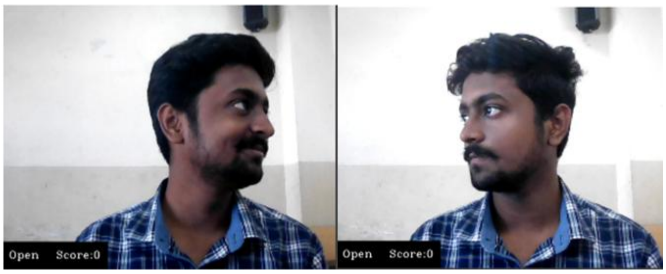

Figure 6. Face improperly aligned

Figure 7. While wearing a specs

Figure 8. Face properly aligned

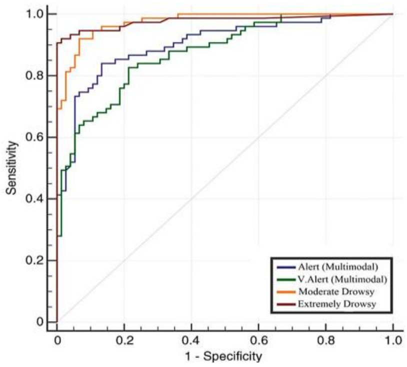

Figure 9. Performance evaluation

4. CONCLUSION

According to recent findings, the accuracy of sleepiness detection systems is much increased by examining a series of photos as opposed to a single frame. Our results offer unmistakable proof that combining fuzzy logic and deep learning lowers false positives to a controllable level, enabling the system to function constantly without needlessly upsetting alert drivers. The false positive rate was only 7%, meaning that only one out of 60 videos of conscious drivers produced an inaccurate alarm. In 58 out of 61 films of drowsy participants, the suggested technique correctly identified exhaustion, achieving 96% accuracy in detecting drowsiness. To increase the identification of fatigue and handle edge circumstances, more advancements are needed. Additionally, the model provides insights into behavioral indicators associated with weariness by illustrating the interaction between the mouth and eye states during speaking activities. The study's efficiency, which comes from using a single deep learning model instead of merging several CNN architectures, is one of its main advantages. For a more thorough approach, future versions of the system will incorporate head position analysis and integrate it into an embedded system.

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AUTHOR CONTRIBUTIONS STATEMENT

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Shakeela Joy Arul Dhas	✓		✓	✓			✓	✓		✓	✓			
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author Raghavan Sheeja on request.

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