Driver Drowsiness Detection System Using Hybrid Features Among Malaysian Drivers: A Concept

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Abstract. Drowsiness is one of the most critical factors contributing to a high number of crashes in Malaysia. Several types of driver drowsiness detection (DDD) systems have been developed to tackle this problem. They are based on vehicle diagnostics, physiology, or facial recognition. However, these systems have several limitations in terms of reliability and intrusiveness. Therefore, a hybrid approach based on vehicle diagnostics, physiology, and remote sensing information is proposed to tackle this problem. The training and test data are collected from the test subjects by driving the instrumented vehicle on North-South Expressway at 4 different periods: morning, afternoon, evening, and night. The training data is then used to train the deep learning model in classifying the driver's drowsiness. A recurrent neural network is used in the system because it has a temporal characteristic that can be utilised to predict the driver's drowsiness. It can also incrementally learn the features through backpropagation. Once the DDD system is developed, the test data is fed into the deep learning model to determine the model's accuracy in drowsiness detection. Lastly, the test subjects must drive the car with the DDD system at 4 different periods. The hybrid features and deep learning are expected to enhance driver drowsiness detection accuracy compared to existing techniques. A survey is conducted to investigate the possibility of promoting the proposed system to other drivers in Malaysia.

Keywords: Deep Learning · Vehicle Diagnostics · Physiology · Remote Sensing · Hybrid Features · Real time · Driver Drowsiness Detection

1 Introduction

Road traffic accidents have always been a significant public health problem in the world. According to the Global Status Report on Road Safety 2018 published by World Health Organization [1], the number of roads traffic deaths on the world's road remains unacceptably high. Road traffic accidents have been the eighth leading cause of death, contributing to 1.35 million deaths in 2016 as shown in Fig. 1. In Malaysia, a similar trend of road fatalities due to driver drowsiness is observed.

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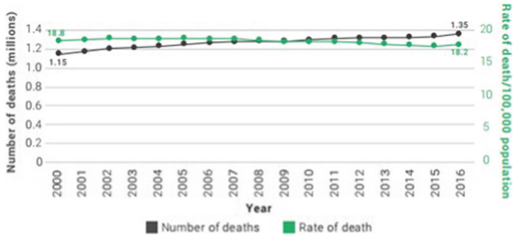

Fig. 1. The number of deaths on the road worldwide from the year 2000 to 2016 [1].

Risky driving, speeding, alcohol, drowsiness, and failure to wear seat belts are the main factors that cause road accidents to happen. According to the Malaysian Institute of Road Safety Research (MIROS) Crash Investigation and Reconstruction (2007–2010) [2], fatigue is one of the most critical factors in causing road traffic accidents as it contributes to a high number of crashes and causes more than 3 fatalities per case. Based on the study done by the World Health Organization [3], the factors that predispose a driver to fatigue are long work period before trip, monotonous road, and poor quality of sleep.

Therefore, in order to solve this worrying issue, the driver drowsiness detection (DDD) system has come into play in recent years. DDD system is a system used to identify the driver's drowsiness by capturing certain characteristics of the driver that exhibits during drowsy driving. There are various types of DDD system which implement different techniques to detect driver drowsiness. According to B. Reddy et al. [4], the techniques used can be classified into 3 categories. They are vehicle diagnostics, physiology, and facial recognition [5].

Based on M. Fernandes [6] and A. Sahayadhas et al. [7], the vehicle diagnostics based DDD systems are nonintrusive to the driver, and they produce satisfactory results in drowsiness detection. On the other hand, the reliability of the system depends on road geometry and curvature. Besides, the physiological based DDD systems produce a very high level of accuracy in drowsiness detection. However, this class of techniques requires the driver to wear signal measuring tools while driving. Lastly, the facial recognition based DDD systems are nonintrusive to the driver, and they produce great results in identifying the drowsiness of the driver. Nevertheless, they depend on some external factors such as illumination and unexpected features on the face.

Due to each category of the techniques' advantages and disadvantages, the hybrid approach has become noticed in recent years [8]–[10]. The hybrid approach combines three classes of techniques to identify the drowsiness of the driver. The advantage of the hybrid approach is that it increases the reliability and accuracy of the system. However, the hybrid approach is usually expensive, and it also requires more computational power as compared to the previous three approaches.

Based on the survey done by V. Arceda et al. [11] on drowsiness detection techniques, they find out that the drowsiness detection techniques proposed by the researchers are not tested under real road conditions. The testing is carried out under the simulated environment, which is totally different from the real road conditions. The driver may encounter different types of driving scenarios that may affect the driver's alert state.

Besides, C. Jacob´e et al. [12] have suggested using contextual (background) information in drowsiness detection. The contextual information such as vehicle flow and time period are vital as it may influence the driver's state during driving.

In this proposal, the drowsiness detection system based on vehicle diagnostics, physiology, and remote sensing information is proposed. For the vehicle diagnostics information, the steering wheel angle and longitudinal acceleration are constantly monitored through the steering angle sensor and wheel speed sensor, which are built inside the vehicle. That information can be obtained by connecting the data logger to the onboard diagnostics (OBD) socket of the vehicle. For the physiological information, the photoplethysmogram (PPG) is extracted from the driver through the photodiode sensor, which is built inside the health sensor band. The information such as heart rate (HR), R-R interval (RRI) and respiration rate are monitored to determine the drowsiness of the driver. Lastly, for the remote sensing information, a LiDAR sensor is used to determine the vehicle position and identify the road geometry. The remote sensing information is used to increase the reliability of the system by eliminating the false positive.

2 Technology Benchmark

In the vehicle diagnostics techniques, the parameters such as the steering wheel angle, lateral acceleration, longitudinal acceleration, time headway and standard deviation of lateral position are constantly monitored to determine the drowsiness of the driver [7, 8]. When those parameter's value exceeds a certain threshold, it indicates a high probability that the driver is drowsy. In work done by S. Arefnezhad et al. [13], they use 4 different filter indexes, a fuzzy inference system and a support vector machine (SVM) to classify whether the driver is awake or drowsy based on the steering wheel angle. Besides, M. S. Wang et al. [14] investigate the effects of using different combinations of input parameters such as lateral acceleration, longitudinal acceleration and steering wheel angle on drowsiness detection based on a random forest algorithm.

In the physiology techniques, the electrical bio signals such as electroencephalogram (EEG) and electrocardiogram (ECG) are used to determine whether the driver is awake or drowsy [7, 15]. For the EEG method, delta wave (1–4 Hz), theta wave (4–8 Hz), alpha wave (8–13 Hz) and beta wave (13–30 Hz) from 16 channels on the EEG cap are measured and recorded based on international 10–20 system [8]. O. Rahma et al. [16] have shown that when the driver is in a drowsy state, theta wave, alpha wave, and beta wave tend to be higher than those when in an alert state. A. Chowdhury et al. [17] also indicates that an increase in alpha band power in the occipital region is the primary indicator of drowsiness setting in. Moreover, for the ECG method, the parameters such as heart rate (HR), R-R interval (RRI) and respiration rate (breathing frequency) are determined from ECG signals. A. Chowdhury et al. [17] mention that a reduction in heart rate and low frequency to high-frequency bands power ratio (LF/HF) of RRI are observed when the driver is drowsy.

In the facial recognition techniques, the system captures the driver's facial expression by adopting an in-vehicle camera [18]. Then, the driver's drowsiness is recognised by detecting the movement of the head, yawning pattern, eye closure and overall expression of the face [7]. Most of the published papers have focused on the DDD system based on PERCLOS [19]–[21]. PERCLOS drowsiness metric is the first established in 1994 [22] as the proportion of time that the eyes are at least 80% close (percentage of eyelid closure over pupil) reflects a slow eyelid closure rather than a blink. Furthermore, Y. Ed-Doughmi et al. [23] also mention a Separate Head Position Estimation System that detects the head's orientation relative to the camera view. The drowsiness is identified when the driver's head is inclined forward, which indicates a loss of concentration.

The vehicle diagnostics, physiology, and facial recognition techniques have several limitations in terms of their application. Firstly, vehicle diagnostics techniques can only be used in specific driving conditions. For instance, Driver Alert Control (DAC) in Volvo cars operates by detecting the distance between the road line markings and the car [24] as shown in Fig. 2.

Once the driver is drowsy after a long driving period, the system will give an acoustic signal to the driver and show the driver the appropriate place for a break. However, the disadvantage of this system is that it requires good lighting for the line's visibility. In some circumstances, the line markings are occluded, and the system may not detect the distance between the road line markings and the vehicle.

The physiology techniques are reliable and can achieve a high level of accuracy in drowsiness detection. For instance, Y. Ma et al. [25] use a 32-channel EEG acquisition system to collect the EEG signals from 6 healthy volunteers. The result from [25] shows a high level of accuracy (95%) in drowsiness detection. However, the EEG-based DDD system is intrusive [4, 6, 7]. The driver needs to wear various signal measuring tools on the body. Therefore, they may feel uncomfortable during driving. Due to this reason, the

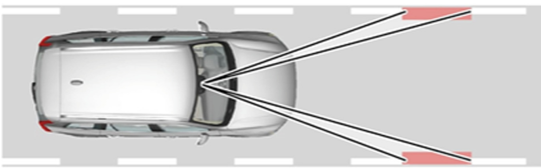

Fig. 2. Driver Alert Control (DAC) which is used in Volvo cars [24].

Table 1. Advantages and disadvantages of different types of driver drowsiness detection system

Driver Drowsiness System	Advantage	Disadvantage
Vehicle diagnostics	• Satisfactory accuracy • Non-intrusive	• Not reliable (may give false positives due to road geometric and curvature)
Physiology	• High level of accuracy • Reliable in any driving conditions	• Intrusive in nature (need to wear signal measuring tools)
Facial recognition	• Great accuracy • Non-intrusive	• Accuracy is affected by changes in lighting and unexpected features on the face

in-ear EEG sensor has become popular to reduce intrusiveness, as shown by T. Hwang et al. [26]. Besides, although an ECG-based DDD system can be used in a nonintrusive way by applying the proximity sensors, it is found that the detection rate of the system depends on the accuracy of the sensors close to the driver [17].

For the facial recognition techniques, great accuracy is achieved in drowsiness detection. For example, T. Vu et al. [18] has achieved an overall accuracy of 84.81% in drowsiness detection without any post-processing. Besides, the system also works at high speed of about 100 frames per second. However, the system has several disadvantages. Firstly, the system's accuracy drops when there is an unexpected feature on the driver's face. For instance, when the driver wears glasses and sunglasses during driving, the system's accuracy drops to 77.97% and 74.08%, respectively, compared to when the driver is barefaced (86.75%) [18]. Secondly, the accuracy of the system also depends on the illumination (changes in lighting). Based on the work published by J. C. Chien et al. [27], they mentioned that better results are obtained when the system is tested under better lighting conditions such as daylight. According to [4], the authors have suggested using an infrared (IR) camera to capture the driver's behaviour at night situation. A summary of the three classes of techniques is shown in Table 1.

Due to the limitations of the three classes of techniques, the hybrid approach has gained the attention of researchers. For instance, J. Gwak et al. [8] and C. Jacob´e et al. [12] have utilised physiology (EEG, ECG), facial recognition (eye closure, movement of the head) and vehicle diagnostics (steering wheel angle, position on the lane) to identify whether the driver is in a drowsy state. Furthermore, Q. Abbas [9] has used the ECG signals and PERCLOS to determine the drowsiness of the driver. The main advantage of the hybrid approach is that the information obtained from 1 class of techniques can be used to complement the other classes of techniques. For example, when facial recognition information cannot be extracted during night-time, the vehicle diagnostic and physiological information can determine the driver's drowsiness.

On the other hand, the hybrid approach's disadvantage is that a higher cost is needed to construct the system because more signal measuring tools are needed to detect the driver's drowsiness. Moreover, the system also requires higher computational power. Since the hybrid approach combines vehicle diagnostics, physiology, and facial recognition to identify drowsiness, the computer needs to process more information than the different techniques. If any delay occurs during the detection process, a road accident may happen. Therefore, the hybrid approach needs higher computational power to detect the driver's state in a short time under actual road conditions.

Last but not least, most of the researchers test their systems under the simulated environment instead of actual road conditions [11] because the simulated environment is different from actual road conditions. Under the actual road conditions, the driver may encounter different states of vehicle flow, which may affect the driver's alert state. For example, the driver may feel more alert when driving in congested traffic than driving on a monotonous road. Furthermore, different periods affect the drowsiness of the driver. Based on the study done by World Health Organization [3], young people (up to 25 years old) are prone to drowsy driving when they drive the car at the time between 02:00 and 05:00.

Table 2. The function of the human parts which are used to control the vehicle

Human Parts	Function
Hands	• Control the direction of the vehicle through the steering wheel
Legs	• Regulate the speed and acceleration of the vehicle through the acceleration and braking pedals
Eyes	• Receive the information and monitor the objects surrounding the vehicle
Brain	• Make appropriate judgements when the driver encounters different types of driving scenarios

3 Methodology

The parts of the human used to control the vehicle are hands, legs, eyes, and brain. Their functions are shown in Table 2. Based on the human parts' function in Table 2, a driver drowsiness detection (DDD) system can be constructed. The DDD system works by governing the human parts, which control the vehicle through the sensors mounted on the vehicle.

Firstly, the operation of human hands can be monitored through the steering angle sensor (SAS). The SAS is used to measure the steering wheel position angle and the rate of turn. It is usually located behind the steering wheel and wrapped around the steering column. Secondly, the operation of the human's legs is examined through the wheel speed sensor. The wheel speed sensor is used to read the rotational speed of the wheel. It is usually located at the side of the wheel axle. The steering angle sensor and wheel speed sensor can be obtained by connecting the data logger to the onboard diagnostics (OBD) socket. Onboard diagnostics is a computer system used to collect information from a network of sensors built inside the vehicle. OBD then uses the information obtained from the sensors to regulate the car systems.

When the driver drives on the highway, the vehicle is usually kept at a constant velocity, and a gradual increase in steering wheel angle is typically observed. However, when the driver is drowsy, his hands and legs can no longer control the vehicle's direction and speed. Therefore, a sudden increase in steering wheel angle and longitudinal acceleration may occur frequently and unintentionally. The DDD system can tell whether the driver is drowsy while monitoring the steering wheel angle and longitudinal acceleration.

Furthermore, the human's eyes' operation can be represented by the vision camera or LiDAR (Light Detection and Ranging) sensor. The vision camera captures the images around the vehicle and sends these images to the embedded system for further processing. Image processing usually involves a deep learning model (convolution neural network). This deep learning model is trained so that the vehicle can detect and recognise the surrounding objects, such as nearby vehicles and pedestrians. On the other hand, the LiDAR sensor works by illuminating laser light to the target object and measuring the time requires for the light to return to the sensor. Due to the differences in laser returning time and wavelengths, the LiDAR sensor can make a digital 3D representation of the target objects. Therefore, by applying the LiDAR sensor on the vehicle, the digital 3D representation of the objects surrounding the vehicle can be constructed, and the vehicle can see the objects surrounding it. Then, the LiDAR sensor's information can be utilised to determine the vehicle position and identify the road geometric.

The LiDAR sensor is selected in the DDD system because the vision camera is not reliable when the driving condition is poorer. For instance, when the driver encounters terrible weather, such as fogging or raining, the fog or raindrops may affect the quality of the image captured by the camera. Due to this poor image quality, the vehicle may not identify the surrounding objects from the captured image. Besides, information such as the steering wheel angle and longitudinal acceleration sometimes will produce false positive results. For example, when the vehicle passes through a curvature on the road, there is a sudden increase in the steering wheel angle. Therefore, the DDD system may falsely inform the driver is in a drowsy state. Applying the LiDAR sensor can understand what is happening to the vehicle's surroundings by identifying the road geometric. As a result, it can eliminate the false positive, and the DDD system will know that the vehicle is passing through the curvature instead of weaving around the lane due to drowsy driving.

Moreover, the brain's operation can be supervised by implementing a photoplethysmogram (PPG) due to the tight coupling between neural activity and blood flow. PPG is an optical measurement of the arterial volume using a light source and a photodetector (photodiode sensor). Firstly, the light source emits low intensity infrared, green light to the skin. Then, the photodiode sensor will detect how much light is being reflected from the skin. The amount of the reflected light changes according to the blood volume caused by capillary dilation and constriction. Hence, the heart rate of the driver can be estimated. The main advantage of PPG over ECG is that the driver's physiological information, such as heart rate, respiration rate, and R-R interval, can be obtained in a non-invasive way. It is because ECG is obtained by measuring the heart's electrical activity through multiple electrodes. Therefore, the driver may feel irritating during driving. Moreover, PPG can determine small changes in blood volume, giving it a higher precision than ECG.

PPG is employed in the DDD system as the fail-safe device because the vehicle diagnostics information sometimes cannot determine the driver's drowsiness. For example, when the driver is drowsy, the steering wheel may hold still while keeping the vehicle at constant velocity (cruise control is activated). Consequently, the steering wheel angle and longitudinal acceleration cannot decide whether the driver is in a drowsy state. Thus, PPG is applied in the DDD system since it can determine the driver's mental state through the sensor, which is built inside the health sensor band.

Next, the data is collected from the test subjects. This collected data will be separated into training data and test data. The training data is used as the ground truth to teach the deep learning model on how to classify the driver's drowsiness, while the test data is used to measure the model's accuracy once the training is completed. This proposal will collect the data by randomly selecting 12 test subjects to drive the car on North-South Expressway. There are in total of 6 groups of the test subject. Firstly, the test subjects are divided into 2 main groups: male and female, with 6 persons per group. Then, the male and female groups are divided based on different ages. They are young (18 - 35 years old), middle-aged (36 - 55 years old) and elderly (56 years old and above) with 2 persons per group. These test subjects are required to complete 2 h driving course on the highway at different periods. There are 4 different time periods: morning (08:00 - 10:00), afternoon (14:00 - 16:00), evening (20:00: 22:00) and night (02:00 - 04:00).

Besides, the instrumented vehicle will be installed with the sensors (steering angle sensor, wheel speed sensor, and LiDAR sensor) while the test subject is wearing a PPG sensor. Inside the instrumented vehicle, a desktop computer will be installed and powered by the uninterruptible power supply (UPS). When the test subjects drive the instrumented vehicle on the road, the sensors' readings will be transmitted from the sensors to the computer in real time. The MATLAB software is utilised to record the readings because it has built-in toolboxes which can be used to capture and store the readings from the sensors. After collecting the sensor readings, they are evaluated to determine the level of drowsiness of the driver.

Furthermore, a camera will be installed inside the vehicle to record the driver's actions during driving. The video from the camera is then evaluated to determine the level of drowsiness of the driver based on observer rated sleepiness (ORS) [28]. In this method, the position and activities of the arms, hands, upper body, head, and facial movements will be observed to determine the driver's level of drowsiness. Once the video is evaluated, the results will be compared with the results of the sensor readings to ensure the correct labelling of the data.

After obtaining the information from the vehicle sensors, LiDAR sensor and PPG, a pre-processing step is usually performed to eliminate the noises in the signals received. It is because the noises can distort the signal shape and result in a wrong diagnose. For instance, the readings from the steering angle sensor and wheel speed sensor suffer noises from the vehicular electrical system, and the vibration of the engine, chassis, and tires [29]. In the LiDAR sensor, the LiDAR echo signals can easily be contaminated by the strong background light [30]. This background light can affect the retrieval accuracy and effective detection range of the LiDAR sensor. Besides, during PPG measurement, two types of noise are typically observed, which are high-frequency noise, and movement noise [31]. High-frequency noise is caused by electrical noise, while movement noise is caused by the voluntary or involuntary movements of the test subject. The filters such as low pass filter and adaptive filter are employed to eliminate the noises to ensure the correct signals are received for diagnosis.

Besides eliminating the noises from the signals received, feature extraction and selection are also implemented to ensure that the deep learning model can be appropriately trained. Feature extraction is a process that looks for the signal characteristics (features) that define the drowsiness of the driver. Once the features are extracted, the feature selection is made to filter out the features that are not important in drowsiness detection so that the deep learning model can be trained faster.

After extracting the features and removing the features that are not important in drowsiness detection, the deep learning model is trained to classify the driver's drowsiness. The machine learning models which the researchers commonly use are support vector machine (SVM), random forest (RF), k-nearest neighbour (kNN) and deep learning models. In this proposal, deep learning models will be employed to classify the drowsiness of the driver. The reason is that deep learning models can achieve a high level of accuracy when they are trained with a massive amount of data. Besides, in traditional machine learning models such as SVM, RF and kNN, the features need to be identified by a domain expert to reduce the complexity of the data and make the patterns more visible for the learning algorithms to work. The deep learning models can incrementally learn the features through backpropagation by comparing with the target value and adjusting the weight.

There are two types of deep learning models that are commonly used in drowsiness detection. They are discriminative and representative deep learning models. Firstly, they can adaptively learn the discriminative features based on the pre-known label (ground truth). Those discriminative features are usually recognised through nonlinear transformation. After extracting the features, they are capable of classifying the input data through probabilistic distribution. Example of discriminative deep learning models is an artificial neural network (ANN), recurrent neural network (RNN) and convolution neural network (CNN) [32]. Secondly, they can learn the representative features from the input data for the representative deep learning models. Hence, they are only capable of extracting the features from the input data. They cannot classify the input data. Example of representative deep learning models is autoencoder (AE), deep belief network and restricted Boltzmann machine (RBM).

A recurrent neural network (RNN) is proposed to classify the driver's drowsiness in this proposal. The advantage of RNN over other deep learning models is that it can model a sequence of data (time series). Hence, each sample can be considered to be dependent on the previous one. Due to the temporal dependency of RNN, it can be utilised to make a prediction based on the time series data. For example, RNN can predict when the driver will change from a normal state to a slightly drowsy state based on the results obtained

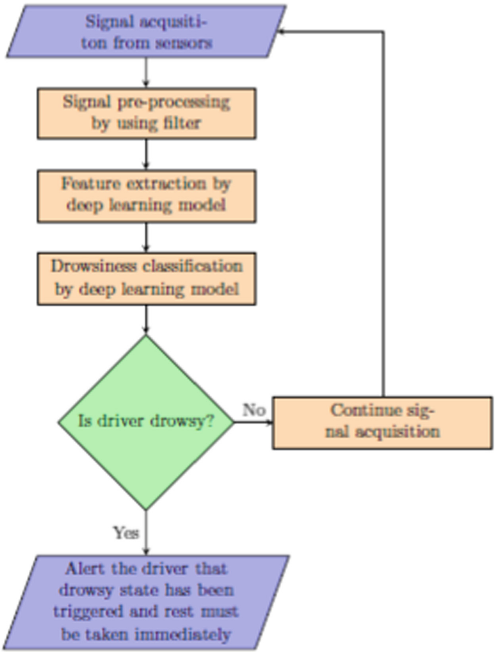

Fig. 3. The flow chart of the proposed driver drowsiness detection system

at different time steps. Then, it allows the driver to act (take a break) before the driver falls asleep during driving. Thus, road accidents can be avoided. The flow chart of the proposed system is shown in Fig. 3.

Once the DDD system is developed, the test data is fed into the deep learning model to determine the system's accuracy by comparing the test data with the predicted data of the deep learning model. After that, the test subjects must drive the instrumented vehicle with the DDD system at 4 different periods. After driving the instrumented vehicle, a survey regarding the effectiveness of the DDD system in preventing drowsy driving is conducted among the test subjects. The test subjects will be asked to fill in a questionnaire. Lastly, the possibility of promoting the proposed system to the other drivers in Malaysia will be investigated based on the feedback given by the test subjects.

4 Conclusion

In Malaysia, drowsiness is one of the most important causes contributing to a high number of collisions. To address this issue, many types of driver drowsiness detection (DDD) systems have been created. They use vehicle diagnostics, physiology, or face recognition to make their decisions. However, there are numerous drawbacks to these systems in terms of dependability and intrusiveness. To address this issue, a hybrid method based on vehicle diagnostics, physiology, and remote sensing data is presented. In this system, the vehicle diagnostics information is obtained from the steering angle sensor and wheel speed sensor through the onboard diagnostics (OBD) socket. For the physiological information, it is acquired through the photodiode sensor built inside the health sensor band. The remote sensing information such as road curvature and vehicle position are obtained through the LiDAR sensor. To ensure correct signals are received from the sensors, the filters are applied to remove the noises presented in the signals. The hybrid driver drowsiness detection system will be tested in a real time environment mode at 4 different times under different environmental conditions. When compared to previous approaches, the hybrid features and deep learning are predicted to improve driver drowsiness detection accuracy. A study is being undertaken to see if the suggested method may be promoted to other Malaysian drivers.

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