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Driver drowsiness detection using saliency SNN: A new paradigm for improved road safety

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ABSTRACT: The development of smart/intelligent cameras has allowed for the detection of driver drowsiness, which in turn alerts drivers and reduces accidents caused by fatigue. In this work, a new framework is proposed that uses deep learning to detect driver drowsiness based on eye state while driving. The Viola-Jones face detection algorithm is used to detect the face and extract the eye region from face images. A striking neural network is used to extract features from dynamically identified key frames from camera sequences and used during the learning phase. Preprocessing, feature extraction, and training the model are the three primary steps of the suggested approach. In preprocessing, face detection is used, and in feature extraction, EAR, NLR, and MOR are employed. Training the models is done using CNN-LSTM, ELM, and Saliency-SNN. Of these, the Saliency-SNN method outperforms the more conventional CNN-LSTM and ELM approaches.

Keywords: Electroencephalogram (EEG), Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), Liquid State Machine (LSM), Electrocardiogram (ECG)

1 INTRODUCTION

Publications from the World Health Organisation rank traffic accidents among the top 10 killers worldwide. These incidents are primarily caused by drivers, according to the reports. Therefore, detecting driver fatigue could be a practical way to reduce the occurrence of accidents. The improved performance of ADAS and DMS leads to increased road safety, which is an additional benefit. There are a few different kinds of drowsiness detectors, but the three main ones are vehicle-based, signal-based, and face feature-based. In an effort to determine whether the driver is getting tired, methods that depend on the car itself monitor parameters such as acceleration, lateral position, and steering angle. However, jobs requiring processing in real time are beyond the capabilities of these technologies. Using signal-based techniques, we can estimate drowsiness from psychophysiological measurements. Electroencephalogram (EEG), Electrooculogram (EOG), and operations of are the most studied and used physiological signals. The autonomic nervous system is augmented by the electrocardiogram (ECG), the skin temperature, and the galvanic skin reaction together with electrical activity measured by electromyography (EMG) in muscles. It is imperative that these methods account for invasive captors, which may impair driving. Not only are face feature-based approaches less expensive and more widely available, but they can also evaluate the target in real-time without the need for intrusive sensors.

2 LITERATURE SURVEY

Driving while drowsy increases the likelihood of accidents. [1] In just three or four seconds, a car can traverse the length of a football field, therefore even a few seconds of negligence on a highway can bring devastating outcomes. [2] Drowsy drivers cause a lot of accidents since their cognitive capacity lowers when they're tired. Three times as many accidents occur when drivers are fatigued as when they are alert [3]. There are a plethora of new technologies that can detect whether a driver is becoming too drowsy to drive safely. The rising incidence of accidents associated with drowsy drivers prompted this measure. [4] The installation of a device that detects when drivers are sleepy can lead to a decrease in accident rates, financial losses, and casualties. Timely detection of fatigue and sleepiness is made easier using this technique. [5] There are a number of ways that driver drowsiness strategies can be classified. Consider the method for detecting lethargy. Numerous sub-techniques can be derived from it, depending on factors such as image or EEG analysis, vehicle behaviour, AI, etc. Many people are interested in learning more about the possibility of using sensors and cameras to identify drowsy drivers, which could lead to the prevention of fatal accidents [6]. Companies like Tesla and Mercedes-Benz are among many that deploy driver assistance systems. An ongoing effort has been made to enhance the accuracy and precision of sleepiness detection models [7]. In order to capture data about behaviour, a camera is used by Pay attention to the driver's body language, such as head swaying, yawning, and eye blinking, and inform them if you notice any signs of exhaustion. A review of techniques for identifying lethargy was published in [8]. A system of multiplexed sensors that might detect driver weariness in real-time in their study [9]. Creating a smart sensor network that could communicate wirelessly was the primary objective. Its operator and occupant were immediately notified of a first-level emergency as it continuously monitored the individual's vital signs via a network of intrusive sensors. Advanced AI-based approaches were employed by [10]. The problem of detecting driver tiredness has been the subject of numerous investigations. [11] The proposed solutions are neatly organised based on the characteristics that indicate drowsiness. [12] Biological characteristics that are constructed from measurements of the driver's vital signs, such as electroencephalograms, electrocardiograms, and electromyograms, are effective in detecting drowsiness. [13] However, these features might be burdensome for drivers due to the need to wear sensors. Another prominent feature based on vehicle driving habits is the measurement of driver weariness, which is connected with things like steering wheel tilt and the frequency of lane deviation.

3 PROPOSED SYSTEM

Drunk driving is the leading cause of death in car accidents, which claim the lives of thousands of people annually around the world. Many lives could be saved if this accident could be reduced with the use of a sleepiness detecting system. To back up our claim, we offer an SNN-based approach that uses sleepiness detection as an object detection job.

3.1 *Preprocessing*

3.1.1 *Face detection*

It is possible that just the eyes region is necessary to detect drowsiness, rather than the entire facial region. The initial stage is extracting faces from the photos using the Viola-jones method. After the face has been located, the eye region can be extracted from the facial images using the Viola-jones method. Jones created the first algorithm specifically for face detection in his work on the Viola-Jones object detection system [14]. Using three methods—Hart-like features, Ada boost, and Cascade classifier—the Viola-Jones algorithm is able to distinguish faces. In this work, we utilised OPEN CV with Python to develop the Viola-Jones object detection technique with a Haar cascade classifier. In order to identify faces in pictures, the Haar cascade classifier employs Haar characteristics.

3.2 *Feature extraction*

In order to extract 68 face landmark points from the video recorded throughout the entire trip, the Python Dlib library was utilised. The dlib package includes an object-identification tool that makes use of support vector machines (SVMs) and a pre-trained face detector. For each set of coordinates, we find their corresponding Euclidean distance. A total of three factors—EAR, NLR, and MOR—have been considered. To determine if the individual is sleepy, these characteristics are fed into Neural Network models and SNN.

3.2.1 *EAR*

It has been calculated using equation 1 and is defined as the ratio of the eye's height to its width. The specifics of the parameters called out in equation 1. If we look at equation 1, we can see that the numerator goes down when we're sleepy since the distance between the vertical points goes down. Closed eyelids will cause the difference between parameters p2, p3, and p5, p6, for example, to equal zero.

$$\frac{\left(|q^2 - q^6| + |q^3 - q^5|\right)}{z * |q^1 - q^4|} \tag{1}$$

3.2.2 *NLR*

Equation 2 yields the value, which is the nose length divided by the measurement's unit value. The equation's parameters have been described in full [15]. Equation 2 suggests that when the subject sits up straight, the length would go up; but, when the subject bends forward or backward, it would go down, suggesting that they are sleepy.

3.2.3 *MOR*

It is calculated by dividing the height of the mouth's extreme points by the breadth of the mouth. When the mouth is open, the height is the measurement of the distance between the vertical points. On the other hand, the breadth is the horizontal gap between the two corners of the mouth. Equation 1.3 has been used to compute MOR, and the parameters referred to in the equation have been shown.

3.3 *Model training*

This section presents a saliency-based feature detection network, two methods of spike encoding (i.e., entropy-based time encoding and linear time encoding), and an architecture for a spiking reservoir neural network. This work proposes a linear spike time encoding method that is computationally more succinct than the current spike encoding schemes. The statistical shape of features and their spatial attributes are included in the entropy-based spike time encoding.

3.3.1 *Spiking reservoir NN*

Third-generation artificial neural networks (ANNs) like SNN are heavily influenced by biology and operate on events rather than data points. In order to identify breast images, this study uses a recursive SNN architecture called the spike reservoir neural network. An input layer, a reservoir computing layer, and a readout layer comprise a spike reservoir neural network, which is also known as a liquid state machine (LSM). The LSM model is a kind of real-time neural network that takes input data that changes over time and projects it onto a space with many dimensions. A three-layer structure consisting of an input layer, a reservoir or liquid layer, and a memoryless readout layer is what makes up an LSM. The neurons that make up the reservoir are known as Leaky Integrate and Fire (LIF) [16]. During the reservoir stage, the LIF neurons are linked recursively by dynamic synaptic connections. In the reservoir, the excitatory neurons are depicted by the red solid circle, while the inhibitory neurons are represented by the black. In the cerebral cortex circuit, the number of inhibitory neurons is four times higher than the number of excitatory neurons. While LIF neurons are also responsible for the readout layer, they do not communicate with one another. Reservoir can take low-dimensional input data and turn it into a high-dimensional internal state. Memoryless readout layer, which generates the LSM‘s ultimate output, takes the internal state as its input.

3.3.2 *Visual saliency detection*

Processing these data streams in real-time is a tremendously taxing operation for the human visual system (HVS). The HVS is limited in its understanding and processing of the data. The term for this kind of selection is visual attention. Two processes are thought to be in charge of this type of attentional behaviour: the bottom-up, stimulus-driven mechanism and the top-down, expectation-driven mechanism. Attributes of the visual scene such as direction, colour, contrast, and action mostly drive bottom-up attention. Computer vision researchers have linked top-down attention to factors including cultural background, experience, and memory. Often referred to as “visual salience,” the former attention mechanism is mostly associated with visual attention due to its simplicity. As an example, we’ll look at a Driver Drowsy image. The features are extracted using the spiking CNN. In order to get the saliency feature map, the two-dimensional feature maps produced by the spike convolution layer are added together and the mask is computed. But in medical imaging equipment, the input power has a linear connection with the colour brightness captured in the image file. So, the picture that shows up on the screen doesn’t match up with the one that the camera took. Before calculating saliency, gamma nonlinearity is applied to fix this discrepancy.

4 RESULT AND DISCUSSION

Worldwide, driver sleepiness is a leading cause of traffic accidents. Drowsiness and deadly accidents are the results of driving in a monotonous fashion for long periods of time without rest. There would be far fewer traffic accidents and more lives saved if drivers’ fatigue could be detected automatically. The suggested system can identify driver drowsiness with an accuracy of about 97% using SNN classifier, according to the empirical results.

Figure 1. Accuracy values for each training time.

We show the average accuracy after ten iterations of training for each given network. Figure 1 shows the Saliency SNN's accuracy value for each training time.

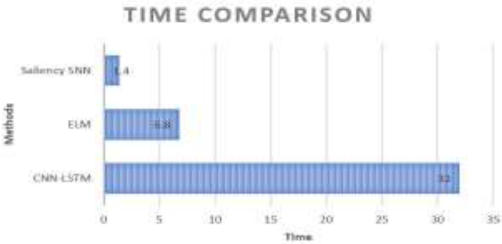

Figure 2. Evaluation of various approaches to the problem of eye closure detection in relation to time.

One important metric to take into account when comparing various approaches is their computational complexity. Methods that are speedier are more dependable in real-time applications. Figure 2 shows the time required to decide on eye closure for each of the given methods. When compared to the ELM and CNN-LSTM models, the Salience SNN is nearly four times quicker and eighteen times faster, respectively.

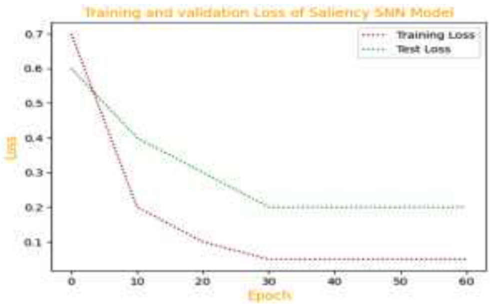

Figure 3. Training and validation loss of the model.

The saliency Spiking Neural Network (SNN) model's training and validation loss sheds light on the model's performance throughout training. Figure 3 shows the ground truth saliency maps and the model's projected saliency maps; the loss function measures the difference between the two and is optimised during model training to minimise it.

5 CONCLUSION

This research introduces a method for detecting driver sleepiness that relies on behavioural measures and NN approaches. It is possible to deduce sleepiness levels from facial expressions. It is possible to deduce the degree of sleepiness from a wide variety of facial traits. Among these behaviours include yawning, eye blinks, and head movements. Building a sleepiness detection system with trustworthy findings is no easy feat; it calls for strong and precise algorithms. Several methods have been investigated for the purpose of identifying sleepy drivers. Given the current popularity of deep learning, it is necessary to reevaluate these algorithms to see how well they detect lethargy. There are primarily three steps to the suggested methodology: preprocessing, feature extraction, and training the model. Prior to feature extraction, face detection is used for preprocessing. EAR, NLR, and MOR are then employed. Training the models is done using CNN-LSTM, ELM, and Saliency-SNN. The Saliency-SNN method achieves an accuracy of approximately 97.3% and outperforms the traditional CNN-LSTM and ELM approaches.

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