Deep Learning based Drowsiness Detection and Monitoring using Behavioural Approach

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***Abstract*- Using deep learning and a behavioural approach, this study presents a real-time detection and monitoring system for tired drivers. The objective is to develop and build software that collects real-time driver behaviour while driving and trains it using convolutional neural networks (CNNs) to anticipate the driver's behaviour. An intelligent video-based gadget, a dataset of drowsy drivers, and CNN architecture were used to achieve this goal. MATLAB and a deep learning technology were used to implement the concepts. Tests revealed that the system has a 99.8% accuracy rate for detecting anomalies. A prototype model of the system was created using MATLAB.**

Keywords*- *Drowsy behaviour, Convolutional Neural Network, Training, Deep learning, MATLAB

I. INTRODUCTION

As per the recent study [1] 90% of travelers depend on the road network to get to and from their destinations. Customers are able to get to their specific commercial service location, habitat, or area by driving to it. This means that a significant portion of their working day is spent behind the wheel, since remuneration is based on the number of passengers, they carry each day. This alone is enough to for the driver's brain to become exhausted and stressed, resulting in drowsiness after long stretches of highway driving. This is why some drivers take preventive steps like as drinking bitter kola, coffee, or alcohol, taking brief refreshment stops, chewing gum, or even smoking in order to counteract the impact of sleepiness. However, nature cannot be manipulated since these old approaches are insufficient or unreliable. Alcohol, for example, increases brain cell tiredness and raises the rate of sleepiness, which works against the driver's goal and may have a terrible impact on the driver's attention, risking the lives of the passengers on board and often resulting in a series of road accidents.

For example, more than 12,077 traffic accidents happened in the last quarter of 2015, resulting in 75400 fatalities, according to figures from Nigeria's federal road safety organisation (FRSC). At least 1758 people were killed and more than 11,000 injured in the first quarter of 2020 in 3,947 crashes involving 6448 vehicles, according to a new annual study from the same organisation. That's why it's necessary to develop inexpensive and accurate detection systems for tired drivers, such as those that use an intelligent-based approach. To address these issues, several research studies on sleepy driving detection systems have been conducted over the last decades, using a variety of different methodologies, including physiological, behavioural, and vehicle-based methods. Electrocardiography, electroencephalography, and physiological sensors are used to access the driver's circumstances in physiological approaches [3], but despite its efficacy, this method is not frequently utilised owing to implementation complexity and unfriendly conditions.

Drowsiness is studied and then controlled using vehicle-based approaches [4]. In this case, the vehicle's nonlinear dynamics during translation are analysed and subsequently automatic cruise control methods are used. Due to high implementation costs, false alarms and delayed response times, this technique is hindered by its efficacy. [5] According to reports, accidents occur within a few seconds of sleepiness, necessitating the necessity for a real-time monitoring and detection system.

On the other hand, the behavioural technique [6] makes use of sensors such as cameras to record the driver's state and processes to recognize the driver's actions while at the wheel. In contrast to vehicle-based and physiological techniques, this methodology is especially designed to understand and process the actions of a driver[47]. It is because of this that a large number of recent articles dealing with the problem of fatigued driving have used this strategy (behavioural), which incorporates a variety of methodologies with image processing and artificial intelligence [8][53]. These systems processed and predicted driving behaviour using real-time photos from a sleepy driver dataset, and if tiredness is detected, the system informs the driver. Computer vision and similarity differential models may be utilised to distinguish between drowsy driving and other conditions of the driver using various image processing techniques such as segmentation and edge detection. A significant percentage of false alerts occurs when the motorist blinks often, especially if they do so at regular intervals. To begin with, ML techniques such as support vector machines, fuzzy logic, Hidden Markov models[48], k-nearest neighbours[49], and clustering approaches[50] have higher detection accuracy than image processing [8], [9], and [10], but they lack common sense and intelligence in terms of data collection and processing, which has hampered system success and global adoption of the technique so far [8, 9, and 10].. Deep learning methods have been used to develop a user-friendly, trustworthy, low-cost, real-time drowsy driver behaviour monitoring and control system.

In machine learning, "deep learning" (DL) is a function that mimics the brain's processing and decision-making processes in a more realistic way. Unlabelled and unstructured data may be learned by this machine without any human intervention. As proven in a case study in which 9000 photos were captured in a five-minute drive, this method is also the most efficient for identifying massive volumes of data [11].

Convolutional neural networks (CNN)[51], long short-term memory (LSTM)[52], recurrent neural networks, and deep belief networks are all examples of deep learning approaches. In contrast, CNN's key benefit over other deep learning algorithms is its ability to automatically locate and extract relevant feature vectors through a hierarchical model. To provide a processed output with exceptionally high precision, this model is built by linking several network layers as a single, completely linked layer. A real-time drowsy driver monitoring and detection system will be built using this technique in this project, making the following contribution to knowledge.

A common-sense approach to drowsy driving will be developed. As a result, a trustworthy system that does not interfere with the driving process will be shown when it is put into operation. There will be a new dataset of tired drivers. An intelligent video-based sleep monitoring device will be developed. A new deep learning model will be developed and implemented.

II. Literature Review

As demonstrated a vehicle-based sleepy detection system based on steering and lane data [14]. However, this approach is susceptible to false alarms due to the fact that other causes like as potholes might induce lane deviation or nonlinearity in the vehicle dynamics, neither of which necessarily imply sleepiness. [15] demonstrated a method for detecting driving stress using physiological sensors; however, despite its efficacy, this technique interferes with the driving condition, which may be a disruption to the driver's focus. There is a need for a sleepy driving detection system that does not communicate directly with the driver but nevertheless successfully monitors and detects the driver. [16], provided a report on a detailed examination of sleepy detection algorithms based on behavioural factors. When compared to other methodologies such as behavioural and physiological, the article concluded that the behavioural strategy was the most effective in detecting drowsiness. The paper claims that a 96.7 percent success rate has been achieved so far using deep learning methods. Aside from the fact that these alterations in the eyes and lips are associated with sleepiness, they have no effect on the rest of the body. CNN and SVM were used to monitor eye activity while driving. The results are very accurate, with a precision of 94.80%. [18] Achieved a 95.8% accuracy rate in detecting weariness using facial cues such as the head, lips, and eyes, while [19] achieved a 93.79 percent accuracy rate in classifying ocular features such as sleep and blinking as sleepy qualities using the viola jones method. Fuzzy logic, an ANN, and a feature descriptor were used in [20]. It was possible to construct an 85.7 percent accurate eye blink detection system for people with disabilities by combining open CV with eye aspect ratio and an Adaboast classifier. A score of 94% was achieved in the system's evaluation. Analysis of the literature showed that the training dataset or training performance constrains all current systems regardless of their underlying causes.

III. The Proposed System

The proposed system was built using a training dataset of video clips including a wide range of driving behaviours characterized as major, minor, and perfect in terms of their severity. Using this data, the suggested system's deep learning technique was trained using the same length and weight parameters.

The video acquisition device was made intelligent and used to gather data; this intelligence was achieved through the use of computer vision to detect the driver's face (since the face is the primary part of the body where drowsiness can be detected) and automatically search for facial points with drowsy features. Only the same number of observations as in the training dataset may be collected. A deep learning technique was used to train on the data that had been gathered. Training resulted in three outputs that might be used to identify driver behaviour, as follows: warning signs are presented if sleepy symptoms like sleep are noticed; if perfect driving conditions are classified, they are displayed; if minor drowsy behaviours such as yawning are classified, sensing drowsy behaviour is displayed.

IV. Methods And System Modelling

This section detailed the steps involved in designing and implementing the proposed sleepy driver detection system:

1) Video Acquisition: Using this technique, the driver's real-time driving behaviour may be captured and stored in a video format for future reference. Using computer vision, the video camera (a hardware device) assisted in the method's performance. An object identification system with a focus on human faces was developed in [22-25] and then implemented into the camera to offer computer vision intelligence. 30 frames per second are captured by the camera at a resolution of 200 x 200. Taking this into account, each image has a resolution of 40000 pixels wide by 40000 pixels high, for a total resolution of 200 pixels in height and 200 pixels in weight.

Face tracking and recognition: this is the process of determining if something is human or not. As previously stated, this technique was enabled by a computer vision algorithm [26-30]. The method first equips the camera with face identification and tracking capabilities before collecting data in a series of frames for processing. This diagram (DFD) depicts the video capturing and intelligent data collection procedure as seen in the image below in figure 1.

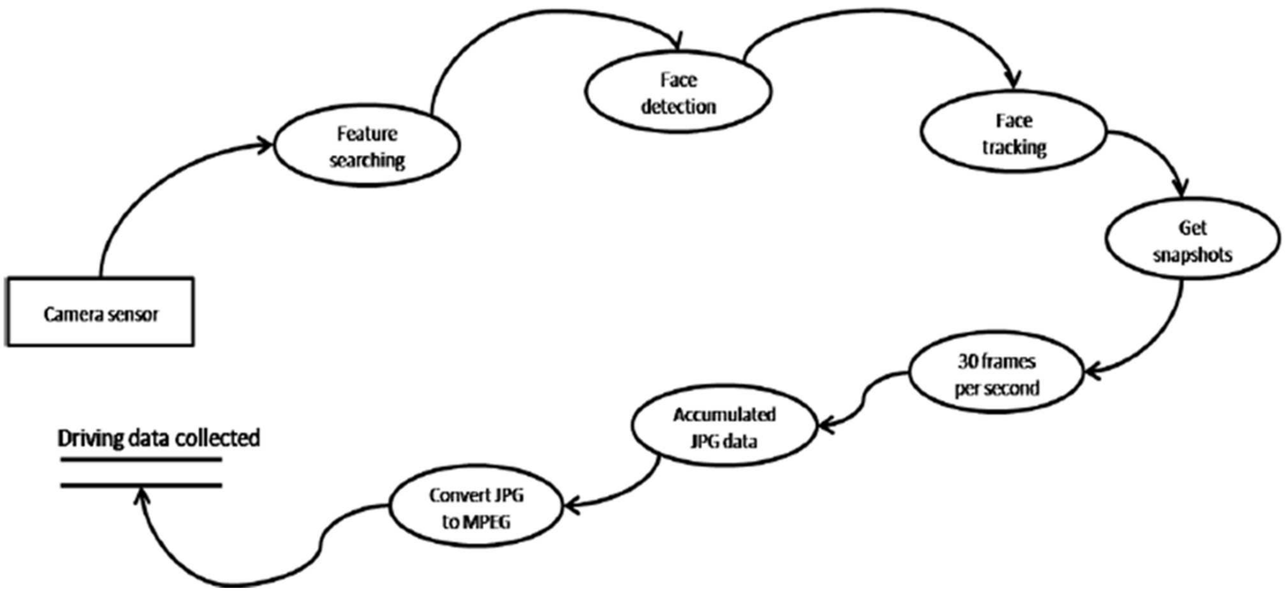

Figure 1: Model of the intelligent video acquisition system

2) Computer Vision: This is a sophisticated technique that was utilised to enhance the camera's capacity to identify objects through the viola Jones Algorithm. The method was designed for identifying, tracking, and collecting face characteristics in [31-33] and [34-38]. This is referred to as face detection.

3) Training Dataset: Only 10 drivers who reported themselves as drowsy were included in this study, and each showed indicators of sleepiness such as frequent eye blinking and closed eyes while driving (micro sleep).

TABLE I. TABLE OF DATA COLLECTION

	Data Classes				
Drivers	Minor drowsy attributes			Critical drowsy attributes	Perfect driving attributes
S. No.	Yawing	Frequent eye blinking	Blinking eye with glasses	Eye closed, face down with glass and face down	Eye open and eyes with glass
1	20	30	30	30	20
2	20	30	30	30	20
3	20	30	30	30	20
4	20	30	30	30	20
5	20	30	30	30	20
6	20	30	30	30	20
7	20	30	30	30	20
8	20	30	30	30	20
9	20	30	30	30	20
10	20	30	30	30	20
Total Video	200	300	300	300	200
Total image frames	18000	27000	27000	27000	18000

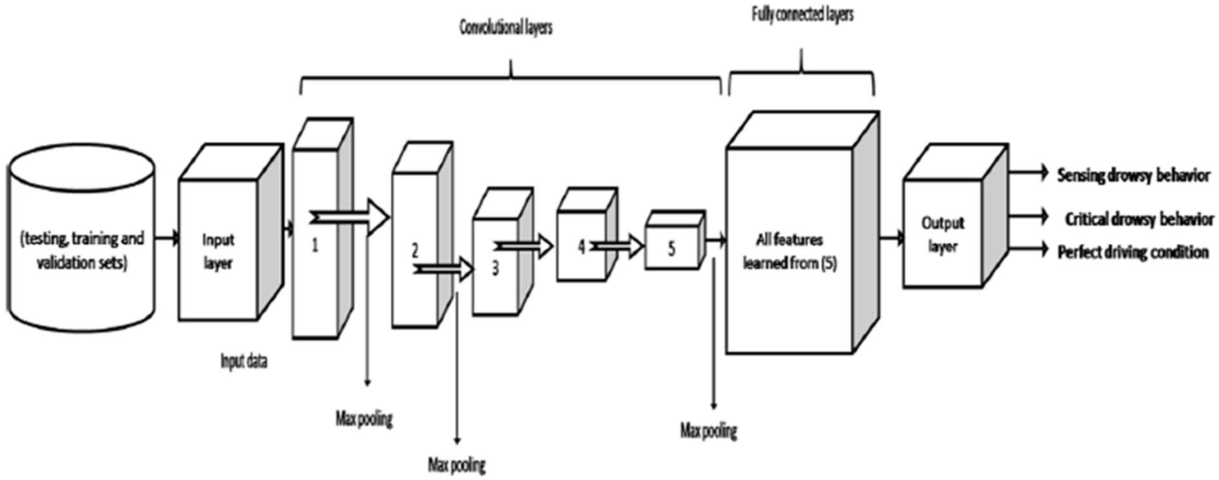

Figure 4: Architectural model of the convolutional neural network

A video camera was used to collect the data, which were then categorized as either critical drowsy, which contains the most significant sleepy symptom, micro sleep, or normal drowsiness. You'll learn how to snooze at the beginning, then you'll learn how to drive perfectly with your eyes open and your face down. It is possible to see the video data that was captured in AVI format at a resolution of 200x200 in the table below [39-40];

Each movie in Table 1 includes a three-second time lapse and comprises ninety frames of pictures. To build the training dataset, each driver submitted an average of 130 clips comprising 11700 frames. Yawning, frequent blinking, and wearing glasses all contribute to drowsiness among drivers. This category contains 80 videos with a total of 7200 frames. 30 video clips comprising 2700 frames, both with and without glasses, are used to determine the class of sleepiness characteristic. Video footage comprising 1800 frames, both with and without spectacles, are used to classify great driving attributes [41-43]. The training dataset consists of 1300 three-second video clips with a total of 117000 frames, and the class diagram below shows how the dataset was assembled;

A. Feature Extraction

Camera-captured video clips may be used to train the deep learning algorithm by feeding them into the system. These photos were scaled to match the training images [44-46] before being fed into the system (200 × 200).

The algorithm for deep learning was as follows: Deep learning is a subset of machine learning methods that is used to classify images. It is used to train the dataset shown in Figure 3 as well as to extract new features from the testing dataset. Convolutional neural network is the deep learning algorithm that was employed (CNN). CNNs are a kind of deep neural network constructed around neurons with learnable weights and biases that are capable of intelligently processing massive amounts of data and making accurate predictions.

The Convolutional Neural Network Design Architecture.

The CNN was built utilizing an input layer, convolutional layers, pooling layers, fully connected layers, and output layers to form a complex architecture for deep learning, as seen in Figure 4.

The model shown in Figure 4 illustrates how a CNN gathers and trains data in order to identify driving behaviour. The following sections cover the CNN's many layers and specifications;

B. Input image layer

The video feed's first layer of the CNN architecture is the input layer, which collects the video frames. When an image has a dimension of (200 x 200 x 3), the CNN uses this layer to determine the number of pixels and channels (RGB colour size) and then passes that information on to the convolutional layers through neurons. The neuron weight is calculated with the channel size set to 12000 and the picture resolution set to 12000. The data were then fed forward to the convolutional layer following the scaling approach.

C. Convolutional Layer

In order to learn the features acquired from the input layers by scanning and progressively updating each convolutional layer with the scanned features until the final layer, which is the fifth convolutional layer, this component of the CNN was developed utilizing multiple convolutions of neurons. To do this scanning technique, we used filters that were functions of the input data, a bias function (which is 1), and a filter dimension of 1. (5 x 5).

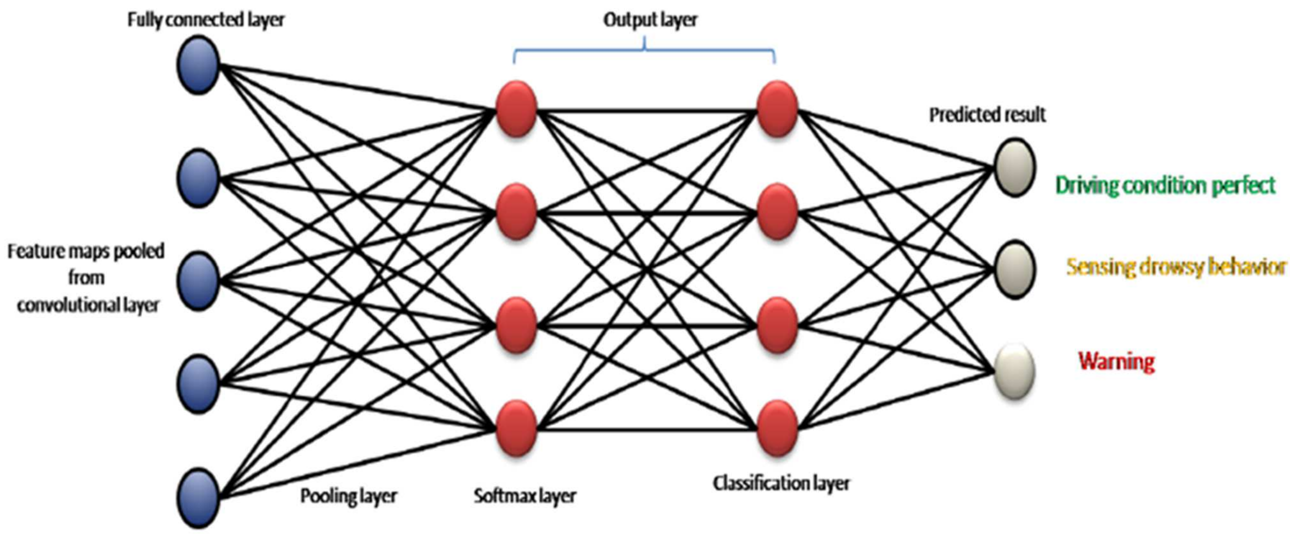

Figure 5: The computational learning architecture

The 5 × 5 section of the input data is used to build a feature map from the 5 x 5 segment of the filter's receptive field, which may be scanned in a single convolution of the query main picture. Filter padding is used to eliminate image data that does not fit inside a valid filter area when scanning fails to properly fit the filter within the map image. A rectified linear unit was used to provide nonlinearity into the CNN in order to ensure that the output from each convolution operation contained non-zero values.

There is just one scanning method in the image's 5 x 5 area, and this feature map shows the results. An array of feature maps is generated as a consequence of the scanning technique, which is continued until all portions of the image have been scanned. Each convolutional layer's output, known as the feature map, is combined in the next layer (see discussion of pooling layer and the type used below). In this scanning process, which continues until the fifth convolutional layer is reached, the bulk of the image data is obtained.

Pooling layer As a result, the number of filters in deeper convolutional layers may be increased at the cost of computing time by down sampling the feature maps to remove duplicate information. The maximum pooling approach is used for pooling. Our technique selected just the feature maps with the biggest pixel values from each array of filtered pixels and used these as strides in each convolution. The steps were forwarded to a completely linked neural network structure, as mentioned in the layer below that is fully connected.

D. Fully Connected Layer

When the preceding convolutional layer has been flattened and fed to a neural network structure for classification using softmax activation, the fully connected layer is responsible for doing so. The diagram below illustrates the neural network.

The structure of the fully connected layer's neural network is shown in Figure 5, indicating how all of the neurons in the previous layer's activation units are used to train the network. The deep learning training tool separates the feature vectors into 30:70 test and training sets throughout this method. As previously stated, the 70% are learned in the convolutional layer, and the 30% test features are used to self-examine the training accuracy using various epoch values until the best result is attained.

E. Output or Prediction Layer

This is the last layer of the network, and it is here that the training's desired results are generated. Using a SoftMax activation function as described in [22], this layer is generated by transforming the input feature vectors into probability distributions with varying probabilities corresponding to the various exponentials of the input video data received from the driver's actions.

V. Implementation

MATHLAB and the deep learning network designer tool were used to create the system. MATHLAB was used to develop the algorithms as application software, using appropriate toolboxes such image capture and computer vision, deep learning, and neural network toolboxes to implement the required models, which were then tested.

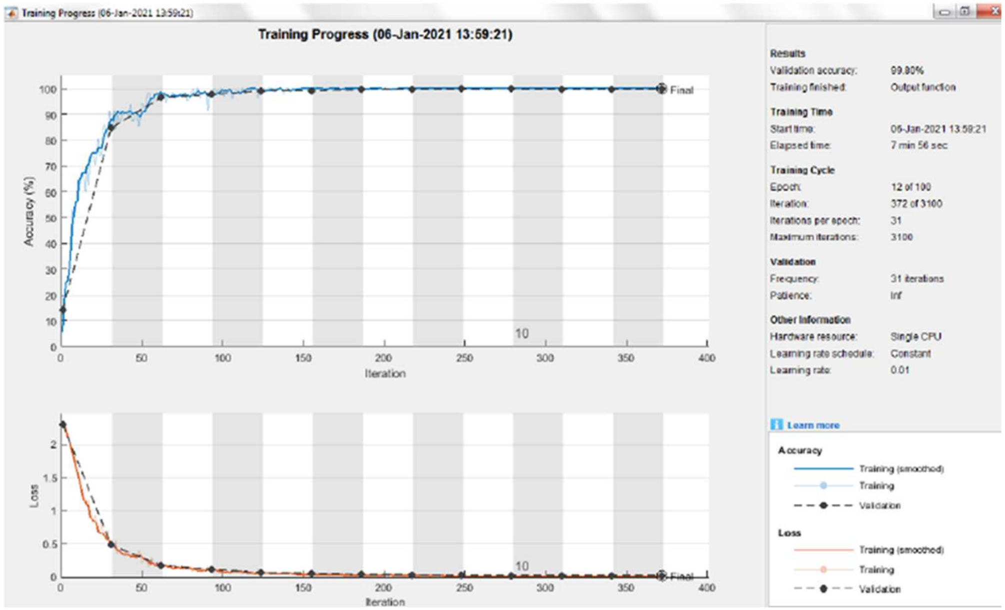

Figure 6: The training result

VI. Results

Training techniques were evaluated using the loss function in equation 3.1, and a prototype system was deployed in real time to test the system's performance. sleepiness detection and monitoring.

1) Training Results: Deep learning training results are summarised in this part of the document. Using equation 1 and table 2 as input, the deep learning tool calculates system training performance, and the results are shown in figure 3;

TABLE II. Deep Learning Training Parameters

Parameters	Values
Number of input channels	3
Filter Dimension	5 x 5
Image Size	200 x 200
Learning Rate	0.01
Momentum Factor	0.75
Gradient	4.79
Weight of Neurons	1200

The result in Figure 6 illustrates the deep learning toolbox's training performance. Convolutional sleepy intelligence was achieved in the fully connected layer of the CNN architecture (see figure 4) by feeding the training dataset forward and training it to create convolutional drowsy intelligence in the fully connected layer. Training iterates steadily and reaches an epoch value of 30 with a 0.001 learning rate and 99.8 percent accuracy at this point in time, according to the data. Prototype system for a tired driver was built using the algorithm that had been effectively trained and learned about the problem of drowsy drivers;

In Figure 7, For the objectives of this research demonstration, a camera coupled to a laptop system was mounted on the dash board and pointed at the driver to record their actions in real-time. A variety of driving and driving-related behaviours were used to test the software and camera's functioning.

VII. Discussions

New system training and testing has been shown via this work. In order to build a sleepy model, the computer used data from the training dataset, and the output was used to categorise future tired behaviour. The result indicates that when tested with sleepy driver and flawless driving attributes, the system was capable of training and predicting the proper behavioural condition in real time with a 99.8 percent accuracy. When evaluating the results, they are compared to the present system, which was discovered via the literature review: As seen in Figure 11, the new system outperforms the old deep learning approach by 18.8 percent.

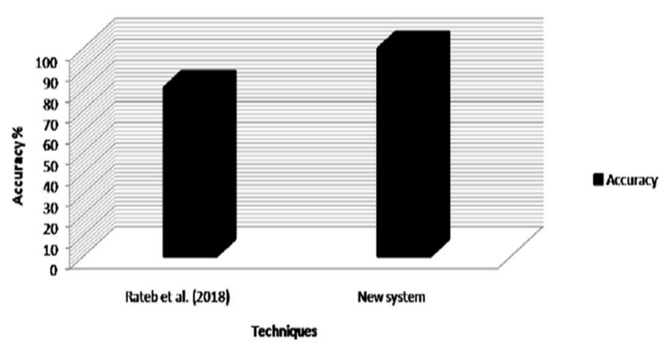

Figure 11: comparative result

VIII. Conclusions

In this essay, we'll explain how an intelligent drowsy driver detection system based on a behavioural approach was successfully built. The study conducted a review of the existing literature on sleepy driving detection systems, finding technological problems, contributions, and drawbacks. According to the research, efforts to detecting sleepy drivers are categorised as behavioural, physiological, and vehicle-based. Behaviour strategies are now in demand because they may treat tiredness straight from the source (the driver) without affecting the driving process. Consequently, behavioural techniques are the current trend.

Behavioral methods have employed a variety of techniques such as machine learning and image processing to tackle the drowsiness issue, but despite their effectiveness, they suffer from false alarms, poor dataset design, and unreliability, to name a few. According to studies on machine learning algorithms like Deep Learning, this technology may be used to recognise tired driving in real-time if built correctly. Due to CNN's practical effectiveness in processing enormous volumes of photo or video data, it was selected above alternative deep learning algorithms. With the right amount of layers and design requirements for each training parameter, the CNN was built, then trained using a deep learning approach with 117,000 frames characterised by various drowsy features using a training dataset of deep learning. MATHLAB was used to develop the system, which was then tested in a real-world driving situation. The findings indicated a 99.8 percent detection accuracy. Additionally, the result was compared to the current system, and the new method shown an improvement in accuracy of 18.8 percent.

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