A PRATICAL IMPLEMENATION OF AN INTELLIGENT DROWSY DRIVER MONITORING AND DETECTION MODEL

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Abstract

In the field of accident control due to driver's drowsiness, the conventional approach involved monitoring and analyzing the driver's physiological signals such as electrocardiography (ECG) and electroencephalography (EEG). However, these methods were complex and required high maintenance, prompting the need for alternative driver monitoring techniques. Driver drowsiness is a significant contributing factor to many vehicle accidents, impacting global human mortality rates. In this study, a convolutional neural network (CNN) was employed to develop a drowsy driver detection system. The dataset used for training the CNN model consisted of drowsy driver samples collected from the UCI repository. The trained model was then utilized to create the drowsy driver detection system. The classification model developed with CNN exhibited an impressive 99.7% accuracy in detecting drowsy behavior. Subsequently, the model was tested in practical experiments, where it successfully identified instances of drowsiness with high precision. This research highlights the effectiveness of using CNN for drowsy driver detection, providing a promising solution to mitigate the risks associated with driver drowsiness and reduce the occurrence of accidents caused by this factor

Keywords: Drowsy Driver; Convolutional Neural Network; classification, experiment, driver

1. INTRODUCTION

Over 1.2 million fatalities and 50 million injuries occur annually due to road traffic accidents, highlighting the urgent need for effective solutions. Maninder and Amrit (2014) predicted that without immediate action, road accidents would become the third leading cause of human mortality by the year 2021, surpassing malaria, HIV/AIDS, and other acts of violence. Factors such as poor road conditions, speeding, and driver drowsiness have been identified as major contributors to accidents. In fact, drowsy driving alone accounts for more than 20% of road-related fatalities, resulting in over 657.4 deaths worldwide each day (Barr et al., 2019). While various technologies, such as cruise control systems, autonomous vehicles, computer vision for pedestrian detection, and intelligent road sign detection systems, have been implemented to mitigate accidents, the problem of drowsy driving remains unresolved. Unless a reliable system can be developed to detect and alert drivers of their unstable physiological state leading to drowsiness in real-time driving scenarios, accidents will persist (Gwak et al., 2018).

Numerous studies have explored the detection of drowsy driving using physiological, cognitive, and vehicle-based approaches. Physiological approaches utilize electrocardiography, neuro-imaging, and physiological sensors to assess the driver's condition. Although these methods provide accurate data, their complexity and maintenance requirements limit their widespread use (Mardi, 2011). Vehicle-based approaches evaluate drowsiness through steering wheel motion and braking patterns, relying on the condition of the roads. Recent techniques incorporate automatic braking systems, smart power steering controls, adaptive cruise control systems, and more. However, despite their effectiveness, the US National Highway Safety Administration reported a 23% increase in accident rates despite the implementation of these preventive measures (Noori and Mikaeili, 2016). Behavioral methods focus on the driver's behavior and employ smart cameras to capture information and detect actions while driving. Recent studies have utilized image recognition and artificial intelligence methodologies to address drowsiness. These methods analyze real-time images from datasets of drowsy drivers, processing and predicting driving behavior, and alerting the driver when drowsiness is detected (Barr et al., 2019). In light of these challenges, this study proposes an intelligence-based drowsy driver monitoring and detection system that is reliable, user-friendly, and affordable for all drivers. The system will collect real-time drowsy driving data and employ artificial intelligence techniques to understand and predict the driver's behavior during sleep, enabling accurate identification of future drowsiness-related actions

2. LITERATURE REVIEWS

Taner and colleagues (2018) conducted a pioneering study on drowsy driver detection systems that focused on analyzing eye blink patterns. Their approach leveraged the horizontal symmetry of the eyes to detect visual changes in eye positions. Using a high-resolution webcam and a comparable differential model, they achieved an impressive accuracy of 84% with a minimal 1% false positive rate. However, the study highlighted the need to address the lengthy training time delay of 12 seconds to enhance the system's efficiency. In a separate research effort, Charlotte et al. (2018) explored the adaptation of artificial neural networks for enhanced driver monitoring and drowsiness detection. They devised mathematical models capable of detecting minute-to-minute levels of drowsiness and predicting outcomes accordingly. By implementing these models using Simulink, they achieved moderate accuracy rates of 40% for drowsiness prediction and 80% for drowsiness detection. Although their results were promising, further improvements are necessary to enhance system performance and increase overall accuracy. Agustina and her team (2016) delved into the automatic detection of drowsiness in EEG records through multimodal analysis. They employed a neural network classifier and employed a selection procedure based on the Wilks criterion to identify distinct alertness and sleepy periods. By utilizing seven input parameters, they attained a commendable accuracy of 87.4% for alertness and 83.6% for drowsiness detection. However, additional research is needed to refine and improve the accuracy of their approach. Another noteworthy study by Manoram and Anil (2018) proposed a drowsy driver detection and security system that utilized artificial neural networks and image processing techniques. Their method exhibited a remarkable accuracy rate of 94%, showcasing its potential effectiveness. Nevertheless, the study identified a processing delay of 19 seconds, primarily caused by the employed training algorithm. Consequently, future research should focus on optimizing the training process to minimize such delays and further enhance the system's performance. Lastly, Ashish and Rusha (2018) developed a driver drowsiness monitoring system that integrated machine learning with visual behavior analysis. Through the utilization of a webcam for real-time data acquisition and image processing methods, they successfully trained a machine learning model to predict driver behavior, achieving a sensitivity of 92.5%. Despite their accomplishments, the study emphasized the need to address the processing delay of 15 seconds to improve the system's efficiency. Collectively, these studies have significantly contributed to the field of drowsy driver detection systems. However, further research is warranted to overcome limitations such as training time delays and enhance system performance and accuracy through practical validation.

3. METHODOLOGY

The methodology for the study started with data collection of drowsy driver from the UCI Machine Learning Repository: The sample size of data collected is 20000 samples of drowsy behavior which considered two attributes which are 1000 eye open samples and 1000 eye closed samples of video files. Other attributes of drowsiness such as yawning, heads down, continuous, eye blinking, yawing and head down were collected through practical experimentation and then processed for compatibility before fusion into the UCI drowsy dataset. These data was used to train a convolutional neural network using Matlab tool and then generate a drowsy driver algorithm which was used to develop the drowsy driver monitoring and detection system.

4. How the CNN Works

In this work the Convolutional Neural Networks (CNN) used has one input layer with image size of 180x 180, three convolutional layers and one fully connected layer. The figure 1 presented the flow chart of the CNN. CNN operate by performing a series of operations to analyze images or grid-like data. The initial step involves convolving small filters, known as kernels, over the input image. Through dot products between the filter weights and corresponding pixel values, convolutions extract local features and capture spatial relationships within the image. To introduce non-linearity, an activation function such as the Rectified Linear Unit (ReLU) is applied element-wise to the output feature maps after each convolution operation.

Pooling layers come next, downsampling the feature maps obtained from the previous convolutional layers. Max pooling, a common technique, selects the maximum value within small regions of the feature map. This process reduces spatial dimensions while preserving essential information. Following pooling, the pooled feature maps are flattened into a 1D vector. This step connects the convolutional layers with fully connected layers (dense layers) that come after. Dense layers are similar to those found in traditional neural networks, responsible for learning intricate patterns and making predictions. The final layer of the CNN is the output layer, generating the desired output for the given task. For instance, in image classification, the output layer can comprise multiple nodes, each representing a class, and use softmax activation to produce class probabilities. Once the CNN architecture is defined, it is trained using labeled datasets. During training, the network is fed with input samples, and the predicted outputs are compared to the ground truth labels. Weights are adjusted using optimization algorithms (back-propagation) to minimize the discrepancy between predicted and true labels, thereby improving the model's accuracy. After training, the CNN is ready for inference on new, unseen data. It takes an input image, passes it through the network, and generates predictions or feature representations. This allows the CNN to be utilized for drowsy driver behavior classification.

4.1 DESIGN CALCULATIONS FOR THE CNN

Given the input layer parameters as: Image size: 180 x 180; three convolutional layers with a filter size of 3x3; Number of filters: 32 for each layer

Convolutional Layer 1: Input size: 180 x 180; Filter size: 3 x 3; Number of filters: 32

Calculating the output size of Convolutional Layer 1: Output size: ((180 - 3 + 2(0)) / 1) + 1 = 178; Number of parameters in Convolutional Layer 1: (3 x 3 x 3 x 32) + 32 = 896;

Convolutional Layer 2: Input size: Output size of Convolutional Layer 1 (178 x 178); Filter size: 3 x 3; Number of filters: 32. Calculating the output size of Convolutional Layer 2: Output size: ((178 - 3 + 2(0)) / 1) + 1 = 176; Number of parameters in Convolutional Layer 2: (3 x 3 x 32 x 32) + 32 = 9248

Convolutional Layer 3: Input size: Output size of Convolutional Layer 2 (176 x 176); Filter size: 3 x 3; Number of filters: 32; Calculating the output size of Convolutional Layer 3: Output size: ((176 - 3 + 2(0)) / 1) + 1 = 174; Number of parameters in Convolutional Layer 3: (3 x 3 x 32 x 32) + 32 = 9248

Fully Connected Layer: Input size: Output size of Convolutional Layer 3 (174 x 174); Number of neurons: Let's say we have 64 neurons; Calculating the number of parameters in the fully connected layer: Number of parameters: (174 x 174 x 64) + 64 = 1,909,632

Overall, the CNN architecture with three convolutional layers has a total of 896 parameters in Convolutional Layer 1, 9,248 parameters in Convolutional Layer 2, 9,248 parameters in Convolutional Layer 3, and 1,909,632 parameters in the fully connected layer.

4.2 The System flow chart

The system flow chart in figure 1 presents the training performance of the CNN algorithm with the data of the drowsy drivers collected. This data is feed to the convolutional layer of the CNN which first dimension the input size of the images to 180x 180, then filter is used to scan the receptive fields of the image pixels for feature map extraction, and then formulation the first convolutional layer till the last convolutional layer as defined in the design calculations. The extracted features are then flattered and feed to a fully connected layer which used back-propagation algorithm to train the data and generate the drowsy classification model. Before the final output of the model generation, it was evaluated considering accuracy and loss function. The accuracy checks the correctness of the drowsy feature detection of the model while the loss function was used to check the error between the actual drowsy features and the predicted drowsy features. When the results of these evaluation parameters are acceptable which is accuracy approximately 100% and loss unction approximately 0%, then the training stops after the results are validated. This model of the drowsy driver was used to develop a drowsy driver detection system which collected input data of drowsiness and then classify with the drowsy driver classification model developed to detect drowsy behavior in real time as presented in the figure 2.

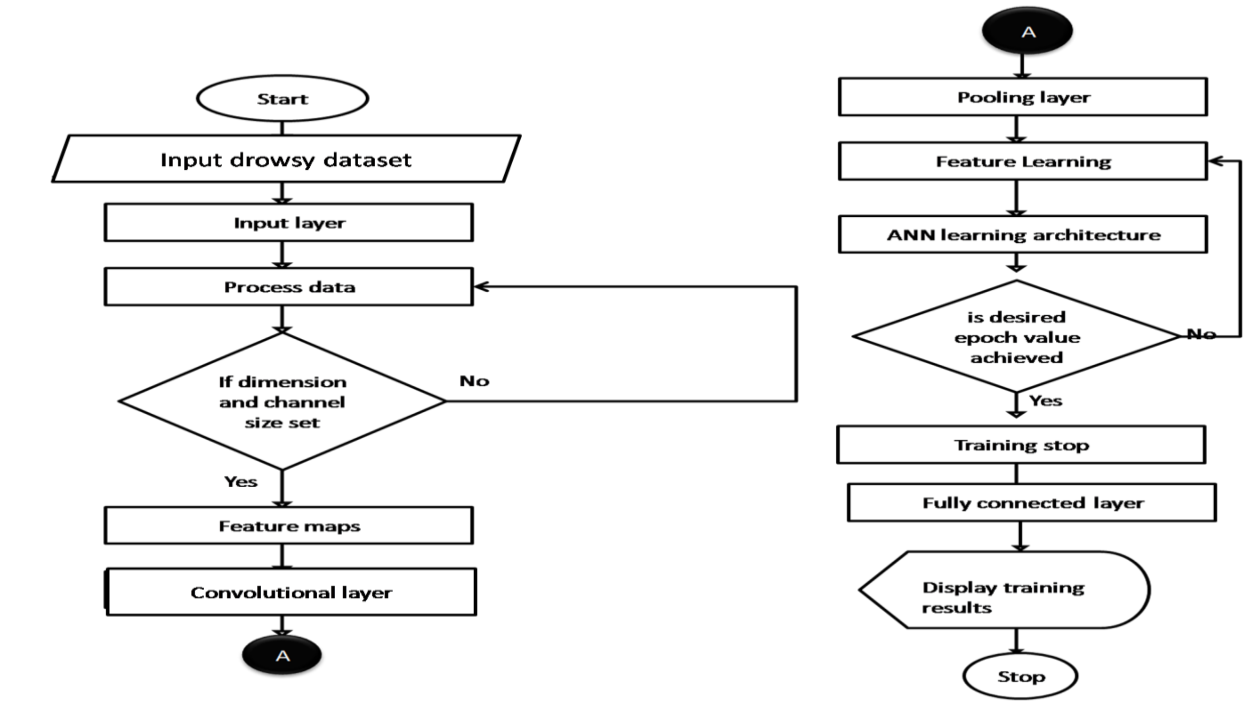

Figure 1: Flow chart of the CNN training with drowsy dataset

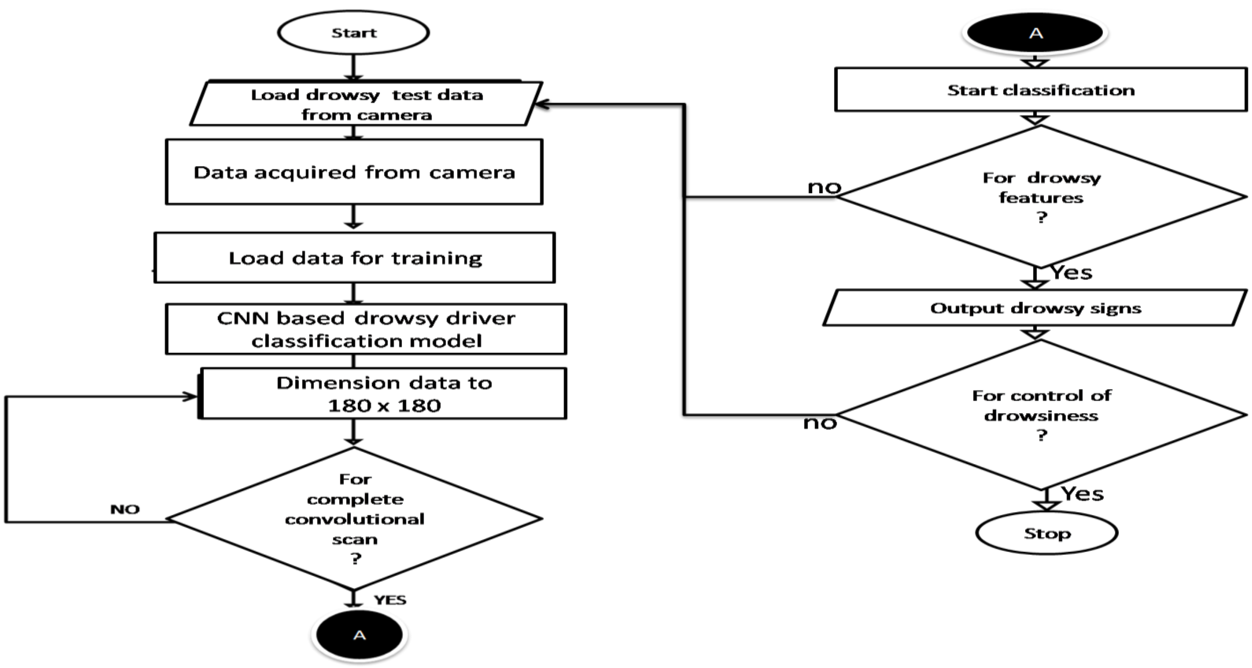

Figure 2: The Flow chart of the drowsy driver detection system

5. SYSTEM IMPLEMENTATION

The model was used to implement the drowsy driver software in figure 3 and then tested considering various drowsy driver features through practical experiment. The experiment was performed installing the software inside Laptop and then connected to a camera, and tested inside a car while displaying drowsy behavior in a safe environment as reported in the figure 4.

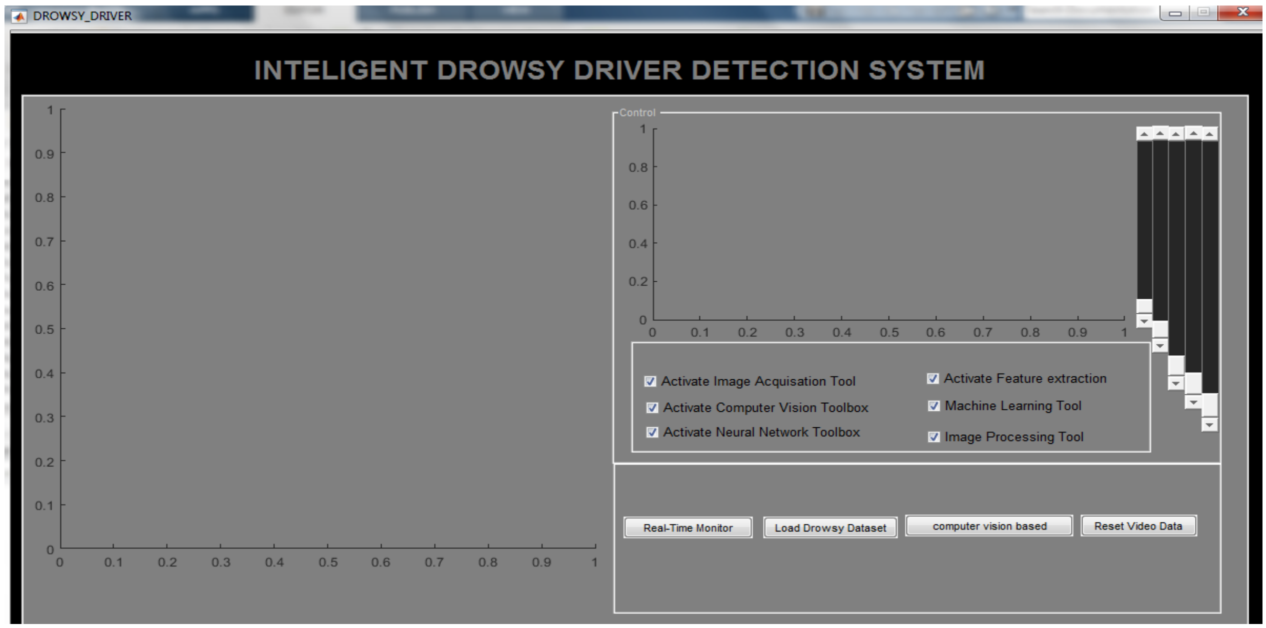

Figure 3: The system's implementation

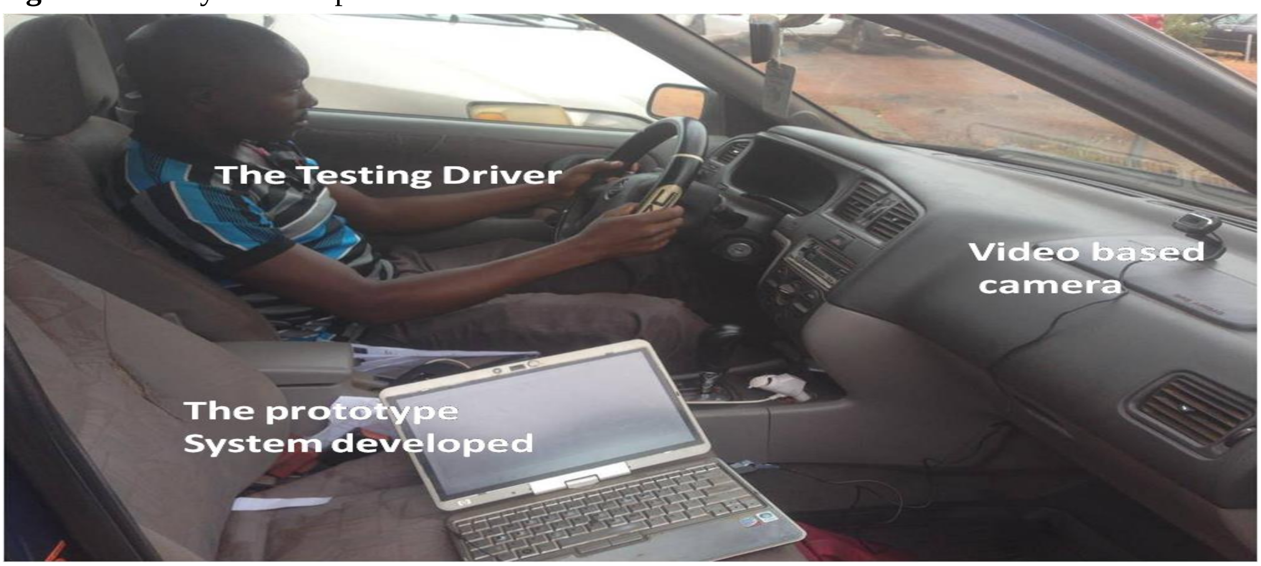

Figure 4: system installation

From Figure 4, the laptop system, which serves as the monitoring screen for this demonstration, was connected to the camera positioned on the dash board and intended to record the driver's actions in real time. The software and camera's performance were then assessed when the driver was in control of a car and displaying a range of behaviors that were ascribed in the data model.

6. RESULTS AND DISCUSSION

Before the system testing, the model generated by the CNN was evaluated and the result was presented in the figure 5, using a deep learning training toolbox.

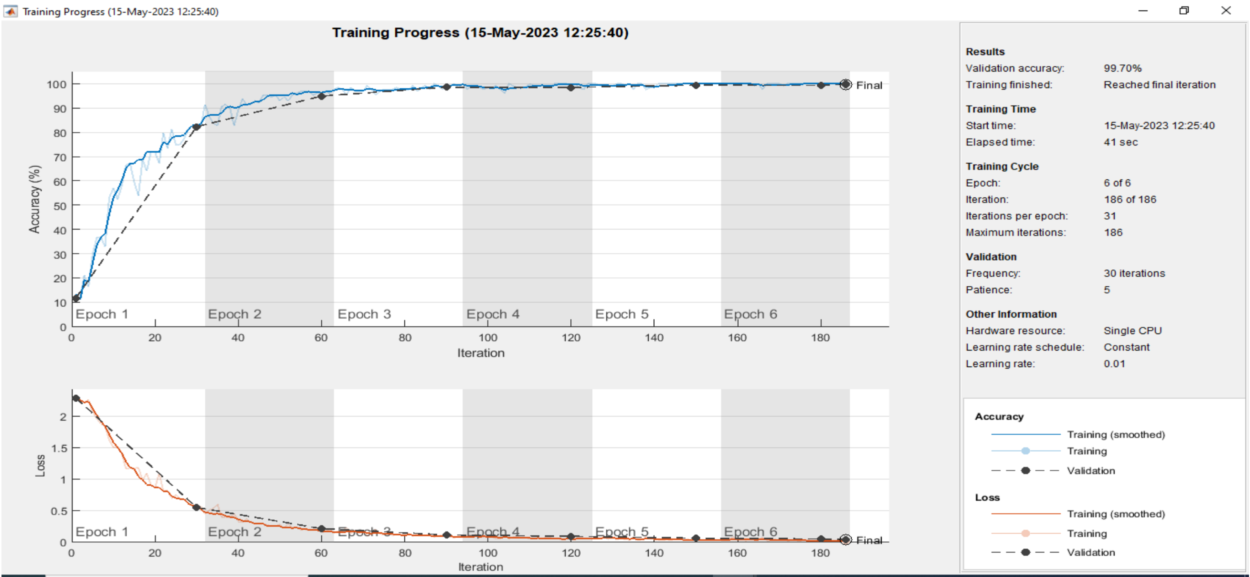

Figure 5: Training result of the CNN based drowsy model

From the result of figure 5, after training and validation of the drowsy drover model, the result reported 99.70% accuracy and loss unction approximately zero. The implication is that the CNN correctly learn the drowsy features and the error between the predicted drowsy features and actual drowsy features is approximately zero. To this end, the model was used to develop the software application, whose tested result is in figure 6.

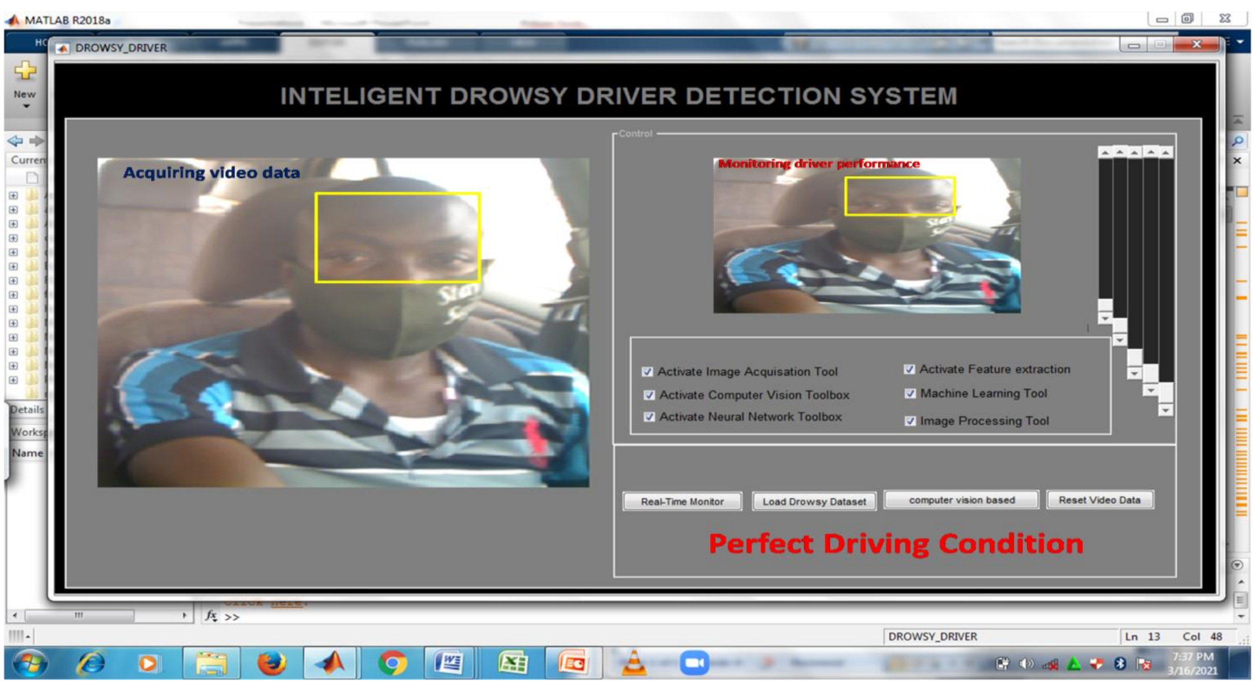

Figure 6: Result of drowsy detection system

In the figure 6, the software was tested on a driver under perfect driving condition, i.e without drowsy behaviors, and it was observed that these features were detected and classified as perfect driving condition. The next result display when it was tested with drowsy features as shown in the figure 7;

Figure 7: Result with drowsy behavior

The figure 7 presented the performance of the software when tested displaying drowsy behavior (Yawing and continuous eye closed). From the result, it was observed that the data acquired was correctly classified to detect drowsy feature. This implied that the software was able to correctly detect and classify drowsy behavior in drivers to control and minimize accident.

7. CONCLUSION

This paper has resulted in a powerful real-time drowsy driver detection and classification system. The objectives were accomplished in accordance with the guidelines for the study. Convolutional neural networks enabled the classification process, whilst computer vision enabled the detection process. A number of convolutional layers were used in an artificial neural network's training process, and they were then gathered at the fully connected layer for classification. The system was tested at three drowsy symptom situations: significant drowsy symptoms, minor drowsy symptoms, and regular driving conditions, using a range of self-volunteered drivers who were used in the training process. The system's ability to detect, classifies, and anticipate the driver's status with 99.7% accuracy was demonstrated by the results. It may be inferred that using a Drowsy Driver monitoring and detection system can reduce traffic accidents and protect people and property, hence the null hypothesis of this study should be rejected because it is not significant.

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