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An Intelligent Drowsy Driver Detection System Using Deep Neural Network

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***Abstract*- This paper is on the development of an intelligent drowsy driver detection system using a deep neural network algorithm. The goal is to build an adaptive system that follows, monitors, and detects when a driver is displaying critical drowsy signs while driving. This was achieved using computer vision and deep neural network approach which was configured as convolutional neural network architecture. At the end of the training process, the features were classified and labelled as perfect driving condition, sensing drowsy behavior and critical drowsy behavior. The critical sleepy symptoms are a categorization of potentially harmful sleepy characteristics including sleep, micro sleep and face down while driving. The categorization of minor sleepy traits entails features such as yawning, eye blinking and other drowsy symptoms while the perfect driving conditions are attributes such as two eyes open with a focused gaze. The system was implemented with MATLAB and tested in real live scenarios and the result showed a drowsy detection accuracy of 98.7%.**

***Indexing*- Drowsy Driver, Deep Neural Network, Computer Vision, Adaptive Systems, Convolutional Neural Network.**

I. INTRODUCTION

Accidents are becoming a common trend today in all social media platforms, national news, and daily newspapers. Every year an average of 12,077 road accidents occurs, resulting to about 75400 fatalities [1]. The term "fatality" connotes the death of loved ones such as spouses, children, parents, loss of properties, among other things. The causes of these accidents can be linked to the following; reckless driving, inattention while driving, lack of proper driving ability, driving too fast, bad roads, system failure on the vehicle, and poor physiological condition.

Over time, different methods have been implemented in reducing road accidents. Some of the methods involve the use of administrative procedures such as the required use of driving licenses for all drivers, the use of speed control signs (maximum speed limit for various routes), and the use of law enforcement agents among other safety regulations. Technical measures applied include the use of an automated brake control system and cruise control system, speed monitor, lane departure warning system among others.

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However despite the success achieved by these measures, the rate at which accidents occurs incrementally each year clearly reveals that these traditional measures are just not sufficient resulting in the need for a better system. Accident prevention and control systems have attracted much research interest recently, with the aim of identifying the main cause of accidents and proposing a one-time solution. According to the authors in [2, 3&4] poor physiological state of the driver, causes most of these incidents resulting to over 20% of all car-related accidents.

A drowsy driver is one who expresses attributes such as constant yawing, excessive consecutive eye blinking, drooping head, and micro-sleep among other fatigue behaviors while driving. These behaviors are very dangerous if not detected and controlled immediately, because within seconds accident can happen and destroy lots of lives and properties.

Neural networks are machine learning models used to simulate the learning process that occurs in human neural system. Being one of the most powerful learning models, they are useful in automation of tasks where the decision of a human being takes too long, or is imprecise [5]. Generally, there are three major approaches to drowsiness detection: physiological approach [6], vehicle based approach [7] and behavioral approach [8]. The physiological approach is faced with the challenges of the complexity in its design and interference with the driving process when installed, as the system is attached to the driver's body to collect data for processing. The vehicle based approach is faced with the problem of false alarm since it is designed to respond based on linearity and various factors other than drowsiness, like bad roads, pot holes can induce nonlinearity on the vehicle. Today's tendency is to use a variety of approaches, primarily image processing and artificial intelligence. Image processing technique such as color based approach; segmentation and others were examined in [9]. Several artificial intelligence techniques can be implemented in drowsiness detection [10]and their effectiveness can be improved if quality data is fed into the network. To achieve this improved quality data collection, computer vision will be used in this work, while deep neural network will be adopted for the training system developed in this work. The training model developed will be evaluated using MATLAB.

II. MATERIALS AND METHODS

The proposed system was developed using several techniques as shown in fig.1. The video acquisition system is for the collection of real-time drowsy data via a video camera, computer vision algorithm is for the control of the operation of the camera. The face detection technique detects the driver's face which is the main part of the body with visual drowsy features. The data acquired after face identification were fed forward to the deep neural network for training and classification of driving behaviour in a specified picture format.

At the completion of the training process, the features are classified and labelled as perfect driving conditions, sensing drowsy behavior or critical drowsy behavior. The critical sleepy symptoms are a categorization of potentially harmful sleepy characteristics including sleep, microsleep and face down while driving. The categorization of minor sleepy traits entails features such as yawning, eye blinking and other drowsy symptoms while the perfect driving conditions are attributes such as two eyes open with a focused gaze

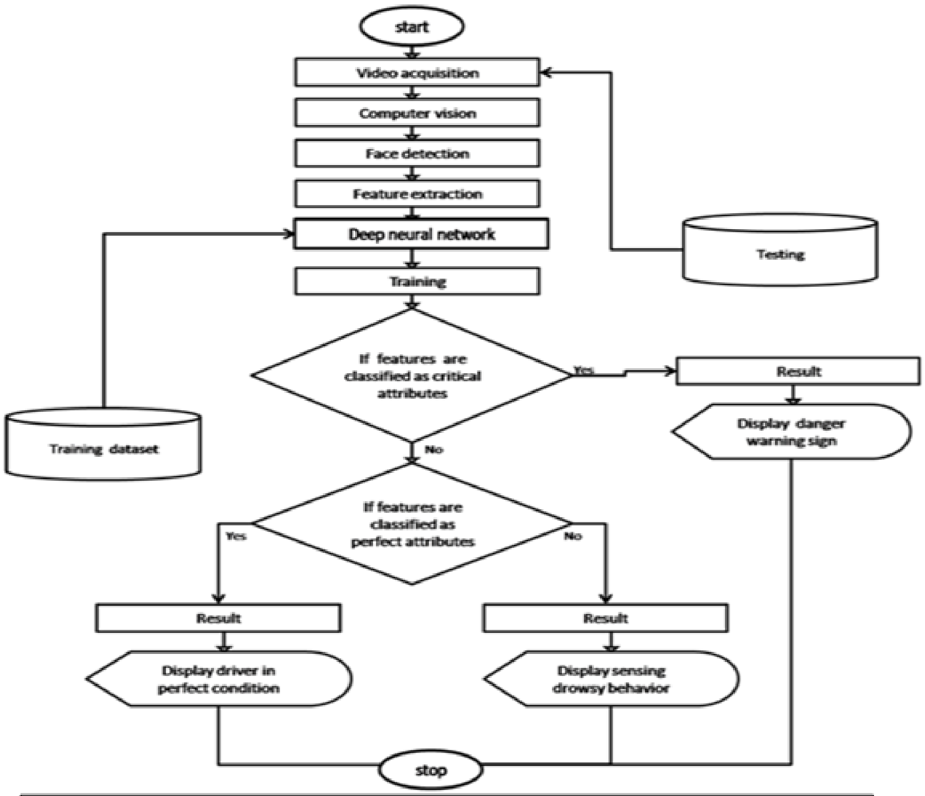

Fig. 1: Flow diagram of the proposed system

A. System Design

This section is on the design of the improved data acquisition device and the development of the convolutional neural network model used for the training process. The design was done with the use of a universal modeling diagram and discrete mathematical

i. The data collection system

Using a facial detection algorithm, an improved data collection system was developed. The Viola Jones algorithm [9] was used for face detection and collection of drowsy features. Because of its capacity to search and identify, the algorithm was deployed to track facial features using Haar characteristics which are rectangular features to detect the location of facial feature points in the image. These features identified are assigned a number, and if less than 10 the system assumes that the focus and searching process is not valid and continue searching for points, else image frames are extracted from the data and synchronized in video format of resolution 32 x 32 pixels, 1024 pixel quality and then fed forward for training. The algorithm is represented using flowchart in fig.2.

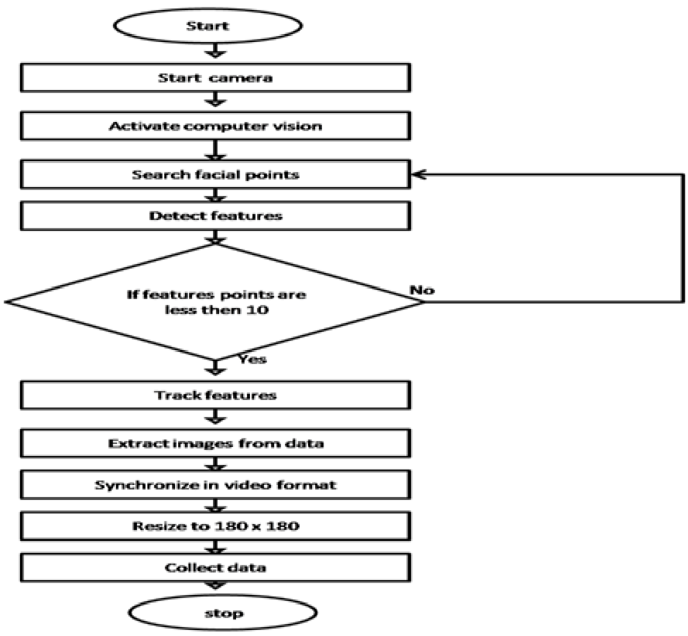

Fig.2: The data collection system design flow

ii. Entering text

The convolutional neural network (CNN) is the training approach employed. The CNN was designed and configured as shown in the flow chart of fig.3 (a) & (b)

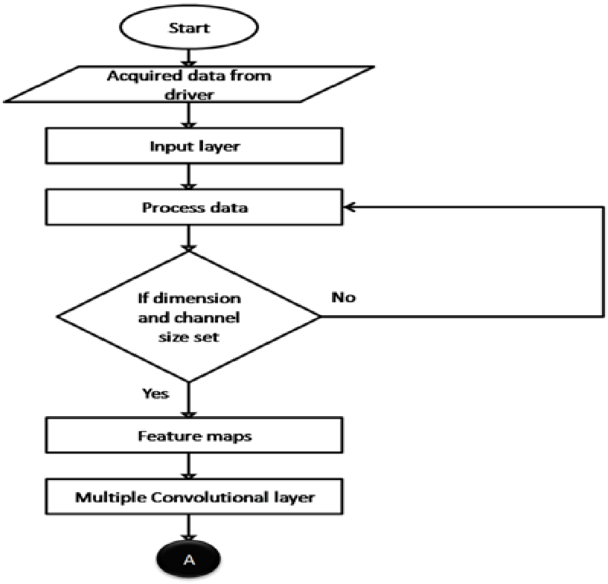

Fig. 3 (a): Flowchart of the CNN design

In the figure, the driver's face automatically configured as 32 x 32 pixels image was fed to the input layer of the CNN. The input layer processed the image by dimensioning it into 32 x 32 x 3 which shows the degree of fineness and the RGB image's color channel. The image was scanned in the first convolutional layer using filters. The filter size is 5 x 5 x 3 and it is used to look at the receptive fields of the image. This process is called convolution. The scanning process extracts key pixels from the image as feature maps as shown in fig. 4.

From the figure 4, the filters scan and extract feature from the receptive field as shown above, however before these maps are pooled to the next layer for another convolution, nonlinearity was added using rectified linear unit to guarantee that any negative values were removed and replaced with zero. The parts of the primary picture where the filter did not fit in adequately were padded during the scanning process and the output feature vectors are displayed using the model shown in equation 1.

$$F_o = \left[\frac{F_i + 2_p - k}{s}\right] + 1 \qquad (1)$$

Where F_o is the output features, F_i is the input features, p is the padding of the convolutional layers, s is strides size, k is the kernel size. The pooling method used for the output in the model is the maximum pooling technique which selects only the highest pixel values from each filter convolution and then arranges in a matrix array.

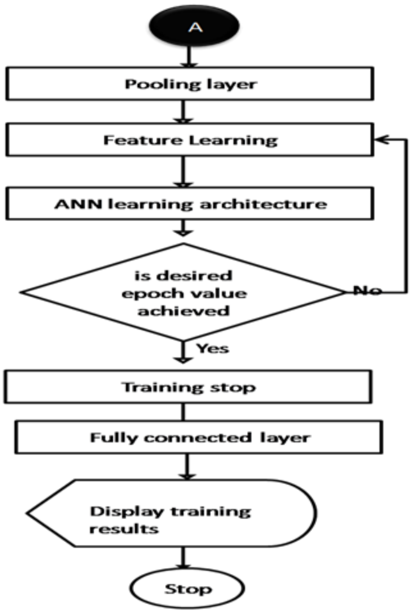

Fig. 3(b): Flowchart of the CNN design

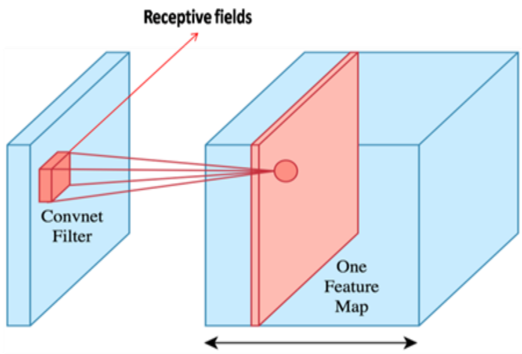

Fig. 4: convolution process

Fig. 5 presents the final feature map pooled from the last convolutional layer which is flattened as a vector and fed to the fully connected layer. All the feature vectors were collected and fed forward to the neurons of a multi layered artificial neural network structure for training using the entropy function in equation 2;

$$E(\theta) = -\sum_{i=1}^{n}\sum_{j=1}^{k} t_{ij}\, In_{yj}\,(x_i, \theta), \qquad (2)$$

Where, t_{ij} denotes that the i^{th} sample belongs to the jth class, and $y_r(x_i, \theta)$ is the output for sample i and Θ is the parameter vector. The output $_r(x_i, \theta)$may be understood as the likelihood that the network would correlate i^{th} input with class j, that is $P(t_j = 1|x_i)$ [11]

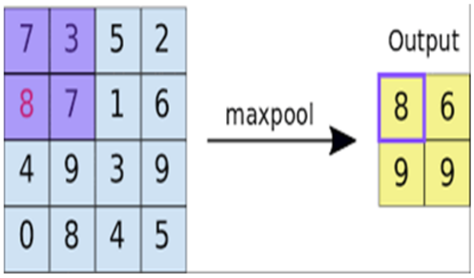

Fig 5: Pooling Operation from the Last Convolutional Layer

The softmax function is used to activate the output unit which predicts the normal probability distribution of the input exponential as the output result. The architectural diagram for the CNN is presented in fig.6.

From the architecture, the drowsy data was dimensioned by the input layer and extracted into the convolutional layers by the filters via a convolutional process and maximum pooling technique. To guarantee that only valid feature vectors are pooled from one convolutional layer to the next, ReLU was utilized to add nonlinearity. The final feature maps are flattened by the completely connected layer and fed to the artificial neural network to use the softmax function in the output layer for training and classification.

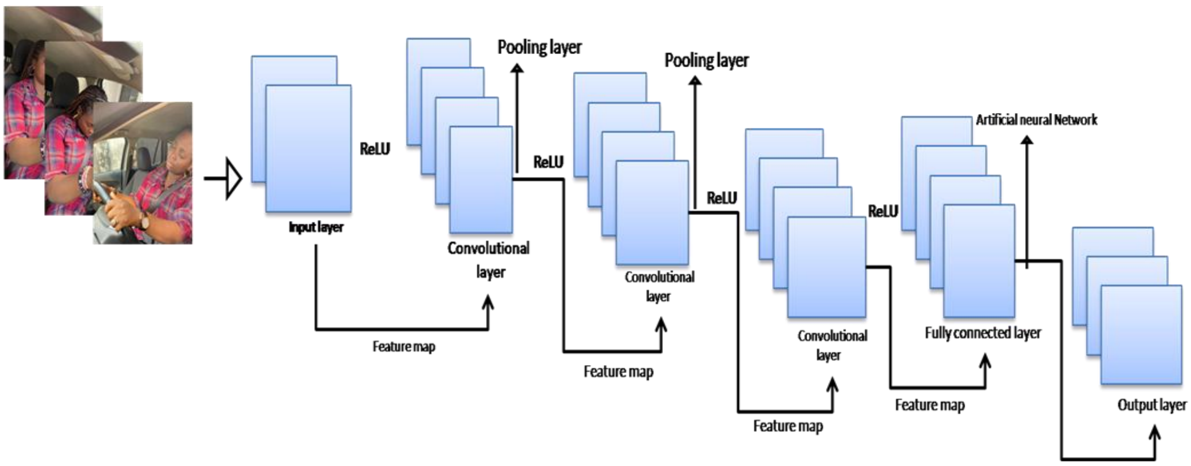

Fig. 6: The convolutional neural network architecture

The MATLAB programming environment which is embedded with neural network toolbox, deep learning toolbox, statistics and machine learning was used to run the developed models. The deep learning tool was used to train the drowsy data collected from the video device

III. RESULTS

The result were reported in two sections which are the deep learning training performance evaluation and the prototype implementation result when tested with real live drowsy behaviors. The performance was measured using the models in equation 3 for accuracy and equation 4 for validation.

A. Performance evaluation

The total properly categorized positives and negatives divided by the total number of samples in the drowsy dataset yields the overall accuracy of a classifier. The accuracy is computed by the deep learning tool using the model below;

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

The true positive rate is TP, the true negative rate is TN, the false positive rate is FP, and the false negative rate is FN.

B. Deep learning training result

This section presents the result of the deep learning training performance using deep learning toolbox in MATLAB. The system automatically splits the feature vectors into test, training and validation which is set in a ratio of 70:15:15 respectively before using the toolbox of deep learning in MATLAB to train. During this learning process the filters scan the images for learning feature vectors in each layer of convolution and feeds same to the other layers to continue until the whole image is complete learned. The training process was performed using the training parameters in table 1.

Table 1: Deep leaning training parameters

Parameters	Values
Training epochs	100
Size of hidden layers	10
Iteration per epoch	31
Training segments	30
Neuron weights	540
Filter size	5 x 5 x 3
Image dimension	180 x 180 x 3
Image pixel	32400
Total feature maps	176
Initial feature map	75
Learning rate	0.001
Minimum reference value	-0.7
Maximum reference value	0.7

The training process was performed loading the dataset designed into the deep learning training toolbox, then train and monitor the performance as shown in fig.7.

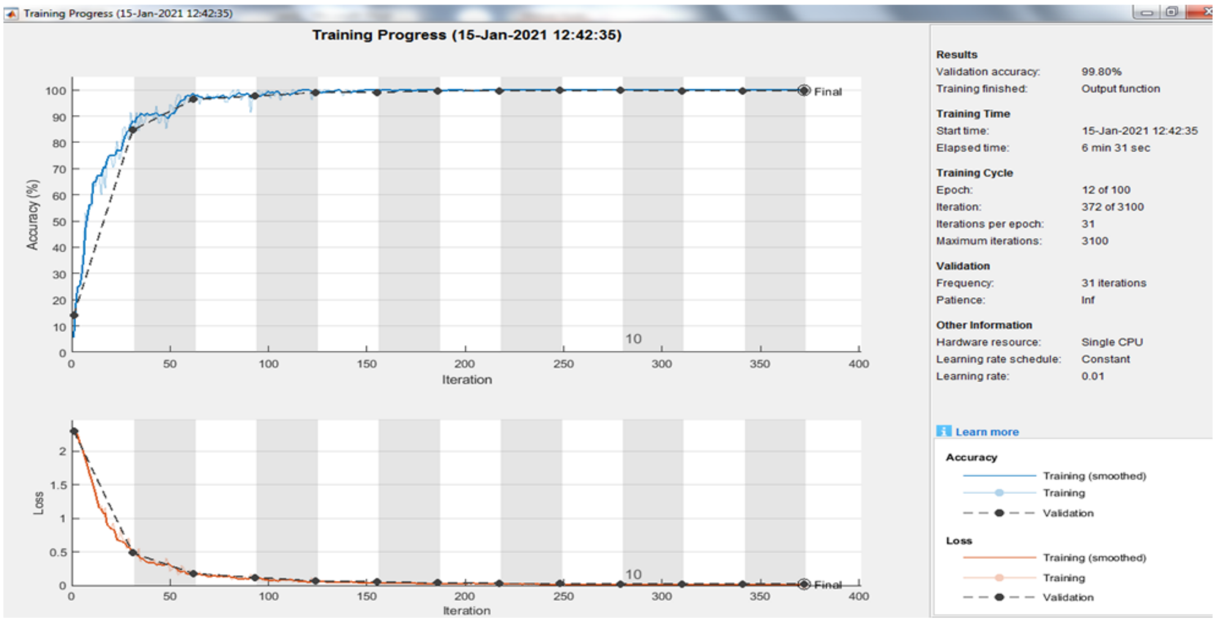

Fig.7: The training result with deep learning tool

Table 2: Ten-fold training results

Training times	Accuracy (%)	Loss (%)
1	98.9	1.1
2	98.1	1.9
3	98.1	1.9
4	99.1	0.8
5	98.2	1.8
6	99.0	1.0
7	98.1	1.9
8	99.7	0.3
9	97.9	2.1
10	98.9	1.1
Average	98.7	1.3

When the training dataset was fed to the CNN architecture and following the already explained deep learning training procedure, the result was obtained. During this training process, the test vectors are used to check the system performance using a multi-class entropy function presented earlier in equation 2 while the performance is measured and presented as 99.8% in the deep learning tool based on the evaluation model in equation 3. Validation features are employed to validate these results based on the model in equation 4 and the results are recorded in table 2;

$$CVA = \frac{1}{10}\sum_{1}^{10} Ai \qquad (4)$$

Where CVA stands for Cross-Validation Accuracy, A is the accuracy measure for each fold. The results are generated performing other series of training based on the validation model above and then reported as shown in table 2.

As seen in the results in table 2, the dataset was trained using the deep learning toolbox 10 times and the result presented for accuracy and loss respectively. The total performance was calculated using the formula in equation 4 and the result produced an accuracy result of 98.7%.

IV. CONCLUSION

In this work an intelligent real time drowsy driver detection and classification system was developed. Computer vision was used to carry out the detecting procedure, whereas the classification process was made possible with convolutional neural network. The training process occurred in series of convolutional layers and then grouped at the fully connected layer for classification using an artificial neural network. The systems were put to the test using a variety of self-selected drivers who were utilized in the training process, and the results revealed that they were precise in detecting critical drowsy symptoms, normal driving conditions and minor drowsy symptoms.

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