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Comparative Study on different algorithms for Drowsiness Detection

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***Abstract* – There has been an increase in safety systems in cars and other vehicles and many are now mandatory in vehicles, but all of them cannot help if a driver falls asleep behind the wheel even for a brief moment. As studies suggest that accidents due to drivers getting drowsy or sleepy account for around 20% of all accidents and on certain long journey roads it's up to 50%. It is a serious issue and most people that have driven for long hours at night can relate to the fact that fatigue and slightbrief state of unconsciousness can happen to anyone and everyone. Many misfortunes can be avoided if the driver is alerted in time.**

Several applications were built using VGG-16 and ResNet50 but there is a chance for improvement in the performance of the models. The proposed research gives a detailed comparative study of performance of various convolutional neural networks (CNNs) that can be applied in this application of drowsiness detection which can give efficient results using different parameters like architectures and optimizers. MobileNet, Densenet, and ResNet50 and VGG16 are the pre-trained neural networks used in this study. The proposed work has achieved an accuracy of 99.52 percent for MobileNet using Adam optimizer. Along with this, a security system is built using facial recognition library which will perform facial detection and verification and give access of vehicle to authorized persons only and alert if any unauthorized user tries to access the vehicle.

***Keywords* – VGG16, ResNet50, MobileNet, DenseNet, Transfer learning, Optimizers**

I. INTRODUCTION

Drowsy driving is one amongst the common causes of road accidents leading to injuries, even death and significant economic losses to drivers, road users, families, and society. Thus, driver drowsiness detection has been considered a major potential area so as to prevent a huge numberof sleep-induced road accidents.

This paper focuses on determining eyelid movements and analyzing eye status for drowsiness detection. This system will extract eye images from the face images of driver using live video capture and a model which is trained using two adaptive deep neural networks based on MobileNet, DenseNet, VGG16 and ResNet50 and finally if driver seems to be drowsy then immediately an alert call will be given to the driver. This paper provides meaningful solutions in practice to prevent unfortunate automobile accidents caused by drowsiness.

And as a part of security for vehicles, this paper implements a security system built using facial recognition library which will perform facial detection and verification and give access of vehicle to authorized persons only and alert if any unauthorized user tries to access the vehicle.

II. LITERATURE SURVEY

[1] In a bid to increase accurateness and accelerate drowsiness detection, several approaches have been proposed. The first previously-used approach is based on driving patterns, and it is highly dependent on vehicle characteristics, road conditions, and driving skills. To calculate driving pattern, deviation from a lateral or lane position or steering wheel movement should becalculated.[2] While driving, it is necessary to perform micro adjustments to the steering wheel to keep the car in a lane. Krajweski detected drowsiness with 86% accuracy on the basis of correlations between micro adjustments and drowsiness. Also, it is possible to use deviation in a lane position to identify a driving pattern.

[3] In this work, the car's position respective to a given lane is monitored, and the deviation is analyzed. Nevertheless, techniques based on the driving pattern are highly dependent on vehicle characteristics, road conditions, and driving skills. [4] This technique employs data acquired from physiological sensors, such as Electrooculography (EOG), Electrocardiogram (ECG) and Electroencephalogram (EEG) data. EEG signals provide information about the brain's activity. The three primary signals to measure driver's drowsiness are theta, delta, and alpha signals. Theta and delta signals spike when a driver is drowsy, while alpha signals rise slightly.This methodology, according to Mardi, is the most accurate, with an accuracy rate of over 90 percentage. The biggest problem of this strategy, however, is that it is obtrusive. It necessitates the attachment of numerous sensors to the driver's body, which may be inconvenient. Non-intrusive approaches for bio-signals, on the other hand, are far less exact.

[5] Another paper attempted to address the issue by creating an experiment in order to calculate the level of drowsiness. A requirement for this paper was the utilization of a Raspberry Pi Camera and Raspberry Pi 3 module, which were able to calculate the level of drowsiness in drivers. The frequency of how often head tilting and blinking of the eyes was captured was used to determine whether or not a driver felt drowsy. The accuracy of face and eye detection was calculated to be 99.59 percent after a test on ten subjects. However, it employs the Haar-Cascade classifier, which is inefficient when dealing with large datasets. Computer Vision, which is based on the extraction of facial features, is another technology. It makes use of behaviours like eye closure, yawning duration, head movement, and gaze or facial expression. Danisman [6] used the space between eyelids to measure three stages of tiredness. This calculation took into account the amount of blinks per minute, which is assumed to rise as the driver becomes more drowsy.

The mouth and yawning behaviours are used by Hariri[7] to measure sleepiness. For face and mouth detection, the modified Viola-Jones[8] object detection algorithm was used. Deep learning methodologies, particularly Convolutional Neural Networks (CNNs) methods, have recently gained popularity in solving classification problems. [9] Park developed a new architecture employing three networks. The first network [10] uses AlexNet consisting of three Fully Connected (FC) layers and five CNNs to reveal the image feature. Furthermore, 16-layered VGG-FaceNet14 is used to extract facial features in the second network. FlowImageNet15 is used for extracting behavior features in the third network.This approach achieved 73% accuracy.[11] This paper used Artificial Intelligence-based advanced algorithms were used to detect driver fatigue and the rate at which the driver is drowsy. It uses eye and mouth vertical distances, eye closure, yawning. Although the proposed classifiers are good enough to give reasonable results, still there is a lot of latitude for improvement in their performance. A more robust drowsiness detection classifier can still be improved by researching on other datasets.

[12] Using a Human Computer Interaction system implemented on a Smartphone, this paper suggested a drowsiness detection system based on driver face image behaviour. If it detects that the driver is drowsy, it will alert the driver and send a notification to the driver's smartphone. The device used the PERCLOS algorithm to detect eyes and had a blink rate accuracy of 98.7%. The goal of this paper was to install a surveillance system that alerted the driver.

[13] The purpose of this study was to develop an intelligent wireless sensor network that could detect and monitor driver drowsiness in real time. It's made up of a slew of non-obstructive sensors that constantly monitor the driver's physiological factors and warn the driver and passengers when they're in danger. If the driver's condition does not improve after the first level alert, the second level alarm will be sent to the nearest police station or rescue teams via the available wireless ad-hoc network, along with the vehicle identification number and real-time location coordinates of the driver.

III. PROPOSED WORK

The block diagram of the proposed system is shown in Figure 1. It shows the complete end-to-end workflow of the system.

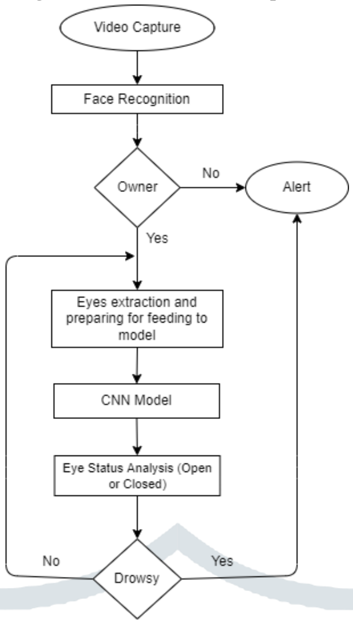

Figure 1. Block Diagram of Proposed system

It starts with live video capture and constantly detects the faces. When a face is recognized as an unauthorized user, it starts playing an alarm sound to alert the owner. When a face is recognized as an authorized user (owner), it grants the access to vehicle and starts detecting features (i.e., eyes). It extracts eye images from frames and fed to the CNN model (i.e., MobileNet with adam optimizer) which predicts whether they are close or open. If the eyes are predicted to be closed for a certain threshold, it alerts the driver using an alarm sound.

A. Face Recognition Model

The face recognition library is based on dlib's state-of-the-art deep learning-based face recognition. Dlib is a C++ toolkit that includes, but is not limited to, machine learning algorithms and tools for creating complex programs that deal with real-world scenarios. When evaluated on the public benchmark Labeled Faces in the Wild [14], the face recognition module obtained 99.38 percent accuracy. The face recognition model can discover faces in a photograph, identify a face, find the facial features of a face in a picture, and manipulate the facial features, among other things. However, only two of these functionalities are used in this paper: locating and recognizing faces.

B. Drowsiness Detection Model

The drowsiness detection model in this paper makes use of a model trained using MobileNet and Adam optimizer which achieved a training accuracy of 99.52 and validation accuracy of 99.23. The model building involves several processes which are discussed below.

Data Acquisition

This paper uses MRL Eye Dataset [15]. This is a large-scale dataset of around 84 thousand human eye images of 37 different people captured in various driving conditions using three different sensors.

Data Pre-Processing

The dataset contains 37 folders containing eye images of 37 different people. Now we create two different folders and separate all the eye images into two folders namely open and closed. Since the pre-trained models like DenseNet, VGG16 and ResNet50 require input image of dimensions 224 x 224 x 3, we up sample every image in the dataset. Then we create features and labels for training the model.

Model Designing and Training

The pre-trained models like MobileNet, DenseNet, VGG16 and ResNet50 are used for ImageNet dataset which classifies 1000 different classes. In our paper, we have only two classes (i.e., open and closed).

So, we use the technique of Transfer learning for using the pre-trained models so as to work for our dataset. We modify final layers of models so that the model can classify two different classes.

Then we fit our data to the model after Transfer learning so that the model can learn and adapt to our dataset. These models will be trained for several epochs until the loss is converged to certain reasonable extent.

Drowsiness Detection

Firstly, the video capture is taken from a camera using OpenCV library. On every video frame, facial detection and eye detection is done using Haar-Cascade Classifier. Next, isolating the left and right eye from the face and up sample it to 224 x 224 x 3 to feed it to the trained model. For each eye image in frame, the predicted eye state is analyzed and if the eyes are predicted to be closed for a certain period it will alert the driver using an alarm sound.

IV. IMPLEMENTATION

The paper has multiple phases in its design. The first phase involves Vehicle security system. For this, face_recognition library in python is used to detect and identify the users and alert if any unauthorized user tries to access the vehicle.

The second phase is Drowsiness Detection system. This requires selecting a dataset and pre-processing it as per our architectural requirements. The data was collected form MRL Eye Dataset which has 84,898 eye images of 37 different people (3 men and 4 women). Then we created a dataset from the original dataset by manually segregating open and closed eye images to two different folders.

The preprocessing was done according to the models being built. DenseNet, VGG16, ResNet50 require input images of size 224 x 224 x 3. MobileNet takes any image of dimensions above 32 x 32 x 3. So, as a standard case we considered 224 x 224x 3 and up sampled all the images to these dimensions.

Since the dataset consisted of 84900+ images and training the model every time on all these 84K images to decide the values of some parameters and hyperparameters will be expensive both in terms of computational power time, we created a mini dataset consisting of around 3898 images by picking around 100 images randomly from the 37 different persons' eye images and trained the model on this mini dataset.

Transfer learning was used in this system which means that we modify last few layers of existing pre-trained models so that the model will be able to classify the input data into required number of tensors. We also set some parameters in the initial layers of the architectures in order to prevent over-fitting.

We train the models by using various optimizers for each pre-trained model. While training we also calculate the validation loss on validation dataset and save the model only if it is less than the minimum validation loss and has good accuracy for both training set and validation set in order to avoid over-fitting or under-fitting. After this we consider the best model and use it for the drowsiness detection system.

The binary cross entropy loss function was used to calculate the error of the model and based on this we analysed the performance of the model using accuracy metrics on the training or validations sets. Higher accuracy indicates a better performance of the model.

This system constantly monitors the face of driver and extracts eye images from the frames of video capture, up-sample them to 224x224x3 and then feed them to the model. CNN model analyses the eye status and predicts whether they are closed or open. If the eyes are closed for more than a threshold value, an alarm is generated using winsound library in python.

V. RESULTS

A detailed comparative study has been performed for the drowsiness detection using four pre-trained models namely MobileNet, DenseNet, VGG16, ResNet50 with various optimizers (Adam, SGD, RMSProp, AdaGrad and Adadelta) used for each of the algorithm. The accuracies of every model are listed in below tables and graphs.

The best performance was shown by model built using MobileNet and Adam optimizer with a training accuracy of 99.52% and validation accuracy of 99.23%.

	optimizer	loss_function	accuraccy	val_accuracy	loss	val_loss
0	adam	binary_crossentropy	99.52	99.23	1.03	6.52
1	adam	hinge	98.40	98.46	51.75	50.01
2	sgd	binary_crossentropy	99.60	98.46	2.06	8.76
3	sgd	hinge	99.06	96.92	52.20	50.26
4	rmsprop	binary_crossentropy	99.12	97.95	2.62	4.88
5	adagrad	binary_crossentropy	99.14	97.44	3.60	6.06
6	adadelta	binary_crossentropy	93.24	91.03	23.00	24.57

Figure 2. MobileNet models comparison

Figure 2 shows the accuracies and losses of all the Mobilenet models built using various optimizers.

	optimizer	loss_function	accuraccy	val_accuracy	loss	val_loss
0	adam	binary_crossentropy	99.23	98.21	2.56	6.55
1	adam	hinge	98.18	52.56	51.85	96.91
2	sgd	binary_crossentropy	99.74	97.95	0.90	7.20
3	rmsprop	binary_crossentropy	98.86	98.97	3.44	7.96
4	adagrad	binary_crossentropy	99.83	98.97	1.43	2.81
5	adadelta	binary_crossentropy	94.64	93.08	18.58	20.44

Figure 3. DenseNet models comparison

Figure 3 shows the accuracies and losses of all the Densenet models built using various optimizers.

	optimizer	loss_function	accuraccy	val_accuracy	loss	val_loss
0	adam	binary_crossentropy	95.81	94.87	12.81	11.76
1	sgd	binary_crossentropy	94.30	94.36	15.61	14.16
2	rmsprop	binary_crossentropy	49.14	51.79	69.33	69.31
3	adagrad	binary_crossentropy	94.04	95.90	16.01	12.39
4	adadelta	binary_crossentropy	79.96	88.97	55.73	54.67

Figure 4. VGG16 models comparison

Figure 4 shows the accuracies and losses of all the VGG16 models built using various optimizers.

	optimizer	loss_function	accuraccy	val_accuracy	loss	val_loss
0	adam	binary_crossentropy	99.20	47.69	2.67	682.81
1	sgd	binary_crossentropy	99.46	47.69	2.28	115.37
2	rmsprop	binary_crossentropy	85.12	52.31	36.75	2035.53
3	adagrad	binary_crossentropy	98.49	96.62	4.83	12.70
4	adadelta	binary_crossentropy	95.81	80.51	12.31	45.11

Figure 5. ResNet50 models comparison

Figure 5 shows the accuracies and losses of all the ResNet50 models built using various optimizers.

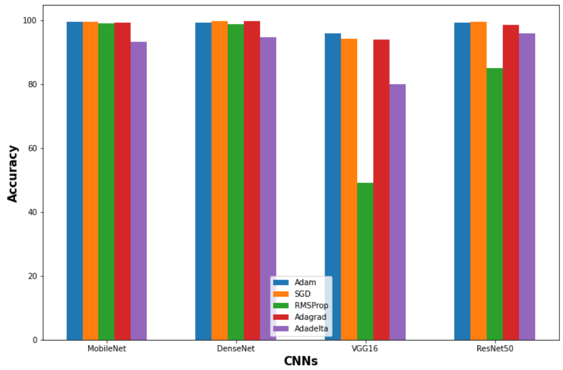

Figure 6. CNNs vs. Accuracy

Figure 6 shows the bar graph comparing the optimizers in each model against accuracy.

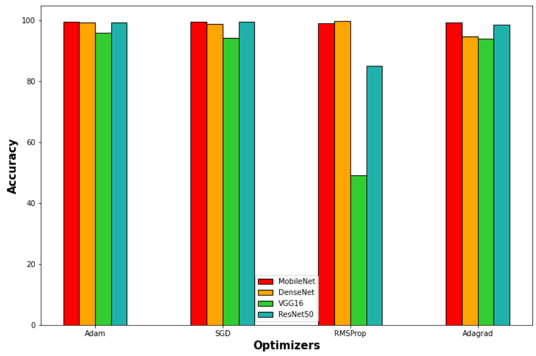

Figure 7. Optimizers vs. Accuracy

Figure 7 shows the bar graph comparing the models among the Optimizers against accuracy.

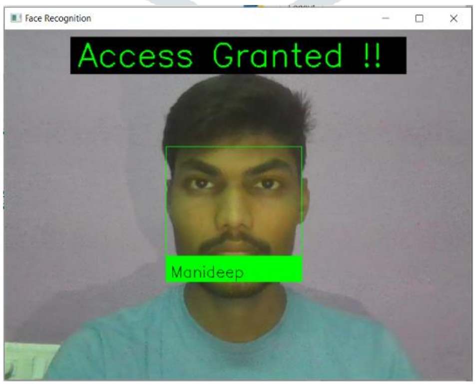

Figure 8. Granting access to authorized users

Figure 8 shows the system granting access to authorized users.

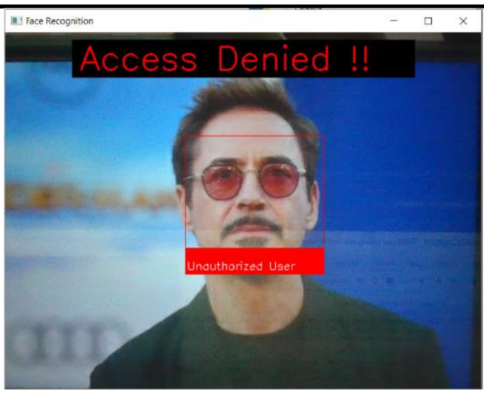

Figure 9. Denying access to unauthorized users

Figure 9 shows the system denying access to unauthorized users.

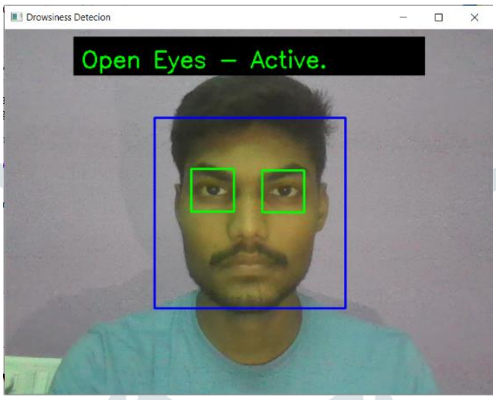

Figure 10. Active Eye status

Figure 10 shows the system detecting eyes and classifying it as active.

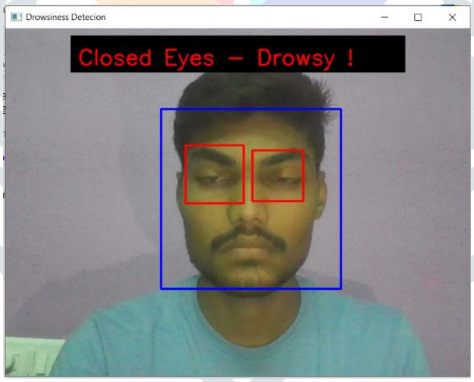

Figure 11. Drowsy Eye status

Figure 11 shows the system detecting eyes and classifying it as drowsy.

VI. CONCLUSION

In this paper, a vehicle security system is built using face recognition library in python. It identifies the faces of users and gives access of vehicle to authorized users only and alert if any unauthorized user tries to access the vehicle. We discussed the existing solutions on drowsiness detection. Many successful models with good accuracy have been made but there is still chance for improvement. This paper gives a detailed comparative study of performance of different algorithms with various optimizers and produced a drowsiness detection system using the best performing model (i.e., MobileNet with Adam optimizer) with a training accuracy of 99.52% and validation accuracy of 99.23%. This system analyzes driver's eyes for detection of drowsiness by extracting eyes from each frame using Haar Cascade classifier and then feeding it to the CNN model to predict eye state as open or close. Finally, after analyzing the eye images, it alerts the driver if the eyes are closed for a certain threshold value.

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