Reduction of Car Crashes by Identifying The Driver's Drowsiness and Emotions using Multilayer CNN

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***Abstract*—Car crashes has accounted to a lot of deaths in the recent time stating the aggressive development in the car industry. Most of the accidents has been related to human negligence such as inattentiveness to the driving methods, drowsiness while driving and different behaviour related emotions. In this research project, a novel approach is designed to detect the driver's drowsiness and different emotions such as anger, sadness and excitement using advanced deep learning techniques. Convoluted neural networks has been devised in this approach to extract the information of driver's facial reaction from the live feed video. Different factors are established in this approach such as drowsiness, anger, sadness and excitement which are derived from the live video feed and then are injected to the pre-trained CNN model to determine the level of intensity of each factor. Model's output is being used to trigger an alarm system which in turn alerts the driver if the values of different factors crosses the threshold level. Based on various evaluation parameters used for assessing the model's efficiency, the model is able to outperform other models with an accuracy of 86.98%in detecting the drowsiness and different emotion pattern of the driver from the live feed. The project aims to reduce the car crash accidents by alerting the driver in case of the abnormality seen during the entire journey which in turn reduces the death rate due to the accidents.**

I. INTRODUCTION

Fatalities due to car accidents has been in a steady increase due to the increased number of car sales and negligence driving. Reports from association for safe international road travel states that approximately 1.35 million people have faced death due to car accidents with a daily number of 3700. Though accidents happen due to unforeseen circumstances such as vehicle malfunction and natural scenarios, negligence driving contributes to a maximum amount of deaths considering the whole number. The car crashes not only endanger the lives of the people in the car but also the pedestrians walking on the road too. Approximately 3% of the GDP is spent for attending and resolving the damage occurred due to the accidents happening around the world as stated by world health organisation. The important contribution of human negligence is due to the driver's drowsiness and fatigue. 60% of the drivers interviewed by national survey committee has accepted that they have felt sleepiness while driving. 73.5% of the deaths recorded due to car crashes has drowsiness as the main reason for the accident. Even though the drivers accept that they felt sleepiness during driving, there is no way to detect and identify the drowsiness factor and also no standardised system and rules to alert the drivers. This project aims to create an innovative way of identifying the driver's drowsiness and alerting them using deep learning techniques. Deep learning techniques has been constantly evolving with new techniques for prediction and classification. With the advanced usage of artificial neural network, the model's ability to predict and classify has been more accurate and has the ability to handle a lot of data. Classification of the pictorial images is performed by the convoluted neural network which work similar to the artificial neural networks. The drowsiness factor of the drivers can be identified by extracting the facial expressions through a video feed which monitors the driver's facial expression and implying it to the Convoluted neural network to identify the state of the driver. The CNN uses the pre-trained model which is trained using huge number of sample data to identify if the driver's drowsiness based on the facial expression feed of the driver. The model could then be integrated with the display or car's alarm system to raise alarm. This approach could help the drivers stop driving in case of the alarm which could in-turn reduce the accidents.

Due to the advancement in the car technology, many innovative systems have been installed to detect the driver's characteristics. Most of the systems are inbuilt and comes as part of manufacturing process which it expensive and difficult for the average people to buy. This proposed approach is a standalone model which could be installed in low level cars as well as high level cars. Usage of cloud technology to run the algorithm and connecting the device from the car to the cloud makes it a viable motion for large amount of people to opt for it. An innovative approach towards detecting the driver's emotion could also strengthen the model and additional factors for prediction could increase the efficiency of the model. Emotions of the drivers while driving the car plays a major role in how the car is driven on the roads. Different emotions among the drivers can significantly decrease the driver's attentiveness towards the road symbols and can increase the accidents rate. A report from EHS today has stated that about 90 percent of the car crashes happening due to human negligence could be traced back to anger and sad emotions of the driver's behind the wheel. Considering the most probable emotions such as anger, sad and excitement as input factors for the deep learning technique could increase the effectiveness of the model in predicting the car crashes. Emotion detection has been a highly researched topic using deep learning techniques which in turn uses the human's facial changes to identify the kind of emotion displayed from the user. The point techniques use the identification of human's nose, eyes, mouth and other factors and the changes in the relative positioning of these marks determines the emotion of the user. This is parallelly used with the drowsiness detection model to detect the emotions which could cause car crashes and alert the driver. There are some exceptions made to the model to identify regular blinking and emotions with less magnitude which improves the precision of the model in identifying and alerting the drivers. The project's main purpose would be to avert the car crashes by alerting the driver in case of the drowsiness and different high-level emotions. The literature review has been performed in the next section to identify the existing models in the research area and to critically analyse the work. The methodology section explains the deep learning techniques used for classifying the images and the entire implementation working of the model. The evaluation section describes about the parameters against which the model is evaluated and verified for the different metrics.

II. Literature Review

The literature reviewed for this project has variety of features extracted in order to detect the drowsiness and emotions of the driver by using few sets of techniques mostly classification and regression techniques.

A. Feature Selection

[1] had focused on the research of detecting drowsiness of the driver based on the feature selection of eye area. The factors selected were the shape and texture of driver's eyes. It was concluded that only selecting eyes are insufficient for detecting driver's drowsiness and wearing sunglasses also reduces the accuracy of the detection. [2] have also chosen the entire face as the feature for the research. facial landmarks has been used as input features and the analysis has been done on the facial landmark coordination. While using facial expressions for feature extraction has given acceptable improvements in the results of this research, it is expressed that analysing head movements can give more improvement in the research.

Studies performed by [3]involves extracting the facial landmarks in terms of driving mode, yawning, slow blink rate, conscious laughter and dizzy dozing to detect the drowsiness. This study concluded with 81% of accuracy and stated that wearing sunglasses has reduced the accuracy of the model in few cases. In an different approach, it is also seen that [4] have combined face and eyes for feature extraction. Along with facial expressions, the eyes blinking pattern is also analysed to detect the drowsiness of the driver. Though this research has achieved a good performance, it was observed that the occultation cases have affected the detection of eyelids and iris. such cases would require an additional feature like yawning. Research done by [5] considers only the eyes as feature for the model which was not considered satisfactory. Good quality of work has been done in detection of drowsiness with the help of eye blinking pattern and frequency including a detailed study of using a good resolution of image detection techniques. The eye blinking pattern gave 94% of accuracy in detecting drowsiness but accuracy rate was still affected with the use of glasses.

Research conducted by [6] is based on identifying the yawning of the vehicle driver to detecting the drowsiness factor. In this research the degree of expansion of the mouth is calculated to detect the yawn. As this system only detects the yawning of the driver, this makes it less reliable as yawning cannot confirm a person's drowsiness factor.. This research is an attempt of researcher [7] to provide a low-cost driver detection system based on Machine learning classifiers. This system provides an analysis based on facial landmarks such as eye aspect ratio, mouth opening ratio and nose length ratio with the help of techniques such as Bayesian,Support Vector Machine (SVM) and Fisher's linear discriminant analysis (FLDA) classifiers concluding that system provides an acceptable accuracy along with impressive sensitivity and specificity for SVM and FLDA. As this system is an offline system, it needs to be upgraded for practical application.

On contrary, an advanced drowsiness detection system by [8] is considered with detailed features such as mouth opening ratio (MOR), nose length ratio (NLR) and eye aspect ratio (EAR). Another combination of features used here [9] in the research includes face detection and landmark detection techniques and then this features are given as input to three CNN model to detect drowsiness based on face, eye and mouth state. The model initially extracts facial region from the image and then it extracts landmarks like face, eye and mouth using ladmark detection technique. These extracted landmarks are given as input to subsequent CNN model to detect drowsiness of drivers. Drivers drovsiness state is decided based on combined results of all the three models.In both studies, the researcher concluded that the performance of the model was satisfactory, and it can be used in practical.

A unique study by [10] is performed on the drowsiness of the driver which includes the features based on behaviour of the driver while being drowsy. The study has used the hybrid of physiological, behavioural, and subjective measures to study deeply about actual situations of the driver in drowsiness to give a more reliable solution.

A good attempt of presenting a drowsiness detection model by [11] uses the features which has proven to be effective such as facial expressions and head movements. All possibilities and practical situations are considered in the research whereas all the factors considered are on the final stage of drowsiness and not for the beginning or the middle stage.

B. Techniques Used

Not only using relevant feature selection but using relevant features with accurately performing techniques are proven to give best results in researches.
Some of the widely chosen techniques for this application is convolutional neural network. [12] has used CNN to detect the drowsiness of the driver from the data collected from EOG (Electrooculography).In this research to detect the drowsiness of the driver Electrooculography which was called as EOG is used . In this approach data was extracted using electrodes and the signals are filtered and data has been prepared. This dataset has been used to train the CNN model with 2 convolution layer and 1 fully connected layer . This methods didn't use any activation layer to reduce the outliers and the model was trained with only two feature characteristics eyes open and closed beacuase of this very low accuracy has been achived. Therefore, if the model has been trained with all the facial features then the accuracy would have been increased and better output classification would have been attained. It was concluded that analysing the samples of the collected data using deep learning methodology such as CNN improves the stability of the model.
Convolutional neural networks perform better than the other techniques are validated and identified by [13] based on a comparative study. Performance of Support vector machine and hidden markov model is compared with the performance of convolutional neural networks to detect the drowsiness where CNN showed the highest accuracy.
An application of early detection of drowsiness is performed by [14] using Logistic regression, support vector machine, random forest and KNN classification to compare and identify the better performing model. [14] concludes that Random forest technique resulted into the better performing model, a superior technique shall be used in future work to improve the performance. The research by [15] is performed using the support vector machine technique to detect the drowsiness of the driver has shown a 100% accuracy in giving out the results of detection. It might be observed as overfitting of the model and model may not be flexible for practical use. [15] has concluded that the future work should try reducing the accuracy of the model to make the model flexible for pragmatic purposes.Convolutional neural network is used by [16] to implement a model which can access the fitness of the driver to drive the vehicle based on the detected features. This implicates that the initial as well as high level of drowsiness was detected with this model by 85% of accuracy which is ideal in terms of flexibility.
Another driver drowsiness detection model by [17] , which is based on artificial intelligence has used both convolutional neural networks and support vector machine techniques to identify the drowsiness factor. Convolutional neural network has been used for pre-processing of the images whereas SVM has been used to classify and analyse the state of the eyes. The model resulted with accuracy of more than 90%.Support vector machine classifier is used by [18] to achieve a good level of accuracy, but it has considered eyelids movement as the only feature for analysis. This research is concluded to be considered for improvement with respect to practical use. deep neural networks are also used with embedded system to detect the drowsiness by [19] where he has proposed a new model which could be more reliable compared to other algorithms. The accuracy was observed to be greater than 90%.
Two layered artificial neural networks are used by [20] to detect the drowsiness via image processing. Applying the layers of hidden layer network and autoencoder network has shown better results in classification with 100% accuracy rate.Comparison of the performance by different classifiers like Bayesian classifier, FLDA and SVM is studied by the researcher with respect to detection of drowsiness of driver where it is found that FLDA and SVM give better performance. It is observed that SVM is widely chosen and performs well within smaller bucket, but Deep neural networks techniques are taken in consideration by researchers for advance and better performing model improvements.

III. Methodology

Data Mining is used to get useful insights from the data. Using this process, deriving a solution from the complex data patterns is easy and the same can be used to extract information from the data. widely used methodologies in data mining process are the Knowledge discovery in database (KDD) and Cross-Industry Standard Process (CRISP). due to the easy implementation and robust nature, KDD methodology is used to process the facial analysis image data.

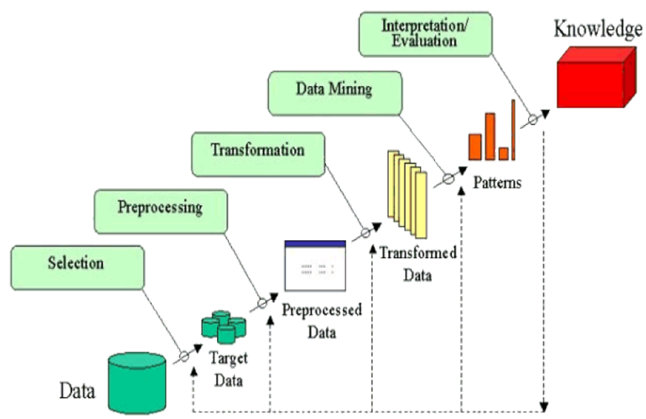

Fig. 1. KDD Process Flow

A. Data Selection

In this study obtaining the driver facial emotion and drowsiness detection is the key focus. Due to the scarcity of publicly available dataset on facial expression of drivers the dataset was generated by our own facial images and is used to build the model. Computer vision was used to capture the various facial characteristics and 6 videos was captured with 4 subjects. The videos clips are recoded in 640 * 480 pixels without audio and it was converted to 30 frames per second. each video consists of different scenarios and behavioural characteristics similar to the driver and also mix match of both the gender. The video consists of both the emotions and drowsiness features which are recorded by different physical attributes and also in depth to each frame level. the reason behind this is when it gets converted and used for analysis ,the accuracy of training the data will be high. Physical drowsiness attributes like eyes blink, yawing, eyes closing is picked and recorded. For emotion detection, factors like excitement, sad and angry were created captured in the video. Using these 4 different subjects 2 subjects will be used to train the CNN model and remaining subjects will be used to test the model. After recording, the videos are processed and converted to images. The images are taken in a time interval of 30 seconds per frame and are manually labelled based on their characteristics. Therefore, at the end of the data selection process the total number of data was 24,000 including emotions and drowsiness features for both the genders. figure 2 shows the sample dataset.

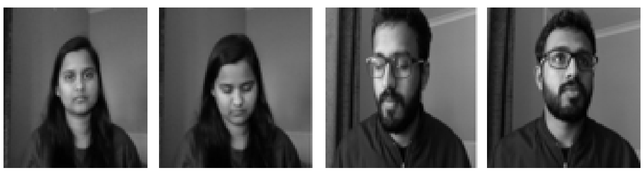

Fig. 2. Facial Analysis Dataset

B. Data Pre-processing and Transformation

In this step the videos recorded for the data creation purposes has been converted to images using OpenCV library in python. Every video was converted to 30 seconds per frame and in total 24,000 images were produced with different physical attributes. Facial landmarks from OpenCV library were used to extract the feature from the images. Features like Eyes, Mouth, pupil and facial expression were captured from the Landmarks. There are totally 68 facial landmarks in each frame but only the key feature was extracted in each frame based on the facial drowsiness and emotion detection. After the feature extraction, image resolution has been degraded to 24 * 24 resolution so that all the image will have the uniform resolution. Rescaling part is done by downgrading each pixel in all the image by dividing each pixel by 255 So that each pixel range is between 0 and 255. After the rescaling step, data has been transformed to grayscale colour and it has the pixel value between 0 and 255. Data augmentation steps have been applied in order to avoid the overfitting of the model. All the data transformation part is done using a function which was written in python as a part of automating the flow.

C. Data Modelling

1) Proposed Approach

In this research multilayer convolution neural network is used to classify the image based on the facial expression of the driver. CNN is mainly used to find the complex pattern in the image data it will assign weights to every image and then it will use the weights to differentiate the image. These weights are connected to the neurons which will perform the operation based on the input weights value. There is more than one hidden layer used to process the image and activation function is used to reduce the size of the image. In this process backward propagation has been used to change the value in the weight based on the loss value. This model was iterated till the local maxima is reached and the loss value is minimum. The model architecture used in this project has 3 convolution layer and 3 pooling layer and 2 fully connected layer

2) Model Architecture

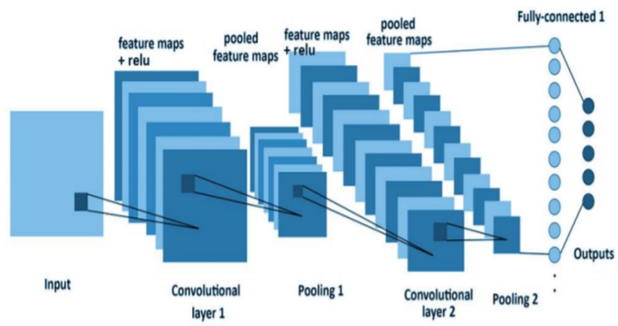

Fig. 3. Model Architecture

- **Convolutional Layer**
  In this layer the input feature which were extracted is passed as an input to the convolution layer , In this process 2D image has been used as an input and converted to a grey scale image .This image is passed to the hidden layer 1 which has 32 neurons with kernel size 3. The convolution neural network will perform weights operation based on filter and the feature maps has been sent to activation layer Rectified Linear Unit(ReLU) .In the activation layer the ReLu will activate the neuron based on the certain quantity. If the pixel value is less than 0 then the node won't get active and it will activate the node if the value is positive, it means that node is contributing to identify the dependent variable. There are also few activation functions like SIGMOID and TANH when compared between these ReLU function performed better in predicting the output. Below is the model layers and node size.
  - Convolutional layer; 32 nodes, kernel size 3
  - Convolutional layer; 32 nodes, kernel size 3
  - Convolutional layer; 64 nodes, kernel size 3
  - Fully connected layer; 128 nodes
  - Fully connected layer; 4 nodes

- **Pooling Layer**
  After the activation function, the pooling layer is used to

minimize the image size by taking only the highest pixel value from the image. The reason to shrink the image is to reduce the complexity of the layer. In this layer to reduce the weights and identifying the maximum pixel each and every piece of image will be scanned to produce a highest pixel weighted image. There are many types of pooling layer and in this project max pooling was used it has the important feature of avoiding over fitting of the model.

- **Dropout**
  This function was used to deactivate the neurons while training the model. Main advantage of this function is it reduces the overfitting of the data by allowing only few features to train and predict the weight after completion the other neurons will get activated and their weights will be predicted. Therefore, this on and off method can be used to increase the model training capacity and reduce the gradient problem. In this project 0.5 is used as a dropout rate.
- **Fully Connected Layer**
  The shrink image from the pooling layer which has the high pixel value of the image will be transformed to a single list or vector and then the classification will be done based the highest weight value in the stacked-up list. This List will be compared with the input image and then the classification of the object will be happening. Since this is a classification problem SOFTMAX has been used has an activation layer in the output layer.

IV. Implementation

In this section our approach to detect the driver's drowsiness and emotion will be explained by the below step by step process. there are totally 5 steps involved in this process. figure 4 shows the proposed implementation flow.

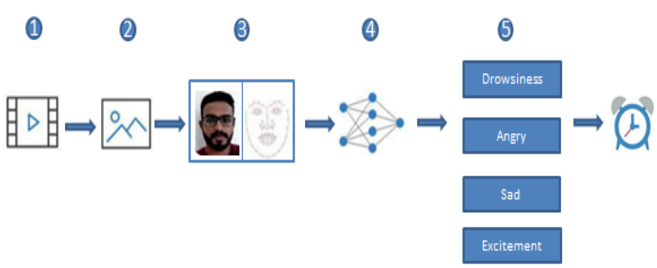

Fig. 4. Implementation

1) **Taking images from the video**
   In the first step video is recorded using the webcam and it was accessed by OpenCV library in python. To capture each frame the webcam was processed to multiple loops, and to record and capture cv2.VideoCapture (0) function is used from OpenCV library. Once the video has been recorded it is converted to images at the rate of 30 seconds per frame using cap.read() function.

2) **Detecting the face from the image**
   After converting the videos to images the image dataset has been classified based on the physical attributes. Then the feature extraction process to extract or detect the facial expressions in the image was done using Region of interest (ROI). ROI will take the input image as grey scale and the image has been transformed to grayscale and feature extraction part has been carried out.

3) **Processing the image to feed to CNN model**
   Before training the model, the images has to be in correct dimension and the size of the pixel has to be equal for all the images. Therefore, all the grayscale image data has been resized to 24 *24 pixel and then to normalize the data the pixel vale has been divided by 255.By doing these things over fitting of the model has been reduced. After this process the images will be splitted to training and testing dataset.

4) **Training the model**
   Features which were extracted from the image were given as an input to train the model. Multilayer CNN is used to build the model which has 3 convolution layer and 4 fully connected layer. For the input layer ReLU activation function is used and at the output layer softmax is used. Therefore, the input will pass through all these layers and weights are assigned in each layer. To avoid the overfitting of the data, dropout technique is used. Training of the data will be performed till the loss rate values is low and until that back propagation will happen and the new weights will be obtained based on the learning rate. In this project Adam is used as an optimizer to reduce the loss value if the prediction goes wrong. After the model was trained it was tested against the test data and the model is saved in a file for its flexibility.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 22, 22, 32)	320
max_pooling2d_1 (MaxPooling2	(None, 22, 22, 32)	0
conv2d_2 (Conv2D)	(None, 20, 20, 32)	9248
max_pooling2d_2 (MaxPooling2	(None, 20, 20, 32)	0
conv2d_3 (Conv2D)	(None, 18, 18, 64)	18496
max_pooling2d_3 (MaxPooling2	(None, 18, 18, 64)	0
dropout_1 (Dropout)	(None, 18, 18, 64)	0
flatten_1 (Flatten)	(None, 20736)	0
dense_1 (Dense)	(None, 128)	2654336
dropout_2 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 4)	516

Total params: 2,682,916
Trainable params: 2,682,916
Non-trainable params: 0

Fig. 5. CNN Parameters

5) **Model Extraction**
   Finally, the model was trained and it is saved as a

file so that the model can have flexibility in using even in a mobile application. This trained model will classify whether the driver is in drowsiness, angry, sad or excitement based on the facial landmarks. As a part of novelty this research also had a real time score calculation for the drivers based on the above facial attributes. A threshold value has been set and if the driver is drowsy or if the driver is very angry, sad or excitement alarm will be triggered as a preventive measure.

V. Evaluation

This section will briefly evaluate the developed model based on following techniques. Scikit learn python library is used in all of the methods to get required results.

A. Accuracy

Accuracy represents the percentage of accurately classifying given input image into one of the two given classes i.e. driver's eyes are open or driver's eyes are closed. It is a ratio of total number of correctly classified samples and total number of samples. The model is validated against test data which consists of 2645 sample images and it has correctly classified 2300 samples. So, the accuracy of the model is 86.98%. Figure 6 represents accuracy vs epoch graph for training and testing data. The proposed model is learning in each epoch and getting better. The val_accuracy and accuracy are getting better after 8th epochs and best accuracy was found in 9th epochs.

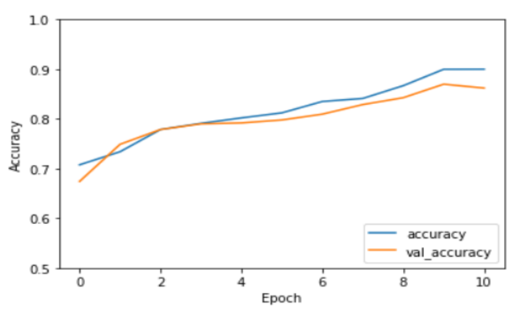

Fig. 6. Accuracy vs Epoch Graph

B. Confusion Matrix

This method will create a matrix for all the input samples based on prediction types. True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) are the types of predictions used in confusion matrix. TP is correctly predicting driver's eye is closed. TN is for driver's eye is open while it is actually open. FN represents number of outcomes in which driver's eye is open but model predicts it as closed. TN consists of outcome in which driver's eye was closed but model predicts driver's eyes are opened. Following figure demonstrates confusion matrix for proposed model.

```
array([[11558, 1622],
       [1810, 8910]])
```

Fig. 7. Confusion Matrix

Correct prediction of positive cases among all positive samples is 0.8646 and this is called as Recall. The precision 0.8769 represents 20468 actual positive cases among all the positive cases in validation set.

$$Recall = \frac{TP}{TP+FN} \quad Precision = \frac{TP}{TP+FP}$$

C. F1 Score

It is calculated as 2*((precision*recall)/(precision + recall)). F1 score represents the relation between precision and recall. F1 score value lies between 0 & 1 whereas 1 represents best model and 0 represents worst model. The F1 score for proposed model is 0.8706 which represents a better model as it is tending towards 1. The calculated F1 score value also represents higher balance between precision and recall. The balanced model always gives better result as compare to unbalanced model.

D. Cohen's Kappa Coefficient

Kappa coefficient is inter-rater relation between categorical variables. It is more robust, as it is considering possibilities of outcomes occurred by chance. Following formulae is used to calculate kappa coefficient. P_0 is the observed outcome same as accuracy and Pe is hypothetical probability of getting desired outcome. Kappa coefficient for proposed model is 0.8811. This represents close relation between categorical variables. The kappa coefficient value demonstrates the reliability of proposed model to get desired output so, based on the acquired kappa coefficient value we can conclude that the proposed model is reliable to detect drowsiness among drivers.

$$k = \frac{p_o - p_e}{1 - p_e}$$

VI. Results

The model is tested in real driving scenarios using computer vision. OpenCV library of python is used to capture real-time videos. This captured video is then converted into multiple frames of required pixel which is then given as input to the model. For more safety of drivers proposed model is integrated with alarm system and this alarm gets triggered whenever driver's facial expressions or closed eyes are for long period of time. Score of 15 or more triggers alarm to notify and alert the driver. A real-time driving scenario in daylight and night time is tested using this system. Following figure represents outcome of the tested scenarios.

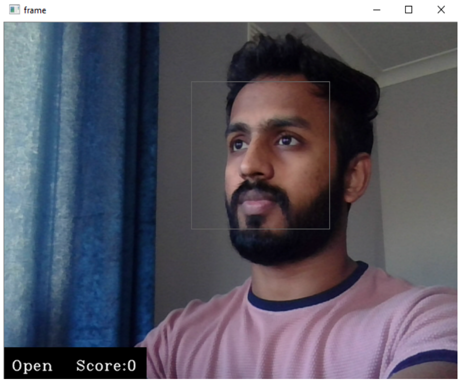

Fig. 8. Open Eye scenario

In figure 8 user is driving properly without drowsiness so score is 0.

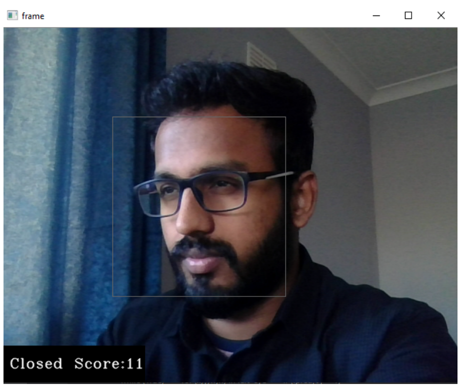

Fig. 9. Closed Eye Scenario - Moderate

Driver in figure 9 is moderately drowsy with score of 11.

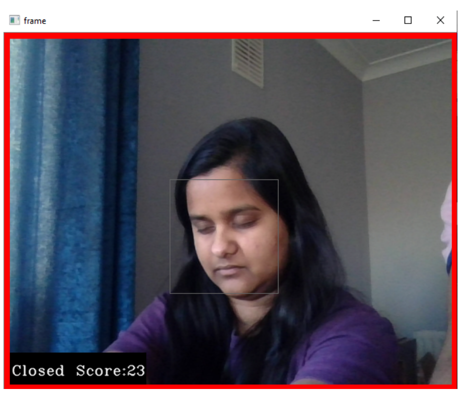

Fig. 10. Closed Eye Scenario

In figure 10 driver is drowsy so score is 22 and red outline is highlighted as score is in critical range. Also, alarm is triggered to alert the driver.

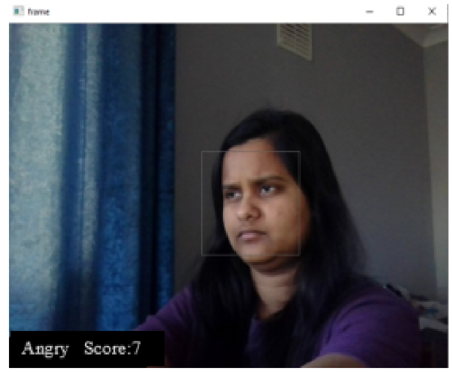

Fig. 11. Angry Emotion Scenario - Moderate

Figure 11 represents driver driving with slight angriness and score is 7.

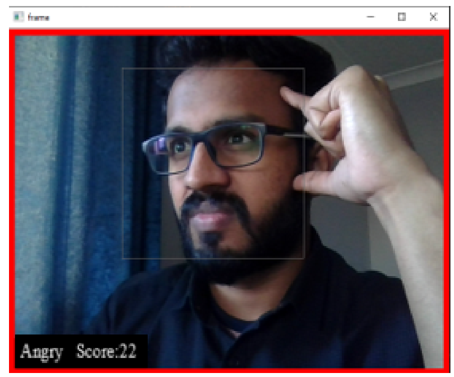

Fig. 12. Angry Emotion Scenario

Figure 12, represents the driver driving in an angry situation. The score is 22 and as it has crossed threshold value red outline is highlighted and an alarm is triggered to alert the driver. According to the results of evaluation methods lighting condition and eye condition plays a vital role in accuracy of this model. Also, Model was less accurate while classifying scenarios in which driver is wearing sunglasses because driver's eye condition was not clearly visible. Moreover, luminosity also affected accuracy of model which subsequently increased error rate by 4%. The model has provided best accuracy of 86.98% and consumes less storage which makes proposed model easily integrable using embedded systems to detect facial emotions and drowsiness.

VII. Conclusion

Detecting and alarming the drivers has been the primary objective of this project as there are no standardised systems to detect and alarm the drivers. The difficulty in obtaining the dataset to train the data is overcome by an innovative approach which lead to creation of a huge dataset. Usage of neural networks has not only increased the efficiency of the model to an accuracy rate of 86.98% but allows flexibility and re-usability of the code. classification and identification of the image recorded from the live feed of the drivers has been used to identify the drowsiness and different emotions related which are seen as a causal factor for majority of the car accidents. The future work of this project would be to make this model a standalone program so that it could be easily be installed in all types of cars. This model could be improvised with additional factors such as monitoring the road lines and integrating the drivers vital signs to accurately predict the driver's behaviour while driving which could further lead to decrease in the accident rates.

REFERENCES

[1] J. Jo, S. J. Lee, K. R. Park, I.-J. Kim, and J. Kim, "Detecting driver drowsiness using feature-level fusion and user-specific classification," *Expert Systems with Applications*, vol. 41, no. 4, pp. 1139–1152, 2014.

[2] K. Dwivedi, K. Biswaranjan, and A. Sethi, "Drowsy driver detection using representation learning," in *2014 IEEE international advance computing conference (IACC)*. IEEE, 2014, pp. 995–999.

[3] R. Jabbar, K. Al-Khalifa, M. Kharbeche, W. Alhajyaseen, M. Jafari, and S. Jiang, "Real-time driver drowsiness detection for android application using deep neural networks techniques," *Procedia computer science*, vol. 130, pp. 400–407, 2018.

[4] W. Mahdi, B. Akrout, R. Alroobaea, and A. Alsufyani, "Automated drowsiness detection through facial features analysis," *Computación y Sistemas*, vol. 23, no. 2, pp. 511–522, 2019.

[5] T. Danisman, I. M. Bilasco, C. Djeraba, and N. Ihaddadene, "Drowsy driver detection system using eye blink patterns," in *2010 International Conference on Machine and Web Intelligence*. IEEE, 2010, pp. 230–233.

[6] T. Wang and P. Shi, "Yawning detection for determining driver drowsiness," in *Proceedings of 2005 IEEE International Workshop on VLSI Design and Video Technology, 2005.* IEEE, 2005, pp. 373–376.

[7] A. Kumar and R. Patra, "Driver drowsiness monitoring system using visual behaviour and machine learning," in *2018 IEEE Symposium on Computer Applications & Industrial Electronics (ISCAIE)*. IEEE, 2018, pp. 339–344.

[8] S. Mehta, P. Mishra, A. J. Bhatt, and P. Agarwal, "Ad3s: Advanced driver drowsiness detection system using machine learning," in *2019 Fifth International Conference on Image Information Processing (ICIIP)*. IEEE, 2019, pp. 108–113.

[9] C. Yu, X. Qin, Y. Chen, J. Wang, and C. Fan, "Drowsydet: A mobile application for real-time driver drowsiness detection," in *2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*. IEEE, 2019, pp. 425–432.

[10] A. Sahayadhas, K. Sundaraj, and M. Murugappan, "Detecting driver drowsiness based on sensors: a review," *Sensors*, vol. 12, no. 12, pp. 16 937–16 953, 2012.

[11] E. Vural, M. Cetin, A. Ercil, G. Littlewort, M. Bartlett, and J. Movellan, "Drowsy driver detection through facial movement analysis," in *International Workshop on Human-Computer Interaction*. Springer, 2007, pp. 6–18.

[12] X. Zhu, W.-L. Zheng, B.-L. Lu, X. Chen, S. Chen, and C. Wang, "Eog-based drowsiness detection using convolutional neural networks," in *2014 International Joint Conference on Neural Networks (IJCNN)*. IEEE, 2014, pp. 128–134.

[13] M. Ngxande, J.-R. Tapamo, and M. Burke, "Driver drowsiness detection using behavioral measures and machine learning techniques: A review of state-of-art techniques," in *2017 Pattern Recognition Association of South Africa and Robotics and Mechatronics (PRASA-RobMech)*. IEEE, 2017, pp. 156–161.

[14] J. Gwak, M. Shino, and A. Hirao, "Early detection of driver drowsiness utilizing machine learning based on physiological signals, behavioral measures, and driving performance," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2018, pp. 1794–1800.

[15] A. L. A. Ramos, J. C. Erandio, D. H. T. Mangilaya, N. D. Carmen, E. M. Enteria, and L. J. Enriquez, "Driver drowsiness detection based on eye movement and yawning using facial landmark analysis." *International Journal of Simulation–Systems, Science & Technology*, vol. 20, 2019.

[16] M. García-García, A. Caplier, and M. Rombaut, "Sleep deprivation detection for real-time driver monitoring using deep learning," in *International Conference Image Analysis and Recognition*. Springer, 2018, pp. 435–442.

[17] M. J. Flores, J. M. Armingol, and A. de la Escalera, "Real-time warning system for driver drowsiness detection using visual information," *Journal of Intelligent & Robotic Systems*, vol. 59, no. 2, pp. 103–125, 2010.

[18] S. Hu and G. Zheng, "Driver drowsiness detection with eyelid related parameters by support vector machine," *Expert Systems with Applications*, vol. 36, no. 4, pp. 7651–7658, 2009.

[19] B. Reddy, Y.-H. Kim, S. Yun, C. Seo, and J. Jang, "Real-time driver drowsiness detection for embedded system using model compression of deep neural networks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, 2017, pp. 121–128.

[20] T. Vesselenyi, S. Moca, A. Rus, T. Mitran, and B. Tătaru, "Driver drowsiness detection using ann image processing," in *IOP Conference Series: Materials Science and Engineering*, vol. 252, no. 1. IOP Publishing, 2017, p. 012097.