International Conference on Recent Trends in Data Science and its Applications
DOI: rp-9788770040723.126

Driver Drowsiness Monitoring and Detecting System Using Deep Neural Network

Swetha M
Master of Technology
Department of Data Science and Business System
SRM Institute of Science & Technology
Chennai, India

Jeba Sonia J
Department of Data Science and Business SystemSRM
Institute of Science & Technology
Chennai, India

Abstract— **The topic of this paper examines the problem of driving safety and offers a fresh perspective. system for driver drowsiness monitoring and Detection. World has seen many of the accidents occur due to driver's fatigue and a small-scale distraction factor while driving the vehicle. The system is design such that it will precisely scrutiny the eye blink & yawn. Dissimilaritycovering the eyeand mouth will differ as per eye blink and yawn. Road accidents are verycommon now a days and the main reason behind them is mostly due to drivers drowsiness.This can occur during daytime or at night depending on the health and the daily routine cycle of the driver. The World Health Organisation reported that 1.26 million people died as a result of traffic accidents in 2016. deaths worldwide This research proposes a novel method for real-time sleepiness detection. This strategy is based on a deep learning technique that may be used with Android apps. with high accuracy. Sleep is an involuntary action in our body which we can't control specially when we are sitting in a confined space. This proves to be life threatening not only for the drivers but also for all the passengers travelling. minimal network proposed an accuracy of more than 80%.**

Keywords : Driver,Deeplearning,Opencv,Keras

I. INTRODUCTION

Drowsiness is a primary contributor to driver impairment, which leads system (DMS). This feature was further contrasted to and combined with data from vehicle-based sensors. In this work, We present a low-cost,fully autonomous approach to an issue of fatigue detection. Using a standard camera, we determine the pattern of longer length eye-lid closures.The length of time spent between the lower and upper lids connected is the duration of one eye blink. The pattern identifies fatigue before the driver takes asleep and alerts him via voice messages. To collisions and fatalities. Drowsiness may be detected using numerous installed in a car. Other applications like Netflix at the time, the types of sensors, according to research. In a high-fidelity driving popularity of Hotstar and other streaming services with platforms simulator.

It should be noted that while they are often available in expensive cars, the use of devices such as tiredness detecting safety systems is uncommon and not widely used among drivers. According to surveys conducted in 2019, there has been an increase in the embedding including that is most commonly used in automobiles. Additionally, deep learninghas made dramatic strides in machine learning during the past few years. As a result, implementing these novel technologies and methods can bea useful way to both increase the effectiveness of the real-time driver sleepiness detection system that is already in place and provide drivers a tool they can consume.

1.1 Scope

The proper application of outside influences for measuring fatigue, such as automobile states, sleeping habits, weather conditions, and mechanical data, may be the focus of future research., and so on. Driver sleepiness is a huge hazard to highway safety, and it is especiallyacute for commercial vehicle operators. This major safety issue is exacerbated by. Demanding work hours, 24-hour operations, substantial annual miles, and exposure to harmful environmental conditions. An essential stage in a series of preventive measures needed to address this issue is to monitor the driver's level of inattentiveness and provide feedback on their state so they may respond appropriately. Neither the zoom nor the camera's direction can be changed while the system is in use. Future work might involve automatically enlarging The eyes can then be located once. The system's accuracy can be increased by adjusting additional factors like the vehicle's condition, the presence of foreign objects on the human face, and so on. It is possible to develop a tool that can alert users or stop them from dozing off.

1.2 Methods

1.2.1 Deep Learning

Prior to the development of Convolutional Neural Network, the image recognition was being backed up on the traditional algorithms. But for the image processing, based on what the model is going to recognize the features must be recognized as per the requirement. But this processmay be seen as a challenge due to the fact of defining features for different image types. A Model may study the feature and its representations on behalf of this which leads to deep learning representing the features for image on several levels of representation This project utilizes the neural network to recognize plant leaf images, and the pre-trained models are used to evaluate the performance based on the comparison of accuracy.

1.2.2 Multilayer Perceptron

A MLP, which is a is an artificial neural network with feedforward propagation that transforms a set of inputs into a set of outputs. An MLP is a directed graph connecting the input and output parts of the many layers of node input. The network is educated through MLP using backpropagation. A deep learning method is MLP.

A perceptron with multiple levels is a kind of neural network that joins several layers in a graph that is directed, which means that there is onlyone possible signal path across each node. A nonlinear function for activation is present for each node in addition to the input nodes. An MLP employs the supervised learning method of backpropagation. MLP uses many layers of neurons, making

DOI: rp-9788770040723.126

it a deep learning technique.MLP is frequently. Guided problem solving frequently makes use of MLP. Interests include studying learning, computational neuroscience, and parallel distributed processing. Examples of applications include speech recognition, image recognition, and machine translation.

II. Literature Study

Numerous researchers have studied driver fatigue and drowsiness in the literature and have proposed various methods based on a variety of metrics. In addition, many automakers have created their own driver fatigue and drowsiness systems to increase the quality and security of their products and minimise losses brought on by drowsiness.

In 2019, Deng et al. proposed a method for face detection. that tracks the face while employing landmark locations to find fatigued drivers. They looked for indicators like yawning, closed eyes, and blinking.

Zhao et al. (2019) employed a face scenario classifier that used both landmark points and texture. They evaluated the function of each facial feature for detecting exhaustion, taking into account features like the nose, lips, and eyes. In the end, they believe that the lips and eyes are the most prominent signs of exhaustion.

Kim was et al. created a fuzzy-based method for classifying each eye's condition. They utilise the HSI and CMYK spaces' I and K colour information in their approach. The ocular region is then binarized using the fuzzy logic system based on I and K inputs.

Driver Safety Development: Real-Time Driver Drowsiness Detection System Based on Convolutional Neural Network Maryam Hashemi et al., suggested (2020) in the dataset they proposed new comprehensive data and it work with (FD-NN and TL- VDD) and they target for high accuracy and fasten.

Rateb Jabbar et al., (2019) proposed Driver Drowsiness Model using CNN for AndroidApplication In this paper they detect the facial expression by the smartphone with storage capacity with the convolution neural network technique they increased the accuracy.

Seok-Woo-Jang et at., (2020) author proposed an implementation of detection system drowsy driving prevention using image recognition an IOT the data set they used facial expression and eyeblink from that facial technology and STT are used to desired to avoid drowsiness while driving.

Chaoyang et at., (2020) author proposed Unsupervised drowsy driver detection with RFID where traffic is increased and it became important factor for human life in this paper, they proposed lowcost fatigue detection system sense drivers nodding movement using commodity RFID with highly accuracy and validation for the real timescenarios.

Ghoddoosian et al. (2019) presented a sizable real-world dataset with 30 hours of video, a variety of material, and both covert and overt signs of drunkenness. The method's main element, a Hierarchy Multi-scale Long-Term, Short- Term Memory (HMLSTM) network, is fed sequentially by recognised blink features.

Krajewski et al. (2018) On the basis of connections between small modifications and fatigue; 86% of the time, drowsiness was correctly identified. Additionally, lane position deviation can be used to identify a driving pattern. In this case, the car's position in relation to a certain lane is monitored, and the deviation is investigated. However, tactics based on driving patterns all heavily depend on driving abilities, road circumstances, and vehicle features.

Anitha et al. (2020) aimed to enhance the performance of face detection algorithms and monitor the driver's eye in a video input. In order to discriminate between normal blinking and falling asleep, recurrent neural network models (RCNN) are frequently utilised in the driver sleepiness detection sector.

Rashid et al. (2020) analysed the situation, difficulties, and potential answers for the EEG-based brain-computer interface. They also briefly covered the most popular time-frequency-spatial-domain, time-domain, and spatial-domain aspects for brain-computer interfaces in their work.

III. Proposed Methodology

3.1 System Proposed

We using a Deep Neutral Network, generally known as an MLP. The MLP is a straightforward neural network made up of connections that represent the neurons that make up the output from the input class.One or more inputs that mimic dendrites are provided to the artificial neuron, which then collects them using connection weights before producing. a class.Fig.

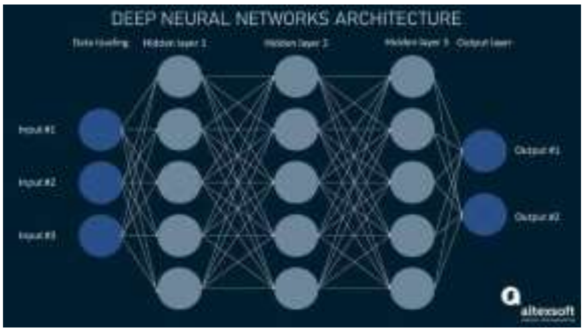

Fig 1. Deep Neural Network

In other words, the function fu(x) for one-hidden-layer MLP is stated as fu(x)=A (b + W (s (b+W x)).

3.2 Dataset-Taken

The investigation of the Driver Drowsiness Detection Dataset will be the main focus of this study. There are 22 people of different ethnicities in the overall dataset component, including the training dataset and testing dataset.

3.3 Dataset Preprocessing

To decrease the unwanted data and noise from the data, we do pre-processing and this will make the accuracy increase and speed-up the executing. Data-pre-processing is

DOI: rp-9788770040723.126

done with Data-Augmentation, which is getting the different characteristics of the data images and combining it. Rotation, flip, zoom, fill, shear etc are the methods which is applied on every image for augmentation. Library which is used for augmentation is Keras.

3.3.1 Augmentation Of Data

For getting big accuracy, the deep-neural network will need a lot of data. Sometimes the image sizes will not be enough for this. So, at this kind of places, we will use some data methods like flipping, rotating, zooming, shearing etc. to each image. These techniques will make new set of datasets which will be good for training purposes. It creates a new set of images from the already existing data and this process is called data-augmentation. The images needed for the training is not captured by ourselves. This is already available in public. The meaning of the term augmentation of data means that, different techniques like rotation is applied. Some of the data-augmentation techniques are as, Geometric-transformation, color-spacee-augmentation,filtering applied to kernel , picture blend, erasing randomly, feature-space-augmentations, adversarial-training, generative-adversarial-network, neural-style-transfer,meta learning. Data augmentation strategies target overfitting at the training dataset, which is the source of the issue. This is done with the expectation that augmentations will allow for the extraction of more data from the original dataset. By data warping or oversampling, these augmentations artificially increase the size of the training dataset. Warping of data augmentation changes the already available images but it will remain the labels. In this technique, the methods are processes like erasing randomly, adversarial-training, colour changes such as Gray and geometric such as rotation, flip etc, and neural-style-transfer. Over samples are added to the training images to get the synthetic styles. The example of synthetic styles is blending of images, augmentation of feature-space, and generative-adversarial-networks. The data augmentation safety is ensured by retaining the labels and hence changing the data content will not affected by it. This process is safe for general image identification tasks such as identifying cat and dog, but this is not a good practice when comes to tasks like digit and signs. In that case, rotation and flip will create meaningless data. For forecasts which is un-certain, the non-labelling technique will be efficient. Post-augmentation labelling is adjusting for this method to ensure this. The label as well as non-label preservation to the data will be giving better performance for the training as well as increase the accuracy in prediction-time.

3.4 Deep-Learning

This is a sub part of AI which calls artificial intelligence. Deep- learning is the technique which is under AI which is idea from brainof human and the neurons and learning process of it. There will have neurons like human and will act somewhat similar to them. We have used 2156 images for the deep learning purpose, which is learning the features of each image with neurons. There should be training as well as test data for this because if we use the same data which we have used for the training is taken for the testing as well will notgive good accuracy. So that we will split the whole data into training-testing data. The number of layers in MLP which is Consequently, the acquired videos Videos of scenarios were captured during an experiment using an infrared (IR) illumination with a resolution of 640 by 480 in AVI format. The experiment's goal was to obtain IR videos, which were then included in the dataset collection. For the model to comprehend all of the subtleties and variations in the photographs, more data is required during the deep neural network training phase. By performing a series of augmentation methods on the images extracted from video frames—a common method for boosting the number of training points—data augmentation was used to create new images.

3.5 Multilayer Perceptron

Multilayer perceptrons may acquire knowledge throughout the training process. Iterations are used during this procedure to ensure that errors are kept to a limited. achievable until the required input-output mapping has been achieved; in this case, a collection of training data containing:

$$h(x)=s\ (b+W\ x)$$

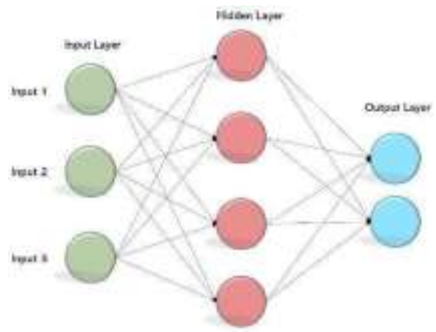

Fig.2.Architecture

IV. Modules

4.1 Creation Of Models

The method utilised to develop a neural network architecture to which the driver is drowsy, is described in this section.

The proposed technique would classify movie frames according to recognisable facial characteristics obtained by MLP. method is summarised in Figure 3.

All of these participants were observed in both daytime and nighttime driving conditions, including conventional driving mode, yawning, sluggish blinking, aware chuckling, and dizzy dozing.

DOI: rp-9788770040723.126

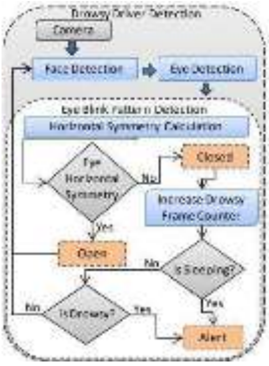

Fig 3 Model Diagram

Our strategy comprises of five steps:

Extracting Real-Time Videos :

The dataset is searched for videos of drowsy drivers in the first stage. 18 subjects were used for the training dataset in this study, whereas 4 subjects were used for the evaluation datasetan image.

Third phase:Using photos to extract landmark coordination:

The Dlib18 library is used in the third phase to manage the neural network graph from photos.

In order to map the face structures, this library is really utilised Python was used to construct the open-source library known as Dlib.Robotics, cloud computing, the Internet of Things, and embedded systems are just a few examples of server-side applications that use machine learning algorithms. Keras detects face landmarks using OpenCV's built-in driver drowsiness feature-based cascades.

This effective machine learning-based method for object detection was put forth by Paul Viola and Michael Jones19. Positive and negative pictures, in particular, are utilized to train a cascade function. As a result, it can recognize things in other photos.

Fourth step: teach the algorithm the neural network which possibly gets output and it similarly workedand every input and output will reducedthree hidden layers and is detailed in Algorithm 1.During this step, a training process ensures that various predictions are made.

The fifth phase: Extracting the modelFinally, the computer can determine a driver's drowsiness level based on a landmark on their face.

The measures used to effectively assess Precision, recall, and F-Score measure the proposed system's efficient performance. The robustness and effectiveness of the algorithm are assessed using metrics like Precision and Recall rates, which are researched and computed depending on the recognition rate.that when all elements, including motion, illumination, and eye conditions, are considered, the suggested system has the best recall rate. the system's recommended measures' mean value.

If the result falls into one of the established categories—such as closed eyelids, exhausted, or sleepy expressions—our system examines the input and recognises whether the driver is classified and informed based on the driver's facial expression.Two video clips of drivers exhibiting a variety of facial expressions were used to examine the experiment's outcomes. The movies are captured in real time with variable and unpredictable lighting. Various mouth states, including normal, yawning, talking, and singing, are included in the datasets.

In the video input, we observe that 'Head Yaw,' 'Eye Gaze,' and 'Phone'are the key reasons for driver inattention from generic feature reveal theregions of driver inattention and specific facial feature block may be utilised to reason about the driver inattention.Driver attention rating is a very subjective topic, and the factors responsible for predicting this rating (head attitude, eye gaze, face area, etc.) may differ from one driver to the next.

4.1 Eye Blink Detection

In the situation of missing eyes, In order to determine the exact position of the eyes, we used the prior eye placements in reference to the detected facethe eyes. The position is determined if only one eye is absent by comparing the detected eye's present dx and dy coordinates to where it was in the previous frame. The prior location of the missing eye location is then added to the displacement variables dx and dy to recognise various eye patterns (both open and closed), we first use (1), (2),and (3) to conduct contrast stretching.

err" = high'– low" for in --→2

err- = high-– low-. For out--→3

The region of interest was then divided horizontally into two parts (Upper and Lower) by a line going through the centre pupil of the eye. Due to the An open eye design possesses horizontal symmetry, whereas a closed eye pattern does not, due to the round form of the eye.

Idiff =(VF(Up(I'))-Low(I')) –4

I sum = ∑width, height Idiff (i, j), i=0j=0 ---5 I state = { open I sum<T {close I sum >T} ---6

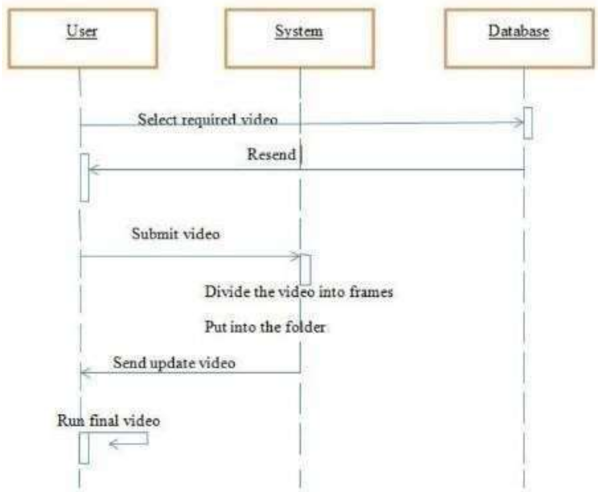

Fig 5: Sequence Flowchart

We proposed using the symmetry property to distinguish between open and closed eyes. We found the

International Conference on Recent Trends in Data Science and its Applications
DOI: rp-9788770040723.126

horizontal using (4), (5), and (6). Idiff If I is the contrast-stretched and normalised image, indicates the symmetry of the eye. VF(I) represents the top whereas Low(I') represents the bottom half of the image.Sum is the total sum value of the Idiff picture, and I state is the detected eye status taking the Isum value into account.

4.1.1 Detection Drowsiness

Drowsiness can be detected using three approaches, which we discussed in TABLE 1. Given that the average time of an eye blink is less than 400. As a result, we set TDrowsy=400ms and TSleeping=800ms.

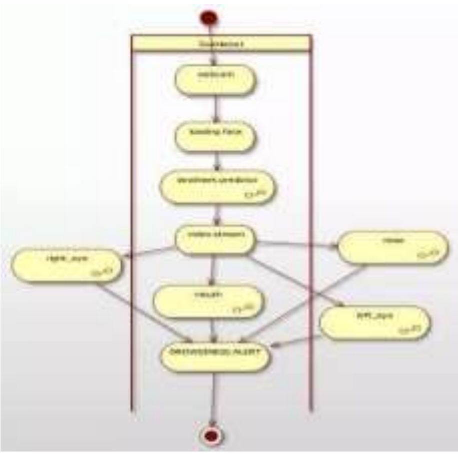

Fig. 4 Activity Diagram

TABLE 1

Drowsiness Level	Description
Awake	Blink duration<Tdrowsy
Drowsy	Blink duration>Tdrowsy and Blink duration<Tsleeping
Sleeping	Blink duration>T sleeping

The detection of drowsiness is intimately linked to the detection of eye blinks. The threshold values are compared to the timing of closed-eyes events.The TDrowsy and TSleeping values correspond to 10m and 20m distances in the case of a 90km/h car, giving the system enough time to deliver a warning signal to the driver.

Detection of Mouth

Some driver hypovigilance systems detect the mouth based on red colour features of the lips, but they can only function properly in appropriate lighting conditions.

Face Identification

Face tracking is a technique for detecting the presence of a face in an image or video. Face tracking mostly works by comparing existing andnew face features. It is widely utilised in real-time technologies.

4.2.2 Decision Making

It is determined if the individual in question is drowsy or not based on the extracted characteristic calculation and symptoms. If the preceding stages are successful, it results in more accurate decision making.

We divided the desktop-based strategy into two major components, namely hardware and software. The hardware section is also divided into two sections:

i) processing hardware and ii) imaging hardware. We will now go over the use of imaging techniques in greater detail. The flow diagram of our discussion about desktop-based techniques is shown in Fig.Every film

Each movie takes about 6 minutes to extract the face features from a sample of 50 frames.

The clip has 50 frames per image, and it takes an average of 6 minutes per movie to extract facial features.It takes roughly 1.2 seconds to predict the driver rating using Attention-based AutoRate. The model runs in 7 minutes and 20 seconds, therefore real-time performance cannot be provided.

A state-of-the-art approach was used to extract the features, output type, output dimension, and performance of various pre-trained models from the precise information about the feature.

RESULTS

First, we will arrange a camera that scans the stream for faces; if a face is identified, facial landmark detection is added, and the eye domain is removed.

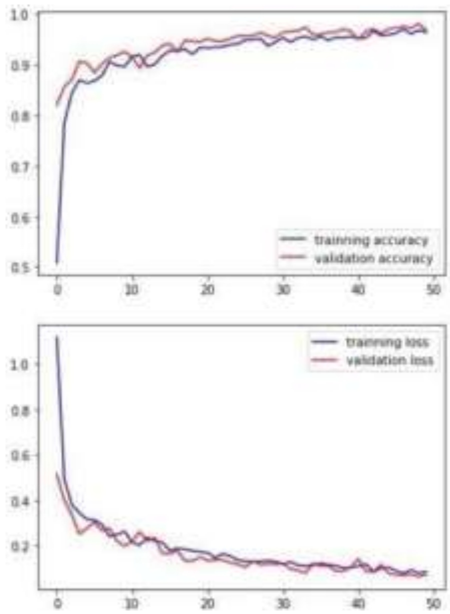

Fig 7.Accuracy Graph

THE BENEFITS Below are some of the many benefits of the adopted technique or system:

1. The presence of sleepiness.
2. A reduction in traffic accidents.
3. This approach has real-world applications.

CONCLUSION

Using the symmetry characteristic, we proposed a new method for detecting eye blinks. Because it operates within the same frame, the proposed system is not affected by head movements. In order to determine the driver's condition, the system's job is to identify facial landmarks in photographs

DOI: rp-9788770040723.126

and input the generated. The method's objective is to shrink the model because embedded systems can't use current applications they have a small amount of computing and storage. The experimental results demonstrate that the employed model is modest in size and 90% correct. As a result, it can be included in sophisticated driver-assistance systems. The algorithm- based deep neural network detection method for driver drowsiness Keras and OpenCV aretwo examples. However, there is still room for improvement in terms ofperformance. The next step willbe to identify the driver's distraction andyawning.

FUTURE WORK

Android devices are widely available and affordable, and smartphone- based approaches are becoming more and more common. However, the real-time detection rate is less precise than the desktop-based method.The most difficult challenges with driver sleepiness detection systems are related to detection in low-light conditions. Scientists can develop it so that detecting systems can be simply conducted. The accident rate will thereafter gradually decrease day by day.

REFERENCES

[1] U. Budak, V. Bajaj, Y. Akbulut, O. Atila, and A.Sengur, "An effective hybrid model for EEG-based drowsiness detection," IEEE Sens J. vol.19, no. 17, pp. 7624–31, 2019.

[2] W.L. Zheng, K. Gao,G. Li,W. Liu, C. Liu,J. Q. Liu and B. L. Lu, "Vigilance estimation using a wearable EOG device in real driving environment," In: IEEE Transactions on Intelligent Transportation Systems. 2019.

[3] H. Lee, J. Lee, and M. Shin, "Using wearable ECG/PPG sensors for driver drowsiness detection based on distinguishable pattern of recurrence plots," Electronics, vol. 8, no. 2, p. 192, 2019.

[4] R. Ghoddoosian, M. Galib, and V.Athitsos, "A Realistic dataset and baseline temporal model forearly drowsiness detection.,"In: Proceedings of the IEEE conference on computer vision and pattern recognition workshops, pp. 0-0, 2019.

[5] Sukrit Mehta, et al. "Real-time driver drowsiness detection system using eye aspect ratio and eye closure ratio." In: Proceedings of international conference on sustainable computing in science, technology and management (SUSCOM), Amity University Rajasthan, Jaipur-India, 2019.

[6] J. Anitha, G. Mani, and K. Venkata Rao, "Driver drowsiness detection using Viola Jones algorithm," In: Satapathy S, Bhateja V, Mohanty J, Udgata S, editors. Smart intelligent computing and applications. ion Smart innovation, systems and technologies, vol. 159. Singapore: Springer; 2020.

[7] Y. Ji, et al. "Fatigue state detection based on multi- index fusion and state recognition network," In: IEEE Access, vol. 7, 2019.

[8] Moshika, A., Thirumaran, M., Natarajan, B., Andal, K., Sambasivam, G., &Manoharan, R. (2021).Vulnerability assessment in heterogeneous web environment using probabilistic arithmetic automata. IEEE Access, 9, 74659-74673.

[9] Y. Ed-doughmi, and I. Najlae, "Driver Fatigue Detection using Recurrent Neural Networks," In: Proceedings of the 2nd International Conference on Networking, Information Systems & Security. 2019.

[10] Rajesh, M., &Sitharthan, R. (2022). Image fusion and enhancement based on energy of the pixel using Deep Convolutional Neural Network. Multimedia Tools and Applications, 81(1), 873-885

[11] Y. Xie, K. Chen, and Y. L. Murphey, "Real-time and Robust Driver Yawning Detection with Deep Neural Networks," Proceedings of the 2018 IEEE Symposium Series on Computational Intelligence, SSCI pp. 532– 538, 2019.

[12] S. Mehta, S. Dadhich, S. Gummer, and A. Jadhav Bhatt, "Real-Time Driver Drowsiness Detection System Using Eye Aspect Ratio and Eye Closure Ratio," SSRN Electronic Journal,pp. 1333–1339, 2019.

[13] P. Peyrard, "Personal system for the detection of a risky situation and alert," Feb. 28 2019, uS Patent App. 16/178,365.