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Driver Drowsiness Detection Using Convolutional Neural Networks

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Abstract: Accidents are now increasingly increasing as more cases are caused by driver drowsiness. To reduce these situations we were working on something that could reduce numbers and get accidents early. Seeing a drowsy driver behind the steering wheel once and warning him could reduce road accidents. In this case drowsiness is detected using an automatic camera, where, based on the captured image, the neural network detects whether the driver is awake or tired. Convolutional Neural Network Technology (CNN) has been used as part of a neural network, where each framework is examined separately and the average of the last 20 frames are tested, corresponding for about one second to a set of training and test data. We analyse image segmentation methods, construct a model based on convolutional neural networks. Using a detailed database of more than 2000 image fragments we are training and analysing the segmentation network to extract the emotional state of the driver in images.
Keywords: Convolutional neural network, driver drowsiness, defined database, image segmentation, segmentation network

I. INTRODUCTION

Statistics from the National Highway Traffic Safety Administration (NHTSA) show that approximately 2.5% of all deaths during an accident are caused by drowsy driving [1]. In 2015 alone, the total number of accidents related to drowsiness was over 72,000. Surprisingly, car crashes caused by non-violent driving are more common than those caused by drunk drivers [2]. People who drive late are slightly slower in their response time compared to normal working drivers. Drowsy driving, on the other hand, makes drivers more vulnerable to micros sleeps.

With nearly 1.4 million people dying on the roads every year thus making it the seventh leading cause of death in 2016 [3], it is not surprising that the automotive industry, research institutes, and other government agencies are developing technologies that protect these conditions. Among the many crash procedures and other safety features performed on new cars, there is much interest in getting tired and drowsy drivers that by using cameras, sensors and other devices to warn and thus avoid fatal crashes.

Car companies such as Mercedes-Benz [4], Tesla [4], and others have their own types of driver assistance programs. Such as flexible boating controls, automatic braking systems, navigation alerts and steering assistance. This technology has helped drivers to prevent accidents. Samsung recently partnered with Eyesight [5] to track drivers' attention by studying facial features and patterns. Such a tracking system could alert drivers to be more cautious while driving. Although these developments exist most of these programs are patented and limited to high-end vehicles.

There has been a dramatic increase in the number of cars installed by Android Auto or Apple Car these days. Most of the cars being introduced now have built-in features. Such features are now readily available in low-end cars as well. As a result, drowsiness programs can be easily upgraded around the built-in Android and iOS platforms. Embedded devices or mobile phones that can easily pair these car dashboards can be used to improve driver behavior detection using simple camera settings and state of the art computer programs powered by Deep Learning.

Microsleeps have a short period of time in which the driver is blindfolded and does not see any visible information and thus is unable to react when the vehicle is off the line or when the vehicle is stopped due to heavy brakes. Upon arrival of new sensors and radars on high-performance vehicles, vehicles can alert or take action to avoid such accidents. While this is a major improvement, it can also be helpful if the car knows that the driver is asleep and asks him to rest. Also, another common problem with current machine watch models is the fact that most of these algorithms are large (of large size) and require dedicated Hardware to run the models produced. They do not perform well on low-power counting devices. This paper describes an algorithm for obtaining in-depth acquisitions based on learning that would allow such interventions, In addition, they are simple and easy to configure on any mobile or embedded device.

The other paper is divided as follows. In Phase II, book reviews are reviewed, introducing a few technical programs for driver drowsiness detection systems. In the Solution and Methodology III section, the proposed algorithm and the CNN and Facial Landmark Detection (D2CNN-FLD) process are described.

II. LITERATURE REVIEW

As sleep-induced crashes represent a significant portion of vehicle crashes in the world, researchers and automotive com- panies have created different solutions ranging from finding patterns in driving habits to analyzing brain waves and vitals of the driver while driving. Most of these solutions are backed by some predictive algorithms powered by statistics and machine learning. The most common ones can be broadly divided into three categories as described in the following paragraphs.

One approach is to find changes in vehicle behavior, such as the one proposed by McDonald et al. [6]. He created a contextual and temporal algorithm that utilizes the steering angle, vehicle speeds, and accelerator pedal positions. These values are passed into a Bayesian Network which determines if a driver shows characteristics of drowsy behavior. The algorithm was found to have lower false-positive rates than PERCLOS [7] methods, which predicts drowsiness based on eyelid movements and patterns. The takeaway from this study was that to predict correctly, the context of the situation is crucial. The data that it captures over a previous 10-second period is vital in understanding whether the person is at risk of drowsiness related lane departures.

A second approach is based on studies focused on using the drivers' vitals, brain waves, and readings from Electro- Encephalo Grams (EEG's) to make predictions. Wei et al.

[8] made comparisons between non-hair bearing EEG Brain- Computer Interfaces that are easy to wear and less intrusive than the lab-based whole scalp EEG's which are less comfort- able. The study showed that non-hair bearing devices had no significant reduction in performance when compared to whole- scalp EEG. Thereby with this finding one may develop less intrusive and comfortable headbands. EEG alone is unable to detect all stages of drowsiness, so Kartsch et al. [9] used EEG with Inertial Measurements Units (IMU) sensors to detect 5 levels you fall asleep with 95% accuracy. The team included behavioral data from IMU and EEG information to determine drowsiness. Another downside to the EEG system was the power requirements of these devices. Their technology also facilitated the implementation of an ultra-low power (PULP) platform on a microcontroller that extended battery life by approximately 46 hours, thus creating devices that are always wearable and require minimal maintenance. Tateno et al.

[10] developed a system that simply uses to monitor the heart rate to detect human breathing and thus cause drowsiness. This method was found to be an effective respiratory and thus complete.

Another process is to use the power of computer vision. The latest developments in Deep Learning have provided new tools for computer-assisted finding and segmentation. Computer-related applications use these methods for object acquisition, health and wellness, and even agricultural applications [11]. The biggest impact on this space has been the image data. As drivers' facial expressions change dramatically when they are tired, computer scientists have tried to apply this and use it to provide solutions for drowsiness. Tayab Khan et al. [12] suggest a solution to measure the angle of inclination of the eyelid and thus indicate whether the eyes are closed or not.

They have achieved 95% accuracy in this way, but the limit is that there needs to be enough light for this method to work as it works poorly at night. Shakeel et al. [13] used the MobileNet-SSD architecture to train a custom database of 350 images. The model was able to achieve a Mean Average Precision of 0.84.

The system was expensive and efficient as the algorithm could be installed on an Android device and the camera stream could be split in real time. Celona et al. [14] proposed a Multi-Task Driver Monitoring Framework-based framework that analyzes the eyes, mouth, and head at the same time to predict the level of sleepiness.

This study was performed on the NTHU database [15]. Another study by Xie et al. [16] used sequential learning and learning transfers from video clip yaws to YawDD and NTHU-DDD database. This program was more precise and was powerful in changing the face and face of the camera. Mehta et al. [17] developed an Android app that can detect landmarks on the face and use Eye Aspect Ratio (EAR) and Eye Closed Ratio (ECR) to predict driver drowsiness based on machine learning models with 84% accuracy.

The approach that many companies try to follow is to combine the three different strategies outlined above and then use more inputs to come to a decision. Start-up Ellcie-Healthy [18] has developed a smart glass that integrates a sleep-depriving app by incorporating blink discovery, eye tracking, and critical monitoring. The smart glass monitors this input and provides additional intervention by crying and thus asking the driver to rest. Integration techniques require multiple sensors such as infrared, cameras and heart rate monitors on a single platform to deliver the best results. However, these tools are very expensive and need to be set up with related solutions.

All of these new features in the deep learning space will be costly, large model with high calculation requirements.

Fig. 2. Video preprocessing outline

This is a disease of deep learning. In our previous work [19] [20] a machine learning model that classifies sleep images using a multi-spectrum-based perceptron [D2MLP-FLD] model was proposed. The result was a decent 81% accuracy when constructing a model that was 100KB in storage size. The idea proposed in this paper is to improve the algorithm and build a simple application in terms of functionality to detect the drowsiness.

III. METHODOLOGY

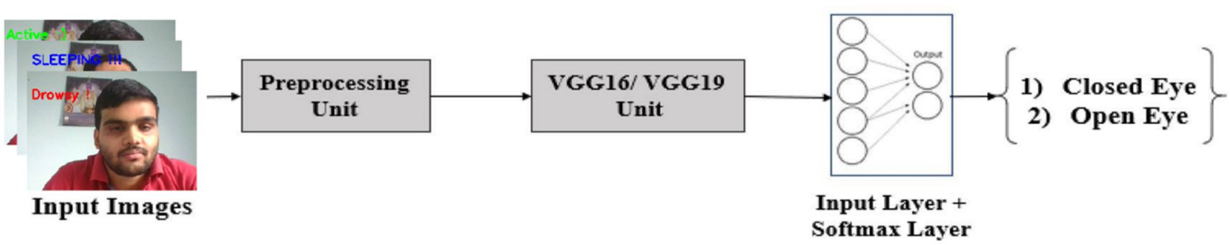

Fig.1 System Block Diagram

This is the concept of learning transfer and the previously developed CNN used to extract features.For this purpose, VGG16 and VGG19 have been selected as proposed pre-trained networks.VGG16 is a deep convolutional neural network proposed by Simonyan and Zisserman. And another network is included in this network architechture, the Fully Designed Neural Network (FD-NN).
VGG16 contains 16 layers and is trained in the ImageNet database, which contains a large number of images and has 1000 classrooms. IVGG19 is an in-depth version of VGG16 with 19 layers. It has also been trained in the ImageNet database.A network designed for images with a size of 224 × 224 pixels, however, can mean another size, either.
These networks study low-level features by ImageNet data, and high-level features are released with the last three layers added in full. The first layer is the input layer, the second is to work with the Relu function, and the last layer is the Sigmoid function as the output layer. We call these networks Transfer Learning VGG16 (TL-VGG16) and Transfer Learning VGG19 (TL-VGG19). The structure is the same on both networks, and differs from VGG16 or VGG19. The framework of these networks is presented in the bloock diagram.

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A. Database

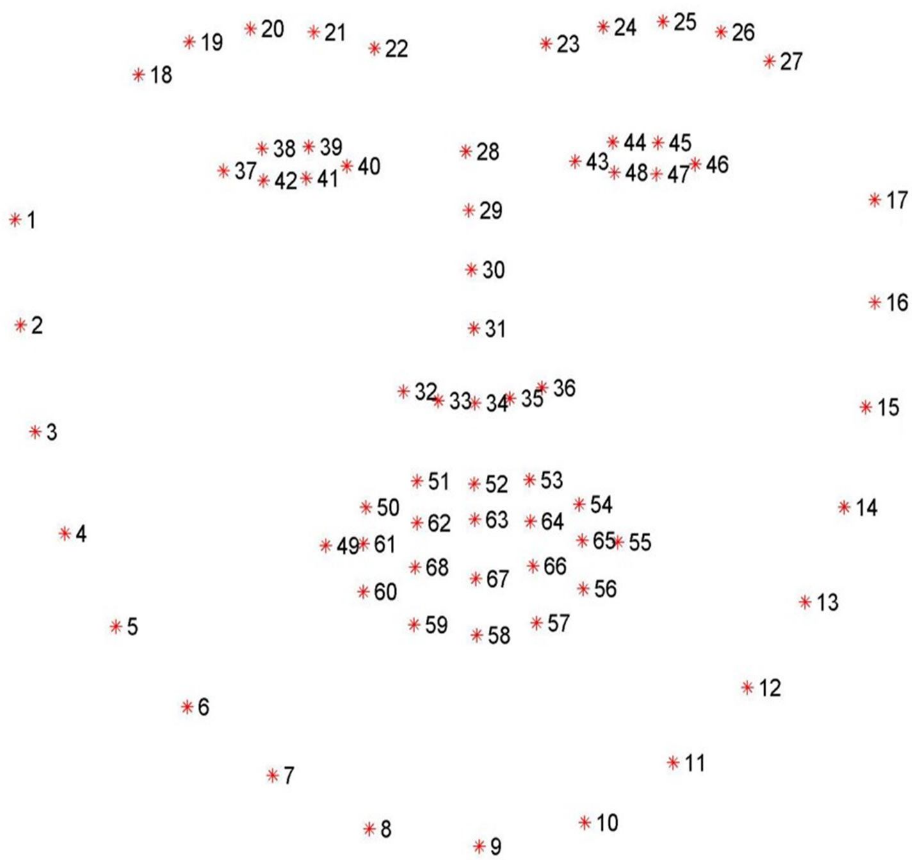
For this model,we have used the preloaded datasets called Face utils which is an opensource wrapper library for the most common face detection models.It also provides multiple face utilities such as face cropping.It has the abilities of cropping and detecting the given face images.

B. Model Preparation

When it comes to image processing, the Convolutional Neural Network (CNN) is the most effective way to prepare a model. CNN can be divided into two main categories. In the first case, it excludes features with the same template The sequence of filters (which leads to feature maps) is followed by a standard section that makes the size that continues to be repeated as a vector in the second half. The second part is similar to the standard Artificial Neural Network (ANN). Accepts vector. The main purpose of this section is to divide it into categories. Relu activation function is applied to all layers but the last layer uses softmax to separate. There are 5 layers to consider. Transformation layer: In this ad the layout of the features occurs through the use of various filters. As a result, we get feature maps. Pool insertion layer: In this layer maps are accepted, reducing the size. All important features are saved. Relu Preparation Background: It is an activation function that has one main purpose of keeping the positive values as they are and without negative values. In this way, you get the job done normally. Fully Combined Layout: The same layer we see in ANN eg :the input layer as vector, hidden layers and layers of final output.

C. Facial Landmarks Detection

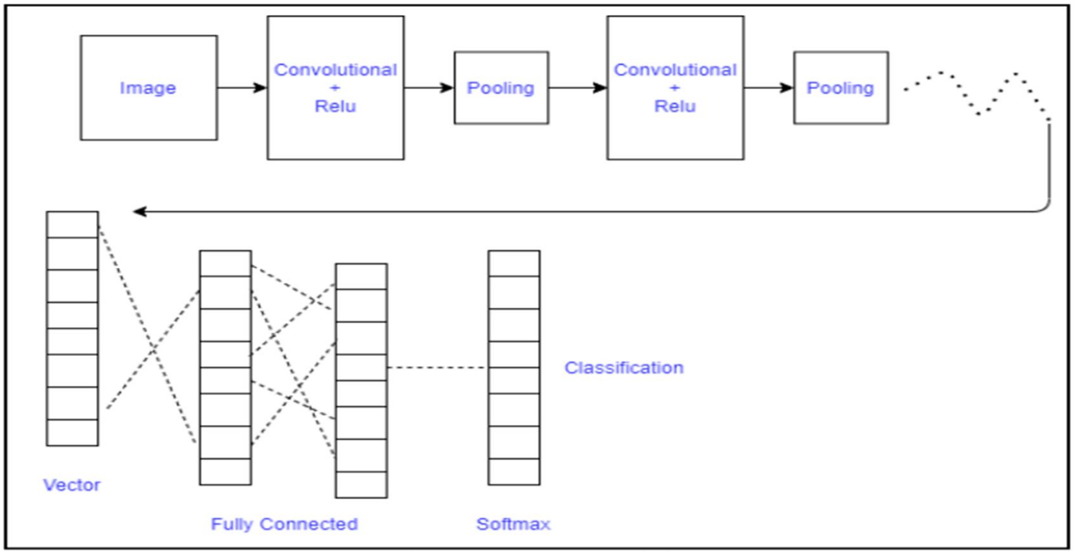
This is the most important vital part of the model where the facial landmarks are being readed and detected which are used for the facial detection.



There were 68 total landmarks per frame but we decided to keep the landmarks for the eyes and mouth only (Points 37–68). These were the important data points we used to extract the features for our model.

D. Pycharm

All the required files are installed needed for image processing and deep learning and are imported to the window which are namely Face utils,numpy,opencv.



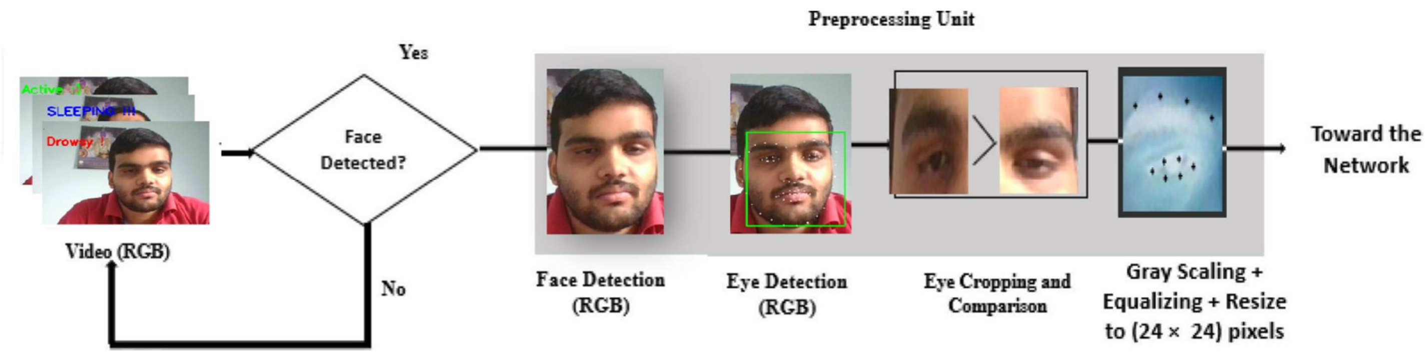


Fig.2 System Flow Chart-1

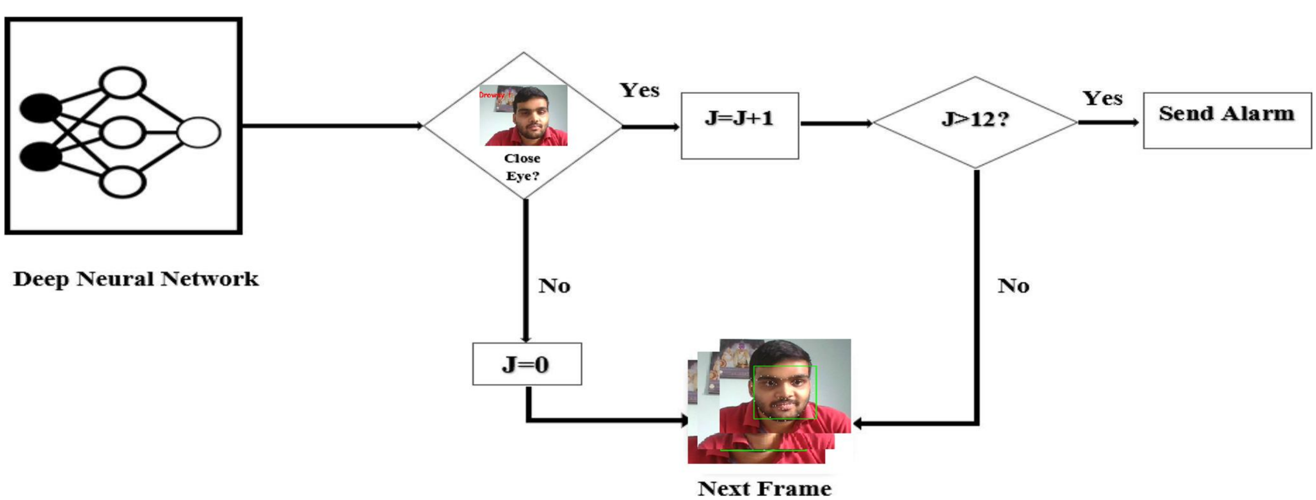


Fig.3 System Flow Chart-2

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IV. COMPUTATION RESULTS

The code is being prcessed in the pycharm project and the detector and predictor windows are opened for the detection of face expressions and here are the below resulting images which showcase the output of the project.

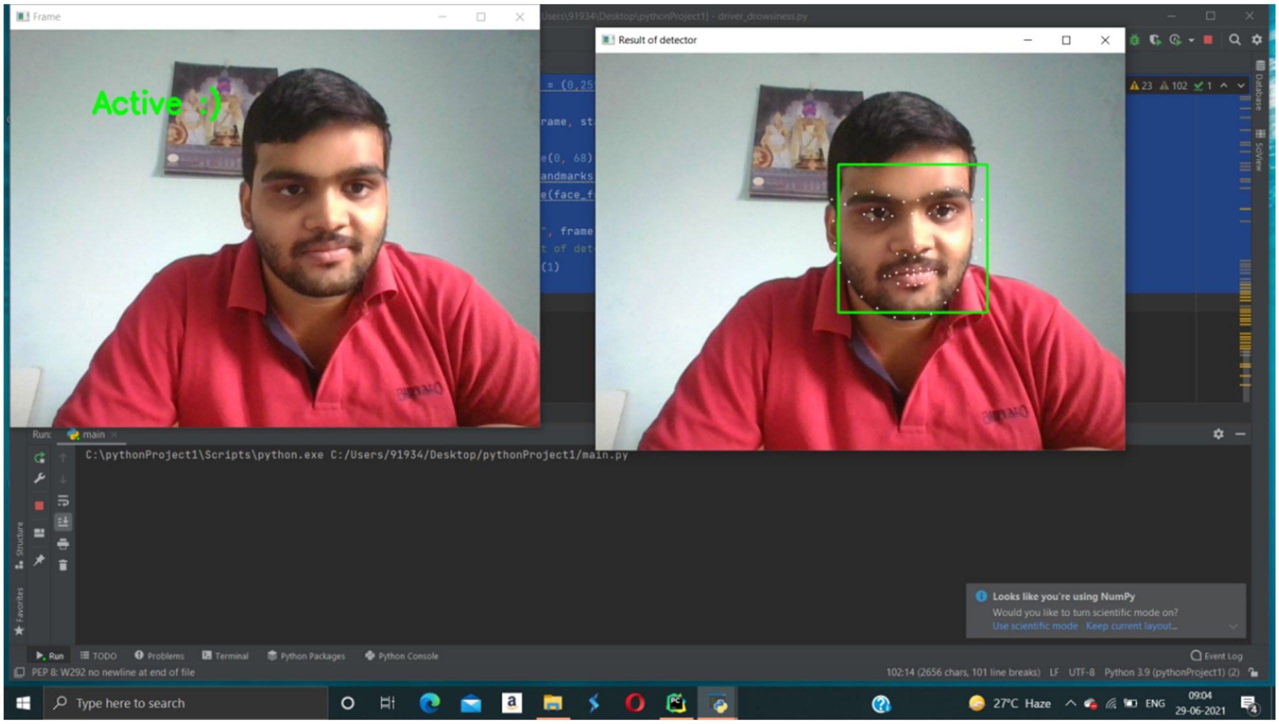

Fig.4 Active state

This is when the person is in active state and this is calculated using EAR(Eye Aspect Ratio) and mouth aspect ratio(MAR) and these values are set to minimal values and if these values are decreased the following below images show the alarm sign to caution the driver and it detects that he is sleeping or drowsy.

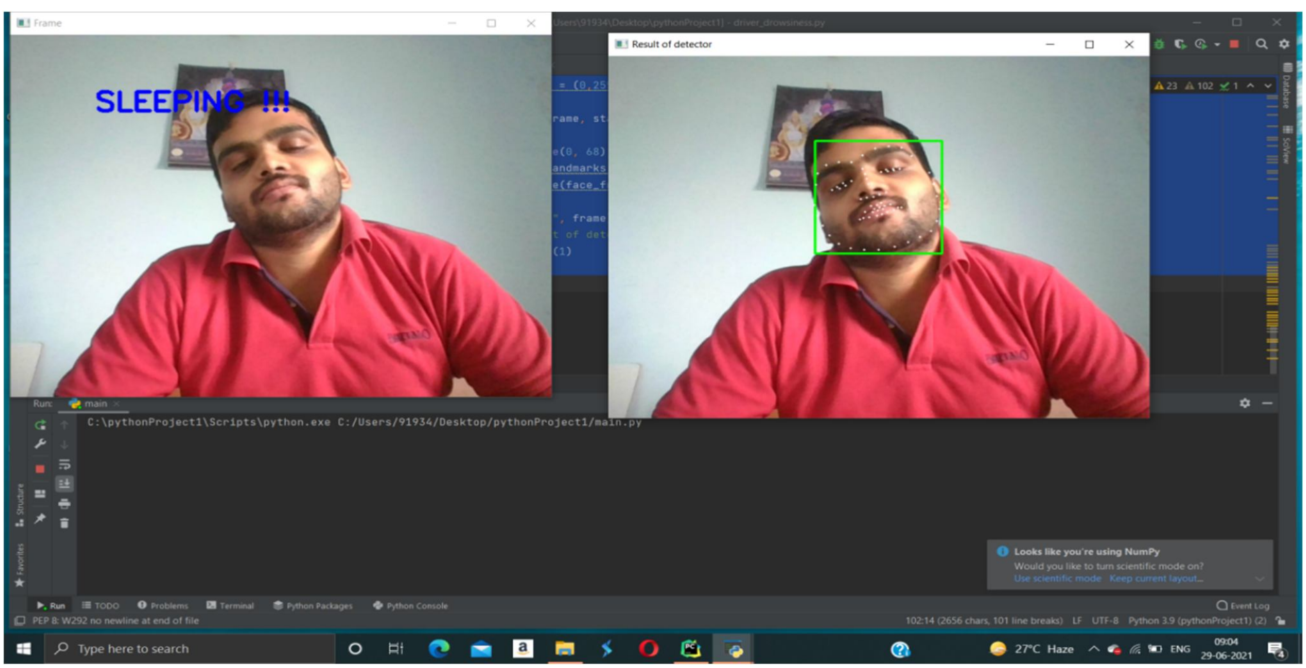

Fig.5 Sleeping State

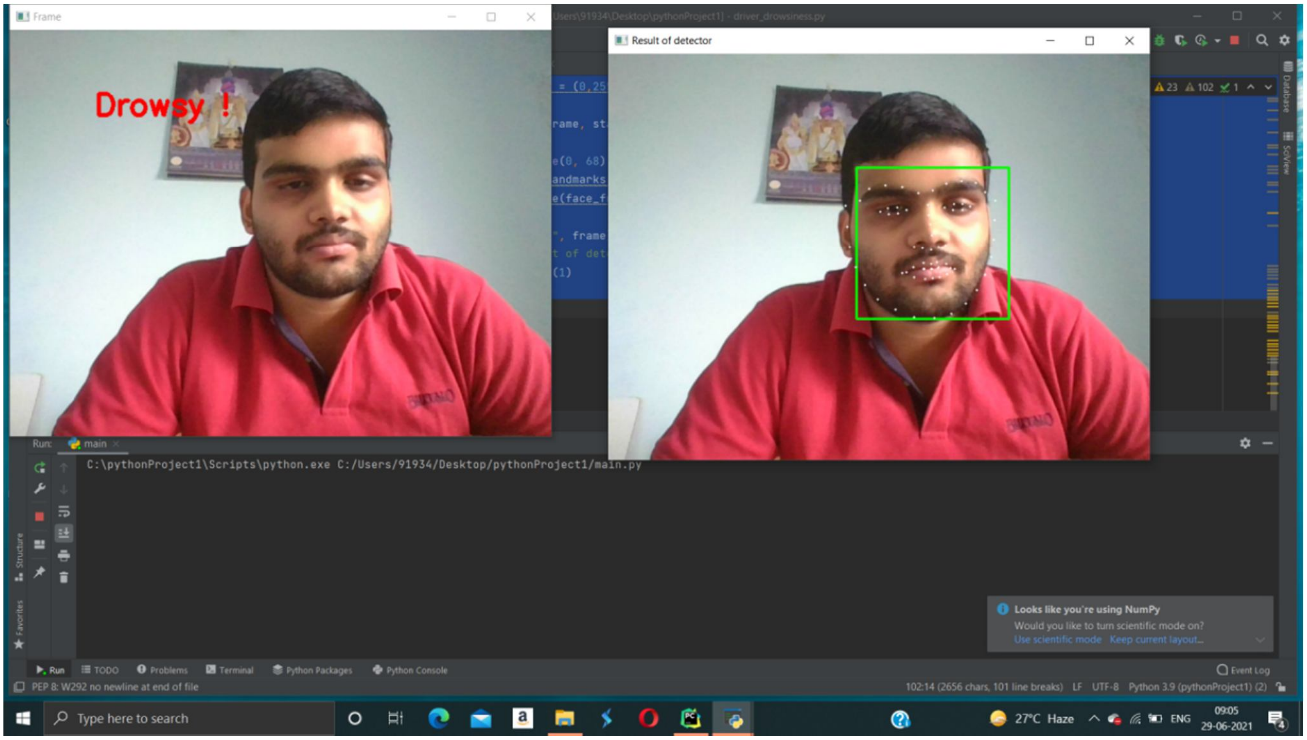

Fig.6 Drowsy State

V. CONCLUSION

This paper provides a modern approach for driver drowsiness detection. In the implementation of such system new practically technologies are used. In this fast and rapidly changing world, this model is the solution. Such service mesh is proposed in this paper. Convolutional neural network is used for image processing and classification into different categories. Softwares like pycharm, face utils, imutils, open cv are used to preprocess and load the data sets and to run this model.

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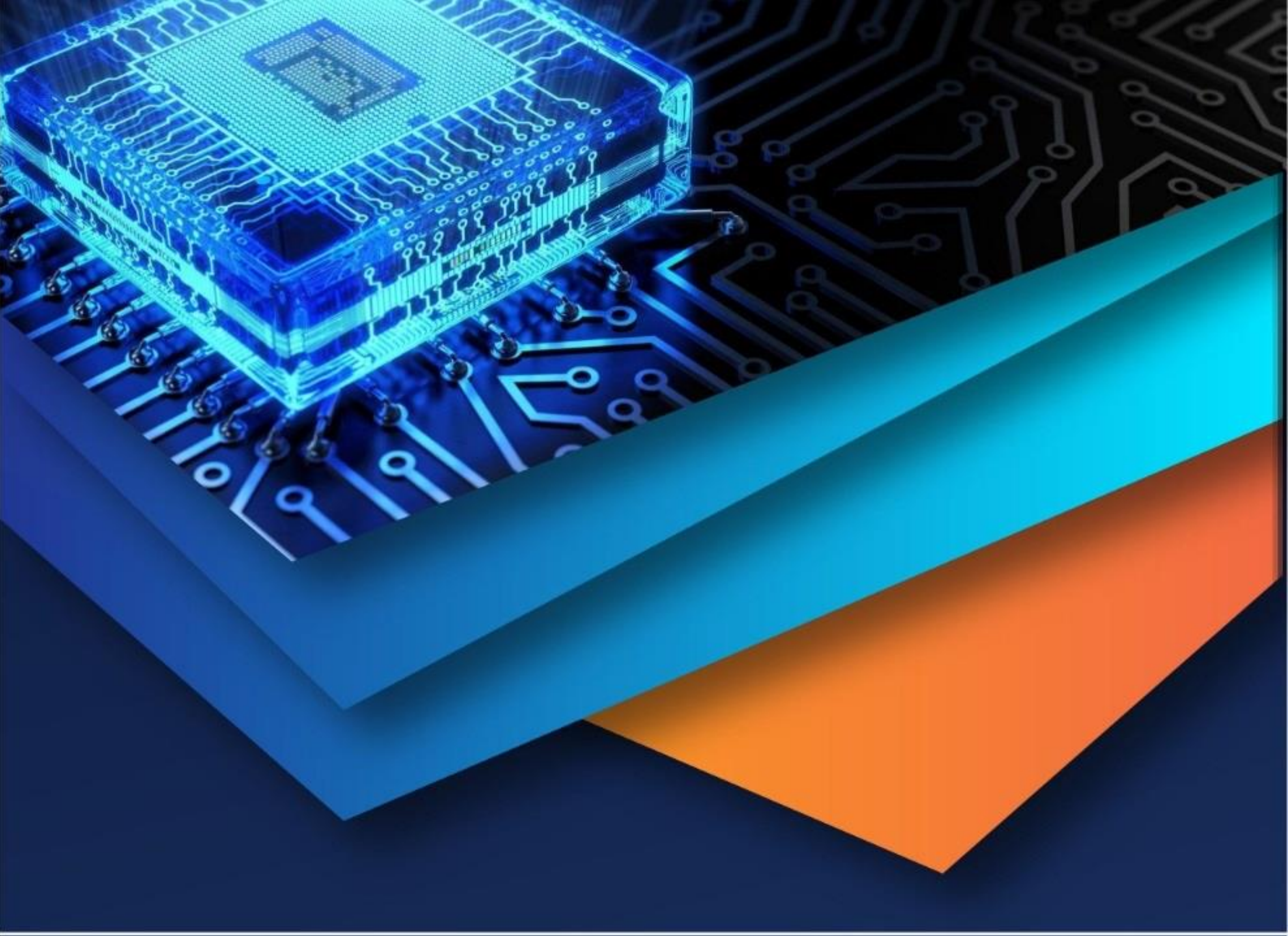

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