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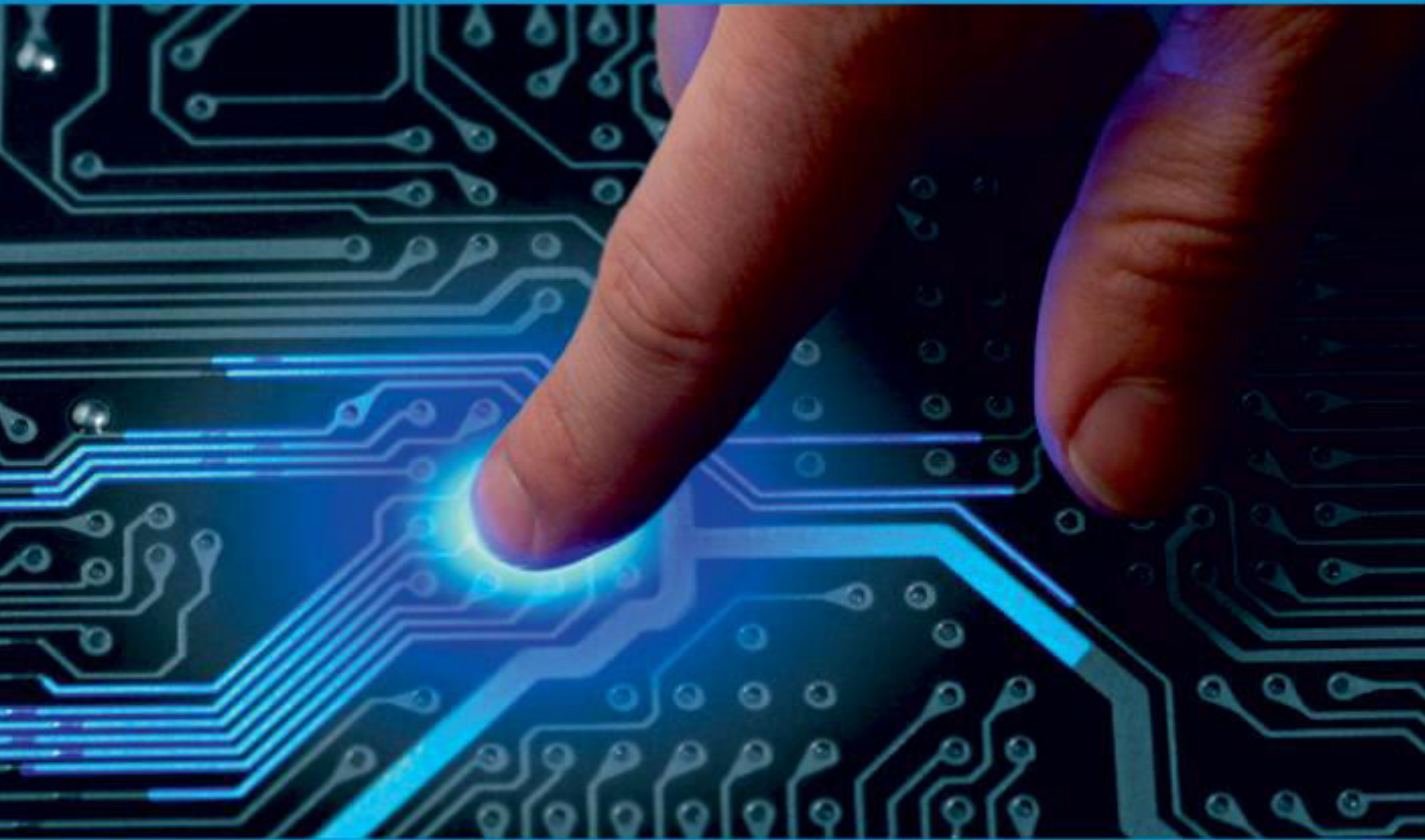

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Driver Drowsiness and Distraction Detection through Machine Learning

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ABSTRACT*:* The increasing frequency of fatal road accidents could be a regarding situation. This has been one amongst the foremost problematic occurrences that have taken plenty of casualties that are extremely worrying data point foe the road authorities and therefore the governments. The increasing incidences are attributed to lack of attention of the driving force or a distracted driver. A distracted driver is one amongst the foremost dangerous and fatal on the road as any vehicle becomes a deadly weapon. The distracted driver is unable to retort to the dynamic conditions on the road and might be the reason for a fatal collision. This situation is unwarranted and should be combatted to boost the security on the roads. For this purpose a good and non-invasive approach for driver distraction detection through the utilization of Machine Learning and image process implementations. The projected methodology implements Region of Interest, Convolutional Neural Networks and call Tree for correct driver distraction detection. The approach has been quantified through the utilization of in depth experimentation that has yielded acceptable performance metrics for the detection paradigm.

KEYWORDS: Region of Interest, Convolutional Neural Network, Decision Tree, Entropy Estimation.

I. INTRODUCTION

In recent years there has been an upsurge in the number of traffic accidents that are occurring throughout the world. This can be attributable to a vast number of automobiles that are being built and employed in big numbers. The growth in the number of automobiles is exactly proportional to the growth in the number of road accidents. Road accidents are extremely dangerous and must be drastically decreased since they result in a large number of fatalities. The last proportion of deaths is made up of young people who still have a lot of life ahead of them. Accidental death is the most painful and honourable way for any living person to die.

Road accidents are caused by a variety of factors. Drowsiness caused by driver distraction might lead to a reduction in the driver's vigilance on the road. This lack of attentiveness may cause the motorist to lose track of the road and end up in another lane. Collisions and other unpleasant results might result from this sort of careless activity. The motorist must pay close attention to the road and devote his entire concentration to driving. Any sort of distraction can lead to risky situations for the driver and other passengers in the area.

Vehicles have become more powerful and quicker through time as vehicle technology has advanced. Because of its great raw power and acceleration, the vehicle may do maximum damage if it is redirected away from the route. These vehicles must be operated with extreme caution and alert to the surroundings to avoid any form of catastrophic or fatal error. Vehicles that carry various commodities and other stuff across long distances are also available. These trucks are extremely dangerous because, due to the tonnage they carry, they have a lot of momentum when traveling at highway speeds.

Because of the large level of inertia, any driver's attention from the road might result in a high-velocity crash. This Momentum can do tremendous damage to any colliding vehicle, perhaps resulting in several fatalities. Therefore, truck drivers must be particularly watchful when driving on roads, recognizing numerous barriers and other events and reacting quickly. A distracted truck driver is one of the most hazardous vehicles on the road, capable of causing widespread fatalities, as evidenced by several data and surveys on road safety conducted throughout the world.

The truck driver is not the major issue, but driver distraction in any vehicle, regardless of size, maybe exceedingly dangerous and adds to the number of road deaths. Drivers who travel vast distances in a short period without stopping

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for rest or sleep to achieve unrealistic deadlines are the most vulnerable to accidents. With the rise in commercialization and other development-related activities, there has been an increase in the volume of transportation in recent years. Therefore, the number of drivers and cars on the road is rising, increasing the risk of a collision or a deadly accident. As all drivers are attempting to meet a deadline, this results in lengthy driving with no respite in between extended periods of driving, resulting in greater driver distraction.

Distracted drivers should not operate vehicles since they might cause accidents in other situations and considerably increase the rate of disaster. For the objective of identifying driver distraction, a variety of approaches have been used. These methodologies have been thoroughly examined in this publication to refine our approach to reducing fatal accidents by detecting driver attention. The examination of traditional procedures yielded useful information that was crucial in reaching the desired outcome. To identify driver distraction precisely, the gadget employs a combination of the region of interest, long short-term memory, and a decision tree. Our developed strategy will be effectively detailed in the forthcoming researches.

This research paper utilizes section 2 for evaluation of the previous researches in the form of a literature survey. Section 3 elaborates on the proposed idea, whereas section 4 discusses the obtained results. Finally, section 5 provides the conclusion and offers the future direction for research.

II. Literature Review

M. Yazdi [1] states that there is a rise in road accidents as a result of tired drivers, which is a significant transportation issue. Therefore, there has been a lot of study on driver tiredness detection systems during the previous two decades. The suggested frame includes yawning detection, which may be determined by looking at the location of the driver's mouth. There are several stages in the yawning process from which the authors may identify yawning, including nose tip detection, mouth area detection, and whether the mouth is open or closed. Thus, effective yawning detection is obtained by using these properties of the facial picture. Therefore, the suggested framework reduces driver fatigue.

C. Yu explains that traffic accidents have resulted in a huge number of fatalities and many more non-fatal injuries. The driver's attention has been the most important factor in many of the incidents[2]. Various driver drowsiness detection frameworks have been created in recent years, however, more research is needed to enhance detection. The facial characteristics of the person are acquired from video frames in the proposed article, and Convolutional Neural Networks are created to separate the state of the face, eyes, and mouth. Therefore, the author claims that the model they created is a low-cost, real-time, practical, and accurate solution.

H. Xu develops a multi-obstacle detector based on the angular properties of E-vectors. These vector characteristics don't require or necessitate any prior knowledge of the obstacles' forms or colors. [3] The use of a detector in various sorts of barriers improves polarization navigation precision. The primary benefits are presented, as well as a variety of basic yet useful description features. There are issues such as polarization skylight navigation and obstacle detection that have been identified. The computations of polarization sensors and patterns of skylight polarization are described in this study.

In the flight safety of aircraft, Y. Zhou emphasizes that the runway plays a vital role as an essential condition for landing and takeoff. Using ASVDR (adaptive singular value decomposition and reconstruction) and combining the Hough line detection technique with the canny operator edge detection technique, the runway region can be properly identified and segmented. The runway area is used to gain a better understanding of the optical flow field, which is assessed using a mixed Gauss background model [4]. According to the simulation findings of the accurately scaled model, the framework proposed by the researcher is viable and correct.

K. Dhakate states that according to statistics supplied by the government, there were about five lakh road accident incidences in India [5]. Distracted driving is defined as when a driver conducts certain bodily motions in the automobile, takes his or her eyes off the road, takes his or her mind off the road, takes his or her ears off the road, eats something, or converses with co-passengers while driving. The suggested framework is utilized to identify behaviors performed by the driver in a real-time context.

A. Assefa explains that the World Health Organization (WHO) research estimates that millions of people are murdered on the road across the world. Motorist distraction is described as when a driver diverts their attention away from the driving process to focus on anything else. A visual distraction, a cognitive distraction, and a biomechanical distraction are the major reasons for this [6]. Therefore, the suggested work uses a stacked auto-encoder and CNN to achieve posture detection. For the aim of segmenting the driver's face and hand, an encoder stacks the hand and face localization.

C. Huang talks about how to spot inattentive drivers. There has been a lot of study done and a variety of methodologies used. CNN's or convolutional neural networks are commonly utilized for complicated image processing applications [7]. There have been some contradictions in the paradigm of picture categorization and recognition in

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recent years. Multiple approaches have been developed, including DenseNet, ResNet, VGGNet, Inception, and AlexNet. The author of the suggested study used an effective and hybrid CNN module, a feature classification module, and a feature concatenation module to accurately detect distracted driving behaviors.

B. Ashaqaqi explains that transportation networks are a critical component of human development. Long travels and fatigued conditions [8] lead drivers to become exhausted and, as a result, may cause accidents. The most common causes of accidents are drowsiness and fatigue. The suggested technology detects driver sleepiness automatically by combining visual input and artificial intelligence. The researcher introduces an ADAS (Advanced Driver Assistance System) technique to minimize the incidence of incidents caused by driver weariness and improve road safety.

M. Machaca explains that the majority of traffic accidents are caused by the driver's insufficient sleep, which causes him or her to fall asleep. To reduce traffic accidents, the authors of the proposed paper introduce a framework to detect driver drowsiness and thus reduce traffic accidents [9]. This may be done via a camera that will always retain its attention on the driver and evaluate the driver's facial structure and process the framework for sleepiness detection, alerting the driver and preventing any additional mistakes. Yawning, shifting the head from side to side, frequent flicker, and other facial expressions indicate that the driver is sleepy.

A. Riztiane explains that the rising incidence of road accidents is directly related to human mistakes, particularly tiredness. The four primary reasons for sleepiness are physical effort, time of day, work, and sleep [10]. The suggested study offered an eye blinking-based methodology in which the length and rate of eye closure are assessed to identify driver tiredness, as well as a yawning-based strategy in which a specified number of yawns is tallied as one of the symptoms to evaluate the driver's level of tiredness.

D. Artanto describes how sleepy drivers are a key contributor to traffic accidents. There have been several studies on road accidents that have found a clear link between traffic accidents and distracted or sleepy drivers [11]. They employed low-cost EMG and ESP8266 Wi-Fi modules to detect driver tiredness in the proposed work. They chose EMG over the camera because it is a simpler technique with a faster response time, allowing it to sound an alert when the driver is asleep. EMG has simply applied it to the skin around the eyelid for a low-cost solution. This produces quick and effective results.

Y. Saito [12] states that according to the latest NHTSA study fatal road incidents as being caused by the driver's tiredness. Driver monitoring systems are classified into two categories: systems that analyze drivers using direct driver-related measures, and systems that monitor drivers using indirect driving-related measures. They employed an eye blinking-based methodology that counts the blinks that are automatically recorded by the proposed system, as well as a drowsiness level based on a facial expression that is measured every 20 seconds using the Kitajima scale.

III. PROPOSED ALGORITHM

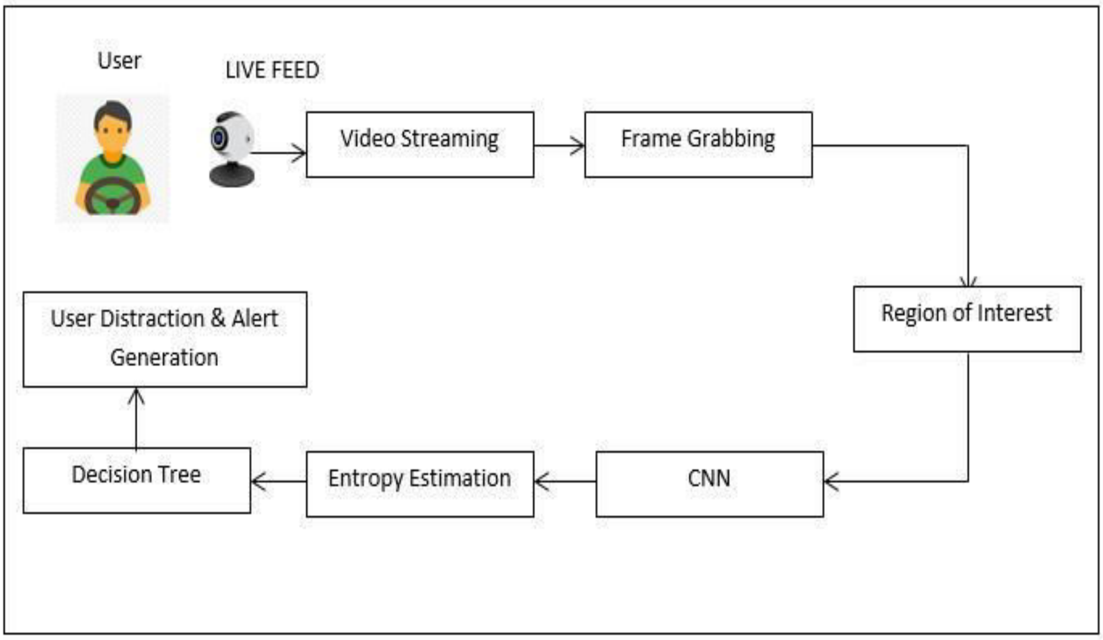

Figure 1: Proposed model for Driver distraction system

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The proposed system for driver distraction detection has been illustrated in the figure 1 given above. There are a number of steps that have been utilized for generating the system which is detailed below.

Step 1: Live video streaming and Frame grabbing:

This step deals with providing the video input to the system for the purpose of evaluation of the person's facial characteristics for any detection or identification of distraction. The inbuilt webcam or an external web camera is utilized for capturing the facial frames of the driver. The open CV platform is an open source approach that allows for the integration of these frames from the device into the Java code. These frames are effectively extracted and then resized after which they are effectively stored for further evaluation by the next module of the system.

Step 2: Region of interest for Skin:

The resized and cropped image extracted from the video streams is provided as an input to this module. This module is touched with the extraction of the main feature for the region of interest in the image. The region of interest in the image is actually the skin of the individuals face. This allows for effective processing of only e the intended part of the image easily. The image is read in an object format as a matrix of pixel values through the buffered image class in Java. The values of the pixel are utilized to determine the red Chroma and blue chroma components for the YCbCr model for skin detection as given in the equation 1 and 2 below.

$$Cb = -0.169 * R - 0.332 * G + 0.500 * B + 128 \quad (1)$$
$$Cr = 0.500 * R - 0.419 * G - 0.081 * B + 128 \quad (2)$$

The calculated values of the blue chroma component and the red chroma component are done through the red green and blue values of the pixel in the image. These values are subjected to classification where in the red, component between 177 to 137 and the blue chroma component between 127 to 77 are selected as the pixels most probably containing skin. These are selected values of the particular range are then further utilised for achieving the value of t through the equation 3 given below.

$$T=Cb+0.6*Cr \quad (3)$$

Once the value of t measured through the blue Croma component and the red Croma component is achieved, it is subjected to the above equation and utilized for the purpose of classification. The value of t in the range of 215 to 199 decides the skin pixel which is effectively extracted and converted into a pure white color. If the t value is not in this particular range then the pixel is converted to black color. Therefore this procedure is repeated consistently for all the pixels in the image until the whole image is converted into a binary image or a black and white image.

The process of Skin detection is mentioned algorithm 1.

ALGORITHM 1: Region of Interest through Skin Detection

//Input : Input image R_{IMG}
//Output: Skin Detected image S_{IMG}
// function: regionofInterest(R_{IMG})
1: **Start**
2: SIMG = ∅ , count=0
3: ***for*** i = 0 to size of breadth of R_{IMG}
4: ***for*** j=0 to size of Height of R_{IMG}
5: col = RIMG [i,j] (PIX)
6: R= col[0]
7: G= col[1]
8: B= col[2]
9: Cb = -0.169 * R - 0.332 * G + 0.500 * B + 128)
10: Cr = 0.500 * R - 0.419 * G - 0.081 * B + 128
11: ***if*** (Cr > 137 && Cr < 177), ***then***

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```
if (Cb < 127 && Cb > 77), then
    t = Cb + 0.6 * Cr;
if (t > 190 && t < 215), then
SIMG [i,j] ( PIX )=[ 255,255,255]
end if, else
S_IMG [i,j] ( PIX )=[ 0,0,0]
end if, else
S_IMG [i,j] ( PIX )=[ 0,0,0]
end if, else
S_IMG [i,j] ( PIX )=[ 0,0,0]
end if
end for
end for
return S_IMG
stop
```

Step 3: CNN First Layer:

This is one of the most important aspects of the proposed methodology which is attached with the accurate identification of distraction in the driver. For this purpose the convolutional neural networks have been utilized. This is the first layer of the convolutional neural network which converts the input facial image into a gray scale image. The change of the color along with the position of the pixels in the image is estimated against the white pixels achieved through the Mask image. This leads to an image with all the edges highlighted which generates a boundary between the colors for effective detection. The features of face such as the mouth and the eyes are well defined and can be seen clearly in the edge images.

The two images the Mask image as well as the edge image are then utilized to make the skin area clear by elimination of redundant regions and blots through traversing the image. This is done by evaluate the pixels in 8 different directions through layers of neurons. Once these positions are evaluated and the skin is cleared of the redundant values this can be provided to the next of the CNN to achieve further processing.

Step 4: Fully Connected Layer:

The image achieved in the previous step with the skin cleared off and the edge images are provided to this layer for the purpose of further extraction of facial features. This approach also utilizes previous outputs for the purpose of understanding a better output for the layer evaluation. In this step of the approach the system colors a red color to the detected skin pixels whereas provides a black color for the rest of the pixels. Once this is done the lengths of the segments of various facial features are evaluated and effectively identified for their variations and changes. This is useful as the distraction of the driver can be detected by a subtle change in the facial features which can be picked up by the system in this step of the procedure.

Step 5: Output Layer and Decision Tree:

The facial feature obtain the previous step along with the various segments of these facial images are utilized in this step as an input. These image segments of the driver's face are used to correct the light first which further improves the brighter parts of the facial features for proper evaluation of distraction. For this purpose a set of multiplier values are extracted for improving the pixel values by amending the current pixel values with these multipliers.

Once the image segments are enhanced through the multipliers and the light is corrected to identify the position of the mouth and the eyes these pixels concerning the facial features are then counted. These pixels are not accurately to the specific region and the entropy of this particular region is evaluated through this pixel count. With the entropy value of a non-distracted face being a benchmark for providing the thresholds to the exam rules of decision tree the obtained values are effectively classified for the distraction detection and a suitable voice alert is raised when the distraction is detected.

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IV. RESULT AND DISCUSSION

The proposed system for effective driver distraction identification through the use of convolutional neural networks has been achieved in in the Java programming language. The laptop used for the development of this distraction detection methodology is equipped with an Intel core i3 processor which is supplemented by 500 GB of storage and 6 GB of RAM. The open source library called open CV has been used to integrate the image capturing mechanism to capture the facial images and provide it as a input to the system.

For the purpose of achieving the performance metrics of the proposed methodology the precision and recall parameters have been assigned. The extraction of the performance of this approach is necessary to quantify the accuracy of the distraction detection methodology which is being developed through convolutional neural network and decision tree algorithms. The measurement of the accuracy of the approach will be useful in determining if these algorithms have been accurately implemented which will be evident through the scores achieved by the precision and recall metrics.

Performance Evaluation based on Precision and Recall

The performance metrics through precision and recall have been assessed through the use of inductor experimentation that has been performed on the proposed methodology. These performance parameters are useful in determining the real accuracy of the evaluation and the actual performance of the methodology. The driver distraction detection is highly useful and can only be viable with a respectable accuracy of the identification through the methodology prescribed in this research paper.

The in-depth information regarding the performance of the approach has been achieved through the precision and recall parameters where each of these parameters are useful in identifying a different aspect of performance of the methodology. The precision parameter is useful for determining the relative performance of the distraction detection on the other hand recall extracts the absolute accuracy for the driver distraction detection.

The precision for this methodology has been conceived as the division of the number of accurate driver distraction identification by the total number of expected driver distraction detections. The recall parameter is on the other hand the absolute accuracy which is derived by the ratio of total number of driver distraction detection versus the total number of expected driver distraction detections.

This has been mathematically conveyed through the equations 4 and 5 given below.

A = The number of correctly identified Driver Distractions
B= The number of incorrectly identified Driver Distractions
C = The number of Driver Distractions not identified

So, precision can be defined as
Precision = (A / (A+ B)) *100
Recall = (A / (A+ C)) *100

The in-depth experimentation done on the prescribed approach for the measurement of precision and recall parameters has been listed in the table 1 below.

No. of expected Distractions	The number of correctly identified Driver Distractions (A)	The number of incorrectly identified Driver Distractions (B)	The number of Driver Distractions not identified (C)	Precision	Recall
35	28	3	4	90.32258065	87.5
59	49	6	4	89.09090909	92.45283019
88	70	9	9	88.60759494	88.60759494
121	100	10	11	90.90909091	90.09009009
138	110	15	13	88	89.43089431

Table 1: Precision and Recall Measurement Table for the performance

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of Driver Distraction Detection

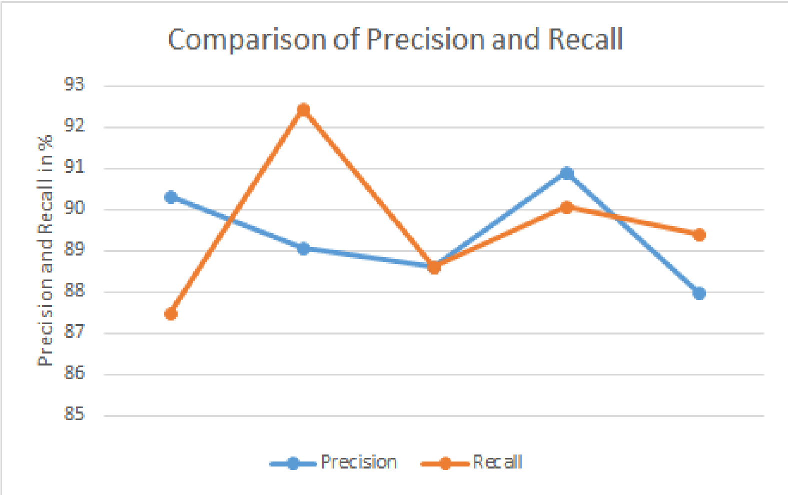

Figure 2: Comparison of Precision and Recall for the performance of Driver Distraction Detection

The outcomes achieved in the table are effectively used to draw a plot graph for precision Andre call parameters for graphical representation in the figure 2 above. As it is evident from the tabulated values and the outcome of the line graph, that the precision and recall parameters achieved for this methodology are well within respectable limits. The value of precision and recall as 89.44 and 89.17 are indicative of an accurate implementation of CNN and decision tree approaches that have been utilized for accurate driver distraction identification in the proposed methodology.

V. Conclusion And Future Scope

The proposed technique for distracted driver detection through the utilization of convolutional neural networks and decision tree has been elaborated in this research article. The driver distraction detection mechanisms that are currently in practice are highly expensive or difficult and invasive ways to implement the approach. This makes it highly difficult for achieving a reduction in the casualties achieved due to the accidents caused by distracted driver. Therefore this methodology utilizes a video stream input which is provided as a input to the proposed methodology through the use of the open CV platform. The frames from this video stream containing the official images of the driver are extracted and resized before being provided to the region of interest evaluation module. This module effectively forms region of interest identification through the use of skin detection by the YCbCr color model. Once the skin has been identified the image is converted into black and white image with the white parts being skin and the black parts being known skin and provided to the next module for evaluation. The CNN module performs effective image segmentation and facial feature extraction through edge formation and provides these values for the entropy estimation. The entropy achieved by this procedure is there effectively provided to the decision tree for threshold evaluation for the distraction detection through the if-then rules designed for the approach. Once a driver is detected to be distracted a voice alert is generated alerting the same. The driver distraction identification approach has been effectively quantified through the use of precision and recall performance metrics which have achieved acceptable levels of accuracy.

The driver distraction approach prescribed in this research can be further augmented in the future research is through convergence of the methodology into an API for easier integration into existing systems.

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