Smart Duo-V-senseNet (SDVN): End-End Integrated Attentive System-Driven ADAS Solution

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Abstract*—The Advanced Driver Assistance (ADAS) platform and its essential features provide a better safe driving dynamics with fewer road accidents. Advanced features of ADAS is frequently seen in the high-end automobiles. Advanced ADAS features such as *lane assist, automatic night vision, collision alert, smart speed mapping, adaptive cruise control, blind spot monitoring, driver risk analysis* are often seen in high-end vehicles. Such a proactive mechanism not only alerts the drivers in threatening situation but also would enable them to respond with immediate actions. Significantly, this features with L4/L5 levels of autonomy provides better precision in a well-structured, disciplined road traffic conditions as seen in most western road traffic. However, the complete deployment of L3/L4 and its caliber itself still remains as open challenge in heterogeneous, chaotic and less-disciplined road traffic environments as seen in Asian countries such as India. In this regard, this paper aims to propose an advanced integrated bi-directional network *Smart Duo-V-senseNet (SVN)* for safe recommendation engine designed for Indian road traffic conditions. Potentially, with the increasing demand of bringing in smart transportation solutions for Indian automotive sector, advanced technologies such as *computer vision & machine learning* would benefit efficient and reliable real-time deployments. This proposed work discuss the data fusion of multi-modal sensor system for integrated In and Out Driver and vehicle analysis with state-of-the-art results that achieved overall 87% in road segmentation. Further, it helps in developing a real-time recommendation system with (L3/L4/L5) levels of autonomy. subsequently, this system-driven solution assists the driver with accurate safer warnings/ recommendations such as lane assist, accelerate/decelerate, safe drivable area navigation scanning from different heterogeneous vehicle, road traffic environmental parameters in less-disciplined traffic scenarios.

Key terms: ADAS, Computer Vision, Machine Learning, Recommendation Engine, Smart Duo-V-senseNet (SVN), Smart Transportation.

I. INTRODUCTION

The growing numbers of road traffic fatal accidents is todayś primary concerns of automotive sectors to bring in ADAS features that could assist the drivers with reduced collisions. As per WHO, it is reported that approximately 1.4 millions of traffic participant die every year in accidents [1]. Of these, most of the influencing factors were found due to the distracted drivers behavior(Human-citric and/or cognitive), less-disciplined traffic with susceptible traffic users. Road traffic accidents were analysed with respect to nature of the road, vehicle type, person cognitive aspects etc. As stated by Ministry of Road Transport and Highways (morth), Govt of India [2], it is observed that the fatalities were caused due to many road parameters such as extremes curved roads, potholes etc. Curved road accidents increased from 5k in 2016 to 18k in 2017 whereas, pothole based accidents increased from 2324 (2016) to 3597 (2017). Road safety awareness alone cannot bring in potential change to avoid such accidents but demand the advanced monitoring solutions. Subsequently, other vehicle parameters like speed, proximity, sensor based assistance etc shows a differential impact over vehicular control aligned to road types. For instance, light motor vehicles(LMV) such as cars, jeeps etc reported with an accelerated collisions from 113.3k (2016) to 113.7k in 2017. Heavy motor vehicles (HMV) such as trucks etc ended with increased fatal collision numbers from 30.9k in 2016 to 33.7k in 2017. Similarly, other cognitive inspired driver distraction based collisions such as improper lane following, drunken drive, mobile phone usage etc resulted in overall 327.45k road accidents.

Importantly, this figures as discussed above due to various internal and external parameters in road traffic environments motivated us to propose an efficient robust real-time recommendation engine *Smart Duo-V-senseNet*. Significantly, this could consider both driver in-vehicle and external road vehicle, traffic parameters towards analysis in less-disciplined traffic environments. The next subsection clearly explains the problem statement, key contributions and organization of the paper.

A. Problem Statement:

To develop a Real-Time Driver Assistance/Recommendation System for Drivers in Indian traffic conditions (SMART Duo-V-senseNet) that would assist the human drivers driving the vehicles in less disciplined, constrained and unstructured road environment for chaotic Indian traffic.

The key contributions in this paper were discussed as follows:

1) The novelty in this proposed architecture is that most of the existing solutions provide a functional specific solutions in ADAS considering individually either for in or out-vehicle entities missing the integrated.
2) Potentially, proposed architecture focus on Duo sensing mechanism based recommendation of safe warnings having both in and out driver, vehicle parameters in heterogeneous road traffic. This could further help in rigorous monitoring of drivers driveability integrating both in and out vehicle data.

3) Novel Dataset for road traffic multi-classification based analysis of driverś distraction based on their spatio-temporal action units.
4) Multi sensor data fusion to monitor and understand the vehicular behaviour with complex traffic density in less-disciplined chaotic road traffic scenarios.
5) Various real-time In-vehicle and Out-vehicle parameters were considered.
6) Decision tree modelling to classify safe/un-safe driving patterns from mixed drivers action sequences.

The In-Out vehicle parameters considered as part of proposed analysis in this proposed work are listed as follows:

In-Vehicle Parameters:

1) Driver Head Pose
2) Driver Eye-Gaze patterns
3) Driver Actions for distracted behavior analysis

External Road Environmental Factors/ Parameters:

1) Lane Detection and Tracking Analysis (Marked vs Un-marked roads)
2) Obstacle Detection & Safe warnings
3) Distance Estimation for collision avoidance with warnings
4) Relation mapping in collision avoidance based on decision rule set

The organization of rest of the paper is as follows:

1) Section II highlights the existing research contributions and key gaps.
2) Section III focus on novel Dataset, Implementation details of the proposed Smart Duo-V-senseNET (SDVN) for real-time deployments and safer driver recommendations.
3) Subsequently, the section IV highlights and illustrates the state-of-the-art results.
4) Finally, the last section V concludes the proposed work providing the next future research directions. Also, the possible enhancements are discussed with an aim to greatly benefit both the research community working on connected vehicles, vehicle platooning etc and other advanced Indian automakers.

The next section highlights the major driver assisting features, sensing mechanisms and real time road traffic challenges in Indian road scenarios bringing in the real need for an advanced real-time driver assisted system.

II. Related Work

This section discuss about the advanced ADAS features and on-going projects, embedded components, vision based algorithms and techniques for road free-space derivable area segmentation, obstacle detection. Further, the multi-sensor mechanism with data fusion such as RADAR, LIDAR, Bluetooth, Radio frequency signal communications etc were discussed with various real time Indian road traffic challenges. However, the integration and deployments of such components with advanced features of L3/L4 levels of autonomy [3] for Indian road traffic conditions still takes considerably longer time.

ADAS and its Projects:

There are a lot of Driver assistance systems available and already working with ready-made solutions. ADAS deals with driver assistance solutions as illustrated in Fig. 1 below.

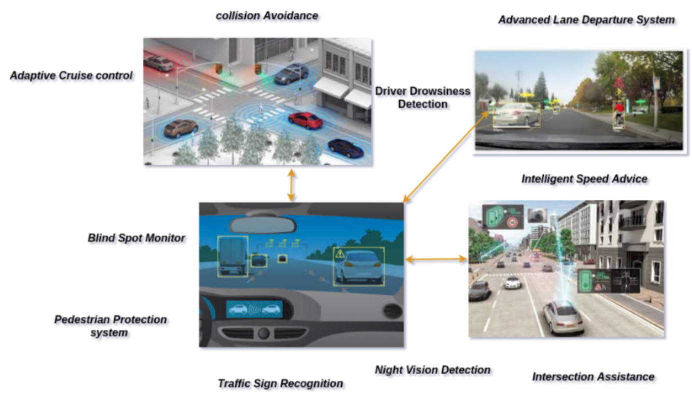

Fig. 1: Illustration of various ADAS features

1) Mobil eye [4] is the global leader in the development of vision technology for Advanced Driver Assistance Systems (ADAS) and autonomous driving. Mobile eye is the first company to introduce to OEM production world a vision only forward collision warning system for multiple vehicles. Its developed with an EyeQ vision processors that perform detailed interpretations to anticipate possible collisions. Mobileye is currently developing its fifth generation SoC, the EyeQ 5, to act as the vision central computer performing sensor fusion for Fully Autonomous Driving (Level 5) vehicles that will hit the road in 2020.
2) Autolic inc [5] developed a forward-looking mono vision sensing system for BMW. its alarms a driver to an imminent collision with vehicles in front and unintentional lane departures.
3) WABCO [6] improves safety contributing to driver effectiveness. It offers adaptive cruise control, active braking, etc.
4) Hyundai MOBIS [7] seeks to make ways for vehicles to be more advanced and intelligent by producing ADAS and driving parts of hybrid vehicles.
5) Carsafe [8]: its a driver safety application for android phones that detects and alerts drivers in case of dangerous driving conditions and behaviour. It uses computer vision and machine learning algorithms to monitor and detect drivers distraction.
6) iOnRoad [9] is an android and IOS based application

that provides a range of personal driving assistance functions including augmented driving, collision warning and black-box-like video recording.

7) DriveSafe [10] is a driver safety application for i phone base devices that detects inattentive driving behaviours and gives responsive feedback to drivers.
8) Walksafe [11] is an Android-based application that aids people that walk and talk, improving the safety of pedestrian mobile phone users. Its uses machine learning algorithms to detect front and back views of moving objects.

1) Multi-Sensor System for ADAS: Recently, due to the advent of self-driving vehicles and road safety applications, multi-sensor data integration for advanced driver assistance systems (ADAS) in the automotive sector has gained much attention. For instance, RADAR sensing in smart transportation systems provide dynamic safe assistance that enable drivers look through the vehicles electronically for complete perception of obstacles. These RADAR mechanism were further categorized as short, medium and long range sensors based on its range coverage. These sensors are actively used in many ADAS application such as blind spot monitoring during intersections, parking and breaking assist, collision control etc. Most of the current available sensor system are based on 24 GHz or 77 GHz. LIDAR (Light Detection and Ranging) sensing systems that typically works based on light waves information. However, the efficient and optimized design and development to handle fusion of sensor information, processing and computational process is still in research phase. For instance, Lidar system such as [12] costs about 7999 USD whereas, the radar costs around 2050 USD approximately. Such initial huge investment might not support most of the start-ups and mid-range auto-manufacturers. Due to these various challenges needs to be addressed specifically for Indian auto-sector considering the following aspects: Deployment, usage, cost and integration. Investing such big amount in embedding advanced 360 degree monitoring sensors [13], [14] is difficult for both automotive sectors and mid range public in developing nations that highly demands an alternative yet effective affordable solutions. Other general tri-axial sensor systems such as *Accelerometer, Gyroscope* and *GPS sensing information* for location tracking etc would help the computational deep learning and machine learning algorithms to investigate the driver and vehicle behavioural patterns in national and state highways, rural, urban, semi-urban and intersections.

2) Vision Intelligence for ADAS: The sensing mechanism as seen with respect to RADAR and LIDAR analyse and perceive the environment virtually based on the distance and target ranges. These may not be appropriate and lacks its full potential under certain challenging road traffic (mixed traffic) and climatic conditions (sunny, rainy, foggy and snowy). One cannot increase the number of multiple senors deployments just to increase the capability of multi-sensing within vehicle, In such situations, camera/vision based sensors will play a prominent role in complete external and in-vehicle analysis of driver. Camera sensors are again categorized based on requirements such as kinetic, depth, monocular, fish-eye, NIR, FIR and Dashcam with RGB, RGBA and RGBD channeled sensing mechanism. For instance, in-vehicle driver distraction analysis may require complete visual perception of driver actions, eye gaze estimation for monitoring and ranking of drivers drivability. These vision based sensor traffic sign boards, traffic lights and other entities that helps in safe recommendations/warnings for drivers. In most of advanced prototypes, test beds such as Google Waymo, Telsa self driving vehicle, high end vision sensors have been embedded for complete understanding of road traffic situations. In this proposed work, we make use of vision based camera sensors, calibrating them for undistorted information.

Segmentation talks in computer vision is further divided in to image based and semantic based segmentation. In the existing literature, few works on segmentation were discussed as follows [15]–[20]. Specific tasks such as drivable area segmentation, obstacle detection requires optimized advanced algorithms.

3) Indian Road Traffic Challenges: The road, vehicle and driver parameters collectively helps in the robust recommendation system to have an integrated analysis of drivers drivability patterns and vehicular behavioral analysis. Significantly, such parameters include vehicle proximity, longitude and latitude values, tri-axial accelerometer signals, gaze and head pose estimation of in-vehicle traffic participants. Deployment of an advanced ADAS features with L4/L5 levels of autonomy have seen a significant impact in well-structured road traffic environments with proper lane discipline. But, in case of Indian road traffic environment, various challenges need to be considered and addresses as listed below:

1) Paved/Un-paved roads
2) Dealing with unstructured/chaotic road traffic
3) Heterogeneous conditions
4) Vehicle types (LMV, HMV... etc)
5) nature/ type of roads (texture, muddy, asphalt, concrete, gravel etc)
6) Broken dividers/potholes (depreciation analysis)
7) Road structures (fly-overs, intersections, one-way with bi-directional flow of traffic etc)
8) traffic participants (pedestrians, cattle, animals etc)
9) traffic entities (traffic sign boards, traffic junction markings, lights etc)

Expecting the fully L5 autonomy with advanced ADAS functionality for such Indian road traffic environments is challenging and time taking. Subsequently, in order to achieve system assisted driving to avoid/reduce the road accidents that occur due to various in-vehicle driver cognitive error or other external road traffic parameters, these *Smart Duo-V-sensNet* was proposed. The design and development of our proposed recommendation engine *Smart Duo-VsenseNet* addresses considering most of the above mentioned challenges for Indian road traffic environments for safe driving experience. The next section discuss on Datasets, proposed architecture and also explains the workflow in-detail.

III. Proposed Methodology

An efficient design, implementation and real-time deployment of a recommendation system is challenging task. Further, it is expected that the recommendation engine provides dynamic warnings based on In-Out vehicle parameters. The proposed system was designed making use of advanced computer vision algorithms, machine and deep learning mechanism to meet and address the above mention Indian road traffic challenges. The real challenge is to handle real-time heterogeneous data streams and also introduce new alternatives for optimized recommendation system with enhanced driver safety. This section explains the Data-sets, pre-processing mechanisms and proposed architecture with clear workflow of integrating multiple networks and decision tree modelling.

1) Data-set & pre-processing: For the experimental purpose, we choose two different datasets that are made publicly available. The In-vehicle driver distraction analysis was completely built from scratch. The dataset considered as part of this experimental analysis were Kitti [21] and IDD [22]. The details of datasets along with their key concerns were discussed below.

A. Dataset Description

1. Kitti Road segmentation dataset:
Kitti road dataset was basically constructed to provide with the road segmentation challenge. The main aim was to find the drivable area free space. Here, the dataset has data for both road and lane estimation consists of 289 training and 290 test images. The kitti dataset is provided with segmentation ground truths (masks) for training samples. It is further divided in to three different categories of road scenes understandings:

1) Urban Unmarked - total 98 instances
2) urban marked - total 95 instances
3) urban multiple marked lanes - total 96 instances

Few samples of Kitti road segmentation dataset is as shown below in Fig. 2. Original image with the corresponding ground-truth information.

Challenges: The kitti road segmentation is having very limited dataset. These data samples are not sufficient enough to train any good machine learning/ Deep learning model. These kitti dataset had been captured with in and surroundings of Karlshue in Germany. Notably, all the samples were observed to be captured in good day light road driving scenarios. These will restrict the scope of any computational model to learn variations of data with respect to different traffic and climatic conditions. This motivates us to think of dataset that introduces varying driving scenarios. Also, the dataset have been constructed with RGB channeled information missing Alpha and Depth channels in case of depth analysis.

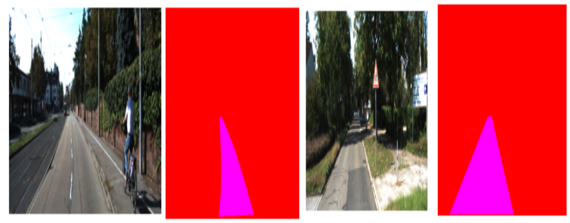

Fig. 2: Illustration of Kitti road segmentation dataset instances

2. IDD segmentation dataset: As mostly observed, standard available public datasets in the space of autonomous driving such as Cityscapes [23], Camvid [24], Nuscenes [25], BDD [26], Mapillary [27] and Waymo [28] etc, have been marked for its decent, constrained driving in well structured road traffic conditions. Less disciplined road traffic and lane keeping along with unconstrained, heterogeneous driving scenarios is specifically seen in Indian driving environments. The Indian Road Driving Dataset (IDD) dataset have been released in 2018 for segmentation and obstacle detection tasks. The dataset was majorly captured in and around the Hyderabad and Karnataka cities. Initial release of the segmentation IDD dataset have in total 10,003 instances. Further, the dataset is split to 6,993 training, 981 validation and 2,029 test samples. These dataset was the first dataset that was released specific to Indian road driving sequences. IDD segmentation dataset totally has 34 classes. Out of which we will be considering only the road class as a primary interest towards the analysis of road drivable area segmentation and navigation. A few samples before and after preprocessing of the colored RGBA mask were shown below in Fig. 3.

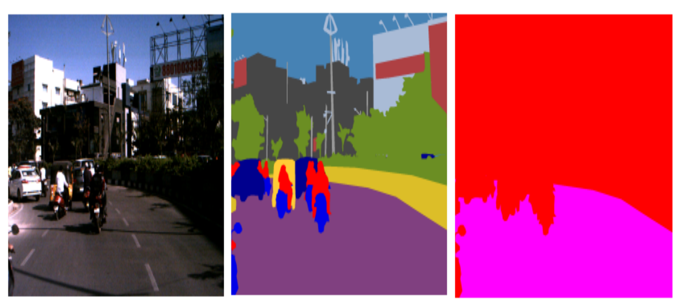

Fig. 3: preprocessing of data for road class - class wise pixel comparison

The state-of-the-art score for road class was reported with 92% mIoU [29]. The other reason on selecting this IDD dataset compared to Kitti was it has the driving sequences captured with an unconstrained road traffic environments. IDD dataset is of 32 bit depth with RGBA channeled information.

3. Driver Distraction Custom dataset: These dataset was one of the contributions as part of this work. Initial Experimental setup in capturing the data is as follows:

1) Camera 1: Captures the driver's front perspective inside the vehicle.
2) Camera 2: Captures external entities such as roads, barriers, etc.
3) Camera 3: Captures the drivers actions from cross view perspective to predict the drivers attention and drive-abilty.

Most of the existing literature such as [30]–[36] have been proposed to deal with driver distraction on drowsiness parameter. However, driver distraction analysis in view of their cognitive actions is still in research phase. In general, driver distraction can be caused due to human-made errors like lane departure, wrong driving or even due to cognitive distraction while performing some actions like mobile usage etc. Typically, the system must be capable of handling any such mentioned parameters and decide the critical levels of safe/un-safe driver drivable patterns. Notably, many other vision based challenges do occur while capturing the data. For instance, texture of the skin, illumination, occlusion geometric and photo-metric challenges based on demographic regions and other specular reflections on driver spectacles. However, to address such real-time challenges data captured needs to have multiple variations. As part of this work, the dataset for in-vehicle driver distraction have been constructed, pre-processed carefully avoiding missing information and/or other distortions. Few samples of driver distraction custom dataset is as shown below in Fig. 4.

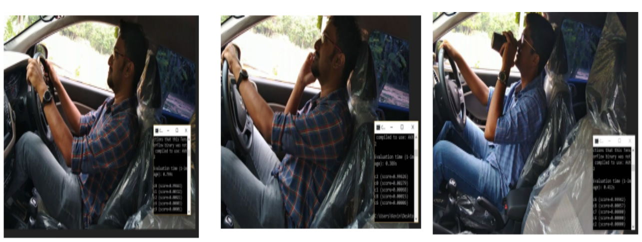

Fig. 4: Illustration of few samples from custom dataset

The dataset provides with multi-classification problem in total of 10 classes as shown below:

1) Safe Driving
2) Texting right
3) Talking on phone right
4) Texting left
5) Talking on phone left
6) Operating an Audio system
7) Drinking
8) Looking behind
9) Grooming
10) Talk to co-passenger

All the above mentioned classes have been chosen based on possible distraction caused due to cognitive imbalances of driver. These data helps in effective modelling of in-vehicle drivers behavior and monitor driver distraction to alert and further recommend with safe/ danger driving situations.

3. Sensor Information: The sensor readings such as tri-axial Accelerometer, GPS and Gyroscope helps in proper analysis of vehicular behavior, analyse the turn patterns and recommend the driver during intersections. However, data from single source is not sufficient. In this work, we captured the tri-axial sensor readings in parallel to vision sensor data. To avoid the correspondence issues, further moving averages of sensor data have been computed. With regular time stamps of every 20 m/s of the sensor information covers 6 frames approximately. The tri-axial information x, y and z provide the vehicle motion. As part of the data capture, G-Sensor Logger android app [37]was utilized to capture and store the sensor readings. Illustration of sensor reading in capture as shown below in Fig. 5.

Fig. 5: Illustration of tri-axial sensor readings

B. Proposed Architecture Smart Duo-V-senseNet (SDVN)

With an intention to provide integrated approach to deal with complete driving environment collectively In and Out space for perception and analysis. The following architecture was proposed.

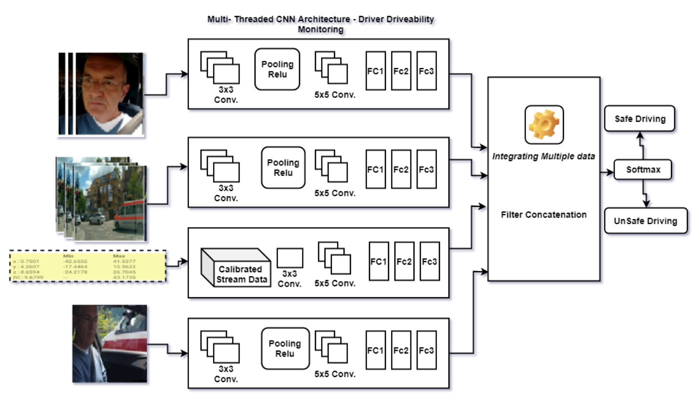

Fig. 6: Proposed Smart Duo-V-senseNet

Multi-Threaded Network flow of proposed architecture is observed in figure 6. Since, most of input streams come from different sources, the camera devices would lead to distortions. Camera calibration is component of the pre-processing process used to calculate the coefficients for real-time alignment in 3D world. Firstly, network rely on extracting features from geometric facial elements and feeding into the network to get feature descriptor/vector. Secondly, it is used to extract the features of obstacles such as vehicles, lane markings or other road environmental factors. Third network is intended to fetch the calibrated version of accelerometer sensor data readings. Mapping sensor data readings with respect to the time stamps of each frame from the input video stream should be used to avoid correspondence issues. Finally, the last network is used to analyze in-vehicle actions of the driver to predict the attentive nature of the driver for safe driving scenarios and to recommend/warn if any unsafe actions are observed. All feature vector concatenation would be introduced for each sub-task. Softmax classifier is then used to predict the safe/hazardous driving environment for collision-free driving. Finally, a rule-based engine such as the decision matrix to analyze and classify the driver attentiveness for safe or critical driving patterns aligned with dynamic changes in the driving environment.

C. Decision-Tree Modelling

To achieve the effective driver monitoring, rule-based engine such as the decision matrix modelling is required further to analyze and classify the driver attentiveness for safe or critical driving patterns aligned with dynamic changes in the driving environment. In the above Fig. 7, a decision tree for driving behavior analysis is modeled. Further a decision tree used to rate the drivers performance during an activity. For each case, details shown in the middle dashed boxes are considered as the variables. Such variables acts as the decision tree inputs. The decision tree outputs are based on each event combinations. For instance if the driver accelerates more during the turns/intersections, an aggressive turn action event is registered. For the turning event, A1 represents the difference between vehicle speed and speed limit. A0 checks the smoothness when making the turn. A2 measures the level of the turn. A3 and A4 represents whether the driver includes side mirror and blind spot check, as well as the turn signals.

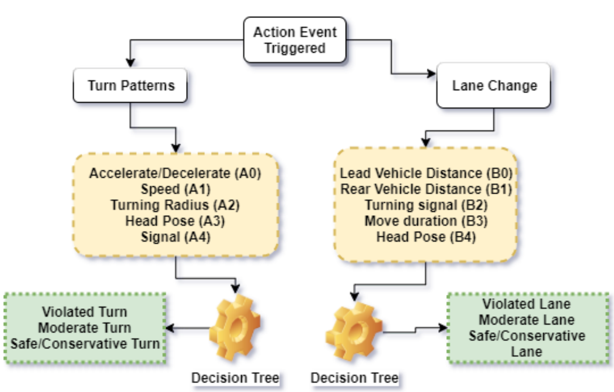

Fig. 7: Decision tree modelling

Parameters B0 and B1 represent the front and rear vehicle distances in the next lane. B3 describes how long does it take to finish the lane change. Distance is set based on pre-defined threshold. B2 and B4 describes the usage of the turn signal and whether the driver checks side mirrors and blind spots. Significantly, all these combinations of action events triggered during driver evaluation helps in complete monitoring and providing dynamic recommendations/predictions for collision free road driving environment. The next section discuss on our results.

IV. Result Analysis

This section represents and illustrates the results obtained. Initially, road segmentation task have been carried out for efficient analysis, visual understanding of the road traffic. This helps in predicting the free space (drivable area) for recommending the collision free driving. For segmentation training purpose, Unet and FPN models have been with learning rate of 0.001 & 0.005, optimizer is Adam, backbone network is Inception resnetv2 and trained for 50 epochs. The model have been trained using Nvidia RTX 2080 GPU. The resultant mIoU scores obtained by training and testing on kitti, training and testing on IDD as shown in Fig. 8 and their illustrations are shown below in Fig. 9.

No	Data set	Split	Model	Hyper-parameters	Train Loss	Train Accuracy	Val Loss	Val IoU	Tested on	Test Loss	Test mIoU	SOTA
1.	Kitti	Train - 289 Test - 290	FCN	vgg16 #Epochs(100) Opt: SGD LR: 10^{-4} Momentum-0.9	0.1073	0.9037	---	---	kitti + few samples of IDD	0.026	93%	97%
2.	IDD	Train (70%)-9805 Val (10%)-1401 Test (20%)-2802	Unet	Resnet34 #Epochs - 08 Opt - Nadam LR: 0.002 Dim: 512 x 512 Loss: bce_jaccard Metric: IoU	0.2331	0.8542	0.2973	0.8136	IDD	0.23	87%	
3.	IDD	Train (70%)-9805 Val (10%)-1401 Test (20%)-2802	Linknet	Resnet18 #Epochs - 04 Opt - Nadam LR: 0.002 Dim: 1024 x 512 Loss: bce_jaccard Metric: IoU	0.6743	0.5752	0.7226	0.5568	IDD	0.66	59%	92%
4.	IDD	Train (70%)-9805 Val (10%)-1401 Test (20%)-2802	FPN	Resnet101 #Epochs - 02 Opt - Nadam LR: 0.002 Dim: 512 x 512 Loss: bce_jaccard Metric: IoU	0.3172	0.8069	0.4571	0.7331	IDD	0.377	78%	

Fig. 8: mIoU score obtained for kitti and IDD datasets

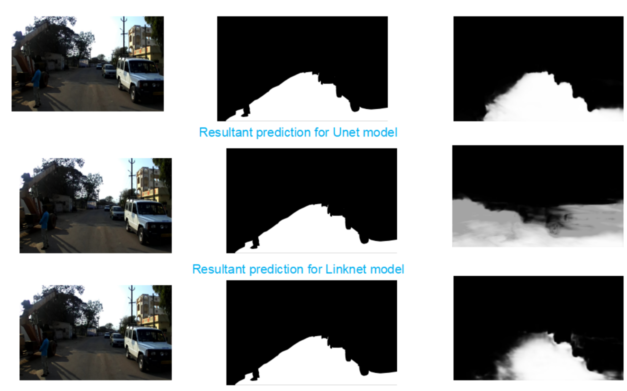

Fig. 9: Illustration of resultant predictions with three different models

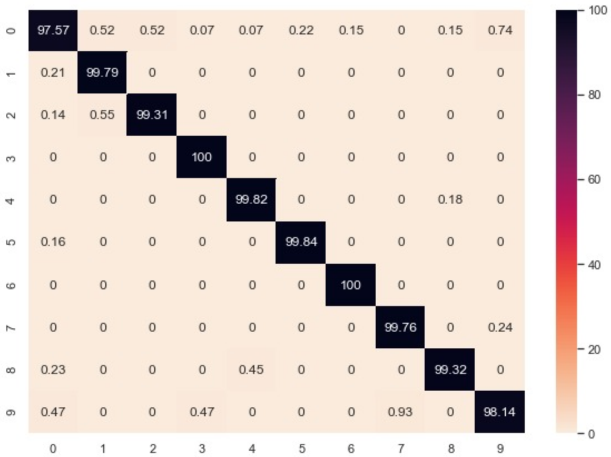

Fig. 10: resultant confusion matrix for driver distraction analysis for 10 classes

In-vehicle driver distraction analysis: For the driver distraction monitoring, own custom dataset have been used for training and testing. The resultant confusion matrix with respect to 10 classes and visualization of results are shown in Fig. 10.

V. Conclusion & Future Research Directions

The novel Smart Duo-V-senseNet have been proposed for providing real-time recommendations to driver in unconstrained, heterogeneous and chaotic road traffic conditions. Initially the need for such reliable architecture was discussed. Later, the impact of camera vision based sensors and other hardware equipped sensors have been compared. The architecture was explained on how each stream of network flows with respect to the diversified data and later concatenate the network with data fusion. Further, decision tree modeling is introduced to analyse all the possible action events by the driver. These will in turn analyse the drivers drivability with respect to vehicle type and different road traffic environments. The results achieved for road segmentation is closer to the state-of-the-art. The driver distraction analysis was trained and tested which gave us a decent accuracy score of overall 99.3%Ḟurther, as part of next research direction and enhancements of this proposed work would be focusing on lane estimation, obstacle detection with distance estimation. finally, conclude that this proposed work would motivate and bring in great benefits to the startups in automotive sector and other research communities working towards system assisted or autonomous driving.

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