

Public Opinion Analysis of Road Accidents & Review of Conventional and Combinational Driver Safety Methodologies with Self Learning Algorithms

Tamilarasi A¹, Sivabalaselvamani D², Rahunathan L³, Adhithyaa N⁴

¹Professor, Department of Computer Applications, Kongu Engineering College, Perundurai, Erode, India.

²Associate Professor, Department of Computer Applications, Kongu Engineering College, Perundurai, Erode, India.

sivabalaselvamani@gmail.com,

³Associate Professor, Department of Computer Applications, Kongu Engineering College, Perundurai, Erode, India.

⁴Junior Research Fellow, Department of Computer Applications, Kongu Engineering College, Perundurai, Erode, India.

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Abstract: Advanced driver assistance and accident detection system is significantly needed to ensure safety for drivers. Drowsiness detection, collision detection and various driver alert systems have penetrated into market with an aim to provide higher security for driver but due to population of vehicle and modification in structure of roads these system fails to answer safety problems that results in severe accidents. In this paper we provide accurate analysis of past recorded accidents in Tamil Nadu state and analysis of public opinion on Accident detection system is carried out using 1004 licensed persons under different ages in three cities (Coimbatore, Erode and Nilgiris) by focusing the major 10 parameters carrying 48 Questions. Findings and implications of this analysis is also discussed in this article. A thorough analysis of recent techniques that are used for AAD (Automatic Accident Detection) and road safety programmes that resolve the pre and post cautionary concerns of accidents in developing countries is addressed with the review of most 4 influencing algorithms in ITS for AAD. 1 Vehicle Detection using Wheel arc Counter Detection Algorithm, 2 Enhancement of V2X Communication using Multi-RAT, 3 Road Curvature Estimation using Circle Fitting Algorithm and 4 Driver Safety System is discussed in this paper. To understand recent computational challenges and extended areas of research in ITS, a hybrid approach of CNN with VANETs for accident detection has been suggested to enumerate the obtained accidental information.

Keywords: - Public opinion, Accident detection, Traffic detection, V2X, Autonomous vehicles, CNN and VANETs

1. Acknowledgement

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2. Introduction

India is a populated country that has second largest road transport network with around 1,15,435 km [82]. As usage of road transport is high, maintenance is also extremely high. One of the key problems in the maintenance sector that is still not adequately handled by transport is maintaining road safety, which results around 1.77 lakh deaths per year in Indian road that is very higher than the number of deaths of all Indians in all wars [81]. It shows that more concentration is needed to avoid accidents.

Driver alert system provides alerts to driver but there are very few systems that provide accident assistance. Reporting the incident to the concerned team with conditioned information is the matter of emergency in accident conditions. Sensitive information has to be passed to the nearest ambulance, health center, police station and the fire station if needed. Vehicle information that caused the accident, details of the driver and severity of the incident are to be transmitted for further action. The incident is considered to be sensitive based on the severity. In 90% of cases, the severity is defined with heavy weighted parameters like speed, angular velocity and direction of the source vehicle and target obstacle. Wu et al, considers Intersection, Distance and Speed-Distance for evaluation of vehicle-pedestrian near crash prediction [85]. We consider 10 major parameters for public opinion analysis, Weather conditions, Road conditions, Driver fatigue and drunken driving, Excessive speed, Vehicle faults, Animal collision, Distracted driving, Young aged driving, Unexpected lane changing and Red light jumping.

The paper is structured as, Public opinion analysis with history of road accidents in Section II followed by section III with a defined relationship, devices, various techniques and algorithms involved in accident detection and prevention. Section IV provides the suggested hybrid approach, Section V portrays results and discussion and Section VI is conclusion.

3. Public Opinion Analysis with history of road accidents

There are several researchers working on crash prediction to link real-time crash chance with traffic and roadways. Based on the motivation of reducing road accidental death that occurs in Indian roads and as the revision on technologies on VANETs and Machine Learning grows it is strongly believed that applying those will resolve the problem but due to huge road users and road structures it is not that much easy thing to implement in Indian roads. In order to identify the exact reason for accidental deaths, data was collected from 1004 road users out of which 382 female users and 622 male users. We have also collected many repository data from police department and Health & welfare department.

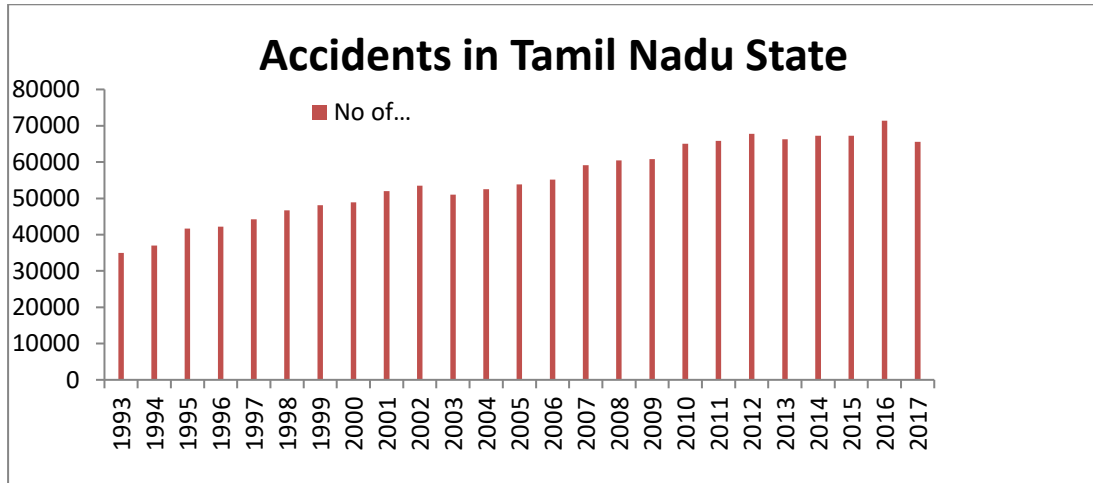


fig. 2.1.

The total number of accidents in Tamil Nadu urban and rural roads, which are recorded with SCRB, Chennai (responsible for data in police department) is shown in figure 1 which has the highest of 71,432 accidents in the year of 2016 and upon that the count is in and around 75 thousand approximately which is found once discussing with the police chief.

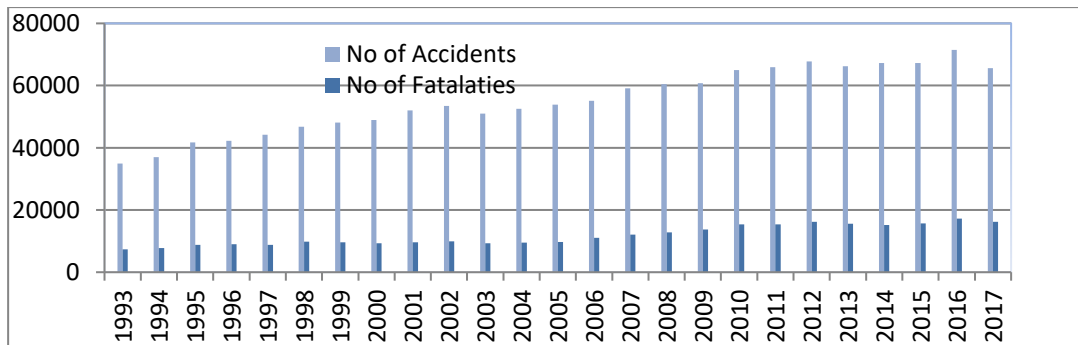


fig. 2.2

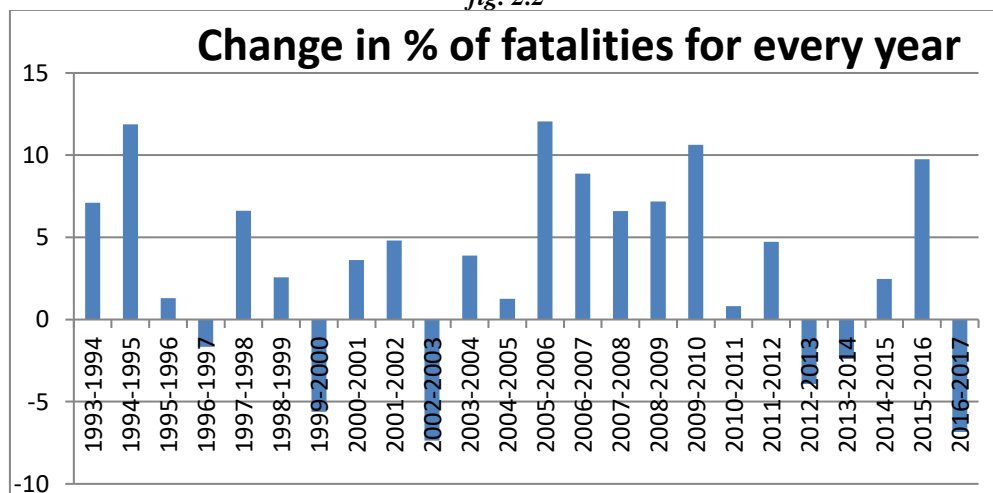


fig.2.3.

It is observed that, there is a steady increase in the growth of fatalities due to accidents of 3.2% as an average of every year. 2003 has around 7% lowest death rate recorded compared to 2002 has been seen as good scenario and it was not maintained because in the next consecutive year of 2016 it has found that 12% of increase compared to 2015. From this implications it can be concluded that the death rate due to accidents will vary accordingly year by year based on several parameters.

We classify accidents into four types based on injuries occurred in accidents, Fatalities, Severe injuries, Minor injuries and non-injuries.

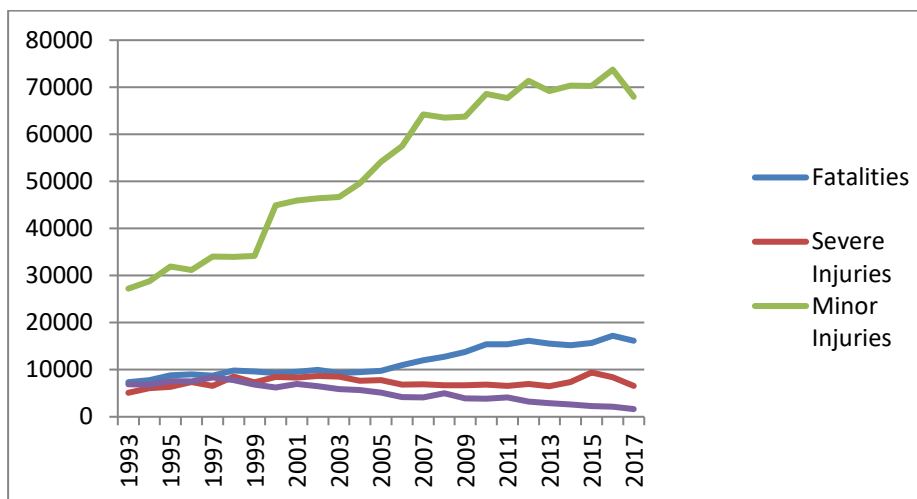


fig 2.4.

As compared to any other three factors, minor injuries are higher which also denotes that the accidents are still happening even after this much researches and implementations in road safety and vehicular technology and infact vehicle accidental death have multiplied by three times from 39,675 in 2003 to 90,729 in 2017. Tamil Nadu recorded second highest road accidents in India in 2017. A questionnaire is formed to collect the public opinion about road accidents which was collected from 1004 persons is given with the support values in table 2.1.

Q no.	Details	Sup port value
1.	Avoiding road accidents due to weather is highly difficult	84
2.	Accidents due to fog will only happen in hills	82.7
3.	Curved roads has high probability of accidents	81.6
4.	U-Turns in hills are more dangerous crash counters	82.2
5.	Cracks and potholes can cause the driver to lose the control of the vehicle	78.9
6.	Inadequate guardrails on curves and overpasses causes upside-down accidents	82
7.	Placing construction materials and utility poles in a way obstructs a drivers vision	81.1
8.	Taking medicines during driving causes drowsiness	80.7
9.	Driver drowsiness will be extremely heavy after having full stomach food	83.5
10.	Crashes due to drowsy driving occurs mostly at night time	81.3
11.	Drunk and driving accidents will frequently occur in rural roads	70.2
12.	Aged drivers (45 to 70 yrs of age) has high risk of fatigue	75.2
13.	It is difficult to always drive within the speed limit	68.2
14.	Speeding always results in loss of vehicle control	73.6
15.	Speeding increases stopping distance once the driver perceives the danger signal	73.6
16.	Speeding leads to high degree of crash severity and further results in severe	68.7

	injuries	
17.	Accidents due to speed will be physically high	73.8
18.	Failures of airbags deployment at necessary times will result in accident	73.3
19.	Improper condition of wiper in necessary/needed times causes crash	72.6
20.	Seats or seatbelts failure unexpectedly results in severe injuries	73.9
21.	Most animal collision accidents are due to dogs	71.1
22.	Animal collision gives higher crash damage for two wheelers when compared to four wheelers	75.3
23.	Honking makes the animal scary and avoids accidents	73.9
24.	Collision of an animal will not cause a fatal death for drivers	71
25.	Since animals are most active around dawn (4 to 6 am) and dusk (6 to 11 pm) drivers should be extra vigilant	69.5
26.	Usage of electronic devices distracts the driver	69.1
27.	Bad emotional state of the driver will result in aggressive driving	69.5
28.	Often driver gets distracted when other occupants needed attention	69.5
29.	Driver always gets distracted if they smoke while driving	70.1
30.	Teenage male drivers are most likely to speed	68.5
31.	Most young drivers will refuse to wear safety equipments that causes severe accidents	68.6
32.	Most of the young drivers don't know road rules	68.3
33.	Most of drunken drivers were young drivers	68.3
34.	Young lady drivers frequently break the road rules	67.7
35.	Failure to perform a "shoulder check" to check blind spots will result in accidents	67.8
36.	Un-Intimated lane changing causes accidents	69.3
37.	Driving slowly in the left lane forces other drivers to travel at faster speeds to change lane	69.7
38.	Rear end accidents occur mostly at night time	69.7
39.	Accidents due to job of an individual are higher (like delivery jobs)	67.3
40.	Accidents caused by private vehicles are more when compared to public vehicles	68.1
41.	Driver education reduces the accidents	63.9
42.	Road monitoring helps in reducing the traffic accident	65.2
43.	It is necessary that all safety equipments are to be used even for small distance driving (<1km)	69
44.	Road accidents is a huge threat to the human society	65.1
45.	Road accidents are preventable	67.9
46.	There is no particular accident detection system in our society	70.7
47.	A alternative traffic control system designed especially for ambulance is needed in India	69.3
48.	Road safety awareness camp is needed at regular intervals	67.9

Table 2.1

Support value is initially collected from public based on individual's score of that statement for 5 and then converted to 100.

$$S.V \text{ for a Statement} = \frac{\text{Sum of values of all the opinions of that statement}}{\text{No.of opinions of that statement}} * 20$$

This S.V is taken for the reduction of factors for further research.

4. Prevention and Detection of accidents

1. Theory behind prevention and detection of accidents

The relative need of efficient driver alert system and automatic accident detection is an action of precaution and postulation of the accidents in road safety. To understand the realistic relationship between prevention (Precaution) and detection (Postulation) of accidents the following theory has to be followed.

$$D \propto \frac{1}{P} \quad \dots(1)$$

P is Prevention of Accidents and D is Detection of Accidents.

2. Assistance from various devices for Accident Detection

The devices involved in Advanced Driver Assistance System (ADAS) are Monocular camera, Stereo camera, Fish eye camera, Charge couple device camera, RADAR, LIDAR, MEMS, NEMS, Gyroscope, IR camera, EEG, GPS, GSM, Multimodal sensor, Vibration sensor, Speed sensor, Alcohol sensor, Proximity sensor, Ultrasonic sensor, Photonic mixer devices and so on. All these devices provide safety to driver but still accident persists due to failure of system or driver carelessness. Several accident detection techniques are available and it is activated when the driver is not able to get alert from ADAS and meet with an accident. When accident occurs, transforming the information from that accident spot to the rescue center for further action is the biggest research challenge in current days.

3. Techniques and algorithms involved in Accident Assistance

3.1 Wheel Arch Counter Detection (WACD) algorithm

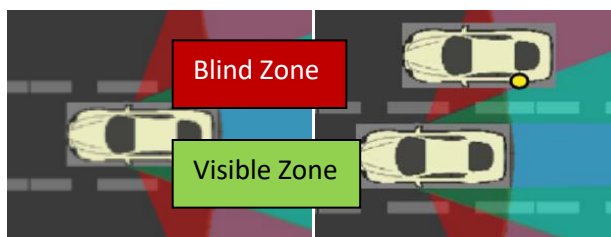


fig.3. 1a

fig. 3.1b

It was introduced by Dooley et al [1], On the rear side of the car, a fish eye camera is positioned to identify the target vehicle (TV) entering the blind zone using calibration technique and monitors the vehicle with the aid of the angular velocity and speed of that vehicle after entering the blind zone, as seen in Fig 1b. The data received from camera is classified using Adaboost classifying technique to identify the TV from 10-40m before vehicle enters into blind zone. Identification of all the zones was a challenging research in which Google cars has produced high potential output using mounted-LIDAR units.

The vehicle safety mechanism with the help of Suspension and Control System (SCS) is an approach of Automatic Cyber Physical Systems (ACPS) that provides knowledge to the vehicle in all zones and is proposed by Naufal et al [75]. It uses four proximity sensors to detect moving vehicle from front, back and sideways [75]. A²CPS Engine is an embedded device fixed in the vehicle that receives data from sensors, other vehicle and from information centre. It takes all computational work and provides Incident Zone Warning (IZW), a safety mechanism used to provide alerts based on the features extracted from the proximity sensors. A few other computer vision methods that are used in road safety applications in **Table 2**.

Table 2 –Some of the techniques used in road safety applications that can be implemented in ITS.

Purpose	Author name	Method / Algorithm	Description
Vehicle Detection	Wang et al [43]	Radar and Vision fusion Algorithm	mmw-Radar and monocular camera is used to identify the vehicle using a the proposed algorithm.
	Shyr-Long Jeng et al [29]	Inverse Synthetic Aperture Radar (ISAR) Algorithm	On the roadside, 2D FMCW radar is used to measure the speed and length of the crossing car.
	Dooley et al [1]	Wheel Arch Counter Detection	Proposed a Blind Zone Detection Method

			using fish-eye camera.
	Fan and Zhu [58]	A New Vehicle Separation Method	Problem of overlapping of the vehicles in on-road videos is addressed and handled with fourier descriptor
	Kosaka and Ohasi [70]	CenSurE and SVM	Vehicle detection using Blob data that is manipulated using CenSurE are received from the fixed monocular camera and classified using SVM
	Dong et al [34]	Enhanced detector algorithm adaptive to parking	The AMR sensor is used both in usual and unnatural situations to identify the car.
Accident Detection	Fogue et al [16]	OBU with VANETs and configured DAU	OBU is introduced to get the accidental information and pass it by VANET for immediate action
	Singh and Mohan [24]	One Class Vector Machine	The snaps for processing are taken with the aid of security videos to identify the accident identification.
	Thomas et al [30]	Video summarization framework	A novel method reducing the cost function to provide the summarized report of accidents
	Nguyen et al [45]	Video condensation algorithm	Proposed a new method for ordering the Minimum number frames of a video which provides maximum understanding of the accident.
Obstacle Detection	Kumari et al [33]	Joint V2V and Long Range Radar (LRR) in a single carrier Band	mm-Wave radar is used for LRR and DSRC std is combined for obstacle detection
	Nyamagod [51]	Real time Obstacle Detection	FMCW radar is used to measure the obstacle on road and provides the conceptual information.
	Wang et al [62]	1T2R, Ray Tracing Technique	FMCW radar is used with one transmitter and two receiver concept for using multipath directions using ray tracing technique. This technique helps in covering most of the

	Dairi et al [42]	Deep Stacked Auto encoders (DSA)- k-NN	obstacles on road A stereo vision camera is used to capture the data and DSA is implemented as the solution for the problem for anomaly detection to detect obstacles.
Animal Detection	Sharma and Shah [4]	Cascade Classifier and HOG	Proposed to avoid the collision of animal.
Lane Detection	Xing et al [10]	ACP Parallel Theory, Lane Detection Framework	Multimodal sensors are used to detect the lane keeping task.
Facial Expression Recognition	Majunder et al [17]	Automatic Facial Expression Recognition system (AFERS) - SOM classifier	A novel deep network framework is created to identify the facial expression with the help of geometric & binary pattern, auto encoders and classifier.
Automated Driving in Highway	Noh and An [22]	Decision Making Framework	Proposed a decision making system using various devices for situation assessment and decision making.
Fog detection	Filonenko et al [31]	Background subtraction method, Boosted using CUDA	High resolution image is taken from the surveillance video to identify the smoke in it using CPU+GPGPU.
	Gallen et al [41]	Back Scattered Veil Detection & Halos Detection	Fog is detected from the image based on the light source emitted from the vehicle and in street lamps.
Pedestrian Tracking	Kwak et al [46]	Weber-Fechner's law, Real time online learning	Proposed an algorithm with two methods to detect pedestrians in different seasons. Weber's law is used to determine the season.
Driver Fatigue Detection	Mandal et al [63]	A fusion algorithm and Spectral Regression	PERCLOS[96] is defined as robust continuous level eye opening and the threshold is set to it. To approximate the eye condition, the Fusion algorithm is used.
Road Curvature Estimation	Lee et al [13]	Circle fitting Algorithm, SVD	In critical visibility conditions, a new approach is proposed to find the curvature of the

			lane.
Enhancement of V2X communication	Lianghai et al [14]	Multi – RAT	Uplink and downlink Latency is measured in unicast and multicast situations to improve the V2X communication.
Collision Avoidance System	Sivakumar and mangalam [48]	A new vehicle collision avoidance system	Radar and speed sensors are used to include the vehicle crash avoidance framework in the proposed closed loop architecture.

The speed factor plays an important role in the study of the causes of accidental deaths; fifty drivers were recruited by Charlton and Starkey to analyze the driver speed choice and it was found that the mean speed is normal among all drivers in varying road situations [93]. Prototype willingness model is developed by Preece et al. [92] to identify fast driving and willingness in text driving is conducted in IBM SPSS Version 24 from the data received from 183 licensed drivers of 17-25 years old drivers and found that most of the positive attitude young drivers were protagonists. Several other factors that cause accidents are red light running, fog or snow, pedestrian crossing, collision of the animal, driver fatigue, multiple vehicle collision, brake failure, unlicensed driving, high beams in NH and SH, distracted driving (not following traffic rules), speeding in turns and un safety stunts[24][30][41][45][63][95][83][86][98][100].

Animal detection technique using Computer Vision (CV) is proposed by Sharma and Shah [4]. This system has major role in densely populated city where animals like dogs, cows, monkeys and donkeys are large in number. In the CV process, the Histogram of Directed Gradients (HOG) is used to define the image characteristics [4]. It is trained under 2200 images. It solves big issue with less accuracy. Farid et al developed Safety Performance Function that computes crash counts for rural areas in four states [84] and one of the hardest predictive problems is critical night time accidents[99] that occur because of dangerous curves when driver is unaware of it. These curves are highly severe at worst climatic conditions like fog.

3.2 Road Curvature Estimation using Circle Fitting Algorithm

Lee et al [13] introduced a method for estimation of road curvature using W-Band FMCW RADAR and Circle Fitting Algorithm that works in all possible critical conditions. The minimum orthogonal squares to minimize the sum of squares in the algorithm of circle fitting are given by

$$F = \sum_{i=1}^n f_i^2$$

Where f can be defined by geometric and algebraic models. Lee et al uses algebraic model, the popular algebraic equation for Circle Fitting Algorithm is

$$A(x^2 + y^2) + Bx + Cy + D = 0$$

The minimization of the simpler function is

$$F(A, B, C, D) = \sum_{i=1}^n (Az_i + Bx_i + Cy_i + D)^2$$

Where $1/(B^2 + C^2 - 4AD) = 1$ and function F in matrix is given by

$$F = \|\mathbf{XA}\|^2 = \mathbf{A}^T (\mathbf{X}^T \mathbf{X}) \mathbf{A}$$

A is parameter vectors and X is (z_i, y_i, x_i) . Lee et al uses function F with time varied vehicle dynamics as main input that is computed by Controller Area Network (CAN) and provided as input for radar sensor through CAN bus. The procedure provides 10-17% more accurate prediction compared to map data.

3.3 Driver Safety System

Driver Safety System (DSS) fall in two categories, Active and Passive Safety Systems (ASS and PSS). ASS provides Advanced Driver Assistance Systems (ADAS) that provide assistance by automatic collision control, braking and lane keeping. PSS are air bags and seat belts kukkala et al [79]. Camera used in computer vision technique is of two major types one is monocular (have only single lens) and other is stereo (more than 2 lens). Stereo cameras provide 3-D data by combining two or more images captured from various lens and it is mainly used for ASS. There are other devices that are used to get input data for ADAS and Accident Detection System (ADS) like IR cameras, LIDAR, RADAR, Ultrasonic sensors and photonic mixer devices. Each pixel of the frame is represented in the form of matrix data. ADAS processes these data around 60 fps in which each frame contains 3 channels (RGB).

It undergoes various processes, such as segmentation, identification and monitoring of objects, measurement of depth and control of structures. Machine learning algorithms such as LR, Gradient-Decent, SVM, k-NN, ANN and CNN gain from ADAS computing [79]. A driver fatigue recognition model works with features extracted from ECG and EEG is proposed by yang et al [2]. Hidden Markov Model (HMM) is used to compute Dynamic Bayesian Network (DBN) at various time stamps is the Collection of Static Bayesian Network (SBN) that is interconnected, the relationship that interconnects SBN is found using 1st order HMM while DBN classifies output to alert the driver. The importance of Electroencephalography in Sleepiness Detection System (ESDS) is given by Balandong et al [80] that act as interface between the human brain and control unit. EEG uses electrodes, these electrodes are fixed at nearest part of human brain to measure EEG signals [80] that extracts features from f8-electrode of EEG then used for SVM and Bayes for supervised learning to provide higher results.

Six key classified features used to define performance include different SDS techniques 1) subjective assessments 2) vehicle-based systems 3) behavior-based driver systems 4) Sleep-Wake mathematical models (MMSW) dynamics 5) human physiological signal-based systems 6) combinations of one or more of these techniques [80]. The conventional technique used to measure the level of sleepiness of the driver and steering wheel movement is the Karolinska Sleepiness Scale (KSS), percentage of eye close (PERCLOS), Bio-Mathematical models are the techniques that plays a major role in the EEG evolving models.

3.4 Autonomous Vehicles

Deployment of software and electronic innovations in automotive industry for connected vehicles is surveyed by siegel et al [78]. Applications of RADAR and LIDAR towards perception to find angular velocity of vehicle are used in autonomous vehicles which in turn increases the production of vehicle with the aim to satisfy and safeguard the customers. RADAR Sensory methods are emerging with luxurious monster vehicle producer like Tesla, Google-Autonomous Vehicle, BMW and Benz where the connectivity of autonomous vehicles of inter and intra vehicle is important in designing of any autonomous vehicles. Sharing of sensor and actuator data is most needed in intra vehicle connectivity, whereas inter vehicle networks share the critical orderly information to another vehicle through VANETs. IEEE 802.11 P is the unique communication protocol used in V2X applications.

3.5 Enhancement of V2X Communication using Multi-RAT

Vehicle to everything communication provides high reliability in processing important information in 5G Cellular networks. Single transmission techniques like LTE-Uu or PC5 will not help vehicle to everything communication, so a Multi radio access technique is introduced by J. Lianghai et al [14]. For Multi-RAT, a hybrid uplink mechanism is designed to boost reliability, it is designed to accept both LTE-Uu and PC5 packets in such a manner that OBU allows to relay the signal from the vehicle to the uplink.

Accident detection is computed using On-Board Unit (OBU) which passes accidental information using VANET to reach the concern [16]. Ki and Lee developed a model to predict accident at intersections using image captured charge couple device camera and feature extracted from moving vehicle is passed to ARRS model [7]. ARRS model analysis and evaluation of captured image is carried out with standard DVR to record and send information from AMP to TMC. Three major steps taken in this algorithm are vehicle extraction, feature extraction and detection of accidents to compute acceleration, position, area detection and compared with threshold to formulate the incident. In a recent paper Yaun and Abdel-Aty proposed a method to identify the accidents at Intersections and Intersection entrances [86]. Some of radar, lidar and sensory methods available are listed in *Table 2*.

3.6 Traffic Detection (TD)

The road congestion detection to control the level of congestion is proposed to overcome many traffic prediction techniques that failed to support the flow of traffic is provided by Kalamaras et al [77]. As a parametric model, autoregressive integrated moving average (ARIMA) is used and k-NN, SVR is used as a non-parametric model to measure the efficiency of both models for traffic prediction. The accuracy of prediction is carried out by normalized root means square error.

An IoT cloud system to provide the traffic analysis is introduced by celesti et al [76]. Fixed sensors sometimes fail to send data through 4G network. This system sends data directly from vehicle to cloud with the help of IoT. Cloud system receives data and processes using #openGTS to provide information about traffic to the passers in the same route with detailed information through GPS. A visual analytics tool is developed and maintained in the cloud server.

5. Hybrid approach (CNN in VANETS)

Convolution neural network has large number of parameters and this serves as an efficient approach in any kind of recent decision making system. Deep learning technique of Convolution Neural Network is used in computer vision and In the NLP method, the Recurrent Neural Network is used. An powerful method of crash prevention would be the combination of the CNN in Vehicular ad-hoc network to make crucial decisions in accident circumstances.

In the recent days most of the computer vision techniques follow CNN. Pixels of an image is represented as value matrix, based on the intensity of a particular pixel, the resulted huge matrix is given as input to convolution layer in Image Recognition (IR) problem. System uses 3D volumes of neurons (Width*Height *Depth) for further computation, For the identification of car license plates, a CNN-based MD-YOLO system has been implemented. The prediction of rotation angle and intersection over union is used to treat real-time conditions and to achieve better results [3]. Deep learning method is implemented in the framework for lane detection using multi model sensors that is capable of receiving the input in various situations [10]. The principle of computational experiments and simultaneous execution (ACP) is used to develop this method to understand, implement and test the lane detection mechanism in artificial society [10]. In CNN, input layer, convolution layer, induction layer, pooling layer, and output (fully connected) layer, there are usually five layers. Others are opaque layers, except for input and output layers.

The output obtained from the CNN chooses to trigger the contact channel. The simplified crash details would be transmitted from the car to everything through the contact channel (V2X). In Vehicle to Everything communication there are several issues that are still not properly addressed in VANET. They are congestion of data from Vehicle to Vehicle (V2V), security of the vehicle data when it is connected to everything which will make the VANET to perform poor. To solve this, all the vehicles should need to get connected only through the base station; warning messages are preferable from the base station to avoid accidents. Activation of vehicle to vehicle communication without the support of base station should only be after the accident to ensure high level security in VANETs. Deep learning and hybridization techniques that are applied in the field of Transportation Systems and Driver Technology will be the enhancement of ITS.

6. Results and Discussion

As a part of opinion analysis in this paper, it is found that the support value received for Q1 is 84% and after that there was the steady decrease in the support value for each and every question. This also shows that people in Tamil Nadu state are little careless about road accidents and thus recorded the second highest road accident fatalities in 2017 among Indian states.

In DSS, Driver Drowsiness Detection (DDD) model developed by Li and Chung [21] used to detect drowsiness produces 96.15% accuracy that is higher than any other Drowsiness detection model and acceptance of driver alert system by driver is assessed by Rehman et al and produced 85% variation in results [90] which gives very low results when compared to Li and Chung[21]. The study of Pylkkonen et al [88] with 53 truck drivers in the intervention to provide the sleepiness countermeasures is failed and proves that driver education is not the sufficient measure for driver sleepiness.

These two results infer us that neither driver education nor driver alert system is sufficient to protect drivers. Accidents are exceptional and even though there are high end auto pilot cars like Tesla s model and Benz F 015, there is still a huge gap in prevention of accidents and it has been proved once Tesla S model failed to protect its driver who met with an accident in auto pilot mode. Thus in order to prevent accident an exceptional hybrid model is suggested in this paper.

7. Conclusion

This paper provides a detailed study to clarify the significance of the accident warning mechanism in Tamil Nadu. Various devices, techniques and methodologies that are used in ITS is detailed in this review with the most 4 influencing algorithms in the ITS which is more popular in various developed countries and several experimental results. Different papers demonstrate that, using the new algorithms and processors such as GPGPUs, the standard computer vision approach can produce more accurate and precise performance. Based on the result of this study the hybrid approach of CNN in VANETs considering security could be the best research suggestion to avoid accidents.

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