An Effectual Adaboost Based Regularization Approach For Risk Prediction In Vehicular Ad-Hoc Networks

S.P.Sasirekha, N.MohanaSundaram

Abstract: With the rapid development in vehicle scale and road traffic, people have encountered safety risks due to vehicle accidents, during benefiting increasing convenience of life. However, Vehicular Ad Hoc Networks (VANETs) have offered the human society with significant information associated with vehicle data, which assists in developing a new methodology to examine vehicle accidents in high traffic scenario. In this investigation, the problem associated with identifying the risk of vehicle accidents have been analyzed and a solution is made using the Adaboost based Regularized boosting for classifying the velocity of vehicle during the process of transportation and to acquire model for accident risk prediction. In this investigation, identifying risk is significantly grounded on big data processing and real time accident data. Initially, Real time traffic dataset is considered, the missing attributes of the dataset will be complemented and the sample features are considered. Secondly, AdaBoost algorithm is utilized for adjusting the computing power of vehicle terminals, which assists in deploying the VANET effectually. Thirdly, Effectual Regularized Boosting is combined with Adaboost to make the classifier to effectual for risk prediction. Finally, simulation results show that prediction model using Adaboost based Regularized boosting algorithm provides Intelligent Transportation System (ITS) and vehicle assistant system with theoretical basis. The parameters such as Notification, End to End delay, Network processing overhead, Reception rate, and Notification distribution are evaluated using MATLAB simulation environment. The proposed method outperforms well in contrast to existing methods.

Index Terms: VANET; AdaBoost; Prediction; regularized Boosting; Network processing overhead

1 Introduction

With increasing advancements in technology and development in standard of living, the number of vehicle utilization is growing drastically. More individual families own their private vehicles, which leads to traffic congestion problem worse in real time [1]. This also paved way for increasing traffic accidents which affects the people's lives seriously. Prediction and prevention of traffic accident plays significant role in examining the traffic accident trends under present traffic scenario [2]. To diminish the occurrence of accidents along with safety awareness, driving technologies has to be enhanced; accident prediction has turns as an extremely effectual method. In context to, intelligent transportation system, numerous applications carry out collection of data from vehicles as gathering real time traffic data raised as an appealing paradigm. In VANETs, data dissemination is extremely significant and larger amount of data are collected from heterogeneous environment providing way to new generation of VANET big data [3]. Vehicles which are utilizing ad hoc sensor and wireless network accumulate huge data from the environment and influences more autonomous applications. The foremost concern of sensor based VANETs are data aging, response time, bandwidth, packet delivery, communication cost and message prioritization [4].

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For the purpose of VANET information dissemination [30], certain routing protocols such as Ad hoc On Demand Distance Vector (AODV), Destination-Sequenced Distance Vector (DSDV), Dynamic Source Routing (DSR), provides effectual outcome of routing in dense traffic environment. Also in VANET technology, information can be encoded on both the route preference and information encoding and exploits it for numerous routing protocols to attain rapid utilization of Big data VANET [5]. Similarly, co-operation between wireless communication and distributed sensing (GPS) is essential to analyze and examine all detection data of vehicles in specific region. Also, information passing through typical tele-matic systems and infotainment like potential privacy implications, efficient data accumulation and secure transportation to enhance data confidentiality and security amongst Road Side Units and vehicles. With respect to road side scenario, occurrence of vehicle accidents is usually merged with diverse reasons. Henceforth, risk prediction is confronting task [16]. But a real VANET associated with big data can provide alert to resolve diverse cause of traffic accident. In this investigation, VANET big data is focussed specifically to achieve the prediction ratio, reduce network processing overhead and so on [17]. The ultimate target is to analyze driving risk and to supply alerts to vehicles at anytime [18]. The significant contribution of this work is to proposes risk prediction model with higher prediction rate and to anticipate an Effectual Adaboost algorithm to enhance eth classification capacity in VANET Big data. Secondly, an effectual Regularized boosting algorithm is provided to analyze the encoded features of real time traffic data scenario. This increases the convergence speed and accuracy of classification outcome significantly. The proposed method outperforms the existing techniques and provides improved results. The parameters such as Notification, E2E delay, Network processing overhead, Reception rate, Notification distribution are analyzed using MATLAB simulation environment. The theoretical background is provided for real time investigation and to offer effectual intelligent transportation systems with driving assistance. The rest of the paper is structured as: Section II spotlights on works associated with VANET data analysis and drawbacks encountered in existing works. Section III illustrates the combined Adaboost and Regularized boosting algorithm to examine risk prediction in VANETs. Section IV depicts simulation setup. Section V provides the numerical results and section VI is results of the proposed work and future directions.

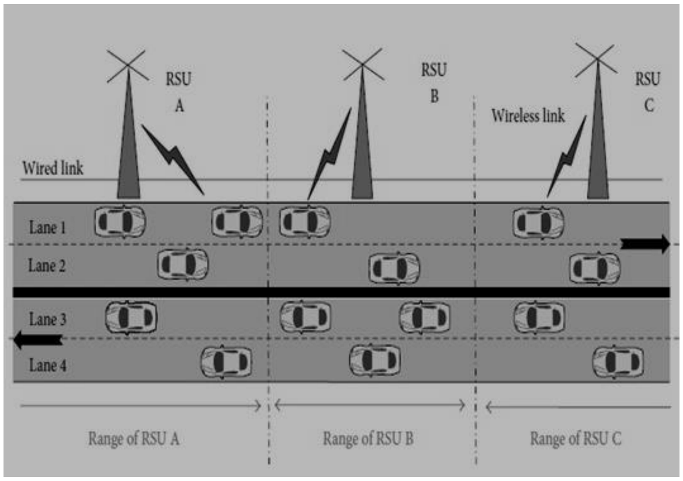


Fig 1: *VANET architecture*

2 Related Works

In [6] Islam Tharwat Abdel-Halim et al. anticipated that stability is crucial to expand execution of reactive protocols, while foreseeing trajectory or vehicles location is helpful to data forwarding and upgrade position-based routing protocols. Traffic management is enhanced by anticipating travelling time, and road security takes advantages over predicting risk. But interesting VANETs characteristics emerge need to a top to bottom investigation for prediction-based protocols to conquer existing difficulties. Moreover, there are enormous research crises in mobility prediction, for example, QoS, clustering and mobility rules prediction. In [7] P. Ganeshkumar et al. anticipate an Emergency Situation Prediction Mechanism (ESPM) is to recognize the probability of accident occurrence in Indian four-lane express highway. The essential target of ESPM is to anticipate emergency circumstance ahead of time, henceforth accident prevention and decreasing the loss of life. ESPM is utilized to perform prediction of emergency circumstance in four stages. The initial three stages (reporting, monitoring and prediction stages) are utilized for expectation and fourth stage is utilized for avoidance. In ESPM, prediction accuracy is registered against vehicle density for three distinct situations. In all the three situations, it is seen that there is small gap between analytical evaluation and iterative results. The outcomes demonstrate that ESPM performance is promisingly increased towards prediction. Prediction accuracy of ESPM against vehicle density is practically over 92 percentIn [8] Swati B. Raut et al. describes about vehicle collision identification and prediction framework is displayed dependent on ICU and IVC. This strategy has been actualized on highway intersection situations. Open Street Map is productively utilized for removing and executing real mao. SUMO, OMNET++ and VEINS gives a decent domain of VANET execution. In the anticipated strategy, ICU monitors vehicles dynamics and calculates collision probability, based on gained information. ICU separates the criticality of possible collision on distance from convergence zone. Iterative results demonstrate collision probability for nearer accident, no accident and crash. In [9] Wanting Zhu et al. proposed a proficient prediction-based data forwarding technique to give efficient and reliable transmission. New link utility expectation procedure is given by utilizing vehicle information and speed about location. Zhu et al. demonstrated that, when anticipated forwarding strategy was brought into routing, superior PDR and E2E delay were accomplished. Moreover, proposed link utility variation with two-hop neighbour data to enhance reliability of selected transmission path. At long, effects of certain key factors are investigated. Iterative outcomes demonstrated that routing protocols with forwarding strategy accomplish reduced E2E delay, particularly in high density region. Average amount of hops amongst source to destination pair was diminished devoid of expanding packet loss probability about by link breakage. Effectiveness of transmission was enhanced as demonstrated by diminished E2E delay. In [10] Gokula krishnan P et al., describes about Road Accident Prevention strategy for moment EWM dissemination to prevent them from accidents. In this way, damage rates can be decreased. In RAP strategy, when RSU forecast probability of accident occurrence or emergency circumstance, VBN structure scatters EWM to vehicles with better reception priority. Execution assessment is performed by utilizing NS-2 simulator. Iterative outcomes depicts that RAP with VBN structure performs effectually than RAP scheme without VBN structure by giving superior EWM dissemination performance based on (I) diminishing S-D distance, (ii) enhancing notification and (iii) lessening E2E delay. In [11] Francisco J. Martinez et al. exhibited warning advertisement framework for IEEE 802.11p, and carries out analysis of inter-vehicle communication frameworks to enhance security. Propagation delay is lower while node density rises. In addition, level of blind nodes exceptionally relies upon this factor. Actually, when node density exceeds specific limit, there exist no blind nodes. This characteristic occurs while flooding propagation of messages works effectually with higher node density. Finally, total packets slightly diminishes when nodes increments because of collisions. In [12] Qiong WU et al. attempted utilizing SVM to accomplish early vehicle accident prediction in VANET. Vehicular Ad hoc Network (VANETs) is fundamentally aimed for generating security applications and anticipating car accident before it happens in real time. This approach considers variable traffic circumstance and towards more realistic driver behaviour. Later on, progressively numerical examination and simulation will be performed to assess effectiveness and usefulness of this scheme. The real time data is utilized to assess this approach and simulate complicated road conditions, for example, various line roads and distinctive types of suggestions. In addition, realistic delays for data processing and data transmission will be considered. In [13] Hamid Menouar et al. exhibited MOPR which is a procedure based on node movement information's, can enhance routing procedure in MANETs, and during high node speed like VANETs. Subsequent to demonstrate execution of MOPR over reactive routing protocols in existing works, this investigation describes new utilization idea of MOPR, new implementation for vehicular systems, which is actualized over proactive routing protocol OLSR. In [14] Hamid Menouar and Massimiliano Lenardi et al. proposed MOPR algorithm grounded on node development data (direction, position and speed), which enhances routing procedure, and for the most part if there should arise an occurrence of nodes' speed, by predicting neighbouring vehicles positions. Subsequent to demonstrating MOPR execution to routing protocol, here MOPR approach is presented that can be connected to position based routing. MOPR was executed over existing position-based routing protocol GPSR. In [15] Huma Ghafoor and Insoo Koo et al. anticipated a novel protocol for highway scenarios. Combination of both channel selection and relay selection in vehicle-to-vehicle communication without considering any roadside units for long-distance paths between source and destination makes this protocol unique from all prevailing protocols of cognitive VANET in the literature. This is position-based protocol where Kalman filter is cast off to analysis vehicles position. With Kalman filter algorithm, this work shows superior performance for PDR and E2E delay. In the future, we will extend this work to city scenarios and also for different channel propagation models in highway and also in cities. In [16] Huma Ghafoor and Insoo Koo et al. proposed a novel routing protocol for VANET for highway situations. Combination of both channel selection and relay selection in vehicle-to-vehicle communication devoid of considering any roadside units for long-distance path among source and destination makes this unique protocol from all prevailing protocols of VANET. This position-based routing protocol with Kalman filter is to predict vehicles position. With utilization of Kalman filtering, the proposed protocol indicates better execution for PDR and E2E delay. In [17] Xi Yu et al. proposes the novel routing protocol AODVVANET by merging vehicles' development data into route discovery process dependent on AODV for VANET application. With the initiation of TWR and termination time estimation, the anticipated protocol can accomplish better routing performance. Simulation results demonstrate protocol effectiveness in diminishing routing load and continuing increasingly stable connections contrasted with AODV.

3 PROPOSED METHODOLOGY

This section describes about the risk prediction in heavy traffic condition. Initially, a system model is provided to depict the road traffic scenario. Secondly, the real traffic dataset is considered for examining the features of vehicle and to deploy the network using Adaboost approach. Thirdly, Regularized Boosting is applied to analyze the classifier strength for predicting the risk condition. This work believes that risk prediction comes under supervised learning objects category. Supervised learning is a technique utilized in labelled training sets to generate functions for analyzing data. By executing this strategy, target data will be classified under certain categories and vehicles density can also be attained.

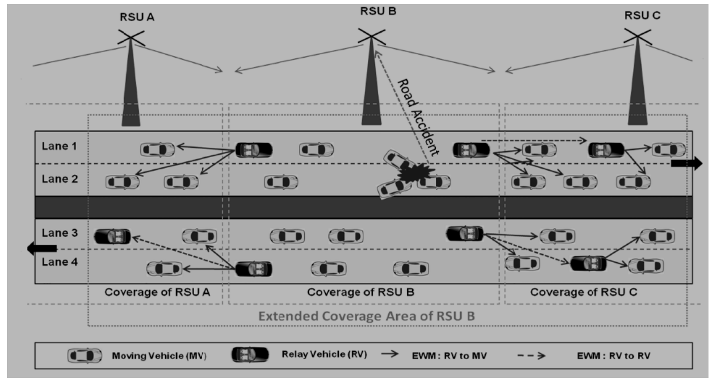


Fig 2: *Real Traffic data scenario for accident prediction*

Initially, this work starts with the collection of road safety data measures from VANET. Road side units and vehicles in VANET transmit data to cloud in real time traffic dataset utilized [19]-[20]. In order to process this dataset, Adaboost approach is anticipated for predicting the traffic accident risk. Significant purpose of this work is to recognize whether vehicles are under risky environment. To achieve the ultimate goal of this investigation, prediction model is built grounded on safety data of specific area and provide driving data input to discriminate vehicle accidents risk [21]. Consider that there is an experimental scenario in a usual urban region. The road safety data was provides as input to the system for pre-processing, filling up missing data [27], balance samples and encodes feature value [22]. Road conditions such as vehicle age, type, driver age, gender and related data features are considered for vehicle and accident dataset with collection of $X = (x_1, x_2, x_3, \dots, x_n)$. The values of 'X' are measured as input samples. Labels in dataset comprises of values such as 0, 1, 2. The prediction model output is given in 'C', which is partitioned into three classes $C = (C_0, C_1, C_2)$ grounded on classification of samples. Output value C_0 specifies that vehicles suffer from little probability of occurrence of accident. C_1 Specifies that vehicles possess certain degree of accident occurrence and finally C_2 specifies that vehicles possess serious fatal event. The above specified events occur on any slight chance of rubbing accident during driving. The higher probability of no accident is also comes under C_0 to make the computation easier [23]. Complete accident prediction process is given in figure 2.

4 IMPROVED ADABOOST ALGORITHM

To execute above mentioned class of road safety data in urban area, this work anticipates an effectual Adaboost approach. While comparing the proposed technique with the existing techniques like deep learning or neural networks, this method can deploy VANET environment effectually, also the training time of data can also be adjusted based on the requirements [28], with reduced computational power for vehicle terminals [24][29 - 39]. Improved Adaboost algorithm can be sub divided into three stages: Input training dataset $T_n = (x_1, y_1), (x_2, y_2), \dots (x_n, y_n)$ where x_i is a feature set, while $y \in \{1, 2, 3\}$ are weaker existing classifier that fails in deployment. The defects encountered in existing techniques like CART, ID3 are provided here for recognizing the efficiency of Adaboost. CART algorithm utilizes recursive segmentation approach. ID3 dealt with discrete attributes and intended to select attributes with huge values. In contrast to ID3 algorithm in entropy, CART computes GINI co-efficient for every sample [25]. Smaller GINI co-efficient with reasonable division, CART procedure generally partitions recent sample set into two sub sample, hence every non-leaf node of decision tree (DT) posse's two branches. Henceforth, DT produced by CART has easier structure and can attain superior precision.

1. Generated rules can be implicit.
2. Calculation is relatively small.
3. It possesses ability to deal with discrete and continuous variables.
4. It shows the significance of certain attributes.

At first, initialize weight of training data as in Equation 1 & 2:

$$T_1 = (w_{l1}, \dots w_{li}, \dots w_{1N}) \quad (1)$$
$$w_{Li} = \frac{1}{N}, i = 1, 2, \dots, N \quad (2)$$

Secondly, for mth iteration ,$m = 1, 2, \dots, M$. Training dataset with weight distributionD_m, to attain basic classifier as in Equation 3:

$$G_m(x): \gamma \rightarrow | \{1, 2, 3\} \quad (3)$$

γ is data for training. Compute error rate of $G_m(x)$ on basic classification outcome of training data, w_{mi} specifies weight of ith sample in mth iteration as in Equation 4 & 5:

$$e_m = \sum_{i=1}^{N} W_{mi} I(G_m x_i \neq y_i) \quad (4)$$
$$\sum_{i=1}^{N} W_{mi} \equiv 1 \quad (5)$$

For normalization at every step, denominator has not been partitioned by sample weight. In contrast to traditional AdaBoost algorithm, classification error rate (CER) has to be $e_m \leq \frac{1}{2}$ for Adaboost approach. Else $a_m < 0$, sample weights have to be revised in subsequent process. Moreover, it is complex to evaluate the CER, $e_m \leq \frac{1}{2}$at every time of validating the features. By considering the error rate of AdaBoost as $\frac{1}{2}$, error rate threshold limit is $\frac{1}{2}$ and positive item X, ensuring $a_m \geq 0$ when $e_m \leq \frac{1}{2}$.
Evaluate classifier coefficient $G_m(x)$ in accordance to error rate e_m as in Equation 6:

$$\alpha_m = \log\frac{1-e_m}{e_m} + \log_2 \quad (6)$$

Revise weight distribution of training dataset in accordance to co-efficient a_m as in Equation 7 & 8:

$$D_{m+1} = (w_{m+1,1}, \dots, w_{m+1,i}, \dots w_{m+1,N}) \quad (7)$$

$$w_{m+1,i} = \frac{w_{mi}}{Z_m} \exp(-a_m y_i G_m(x_i)) \quad (8)$$

With this, Z_m as normalization factor generates D_{m+1} becomes PDF as in Equation 9:

$$Z_m = \sum_{i=1}^{N} W_{mi} \exp(-a_m y_i G_m(x_i)) \quad (9)$$

At last, weight of misclassification samples by classifier $G_m(x)$ is continuously increasing after training, while appropriately classified samples weight is reducing. Henceforth, misclassified sample works in signified role in subsequent iteration.

Design of linear combination of classifier to attain, final classification as in Equation 10 & 11:

$$f(x) = \sum_{m=1}^{M} a_m G_m(x) \quad (10)$$
$$G(x) = sign(f(x)) = sign(\sum_{m=1}^{M} a_m G_m(x)) \quad (11)$$

Linear combination of f(x) executes weight based 'M' classifiers. f(x) value describes instance categories 'x', and specifies classification confidence as function sign provides 3 segmented classifier output. Trained Weak classifiers are merged with strong classifier to attain vehicle risk prediction model. Regularized BoostingRegularization framework is adapted to in this investigation for effectual classification. Let 'H' determines the class of basic features for classification h: X → { -1, 1}, which generally comprises of simple rules as mentioned in AdaBoosting strategy in section above. These classes need finite dimensionality of vehicle movement. This can be determined with class function f: X → [-1, 1] as attained in combination of features with classifier H as in Equation 12:

$$\sum_{i=1}^{t} \alpha_i = 1, h_1, \dots, h_t \in H \quad (12)$$

Every $f_n \in F$ defines classifier $h_{f_n} = sign(f_n)$ and the generalization error for computing the features $L(h_{f_n})$ is specified by $L(f_n)$. The error attained during the training process is provided as in Equation 13,

$$L_n(f_n) = \frac{1}{n}\sum_{i=1}^{n} I_{[hf_n(X_i) \neq Y_i]} \quad (13)$$

Determine $Z(f) = -f(X)Y$ and $Z_i(f) = -f(X_i)Y_i$. Indeed of reducing the misclassification strategy $\sum_{i=1}^{n} I_{[hf_n(X_i) \neq Y_i]}$, regularization helps to effectively reduce the computational complexity of function $Z(f)$. For example, Adaboost utilizes exponential function, if there is an exponential loss due to computational complexity, the cost for determining vehicle terminal computation is given as follows: Determine the velocity of vehicle terminal by positive speed [26], differentiable, increasing and slightly rising speed as function $\delta: R \rightarrow R^+$ and consider that $\delta(0) = 1$ and $\lim_{x\to\infty} \gamma(x) = 0$. The computational cost and velocity determination are provided correspondingly as in Equation 14 & 15:

$$C(f) = E\emptyset(Z(f)) \quad (14)$$

$$C_n(f) = \frac{1}{n}\sum_{i=1}^{n} \emptyset(Z_i(f)) \quad (15)$$

The iterative determination of regularizing is terminated to consider the approximation functionality of minimization computation complexity of vehicle terminals. To eliminate overfitting, the below given regularization process has to be developed. The cost determination is given in Equation 16 & 17:

$$C(f) = \frac{1}{n} \sum_{i=1}^{n} \emptyset_\lambda(Z_i(f)) \quad (16)$$

$$C^{\lambda}\ (f) = \ E\emptyset_{\lambda}(Z(f)) \qquad (17)$$

Then, with sample determination 'n', regularization parameter of vehicle velocity is given by λ, thus the regularized booster will consider the classification process as given in Equation 18:

$$h_n = sign(f_n^{\lambda}) \qquad (18)$$

Where, f_n^{λ} provides reduces (C_n^{λ}) over $f\ \in F$, that is as in Equation 19,

$$\mathbf{C}_{\mathbf{n}}^{\boldsymbol{\lambda}}\left(\mathbf{f}_{\mathbf{n}}^{\boldsymbol{\lambda}}\right) \le \mathbf{inf}\ \mathbf{C}_{\mathbf{n}}^{\boldsymbol{\lambda}}\ (\mathbf{f}) + \epsilon_{\mathbf{n}} \qquad (19)$$

Where,

n → 0 and n →∞. The minimization of features for classification reduces the complexity of computation in vehicle terminal and vehicle velocity can be determined.

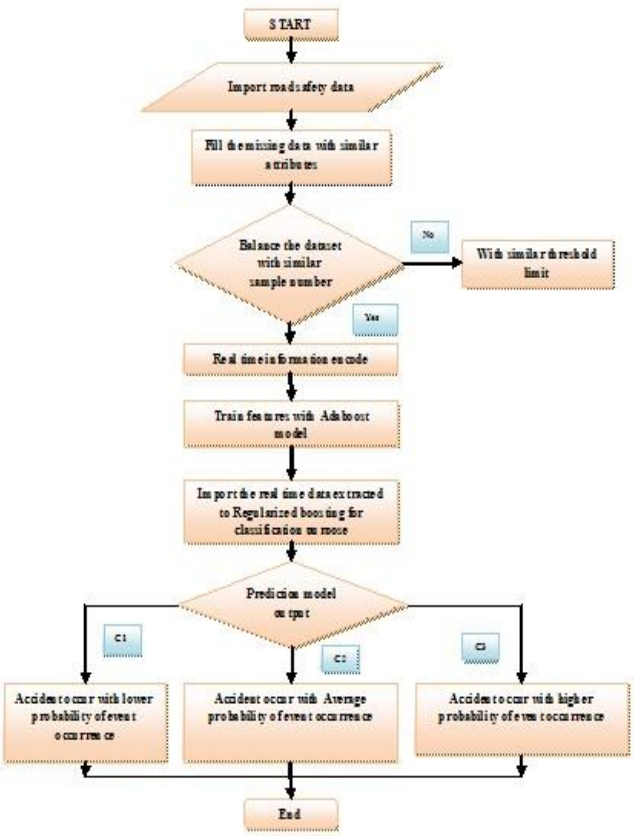


Fig 3: *Flow diagram of the proposed work*

5. SIMULATION SETUP

In this investigation, MATLAB 2018a was utilized for simulating anticipated technique. The parameters related to simulation are given in the table I. In this current scenario, consider there are 150 vehicular nodes available in simulation environment. Maximum node speed was considered to be 60 km/h. Here, speed refers to original vehicles speed; it may be any values amongst 0 and 80 during simulation. Simulated outcomes attained executing time for 10 time's average. The below given table I specifies the nodes that are distributed in simulation environment. In simulation process, two kinds of nodes are utilized. Initially, Road Side Unit (RSU) is placed as stationary or fixed nodes. Secondly, vehicles that move are considered as mobile nodes. The simulation is carried out involving all four lanes (two lanes in every direction) of highway. While executing the experiment, vehicle nodes are provided into four lane highway road segment at diverse intervals to maintain heterogeneous traffic with various inter-distances amongst vehicular nodes. For instance, traffic injection rate is 1/20, and then nodes are provided to highway road segment lane in 20 seconds and determined as traffic injection rate (TIR). As well, diverse TIR are utilized while simulating proposed experiment such that 1/50, 1/75, 1/45, 1/25 and 1/10 correspondingly.

TABLE I: *SIMULATION PARAMETERS AND VALUES*

PARAMETER	*VALUE*
NETWORK SIZE	*100 * 100 METRES*
TOTAL LANE	*4 LANE*
MOBILITY MODEL	*VEHICLE MOVEMENT*
PROTOCOL	*IEEE 802.11P*
VEHICLE SPEED	*60-90 KM/H*
DENSITY	*20-100 IN 400 METERS*
VEHICLE COUNT	*200-300*
SOURCE	*RSU*
TRAFFIC INJECTION RATE	*1/50, 1/75, 1/45, 1/25 AND 1/10*
NOTIFICATION RANGE	*500 METRES*
MESSAGE EXCHANGE RANGE	*100 MILLISECONDS*
SIMULATION TIME	*300 SECONDS*

The behavior of vehicle nodes in highway road while undergoing mobility leads to lane change, sudden change, acceleration, overtaking and deceleration can be achieved using the proposed network design model. While varying VIR, density may be altered from dense to sparse and vice versa. For enhancing the simulation process, vehicles have to move in random direction by modifying the VIR and vehicles speed. Mobility for Adaboost based regularized boosting without and with network structure is generated using the simulation parameter as in Table I. These mobility patterns of VANET are in MATLAB environment for execution.

6. RESULTS AND DISCUSSION

The simulation outcomes demonstrate that the proposed Adaboost with regularized boosting works well in prediction the features of real traffic data and to enhance classifier efficiency by overcoming the drawbacks of weak classifier. There are two processes while performing simulation. 1) Adaboost for selecting the effectual features. 2) Regularized boosting for identifying the classifier efficiency in risk prediction. Data disseminated from mobility nodes of network losses some values; this can be rectified by information encoding strategy. The value will be filled with similar attributes for computation. To analyze the performance of the proposed method, performance metrics such as Notification, E2E delay, Reception rate, Network processing overhead and notification distribution is discussed below: Notification: Number of vehicles notified successfully with source (RSU) against total number of vehicles in traffic scenario. E2E delay: Time taken to arrive at destinations from source. E2E delay includes propagation, transmission and processing delays for all individual links amongst nodes in transmission path. Queuing delay will not be considered in this scenario as data has to be disseminated instantly. Reception rate: It is defined as percentage of vehicles intends to receive notification productively. Network processing overhead: It is defined as number of messages utilized by network for processes such as transmission identification, Reception identification, assignment and prioritization. Notification Distribution: It is defined as sum of notifications over normal, sparse and denser region.

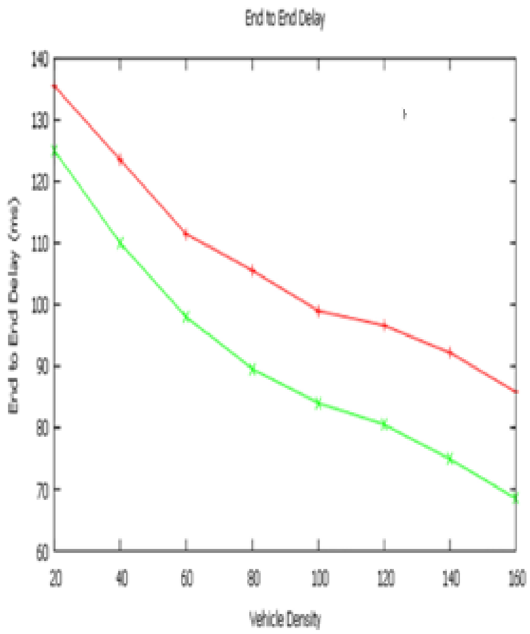


Fig 4: *E2E delay Vs Vehicle density*

Figure 4 shows E2E delay computation of anticipated Adaboost based regularised boosting technique with the existing method. The delay of proposed framework is reduced drastically. Feature selection based on real traffic data is considered to be significant for the enhancement of the proposed work.

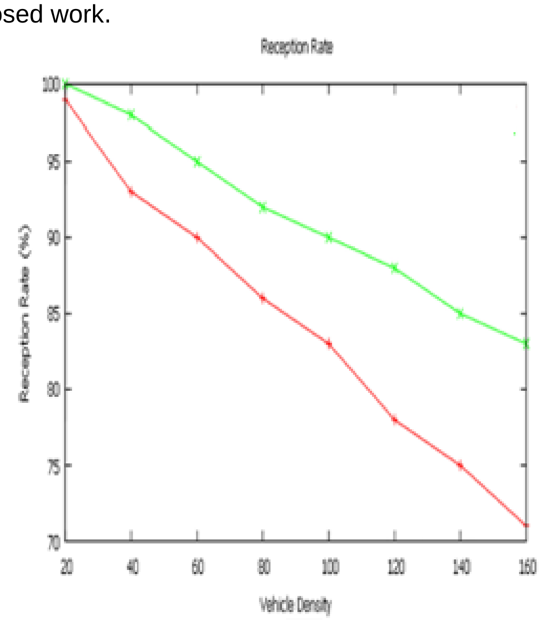
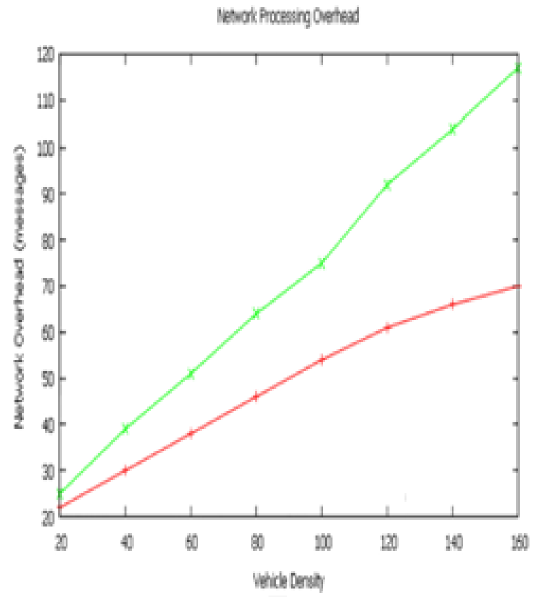


Fig 5: *Reception rate Vs Vehicle density*

Figure 5 shows the reception rate computation of the proposed Adaboost based regularised boosting technique with the existing method. Reception rate of proposed framework is increased drastically. Information encode based on real traffic data is considered to be significant for the enhancement of the proposed work.



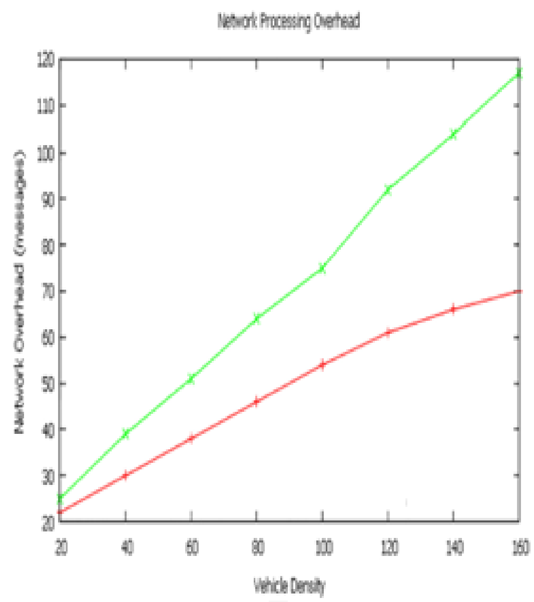


Fig 6*: Network overhead Vs Vehicle density*

Figure 6 shows Network overhead of the proposed Adaboost based regularised boosting technique with the existing method. The network overhead varies when the traffic injection rate varies. TIR will be 1/50, 1/75, 1/45, 1/25 and 1/10 correspondingly.

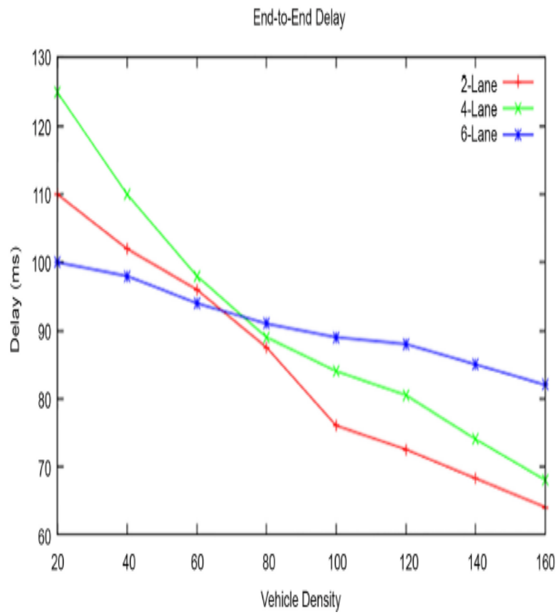


Fig 7: *End to End delay Vs Vehicle density*

Figure 7 depicts E2E delay computation of the proposed Adaboost based regularised boosting technique with the existing method. The delay of proposed framework is reduced drastically. Feature selection based on real traffic data is considered to be significant for the enhancement of the proposed work. Various high way lanes are considered and the simulation is tested under various setup.

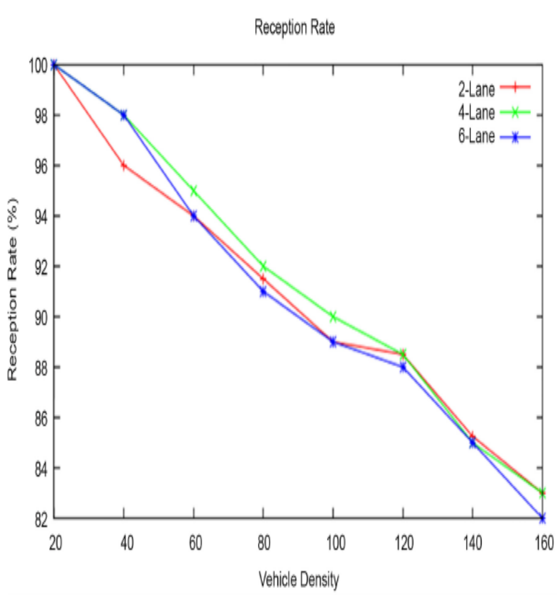


Fig 8: *Reception rate Vs Vehicle density*

Figure 8 shows the reception rate computation of the proposed Adaboost based regularised boosting technique with the existing method. Reception rate of proposed framework is increased drastically. Information encode based on real traffic data is considered to be significant for the enhancement of the proposed work. Reception rate is considered on lane 2, lane 4 and lane 6 correspondingly.

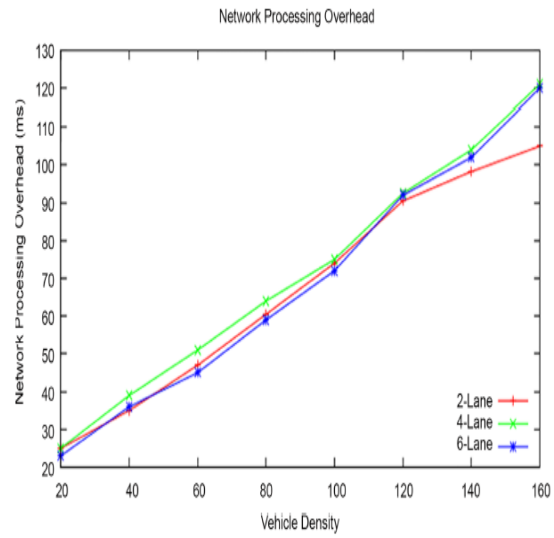


Fig 9: *Network overhead Vs Vehicle density*

Figure 9 shows Network overhead of the proposed Adaboost based regularized boosting technique with the existing method. The network overhead varies when the traffic injection rate varies. TIR will be 1/50, 1/75, 1/45, 1/25 and 1/10 correspondingly. Different highway traffic lane is considered here: lane 2, lane 4 and lane 6.

7. CONCLUSION

This investigation attempt the utilization of effectual Adaboost based regularized boosting for feature determination and classification in highly risk traffic environment. This assists in predicting the risky scenario in high dense environment. Vehicular Ad hoc Network (VANETs) significantly attempts to develop safety applications and identifying accidents before it happen and can save life in real world scenario. This approach considers various changeable traffic situations towards more realistic driver characteristics. Parameters such as Notification, E2E delay, Reception rate, notification distribution and processing overhead are measured and effectual realistic outcomes are attained with the proposed method. In future, more simulations and numerical analysis will be performed to examine effectiveness and usefulness of this method. The work will also be extended based on real data to perform simulation in more complicated situations like multiple line roads and various suggestions. However, realistic delay for data transmission and processing will also be considered.

In future, an attempt for computing real time scenario based on RSU will be made. Hence, prediction rate and performance can be computed efficiently. Prediction of emergency and prevention of accidents using big data will be challenging tasks. Dealing with big data processing using deep learning will also pave the way for higher success rate

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