

Monitoring and Detection of Abnormal Driving Behavior Using Smartphone

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Abstract –Internet of Things (IoT) is the main technological revolution in mobile computing, information and communication systems, describing a world of networked, digital elements where everything is interconnected. To improve Driving Safety, Monitoring the behavior of Real-time abnormal driving is a major part. The driving behaviors are usually monitored with the help of mobile phones and an additional hardware (sensors and cameras), it provides only coarse-grained result, i.e., abnormal driving behaviors are marked off from the normal ones. The fine-grained monitoring system can inform drivers and alarm them about their abnormal driving behaviors and it can inform regarding the same to the monitoring system. This work uses smartphone sensing and machine learning techniques and does not require any additional hardware other than the sensors that comes inbuilt with the smartphones such as accelerometer, orientation sensor and magnetometer sensors. This identifies specific types of abnormal driving behaviors such as Weaving, Swerving, Side slipping, Fast U-turn, Turning with a wide radius and sudden braking. Two machine-learning methods, Support Vector Machine (SVM) and Neuron Networks (NN) respectively, are used to train the features of driving behaviors and obtain a classifier model which can not only distinguish abnormal driving behaviors from normal ones but can also identify specific type of abnormal driving behavior.

Index Terms— Vehicle driving, Abnormal driving behavior, Accelerometer, Orientation sensor, Global Positioning Systems, Support Vector Machine (SVM), and Neural Networks (NN)

1. INTRODUCTION

Crashes caused by impairment of alertness in vehicle drivers pose a serious danger to people, not only to drivers themselves but also often to the general public. According to WHO, of the 56.4 million deaths worldwide in 2015, Road injuries killed 1.3 million people, about three-quarters (76%) of whom were men and boys [1]. At the present time cars and other private vehicles are being used daily by large numbers of people. The biggest

problem regarding the increased use of private transport is the rising number of fatalities that are occurring as a consequence of accidents on the roads; the associated expense and related dangers have been recognized as a serious problem that is being confronted by modern society. During these tragedies, drunk driving and reckless driving is one of the main causes. During crashes, tens of thousands of people were killed, and much more people injured. Besides being a great threat to public safety and health, drunk driving imposes a heavy financial burden on the whole society, especially on the healthcare sector. And reckless driving is a type of traffic violation in which a driver displays complete disregard for on-the-road signs, signals, and laws.

It is a common cause of car accidents, and, because it usually involves high speeds or extremely dangerous driving tactics, it often results in the injury or death of one or more people involved. In recent years, there has been tremendous growth in smartphones embedded with numerous sensors such as accelerometers, Global Positioning Systems (GPSs), magnetometers, multiple microphones, and even cameras.

The scope of sensor networks has expanded into many application domains such as intelligent transportation systems that can provide users with new functionalities previously unheard of. Moreover, the competitive nature of mobile device market has driven smartphone manufacturers to include a wide variety of sensors capable of acquiring vast amount of useful data. Driving behavior analysis is also a popular direction of smartphone-based vehicular applications. However, in most of the existing works on driving behaviors detection using smartphones can only provide a coarse-grained result using thresholds, i.e. distinguishing abnormal driving behaviors from normal ones.

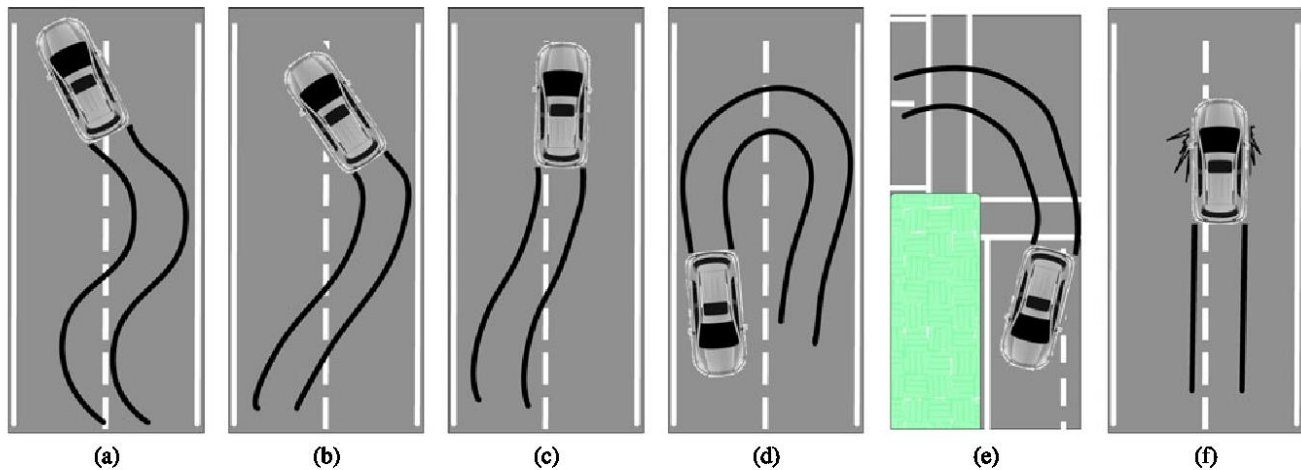


Fig. 1. Six types of abnormal driving behaviors: (a) Weaving (b) Swerving (c) Side slipping (d) Fast U-turn (e) Turning with a wide radius (f) Sudden braking.

In previous work they focused on giving fine grained result using the smartphone sensors like accelerometer, orientation sensor. The fine-grained abnormal driving behaviors monitoring is able to improve drivers' awareness of their driving habits as most of the drivers are over-confident and not aware of their reckless driving habits. Additionally, some abnormal driving behaviors are unapparent and easy to be ignored by drivers. If we can identify drivers' abnormal driving behaviors automatically, the drivers can be aware of their bad driving habits, so that they can correct them, helping to prevent potential car accidents. Furthermore, if the results of the monitoring could be passed back to a central server, they could be used by the police to detect drunken-driving automatically or Vehicle Insurance Company to analyze the policyholders' driving habits.

In this paper we propose energy efficient abnormal driving behavior system. And we have also included a monitoring system in the server side, So that the drivers can view their driving behaviors and they can also post reports [9] on other drivers about their driving behavior which they have witnessed on real time. In addition to accelerometer and orientation sensor we also included global positioning system to get the location of the event and for other purposes.

Like the previous work here we give a fine grained result. According to the U.S. NHTSA's study on drunk driving [12], there are six types of abnormal driving behaviors defined, and they are illustrated in Fig.1 Weaving (Fig.1(a)) is driving alternately toward one side of the lane and then the other, i.e. serpentine driving or driving in S shape; Swerving (Fig.1(b)) is making an abrupt redirection when driving along a generally straight course; Side slipping (Fig.1(c)) is when driving on a generally straight line, but deviating from the normal driving direction; Fast U-turn (Fig.1(d)) is a fast turning in U-shape,

i.e. turning round (180 degrees) quickly and then driving along the opposite direction; Turning with a wide radius (Fig.1(e)) is turning cross an intersection at such an extremely high speed that the car would drive along a curve with a big radius, and the vehicle sometimes appears to drift outside of the lane, or into another line; Sudden braking (Fig.1(f)) is when the driver slams on the brake and the vehicle's speed falls down sharply in a very short period of time.

Since smartphones plays a vital role in everyone's day to day life, it is used for many vehicular applications [4][5][6][7][9]. This work uses smartphone sensing and machine learning techniques. By extracting unique features from the readings of smartphone sensors, we can detect and identify the six types of abnormal driving behaviors above. To realize a fine-grained abnormal driving behaviors detection and identification, we face the following great challenges. First, patterns of driving behaviors need to be identified from readings of smartphone sensors. Second, the noise of smartphone sensors' readings should be removed. Finally, the solution should be lightweight and computational feasible on smartphones. Specifically, we make the following contributions:

- We use a data set which contains the features to identify the patterns of abnormal driving behaviors by empirically analyzing the features which contains driving traces collected from real driving environments.
- We use two machine learning method respectively, SVM and NN, to train the features of driving behaviors
- We propose a system which not only detects the specific abnormal driving behaviors but also alerts the driver. In addition to that we provide a platform so that the drivers can view their driving behaviors and

complaint other drivers which are witnessed by himself or by herself.

- The main purpose of the system is to build an energy efficient system. This is done by detecting the motion of the user and if the user is driving then the sensors will start the take readings if not they remain off.
- And we included Global Positioning Systems to retrieve the exact location of the events. GPS can be also used to check the road anomaly.

2. RELATED WORK

M. V. Yeo et al. [3] proposed a system which uses an electroencephalographic (EEG) to detect the drowsiness of the driver. It monitors and record electrical activity of the brain. And by using SVM machine learning method it identifies and differentiates the drowsiness from alertness. It is only based on driver's physical state and it is expensive to implement since it requires EEG.

S. Reddy et al. [4] proposed a system to detect the transportation mode of the user by using smartphone sensors like accelerometer and GPS. It doesn't use any learning based determination. Only efficient in finding the movement pattern of the user but No consideration for the detection of any abnormality.

J. Dai et al. [5] proposed a system which Detects and alerts of dangerous vehicle movement. This is done by using mobiles embedded sensors for detection. It provides a coarse grained result which distinguish the abnormal driving behaviors from normal driving behaviors.

H. Eren et al. [6] proposed a system to understand the driver behavior using smartphone sensors like Accelerometer, gyroscope and magnetometer sensors. It is Simplistic and user-friendly system. It shows only whether it is safe or unsafe driving.

M.Fazeen et al. [7] proposed a device that is not only already in abundance but portable enough has well to be one of the most effective multipurpose device that is able to analyze and advise on safety conditions. This is used as an alternative device for ADAS's. Road anomaly detection and Pothole detection are main purpose of the device.

S. Al-Sultan et al. [8] focuses on developing a novel and non-intrusive driver behavior detection system using a context-aware system in VANET to detect abnormal behavior's exhibited by drivers, and to warn other vehicles on the road so as to prevent accidents from happening.

C. Saiprasert et al. [9] proposes a novel dangerous driving report system using a smartphone platform. An algorithm is proposed to detect anomaly in speed profile in order to detect whether a vehicle is speeding using GPS.

Y. Wang et al. [10] utilizes smartphone sensing of vehicle dynamics to determine driver phone use, which can facilitate

many traffic safety applications. It capture differences in centripetal acceleration due to vehicle dynamics while using smartphone.

J. Yu et al. [11] utilizes smartphone sensors to estimate the vehicle speed, especially when GPS is unavailable or inaccurate in urban environments. And it uses accelerometer and gyroscope sensors. It also senses making turns, stopping, passing over uneven road surfaces.

3. PROBLEM FORMULATION

In this section, the problem will be described in detail. We will say about application scenarios and system model.

3.1 Application Scenario

Road injuries has become one of the top ten causes of death according to statistics which was published by World Health Organization (WHO) on January 2017. The statistics says that about 1.3 million people were killed due to road injuries in the year 2015 [1]. The report also says that about 76% of those whom were boys and men. Low-income countries had the highest mortality rate due to road traffic injuries with 28.5 deaths per 100000 populations whereas the global rate was 18.3. Road injuries were also among the leading 10 causes of death in both lower-middle- and upper-middle-income countries. Studies show that most of the road injuries are caused mainly due to human factors such as performing abnormal driving unknowingly, drunken driving, reckless driving and so on. Therefore, developing a monitoring system which will monitor driver's abnormal driving behavior is a necessary one which will help the drivers to know about their abnormal driving behavior pattern and also the officials can be alerted with the frequent reckless drivers.

Various abnormal driving detection systems has been proposed. Most of them focus on providing the coarse grained result [2][5][6] which will say whether the driving is safe or unsafe rather than saying about the particular abnormal driving performed by the driver. Among that most of them make use of external hardware, sensors, etc. Whereas there are some systems [2][3][8] which provide fine grained result in which the specific type of abnormal driving behavior can be detected using inbuilt smartphone sensors as well as some other systems with external hardware, sensors, etc.

However, those proposed systems while implemented in real world driving conditions seems to be more power consuming [8][3]. As a result of this the power retained in the smartphones started to drain sooner which become one of the major disadvantage. Hence this paper proposes a system which will make use of the sensors one by one. Initially the motion of

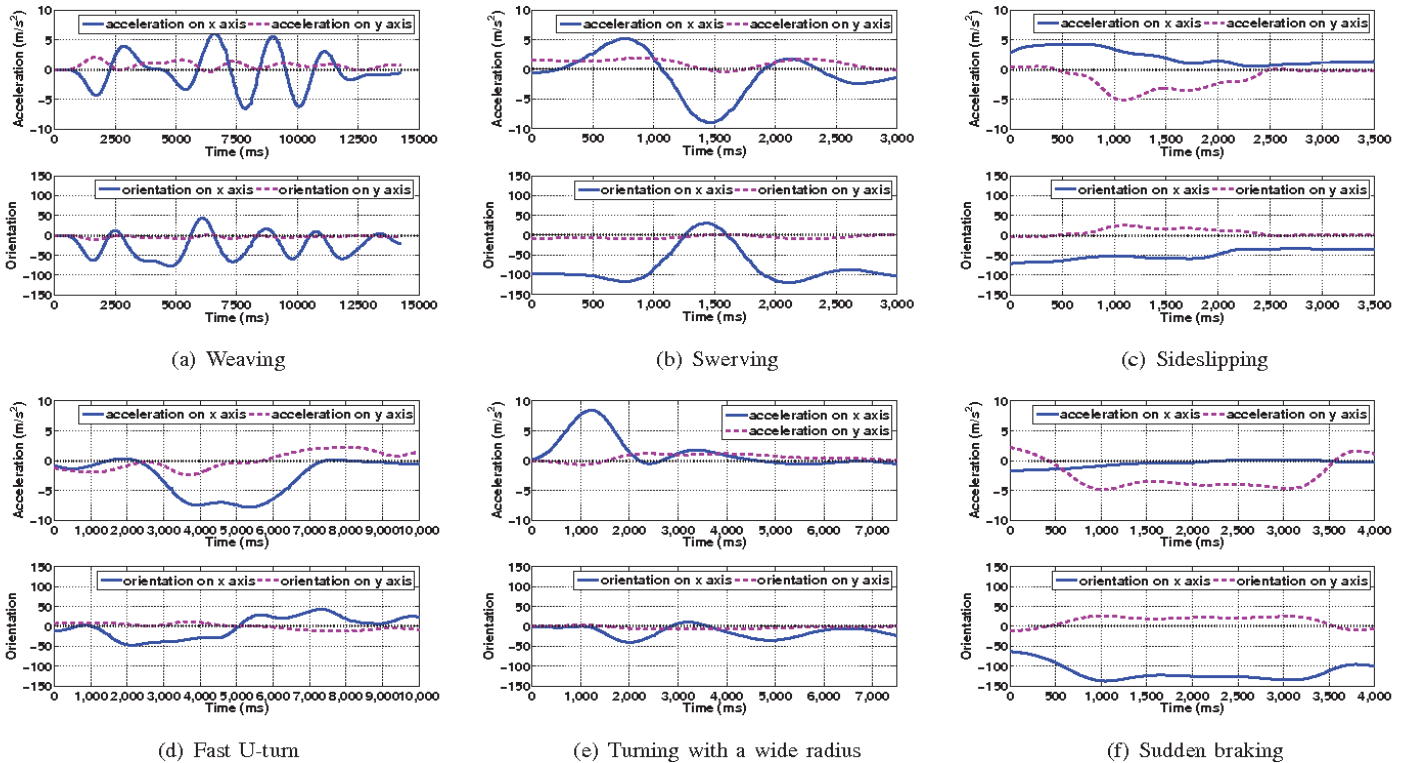


Fig. 2: The acceleration and orientation patterns of the six types of abnormal driving behaviors from an accelerometer and an orientation sensor's readings.

the user is detected by making use of the accelerometer sensor alone. Once when it confirms that the user is driving a vehicle the orientation sensor begins to record the reading along with the accelerometer sensor. And also GPS comes into action only when the values of those sensors exceeds the previously calculated threshold values. Thus the step by step startup of the sensors helps in consuming the power to a great extent.

3.2 System definition

The six types of abnormal driving behaviors are explained one by one. The definition is provided using the graph obtained from the previous work of fine grained abnormal driving detection [15]. Let acc_x be the acceleration value on x-axis and acc_y be on y-axis in a graph. Let the orientation values plotted on x-axis and y-axis be ori_x and ori_y respectively.

Definition 1. (Weaving) While driving constantly changing lanes and passing in between cars, most often at a high speed and in a dangerous manner. Someone who is weaving basically wants to overtake Everyone on the road, both on their lane and others. Almost exclusively met when multiple lanes are going in the same direction, especially on highways. While explaining in the graph we can say that a drastic fluctuation is observed on acc_x and this fluctuation continues for a period of

time, while acc_y remains smooth. Both the standard deviation and the range of acc_x are observed to be very large and the time duration is also observed to be long. While the mean of acc_x is around to be zero. In addition, we can observe that the orientation values are similar to the patterns of acceleration values.

Definition 2. (Swerving) Swerving can be defined as an abrupt turn away from a generally straight course. Swerving might occur directly after a period of driving when the driver discovers the approach of traffic in an oncoming lane or discovers that the vehicles is going off the road. Since swerving is found to be an abrupt, instant behavior, the duration of time period is very short. While explaining graphically, generally, when this kind of driving occurs, a great peak in the value is observed on both acc_x and ori_x values. The range and standard deviation of both acc_x and ori_x is also observed to be large, whereas the value of mean is not near to the value of zero. In addition to this both the values of acc_y and ori_y are observed to be flat during swerving.

Definition 3. (Side Slipping) When side slipping seems to happen, in the graphical representation the value of acc_y is observed to fall down sharply. The minimum value and mean value of acc_y are observed to be negative, whereas the range

of acc_y is found to be large. In addition to this it is observed that acc_x in side slipping is not near to the value of zero. If the vehicle seems to slip towards the right side, it is observed that acc_x would have a positive value, while if it is towards left, then it is said to have a negative value. But the mean value of acc_x seems to be not near zero. While considering the orientation, it can be observed that there are no obvious changes. Since side slipping is found to be an abrupt driving behavior, the time period of duration is short.

Definition 4. (Fast U-turn) When a driver seems to turn right or left at a fast speed in U-shape, in the graph it can be observed that acc_x rises quickly to a very high value or drops fast to a very low value, respectively to the side of the turn. In addition to this it can also be observed that the value would last for a period of time. The standard deviation of acc_x is thus seem to be large on the beginning and ending of a fast U-turn, whereas the mean value of acc_x is far from the value of zero and the range of acc_x seems to be large. However, when it comes to acc_y , no obvious changes can be observed. Moreover, it can be seen that the value of ori_x would pass over the zero point. Specifically, it can be said that ori_x would change either from positive value to negative value or from negative value to positive value, depending on the original driving direction. The standard deviation and value range of ori_x is found to be large. Also the values of mean in the first half and second half of ori_x would be of opposite sign, i.e. one positive and the other negative. It is observed that it may take a long period of time to finish a fast U-turn when compared with other behaviors, so therefore in turn the time duration tends to be long.

Definition 5. (Turning with a wide radius) When turning at an extremely high speed, while observing the readings in a graph the value of acc_x seems to have a high magnitude for a period of time, whereas the value of acc_y is found around to be zero. It is observed that the value of mean of acc_x is far from zero which in turn makes the standard deviation of acc_x to be large. While it comes to the value of orientation, a fluctuation in the value of ori_x is observed, whereas ori_y seems to be smooth. It is observed that the value of standard deviation of ori_x is relatively large, whereas the value of mean of ori_x is not near to the value of zero since the direction of the driving is changed. It is also observed that it may take a long period of time to complete a turning with a wide radius, so thus in turn the duration of time period becomes long comparatively with other driving behaviors.

Definition 6. (Sudden Braking) When a vehicle brakes suddenly, meanwhile in the graph we can observe that the value of acc_x remains flat while the value of acc_y sharply

downs and it remains negative for some time. This results in maintaining the standard deviation and value range of acc_x to be small. While observing the value of acc_y , the standard deviation seems to be large at the beginning and ending during a sudden braking period and the range of acc_y seems to be large. However, it can be observed that there are no obvious changes on both the values of ori_x and ori_y . Since it can be observed that sudden braking is an abrupt driving behavior, it seems that the time duration is also short.

Table. 1: Basic Features

$range_{acc,x}$	subtraction of maximum minus minimum value of acc_x .
$range_{acc,y}$	subtraction of maximum minus minimum value of acc_y .
$\sigma_{acc,x}$	standard deviation of acc_x
$\sigma_{acc,y}$	standard deviation of acc_y
$\sigma_{ori,x}$	standard deviation of ori_x
$\sigma_{ori,y}$	standard deviation of ori_y
$\mu_{acc,x}$	mean value of acc_x
$\mu_{acc,y}$	mean value of acc_y
$\mu_{ori,x}$	mean value of ori_x
$\mu_{ori,y}$	mean value of ori_y
$\mu_{acc,x,1}$	mean value of 1st half of acc_x
$\mu_{acc,x,2}$	mean value of 2nd half of acc_x
$max_{ori,x}$	maximum value of ori_x
$max_{ori,y}$	maximum value of ori_y
$min_{acc,y}$	minimum value of acc_y
T	time duration between the beginning and the ending of a driving behavior

Definition 7. (Normal Driving) Normal driving behavior means smooth and safe driving with few and small fluctuations. Since there are few drastic actions in a normal driving behavior, the values on both acc_x and acc_y are not very large. So the mean, standard deviation, maximum and minimum values in acceleration on x-/y-axis are near zero. When it comes to orientation, a normal driving behavior presents smooth most of

time. So the standard deviation and range of orientation are small.

We find that each driving behavior has its unique features, e.g. standard deviation, mean, maximum, minimum, value range on acc_x , acc_y , ori_x and ori_y , as well as the time duration. Therefore, we could use those features to identify specific types of abnormal driving behaviors using machine learning techniques.

3.3 Detecting and Identifying Abnormal Driving Behaviors

After we obtain a classifier model, we are able to detect and identify abnormal driving behaviors in real driving environments using the model. In order to identify current driving behavior using the model, we should input features extracted from patterns of a driving behavior. SafeDrive thus need to determine the beginning and ending of the driving behavior first, i.e. cutting patterns of the driving behavior. The method of sensing the beginning and ending of a driving behavior is proposed based on an analysis on the acceleration and orientation patterns of all types of driving behaviors. Specifically, when an abnormal driving behavior begins, the standard deviation of either the acceleration or the orientation values sharply rise to and keep a relatively high value until the driving behavior ends, while in most normal driving behaviors, the standard deviation always presents as low and smooth. Moreover, during an abnormal driving behavior, the magnitude of acceleration on either x-axis or y-axis presents an extremely high value. But when driving normally, the magnitude of accelerations seldom reaches to such a high value.

Therefore, it is simple but effective that we monitor the standard deviation of acceleration and orientation as well as the magnitude of acceleration of the vehicle from smartphone sensors to cut patterns of driving behaviors. In real driving environments, we retrieve readings from smartphones' accelerometers and orientation sensors and then compute their standard deviation as well as mean value in a small window. If a vehicle is under normal driving, SafeDrive compares the standard deviation and the mean value with some thresholds to determine whether an abnormal driving behavior begins

After cutting patterns of a driving behavior, effective features can be extracted from the driving behavioral patterns and then sent to the classifier model. Finally, the model outputs a fine-grained identification result. If the result denotes the normal driving behavior, it is ignored, and if it denotes any one of abnormal driving behaviors, SafeDrive sends a warning message. The warning message will be sent both to the driver and to some remote receivers. The drivers can be aware of their bad driving habits from the warning messages along their

driving, so that they can make targeted corrections of their bad driving habits, helping to prevent potential car accidents. Furthermore, the identification results can be passed back to a remote central server. On that case, the remote server can call the police automatically once a traffic accident occurs, which may save lives in case the victims have difficulty doing so by themselves (i.e. in case they lose consciousness or cannot move). In addition, the automatic recorded warning messages along with the specific car/driver may help identifying the driver in hit and-run accidents. Those warning messages stored in the central server may also help the vehicle insurance company to analyze the policyholders' driving habits, so that the insurance company may offer a more preferential car insurance policy to drivers with good driving habits, and a harsh policy to those with a long history of warning message lists.

4. SYSTEM DESIGN

In this section, we introduce the design and implementation of our abnormal driving behavior monitor and detection system which determines the drivers driving behavior accurately through sensing driving conditions using smartphone sensors. And this system does not depend on any pre-deployed infrastructure and additional hardware.

The monitoring and detection system consist of two modules, as presented in Fig. 2. They are (1) Offline module and (2) Online module. The Online module has (1) Server module and (2) Client module.

In the offline part, trains a classifier model using machine learning techniques based on the collected data, which could identify specific types of driving behaviors. In the Feature extracting, effective features are extracted from specific types of driving behavioral patterns using smartphone sensors [6]. Afterwards, the features are trained in the Training and a classifier model would be generated which can realize fine-grained identification for various types of driving behaviors. Finally, the classifier model is output and stored to Database.

The online part, consist of (1) server module and (2) client module. The client module is responsible for collecting the features of the driving from the readings of the sensors. First it determines the user's transportation mode using accelerometer. If the user is riding a vehicle, then the sensors starts to take the readings or it stays without doing any process related to detection process. The readings are taken from accelerometer, orientation sensor and global positioning system. Then the readings are passed to cutting driver behavior pattern to check whether there is any sharp deviation in readings. The extracted features from patterns of the driving behaviors are monitored, then identifies whether one of the abnormal driving behaviors occurs based on the data set which consist of predefined driving

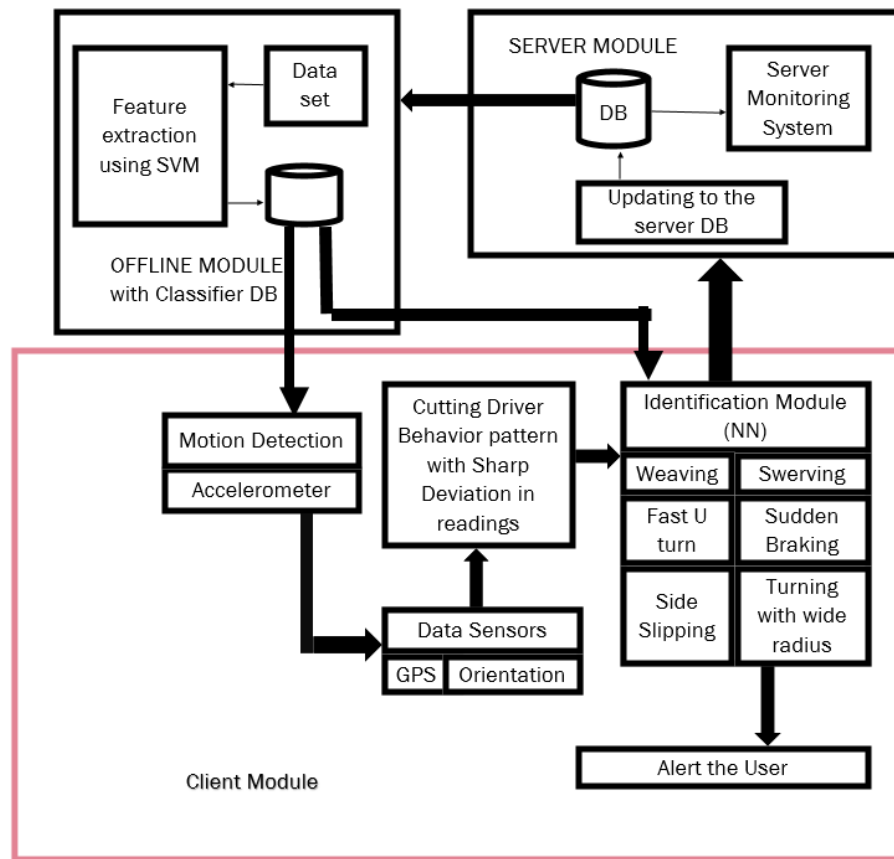


Fig. 3: System Design.

behavior. Then using NN algorithm the specific type of abnormal driving behavior is identified.

Finally, if any of the abnormal driving behaviors were identified, a warning message is sent to drivers. These readings will be updated in the driver’s profile. In the server module the data’s will be kept in database and also update in data set for future use. Using the application or the website the user that is the driver can view their driving behavior reports updated on their profile. And they can also remark others driving behavior. This helps in investigating accidents. Let us see how the system works and we will describe each module in detail.

4.1 Offline module

In the Feature Extracting, effective features are extracted from specific types of driving behavioral patterns on acceleration and orientation. The dataset is obtained by the traces from the accelerometers and orientation sensors readings on 20 drivers for about 4 months. But this project makes use of the above mentioned dataset downloaded from online to extract features from the dataset. The main difference between various driving behaviors lies in the maximum, minimum, value range, mean, and standard deviation of acc_x , acc_y , ori_x and ori_y and t . Therefore, those values can be used as features for training.

There is a sharp deviation from the normal and the abnormal. Therefore, we manage to distinguish abnormal driving behaviors from normal ones with only two features. The variation in normal vs abnormal values of t , $\max_{ori,x}$, $\max_{ori,y}$, $\sigma_{ori,x}$, $\sigma_{ori,y}$, $\sigma_{acc,x}$, $range_{acc,x}$, $\min_{acc,y}$ and $range_{acc,y}$ manage to distinguish abnormal driving behaviors from normal ones. Here we use Support Vector Machine Algorithm. In practical implementation of the system the R Studio software is used to implement the SVM.

The SVM algorithm is implemented in practice using a kernel. A kernel is a similarity function. It is a function that you, as the domain expert, provide to a machine learning algorithm. It takes two inputs and spits out how similar they are. Here one input is normal driving readings tuples of sensor traces and other is the abnormal samples extracted from the accelerometer and orientation sensors.

$$k(x_i, x_j) = \exp\left[-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right]$$

$$i, j = 1, 2, 3, \dots, m$$

$$\text{where, } \|x_i - x_j\|^2 = \sum_{i=1}^m (x_i - x_j)^2.$$

Thus the features are extracted from the data set and they are provided to the online module for classification. In the similar way the accelerometer reading for the user's activity whether the user is still or the user is driving the vehicle can also be extracted in the offline module.

Algorithm 1 SVM (training_set, input_sample)

```

1: for i = 1, 2, ..., m do
2:   for j = 1, 2, ..., 16 do
3:      $x_j^{(i)} \leftarrow \text{training\_set}(i, j)$ 
4:   end for
5: end for
6: for i = 1, 2, ..., m do
7:   for j = 1, 2, ..., 16 do
8:      $l_j^{(i)} \leftarrow \text{input\_sample}(i, j)$ 
9:   end for
10: end for
11: repeat
12:   for i = 1, 2, ..., 16 do
13:      $\sigma = \text{sqr}t\left(\frac{x_k^{(i)} + l_k^{(i)}}{2}\right)$ 
14:      $J \leftarrow \sum_{k=1}^{16} (x_k^{(i)2} - l_k^{(i)2})$ ;
15:      $f_j^{(i)} = e^{-J/2\sigma^2}$ 
16:   end for
17: until  $i \leq m$ 
18: for i = 1, 2, ..., m do
19:   for j = 1, 2, ..., 16 do
20:      $\vec{\theta}_i \leftarrow \{\min(f_j^{(i)}), \text{Type}(f_j^{(i)}), \sigma\}$ 
21:   end for
22: end for
23: Return  $\vec{\theta}_i$ 

```

The Algorithm 1 defines how the SVM extract features from the input training data set and input sample values that are being obtained by collecting the features of accelerometer and the orientation sensor readings. The kernel function computes the similarity between the training set and input sample and classifies them and output will be of a Vector containing

standard deviation, minimal kernel value and type of driving behaviour.

Table. 2: Notations used in Algorithm. 1

m	Number of samples in training set
$x_j^{(i)}$	Training set values
$l_j^{(i)}$	Input samples values
σ	Standard deviation of training set and input samples
$f_j^{(i)}$	Similarity or kernel function
$\vec{\theta}_i$	Vector containing σ , minimal kernel value and type of driving behaviour.

4.2 Online module

The online part, consist of (1) server module and (2) client module.

4.2.1 Client module

The client module is responsible for collecting the features of the driving from the readings of the sensors. The work-flow of the client module is given below.

First the motion of the user is listened by the accelerometer. Usually the raw accelerometer reading's z-axis reading denotes the motion of the user along the z-axis direction. When it crosses the reading which is extracted by the SVM in the offline module then it is taken that the user is driving the vehicle. Once the user is marked to be in driving state then the Orientation and GPS along with the accelerometer sensor starts listening. The accelerometer sensor is said to be less power thirst in comparison with the other two sensors. So, we are using accelerometer alone for motion detection and thus we can avoid battery drainage when the mobile is in idle. The readings obtained from accelerometer, orientation and GPS while driving are checked for sharp deviation and if any given to the identification module where neuron networks are employed to classify the abnormal driving using the features extracted from the offline module. The driver ID along with the details of abnormal driving are send to the server module.

4.2.2 Server module

The server module has the database in which the detected abnormal driving will be send from the client module. It also has a monitoring system in which the administrator can view the abnormal driving of the users. Further these data are used

as a data set input to the offline module from which the features are extracted further.

Neuron network is a decision tree algorithm. In this algorithm a decision tree is used to map decisions and their possible consequences. This method allows the problem to be approached logically and stepwise to get to the right conclusion.

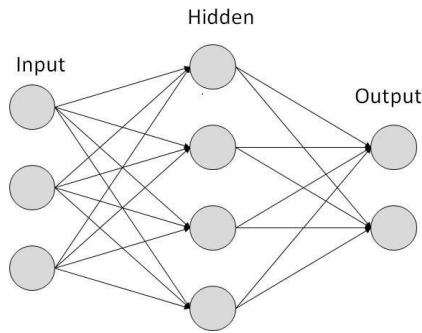


Fig.4: Neuron network representation

The Algorithm 2 explains how the Neuron Networks functions. The inputs will be the trained features that is being extracted by the SVM algorithm and the sensor input that are recorded currently. The sensor inputs are recorded for 4 or more samples. The neuron networks have 3 layers the input layer, the hidden layer and the output layer. In the input layer the input values are fed in. In the hidden layer the activation function compares the recorded input value with the features that is being extracted by the SVM algorithm and assigns the unit's value accordingly. The output layer compares every previous layer outputs and maximum of that will be the detected abnormal driving behavior. The type of the driving behavior is returned. Type 0 denotes the driving is normal and others respectively.

Table. 3: Notations used in Algorithm. 2

L	Number of hidden layers
S	Number of units in each layer
N	Number of sensor input data recorded
$h^{(i)}$	i^{th} hidden layer
$\theta_{j,0}^{(i)}$	Value of extracted features.
x_0	Bias unit
x_i	Values of recorded sensor inputs
$h_i^{(out)}$	Output layer.

Algorithm 2: NN (trained_set, sensor_inputs)

```

1: Type ← 0
2: L ← trained_set.samplelength
3: S ← trained_set.GetNumberOfAbnormals()
4: Initialize  $h^{(1)}, h^{(2)}, \dots, h^{(6)}$  layers
5: for  $i = 1, 2, \dots, S$  do
6:   Initialize  $h_1^{(i)}, h_2^{(i)}, \dots, h_s^{(i)}$ 
7:   Assign  $\theta_{i,0}^{(i)}, \theta_{i,1}^{(i)}, \dots, \theta_{i,s}^{(i)}$  feature values
8: end for
9: n ← sensorinputs.length()
10: for  $i=1, 2, \dots, n$  do
11:   Assign every sensor inputs to input layer ( $x_i$ )
12: end for
13:  $x_0 \leftarrow 1$ 
14: for  $j=1, 2, \dots, S$  do
15:   if  $(\theta_{1,0}^{(j)} < x_j)$ 
16:      $Z \leftarrow x_0$ 
17:      $h_1^{(j+1)} \leftarrow \frac{1}{1+e^{-Z}}$ 
18:   endif
19: end for
20: for  $i=1, 2, \dots, L$  do
21:   for  $j=1, 2, \dots, S$  do
22:     if  $(\theta_{j,0}^{(i)} < h_j^i)$ 
23:        $z \leftarrow x_0$ ;
24:        $h_j^{(i+1)} \leftarrow \frac{1}{1+e^{-z}}$ 
25:        $h_j^{(i+1)} \leftarrow 0$ 
26:     end if
27:   end for
28: end for
29: for  $i=1, 2, \dots, 6$  do
30:    $z \leftarrow \theta_{i,0}^{(out)} h_0^{(L)} + \theta_{i,1}^{(out)} h_1^{(L)} + \dots + \theta_{i,s}^{(out)} h_s^{(L)}$ ;
31:    $h_i^{(out)} \leftarrow \frac{1}{1+e^{-z}}$ ;
32: end for
33:  $J \leftarrow h_0^{(out)}$ 
34: for  $i=1, 2, \dots, 6$  do
35:   if  $(h_i^{(out)} > J)$ 
36:      $J \leftarrow h_i^{(out)}$ 
37:   end if
38: end for
39: Return Type
    
```

Fig.4 shows how a neuron network takes a decision. Here in our work the inputs will be the values from the sensors, conditions are provided by the features extracted from the SVM, the output will be the type of abnormal driving that is being detected.

5. SYSTEM EVALUATION

In this section the vehicular motion detection and power consumption of our system are evaluated.

5.1. Evaluation of Vehicular motion detection.

We implemented drive sense in the android platform. The user interface of the client side module that actually detects the vehicle motion initially and then triggers the orientation sensor. For the evaluation of the proposed vehicle motion detection module we collect data from 10 users initially for about 7 days. Recording the detection for 7 days we get 118 samples with its elapse time of detection. Here, is some definition for the evaluation metric which we use for the analysis.

Definition 7. (True Positive) True positive T_p refers to the number of detections that are same as the ground truth.

Definition 8. (False Positive) False positive F_p refers to the number of detections that are false in the reality.

Table. 4: Notations used in evaluation

T_p	True Positive
T_N	True Negative
F_p	False Positive
F_N	False Negative
A_c	Accuracy
TPR	True Positive Rate
FPR	False Positive Rate
PRE	Precision

Definition 9. (True Negative) True negatives T_N refers to the number of non-detected vehicular motions which are actually non-vehicle motions in the reality.

Definition 10. (False Negative) False negatives F_N refers to the number of non-detected vehicle motions that are actually vehicle motion while considered in reality.

Definition 11. (Accuracy) Accuracy A_c is the probability that the identification of the vehicular motion which will be the same as the ground truth.

$$A_c = \frac{T_p + T_N}{T_p + T_N + F_p + F_N}$$

Table. 5: Confusion Matrix.

	T_p	T_N	F_p	F_N	TPR	PRE	FPR	A_c
1	18	20	0	2	0.9	1	0	0.95
2	19	20	0	1	0.95	1	0	0.975
3	17	20	0	3	0.85	1	0	0.925
4	18	20	0	2	0.9	1	0	0.95
5	17	20	0	3	0.85	1	0	0.925
6	19	20	0	1	0.95	1	0	0.975
7	20	20	0	0	1.0	1	0	1

Definition 12. (False Positive Rate) False positive rate FPR is the probability that a vehicular motion is not identified correctly.

$$FPR = \frac{F_p}{T_N + F_p}$$

Definition 13. (True Positive Rate) True positive rate TPR is the probability that all the vehicular motions that are detected by our system. In other words, the proportion of vehicular motion instances that are detected by our system as vehicular motion.

$$TPR = \frac{T_p}{T_p + F_N}$$

Definition 14. (Precision) Precision is calculated as the number of correct positive vehicular detections divided by the total number of detections. In other word it is the proportion of vehicular motions that are detected by our system as driving which are actual vehicular motion in reality.

$$PRE = \frac{T_p}{T_p + F_p}$$

The Fig.5 shows the comparison between the True positive rate and False positive rate. The results show that our system has good true positive rate and has zero false positive rate since there is no negative detections, our system will not detect the vehicle at rest as it is in motion.

The Fig.6 shows the comparison between the precision and recall. The evaluation results show that our system has a high precision and an good recall. The high precision is due to zero false positives.

The average Accuracy A_c of the vehicular motion detection is 95.7%.

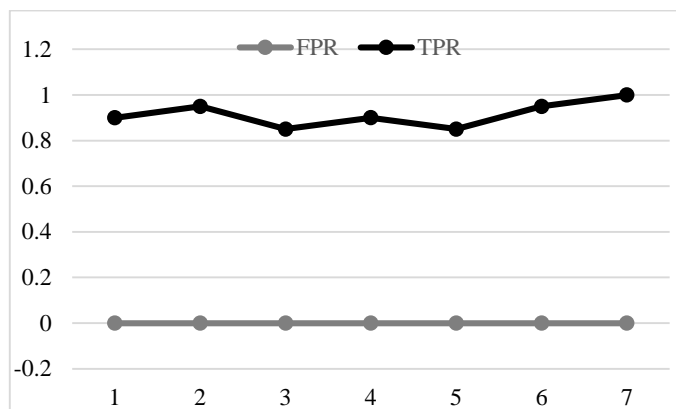


Fig. 5: Comparison between TPR and FPR

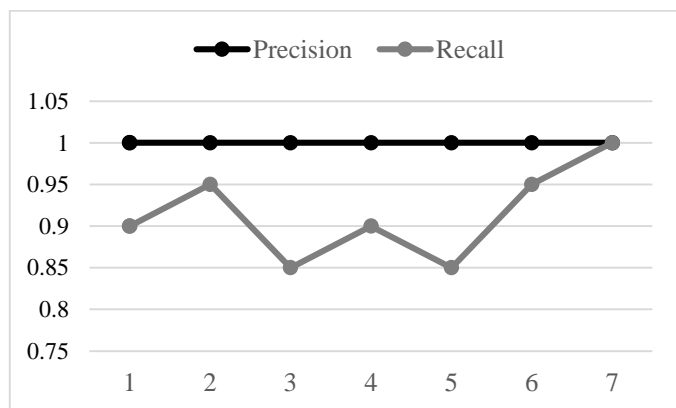


Fig. 6: Comparison between Precision and Recall.

5.2 Evaluation of Power consumption in smartphone.

In the previous work of fine grained abnormal driving detection, the sensors such as accelerometer and orientation sensors keep sensory data at high sampling rate which may result in heavy energy consumption. Keeping them listening throughout the smartphone working as well as idle time may result in heavy drainage of battery. Hence they preferred low sampling rate or sampling frequency in order to make more energy efficient. However, this will affect the accuracy of detection of the abnormal driving.

In the previous work among the application under 300 Hz provides high accuracy but consumes lot of energy of the smartphone. The main goal of our work is to reduce the

smartphone energy consumption while not affecting the sampling rate and its proportional accuracy. It is evident that the orientation sensor and GPS consumes lot of energy when compared to the accelerometer sensor. The accelerometer's Z-axis denotes the forward motion of an object, which is sufficient for detecting the vehicular movement. This concept is used in our work to detect the vehicular motion. Initially registering the orientation sensor later on when triggered as driving will drastically reduce the energy consumption in idle time. Triggering the orientation sensor only at the time of driving will register the sensor reading only at the vehicle motion or driving mode and does not register at the idle time of the smartphone. The orientation sensor and accelerometer can be used at a sampling rate of 300 Hz which further does not affect the accuracy of the system.

Table. 6: Experimental results on power consumption.

	Not running Drive Safe	Running Drive Safe without vehicle motion detection	Running Drive Safe with vehicle motion detection
Samsung Galaxy A5	100	148	115
Redmi Note 4	100	142	113
Nokia 3 (android)	100	144	114
Honor 6+	100	137	108
Samsung Galaxy J7	100	153	118

For the evaluation of the power consumption of our application the dataset is obtained with experimental mean using power metrics. All the applications and services (E.g. Wi-Fi, networks, and cellular data) are at offline mode during the experiment. Each time three smartphones of same type are taken for two days (48 hours exactly), one smartphone with no app at all, the other one with the app which is running without the vehicular motion detection feature with a sampling rate of 300 Hz and the final one is running the Drive Safe application only. With vehicular motion detection feature at the same sampling rate of 300 Hz the experimental analysis involved 3 hours of vehicle travel per day which means 6 hours of

vehicular motion. Rest 42 hours of idle time all the three smartphones are subjected to the same experimented timeline. The same experiment is repeated with five different smartphones with different processors, chipsets and features having the three sensors namely Samsung Galaxy A5, Nokia 3, Honor 6+, Redmi Note 4 and Samsung Galaxy J7 (2016).

The energy consumption of the device without running Drive Safe is normalized to 100%. At the normalized percentage the power consumption of other two cases are noted. The Table 6 shows the experimental results obtained.

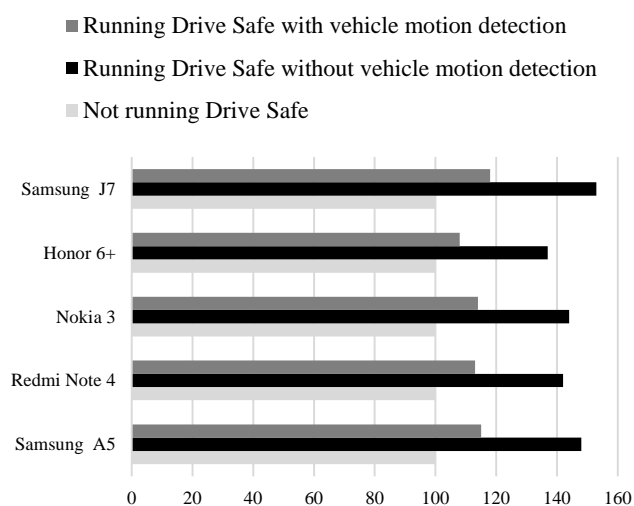


Fig. 7: Comparison of power consumption on various smartphones

The Figure. 7 shows that the energy consumption is significantly reduced when running the Drive Safe with vehicular motion detection feature with the same sampling rate of 300 Hz. Further this reduces the power constraint and increases the usability of the application. Thus the evaluation results show that our work overcomes the shortcomings of power drainage in the smartphone without much difference in the accuracy compared to the previous work.

6. CONCLUSION

In this paper, we address the problem of performing abnormal driving behaviors detection without motion detection in the previous works and this provides fine grained detection

of abnormal driving behaviors. The SafeDrive identify specific types of abnormal driving behaviors by sensing the vehicle's acceleration and orientation using smartphone sensors. This identifies Weaving, Swerving, Side slipping, Fast U-turn, turning with a wide radius and Sudden braking in addition the smartphone's orientation sensor is registered only at the time of vehicle motion thus drastically reduces the power drainage of the smartphone at the idle time.

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