Accident Detection and Classification using IoT Fusion-Enabled Framework with Machine Learning Classifiers

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Abstract

Increasing the number of vehicles on the road is the major cause of accidents which may cause death and disability of people. This factor could be overcome with timely information. The proposed system mainly focuses on improving the accuracy of detecting an accident along with the severity. This technique helps to report the accident information to the emergency service providers. The dataset contains information about microcontrollers, GPS, and different sensors for determining the accident and the physical parameters of the moving vehicle. Machine learning classifiers K-Nearest Neighbor, Random Forest, and Gaussian Mixture Model show the most accurate classifier, in which KNN and RF help to get better results for detecting accidents. The performance of RF and KNN showed better results than the GMM. The proposed model creates a fusion model by an ensemble of the KNN and RF to get more accurate results in accident detection and an experiment is done to show the fusion results.

Keywords*—Internet of Things, Accident Detection, VANETS, RF, KNN, GMM.*

I. Introduction

Road accidents are increasing due to the high rise of vehicular transportation over the world. WHO, surveys in 2018 that around 1.35 million human lives got victims of road accidents. Speedy information towards emergency service providers may help to provide timely first aid to the patient which may very precious for the survival of the victim's life considering the principle of the golden hour [1]. Technology has been used in the past for the EMS after an accident in terms of communication and information [2]. Many types of research performed for improving the accuracy to get better results on the severity of accidents, or the important factor in reducing the rescue period [3,4].

Contribution to this work: Main focus of this work is on expecting, avoiding, and discovering road accidents with improved accuracy for reducing the rescue span after a smart vehicle accident. This approach employs a stacking ensemble to combine the outputs of K-Nearest Neighbor, and RF (Random Forest) classifiers and finds that the performance of this fusion model is superior to that of these classifiers when employed alone. The suggested solution is practical, affordable, and can be installed in any car.

II. Related Work

Road accident detection, localization, reporting, modeling, and analysis have all been done using an IoT medium in various research projects. In this section, some recent work and different contributions of the researchers have been discussed for accident detection. Dashora, C. et al. presented an accident detection model that employs an accelerometer to read two simultaneous accelerations and send the data to the cloud [5]. The accident is located by computing the difference between two accelerations. The difference will be beneficial if the automobile crashes from the front while traveling at a high speed. If the car is engaged in a collision from the back, the difference will be negative and have a negative value since the speed of the car will suddenly increase.

A method for detecting car collisions based on the Internet of Things was also suggested in [6]. The system was improved with the addition of a vibration sensor to track the driver's health and phone or SMS the driver's emergency contacts in case of an emergency. Additionally, several methods that rely on a smartphone have been suggested. To identify low-speed and high-speed auto accidents, Ali and Alwan [7] created a technique that comprises many examples. If a smartphone accelerates more than four times while traveling at a fast pace, an accident has occurred, and the program on the smartphone can detect it. The severity of the vehicle fall-off has been divided into three categories by Kumar et al. using accelerometer, GPS, and barometer sensors [8]. With an average F1-score of 0.95, the severity of the fall-off has been classified using a supervised machine learning model based on KNN (K-Nearest Neighbor).

To detect accidents, sensor fusion has been utilized in many tasks. To our knowledge, no significant study has been described in the literature on accident classification, particularly about improving accuracy. To follow road events in real time, Zhang et al. attempted to combine data from several sources by merging measurements with social media tweets. The authors claim that using several data sources enhances prediction accuracy when using the SVM as a classification model with 5-fold cross-validation [9].

Table 1. Existing Systems

Ref	Accuracy	Classification	Android Based	Reporting	Medium	Fire Sensing
5	L	N	N	M	Wi-Fi	N
6	L	N	N	A	4G/LTE	N
7	L	N	Y	A	4G/LTE	N
8	H	A-T	Y	A	4G/LTE	N
P-I	H	S-L	N	A	4G/LTE	Y

Low = L, High = H, Yes = Y, No = N, Manual = M, Automatic = A, Accident Type = A-A, Severity Level = S-L, Proposed Idea = P-I

In this study, a novel sensor fusion-based approach to identifying and categorizing accident occurrences is suggested. This approach has not yet been used in any other recent studies. To increase the precision of accident classification, a unique sensor fusion framework that applies sensor fusion (or model fusion) at several stages of processing has been tested.

III. Model

The IoT-enabled architecture, as depicted in Figure 1, communicates vehicle accident detection and classification as well as the accident type and location to the appropriate agencies for an immediate and targeted rescue effort. To solve this study topic, sensors of a microcontroller are utilized to read the values of four different vehicles' motion-related physical and environmental data, including vehicle acceleration, speed, and elevation change, and a maximum of pitch, roll and weather attributes considered in the data.

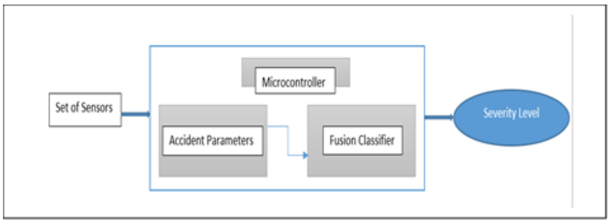

Fig 1. Proposed System Model

A. Microcontroller

The classifier receives the computed criterion values from the microcontroller once it has assessed the input. To guarantee precise judgments are made while utilizing the fewest amount of resources and computing power, the acquired data are processed every 10 ms.

B. Accident Parameters

This section provides descriptions of the system variables, detection strategies, and sensor types.

Speed: By monitoring the produced magnetic pulse, which is proportional to speed, the Hall Effect sensor calculates the speed of the vehicle. It is turned on by the magnetic field and is controlled by a single permanent magnet fastened to a car's wheel. The p-type semiconductor material used to make the sensor is shaped like a rectangle and continuously conducts current through it. The charge carriers are then deflected to either side of the semiconductor slab as a result of the effect the magnetic field has on the semiconductor. Concerning the intensity of the magnetic field, this produces a measurably high voltage.

Severity: The accident spot is identified by a force sensor that monitors weight, squeezes, and physical pressure. The sensor is a variable resistor, which means that its resistance varies in reaction to applied pressure. Since there are several layers, the pressure causes the resistance to decrease as more resistant carbon pieces come into contact with the conductive traces [10].

Latitude and Longitude: By calculating the rotation and altitude, an accelerometer was used to detect a vehicle's rollover and fall-off caused by an accident as shown in Figure 2. Any accelerometer's data sheet identifies the x, y, and z axes positively on its packaging. The roll ⌀ and pitch ϴ angles of a vehicle around the x and y axes are computed to estimate the rollover event, with a rollover occurring when the roll ⌀ or pitch ϴ angles are more than 90 degrees [11].

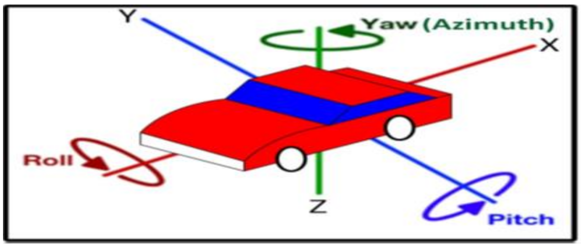

Fig 2. Latitude and Longitude

Flame and Smoke: Vehicle fire accidents typically have high severity levels and may need specialized medical attention. To detect fire, our technology detects flame and smoke. A photonic sensor that transforms incoming photons into charge carriers is employed for flame detection. It responds to electromagnetic radiation emitted by fires, including infrared, visible light, and ultraviolet radiation. The flame may be seen if the wavelength is greater than 0.7 m. The sensor monitors emission at several small or extensive wavelength areas, either in a mix of (IR) and (UV) regions or solely in various infrared regions, to prevent false alarms [12].

IV. Experiment

For the experiment, the FARAS dataset has been used to check the severity level with the help of a fusion model and evaluate the accuracy. Figure 3 depicts the framework for learning classifiers in the proposed work. Firstly, the data normalization is applied for features extraction, and the separate evaluation of the three models has been calculated shown in Table 2. Secondly, the compression method is applied to the data set for the evaluation of the GMM and fusion model. A fusion model is applied to the dataset to find out the accident's severity level and the visualization is shown in Figure 4. The results of the fusion model depict that if the classifiers ensemble in a specific manner it will improve the results. In my opinion, different datasets and fusion models can be tested for further improvement with different classifiers and feature extraction techniques.

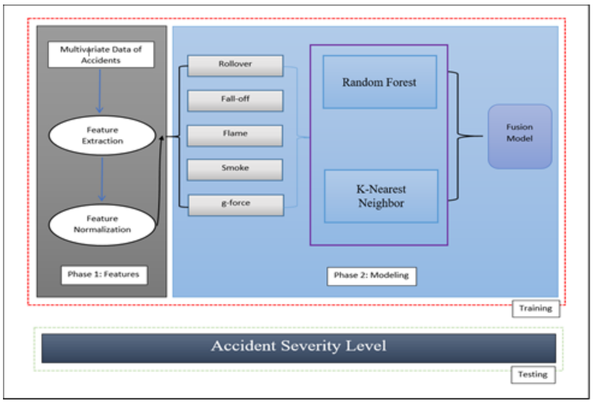

Fig 3: Accident Detection and Classification

Table 2. Results of the ML Classifier vs Fusion Classifier

Model	MAE	RMSE	CC	PARAM
KNN	0.32	0.52	0.22	K=19
RF	0.35	0.52	0.18	MaxDepth=7
GMM	0.56	0.66	0.48	BatchSize=100
Fusion(KNN+RF)	0.29	0.48	0.17	KNN+RF

MAE= Mean Absolute Error, RMSE= Root Mean Square Error, CC= Correlation Co-efficient & PARAM= Feature Selection

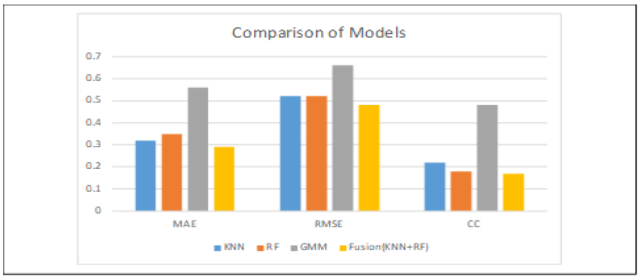

Fig 4: Results of ML Classifiers and Fusion Model

V. Conclusion

This study introduced a generic IoT-based system for accident detection and categorization that works well with any type of vehicle. It prompts an early response to accidents by getting in touch with the required parties. Accidents are discovered, categorized based on their severity, and the emergency services providers are informed of the crucial details. To find the best accurate model for accident severity level class, a comparative fusion research between several machine learning classifiers was carried out and the parameters are showing better results for the proposed idea framework.

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