Street SAFE - Road Fault Monitoring and Reporting

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ABSTRACT

Maintaining roads have become challenging as road users are on the rise. Tough weather conditions and high traffic make road surfaces deteriorate swiftly. Manual detection on these defects is not efficient. Due to the rise of smartphone use, the accelerometers in the smartphone are employed for road fault classification. Supervised machine learning classification models of data pertaining to pothole, speed bump, hazard line, smooth road, uneven road, turn, and hard stop are trained with the Random Forest (RF) and Support Vector Machine (SVM) algorithms, which is then utilized in StreetSAFE (Smartphone Assisted Fault Examination), a machine learning aided system to detect road faults and report them in real time. Using statistical parameters, the system is found to able to distinguish road surface conditions. The system can potentially predict road damage, facilitate maintenance and resource management.

Keywords: *Machine learning, statistical features, accelerometer, road faults.*

I. INTRODUCTION

Plenty of road accidents happen because of bad road surface conditions such as potholes. Road surfaces become damaged over time due to factors such as location, traffic, weather, engineering solutions and materials. However, state municipalities strive to maintain perfect road surface condition and repair damaged roads immediately but due to bad weather and the unforeseen loads of traffic, this cannot be done as soon as possible. As such, detecting the damaged road surfaces and to notify both the municipalities as well as road users becomes important.

StreetSAFE is an online monitoring dashboard for local councils to identify location of road faults such as potholes or uneven roads. Utilizing sensors on smartphones (accelerometer, GPS, etc.), the phone will collect positional and vehicle dynamics data and send them over to the Cloud to be stored, and data collected is then used to identify road faults in real time.

II. LITERATURE REVIEW

Seraj, et al., developed a road pavement monitoring system for anomaly detection using smartphones equipped with GPS, accelerometer and gyroscope called RoADS [1]. During the study, Seraj, et al., found out that bounce is the effect of pothole on the vehicle, measured by vertical acceleration and rotational movements [1].

Alqudah and Sababha analyzed road surface conditions using embedded smartphone sensors with a statistical approach based on smartphone embedded gyroscopic sensors data to monitor and detect road surface conditions and abnormalities [2]. Alqudah and Sababha found out that the variability of gyro rotation data is an indicator of the presence of irregularities in road surface such as roughness or potholes and measured using the variance [2].

A crowdsourcing road surface monitoring system called CRSM was developed that was able to detect road potholes and rate the road roughness levels through a hardware module installed on distributed vehicles and wirelessly connected to a central server [3]. The CRSM module was consisted of a microcontroller (MCU), a GSM module, a GPS device and an accelerometer sensor to identify road vibration and obtain location and vehicle velocity during the vehicle travel. CRSM provided a road roughness classification algorithm to determine the road roughness level and an improved Gaussian Mixture Model so that the event detection threshold can be changed to a parameter which is roughly linear with the current velocity together with learning rate updated based on a high learning rate which is used for big velocity changes as opposed to a small learning rate for small velocity changes [3].

Fouad, et al., used the smartphones sensors such as the accelerometer, the gyroscope, and the GPS to detect speed bumps and evaluate the existence of road speed bumps using rough mereology theory [4]. In the classification phase, to get the top-N recommendation it used three classification equations (user-item pair, similarity symmetric, weighted sum form) and compute the recommendation value obtained from each equation. After the data was pre-processed, an intelligent multi-agent recommender system model was used to evaluate the classification quality of the proposed framework and the mean absolute error (MAE) was calculated to show the irrelevance between the recommendation value predicted by the speed bumps recommender system and the actual evaluation value [4].

Strutu, et al., were working on a mobile sensor network-based road surface monitoring system [5]. It was a low-cost system which needed only accelerometers and GPS, and was consiste of 2 platforms which included a mobile platform installed on vehicles and a central server. Real time pothole detection algorithm was running on the mobile platform. When the road defect was identified, GPS coordinate, timestamp, associated peak value and associated picture was recorded. In the central server, second layer computing algorithms were applied to recorded data from the mobile platform to discover false positives such as railway crossings and speed bumps, and final results were shown on a geographic information system (GIS). Road bumps can be differentiated from potholes through symmetrical touch of both wheels at the same time, while a pothole has asymmetrical touch on one side of the wheel. This meant deceleration on the Y axis because of the vehicle slowing down. In the case of potholes, the lateral acceleration of the X axis is much higher [5].

Syed, et al., defined pothole as step deformation with a given depth that affect the amplitude of tire bounce [6]. In this case, one side of the tire steps into a pothole in a horizontally launched projectile motion, undergoes impact and exits through a bounce while another side of the tire goes smoothly on the road. The acceleration response for road potholes of different depths along Z axis and sharp change in acceleration value of Z axis over a short time window are observed normally for a pothole, while rate of change of acceleration value of Z axis indicates anomalies [6].

Gunawan, et al., proposed a vibratory-based method for road damage classification using the smart phone 3D accelerometer and geo-location. It is a pothole monitoring system that utilized the X and Z axes values from the accelerometer [7]. X axis represents vehicle-side direction and Z axis represents vertical direction of the vehicle and the potholes is assumed to produce large vehicle acceleration in the X and Z axes [7].

Rishiwal and Khan also worked on an automatic pothole and speed breaker detector on smartphones [8]. Potholes are reflected by the sudden change in downward direction of the Z axis, speed breakers reflect on the sudden change in upward direction of the Z axis. The threshold acceleration is set to identify the severity of potholes and speed breakers and once anomalies detected; GPS coordinate is sent to the global server [8].

Jang, et al., implemented a road surface condition monitoring system via multiple sensor-equipped vehicles made up of a vehicle client (mobile data collection kit) and a back-end server [9]. Accelerometer, GPS sensor, local storage and a micro-computer made up the vehicle clients. The data logging algorithm records the data only when the root mean square values in both Y (left-right) and Z (up-down) directions exceed their thresholds that is pre-determined based on manually labeled ground truth such that data on non-smooth road segments can always be recorded. Jang et al. (2015) defined the impulse class as sudden vibration observed, such as pothole will mostly produce narrow and tall spike in acceleration response, rough class as long period of vibration such as bumpy roads, and smooth class as no significant vibration, such as smooth roads [9].

Harikrishnan and Gopi also worked on vehicle vibration signal processing for road surface monitoring. Raw data was collected and segmented into group of samples to identify occurrence of multiple abnormal events [10]. Gaussian modelling was used to identify event of significant abnormalities such as sudden change in Z axis acceleration. The severity of the event was computed by making use of the relationship between acceleration and displacement. This is because Z axis is numerically double integration to obtain vehicle displacement which approximately equal to event severity [10].

Taniguchi and Hisamatsu monitored road surface condition using bicycle-mounted grid laser light that was very different from using smartphone sensors [11]. The system monitors the road surface condition through image processing. The system consisted of only 2 elements, a laser module and a camera module. It used template-matching based method for detecting road surface condition from images obtained from the camera module. The template was developed from an image which contained laser light patterns on good road surface condition. Color components of laser light was extracted from obtained image and template image. Normalized correlation coefficients were calculated for each pixel in the obtained image and if the result was high, it meant good road surface, otherwise bad road surface [11].

III. METHODOLOGY

The overview of the proposed methodology plan is shown in Fig. 1. A Xiaomi Redmi Note 3 Pro is used as the hardware platform to collect the data. It is powered by Qualcomm MSM8956 Snapdragon 650 hexa-core processor together with 3GB RAM. It is equipped with accelerometer, gyroscope and GPS. The phone is connected to a working mobile network during the whole project to make sure the GPS is accurate.

On the software side, the application StreetSAFE is used as shown in Fig. 2. Google Cloud Storage platform is used for data storage. The online reporting dashboard incorporates the Google Maps to show the location of the road faults. The service is hosted on the Google App Engine which provides a cron object that automates the data pipeline update every 20 minutes.

For data collection, the collected data consists of 7 road surface conditions event such as potholes, speed bumps, hazard lines, smooth road, uneven road, turn, and hard stop recorded within 5 to 15 seconds each. The data is retrieved from the Google Cloud Storage platform and statistical data are extracted from the raw data for use in training the classification model. The raw data are made up of the X, Y, and Z axes from accelerometer readings. Statistical data provide more information and generating the classification model from the statistical data can improve quality of the classification model [12].

Feature selection is utilized to decrease the feature size as only relevant features are employed. Two different classifiers are employed, namely Random Forest and SVM. Random Forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and use averaging to improve the predictive accuracy and control over-fitting. It undertakes dimensional reduction method so that it can handle huge data set with higher dimensionality to identify most significant variables.

Support Vector Machine (SVM) employs the hyperplane in multi-dimensional space to perform classification of different class labels which can handle multiple continuous variables and categorical variables. It has been used widely for classification and regression analysis. SVM classification can be performed with linear, non-linear, and polynomial kernels.

Ten-fold cross validation is used to evaluate classifier performance and the Correct Classification Rate (CCR) is used as the measure, indicated by , where TP is the recall or true positive that the extent of positive cases are effectively recognized, TN is the true negative that the extent of negatives cases are grouped effectively, FP is the false positive that the extent of negatives cases were mistakenly delegated positive, and FN is the false negative that extent of positive cases were inaccurately named negative.

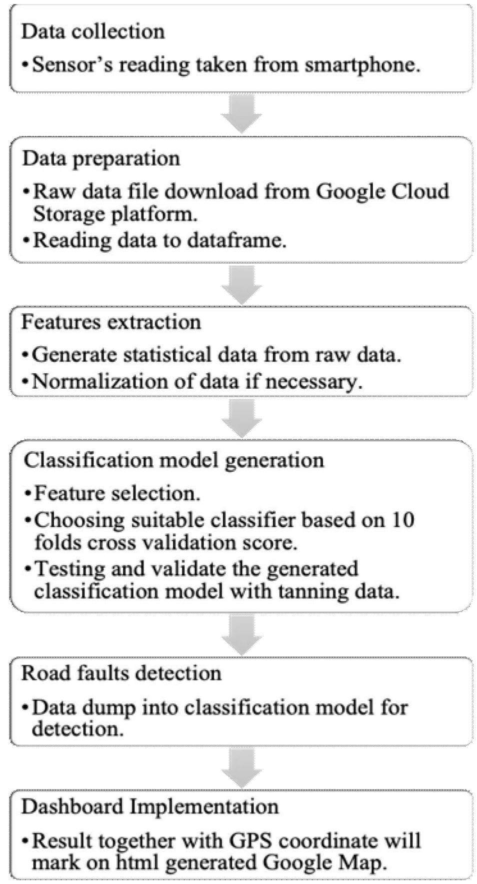

Fig. 1. Overview of proposed methodology.

After classification, the result together with GPS coordinates will marked on the dashboard map (Google Maps). Every single GPS coordinate together with its predicted road faults of the route travelled is plotted on the map.

Fig. 2. StreetSAFE, an application that utilizes the accelerometer, gyroscope, and GPS for data collection.

IV. RESULTS AND DISCUSSIONS

A prototype is developed to show the monitoring dashboard as well as map. Fig. 3 shows the detected road condition markers plotted on the travelled route. Fig. 4 shows a location search box while Fig. 5 shows the legend of the classified road conditions.

Fig. 3. Makers plotted on travelled route.

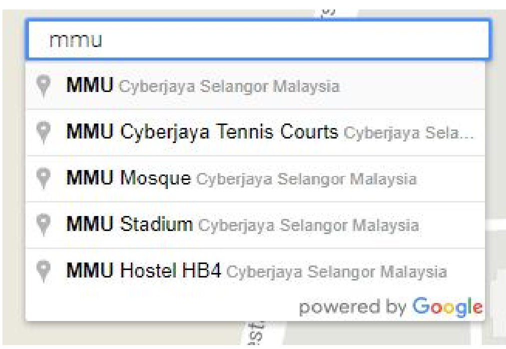

Fig. 4. Location search box.

Fig. 5. Legends indicating the road conditions.

Three different sources of training data were used which are old, new, and combination of both. Old training data was collected by Yap et al., with a total of 350 records [12]. The new set refers to the data collected using the StreetSAFE application on a Xiaomi Redmi Note 3 Pro, and a Proton Preve was used to collect the training data, also totaling 350 records. The combined training data refers to the merged set of the old and new set to form a total 700 records.

Fig. 6 shows the classifier setting scores with feature selection using Reduced Feature Elimination (RFE) algorithm at 70% having the best score. Moreover, Table I shows the average 10-fold cross validation scores. From Table I, the new set give the best score and the RF classifier gives the best result. The details of the selected model’s score are visualized using normalized confusion matrix which is shown in Fig. 7. Hazard line, hard stop, smooth road, turn and uneven road achieved 100% accuracy while pothole and speed bump only achieved 82% and 84% accuracy.

A journey is segmented into windows for classification. As each labeled data is recorded during the specific road condition, a moving window is required to properly produce identifiable data. For example, a labeled pothole data contains only 70 to 100 accelerometers entries over a 10 second interval. As such a journey is segmented with windows with 200 entries with moving overlap of 50 entries. This setting is optimized for all the road conditions.

Factors that affect accuracy include the make of a car. In the data collection, 2 different vehicles with different make and age were used to record data. The vehicle with the age more than 10 years will generate more noise in the data collected compared to the one with an age of less than 5 years. This is due to wear and tear, thus the presence of vibrations in an older car is more pronouced..

A driver’s driving pattern also affect the the classification. The handling of vehicle acceleration, break, and steering cause differences in the recorded data, for example in the sudden increase on acceleration of a vehicle, causing a sudden spike in the accelerometer reading. The angle or torque of the vehicle’s turn may cause differences in reading as well.

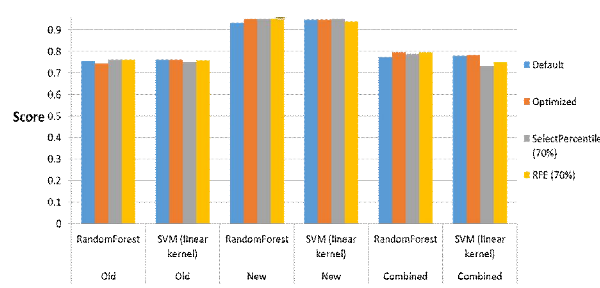

Fig. 6. Comparison of classifier setting.

Table I. Optimized classifier with 70% RFE feature selection 10-fold cross validation scores.

Data Source	Classifier	Score
Old	RandomForest	0.763
Old	SVM (linear kernel)	0.760
New	RandomForest	0.951
New	SVM (linear kernel)	0.937
Combined	RandomForest	0.796
Combined	SVM (linear kernel)	0.750

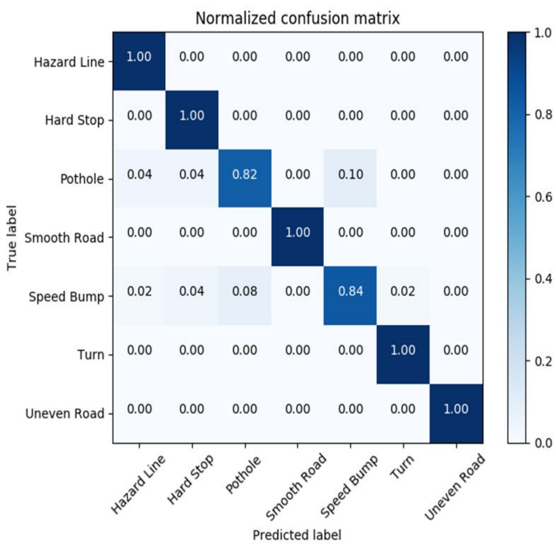

Fig. 7. Normalized confusion matrix of optimized Random Forest classifier with RFE feature selection method using 70% of total features.

V. CONCLUSION

A road fault monitoring and reporting system is introduced which utilizes a classification model using statistical parameters to classify road surface conditions. The model is found to able to distinguish road surface conditions. The system can potentially predict road damage, facilitate maintenance and resource management.

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