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SMART PHONE BASED POTHOLE DETECTION AND ALERT SYSTEM

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Abstract : Potholes are a major cause of road accidents and vehicle damage, while existing detection methods mainly rely on manual inspection or simple threshold-based sensor techniques with limited accuracy. This project proposes a smartphone-based pothole detection and alert system using accelerometer and gyroscope sensors. The collected sensor data is pre-processed and analysed using a Random Forest machine learning classifier, which provides improved detection accuracy by effectively distinguishing potholes from normal road conditions. Detected potholes are tagged with GPS coordinates and stored for future reference, and when a user approaches a known pothole location, the system generates an alert to enhance driving safety and reduce vehicle damage.

IndexTerms **– Gyroscope, Accelerometer, Random forest, GPS…**

I. INTRODUCTION

Road transportation is very important for the economic and social growth of any country. A well-kept road network makes it easier for cars to move around, makes travel more efficient, and makes the roads safer for everyone. But many areas have big problems with road surface problems like potholes. Heavy traffic, bad road construction, water seepage, and changing weather can all cause potholes to form. These problems with the road make driving less comfortable and are dangerous for both drivers and pedestrians. Potholes can do a lot of damage to cars, like puncturing tires, breaking suspensions, and throwing off alignment. In a lot of cases, hitting a pothole without warning causes an accident, especially for small cars and two-wheelers.

Potholes also make traffic worse because drivers often slow down or change lanes suddenly to avoid them. So, finding and reporting potholes early is very important for keeping roads safe and the transportation system in good shape. Road maintenance authorities have always found potholes by looking for them by hand. This process needs a lot of money, time, and people to do. Also, manual inspections are usually done on a regular basis instead of all the time, which means that potholes can go unnoticed for a long time. This means that road maintenance departments may not get information about road damage quickly, which can cause repairs to take longer. Smartphones are now powerful devices with many built-in sensors, like accelerometers, gyroscopes, and GPS modules, thanks to modern technology.

These sensors can record motion and vibration data that happens when a vehicle moves over different types of road surfaces. These sensors can pick up the sudden vibration or shock that happens when a car drives over a pothole. This makes smartphones a useful and cheap way to keep an eye on road conditions. Machine learning can make systems that find potholes even more accurate. The Random Forest classifier is one of the most popular machine learning models because it can work with complicated datasets and give accurate classification results.

fig. 1. Potholes

Along with finding potholes, using GPS technology lets the system record the exact location of the potholes it finds. These types of warning systems that use location can make driving much safer by letting drivers slow down or change their route ahead of time. The smartphone-based pothole detection and alert system used to detect the fig 1 represented potholes in an efficient, automated, and low-cost way to keep an eye on the roads. The system can keep an eye on road conditions all the time, find potholes accurately, and send users real-time alerts by using common smartphone sensors and machine learning algorithms. This method not only makes the roads safer, but it also helps road maintenance authorities find damaged parts of the road quickly and easily

II. PROPOSED METHODOLOGY

The suggested method is to create a smartphone-based pothole detection system that uses built-in sensors and machine learning to automatically find problems with the road surface. While the car is moving, the system collects motion data from the smartphone and uses that data to figure out if there is a pothole. The system uses sensor data processing, machine learning classification, and GPS location tagging to keep an eye on road conditions and make driving safer in a cost-effective way.

The first step in the proposed methodology involves the acquisition of data. The modern smartphones come with numerous sensors that include an accelerometer sensor that measures the mobile device has moved and the gyroscope sensor that measures the orientation of the mobile device along the x, y, and z axis; therefore, when a vehicle travels over any type of road surface, the accelerometer and gyroscope on the smartphone will collect the various vibration and motion readings of each surface the vehicle travels over. The smartphone will continue to collect the accelerometer and gyroscope readings of the vehicle while the vehicle is in motion.

These readings will allow for the calculation of vibration patterns caused by the normal road conditions or potholes. The GPS on the smartphone will record the geographical location of the vehicle so that any detected potholes can be plotted with their corresponding longitude and latitude coordinates. Next, we'll preprocess the data and prepare the raw sensor data for analysis. Raw sensor signals contain noise as a result of factors like driving speed, road texture, and sensor orientation. the dataset is divided into training and testing subsets. The system demonstrated the practical viability of deep learning-based safety assistance systems .We can improve the quality of the raw sensor data through preprocessing techniques; this includes eliminating noise from the sensor readings, removing gravity effects from accelerometer readings, and normalizing the processed sensor data so they have similar values. Once cleaned, we will segment the data into smaller time segments (or sliding windows) to facilitate analysis of vibration behaviour in a shorter time frame.

Once the feature extraction steps have been completed, features provide meaningful characteristics that result from the processing of the sensor information. Features will not only consist of the raw values from the sensors and raw data from a data window, but will also include several statistical features of the data from the data window. Examples of the types of features provided by the feature extraction process are peak acceleration, root mean square (RMS), variance of the data, jerk (the rate of change of acceleration), and gyroscope variance. The features provide an indication of how strong of a vibration is experienced by the vehicle and how these vibrations behave. The events that will be detected by the use of these statistical features are mostly due to potholes, which cause significant spikes or abnormal motion patterns in the vehicle as compared to normal vehicle movement.

The next step in the process is the classification stage of the project, which uses an algorithm called Random Forest to perform the analysis of the feature extracted data to classify the road conditions. Random Forest is an ensemble learning algorithm that performs classification using multiple decision trees in conjunction with one another to help produce a prediction for the input data. A Random Forest model is trained using older labelled data that has been gathered from the sensors. This labelled data will consist of data points from the sensors that are either labelled as a pothole, or that they are based on normal road movement. By training the algorithm using this historical labelled data, the algorithm can identify the patterns that are associated with pothole data compared to those associated with normal road data and therefore, it will be able to classify the newly received sensor data according to whether or not the detected vibration refers to a pothole or whether it refers to a normal road condition.

The working of the proposed model with the module breakdown and Once a pothole has been identified by the algorithms in place, the system will feed in the GPS coordinates of the actual event to save in the database. The coordinates are taken from the GPS on the smartphone and a new pothole has now been saved with the GPS coordinates and timestamp, when they have been detected, and how many have been detected since the last poll. All of these data points will allow for a complete mapping of potholes for planning to repair them and future maintenance.

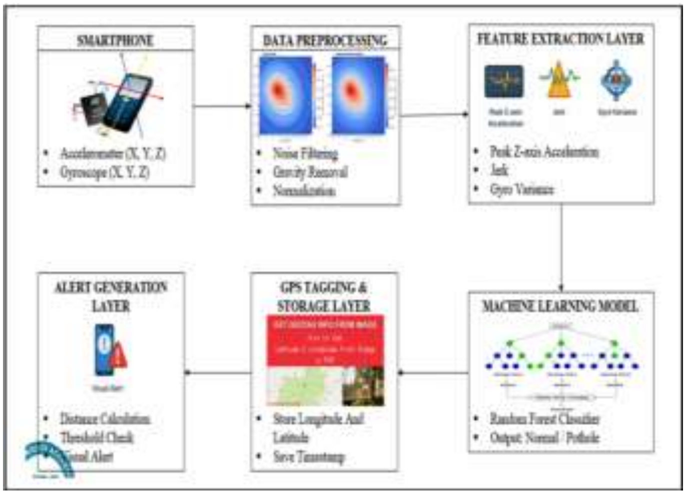

fig. 2. system architecture

Here fig 2 represents the working of the proposed model with the module breakdown and the system will provide a driver with an alert whenever they are within a certain distance of a previously detected pothole location. If a user is near a previously detected pothole, the system will calculate the distance from their current location to the stored pothole location. If it falls within the distance of the set threshold, then the system will generate an alert either visually or by message on the user's smartphone. Providing this warning allows users to slow down and change their driving behaviour before approaching the pothole, thereby reducing the potential for accidents, and damage to their vehicles.

The proposed methodology establishes an intelligent pothole detection system that combines smartphone sensor technologies, data processing methods, and machine learning algorithms. The use of generic off-the-shelf smartphones and the dependence thereon provide a relatively inexpensive and closely scalable option for monitoring streets. Furthermore, the capability to detect a pothole and transmit a location-based alert to a user or authority in real time creates a valuable tool to help enhance the safety of transportation systems while assisting government agencies in keeping up with the needs of their roadways.

III. DATA PREPROCESSING AND TRAINING MODEL

1. Acquisition of Raw Sensor Data

At the beginning of the system operation, raw sensor data is collected from an Android phone that is mounted on the moving vehicle. The data is collected using embedded accelerometers and gyroscopes that constantly collect information about the movement of the device. Accelerometer data collection takes place along the X, Y, and Z axes of the vehicle, representing vibrations that occur due to the road bumps. At the same time, gyroscopes measure the angular acceleration of the device. Every sensor reading is accompanied by the corresponding GPS coordinate and timestamp.

2. Filtering of the Collected Sensor Data

It is known that raw data collected by the sensors can be corrupted by noise. Therefore, data filtering is required in order to get rid of useless fluctuations in the data. Filtering includes application of low-pass filter that removes all the noise from the collected data. It is also important to remove the gravitational component from the accelerometer readings in order to analyze vibration patterns.

3. Data Normalization

The process of normalization comes next after noise removal and ensures consistency in terms of scale among all input variables. As each sensor produces different readings and these may not have the same scale, the process of normalization using any technique like min-max or standardization will be performed. This makes sure that all feature variables are in similar ranges, thus preventing possible bias in the machine learning algorithm. This is because a normalized dataset will help the algorithm learn patterns easily.

4. Data Segmentation Through Sliding Window

For analyzing continuous streams of sensor data efficiently, we use the process of data segmentation. In this process, the stream of data is divided into small windows which are nothing but chunks of data collected for a small period of time, usually less than 50 milliseconds. These small windows help us analyze the pattern in a particular section of data and find anomalies, for example, a spike in reading caused by hitting a pothole.

5. Feature Extraction

Feature extraction becomes the key step for turning sensor signals into meaningful inputs for further modeling. Various features are derived from each segmented window. They include peak acceleration, root mean square (RMS), variance, and jerk that refers to acceleration's changing velocity. Moreover, features based on angular variance of a gyroscope are extracted. With the help of the extracted features, it is possible to measure and detect vibration levels and determine the difference between normal roads and potholes.

6. Data Labeling

As part of developing a supervised machine learning model, extracted features need to be labeled by taking into consideration what type of road the vehicle moves through. Two types of labels can be used: "pothole" and "normal road." The labeling is done according to the behavior of sensors or experimental observations of sensor patterns. Accurate labeling is vital as it will influence the effectiveness of the trained model.

7. Model Selection

Random Forest becomes the chosen classifier as it ensures high performance and good results. The Random Forest method is used to generate many decision trees using training samples and combining predictions obtained from them to derive a final output.

8. Model Training

The labeled data set will be used in the model training stage for training purposes of the Random Forest Classifier. The input features for the model will be used as input variables whereas the labels of the data points will act as target output values. By analyzing the distribution of input features of different classes, the model learns about relationships of features to specific road conditions.

9. Model Evaluation

Upon the completion of training, the model will be put under testing phase. In order to evaluate the performance of the algorithm, performance metrics like accuracy, recall, and precision will be employed. Based on the obtained score of these performance measures, it will become clear whether or not the model is capable of generalizing well with respect to new data instances.

10. Model Deployment

Finally, the deployment of the trained model will be made inside the pothole detection system. Similar to previous stages of our approach, incoming data from smartphone sensors will go through the preprocessing stage.

11. Real-time Prediction and Detection

During the deployment process, the system will constantly analyze real-time sensor data and make predictions from them. The trained Random Forest will classify whether each data set represents a pothole or not. Once a pothole is identified, it will be considered as a vibration that should result in certain actions.

12. Results' Recording and Alerts

Once a pothole has been detected, the GPS coordinates of the location where it has been found will be saved into a database. Moreover, alerts may be sent out whenever necessary. These features improve road safety and can be used in Intelligent Transportation Systems.

III. RESULTS AND DISCUSSION

The proposed smartphone pothole detection system is effective at detecting and identifying road surface faults through the use of mobile sensors and machine-learning algorithms. Sensors were deployed to collect live data from a smartphone mounted inside a moving vehicle on a variety of roads. While on this test trip, the tests used accelerometer and gyroscope sensors which captured both the motion and vibrational data continuously. This collected data was later analyzed and processed using the trained random forest machine-learning model. Based on the results obtained, the proposed system can accurately detect potholes as well as differentiate between potholes and normal road conditions.

fig. 3. user interface

The Fig 3 shows how the system extracts both accelerometer and gyroscope signals to provide an overall view of motion, reducing false detections and providing a more reliable classification process. When using machine learning techniques like Random Forests to classify road surfaces, the system achieves high accuracy by combining multiple decision trees to avoid overfitting and create better predictions. In training, Random Forest learned the vibration patterns of potholes based on features extracted from the sensor data, and when new sensor data was used to test it, Random Forest was able to classify road surfaces accurately. These results prove that applying machine learning techniques to the detection process enhances detection accuracy compared with threshold-based methods.

One key feature of this product is its ability to map precise locations of potholes using global positioning system (GPS) technology. When a pothole is detected using the machine learning model, the GPS coordinates (longitude and latitude) of that location are recorded automatically to the database along with the time of detection. Accumulating database entries over time allows for the creation of an accurate pothole map and will provide valuable information to road maintenance organizations, to assist them in identifying damaged portions of roadways, and efficiently planning repair operations.

The tests conducted also supported the claims that mobile phones can be used as a cost-effective and scalable system for monitoring roads. The technology can be developed based upon commonly available sensors located in a mobile phone, contrasting with existing systems that use specialized devices, which can be very expensive. This gives rise to a large user base who will therefore be able to provide data for crowdsourcing sensor information from many different vehicles. Therefore, as more users continue to provide sensor data as part of the system, improvements in the accuracy of the road condition information should also continue to occur.

TABLE 1. PERFORMANCE EVALUATION METRICS

Methods	**Evaluation Metrics**			
	Accuracy	***Precision***	***Recall***	***F1-Score***
Proposed Method	90%	93%	91%	92%
Existing Methods	84%	88%	85%	86%

The Table 1. shows the performance of the proposed system using precision, recall and F1-score. The results indicate accuracy compared to existing methods.

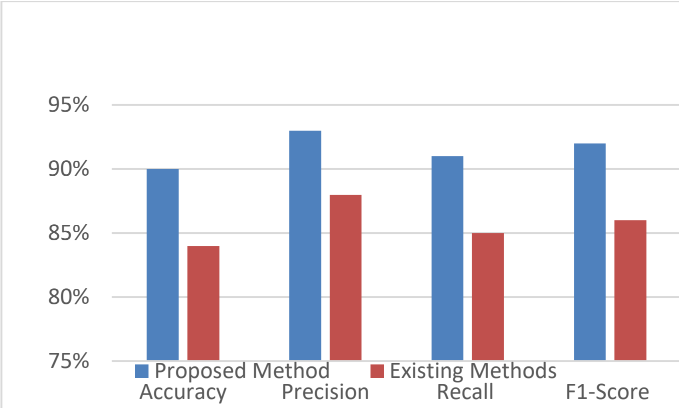

fig. 4. evaluation metrics

While the initial experimental results were promising, a few challenges were identified during the experimentation phase of this trial. Issues such as vehicle speed, placement of a mobile phone, and differences in pavement surfaces can all affect the information reported by the sensors. For example, in some cases, a sudden stop by a vehicle, speed bumps, or rough pavement may generate the same vibration pattern as a pothole. However, by applying multiple sensors and machine learning techniques, the possibility of false positive results can be reduced. In addition, further improvements can occur through the development of larger datasets and the use of more sophisticated machine or deep learning techniques.

This product has also demonstrated its ability to generate alerts for users. When a user travels into the vicinity of a detected pothole, the product assesses how far away they are by determining the distance between the current GPS coordinate of the user and the stored GPS location of the pothole. If this value falls within a pre- defined stale distance from the pothole, the user will be alerted either audibly and/or visually via their smartphone. their speed or avoid sudden braking, both of which enhance safety and reduce the likelihood.

TABLE 2. COMPARITIVE ANALYSIS OF DIFFERENT METHODS

Algorithms	Accuracy
Support Vector Machine	80%
Random Forest	82%
CNN	83%
ANN	84%
Random Forest+ Filtering (Proposed Method)	85%

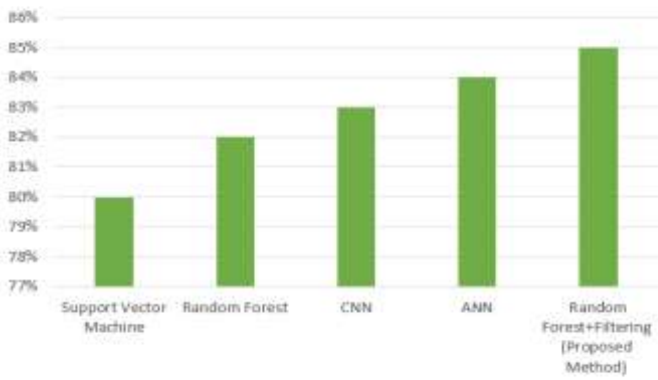

fig. 5. pothole detection accuracy comparison

The bar graph illustrates a steady improvement in pothole detection accuracy as methods evolve from basic threshold-based techniques to more advanced machine learning models. Early approaches like accelerometer thresholding achieve relatively lower accuracy (78%), while methods incorporating algorithms such as SVM, Random Forest, and ANN show noticeable improvements, reaching above 80%. The proposed method, which combines smartphone sensor data with filtering and Random Forest, achieves the highest accuracy of 85%, demonstrating that integrating data preprocessing with robust machine learning techniques leads to better detection performance.

V. CONCLUSION

A new smartphone app will allow users to identify potholes, improve road safety, and help monitor general road surface conditions. Road users are faced with a lot of challenges due to potholes on the road. For example, potholes are the most important factor impacting vehicle travel. Potholes can cause damage to vehicles and create serious accidents when drivers hit them. Other methods of identifying potholes have typically been manual inspections and/or complaints. Both of these methods have been very inefficient and time consuming. The proposed solution is a cost effective automated solution using the sensors in smartphones and applying machine learning to determine the presence of potholes.

In addition to using GPS, the app will utilize the accelerometer and gyroscope sensors located in the mobile device. As the vehicle travels on the road, the smartphone will create a continuous log of the vibrations and motion detected from the vehicle. While traveling over potholes or different surface conditions (i.e., uneven surfaces), the accelerometer and gyroscope will detect variations in the motion of the vehicle. After the phone has collected this raw vibration data, several preprocessing procedures will be performed to eliminate noise, remove gravity, normalize the data, and segment the data to create a higher quality dataset to be analyzed.

Once pre-processed, feature extraction involves obtaining peak acceleration, root mean square (RMS), variance, and jerk from the sensor signals. The extracted features are representative of the vibration characteristics that occur to the vehicle due to the road surface. A Random Forest machine learning classifier is able to distinguish between normal road surfaces and potholes using the extracted features and is then trained on these data uses to classify future sensor data as normal or pothole-like based on the learned vibration pattern.

When the system detects the presence of a pothole, it uses the GPS module from the smartphone to automatically log the GPS coordinates of the detected pothole location. This information can be stored in a database with the date/timestamp of the detection, allowing a pothole location map to be generated. The system uses an alerting mechanism to notify drivers when approaching a previously detected pothole location. In this way, drivers can have an opportunity to make precautionary measures (speed reduction, lane change) before they reach the pothole, which may reduce the number of accidents and/or damage to vehicles.

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