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Deep Learning Approach to Detect Potholes in Real-Time using Smartphone

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***Abstract*— Detection, and mapping of potholes in a precise and punctual manner is an essential task in avoiding road accidents. Today, roadway distresses are manually detected, which requires time and labor. In this paper, we introduce a system which uses deep learning algorithms and is integrated with smartphones to detect potholes in real-time. The user interface of the system is a smartphone application which maps all potholes on a route that the user is traveling. Simultaneously, deep learning object detection algorithm: Single Shot Multi-box Detector (SSD) looks for potholes using a mobile camera in the background. As soon as an unregistered pothole is detected by SSD, coordinates of the pothole are updated to the database in real-time. Accelerometer and gyroscope readings are continuously taken and assessed by a Deep Feed Forward Neural Network model to detect unregistered potholes. This dual mechanism of camera- based as well as accelerometer-gyroscope based detection not only cross validates detections but also provides stable results even if one mechanism fails. The pothole co- ordinates are rendered on the map user interface that can be accessed in the same application. This system with map/navigation feature as front end and two-fold deep learning pothole detection algorithm in backend is an efficient and a zero cost solution for real-time pothole detection.**

Keywords— Pothole Detection, Deep Learning, Deep Neural Network, Object Detection

I. INTRODUCTION

Potholes are a major cause of accidents all over the world and are prevalent in countries greeted heavily by rain. In India, over 9300 fatalities and about 25000 injuries are caused due to potholes in the past 3 years[1]. Riding over the potholes regularly also damages the vehicles that may result in accidents. The logical interpretation of these statistics gives a firm conclusion that some advancement in technology must be implemented for a fast and reliable system to detect potholes which would indeed help prevent road accidents.

A. Related Work

There are several methodologies for sensing potholes on roads. Some of these systems either use accelerometer-based detection or Camera-based detection. However, depending only on one type of detection method is inefficient and not reliable.

The method used by K. Zoysa et al [2] analyses vibrations given by accelerometer when passing over a pothole to detect a pothole. This system lacks real-time data processing and doesn't alert users instantly. The proposed system is restricted to roads serviced by the bus routes which limits the area covered for pothole mapping.

Yu and Yu[3] uses the Accelerometer along with the oscilloscope connected to a laptop to achieve real-time analysis. This system requires additional hardware i.e. accelerometer and oscilloscope which increases the cost of implementation.

Vigneshwar.K and Hema Kumar.B [4] uses image processing based detection to identify pothole in an image. The different techniques used in the paper provide good accuracy on static image but would be slow to detect pothole in real time.

Laser scanning has good performance, compared to other methods. Approach mentioned by K. C. P. Wang[5] and K.T. Chang et al[6] is able to collect detailed road-surface information using reflected laser pulses to create digital models. Though laser scanning is precise, the equipment needed is highly expensive. Furthermore, this method cannot be used for fast pothole detection over large area.

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Aspects in which Our System for pothole detection is distinct from the prior works:

(a) Two-fold cross verification mechanism i.e. Camera-Based as well as Accelerometer and Gyroscope-Based.

(b) No use of any external hardware sensor as both accelerometer and camera are present in almost all smartphones.

(c) Not restricted to certain areas as once the model is trained, the trained model can be used

(d) to detect potholes anywhere.

(e) Provide Real-Time updates to users.

(f) System improves over time.

II. OVERVIEW

The system requires only a smartphone and no other external hardware. The user mounts the smartphone on a mobile holder stand on their vehicle and opens the mobile application. After entering the details of the destination location, all the previously detected potholes recorded on the database are indicated on the route with the help of markers on the map. The accelerometer and gyroscope sensor as well as camera continuously run in the background and scans for new potholes that haven't been previously detected.

For detection through accelerometer and gyroscope, a substantial amount of training data was collected, which was used to train a Deep Feed Forward Neural Network (DNN) model. Whenever the user passes over a pothole, it causes a deviation in the accelerometer and gyroscope readings. Our DNN model which was trained to classify potholes based on accelerometer and gyroscope readings, classifies if these readings signify a pothole or not pothole (minor jerks or vibrations).

For detection through camera, a Single Shot Multi- box Detector (SSD) was trained on pothole images. The camera would continuously get the live feed and the trained SSD algorithm detects potholes in real time.

If either one of these mechanisms detects potholes, the co-ordinates of the pothole location are uploaded on the database. If a pothole co-ordinate has been detected by both camera as well as accelerometer and gyroscope, then it indicates a strong possibility of a pothole.

Summarising, the front end of the application would provide map/navigation with all recorded co-ordinates marked on the map and simultaneously in the background, the two-fold backend algorithm tries to search for new potholes.

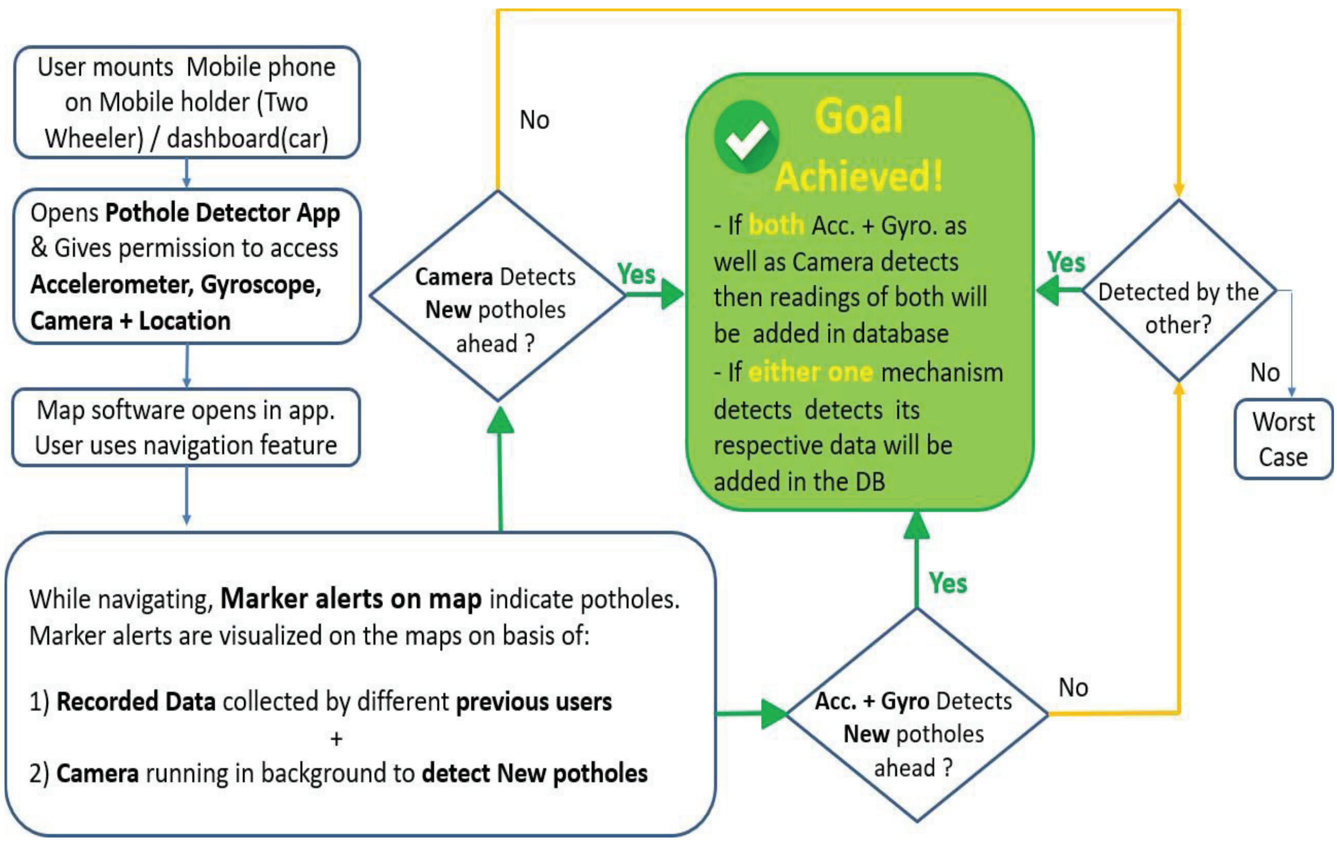

Fig. 1. Overall Pothole Detection System Flow

III. METHODOLOGY AND IMPLEMENTATION

A. Camera-Based Pothole Detection

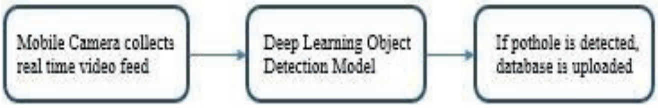

Fig. 2. Flow of Camera-based Detection

A continuous video feed is taken from the camera running in the background of the android application and is broken down into frames of images. These images are passed as input to a custom trained Single Shot Multi-box Detector (SSD) Object Detection model, which detects if the image contains pothole. If the pothole is detected then co-ordinates of the location are fetched from the app using GPS and are added to the online database.

1) *Real-Time Image Acquisition:*

The android application runs the camera of the smartphone on a background thread. The video feed collected from the camera is divided into multiple frames of images and these images are passed to custom trained object detection model : SSD: Single Shot MultiBox Detector[7].

2) *Single Shot Multi-Box Detector:*

SSD is a single deep neural network used for object detection. It provides bounding boxes around objects detected with respective confidence scores. It uses a small convolutional filter to predict object categories and these filters are used to multiply feature maps to perform detection at multiple scales. This results in high-accuracy detection even in low-resolution images.

SSD is faster and provides better accuracy than R-CNN and YOLO as discussed by Andrew G. Howard et al[8] and Nikhil Yadav, Utkarsh Binay [9].

SSD-Mobilenets are derivatives of SSD and are specially designed to support devices with low computational abilities like Mobile Phone.

3) *Tensorflow Object Detection API:*

Tensorflow object detection API[10] is a framework which provides different pre-trained deep learning models and provides transfer learning functionality. Transfer learning was used to import a standard SSD model and Tensorflow was used to train this model on the collected custom dataset.

Furthermore, TensorFlow Lite was used to convert this model into a lightweight model which can be integrated on Android applications for real-time detection.

4) *Dataset & Annotation:*

For training the SSD model, a dataset was created by capturing more than 100 Pothole images by using a Mobile camera mounted on a two-wheeler vehicle. Potholes in the images were annotated using LabelImg[11] which generated a XML file for each image. Further, details of all images as well as XML files were converted to CSV format and later to TensorFlow RECORD format.

5) *Training:*

The training was performed on Google Colaboratory, a cloud service with a robust GPU for accelerating training speed.

Google Colaboratory specifications:

- 1xSingle core Hyperthreaded Xeon Processors @2.3Ghz i.e.(1 core, 2 threads)
- RAM: ~12.6 GB
- GPU: 1xTesla K80, compute 3.7, having 2496 CUDA cores, 12GB GDDR5 VRAM

Fig. 3. Pothole Detected by Custom Trained SSD

B. Accelerometer and Gyroscope Based Pothole Detection

The Deep Neural Network was trained on a dataset with 7 input parameters. The 7 parameters included 3 accelerometer readings (x, y, z axes), 3 gyroscope readings (x, y, z axes) and the speed of the vehicle. A separate android application was built to collect this dataset.

1) *Acquiring the Dataset:*

One of the critical aspects which determine the accuracy of a DNN model are the parameters that are fed into the model as input. When the vehicle moves over a pothole, the vibrations and the unsteady movements of the vehicle is captured by the gyroscope sensor which measures the deflection in the rotational velocity. The accelerometer sensor measures acceleration along the x, y, z axes. The speed of the vehicle is an important factor which influences the gyroscope and accelerometer values and hence is considered as the seventh parameter for the DNN model.

The android application which was built for acquiring the dataset extracts the accelerometer and gyroscope readings along the x, y and z axes as well as the speed of the vehicle. The smartphone was mounted on a '2019 Honda Activa 5G' and the application collected readings at the rate of 5 readings per second. The data was manually labeled by clicking a button when the vehicle passed over a pothole. The vehicle was driven for around 45 minutes and a dataset with more than 15,000 observations was collected which involved 125 labeled potholes.

2) *Data Pre-processing:*

Ideally, the readings should be of the exact moment when the vehicle moves over a pothole. The application gives the readings at a high frequency of 5 readings per second. Hence, it was not possible to acquire the readings at the exact moment when the vehicle was over a pothole. To counter this, a preprocessing technique was developed such that on clicking the button to label the pothole, the RMS (Root Mean Square) values of the past 10 readings (equivalent to the readings recorded in the previous 2 seconds) was calculated and stored in the database. The RMS method served as a high pass filter which suppressed the noise as well as further enhanced the positive pothole readings.

3) Training and Architecture of the DNN Model:

The Deep Feed Forward Neural Network was trained on this dataset. The DNN model extracted patterns and detect trends from the obtained dataset in order to classify whether the readings indicate a pothole or not-a- pothole.

The architecture of the DNN model involved a visible layer, two hidden layers and, an output layer. The visible layer consisted of 7 neurons for the 7 input parameters respectively. The first hidden layer had 64 neurons while the second hidden layer had 32 neurons. The Rectified Linear Unit Activation function was used at the hidden layers . The Sigmoid function was used at the output layer as the activation function. The Binary Cross Entropy and Adam were used as the objective function and the optimizer function respectively. The Adam optimizer helps especially when the data is sparse, having less frequency. The batch size used was 128. The hyperparameters were selected from a pool of hyperparameters after performing parameter tuning using Grid Search method.

```
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 64)                448
_________________________________________________________________
dense_5 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_6 (Dense)              (None, 1)                 33
=================================================================
Total params: 2,561
Trainable params: 2,561
Non-trainable params: 0
```

Fig. 4. DNN Model Summary

4) Comparison:

After training the Deep Neural Network, a Support Vector Machines (SVM) model was also trained with similar input parameters and the comparative study is mentioned in the following table.

TABLE I. COMPARISON OF DNN AND SVM MODEL

Model Name	**Accuracy**
Deep Neural Network (Proposed Model)	96.7%
Support Vector Machines	92.9%

5) Real-Time Pothole Detection

The machine-learned model was converted to TensorFlow Lite to obtain a lightweight model that is deployed on smartphones for real-time pothole detection. As mentioned in 3.2.2 (Data Pre-processing), the RMS value of the past 10 readings are calculated and fed into the model as input. If the model classifies the reading as a pothole, the corresponding location co-ordinates is added into the database. These co- ordinates are marked on the map and this becomes visible to the other users of the system.

IV. CONCLUSION

In this paper, a deep learning-based system integrated with an android app was developed to detect potholes and also display the detected pothole locations on the map. The system follows two-fold cross verification mechanism to detect potholes using the camera as well as accelerometer and gyroscope sensors of the Android device. Camera-based detection uses lightweight, custom trained Single Shot Multi-Box Detector-MobileNet, a deep learning algorithm with TensorFlow object detection API. Accelerometer and gyroscope detection uses a custom trained Deep Feed Forward Neural Network. SSD provides fast real-time detection of potholes while the DNN model gives a better accuracy as compared to traditional machine learning algorithms. These two trained models were integrated into a single android application and deployed on android devices using TensorFlow Lite.

The following system would not only reduce accidents and save lives, but also can be used by road maintenance authorities for inspection and repair, navigation service providers to improve suggestions for the optimum route and autonomous vehicles to avoid potholes.

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