DETECTING A POTHOLE USING MACHINE LEARNING

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

Certified that this project report titled "**DETECTING A POTHOLE USING MACHINE LEARNING**" is the bonafide work of Pulkit Mathur (21BCE11602),Shreyansh Vijayvargiya(21BCE11289), Rohit Panjwani(21BCE11289), Anurag Mishra (21BCE11288), Sumukh Gupta(21BCE1199) who carried out the project work under my supervision. Certified further that to the best of my knowledge the work reported here does not form part of any other project/research work based on which a degree or award was conferred on an earlier occasion on this or any other candidate.

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Last, but not the least, I am deeply indebted to my parents who have been the greatest support while I worked day and night on the project to make it a success.

ABSTRACT

Our project "**Detection of pothole using machine learning**" includes detailed study and analysis of three pothole detection models and also an initial prototype of pothole detector using vision based and CNN model.
The Potholes are a structural damage to the road with hollow which can cause severe traffic accidents and impact road efficiency. In this paper, we propose an efficient pothole detection system using deep learning algorithms which can detect potholes on the road automatically. Four models are trained and tested with pre-processed dataset, including Vision-based, YOLO V5, CNN. In the phase one, initial images with potholes and non-potholes are collected and labelled. In the phase two, the four models are trained and tested for the accuracy and loss comparison with the processed image dataset. Finally, the accuracy and performance of all four models are analysed. The experimental results show that the CNN model performs best for its faster and more reliable detection results

Introduction

This paper focuses the automated pothole-detection methods can be classified into three types according to the technology used in the pothole-recognition process: a vision-based method, a vibration-based method, and a 3D reconstruction-based method. In this paper, three methods are compared, and the strengths and weaknesses of each method are summarized.

The general process of pothole detection consists of four steps: data acquisition, data pre-processing, feature extraction, and pothole classification. The pothole classification step determines the existence of potholes by applying a pothole-detection algorithm based on the features.

A pothole is a hole in a road surface that results from gradual damage caused by a traffic and weather conditions which may cause accidents To contribute to the prevention of traffic accidents and the smooth flow of traffic. Identifying and managing potholes in advance plays an important role in securing driver safety and preventing traffic accidents.

MOTIVATION FOR THE WORK

The motivation behind the proposed framework lies in the deficiencies of current practice and the potential of gradually and inexpensively converting passenger vehicles into ubiquitous sensors and reporters of the roads' condition. The work presented in this paper is the first step to achieve our objective. We use a window mounted camera on an equipped passenger vehicle that collects visual pavement data. This data is then used to validate our method for automated pothole detection in pavement images.

Problem Statement

Using deep learning and transfer learning techniques to solve the binary image classification problem of separating plain roads and roads with potholes by adopting an accurate model for savings in training time and computational efficiency.

POTHOLE

PLAIN ROAD

Objective of the work

Every year around 3,597 people die due to potholes. More than 30% of people die due to potholes. So, it is extremely vital to detect potholes and fix them as soon as possible to avoid the loss of valuable lives. We have built a model for Pothole Detection using Transfer Learning and CNN which has very high accuracy.

Our model can be deployed very easily and the images from data set that are fed as input to our model. We in our proposed model are trying to detect pot-hole by image processing, grey scaling , formation of contour, and final output will be pothole detected

Literature Survey

- Baek proposed a pothole-detection and -classification method based on edge detection using pavement images as input data. The proposed method consists of three phases: image pre-processing, feature extraction of road damage, and road-damage classification. In the process of image pre processing, RGB image data were converted to gray-scale image data, and the objects in images except potholes were detected via object-detection algorithm. The contour of the pothole in the pre-processed images was extracted via edge-detection algorithm for feature extraction. Potholes were detected and classified via YOLO algorithm in the road-damage-classification phase. It was evaluated by distortion rate and restoration rate of the image, and the accuracy of the classification. The dataset used in the performance evaluation process is the Global Road Damage Detection Challenge 2020 dataset [11]. The experimental results showed that the mean-squared error (MSE) of the distortion rate and restoration rate of the proposed method had errors of 0.2–0.44. The average of the classification accuracy and precision of the proposed method were 0.7786 and 0.8345. The accuracy and precision of pothole detection presented as experimental results of this study are restricted to one pothole in the image data. It is confirmed that the accuracy of pothole detection was relatively low when there were multiple potholes in one image - datum. In addition, it is possible to detect the shape of a pothole by applying

- Park presented a method for automated pothole detection that applied different YOLO models using images as input data. Three YOLO models such as YOLOv4, YOLOv4-tiny, and YOLOv5 were applied in the process of training and testing. The dataset of which is found was composed of 665 pothole images and was divided into training, validation, and testing subsets. First of all, the images in the training subset were converted to be suitable for the various YOLO models. The models were trained and validated until the loss function reached a steady-state line. Next, the performance of three YOLO models was evaluated using mean average precision at 50% intersection-over union threshold (mAP@0.5). The low accuracy when detecting small potholes located at a long distance is a limitation of this study. In addition, it is judged as a limitation that the study was not carried out in bad weather conditions and under insufficient light conditions.

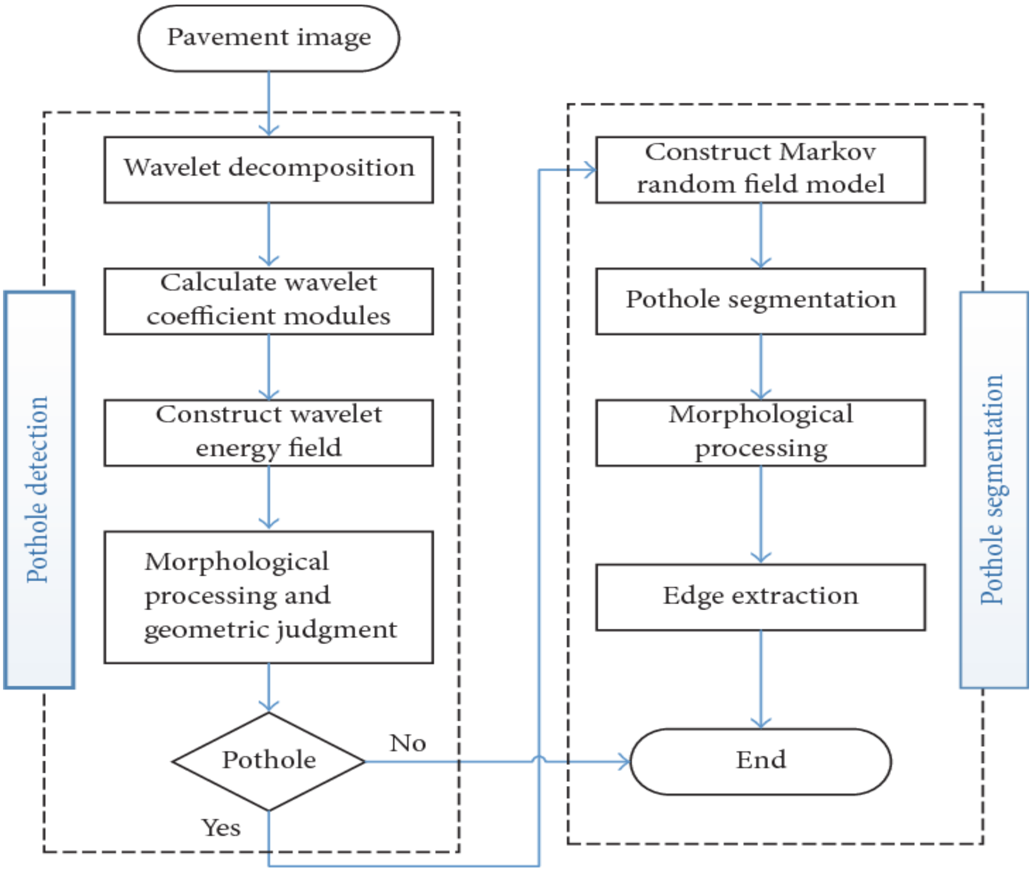
- Deepak Kumar Dewangan proposed a pothole-detection method based on CNN with an embedded vehicle prototype. The system consisted of three modules: a pothole-detection module, a data-processing module, and an embedded autonomous-vehicle-system (AVS) module. The dataset that was used in the process of training in a pothole-detection module was composed of 3915 images. The experimental results showed that the accuracy, precision, recall, and F1 score of the proposed method were 0.9902, 0.9903, 0.9903, and 0.9833, respectively. The authors explained that the proposed method had better performance than the existing methods through the experimental results. It is judged that a real-time pothole-detection system using low-cost edge devices such as Jetson Nano can be implemented based on the research results of this paper.

MODEL 1

METHODOLOGY

A Vision-Based Method (A MATLAB prototype):

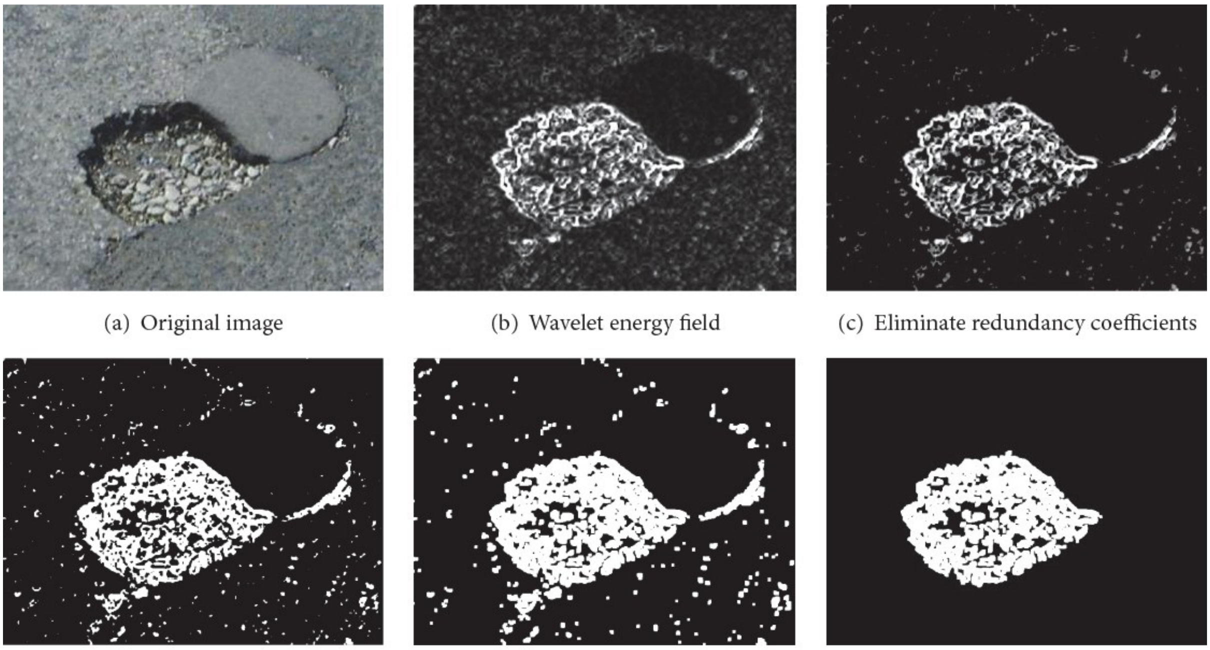
The proposed method consists of two processes: pothole detection and pothole segmentation. In the process of pothole detection, the wavelet energy field of the asphalt image was constructed by morphological processing and geometric criteria. The detected pothole was segmented via Markov random field model and the pothole edge was extracted accurately. The contours within the frame that describe the specific road colour sections are then determined.



- # THE POTHOLE MODEL

The pothole model is derived from the assumption that any strong dark edge within the extracted road surface is deemed a pothole edge if it adheres to certain size constraints. By inspecting Figure 1, it can be seen that one of the characteristics describing the potholes is a large dark shadow area. At this point, potholes that do not have dark edges and only have different color variations within them like sand or dirt are disregarded and will be studied in future work. The size constraints were obtained using the selection of images withheld for parameter tuning. Any shape of contour that meets these conditions is deemed a pothole by the algorithm.

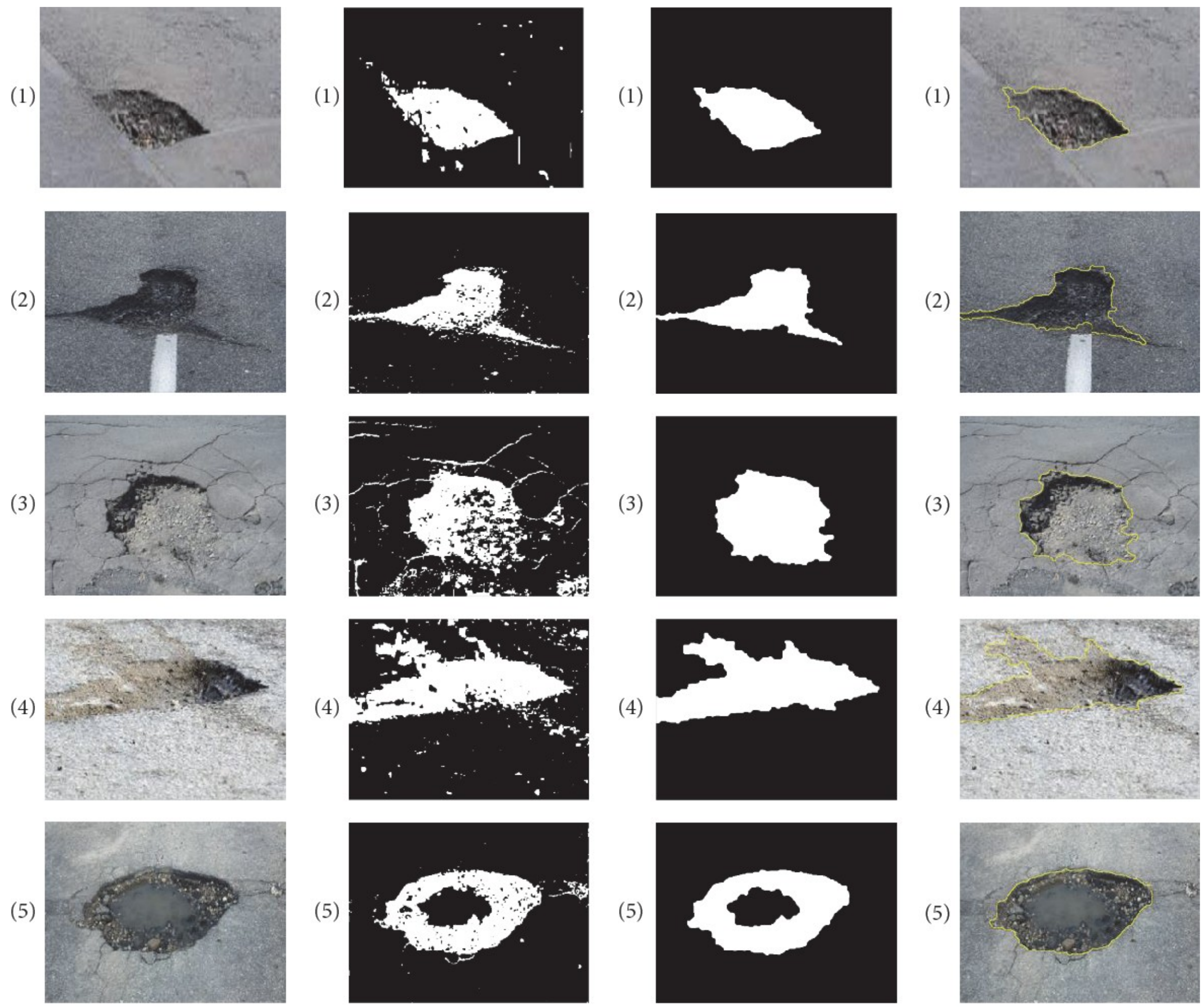
- # WORKING OF ALGORITHM



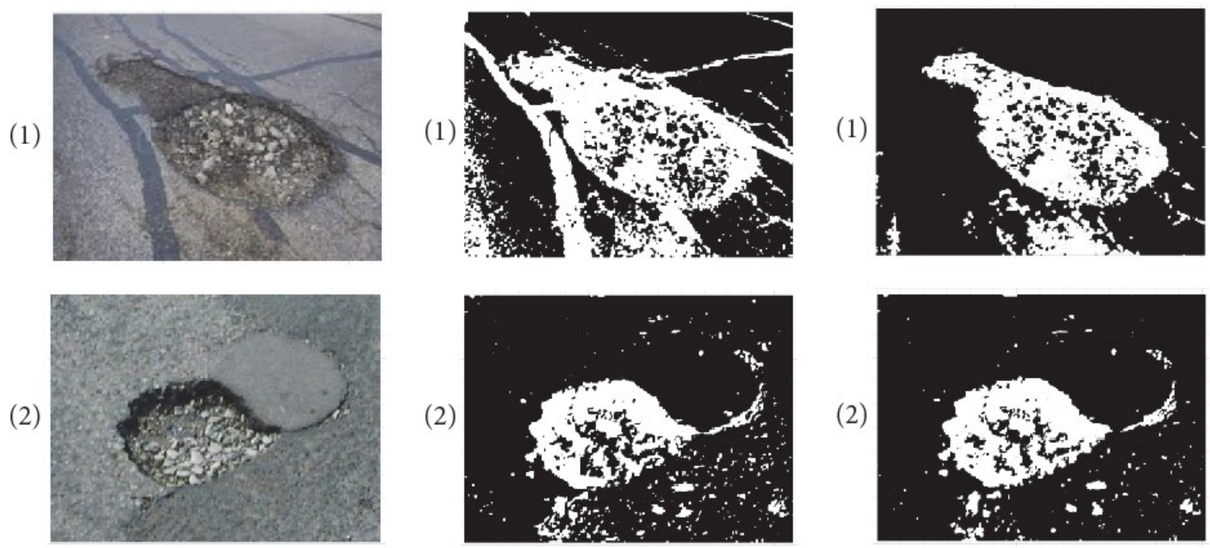
(a) Original image (b) Wavelet energy field (c) Eliminate redundancy coefficients

(d) Binarization (e) Morphological operations (f) Potential pothole region

FIGURE 5: The pothole detection process based on the wavelet energy field.



(a) Original images (b) Initial segmentation results (c) Morphological processing (d) Edge extraction



(a) Original images (b) Segmentation results of method A (c) Segmentation results of method B

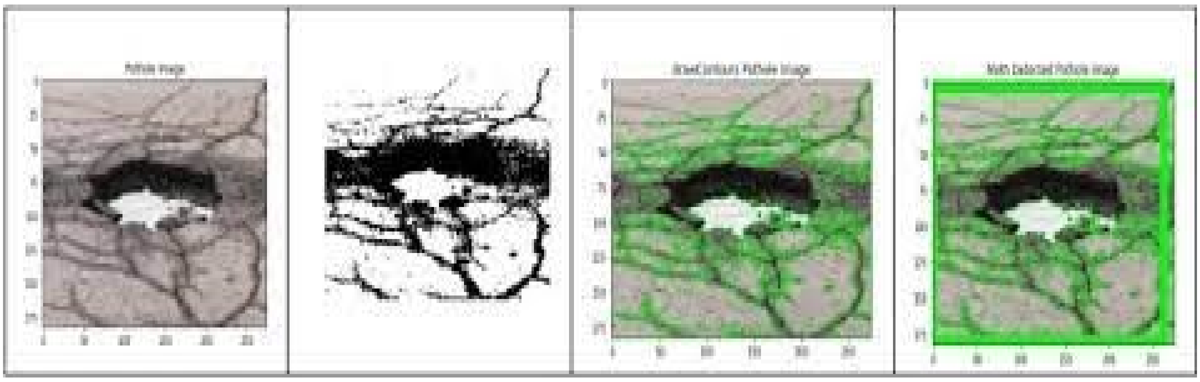
The proposed method consisted of proposed method consists of two processes: pothole detection and pothole segmentation. In the process of pothole detection, the wavelet energy field of the asphalt image was constructed by morphological processing and geometric criteria. The detected pothole was segmented via Markov random field model and the pothole edge was extracted accurately. The contours within the frame that describe the specific road colour sections are then determined.

The last contour detection is then applied to the dilated image to find the potholes within the road section. The contours are filtered and those that do not meet the size constraints of the pothole model are discarded. This last step filters out any small defects in the road that are not classified as potholes as well as the larger contours found on the outer boundary of the extracted road.

Authors proposed applying a more effective mathematic model as a future work to improve the accuracy of pothole detection.

ACCURACY

The experimental results showed that the overall accuracy, precision, and recall of the proposed method were 0.867, 0.833, and 0.875, respectively.



Code: the source code has been attached

MODEL 2

METHODOLOGY

The images in training subset were converted to a format size of 416*416 pixels to meet the input requirement for the chosen architecture. The images were reconstructed mul-tiple times to improve the training performance of the model. The object detection modelwas trained using a desktop computer with access to the Google Colab virtual machine,which allows performing computations on the Tesla K80 GPU with 12 GB of memory.Figure 5 shows the sequence of actions to perform tasks in order to detect potholesin the road surface. In the first step, a pothole dataset was collected from the previous research and the various YOLO models were reconstructed to be suitable for the tasks ofpothole detection. Next, the models were trained and validated until the loss functionreached a steady-state line, which the average loss insignificant changed. The quality of object detection, which requires to draw a bounding box around each detected object in the image, was confirmed by evaluating the performance of an object detector using three metrics (i.e., precision, recall, and mAP) as shown in Equations (1)–(3) .

#PRECISION = TP/TP+FP -------(1)

#RECALL =TP/TP+FN   ---------(2)

$$mAP = 1/n \sum_{i=1}^{n} AP_i$$

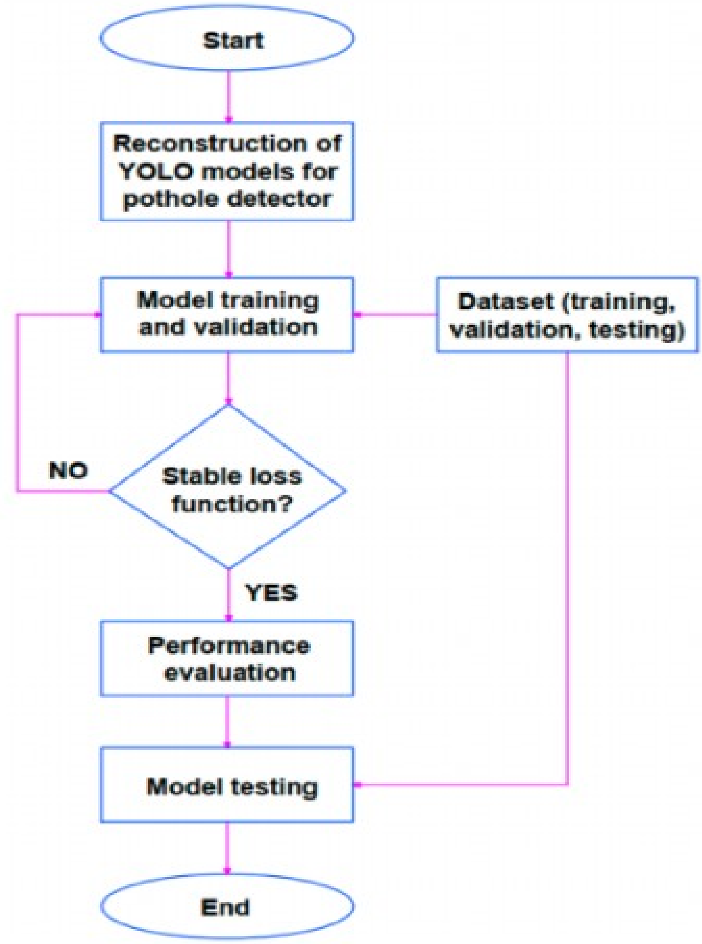


Figure 5. Flowchart of pothole detection using different YOLO architectures.

Table 1. Unnormalized confusion matrix.

Actual \ Prediction	Predicted as Positive	Predicted as Negative
Positive	True Positive (TP)	False Negative (FN)
Negative	False Positive (FP)	True Negative (TN)

As shown in Table 1, True Positive (TP) is the correct detection of an object that exists in the image; False Positive (FP) is incorrect object detection, i.e., the network marks an object that is not in the image; False Negative (FN) is an object that exists in the image but is not detected by the network; and True Negative (TN) is the correct detection of an object that do not exists in the image.

The precision is defined as the ratio of the number of true positives (TP) among those classified as positive (TP + FP), recall is the ratio of true positives (TP) out of those that are actually positive (TP + FN). Mathematically, the precision and recall parameters are two fractions having the same numerator and different denominators. Additionally, both the precision and recall are non-negative numbers and less than or equal to one. High precision means that the accuracy of the objects found is high. High recall means high True Positive Rate, which is the rate of missing positive objects is low.

The model is evaluated by changing a threshold and observing the values of precision and recall. For the precision and recall calculations, N thresholds are assumed and each threshold is a pair of precision (P_n) and recall (R_n) (n = 1, 2,. . ., N). Average precision (AP) is defined by Equation (4).

$$AP = \sum_{n=1}^{n} (R_n - R_{n-1}) P_n$$

The mAP is set to 0.5 for comparing the performance of three models. The YOLOv4 and YOLOv4-tiny models are implemented using TensorFlow; the YOLOv5 model (YOLOv5s) using PyTorch. The maturity of model training was evaluated by stages while alternating between iterations and image resolution. The intersection over union (IoU), which measures the overlapping area between the predicted bounding box and the ground truth bounding box of an actual object, is compared to a threshold in order to classify if a detection is corrector incorrect. The threshold should be specified because the value of average precision (AP) metric depends on the threshold. The threshold is set to 0.3 in this study. Therefore, a detection box is considered as valid only when IoU is greater than or equal to 30%. It is well accepted that human bare eye may not distinguish predictions obtained given a threshold between 0.5 and 0.3 . That is why it is justified to set the threshold to a value less

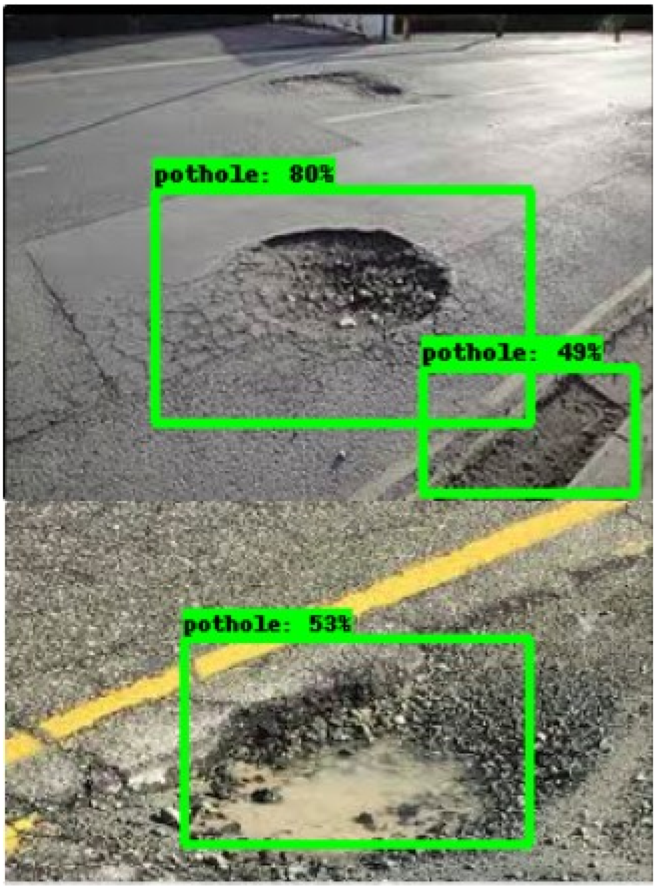
than or equal to 0.3. Given a lower threshold than 0.3, the number of valid detections would be substantially increased, hence, avoiding false negatives in analyzing each image. The current state of the art involved in object detection do create thousands of “anchor boxes”or “prior boxes” for each predictor that represent the ideal location, shape and size of the object it specializes in predicting, calculate Intersection Over Union (IoU) denoting whichobject’s bounding box has the highest overlap divided by non-overlap for each anchor box, identify the anchor box that it detects the object that gave the highest IoU when the highest IoU is greater than 50%, tell the neural network that the true detection is ambiguous and not to learn from that example when the IoU is greater than 40%, and confirm that there is no object when the highest IoU is less than 40%. In this way, the current art works well in practice and the thousands of predictors do a very good job of deciding whether their

type of object appears in an image. Using the default anchor box configuration can create predictors that are too specialized and objects that appear in the image may not achieve an IoU of 50% with any of the anchor boxes. In this case, the neural network will never know these objects existed and will never learn to predict them. The threshold should be specified because the value of average precision (AP) metric depends on the threshold. The threshold

is set to 0.3 in this study. Therefore, a detection box is considered as valid only when IoU is greater than or equal to 30%.

ACCURACY

YOLOv4 achieved a high recall of 81%, high precision of 85% and 85.39% mean Average Precision (mAP). The speed of YOLOv4 processing is recorded around 20 frames per second (FPS) at an image resolution of 832*832. Furthermore, the proposed system detected potholes at distances reaching a hundred meters.
With YoloV5 we have accuracy a little bit higher than previous versions. Its accuracy around being 92% for 700 test images we tested.



Code: the source code has been attached

Model 3

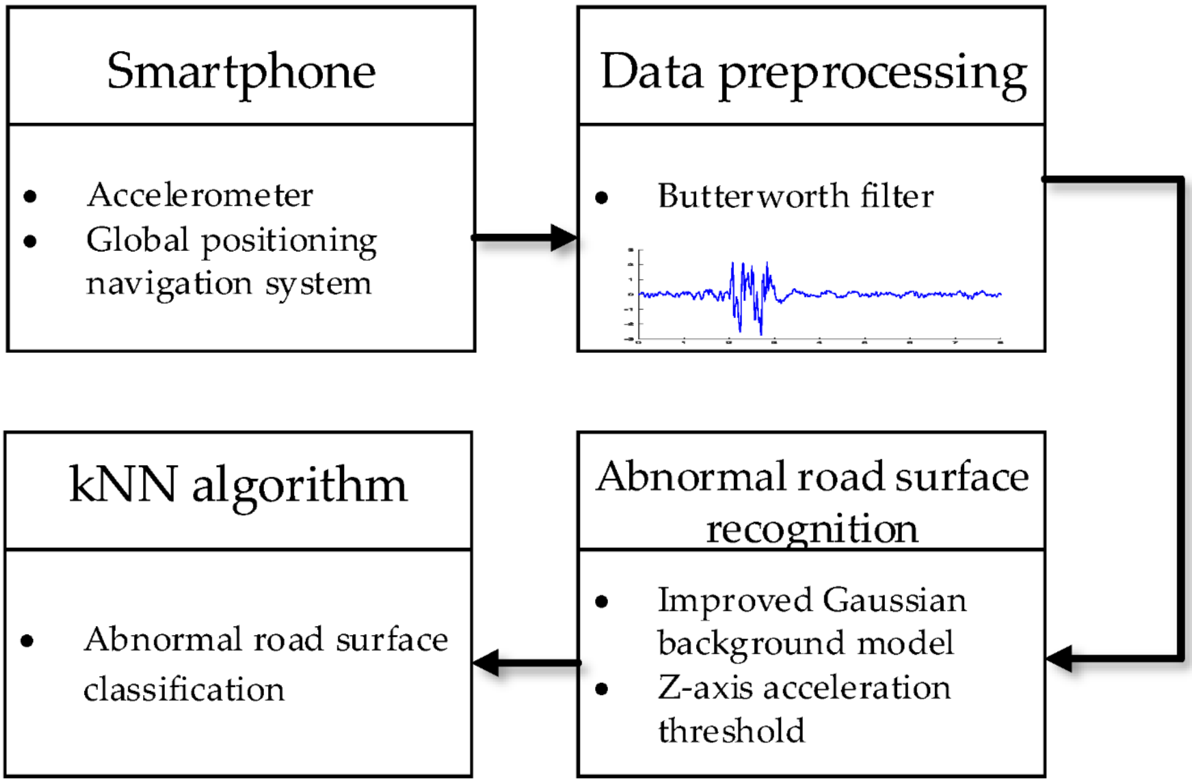
METHODOLOGY

Vibration-Based Method (Type B):

The proposed method consists of three phases: data acquisition and preprocessing, abnormal-road-surface recognition, and abnormal-surface classification. The vehicle speed, acceleration, and position information were collected by the smartphone's built-in accelerometer and Global Positioning Navigation system. The raw data were preprocessed using a Butterworth filter. The improved Gaussian model was used to recognize the abnormal road surface using the z-axis acceleration threshold condition. The training samples and the test samples were collected on two different roads for maintaining independence. The k-nearest neighbor (kNN) algorithm was used to classify the abnormal pavement types, including potholes and bumps.

The contours within the frame that describe the specific road colour sections are then determined.

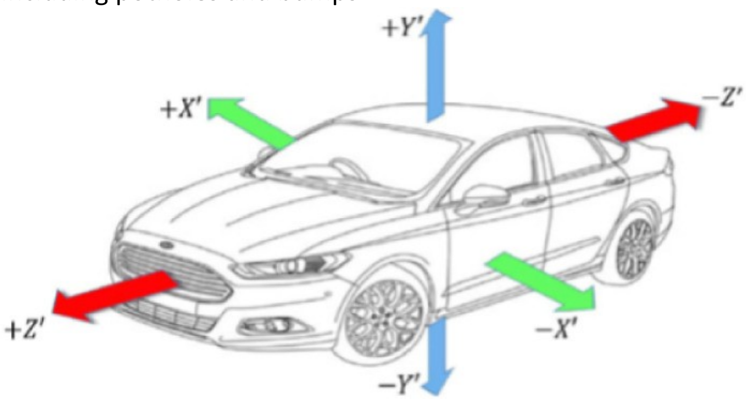
- WORKING OF ALGORITHM



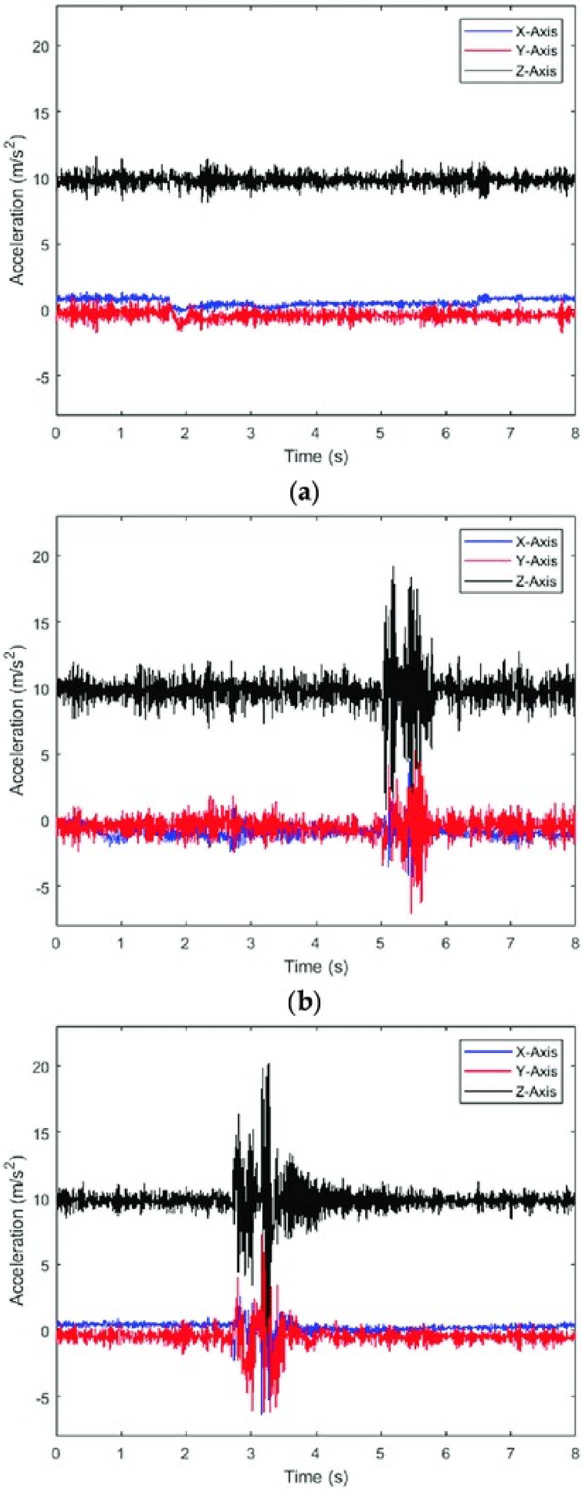
It consisted of

- Experimental vehicle: A-class vehicle (Cavalier) and SUV (Qoros 5)
- The smartphone is fixed on the handrail of the driver's seat
- An Android-based app working on a smartphone (Redmi Note 8 Pro)
- Sampling frequency: 400 (Hz)

The raw data were pre processed using a Butterworth filter. The improved Gaussian model was used to recognize the abnormal road surface using the z-axis acceleration threshold condition.
The k-nearest neighbor (kNN) algorithm was used to classify the abnormal pavement types, including potholes and bumps



Road Surface	Field Measurement	Algorithm Identification	Accuracy Rate
Pothole	151	145	96.03%
Bump	68	64	94.12%



(a)

(b)

(c)

ACCURACY

The accuracy was measured by comparing the field-measurement results for abnormal road surfaces such as potholes and bumps with the identification results of the proposed method. The test result shows that the accuracy of the recognition of the road-surface pothole is 96.03%, and the accuracy of the road-surface bump is 94.12%.

Code: the source code has been attached

CONCLUSION

Feature extraction and training and testing play an important role in vision-based methods. Image-processing technologies such as edge detection and SIFT are applied in the process of feature extraction in those methods. Deep-learning technologies such as CNN, YOLO, and SVM are used in the process of training and testing in those methods. Vibration-based methods generally consist of three steps, namely data preprocessing, feature extraction, and classification. Signal-processing techniques such as filtering, Fourier transform, and correlation are applied in the process of data preprocessing and feature extraction. Machine-learning techniques such as k-nearest neighbor, linear regression, and random forest are used in the process of classification.
The algorithm is successful in the detection of potholes and an attempt will be made to upgrade it to include potholes with no visible edges (due to sand or dirt) in future research.

LINK TO EXCEL SHEET-

https://docs.google.com/spreadsheets/d/1P56ethom31fNXWu57zzlS17noojr1YqyBA2nvN3C2Ks/edit#gid=0