Survey of Road Anomalies Detection Methods

Abstract: Automatic road anomalies detection and recognition systems are essential due to their effect on the comfort and safety of drivers and passengers. Drivers should be aware of bad road conditions and the existence of anomalies in routes to avoid accidents, reduce the possibility of car malfunction, and take the most appropriate way to reach their destinations. These reasons have led to conducting much research to automatically detect and recognize road anomalies. The related studies can be categorized into accelerometer-based techniques and vision-based techniques, which can also be divided based on the possibility of using deep neural Networks techniques or not. In this paper several studies for anomalies detection and classification have been reviewed. We also discuss several types of road anomalies, such as potholes, cracks, and speed bumps. Additionally, road damage detection techniques used for different types of road anomalies, challenges, and limitations of current research.

Keywords: Road Anomalies; Computer vision; Deep learning; Image processing

1 Introduction

Good road conditions are an important sign of the development and economic growth of countries by keeping the movements of goods and people from one place to another as easy as possible and reducing the costs of transportation.

Road conditions also affect the ride quality and safety because bad road conditions and anomalies increase the possibility of accidents, which cause more injuries and loss of lives (Danilescu et al., 2015; Bello-Salau et al., 2019; LOYA and RICARDO, 2019). So, early detection of road damage is a necessity. Road conditions should be monitored continuously to detect anomalies and damages as early as possible, because latency in detecting them increases the number of accidents, traffic jam, and maximizes maintenance costs.

There are several types of anomalies to be studied which are classified into several categories. First, damages are categorized as cracks and other damages. Cracks divided into linear cracks and alligator cracks, each in turn are categorized into different types of cracks. Other damages are rutting, speed pumps, potholes, manholes, separation, white line blur, and crosswalk blur (Maeda et al., 2018).

Detecting road damage cannot be done with a manual check, because it costs time, money, and slows down road maintenance process. So, supporting technology is needed to detect this kind of road hazard (Ragnoli et al., 2018; Carlos et al., 2018).

Two basic data collection methodologies were mainly used to detect road damages; vibration-based detection and computer vision-based detection. The Vibration-based approaches read data from tri-axial accelerometer, analyze data, extract pattern features, then predict the type of anomaly. On the other hand, the vision-based techniques capture images for the roads, prepare them, analyze them to detect anomalies, then recognize these anomalies. Within these two main methodologies, several machine learning, image processing, and deep learning techniques have been proposed (Munawar et al., 2021). Deep learning technologies such as different versions of YOLO (Redmon et al., 2016) , R-CNN detector series (Girshick et al., 2014; Girshick, 2015; Ren et al., 2015) with different CNNs (VGG16, ResNet-152, ResNet-50 and others) as backbone, are widely used in anomalies detection approaches for fast and accurate signal or images analysis, anomalies detection, and classification (Ma et al., 2022; Rastogi et al., 2020).

This review paper discussed state-of-the-art research in road anomalies detection and classification. The paper focused on studying different types of road anomalies such as: potholes, cracks, and speed pumps, either each one alone or together in same study. Different data collectors, methodologies and techniques were analyzed, results of these studies were compared, and the limitations of each research have been identified and clarified. Finally, Future plan to cover the research gap is suggested.

2 Data collection for road anomalies detection methodologies

Road anomalies detection research studies are categorized into acceleration-based and vision-based approaches. For anomalies detection an information should be collected from roads. Two types of data were collected to be analyzed and used for anomalies detection accelerometer signals and images or mixed.

2.1 Accelerometer-based

For accelerometer-based approaches, most researchers use smartphone accelerometers to collect the road data as in (Silva et al., 2017; Seraj et al., 2015)where smartphones accelerometers were used to detect and classify road anomalies. In (Silva et al., 2017), the authors proposed a method to detect road anomalies using smartphone sensors. They collected data using the accelerometer. The collected data are 3-axis accelerometer, latitude, longitude, speed, timestamp, and anomaly. A system called RoADS was implemented in (Seraj et al., 2015) to read inertial accelerometer data. Similarly, (Pandey et al., 2022) used inertial sensor (accelerometer and gyroscope) to collect data from IoS smartphone installed in the car for pothole detection. Furthermore, the authors in (Martinelli et al., 2022) equipped a car with sensors to read acceleration data. while in (Sattar et al., 2021) authors collected raw sensor data and location information by developing a mobile app installed on a smart device (mobile, or tablet). The collected data was linear accelerometer, rotation vector, and location information data. These data was collected from Linear accelerometer sensor, gyroscope, magnetometer and other sensors for road anomalies detection and classification.

2.2 Image-based

On the other hand, the vision-based approaches collects road images either using a mobile camera or a camera installed on a car, as in (Siriborvornratanakul, 2018)\cite{ (Azhar et al., 2016; Rasyid et al., 2019; Haq et al., 2019; Danilescu et al., 2015; Shaghouri et al., 2021; Wang et al., 2018; Doshi and Yilmaz, 2020; Lee et al., 2021; Arya et al., 2021; Mandal et al., 2018; Dung, 2019; Gopalakrishnan et al., 2017; Jana et al., 2022; Rao et al., 2021; Dewangan and Sahu, 2020; Yun et al., 2019; Babu et al.).

These images were captured to detect road anomalies and distresses. Images of potholes in the roads were captured and studied using different tools in (Siriborvornratanakul, 2018;

Azhar et al., 2016; Rasyid et al., 2019; Haq et al., 2019; Danilescu et al., 2015; Shaghouri et al., 2021). In (Siriborvornratanakul, 2018; Haq et al., 2019; Danilescu et al., 2015; Shaghouri et al., 2021), cameras were fixed in the cars to collect images of the specified roads such that in (Siriborvornratanakul, 2018) onboard in-car camera for capturing road images while in (Danilescu et al., 2015) a camera embedded inside the car were used. The situation is almost the same in (Shaghouri et al., 2021) , the camera was mounted on the windshield of the car to capture road images, but the number of captured images was few, so the authors increased the number of images by downloading images from the Internet. In (Haq et al., 2019) , the car was equipped with a stereo apparatus, which consists of two cameras. The videos of the road were taken from both cameras then the images were captured from the videos. Each point of the road had right and left view to be analyzed and construct a 3D view of the roads. A data set developed by (Koch and Brilakis, 2011) Koch et al. were used in (Azhar et al., 2016). This data set contains 120 pavement images; 50 images for training and the other 70 images were used for testing. Also, a wireless portable camera was used to capture images of the potholes in the roads (Rasyid et al., 2019).

In (Mandal et al., 2018; Gopalakrishnan et al., 2017; Jana et al., 2022; Rao et al., 2021; Hacğlu and Başağa, 2022; Dung, 2019) , the authors focused on studying cracks on the roads. Images of cracks were taken using cameras in vehicles as in (Mandal et al., 2018; Jana et al., 2022; Rao et al., 2021; Hacğlu and Başağa, 2022). In (Mandal et al., 2018) , a total of 9053 images were captured from 7 local governments across Japan. Out of the captured images 7240 images were used for training and the other 1813 were used for testing. The captured images consist of different types of cracks to be studied. A total of 136 images were used as a data set in (Jana et al., 2022) , where images were divided as 60 percent training images and 40 percent testing images. The images varied between images that contains cracks and a non-cracked images. While in (Rao et al., 2021) images were collected using a camera and a data set was built. The data set contains images of size 256 $\times$ 256 divided as 2,173 training images (2044 train + 129 validation) and 377 test images. A data set of 323 images with resolution of 4128 $\times$ 2322 were created using a smartphone camera in (Hacğlu and Başağa, 2022).

The other type of used data sets is a public already generated data sets as in (Dung, 2019; Gopalakrishnan et al., 2017) whereas a public concrete data set of 40000 227*227 crack images, and a subset of 1056 images from the pavement distress images data set from the Federal Highway Administration's FHWA's program were used respectively.

Images were captured in (Dewangan and Sahu, 2020; Yun et al., 2019; Babu et al.; Arunpriyan et al., 2019; Patil et al., 2020) for the detection of speed bumps. In (Dewangan and Sahu, 2020). At first, they prepared the primary setup for their study. From black paper sheet and wooden materials, they designed and built streets and speed bumps in different forms (marked and unmarked). After that they built their data set by capturing images for these speed bumps, they took around 550 images. In the next step, they pre-processed the images then used augmentation techniques to increase the number of images in the database to be suitable to use with CNN, after these steps they had around 3400 images in the data set. However, camera and Lidar were used in (Yun et al., 2019) to detect speed bumps. A Raspberry pi camera were used in (Babu et al.) to collect images of unmarked speed bumps from Indian roads. While in (Arunpriyan et al., 2019) , road images were captured using a monocular camera feed placed in front of the vehicle.

Road images and accelerometer data was collected in (Lee et al., 2021; Sprague and Azar, 2022) for anomalies detection, localization, and severity estimation. In these studies car was equipped with a smartphone to collect road images from the camera and the corresponding acceleration data using the smartphone accelerometer. The collected images were used to study the presence or absence of anomalies. When an anomaly is detected in an image the acceleration data correspondent to that image is retrieved from the server storing all the collected data to study the severity of that anomaly if the car has passed over it.

3 Road Anomalies and detection methods

This section presents an overview of the state-of-the art studies for automatic road anomalies detection and classification. From the detected anomalies side, each study focused on detecting and analyzing one or more types of road anomalies. Mainly road anomalies are categorized as cracks, potholes, manholes, rutting, speed pumps, crosswalk blur, white line blur, and many others. This review paper focuses on the studies of detecting potholes, cracks, and speed pumps, either each one alone or detecting more than one type of them.

anomalies detection studies used different techniques for anomalies detection, recognition, and classification such as signal processing, computer vision and image processing with and without the use of DNN.

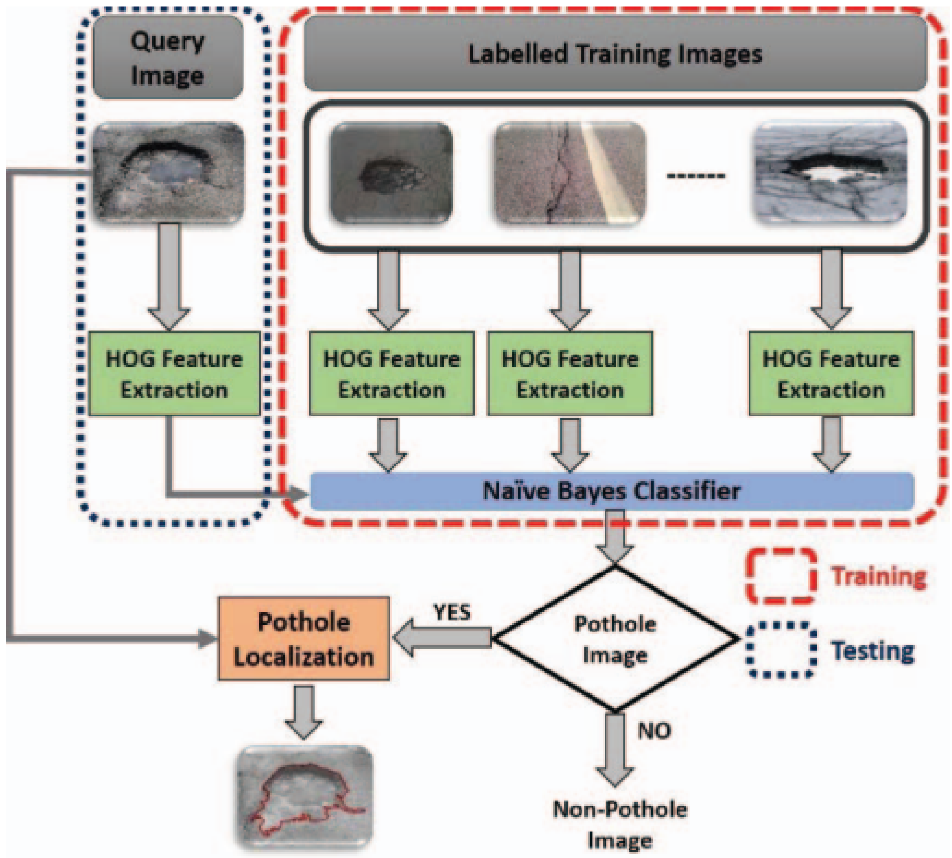
3.1 Potholes

A pothole is hole with different sizes occurs in the road because of bad weather or due to heavy traffic load. Several studies focused on detecting potholes in the roads either from road accelerometer signals, or from road images as in (Pandey et al., 2022; Siriborvornratanakul, 2018; Azhar et al., 2016; Rasyid et al., 2019; Haq et al., 2019; Danilescu et al., 2015; Shaghouri et al., 2021).
In (Pandey et al., 2022) , inertial sensors (accelerometer and gyroscope) data were collected for detecting potholes using a proposed 2-hidden layer 1-D CNN with kernel size 3 model for features extraction, pothole detection and classification.
In (Siriborvornratanakul, 2018) , the authors proposed a road monitoring algorithm. Using this algorithm, they can detect, recognize, track, evaluate, and estimate potholes. The algorithm takes road images, prepares, binarizes them, and applies morphological erosion then dilation to connect white areas and remove black noises from binarized image. Finally, they calculated the pothole-probability score by computing two scores; first one is calculating a difference value between mean intensities of pixels inside and outside each contour. The second one is calculating a ratio of Nsharp/Nall, where Nsharp is the number of sharp contour perimeter pixels and Nall is the number of all pixels in the contour perimeter. Finally, the total score is computed as a contour acceptance score by computing the average of the two pothole-likelihood scores. If the acceptance score of the contour is lower than a predefined threshold, it will be rejected. The resulted contours are the detected potholes.

Machine learning algorithms were used in (Azhar et al., 2016; Rasyid et al., 2019) to classify the images based on pothole/non-pothole images. In (Azhar et al., 2016) , the HOG algorithm was used for features vector extraction, which in turn entered the Naïve Bayes classifier. The Naïve Bayes assigns the label to an input image based upon the maximum posteriori probability as inFigure 1

In (Rasyid et al., 2019) researchers used TensorFlow and OpenCV libraries to detect potholes in images using TensorFlow with a faster RCNN inception v2 pre-trained model. Additionally, the sensor device contains a GPS sensor, IMU sensor, external GPS antenna,

Figure 1 Algorithmic Workflow in (Azhar et al., 2016)



and Microcontroller for control of the sensor and sending it to the Processing Unit is used to localize the pothole. A method for 3D reconstruction of potholes using SIFT key points detector and disparity map was used to create a 3D scene of the pothole in (Haq et al., 2019). In (Danilescu et al., 2015) an approach is developed using morphological algorithms for pothole detection in roads. The pothole detection algorithm goes through the following steps:

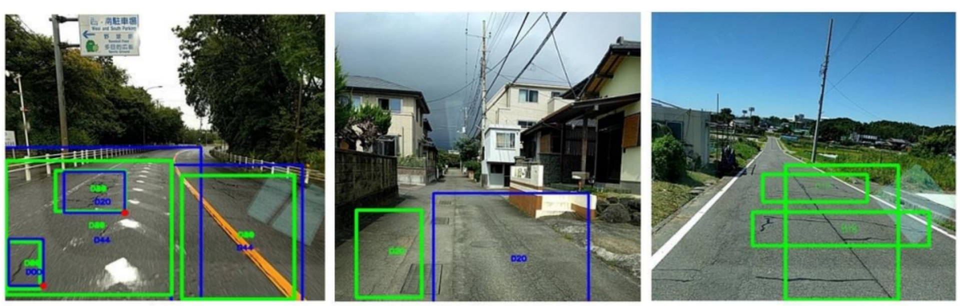
- Cropping road segment from the collected images based on road extraction algorithm by cropping 50% of its height and 40% of the width (20% from each side).
- Removing the noise from the original images by using Gaussian low pass filter.
- Segmenting the foreground from the background by binarizing the image using Otsu's algorithm.
- Skeletonization process is applied to retain the connected pixels only which represent the potholes.

A real-time pothole detection approach was proposed in (Shaghouri et al., 2021) , where authors experimented three types of object detectors on different frameworks, such as: Single shot Multi box Detector SSD on TensorFlow framework, YOLOv3 and YOLOv4 on Darknet framework. All the processing was done on Google Colaboratory (Colab) on images from a combination of two different data sets. The first one is available online, the second one is a combination of images from different sources of the internet and images captured using camera from Lebanese roads. The experiments showed that SSD gives the worst performance and can't be used as a real-time detector. While on the other hand, YOLOv4 was the best results with 81% recall, 85% precision, 85.39% mAP, and a processing speed of 20 frames per second.

3.2 Cracks

Cracks are a kind of distresses in the pavement that causes problems with traffic and driving safety. Early detection of such deterioration is essential before it becomes too severe. In (Mandal et al., 2018; Dung, 2019; Gopalakrishnan et al., 2017; Jana et al., 2022; Rao et al., 2021) researchers focused on studying the presence or absence of road cracks using different deep neural networks. YOLOv2 is used in (Mandal et al., 2018) , and YOLOv2 uses single CNN with standard layer types such as convolutional with a 3×3 kernel and max pooling with a 2×2 kernel. To minimize the data to the shape of 13x13x125 the last convolutional layer is used with a 1×1 kernel. This 13×13 structure represents the size of the grid where the image gets apportioned. All these grid cells predict 5 bounding boxes, and each box described by seven data elements: the values of x, y, width, and height; the confidence score; road crack and no-crack probability distribution as inFigure 2

Figure 2 Classification of predicted crack examples: True Positive-(a), False Positive-(b), False Negative-(c) obtained from YOLO v2 in (Mandal et al., 2018).

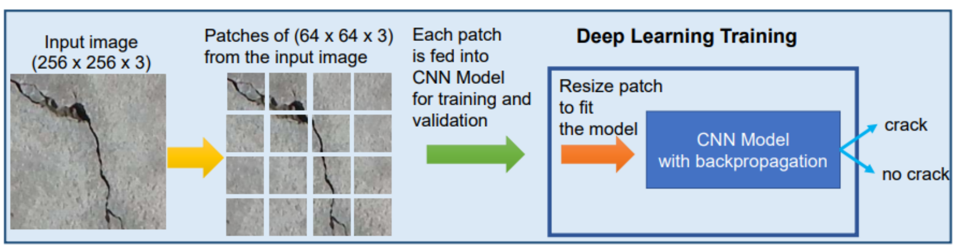


In (Dung, 2019) , the authors used Fully Convolutional Network FCN and VGG16 as the backbone of the FCN to classify each pixel into "crack" or "non-crack" classes. Additionally, crack density computed using pixel density ratio. While In (Gopalakrishnan et al., 2017) , Deep Convolutional Neural Network (DCNN) trained on the 'big data' ImageNet database (VGG16) was used as a feature vector extractor then the vector was entered to several classifiers such as: Single layer NN, Random Forest, Extremely Randomized Tree, Support Vector Machine, and Logistic Regression to automatically detect cracks in images of Hot-Mix Asphalt (HMA) and Portland Cement Concrete (PCC) surfaced pavement.

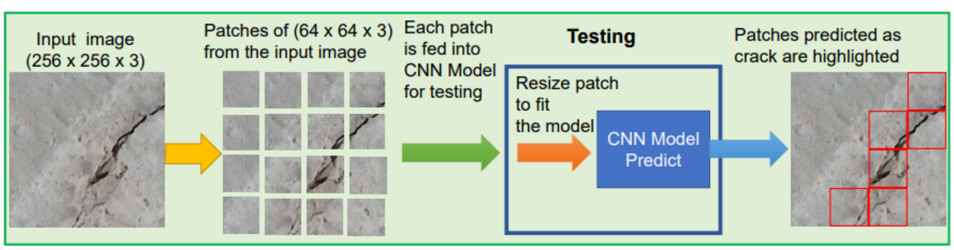
A method was proposed to detect pavement cracks using Deep Learning with transfer learning in (Jana et al., 2022). The proposed model was built based on different pre-trained network architectures namely, Google net, Alexnet and ReseNet101. The network was designed by tuning the training parameters such as setting the initial value of the learning rate, initializing epochs, and choosing optimizer then a dataset of 136 images were used to train and test the proposed model, 60% of images were used as training data the remaining images were used for testing. The results showed that transfer learning using pretrained Google net gave the best performance in detecting pavement cracks because of its adaptability for each iteration, number of layers used in it, and the reduced loss.

Other studies focused on detecting cracks in concrete structure as in (Rao et al., 2021) using different types of CNN and non-overlapping window (patches) were proposed. The proposed approach is shown in Figure 3 . A data set was built for this study, the data set consists of images of crack/non-crack concrete structures divided into 2,173 training images (2044 train + 129 validation) and 377 test images of size 256 $\times$ 256 which produced 32,704 training patches, 2,074 validation patches and 6,032 test patches. The performance of the proposed approach was tested using 15 different CNN models such as VGG, ResNets, AlexNet, Inception networks, and others. Results showed that VGG19 gave the best accuracy of 95%.

Figure 3 Proposed methodology in (Rao et al., 2021).



(a) Training phase



(b) Testing phase

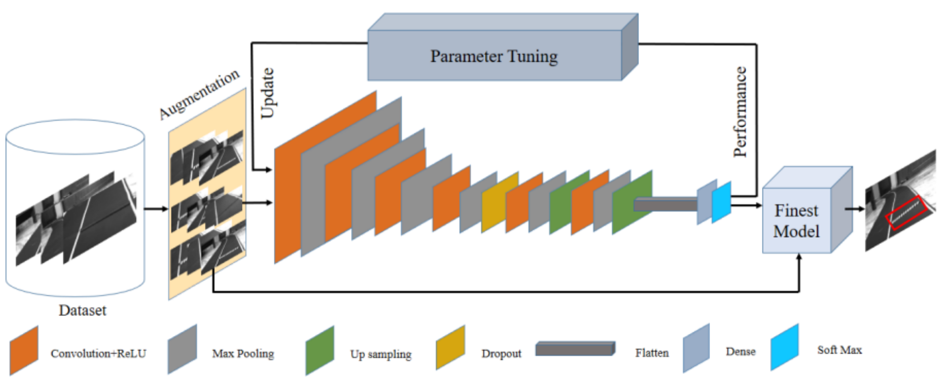
3.3 Speed bumps

A small raised built area in the road called speed bumps is used to force drivers to drive slowly on the road. The lack of awareness of the presence of such bumps and driving fast over them may cause fatal accidents and many other problems. Consequently, automatic detection and alerting the driver to their presence in advance is necessary and limits these problems.

Another research was conducted for detecting cracks in concrete roads using faster R-CNN as in (Hacğlu and Başağa, 2022).

Deep learning approaches for detecting speed bumps are proposed in (Dewangan and Sahu, 2020; Yun et al., 2019; Babu et al.; Arunpriyan et al., 2019; Patil et al., 2020). In (Dewangan and Sahu, 2020) at first, they prepared the primary setup for their study. From black paper sheet and wooden materials, they designed and built streets and speed bumps in different forms (marked and unmarked). After that, they built their data set by capturing images for these speed bumps, they took around 550 images. In the next step, they preprocessed the images then used augmentation techniques to increase the number of images in the database to be suitable to use with CNN, after these steps they had around 3400 images in the data set. After that, they built the CNN with 3*3 and 5*5 filters to extract features vectors, which is transferred to the pooling layer to extract the defined size feature vectors. The defined sized vectors are then sent to the fully connected layer for classification of speed bumps presence. Finally, depending on the size of the boxes drawn around the speed bump, they calculated the distance between the car and the speed bump, the proposed methodology shown inFigure 4

Figure 4 Proposed speed bump detection using convolutional neural network (CNN) architecture in (Dewangan and Sahu, 2020).

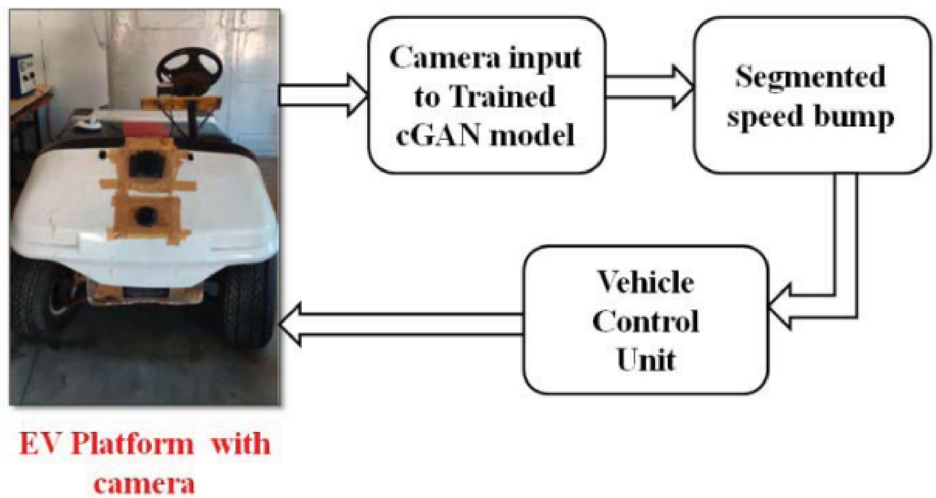


Also, camera and Lidar were used in (Yun et al., 2019) to detect speed bumps. First after preprocessing grayscale images and binarizing them, the pattern of the speed bumps enters the first detector which is a HaaR classifier to detect the regions of the image which are the candidates of a speed bump. Then the second detector is used to filter these regions from the first detector and find only the true speed bumps, using Lidar and camera for this task. Lidar is used to filter objects that have heights more than the vehicle height then HOG is used to extract features from the images, and finally the SVM classifier is used to recognize the speed bumps. The camera and the Lidar are used to calculate the height of the speed bump and the distance from it.

A new approach for detecting unmarked speed bumps is proposed in (Babu et al.). The proposed method used image processing techniques to detect unmarked speed bumps from Indian road images that are collected using a Raspberry pi camera. The images were captured from video, then went through several steps to detect the presence or absence of the speed bump in the image and classify the sharpness level of the detected bump. The model works by at first preprocess the images by converting it from RGB to gray scale images, then apply a Gaussian filter on it to deal with illumination and blur in the image. After that, canny edge detection algorithm was used for identifying edges in the image, and finally Hough transform is used to identify the lines that represents a speed bump based on the line length. The model was tested on a database of 1385 images that were captured in different day times, the results showed the average accuracy of correct detection were 95.5%.

Authors proposed a novel method for upcoming speed pumbs detection for self-driving cars in (Arunpriyan et al., 2019; Patil et al., 2020). In (Arunpriyan et al., 2019) speed bumps were detected using a deep learning algorithm called SegNet. SegNet is a DNN for semantic pixel-wise segmentation. While, GAN were used in (Patil et al., 2020) for segmenting speed bumps by generating an output image with conditioned label, when color image is given as input as in Figure 5 . The generator network generates fake images which are so close to the real input images where discriminator network can't distinguish between real and fake images at the end of
training.

Figure 5 Proposed speed bump detection using GAN in (Patil et al., 2020).

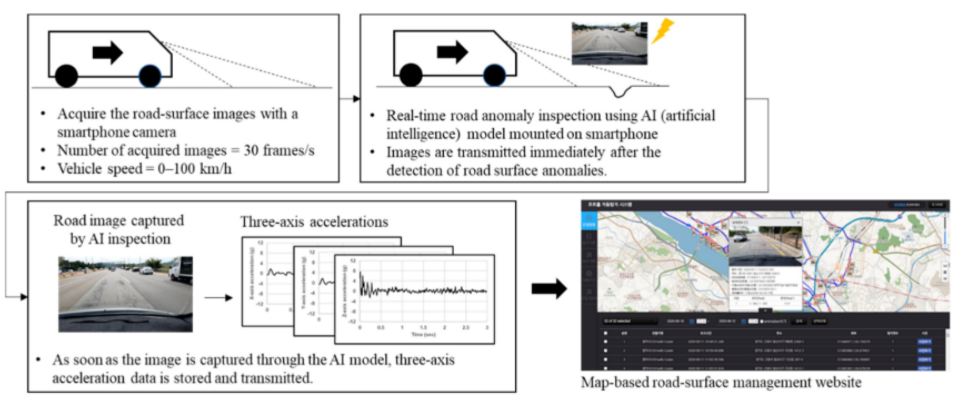


3.4 Multiple types of anomalies

While some researchers focused on detecting only one type of road anomalies, others took in consideration the need of detection of more than one type of anomalies. In (Wang et al., 2018; Doshi and Yilmaz, 2020) authors used Faster R- CNN to detect and classify damaged roads. The proposed method in (Wang et al., 2018) consists of two stages; first input images are pre-processed and augmented, then feature extracted using ResNet-152 feature extractor. After that, feature maps enter the Region Proposal Network as an input then a set of rectangular object proposals with their scores outputted from the network. In the second stage, Fast R-CNN detector is used for each object proposal to extract fixed-length features vector by the Region of Interest (RoI) pooling layer from the feature maps. Then, each feature vector will go through a sequence of fully connected layers to predict the class label of the damage and draw the bounding box. They also studied cracks, crosswalk line, and manholes. In (Doshi and Yilmaz, 2020) an ensemble model is proposed to detect and classify road damages (different types of cracks and potholes) efficiently using YOLOv4 object detector.

In (Lee et al., 2021) , a hybrid approach for checking the presence or absences of road anomalies is proposed, using camera and accelerometer, as shown in figure 2. The road surface images are captured using a smartphone camera from inside the car, the images then entered to FCN model to detect anomalies. When the anomaly is detected, the 3-axis acceleration of the smartphone accelerometer were measured for three seconds. The Z-direction acceleration value used mainly to detect and identify road anomalies and determines the severity of the detected anomalies. In general, when the size of the road surface anomaly increased, the change of the Z-axis acceleration is expected to be larger. They found that when no anomalies on the road, the maximum variations of the Z- axis accelerations were less than 2 m/s\^2. However, when anomalies were detected on the road surface, the variations of the Z-axis accelerations were mostly >2 m/s\^2. Their study showed that if the detected anomaly is a pothole which have irregular shapes, the acceleration varied and distributed extensively than in the other cases. But, for manholes, which have a constant circular shape, the change in value was concentrated on a narrow range. The severity of road-surface anomalies can be identified by comparing the images with the maximum variation of Z-axis acceleration. Overall image acquisition process is shown in Figure 6

Figure 6 Overall image acquisition flow and three-axis accelerations with a smartphone in (Lee et al., 2021).



Another hybrid model was proposed in (Sprague and Azar, 2022) to asses the condition of the asphalt roads, using a smartphone mounted on the car dash-board to simultaneously capture a video of the road and the corresponding acceleration response of a vehicle while driving. The system developed to analyze the accelerometer data. When an anomaly is detected the corresponding frame from the video is analyzed and segmented using semantic segmentation identify the detected anomaly.

Different CNN models for potholes and cracks detection were developed in (Arya et al., 2021) using: two types of YOLOR, three types of YOLOv5 (Yl, Ym, and Ys), and Faster RCNN with different backbones such as: VGG16, ResNet50, MobileNetv2, Inception v3, and finally a proposed CNN called MVGG16 which represents modification of the original VGG16. Experiments were conducted on a data set built using smartphone camera. The images are captured in different daylights from different countries. Experiments showed that Faster R-CNN ResNet50 gave the best accuracy of 91.9%, whereas MobileNetV2 was the worst with 63.1%. the results also showed that MVGG16 improved the performance of the original VGG16 but not the best.

(Martinelli et al., 2022) proposed a real-time low-cost system for extracting information about road conditions. The proposed system read acceleration signals from sensors equipped on a car. These signals were analyzed using short-time Fourier transform to extract features to distinguish different of road distresses (potholes, manholes, and cracks) using different classifiers such as SVM. While in (Sattar et al., 2021) a near real time approach for detecting and classifying road anomalies was proposed. The authors collected data from several sensors, then detect and classify anomalies using modified threshold — based and machine learning approaches (K-means clustering).

4 COMPARATIVE ANALYSIS

This section presents a comparison between the different previously mentioned road anomalies detection approaches. Different used technologies, main features, limitations, and results of state of the art studies of each road anomaly detection approach is discussed bellow.

4.1 Methodology

Different approaches of road anomalies based on the collected and studied road anomalies are presented here: accelerometer-based , vision-based , and hybrid approaches each with different anomaly type.

For accelerometer- based approaches as (Silva et al., 2017; Seraj et al., 2015; Martinelli et al., 2022; Sattar et al., 2021; Pandey et al., 2022) data about road anomalies were collected using an accelerometer and a gyroscope, the collected signals then were analyzed using different signal processing techniques. Finally, different types of classifiers were used to detect and classify road anomalies sum accelerometer based approaches are mentioned in Table 1 . Using accelerometers arises a problem that because of the use of accelerometer, vehicle should go over the anomaly to detect it, which may cause a lot of damage or problems to the var and the driver, or the car could go next to the anomaly and therefore didn't detect it.

On the other hand, to overcome this problem computer vision, or even hybrid models were proposed as in (Siriborvornratanakul, 2018; Azhar et al., 2016; Rasyid et al., 2019; Haq et al., 2019; Danilescu et al., 2015; Shaghouri et al., 2021; Wang et al., 2018; Doshi and Yilmaz, 2020; Lee et al., 2021; Arya et al., 2021; Mandal et al., 2018; Dung, 2019; Gopalakrishnan et al., 2017; Jana et al., 2022; Rao et al., 2021; Dewangan and Sahu, 2020; Yun et al., 2019; Babu et al.)
for vision-based approaches,
road anomalies were detected from images of the roads. Computer vision and image processing techniques were applied to the images to preprocess and analyze them, after that different object detectors were used to detect the anomalies from the image. Finally, different classifiers and DNN were used to classify the image (has anomalies or not) or

Table 1 Accelerometer- based techniques for road anomalies detection

Anomly type	Technology	Input	Real time	Ref
potholes	2-hidden layer 1-D CNN with kernelsize 3 model	Accelerometer and gyro-scope signal	No	(Pandey et al., 2022)
	Signal processingtechniques+ Tree-based classifier	Smartphone accelerationsignal	No	(Silva et al., 2017)
Several Types of anomalies	Wavelet decompo-sition analysis +SVM classifier	Accelerometer and gyro-scope signal	Yes	(Seraj et al., 2015)
	a short-time Fouriertransform + differ-ent classifiers	Accelerometer signal	Yes	(Martinelli et al., 2022)
	Threshold-basedand unsupervisedmachine learningtechniques	Several smart devicesensors as: linearaccelerometer and gyro-scope sensors	Near real time	(Sattar et al., 2021)

classify the detected anomaly. Table 2 shows different vision-based techniques based on the type of anomalies they studied.

There are other studies that used the two methods together either as a confirmation of their results or for detecting, localizing, and estimating the severity of the detected anomaly, and these approaches are summarized in Table 3

4.2 Limitations

Both approaches have limitations either that they focused only on one type of anomalies, neglecting any other obstacles in the road as in (Siriborvornratanakul, 2018; Azhar et al., 2016; Haq et al., 2019; Shaghouri et al., 2021; Jana et al., 2022; Babu et al.), or the limited data sets they used which affects the accuracy obtained especially in the case of using deep neural networks for classification (Azhar et al., 2016; Jana et al., 2022). Also, because some studies made lab experiments only and did not apply their work in real-time or on real roads, and this may affect the accuracy when applied on real roads because of illumination and other environmental conditions as in (Dewangan and Sahu, 2020). Additionally, most research focuses on detecting the anomaly without taking in consideration its size, height, depth, etc. which is important to the decision the driver should take as in (Siriborvornratanakul, 2018; Azhar et al., 2016; Rasyid et al., 2019; Wang et al., 2018; Mandal et al., 2018; Gopalakrishnan et al., 2017; Dewangan and Sahu, 2020). Finally, In the studies that used cameras placed in the car, such as (Siriborvornratanakul, 2018; Rasyid et al., 2019; Dung, 2019) the calibration of camera's place is a limitation for their work because if camera is not in a specific angle it cannot take proper images to be used for anomalies detection and may cause misclassification of these anomalies. Table 4 presents the limitations of previous studies.

4.3 Accuracy

From the results side, the results obtained from the different studies showed difference in performance of these approaches based on the used method for analyzing images and the classification techniques chosen in those papers. For pothole detection different methods and classifiers were used in (Siriborvornratanakul, 2018) without the use of machine learning techniques sample of their results shown in Figure 7.

Other methods for pothole detection used machine learning as in (Azhar et al., 2016) HOG feature extractor with Naïve Bayes classifier was used, the accuracy of their results was 90%. While in (Rasyid et al., 2019) faster RCNN inception v2 pretrained model was used an example of the results is in Figure 8

YOLOv4 was used in (Shaghouri et al., 2021) for pothole detection and gain a precision of 85%. Other approaches are proposed for the detection of speed bumps such as (Dewangan and Sahu, 2020; Yun et al., 2019; Babu et al.; Patil et al., 2020). The overall accuracy of detecting speed bumps was 98.54% in (Dewangan and Sahu, 2020) with the use of proposed CNN. However, in (Yun et al., 2019) researchers used Haar cascade classifier for detecting candidate regions of speed bumps, then HOG feature extractor with SVM classifier are used as second detector to detect speed bumps. The average accuracy of detecting speed bumps was 85.2%, additionally their method takes 10ms processing time than other methods.

On the other hand, in (Babu et al.)researchers concentrated on the detection of unmarked speed bumps, The model was tested on a database of 1385 images that were captured in different day times, the results showed the average accuracy of correct detection were 95.5%.

Table 2 Vision- based techniques for road anomalies

Anomaly type	Technology	Input	Real time	Ref
Potholes	Computer visiontechniques	Images from on-boardcamera, Images fromvideos	No	(Siriborvornratanakul, 2018; Danilescu et al., 2015)
	HOG feature ex-tractor with Na ïveBayes classifier	Images from onlineGoogle + Images from awebcam in a robot	No	(Azhar et al., 2016)
	SIFT detector		No	(Haq et al., 2019)
	Single Shot Detec-tor (SSD)	Images from differentdatasets	Yes	(Shaghouri et al., 2021)
	YOLOv3, YOLOv4	mages from differentdatasets	Yes	(Shaghouri et al., 2021)
	YOLOv2	Images from a smart-phone camera	No	(Mandal et al., 2018)
Cracks	FCN with VGG16as its backbone	public concrete crackdataset of 40,000 227 ×227-pixel images	No	(Dung, 2019)
	Different types ofCNN (VGG16,AlexNet,ResNet101,GoogleNet)	A subset of the pavementdistress images datasetfrom the FHWA's, self-built road images dataset		(Gopalakrishnan et al., 2017; Jana et al., 2022; Rao et al., 2021)
	Faster R-CNN	Smartphone images	No	(Hacğlu and Başağa, 2022)
Speed bumps	Image processingtechniques	Images from a Raspberrypi camera	Yes	(Dewangan and Sahu, 2020)
	CNN with 3*3 and5*5 filters	Images of lab preparedspeed bumps	Yes	(Babu et al.)
	segNet	Images from monocular camera	Yes	(Arunpriyan et al., 2019)
	Generative adver-sial network GAN	Images from monocularcamera	Yes	(Patil et al., 2020)
Several types of anomalies	Fast and faster R-CNN	Images from a smart-phone camera	No	(Wang et al., 2018; Arya et al., 2021)
	YOLOv4, YOLOv5	Road damage datasetsprovided by the IEEEBigData Cup Challenge2020, large road dam-age dataset of smart-phone images	No	(Doshi and Yilmaz, 2020; Arya et al., 2021)

Table 3 Hybrid techniques for road anomalies detection

Anomaly type	Technology	Input	Real-time	Ref
Potholes (De-tection and lo-calization)	Faster R-CNN GPSsensor, IMU sensor	Images from wireless portable camera, GPSdata	No	(Rasyid et al., 2019)
More than one type of anoma-lies	FCN + signal pro-cessing techniques+ Histogram ofacceleration signals(estimate the sever-ity of the anomaly)	Images from Smart-phone camera + smart-phone acceleration signal	No	(Lee et al., 2021)
	signal process-ing techniques+ResNet50	mages from Smart-phone camera + smart-phone acceleration signal	No	(Sprague and Azar, 2022)
Speed bumps	HOG feature ex-tractor + Haar andSVM classifiers +LiDAr (for calcu-lating distance be-tween speed bumpand car)	Camera Images	No	(Yun et al., 2019)

Table 4 limitations of the state of the are road anomalies detection techniques

Road anomalies de-tection approach	Limitation	Ref
Accelorometer-based approaches	1- vehicle should go over theanomaly to detect it, which maycause a lot of damage or prob-lems to the car and the drive 2- vehicle could go next tonot over the anomaly so theanomaly will be missed be-cause there will be no variationin the acceleration data toindicate anomaly presencehere.	(Silva et al., 2017; Seraj et al., 2015; Martinelli et al., 2022; Sattar et al., 2021; Pandey et al., 2022)
vision-based approaches	Focusing on one type of anomaliesneglecting any other types	(Siriborvornratanakul, 2018; Azhar et al., 2016; Rasyid et al., 2019; Haq et al., 2019; Danilescu et al., 2015; Shaghouri et al., 2021; Mandal et al., 2018; Dung, 2019; Gopalakrishnan et al., 2017; Jana et al., 2022; Rao et al., 2021; Hacğlu and Başağa, 2022; Dewangan and Sahu, 2020; Yun et al., 2019; Babu et al.; Arunpriyan et al., 2019; Patil et al., 2020)
	Limited data sets	(Azhar et al., 2016; Jana et al., 2022; Patil et al., 2020; Hacğlu and Başağa, 2022)
	Lab experiments only	(Dewangan and Sahu, 2020)
	Focusing on detecting the anomaly without estimating its severity level	(Siriborvornratanakul, 2018; Azhar et al., 2016; Rasyid et al., 2019; Wang et al., 2018; Mandal et al., 2018; Gopalakrishnan et al., 2017; Dewangan and Sahu, 2020; Patil et al., 2020; Arunpriyan et al., 2019; Hacğlu and Başağa, 2022)
	Calipration of camera in the car	(Siriborvornratanakul, 2018; Rasyid et al., 2019; Dung, 2019; Doshi and Yilmaz, 2020; Lee et al., 2021; Arya et al., 2021; Mandal et al., 2018; Gopalakrishnan et al., 2017; Jana et al., 2022; Rao et al., 2021; Dewangan and Sahu, 2020; Yun et al., 2019; Babu et al.)

Figure 7 One pothole detection result (Siriborvornratanakul, 2018).

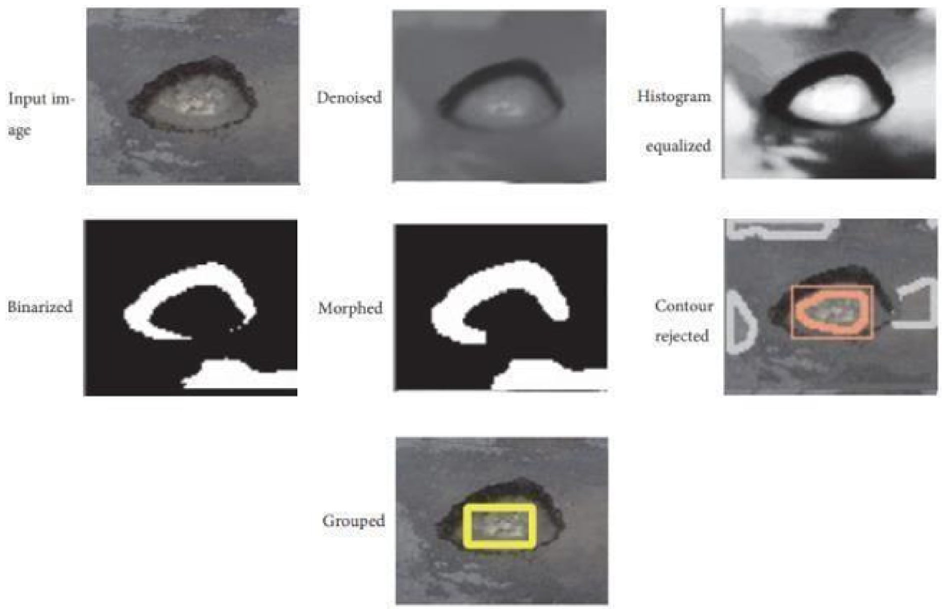
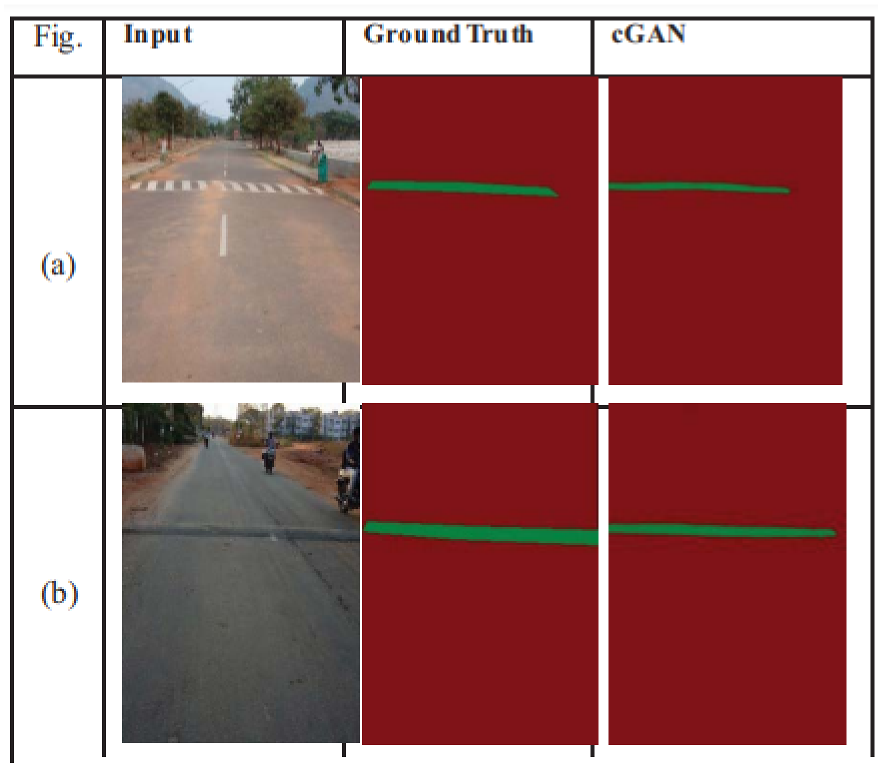


Figure 8 Pothole detection result (Rasyid et al., 2019).

IOU score were calculated in (Patil et al., 2020) for estimating how close is the output segmented speed pump to the input one. Mean IOU score was 93.8%, some of GAN results for peed bumps detection are shown in Figure 9

Figure 9 Speed bump detection using GAN (Patil et al., 2020).



For crack detection different deep neural networks were used. YOLOv2 was used in (Mandal et al., 2018) it achieved an average F1 score of 0.8780 for distress detection. It gained high accuracy when talking about alligator cracks detection, but it had problems with recognition of two types of transverse cracks with F1 scores of 0.7137 and 0.6885. FCN with VGG16, Inceptionv3, and ResNet50 as backbone was tested in (Dung, 2019) the obtained accuracy was almost 99.9 for VGG16 and InceptionV3-based classifiers in contrast with 97.5% when ResNet classifier was used. However, in (Gopalakrishnan et al., 2017) different deep NN are tested for crack detection as Single layer NN, Random Forest, Extremely Randomized Tree, Support Vector Machine, and Logistic Regression. The Best accuracy is 90% gained when using Single NN, while the worst one is 86% when using Random Forest. While in (Rao et al., 2021) after testing different types of CNN models, the results showed that VGG19 gave the best accuracy of 95%. Faster R-CNN as used in (Hacğlu and Başağa, 2022) for concrete road cracks detection. The model accuracy was 100% if it is tested in a sunny day. The condition is different when testing it in sunset, the results became 50% of the original accuracy. From the illumination perspective the detection accuracy differs so that about 70% and 15% of cracks were detected at 6:00–7:00 pm and at 7:00–8:00 pm, respectively. Consequently, the accuracy decreased as the darkness increased.

Finally, some studies take in consideration different types of anomalies for example in (Seraj et al., 2015) FCN model was used for classification of different types of anomalies with accuracy of 87.05% if all 39 extracted features were used. But to enhance the results WEKA was used to determine the most important features, WEKA outputted 10 features. The accuracy of the FCN model improved to become 87.56. Also, in (Arya et al., 2021) different CNN models using: two types of YOLOR, three types of YOLOv5 (Yl, Ym, and Ys), and Faster RCNN with different backbones such as: VGG16, ResNet50, MobileNetv2, Inception v3, and finally a proposed CNN called MVGG16 which represents modification of the original VGG16 were tested for road damages detection. Experiments showed that Faster R-CNN ResNet50 gave the best accuracy of 91.9%, whereas MobileNetV2 was the worst with 63.1%. While in (Sprague and Azar, 2022) the proposed hybrid model achieved 84% recall and 88% precision rates. Despite the good performance this approach have limited and poor performance when tested with small acceleration response anomalies , such as traverse cracks.

5 Conclusion and future work

The presence of anomalies on roads causes severe harm to the people and vehicles and affects economies. So, automatic detection of these anomalies is a necessity. Road anomalies detection techniques are divided into two main approaches: vision-based approach, and accelerometer- based approach. This paper has presented a review of different state-of-the-art approaches and techniques for road anomalies detection. Different developed models and used technologies are discussed in this paper. In addition, comparisons between these studies are conducted, limitations were identified and their results were mentioned.

To overcome the discussed problems, our goal is to develop a new model for road anomalies detection. The proposed methodology will work on finding different types of road anomalies, determine their measurements, and transfer this information to maps such as Google maps or WAZE. The proposed technique will start by collecting images of roads anomalies using drones. Then prepare these images and analyze them. Computer vision and machine learning techniques will be used for feature extraction and classification process. Finally, show these results to the driver on maps.

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