

Road Anomaly Detection Techniques: A Systematic Review for Enhancing Vehicle and Driver Safety

Noor Misbah¹ and Srinath S²

^{1,2}Dept. of Computer Science and Engineering, JSS Science and Technology University, Mysuru, 570006
Email: misbah.noormisbah@gmail.com

Abstract—Road anomalies like potholes, cracks, and debris pose significant risks to vehicle safety and driver comfort, increasing accident rates and maintenance costs. As urbanization and vehicular traffic grow, traditional road monitoring methods struggle to meet the need for real-time, scalable, and accurate anomaly detection. Advances in technology have shifted research in intelligent transportation systems toward the automated detection of road anomalies. This review examines state-of-the-art methods from repositories such as Google Scholar, Scopus, IEEE, Science Direct, MDPI, DOAJ, and Hindawi over the past eight years, covering traditional image processing to advanced machine learning algorithms and deep learning models. By analyzing existing literature, it identifies challenges like the need for robust datasets, real-time processing, and model generalization. The paper also addresses research gaps and suggests future directions for scalable road anomaly recognition systems. This review aims to support researchers, academicians, and tech enthusiasts in understanding the technologies for detecting road anomalies, contributing to safer roads and smoother driving experiences for both human drivers and autonomous vehicles.

Keywords—Road Anomalies, anomaly detection, vehicle/driver safety, machine learning, deep learning.

I. INTRODUCTION

Road anomalies, such as potholes, cracks, and surface irregularities, pose significant risks to both vehicle safety and driver comfort. These hazards contribute to vehicle damage, increase the likelihood of accidents, and escalate maintenance costs for road infrastructure. Monitoring the surface condition of roads has become considerably important because well-maintained road surfaces increase road user safety and comfort levels [1]. As urbanization and vehicular traffic grow, the demand for intelligent driving and autonomous vehicle driving [2], [3] capable of detecting and mitigating these anomalies in real time has become increasingly critical. According to WHO's "Global Status Report on Road Safety 2023" [29], the number of road traffic deaths has fallen slightly to 1.19 million per year, and efforts to improve road safety are having an impact.

In recent years, advancements in machine learning (ML) and computer vision have opened new avenues for road anomaly detection. Traditional approaches, which relied heavily on manual inspections [4] or basic sensor data, are being augmented or replaced by sophisticated algorithms that can process vast amounts of data from cameras, LiDAR, and other sensors. These methods promise higher accuracy and efficiency, thereby improving road safety and maintenance strategies. The structure of the rest of the review paper is as follows.

Section II discusses the classification of road anomalies, problems associated with anomalies II (A), Research Need and Motivation II(B), and Applications of road anomaly detection II(C). Dataset details are discussed in section III, Methodologies in section IV, related works in the literature in section V, challenges and future research directions in section VI, followed by conclusion and references.

II. CLASSIFICATION OF ANOMALIES

Road anomalies refer to irregularities or defects on the road surface that can pose risks to vehicles and drivers. The different classifications and sample images [5] of some anomalies are depicted in Figure 1 and Figure 2 respectively.

The anomalies are broadly classified as Static, Dynamic, and Road Surface anomalies. Static anomalies are fixed, non-moving obstacles present on the road. Dynamic anomalies are moving or temporary obstacles that can change position or appear unexpectedly. Road surface anomalies are irregularities specifically affecting the surface quality and smoothness of the road.

Here is a brief explanation of some common types of road anomalies:

Potholes

Description: Depressions or holes in the road surface caused by the erosion of the underlying materials. They can vary in size and depth.

Impact: Potholes can cause damage to vehicle tires, and suspension systems, and may lead to loss of control, especially at high speeds.

Cracks

Description: A crack in the context of road anomalies refers to a break or fracture in the road surface that can vary in size, orientation, and severity.

Impact: Cracks can worsen over time, leading to potholes and other severe defects. They can also cause discomfort and increase tire wear.

Manhole Covers and Utility Patches

Description: Metal covers or patches for utilities like water, gas, or sewage that are often found in urban areas. These can be uneven or slightly raised above the road surface.

Impact: Uneven surfaces can cause vehicle instability and discomfort, especially for two-wheeled vehicles.

Debris and Obstacles

Description: Objects such as fallen branches, loose gravel, or litter on the road surface. These can vary widely in size and shape.

Impact: Debris can cause sudden swerving or braking, leading to accidents. Large obstacles can cause significant damage to vehicles.

Road Marking Fading/Wear

Description: Faded or worn-out road markings, including lane dividers, pedestrian crossings, and directional arrows.

Impact: Reduced visibility of road markings can lead to confusion and increase the risk of accidents.

Speed Bumps and Humps

Description: Deliberately raised sections of the road designed to slow down traffic. When not properly marked or maintained, they can act as unexpected anomalies.

Impact: Can cause sudden deceleration or damage if hit at high speeds, particularly if not visible.

Drainage Issues

Description: Water accumulation due to inadequate drainage, leads to puddles or even flooded sections of the road.

Impact: This can cause hydroplaning, reduced visibility, and damage to the road surface over time.

Pets and Wild Animals

Description: Pets and wild animals can suddenly appear on roads, often in rural or suburban areas. These animals may cross or wander onto roads unexpectedly, especially during night-time or in poorly lit areas. Unlike static road anomalies like potholes, animals are unpredictable. They may dart across the road, hesitate, or stop abruptly, making them a dynamic hazard for drivers.

Impact: Can cause accident risk, vehicle damage, traffic disruptions, and injury to animals.

Foliage

Description: Foliage refers to leaves, branches, and plant growth that encroach onto roadways. This can occur due to overgrown trees, bushes, or fallen leaves and branches, particularly after storms or in heavily wooded areas.

Impact: Foliage can obstruct drivers' view of the road, traffic signs, signals, and other vehicles. It may also cover road markings, reducing their visibility and effectiveness.

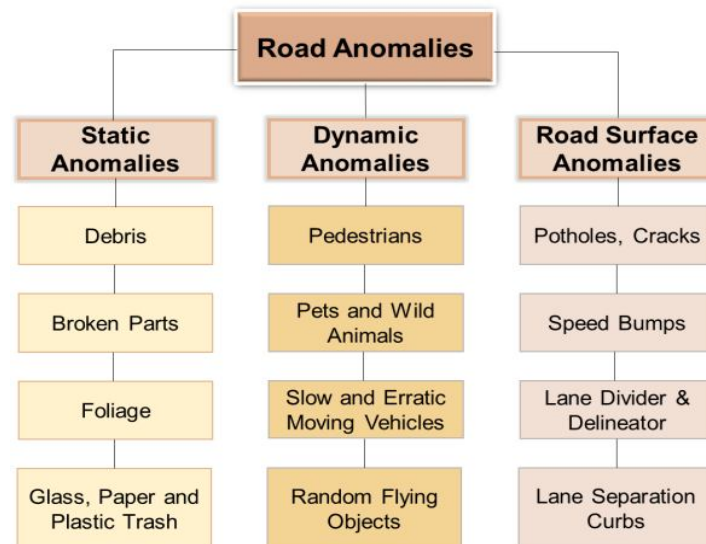


Figure 1: Classification of road anomalies



Figure 2: (a) Road Maintenance Objects & Construction Debris, (B) Debris Fallen on The Road, (C) Road Surface Failure, (D) Potholes, (E) Maintenance Holes, (F) Speed Bump, (G) Farm Animals on Road, (H) Landslide Debris, (I) Wild Animals Crossing the Road

A. Problems Associated with Anomalies

Various problems associated with road anomalies are discussed in this section. There are many news articles taken from various news websites about accidents and deaths due to road anomalies mainly potholes and speed bumps/humps, which have been caused in India. Some of the article headlines have been picturized in Figure 3.

Increased Vehicle Wear and Tear

Road anomalies like potholes [6] and cracks can cause significant damage to vehicle components, including tires, suspension systems, and alignment. Frequent exposure to such anomalies can lead to premature wear and costly repairs.

Increased Accident Rates

Poor road conditions due to anomalies have been linked to higher accident rates, especially in wet or icy conditions [7].

Higher Fuel Consumption

Vehicles driving on roads with anomalies experience increased rolling resistance, which leads to higher fuel consumption. This not only raises the cost of travel but also contributes to higher emissions [8].

Driver Fatigue and Stress

Continuous driving over roads with anomalies can lead to driver fatigue and stress, as they need to be constantly alert to avoid defects. This can increase the risk of accidents due to reduced reaction times [9].

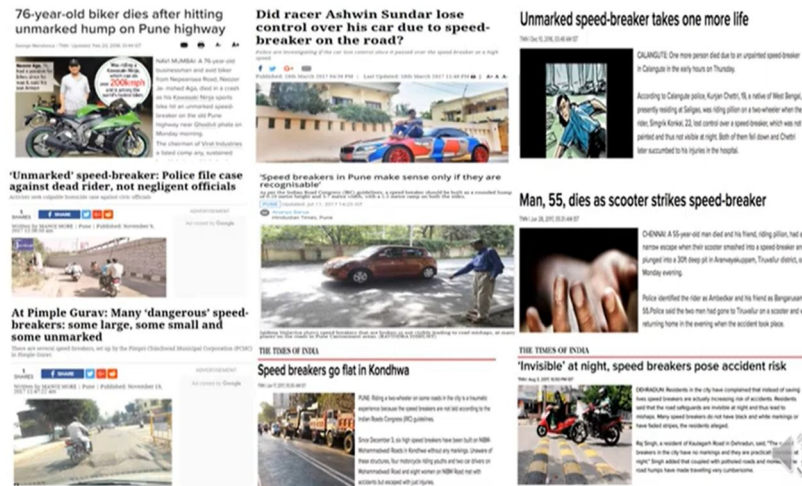


Figure 3: Newspaper headlines of various accidents due to road anomalies (potholes and unmarked bumps)

B. Research Need & Motivation

Addressing road anomalies through early detection and timely maintenance is crucial for ensuring road safety, minimizing costs, and enhancing the overall driving experience. Intelligent driving, often associated with advanced driver assistance systems (ADAS) and autonomous vehicles (AV), plays a crucial role in detecting and responding to road anomalies. By leveraging machine learning and deep learning technologies, intelligent driving systems can autonomously detect road anomalies, allowing vehicles to adjust their speed and suspension settings accordingly for a smoother and safer ride.

By integrating intelligent driving into vehicles in real-time, manual driving can be assisted with early alerts of anomalies, and hence drivers can get sufficient time to control speed and suspension settings ultimately helping to overcome problems discussed in 2.1. By addressing safety, economic, environmental, and technological challenges, research in this field contributes to the development of smarter, safer, and more sustainable transportation systems, benefiting society as a whole.

C. Applications of Detecting Road Anomalies

Detecting road anomalies is critical for enhancing road safety as it allows for timely maintenance, improves driving conditions, and reduces the risk of accidents. Here are some key applications for detecting road anomalies:

Augmented Reality (AR) for Driver Assistance

AR systems integrated into vehicle displays can highlight detected road anomalies in the driver's view, providing real-time visual alerts. It enhances driver awareness and reaction times, reducing the likelihood of accidents caused by unexpected road conditions.

Autonomous Vehicle Navigation

Autonomous vehicles rely on sensors and algorithms to detect and navigate around road anomalies. Accurate detection of anomalies ensures that autonomous vehicles can safely operate in various environments, improving their reliability and public acceptance.

Real-Time Driver Assistance Systems (ADAS)

Advanced Driver Assistance Systems (ADAS) can incorporate road anomaly detection to warn drivers of potential hazards. Alerts for anomalies such as potholes, speed bumps, or debris can help drivers avoid accidents, especially at high speeds or in low-visibility conditions.

Improved Road Quality Assessment

Regular monitoring and detection of road anomalies contribute to a comprehensive assessment of road quality. This helps government agencies and municipalities prioritize road repair projects, allocate resources effectively, and maintain high standards of road safety.

Urban Planning and Development

Detecting and mapping road anomalies helps urban planners identify areas that require infrastructure improvements or redesign. This leads to better road designs that accommodate the needs of both drivers and pedestrians, contributing to overall urban safety.

Dynamic Traffic Management

Traffic management systems can use data from road anomaly detection to reroute traffic away from affected areas or adjust speed limits dynamically. This application helps prevent traffic congestion and accidents caused by sudden stops or lane changes due to road anomalies.

Integration with Smart Cities Infrastructure

Road anomaly detection systems can be integrated into smart city infrastructure, allowing real-time monitoring and management of road conditions. Enables automated alerts to city maintenance teams, dynamic traffic management, and improved urban planning by using data-driven insights to maintain road safety and optimize traffic flow.

Fleet Management and Commercial Vehicles

For companies managing large vehicle fleets, road anomaly detection systems can help reduce vehicle wear and tear by identifying rough or hazardous roads. This can lead to cost savings on repairs and maintenance. Detecting road anomalies allows fleet managers to choose safer routes, avoiding roads that could damage vehicles or delay deliveries.

III. DATASETS REVIEWED

A. Public Dataset Details

The research community can benefit from appropriate public datasets when training & evaluating their road anomaly detection models. A brief description of a few prevalent open-access datasets that have been explored and experimented with in the related literature is listed in Table 1.

B. Private/Custom Dataset Details

Creating private or custom datasets for detecting road anomalies involves several steps like data collection, annotation, augmentation, etc. to ensure the data is relevant, high-quality, and tailored to specific needs. The benefits of having a custom dataset can significantly improve the performance of road anomaly detection models. Public datasets are ideal for quick starts and general applications, while private datasets are better for specialized needs & higher accuracy.

In some cases, a hybrid approach can be adopted, using public datasets for initial development and augmenting with private data for specific needs. A hybrid approach can combine the advantages of both.

Collecting data to train the model for detecting road anomalies can be approached in several ways including manual data collection through field surveys, dashcams, and photographs or using crowd sourced data [10], using static cameras, smart phones, and sensors [11][12] and satellite and aerial imagery (drones) [13], etc. The details of various sensor platforms for data acquisition are illustrated in Table 2.

TABLE I: OPEN ACCESS ROAD ANOMALY DATASETS

Sl. No	Dataset	Description	Volume
1	Road surface anomalies https://www.kaggle.com/datasets/aminumusa/road-dataset	Detect potholes and improve road maintenance; originated from Nigerian highways	2943 good surfaces, 1245 potholes images, Uniform 256 × 256 pixels
2	Speed hump/bump dataset https://www.kaggle.com/datasets/aminagomaa/bump-detection	Contains test and train directories separately, in each directory dataset is split into bump and road class (no bump).	Total 8332 .jpg images of humps/ bumps with varying Conditions, such as different types of humps/bumps, illumination conditions, and geographical locations.
3	Marked & Unmark Hump dataset data.mendeley.com/datasets/xt5bjdh/y5g/1	The dataset consist of speed hump, bumps which has no markings and markings.	450 images of marked and 95 images of unmarked bump.

4	Speed bump and Pothole dataset Roboflow data	3 classes of dataset (normal, speed bump & pothole) split into train and test data.	A total of 2142 .jpg images
5	Road infrastructure defect dataset kaggle.com/datasets/ aniruddhsharma/structural-defects- network-concrete-crack-images	Cracked and non-cracked concrete surface images, Each image is segmented into 256 × 256 px sub-images. Each sub-image is labelled as 'Cracked' or 'no crack'.	Total 13000 images, 2025 cracked and 11.6k no crack images
6	The FishyScapes Benchmark https://fishyscapes.com/	Anomaly detection data for semantic segmentation	No Specific Volume as code automatically generates the dataset from Cityscapes.
7	Caltech-Pedestrian-Dataset https://www.kaggle.com/datasets/kalvinquackenbush/caltechpedestrianandataset	Consists of around 10 hours of dashcam footage. The files have been converted into .seq which contain roughly around 13 minutes of footage each	Approximately 250,000 annotated frames with over 350,000 bounding boxes
8	Pedestrian Detection Data set https://www.kaggle.com/datasets/karthika95/pedestrian-detection	Images for detecting pedestrians in various real-world environments. It contains a mix of training and testing images annotated with bounding boxes.	Volume not mentioned exactly. Note: The dataset contains many images which are not pedestrians.

TABLE II: LIST OF SENSOR PLATFORMS FOR DATA ACQUISITION

Sensor Platform	Advantages	Limitations
Unmanned Aerial Vehicle	Large FOV. High Resolution. In-depth, detailed data. Ease of employment and accessibility in hazardous areas. Flexibility for quick inspections.	Payload and memory restrictions. Legislative restrictions.
Ground Vehicle(GPS & GPR Assembly)	Long-span availability. The array of sensors. High-resolution imagery. Highly dense and occluded terrain	Small FOV. Less cost-effective. High dependency on manpower.
Smartphone	Lightweight technology. Economically viable.	Low-resolution imagery. Limited by RGB data.

IV. METHODOLOGIES OF DETECTING ROAD ANOMALIES

The techniques of detecting and classifying road anomalies range from traditional methods to advanced deep learning approaches, this section describes various methods to detect and classify road anomalies effectively. Extensive research work is done to detect anomalies using image processing, Machine Learning, and some Deep Learning Algorithms. Advanced Deep learning algorithms and Hybrid Models can be explored more in detecting road anomalies to leverage the strength of each one of them.

A. Image Processing & Computer Vision Techniques

Image processing techniques for detecting road anomalies involve edge detection, morphological image processing [14], texture analysis, thresholding [15], etc. Various image processing algorithms that can be adopted in the detection of road anomalies [30] are illustrated in Figure 4, which demonstrates the results of detecting road anomalies.

Pros and cons

Image processing techniques are cost-effective, non-invasive, scalable, and versatile. There are certain challenges with image processing techniques like sensitivity to the environment, more data storage for high-resolution images, camera placements, and computational demands.

B. Machine Learning Approaches

Machine learning (ML) approaches for detecting road anomalies have become increasingly popular due to their ability to handle complex patterns in data, adaptability, and the potential for real-time analysis. Some of the most common machine-learning approaches are discussed below:

Support Vector Machines (SVM) [16] are used to classify road images into different categories by finding the optimal boundary between classes. Random Forest (RF) and AdaBoost for segmenting pothole road anomalies under three different environmental conditions viz: bright, dim, and hazy light conditions [17]. Clustering Algorithms that group similar data points, can be used to identify unusual patterns or anomalies in road surfaces [18]. Machine learning-based speed bump detection results [31] are illustrated in Figure 5, the result includes an area of speed bump, classification results, and speed bump height information.

Pros and Cons

Machine Learning Algorithms for detecting road anomalies are adaptable to different weather conditions, can achieve high accuracies, and provide automation by reducing manual efforts and advanced ML algorithms can be integrated into real-time detection systems. There are certain challenges with ML approaches like requiring large amounts of training data and generalizability issues as models trained on specific datasets might not generalize well to new or unseen road conditions, leading to reduced accuracy.

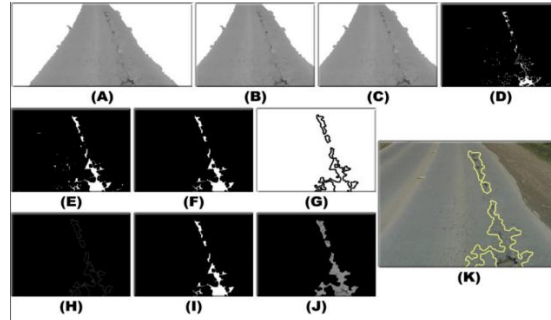


Figure 4: A) segmented road, (B) cropped image, (C) use of HMIN algorithm, (D) image binarization using C.I. = 1%, (E) morphological closing, (F) morphological area open, (G) generating watershed external and internal markers, (H) watershed lines, (I) reconstruction, (J) morphological closing, and (K) creating anomaly borders.

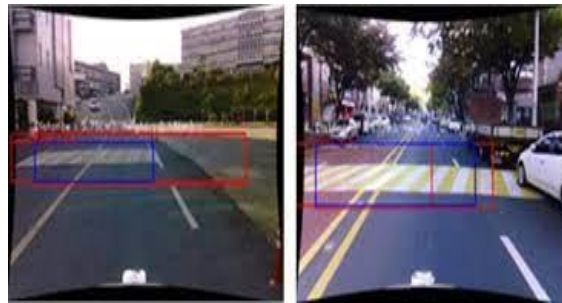


Figure 5: Speed bump detection results [31]

C. Deep Learning Approaches

Deep learning approaches have become increasingly prominent in detecting road anomalies due to their ability to automatically learn complex patterns and features from data. Some of the most common deep-learning approaches are discussed below:

CNNs (Convolution Neural Networks) are specifically designed to process grid-like data such as images. They consist of layers that automatically and adaptively learn spatial hierarchies of features from input images, making them highly effective for image recognition tasks [19], [20]. RNNs (Recurrent Neural Networks) are designed to process sequential data by maintaining a hidden state that captures information about previous inputs [20]. LSTM (Long Short Term Memory) networks, a type of RNN, are particularly useful for learning long-term dependencies and are commonly used in video-based road anomaly detection. Deep Feed forward Networks (DFN) [20], or Feed forward Neural Networks (FNNs), are a class of neural networks where information moves in one direction, from input to output, without any feedback loops. They are simpler compared to recurrent or convolutional networks but can still be effective for road anomaly detection. The other advanced deep learning models that can be used for detecting road anomalies include Auto-encoders, and GANs (Generative Adversarial Networks). The results of one of the most common detection models, YOLOv5m-based road defect classification samples [32] are illustrated in Figure 6.

Pros and cons

Deep learning algorithms give high accuracy and are capable of detecting complex & subtle road anomalies, eliminate the need for manual feature engineering by learning directly from raw data, can be scaled to handle large datasets and complex road environments, and apply to a wide range of anomaly types and adaptable to different environmental conditions. The challenges with the deep learning approach are high computational requirements, complex architectures, training processes, and Interpretability issues as deep learning models are often seen as "black boxes," making it difficult to interpret how the model makes decisions.

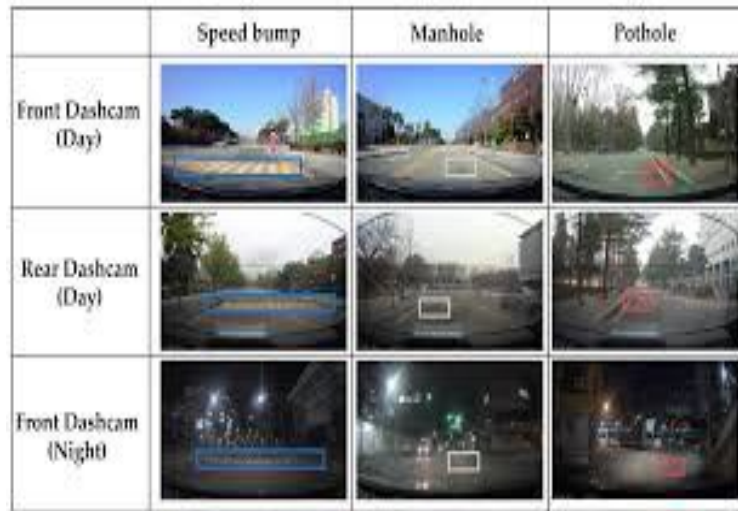


Figure 6: YOLOv5m-based road defect classification samples [32]

D. Hybrid Models

Hybrid models combine multiple deep learning architectures, such as CNNs and RNNs, to leverage the strengths of each leading to more robust and accurate anomaly detection. For example, CNNs can be used for feature extraction from images, followed by RNNs to model temporal dependencies in sequences of frames. Hybrid models can handle multiple types of data and patterns, making them suitable for complex, real-world scenarios.[21] Presents an approach for road surface condition monitoring using motion sensors embedded in a smart phone, it uses a hybrid CNN-GRU or CNN-LSTM model to classify road anomalies into three different classes.

V. RELATED WORK

Various extensive experiments have been carried out and are ongoing, using real-time object detectors to detect and analyze the model complexity and improve the accuracy of different classes of anomalies.

Ref [14] proposes a “Morphological Image Processing for Road Anomaly Detection using 2D images and Video data”, which uses a vision-based algorithm for detecting potholes on damaged roads using 2D images and video data. The research addresses the growing problem of road damage in Romania, primarily due to climate change and increasing traffic. The proposed method utilizes morphological image processing to detect road anomalies such as potholes more efficiently than traditional methods, which often rely on costly and time-consuming manual reviews. By implementing a watershed segmentation algorithm, the study successfully segments roads in images, which could later aid in pothole detection.

Ref [22] proposes a "Deep Learning Based Speed Bump Detection Model for Intelligent Vehicle System using Raspberry Pi" which focuses on the development of an intelligent vehicle system (IVS) that can detect speed bumps using a vision-based approach. The authors propose a deep learning model combined with a real-time embedded system prototype to enhance IVS by detecting both marked and unmarked speed bumps. The system employs convolutional neural networks (CNNs) to extract significant features from speed bump images, captured through an onboard camera, and regulates the vehicle's speed accordingly to avoid potential hazards. The experimental results demonstrated that the proposed model achieved high accuracy (98.54%), precision (99.05%), and F-measure (97.89%), making it comparable to state-of-the-art methods.

Ref [23] presents “Pothole and Plain Road Classification Using Adaptive Mutation Dipper Throated Optimization and Transfer Learning for Self-Driving Cars” which introduces an innovative method for classifying potholes and plain roads using a hybrid deep learning and optimization approach. It combines transfer learning through the ResNet-50 deep network for feature extraction and a novel adaptive mutation dipper-throated optimization (AMDTO) for feature selection and random forest (RF) classifier optimization. Additionally, the authors enhance the Synthetic Minority Oversampling Technique (SMOTE) for dataset balancing, addressing imbalanced road data. The proposed method achieves superior pothole classification accuracy (99.79%), outperforming several existing methods like WOA+RF, GWO+RF, and various transfer learning models such as AlexNet and VGG-19.

S. Pawar, et al.[24] presents the paper titled "Cloud-Based Single Shot Detector Model for Speed Breaker Detection" which uses a deep learning-based approach to detect speed breakers using the Single Shot Detector (SSD) architecture with MobileNetV2. The model processes images captured by an ESP32 Wi-Fi Cam Module and is hosted on the Microsoft Azure cloud platform, allowing real-time detection. The system achieved a mean average precision (mAP) of 97.19% at 50% Intersection over Union (IoU). The results are relayed to an application that alerts users when a speed breaker is detected.

Rozi Bibi, et al.[25] presents the paper titled "Edge AI-Based Automated Detection and Classification of Road Anomalies in VANET Using Deep Learning" which uses a framework that utilizes edge AI and deep learning for detecting road anomalies, enhancing vehicular safety in a VANET (Vehicular Ad Hoc Network) environment. The research focuses on automating the detection and classification of road defects like potholes, cracks, bumps, and plain roads using pre-trained deep-learning models (ResNet-18 and VGG-11). The results demonstrate the effectiveness of the proposed models, surpassing traditional methods in accuracy and reliability for road anomaly detection and classification.

Swapna Kulkarni, et al.[26] presents the paper "Investigation of YOLO Models in the Detection and Classification of Multiple Negative Road Anomalies" which explores the use of various YOLO models for detecting multiple road anomalies such as potholes, speed humps, pedestrians, and vehicles. The study compares nine YOLO variants (YOLOv5, YOLOv6, YOLOv7) using metrics like precision, recall, F1 score, and mean average precision (mAP) on a dataset of 3,391 images. The results demonstrate that YOLOv6s outperforms the other models with a mAP of 71.2%, precision of 74.9%, and F1 score of 70.2%.

Hannan Khan A, et al.[27] proposed a paper "Localized Semantic Feature Mixers for Efficient Pedestrian Detection in Autonomous Driving". The authors introduce the Localized Semantic Feature Mixers (LSFM) model, which replaces conventional Feature Pyramid Networks with a Super Pixel Pyramid Pooling (SP3) module, reducing computational costs. Additionally, a Dense Focal Detection Network (DFDN) is utilized as a lightweight detection head. LSFM outperforms state-of-the-art models across several benchmarks, including Caltech, City Persons, and Euro City Persons datasets, while reducing inference times by up to 55%. The model also improves pedestrian detection in challenging scenarios such as heavy occlusion and small object sizes. For the first time, LSFM surpasses the human baseline in pedestrian detection on the Caltech dataset, demonstrating its potential for real-world applications.

Y. T. Gamage, et al.[28], proposes a paper "Identification of Road Surface Anomalies Using Crowd-sourced Smartphone Sensor Data" which presents a system designed to detect road anomalies such as potholes and speed bumps in real time. The system integrates accelerometers, gyroscopes, vibration sensors, and GPS technology with machine-learning algorithms to identify irregularities on the road. Sensor data from vehicles is processed and compared with data from other vehicles at the same location to confirm the anomalies. This data is stored in the cloud and used to alert drivers through GPS-enabled applications, allowing them to slow down and avoid potential road hazards. The approach improves road safety, reduces vehicle damage, and enhances the overall driving experience. By leveraging real-time data and machine learning, the system offers a scalable solution for continuous road monitoring, contributing to better infrastructure management and road safety.

Chatterjee, et al. [5], propose a paper "Intelligent Road Maintenance: A Machine Learning Approach for Surface Defect Detection" which explores the use of machine learning to automate the detection of road surface cracks, using front-view images captured by consumer-grade cameras. The proposed approach uses superpixel segmentation and texture-based features combined with ML classifiers such as Gradient Boosting, Artificial Neural Networks, Random Forest, and Support Vector Machines to classify road regions into crack and non-crack areas. The datasets used in the paper include road surface images captured in Germany. The dataset includes diverse conditions, such as varying times of day, lighting, and urban or rural environments. A total of 75 videos, each 40 minutes long, were recorded, resulting in images with a resolution of 1242x720 pixels. The results demonstrated that GB and RF performed the best with high accuracy and precision, achieving 92.77% and 91.82% accuracy, respectively, on a test set of 8,828 data points from various locations.

Hadia Hameed, et al.[33] proposed the paper titled "Real-Time Road Anomaly Detection, Using an On-Board Data Logger" which focuses on enhancing real-time detection of roadway surface disruptions (RSDs) such as potholes, manholes, cat eyes, and speed bumps. The authors collected a large heterogeneous dataset using a custom-made device that logs vehicle acceleration and GPS data. They trained machine learning classifiers like SVM(Support Vector Machine), GNB(Gaussian Naïve Bayes), and DT(Decision Trees) using this data to distinguish between different types of road anomalies. The best accuracy was achieved with the Honda City vehicle using Decision Trees, with a False Positive Rate of 1%, False Negative Rate of 5%, and True Positive Rate of 95%.

Ali Anaissi, et al. [34] proposed a "Smart Pothole Detection System Using Vehicle-mounted Sensors and Machine Learning" which introduces a Virtual Road Network Inspector (VRNI) system that leverages vehicle-mounted sensors to monitor road conditions in real-time. This system utilizes accelerometer data from the vertical and lateral axes, processed through two adaptive one-class support vector machines (OCSVM) to detect road anomalies. The first classifier identifies all surface irregularities, while the second differentiates benign anomalies like speed bumps from actual potholes. Evaluated on school buses in New South Wales, Australia, VRNI achieved a high detection accuracy of 97.5%, with a low false positive rate of 4%.

Manjusha Ghadge et Al. [35], "Machine Learning Approach for Predicting Bumps on Road" presents a smartphone-based system, Bumps Detection System (BDS), designed to predict road bumps using accelerometer and GPS sensors. It uses a machine learning approach, applying k-means clustering on the accelerometer data to detect road anomalies. It uses the z-axis of the accelerometer as a key indicator for identifying bumps. A Random Forest classifier further validates the predictions. The detected bumps are mapped onto Google Maps using GPS data to inform drivers in advance of road conditions. The system offers a cost-effective solution, eliminating the need for expensive vehicle hardware and enabling real-time road monitoring through widely accessible smartphone sensors.

H. Bello-Salau et al. [36], "New road anomaly detection and characterization algorithm for autonomous vehicles" presents a novel algorithm for detecting and characterizing road anomalies like potholes and bumps for autonomous vehicles using noisy accelerometer signals. The proposed Road Anomaly Characterization Algorithm (RACA) employs wavelet transformation and scale-space filtering to process acceleration signals and effectively distinguish between different road surface defects. The results show the algorithm's potential for improving road surface monitoring and autonomous vehicle navigation on asphalt roads.

Yuan Yuan, et al. [37], in the paper titled "Anomaly Detection in Traffic Scenes via Spatial-Aware Motion Reconstruction" proposes a novel method for detecting anomalies in traffic scenes from a driver's perspective, particularly relevant to Advanced Driver Assistance Systems (ADAS) and autonomous driving. The method combines motion orientation and motion magnitude features to detect and localize anomalies such as sudden pedestrian crossings, vehicle overtaking, and other hazardous events. The authors introduce a spatial-aware sparse coding approach, which uses a dictionary-based reconstruction method, factoring in both motion magnitude and orientation. These two aspects are integrated using a Bayesian model for improved robustness and adaptability to changing scenes. Results from the experiments on nine traffic video sequences demonstrate that the proposed method outperforms traditional sparse coding techniques, showing higher accuracy in detecting anomalies.

Giancarlo Di Biase et al. [38], "Pixel-wise Anomaly Detection in Complex Driving Scenes", proposes a novel framework for detecting anomalies in complex urban driving scenarios, particularly for autonomous vehicles. The authors address the limitations of current semantic segmentation models, which fail to recognize anomalous objects not present in their training data, such as unexpected items on the road. The proposed approach integrates two methodologies—uncertainty estimation and image re-synthesis—to improve detection. The proposed framework achieved top-2 performance across all evaluated datasets in the Fishyscapes benchmark.

The literature work which is discussed above is depicted in Table 3 below for a quick overview highlighting the key aspects.

TABLE II: HIGHLIGHTS OF EXISTING WORK DONE

Source	Methodology	Anomalies Addressed	Dataset	Performance
Alexandra Dalia Danilescu, Corn eleuRusu [14]	Morphological Image Processing-watershed segmentation algorithm.	Potholes	Self-created 2D images and video data.	Good results for road segmentation. (no specific performance metrics)
Chatterjee et al[5]	superpixel segmentation and texture-based features combined with ML classifiers such as Gradient Boosting(GB), ANN, RF, and SVM	Cracks	Self-created	GB and RF performed the best with high accuracy and precision of 92.77% & 91.82%.
Hadia Hameed et al.[33]	Machine Learning classifiers SVM, GNB, and DT are used	Pothole Manhole Cat eye	Self-created: Accelerometer and GPS data	The best accuracy was achieved with Decision Trees, with an FPR of 1%, FNR of 5%, & TPR of 95%.
Ali Anaissi et al.[34]	two adaptive One-Class Support Vector Machines (OCSVM)	Pothole	Self-created: The acceleration data was sampled at 500 Hz, and	the system achieved an F-Score of 0.96, outperforming previous approaches that scored lower (Z-

			GPS data was sampled at 1 Hz	SVM: 0.82, Z-axis + X-axis: 0.65)
ManjushaGhadge et al.[35]	k-means clustering algorithm, Random Forest classifier	Bump	Self-created: Smartphone accelerometer data.	Successful detection of bumps by leveraging the accelerometer's Z-axis changes.
deepakkumardevangan et al. [22]	A Computer Vision-based CNN model is used to learn the features of speed bumps.	Speed Bump	-Self-created by using a smart camera and Raspberry camera module. - 575 images for marked and unmarked categories of Speed Bumps	Accuracy: 98.54% Precision: 99.05% F-Measure: 97.89%
A. A. Alhussan et al [23]	-ResNet-50 deep network for extracting relevant features from an image. -Selected features are then balanced.A balanced dataset is used to train a random forest model which is optimized through the proposed AMDTO to classify the input image.	Pothole	Data is collected under different weather conditions and augmented	Accuracy: 99.795%
S. Pawar, et al [24]	MobileNetV2 is used for CNN model development.	Speed Breaker	Self-created using a 13-megapixel rear camera on an android phone. - Total 824 images (Striped class)	Mean Average Precision: 97%
Rozi Bibi et al [25]	ResNet-18 VGG-11	Pothole Bump Cracks	<u>Dataset</u> : Public Data sets using the Kaggle repository <u>Performance</u> : measured for both ResNet-18 and VGG-11 by considering 4 classes of anomalies and parameters such as Precision, Recall, Accuracy, and F score. Also, the models are compared with other existing methods (like Image filtering, Morphological Algorithms, etc.)	
Swapna Kulkarniet al.[26]	Uses nine different versions of YOLO	Human Hump Pothole Vehicle	Public datasets- Using Google and Kaggle: Contains 3391 images.	Performance is measured using mean Average Precision (mAP), precision, recall, and F1 score to identify the best-performing model for accurately detecting multiple road anomalies.
Hannan Khan A et al.[27]	- Localized Semantic Feature Mixers (LSFM). - MLP Mixer-based Dense Focal Detection Network - Mixup Augmentation	Pedestrian	Euro City The person dataset [18] contains 47,300 images encompassing Scenes from 31 different cities of Europe.	LSFM shows overall better performance compared to the state-of-the-art methods with significantly reduced inference time.
Y. T. Gamage et al.[28]	Employs ML models such as SVM, Random Forest, and XGBoost for classifying the anomalies	- Potholes - Bumps	- <u>Crowdsourcing</u> : Data is collected from multiple smartphone accelerometer sensors and pre-processed by applying noise removal filters. - Volume: not mentioned.	- Evaluate the models using metrics such as precision, recall, and F1-score. - The XGBoost model achieved the highest accuracy with 89% for pothole detection and 75% for bumps
H. Bello-Salau et al. [36]	Wavelet Transformation (WT) to process raw accelerometer data, Scale-Space Filtering (SSF) algorithm to filter out noise in the acceleration signals & RACA(road anomaly characterization algorithm)	Pothole Bump	Self-created: using NIMyRio (1950) accelerometer mounted at a vehicle, sampled at 30 Hz.	The system achieved a high detection accuracy of 96% for bumps and 94% for potholes, with a low FPR of less than 0.6%.
Yuan Yuan, et al. [37]	-Combined motion orientation and motion magnitude features to detect and localize anomalies. -spatial-aware reconstruction and Bayesian integration	Pedestrian vehicle	Self-created: using the vehicle-mounted camera with an average of 180 frames per sequence and a resolution of 480 x 640.	Effective at detecting anomalies in dynamic traffic scenes.
Giancarlo Di Biase et al. [38]	Uncertainty Estimation Image Re-synthesis using GAN	Unexpected Objects on Roads	Fishyscapes benchmark	The proposed framework achieved top-2 performance across all evaluated datasets.

VI. CHALLENGES & FUTURE RESEARCH DIRECTIONS

A. Challenges

Some of the challenges which may occur in the process of detecting road anomalies are:

- Road anomaly detection systems need to work under various conditions
- (Urban vs. rural, different weather, lighting, and road types). However, existing datasets often lack diversity, limiting the system's robustness.
- Many advanced models, especially deep learning-based ones, require significant computational resources. Achieving real-time detection on edge devices like smart phones or in-car systems remains challenging.
- Implementing complex models in real-time scenarios often increases latency and power consumption, which is a critical consideration for autonomous vehicles and embedded systems.
- Combining data from multiple sensors (e.g., LIDAR, radar, cameras) to improve detection accuracy is complex and requires sophisticated algorithms for data fusion.
- Ensuring that road anomaly detection systems can work seamlessly with existing vehicle systems and infrastructure is challenging due to varying standards and protocols.

B. Future Research Directions

Addressing the above-discussed challenges is essential for improving the performance of intelligent driving systems in real-world scenarios. Research directions listed below highlight the need for continued innovation and collaboration across disciplines to develop robust, real-time, and generalizable road anomaly detection systems that can significantly enhance road safety.

- Leveraging crowdsourcing for collecting and annotating large-scale, diverse datasets can help address the data scarcity and diversity issue.
- Using synthetic data generation techniques (e.g., GANs) to create diverse and balanced datasets for training and testing models.
- Self-supervised and Unsupervised Learning: Developing models that can learn from unlabelled or sparsely labeled data, reducing the reliance on extensively annotated datasets.
- Utilizing attention mechanisms and transformer-based models to improve the contextual understanding of road environments and anomalies.
- Investigating meta-learning approaches to enable models to quickly adapt to new environments and conditions with minimal additional training.
- Researching lightweight models optimized for edge computing devices, ensuring real-time processing with minimal power consumption.
- Enhancing the interpretability and explainability of models (Explainable AI) to ensure that detected anomalies can be validated and understood by human operators.

VII. CONCLUSION

This review paper highlights different approaches like image processing, machine learning, deep learning & hybrid techniques that can be used for the detection of road anomalies. It showcases several works carried out in the detection of road anomalies. This paper gives information about the classification of road anomalies, problems associated with road anomalies, and some commonly used publicly available datasets. In the future, the research can be broadened by adding more types of road anomalies and roads with multiple defects and focusing on automatic control of vehicle action based on anomaly type and prevention can be incorporated in an autonomous vehicle by using less complex deep learning models.

REFERENCES

- [1] Shahram Sattar, Songnian Li, and Michael Chapman, "Road Surface Monitoring Using Smartphone Sensors: A Review", *Sensors* 2018, 18, 3845; doi:10.3390/s18113845
- [2] R. S. Lim, H. M. La, Z. Shan, and W. Sheng, "Developing a crack inspection robot for bridge maintenance," in 2011 IEEE International Conference on Robotics and Automation, pp. 6288–6293, IEEE, 2011.
- [3] P. Prasanna, K. J. Dana, N. Gucunski, B. B. Basily, H. M. La, R. S. Lim, and H. Parvardeh, "Automated crack detection on concrete bridges," *IEEE Transactions on automation science and engineering*, vol. 13, no. 2, pp. 591–599, 2014.
- [4] R. Medina, J. Gómez-García-Bermejo, and J. E. Zalama, "Automated visual inspection of road surface cracks," in *Proc. Int. Symp. Automat. Robot. Construct. (ISARC)*, 2010, pp. 14–20.
- [5] Chatterjee, Sromona, Saeedfar, Pouya, Tofangchi, Schahin, Kolbe, Lutz M, "Intelligent Road Maintenance: A Machine Learning Approach For Surface Defect Detection", (ECIS2018), Portsmouth, UK, 2018.

- [6] GuangtaoXue; Hongzi Zhu; Zhenxian Hu; Jiadi Yu; Yanmin Zhu; Yuan Luo, "Pothole in the Dark: Perceiving Pothole Profiles with Participatory Urban Vehicles, IEEE Transactions on Mobile Computing (Volume: 16, Issue: 5, 01 May 2017).
- [7] BooHyun Nam, A.M.ASCE, and Mohamed Abdel-Aty, M.ASCE," Effects of Pavement Surface Conditions on Traffic Crash Severity", Journal of Transportation Engineering, Volume 141, Issue 10, [https://doi.org/10.1061/\(ASCE\)TE.1943-5436.0000785](https://doi.org/10.1061/(ASCE)TE.1943-5436.0000785)
- [8] Gunnar Svenson, Dag Fjeld, "The impact of road geometry and surface roughness on fuel consumption of logging trucks", DOI:10.1080/02827581.2015.1092574
- [9] John D. Hill, Linda Ng Boyle, "Driver stress as influenced by driving maneuvers and roadway conditions", <https://doi.org/10.1016/j.trf.2006.09.002>
- [10] Gamage Y, Thotawaththa T, Wijayasiri A, "Identification of Road Surface Anomalies Using Crowdsourced Smartphone Sensor Data", 22nd International Conference on Advances in ICT for Emerging Regions (ICTer 2022): 118- 123.
- [11] EshtaRanyal, Ayan Sadhu, Kamal Jain," Road Condition Monitoring Using Smart Sensing and Artificial Intelligence: A Review", Sensors 2022, 22(8), 3044; <https://doi.org/10.3390/s22083044>
- [12] Jamal Raiyn , "Detection of road traffic anomalies based on computational data science", <https://doi.org/10.1007/s43926-022-00025-y>
- [13] Yingchao Zhang, Zhiwu Zuo, Xiaobin Xu, Jianqing Wu, Jianguo Zhu, Hongbo Zhang, Jiewen Wang, Yuan Tian, "Road damage detection using UAV images based on multi-level attention mechanism", <https://doi.org/10.1016/j.autcon.2022.104613>
- [14] Alexandra Dalia Danilescu, CorneleuRusu, " Morphological Image Processing for Road Anomaly Detection using 2D images and Video data", Volume 56, Number 1-2, 2015, Mediamira Science Publisher.
- [15] Marcin Badurowicz, Jerzy Montusiewicz, Pawel Kaczmarek, "Detection of Road Artefacts Using Fuzzy Adaptive Thresholding", IEEE Explore, Funded by the National Science Centre, Poland under CHRIST-ERA program (Grant no. 2018/28/Z/ST6/00563)
- [16] FatjonSeraj, Berend Jan van der Zwaag, Arta Dilo, Tamara Luarasi & Paul Havinga, " RoADS: A Road Pavement Monitoring System for Anomaly Detection Using Smart Phones", Springer, LNAI, volume 9546
- [17] H. Bello-Salau; A. J. Onumanyi; R. F. Adebisi; E. A. Adedokun; G. P. Hancke, "Performance Analysis of Machine Learning Classifiers for Pothole Road Anomaly Segmentation", 2021 IEEE 30th International Symposium on Industrial Electronics (ISIE).
- [18] Zhaojian Li; Dimitar P. Filev; Ilya Kolmanovsky; Ella Atkins; Jianbo Lu, "A New Clustering Algorithm for Processing GPS-Based Road Anomaly Reports With a Mahalanobis Distance", IEEE Transactions on Intelligent Transportation Systems (Volume: 18, Issue: 7, July 2017)
- [19] RoziBibi,YousafSaeed,AsimZeb,Taher M. Ghazal,TajRahman,Raed A. Said,Sagheer Abbas , Munir Ahmad, and Muhammad Adnan Khan, "Edge AI-Based Automated Detection and Classification of RoadAnomalies in VANET Using Deep Learning", Volume 2021, Article ID 6262194, 16 pages, <https://doi.org/10.1155/2021/6262194>.
- [20] Dawei Luo; Jianbo Lu; Gang Guo, "Road Anomaly Detection Through Deep Learning Approaches", 10.1109/ACCESS.2020.3004590
- [21] Abdelkader Hady-Attou, Yacine Kabir, Farid Ykhlef, "Hybrid deep learning models for road surface condition monitoring", <https://doi.org/10.1016/j.measurement.2023.113267>
- [22] Deepak Kumar Dewangan, Satya Prakash Sahu, "Deep Learning Based Speed Bump Detection Model for Intelligent Vehicle System using Raspberry Pi", IEEE SENSORS JOURNAL, 2020
- [23] AmelAlhussan, DoaaKhafaga, El-Sayed M. El-kenawy,Abdelhameed Ibrahim, "Pothole and Plain Road Classification Using Adaptive Mutation Dipper Throated Optimization and Transfer Learning for Self-Driving Cars", Digital Object Identifier 10.1109/ACCESS.2022.3196660
- [24] S Pawar, S Nahar, MD Shaikh, V Meher, S Narwane, "Cloud-based Single Shot Detector Model for Speed Breaker Detection", DOI: 10.1109/ESCIS6872.2023.10099534
- [25] Bibi R, Saeed Y, Zeb A, Ghazal T, Rahman T, Said R, Abbas S, Ahmad M, Khan M, " Edge AI-Based Automated Detection and Classification of Road Anomalies in VANET Using Deep Learning ", Hindawi, Volume 2021, Article ID 6262194
- [26] Kulkarni S, Mittal N, Gupta R, Ponnlagu R, "Investigation of YOLO models in the detection and classification of multiple negative road anomalies", IEEE 2023
- [27] Hannan Khan A, Shariq Nawaz M, Dengel A, "Localized Semantic Feature Mixers for Efficient Pedestrian Detection in Autonomous Driving", IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2023, pp. 5476-5485
- [28] Gamage Y, Thotawaththa T, Wijayasiri A," Identification of Road Surface Anomalies Using Crowdsourced Smartphone Sensor Data", IEEE 2022.
- [29] Global status report on road safety 2023 (who.int)
- [30] Diego Buchinger, Alexandre Gonçalves Silva, "Anomalies detection in asphalt pavements: a morphological image processing approach", <http://dx.doi.org/10.5335/rbca.2014.3661>
- [31] Hyeong Seok Yun, Tae Hyeong Kim, Tae Hyoung Park, "Speed Bump Detection for Autonomous Vehicles by Lidar and Camera", Journal of Electrical Engineering & Technology (2019) 14:2155–2162 <https://doi.org/10.1007/s42835-019-00225-7>

- [32] GyulimKim and Seungku Kim, “A Road Defect Detection System Using Smartphones”, *Sensors* 2024, 24, 2099. <https://doi.org/10.3390/s24072099>
- [33] Hadia Hameed, Suleman Mazhar, Naul Hassan, “Real-time Road Anomaly Detection, Using an on-board Data Logger”, 978-1-5386-6355-4, 2018 IEEE
- [34] Ali Anaissi, Nguyen Lu Dang Khoa, Thierry Rakotoarivelo, Mehriasadat Makki Alamdari, Yang Wang, “Smart pothole detection system using vehicle-mounted sensors and machine learning”, *Journal of Civil Structural Health Monitoring* (2019) 9:91–102 <https://doi.org/10.1007/s13349-019-00323-0>
- [35] ManjushaGhadge, Dheeraj Pandey, DhananjayKalbande, “Machine Learning Approach for Predicting Bumps on Road”, 978-1-4673-9223-5/15- 2015 IEEE.
- [36] H. Bello-Salau, A.M. Aibinu, A.J. Onumanyi, E.N. Onwuka, J.J. Dukiya, H. Ohize, “New road anomaly detection and characterization algorithm for autonomous vehicles”, DOI 10.1016/j.aci.2018.05.002
- [37] Yuan Yuan, Dong Wang, and Qi Wang, “Anomaly Detection in Traffic Scenes via Spatial-Aware Motion Reconstruction”, *IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS*, VOL. 18, NO. 5, MAY 2017.
- [38] Giancarlo Di Biase, Hermann Blum, Roland Siegwart, Cesar Cadena, “Pixel-wise Anomaly Detection in Complex Driving Scenes”, March 21, Available at <https://github.com/giandbt/SynBoost>.