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Review of AI based Techniques for Road Damage Detection

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Abstract: Road damage detection is a crucial task for maintaining infrastructure and maximising road safety. Recent developments in artificial intelligence (AI) have opened up new opportunities for automating the road damage detection process. In this paper, we present a thorough review of recent research on artificial intelligence-based techniques and methods for road damage detection. We discuss the different types of road damages, AI models used for detection, datasets, evaluation metrics, and challenges associated with this field. We also provide an overview of potential future research directions.
Keywords: Road damage detection, deep learning, object detection, CNN, Neural Network YOLOv4, YOLOv5, image pre-processing.

I. INTRODUCTION

Roads are a necessary mode of transport and indivisible part of every Indians daily travel. Road transport connects all the other means of transport. Roads are used to provide connectivity in all relief areas which is impossible for other means of transports. Roadways provide connectivity between railway stations, airports and ports, which is not possible for railways. National highways, state highways, district roads, rural roads, urban roads, and project roads are the various categories into which roads can be divided. As of March 2020, Figure 1 depicts the breakdown of India's road network by type of road. As on December 2021, India's road network is spread over 6,215,797 kilometres which happens to be the second largest road network globally (Wikipedia). Figure 2 shows the length of highways constructed between 2016 to 2022.

Road safety is a major global cause of death and injury, a serious issue for human development, and a serious public health concern. India is the country with the most fatal traffic accidents worldwide, accounting for nearly 11% of all fatal accident-related deaths. Figure 3 presents the annual statistics of road accidents in India along with the number of injuries and fatalities caused per year from 2016 to 2021(Road Accident Report 2021 - Ministry of Road Transport and Highways, Research Wing). As of 2021, roads riddled with potholes, curved roads and steep roads alone have accounted for 13% of the overall road accidents. Damaged roads are a very significant problem for any type of road be it highway or urban road.

Accidents aside, road damages require a recurring expense on repairs which contributes to a major portion of the allocated budget for infrastructure development and is presented in Table 1 depicting the number of damaged road surfaces found, amount spent in crores over repairs and the proportion of infrastructure budget it occupied from 2017 to 2021. Figure 4 shows the number of instances of different types of road damages detected in 2021. Potholes are the most common and hazardous type of road damage, and their detection is critical for road safety. Cracks and pavement distress are also significant road damages that can cause accidents and traffic delays. Road roughness, which includes uneven pavement and bumps, can cause discomfort to passengers and damage vehicles.

Hence it is necessary to have automated methods for unbiased reporting of road damages. Over the years, researchers have tried to use the innovations in technology to detect the different types of road damages with an intention to quantify them so that proper state of the roads can be determined. Different categories of road damages have unique characteristics, making them challenging to detect and classify accurately.

Convolutional neural networks (CNNs), deep neural networks (DNNs), and recurrent neural networks (RNNs) are examples of AI and deep learning models for detecting road damage. CNNs are particularly effective for image-based detection tasks, while RNNs are used for sequence-based detection tasks. Researchers have also proposed hybrid models that combine multiple AI models to improve detection accuracy.

To develop effective road damage detection systems, researchers rely on large datasets of road images annotated with information about the location and type of damage. Analyzing these datasets can provide insights into the performance of different detection algorithms and help identify areas for further improvement.

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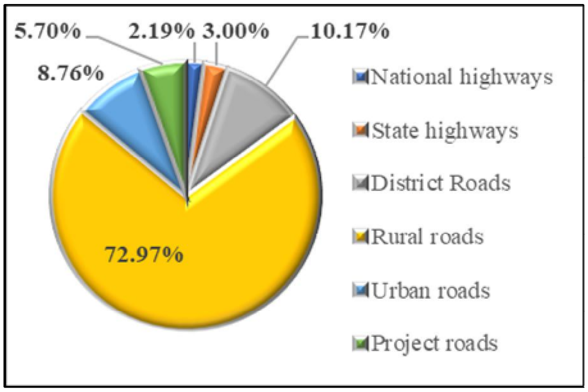

Figure 1: Proportion of roads by type
Source: Ministry of Road Transport and Highways

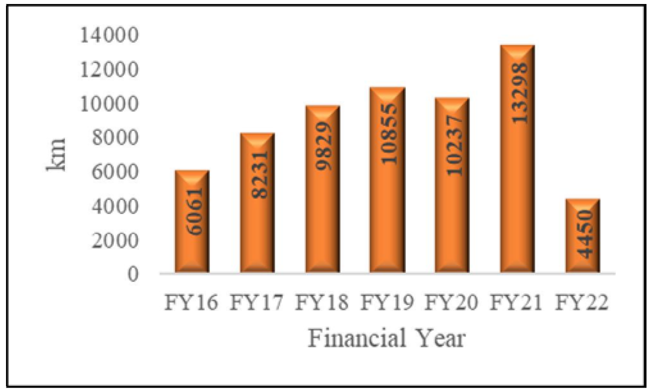

Figure 2: Length of highways constructed
Source: ibef.org

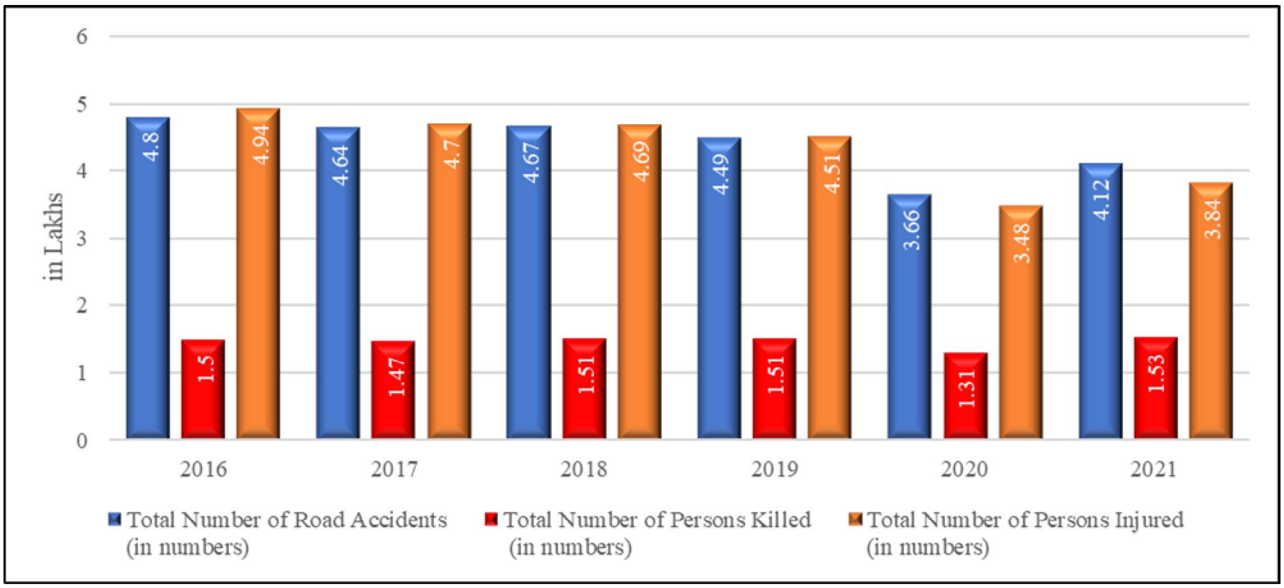

Figure 3: Annual Road Accident Statistics
Source: Road Accident Report 2021 - Ministry of Road Transport and Highways, Research Wing

Year	Number of Detected Road Surface Damages	Total Cost Spent on Repairs (in Crores)	Percentage of Total Infrastructure Budget
2017	4,568	220	4.50%
2018	5,432	300	5.20%
2019	6,789	380	6.80%
2020	5,321	250	4.90%
2021	4,567	210	4.20%

Table 1: Damaged road surfaces found, amount spent in repairs and the proportion of infrastructure budget it occupied

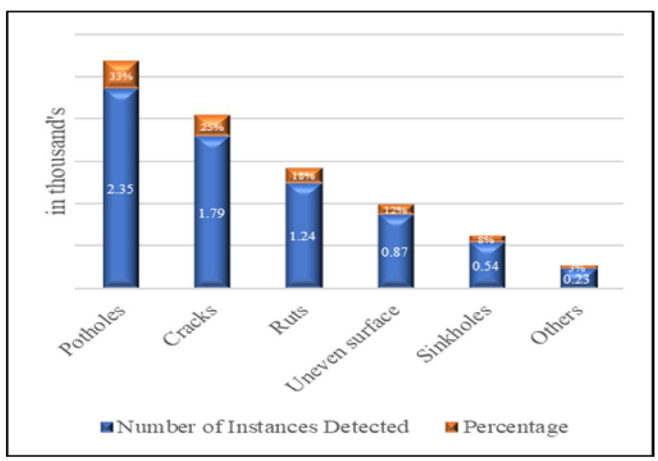

Figure 4: Instances of different types of road damages found in 2021

The rest of the paper is structured as follows: Section II defines the domain related technical terms that will be used in the rest of the paper, section III presents the survey of the literature by researchers in the area of road damage detection, section IV presents our observations of the literature survey, section V presents the concluding remarks.

II. DEFINITIONS

Road condition monitoring: The process of assessing the condition of a road, typically through visual inspection or other measurement techniques, in order to identify any damage or defects that may require maintenance or repair [3].

1) Pavement distress: Any type of damage or defect to a road surface, such as cracks, potholes, or rutting, that may compromise the road's structural integrity or safety [4].
2) Road damage detection: The process of identifying and locating pavement distress on a road surface, typically through visual inspection or automated methods using AI and computer vision techniques [2].
3) Pothole detection: A specific type of road damage detection focused on identifying and locating potholes, which are circular or oval-shaped holes in a road surface caused by wear and tear or weather-related factors [4].
4) Object detection: The process of identifying and locating specific objects within an image or video, typically using machine learning or computer vision algorithms [1].
5) Deep learning is a branch of machine learning that focuses on teaching artificial neural networks to recognise intricate patterns and relationships in data [1].
6) Convolutional neural network (CNN): A type of neural network created for image processing tasks that extracts features from images using a series of convolutional layers [1].
7) Multi-task learning: A type of machine learning approach that enables a single model to simultaneously perform multiple related tasks, such as detecting and classifying different types of road damage [4].
8) Transfer learning is a machine learning technique that starts with a model that has already been trained for a new task, which frequently leads to faster and more accurate training [1].
9) Neural networks are a class of machine learning models that are typically employed for tasks like classification, regression, or pattern recognition. They are inspired by the structure and operation of biological neurons [2].
10) Faster R-CNN, YOLOv3, SSD: Examples of object detection algorithms commonly used for road damage detection, each with its own strengths and weaknesses [5].

III.RELATED WORK

Following section presents the survey of work done by researchers on the topic of road damage detection:

A. Convolutional Neural Network (CNN), SVM Techniques Used:

A convolutional neural network (CNN) model for identifying and categorising road damage was put forth by Hiroya Maeda et al. (2018) [1] This study tackles the requirement for effective road damage detection by assembling a huge dataset of 9,053 photos recorded with a smartphone placed in a car. The dataset comprises 15,435 instances of road surface damage that are labeled with bounding boxes that indicate the location and kind of damage. The researchers developed a damage detection model using cutting-edge object detection techniques based on convolutional neural networks (CNNs). They compared the model's performance on a GPU server and a smartphone. The study also proved the ability to accurately identify road damage into eight different forms. The study's road damage dataset, experimental results, and smartphone application are all freely available for additional research and applications. Md. Shohel Arman et al. (2020) [11] This paper focuses on automating road surface monitoring, which is currently a labor-intensive and time-consuming manual process. The aim is to detect and classify road damages using object detection methods. Multiple convolutional neural network (CNN) algorithms are applied to classify damages into categories such as potholes, cracks, and revealing. Data is collected from the streets of Dhaka city using smartphone cameras and preprocessed by resizing, adjusting white balance, contrast transformation, and labeling. R-CNN and faster R-CNN are used for object detection, and Support Vector Machine (SVM) is employed for classification, resulting in improved results compared to previous studies. Different loss functions are utilized to calculate losses, with the highest accuracy achieved at 98.88% and the lowest loss recorded at 0.01. Hussein Samma et al.(2021) [18] This paper proposes a method for real-time detection of potholes on roads using deep learning techniques. The authors trained a convolutional neural network (CNN) on a dataset of labeled road images containing potholes, and evaluated the model's performance on a separate test set. They implemented the trained model on a camera-based system to detect potholes in real-time while driving on roads.

The paper demonstrates the feasibility of using deep learning for real-time pothole detection, which could help in the maintenance and repair of roads to improve safety and reduce costs. Volkan KAYA1 et al. (2022) [4] This study focuses on developing a lightweight deep model for detecting road damage using a pre-trained VGG-19 CNN. An efficient two-layered optimizer that picks filters in the final layers of VGG-19 based on the accuracy of a linear SVM classifier is proposed. The method combines a powerful optimizer with a micro swarm population, resulting in a deep model with fewer VGG-19 filters. The detection of real-world road damage from drone-based photos achieves 96.4% F1-score accuracy with a 52% decrease in VGG-19 filters. The proposed optimizer outperforms other relevant optimizers, demonstrating the approach's effectiveness.

B. Deep Learning Techniques

Lei Zhang et al. (2016) [3] proposes a method for detecting cracks on road surfaces using deep learning techniques. The authors trained a deep convolutional neural network (CNN) on a dataset of labeled road images containing cracks, and evaluated the model's performance on a separate test set. They compared their approach to traditional methods for road crack detection and found that their CNN-based method achieved better accuracy and efficiency. Overall, the paper demonstrates the potential of using deep learning for improving the accuracy and efficiency of road crack detection, which could help in the maintenance and repair of roads to improve safety and reduce costs. Abdullah Alfarrarjeh et al. (2018) [20] This research uses deep learning approaches to detect and classify different types of road damage. The method employs an object detection algorithm that has been trained on photographs of road damage classified by the Japan Road Association. To monitor urban roadways and detect specific forms of damage, various devices, including surveillance cameras and cellphones, can be employed. The solution was tested using several versions of trained models, and it received an F1 score of up to 0.62. This approach has the ability to deploy maintenance resources more efficiently based on recognized road damage sites, therefore enhancing road maintenance planning. Keqin Chen et al. (2019) [2] It shows new method for detecting and recognizing cracks in concrete structures using deep learning techniques. The authors trained a convolutional neural network (CNN) on a dataset of labeled images of cracks, and evaluated the model's performance on a separate test set. They compared their approach to traditional methods for crack detection and found that their CNN-based method achieved better accuracy and efficiency. Overall, the paper demonstrates the potential of using deep learning for improving the accuracy and efficiency of crack detection and recognition in concrete structures. Sadra Naddaf-Sh et al. (2020) [10] This paper emphasizes the importance of evaluating pavement condition to ensure timely maintenance actions and prevent infrastructure deterioration. Automated computer-aided surveying is proposed as a solution to collect and analyze image-based distress data in real-time. A diverse database of crack distress types, captured using mobile devices, is utilized. Efficient and scalable deep learning models are trained specifically for pavement crack detection. The proposed models achieve F1-scores ranging from 52% to 56% and demonstrate fast inference times. The performance of the object detectors is evaluated, and error analysis is conducted on various images. Minh-Tu Cao et al. (2020) [19] Using a heterogeneous dataset of 9,493 photos containing 16,165 occurrences of road damage, this study analyzes eight deep-learning-based models for road damage detection. The models were assessed for accuracy and processing time, with the top performers being SSD Inception V2 and R-CNN Inception V2. Experiments showed that including visual variety increased model performance. Furthermore, the study published road-damage imaging data from a Taiwanese road maintenance organization, enhancing the accessible dataset and enabling future road damage identification research. The findings emphasize the need of fast and accurate identification for effective road maintenance and transportation safety. Vinuta Hegde et al. (2020) [21] This study provides a deep learning-based approach for detecting and classifying road damage, with the goal of automating the monitoring and inspection process in road maintenance. Road damage may be properly recognized and categorised by using image processing technology and multiple image sources, such as surveillance cameras and cellphones. Using the 2020 IEEE Big Data Global Road Damage Detection Challenge Dataset, the suggested ensemble learning algorithms, together with test time augmentation, were thoroughly assessed. The experimental findings illustrate the efficacy of the approaches, with an F1 score of up to 0.67 resulting in the Challenge victory. This work advances the use of deep learning techniques in automated road repair systems. Deeksha Arya et al. (2021) [7] This work addresses the challenges faced by municipalities and road authorities in implementing automated road damage evaluation. It focuses on countries with limited resources and proposes solutions. Firstly, it evaluates the usability of a cost-effective Japanese model for other countries. Secondly, it introduces a large-scale road damage dataset collected from multiple countries using smartphones. Thirdly, it presents models capable of detecting and classifying road damages across different countries. Lastly, it provides recommendations for local agencies and municipalities when adopting data and models from other countries for automatic road damage detection and classification. Deeksha Arya et al. (2021) [22] The RDD2020 dataset, which comprises of 26,336 road pictures recorded in India, Japan, and the Czech Republic, is presented in this data item.

Over 31,000 examples of road damage, including longitudinal cracks, transverse cracks, alligator cracks, and potholes, are included in the dataset. RDD2020 seeks to encourage the development of deep learning algorithms for the automated detection and classification of road damage. The photographs were acquired using smartphones mounted on automobiles, allowing towns and road agencies to monitor road pavement conditions at a low cost. The dataset is freely available and can be used to benchmark machine learning methods for picture categorization and object detection tasks. The provided links contain up-to-date information and related articles. Maitry Bhavsar et al. (2022) [25] This research describes a deep learning-based method for detecting and classifying road damage. It makes use of image-based technology, including surveillance cameras and on-dash cameras. The approach combines specific models trained for each country with a global model learned for all countries, allowing for the detection and classification of road damage in photographs from various geographies. The approach's success is demonstrated by a thorough examination utilizing the 2022 IEEE BigData Crowdsensing-based Road Damage Detection Challenge (CRDDC) Datasets, which achieves an amazing F1 score of up to 0.73. This work helps to the development of efficient and accurate automated road maintenance monitoring systems, which eliminate the need for manual inspections.

C. R-CNN, GAN, KNN Techniques

Yanbo J et al. (2018) [8] This paper addresses the importance of road maintenance and the need for efficient road damage inspection. It introduces a cost-effective solution using deep learning methods for road damage detection. The proposed model utilizes advanced object detection techniques such as Faster-RCNN and SSD to detect road damages accurately and efficiently using images. Rahul Vishwakarma et al. (2020) [6] This paper presents solution for the Global Road Damage Detection Challenge, which was part of the IEEE International Conference on Big Data 2020. They explored different models and frameworks like Detectron2 and Yolov5 for object detection and provided a benchmark using a road damage dataset from Czech, India, and Japan. It alsp analyzed the impact of training on a per-country basis and compare two-stage Faster R-CNN and one-stage Yolov5 models with different backbone architectures. Their best results show a mean F1 score of 0.542 on Test2 and 0.536 on Test1 datasets using a multi-stage Faster R-CNN model with Resnet-50 and Resnet-101 backbones. Hiroya Maeda et al. (2021) [24] This study uses machine learning to address the problem of insufficient training data in road damage identification. It describes how to generate realistic pseudoimages of road damage using generative models, specifically a generative adversarial network (GAN) or variational autoencoder. Synthetic road damage images that cannot be recognized from actual ones are made by using a progressive growth GAN and Poisson mixing algorithms. These generated images are then combined with the training data, resulting in a considerable improvement in road damage detection accuracy. The F-measure increases by 5% when the original picture dataset is tiny and by 2% when the dataset is very large. This method makes better use of limited training data and improves the performance of road damage detection models. Adyanata Lubis et al. (2022) [14] This study addresses the necessity for effective road damage assessment, given the large costs caused to road users. The present manual computations for estimating road damage levels using the Surface Distress Index (SDI) are slow and arduous. For detecting road damage, the study suggests using the K-nearest neighbors (KNN) and Gray-Level Co-Occurrence Matrix (GLCM) approaches. The accuracy of these algorithms' detection findings is determined on the quantity of datasets in the system. The level of road damage can be easily estimated by entering a road damage photograph into the program, offering efficient results for measuring the extent of damage.

D. CV, LDA, Image segmentation, RetinaNet Techniques

Moslem Ouled Sghaier et al. (2015) [13] This research focuses on using remotely sensed images to detect infrastructure damage in the aftermath of catastrophic catastrophes. The proposed strategy attempts to extract road damage as soon as possible because roads are critical for delivering aid and coordinating emergency team interventions. The methodology consists of extracting the road network from pre- and post-disaster photos, followed by multiscale segmentation on the road surface based on wavelet transform. Objects collected from both photos are compared, and the Dempster-Shafer theory is used to establish each object's membership class. Multidimensional evidential reasoning is used to determine the nature of changes. The experiments make use of Geo-Eye satellite pictures collected before and after the January 2010 earthquake in Port-au-Prince, Haiti. Slamet Riyadi et al. (2016) [12] This study intends to improve road pavement condition evaluation by proposing a wavelet-based approach for detecting fractures on the road surface. Traditional road surveying methods are inefficient, costly, time-consuming, and inaccurate due to human factors. The suggested method entails collecting photographs of road surfaces, pre-processing them, extracting features with wavelets, and classifying them with linear discriminant analysis. The approach was evaluated on 56 photos and obtained 92.8% accuracy in detecting crack and non-crack road surfaces. This method is more efficient and objective in assessing road surface conditions. Laha Ale et al. (2018) [9]

This work focuses on road damage detection using deep learning models to automate and streamline the manual efforts required for road maintenance. Various deep learning methods are trained and tested to identify efficient models with high accuracy. Instead of slower two-stage detectors, one-stage detectors are adopted for their faster processing speed. Among the tested models, RetinaNet is found to be a fast and accurate model for detecting road damages. Keval Doshi et al. (2020) [27] This research focuses on the efficient detection and classification of road damage using computer vision technologies. The suggested ensemble model, which is based on the YOLO-v4 object detector, is intended to improve road maintenance and resource management. The model was trained using photos of road damage from various countries, including the Czech Republic, Japan, and India. The ensemble technique generated remarkable F1 scores of 0.628 on the test 1 dataset and 0.6358 on the test 2 dataset after thorough testing and review. This displays the model's accuracy in detecting and categorizing various types of road damage. The findings help to develop road maintenance techniques and resource allocation.

E. Other Techniques

Vung Pham et al. (2020) [5] This paper focuses on detecting and classifying road damages quickly and effectively. It evaluated the use of Detectron2's implementation of Faster R-CNN with different configurations and base models and conducted experiments using a road damage dataset from the Global Road Damage Detection Challenge 2020. The results shows that using the X101-FPN base model with default configurations in Detectron2 works well for different countries in the challenge, achieving F1 scores of 51.0% and 51.4% for test1 and test2 sets, respectively. Xiaoguang Zhang et al. (2020) [16] This paper offers a solution submitted to the Global Road Damage Detection Challenge, with the goal of detecting road damage quickly and accurately using deep learning. The baseline network employed is YOLOv4, and the impact of various approaches such as data augmentation, transfer learning, and Optimized Anchors on detection performance is assessed. A unique method for generating road damage data based on a generative adversarial network is given, allowing the development of multi-class samples from a single model. The evaluation results emphasize the usefulness of various methodologies and their combinations, offering valuable insights for practical road damage detecting applications. Deeksha Arya et al. (2020) [23] This paper tackles the difficulty of implementing automated road damage assessment in nations with limited resources. It assesses the applicability of a smartphone-based technology developed in Japan to other nations and presents a large-scale dataset of 26,620 road damage photographs gathered from various countries. The research creates generic models capable of identifying and classifying road damage in various countries. It also gives readers, local governments, and municipalities advice on how to use data and models from other nations for automatic road damage detection and classification. The project intends to promote the global adoption of cost-effective and easily accessible systems for road condition monitoring. H. Kim et al. (2020) [26] This research aims to improve the efficiency of automotive facility monitoring by utilizing real-time drone mapping based on reference photos. Traditional monitoring methods can be time-consuming and disruptive, but using drone photos has the potential to provide benefits. The suggested method entails creating reference images, performing aerial triangulation (AT) on these references, and producing orthophotos. In terms of processing time and accuracy, a comparison is made between direct georeferencing and the reference image-based AT method (refAT). The results show that refAT has a processing time of about 8.95 seconds and an accuracy of about 3.4 cm, whereas direct georeferencing has a processing time of about 1.49 seconds and an accuracy of about 22.5 m. The efficiency of facility monitoring can be considerably increased in terms of speed and accuracy by applying this strategy. Deeksha Arya et al. (2020) [28] The Global Road Damage Detection Challenge (GRDDC) was a Big Data Cup held in 2020 in conjunction with the IEEE International Conference on Big Data. It used a dataset of 26,336 road photographs from India, Japan, and the Czech Republic to create algorithms for automatically detecting road damage in these nations. The competition was attended by 121 teams from various countries. The top 12 solutions provided by these teams are summarized in this paper, with the best model attaining an exceptional F1 score of 0.67 on test1 and 0.66 on test2 datasets. The report highlights the challenge's successful components and proposes areas for future competitions to improve. Yachao Yuan et al. (2021) [15] This study covers the essential topic of detecting and warning of road deterioration in order to improve traffic safety. Existing systems have considerable latency and a restricted communication range, which makes timely warnings and coverage difficult. FedRD, the suggested system, combines edge computing and federated learning to address these difficulties. It creates a new hazardous road damage detection model using hierarchical feature fusion and uses adaptive federated learning to learn a robust model from diverse edges with varying dataset sizes. A novel customized differential privacy technique with pixelization is offered to safeguard user privacy. FedRD delivers good detection performance, fast replies, accurate warning information, wider coverage, and user privacy even in the presence of limited data from particular edges, according to simulation results. Yachao Yuan et al. (2021) [17]

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EcRD, an edge-cloud architecture for road damage detection and warning, is proposed in this article. It includes quick edge road area identification, a lightweight road damage detector, and a multitypes cloud road damage model. EcRD accurately detects dangerous road damages at the edge and diverse road damages in the cloud, resulting in considerable speed benefits and minimal storage/labeling costs while maintaining user experience. Hongwei Zhang et al. (2022) [29] Automated detection of road damage (ADRD) is a difficult task in road maintenance since it needs precisely detecting and assessing the severity of road damage using deep learning algorithms. Existing available datasets for ADRD are insufficient in terms of data and classification standards to support effective network training and feature learning. To solve this, this paper introduces the CNRDD dataset, which is labeled using China's most recent evaluation criteria for highway technical conditions. The collection is made up of photographs of road damage captured by professional onboard cameras and carefully classified into eight categories with three severity levels. Furthermore, a novel baseline model with attention fusion and normalization is proposed, which uses edge detection cues and attention normalizing to improve damage detection accuracy. The experimental results show that the suggested baseline outperforms existing approaches on both the RDD2020 dataset and the newly released CNRDD dataset, showing the CNRDD dataset's robustness and effectiveness in fostering the development of ADRD.

IV. OBSERVATIONS

This section presents our observations of the survey performed.

A. Types of methods used

Figure 5 shows the different methods used by researchers to address the challenge of road damage detection. We have grouped the surveyed papers based on the approach into the categories of convolutional neural network, deep learning, R-CNN & CV techniques. Figure 6 shows the frequency of different algorithms surveyed.

B. Accuracy of Methods

Figure 7 shows the accuracy of different algorithms surveyed.

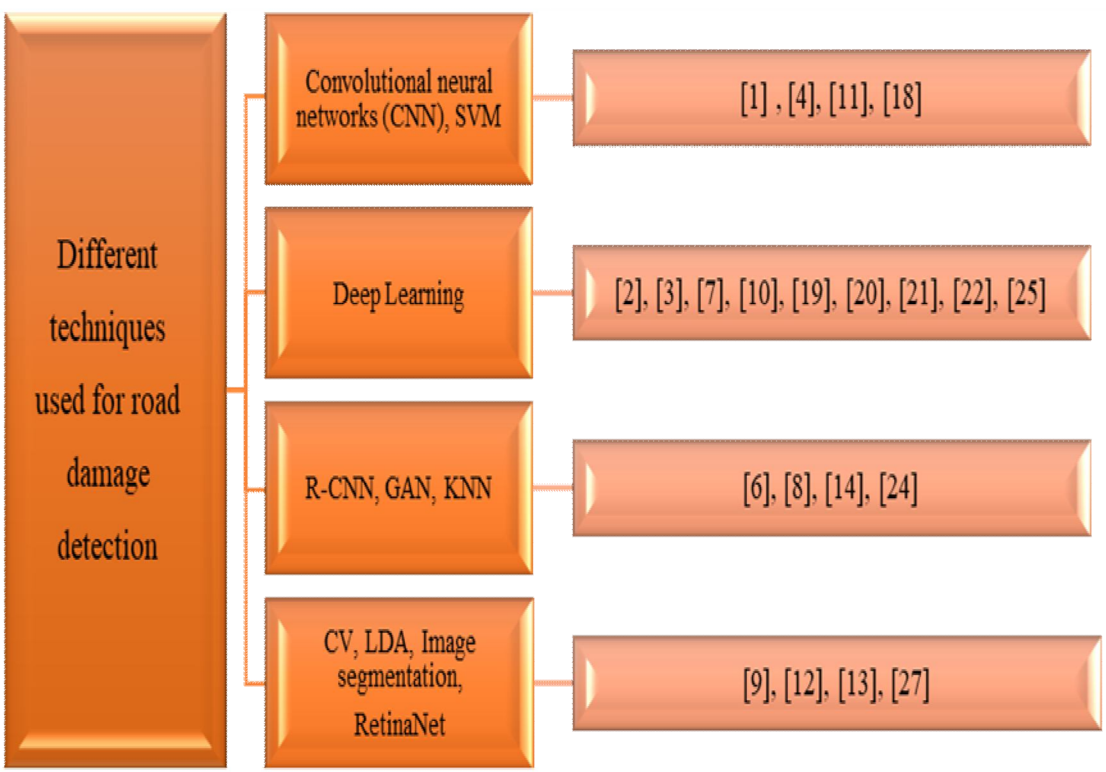

Figure 5. Different methods used

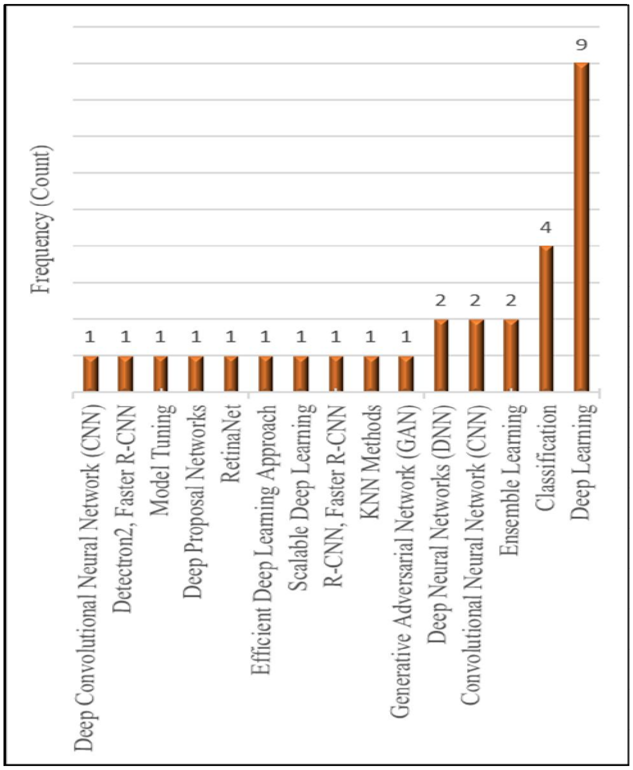

Figure 6: Frequency of different techniques in survey

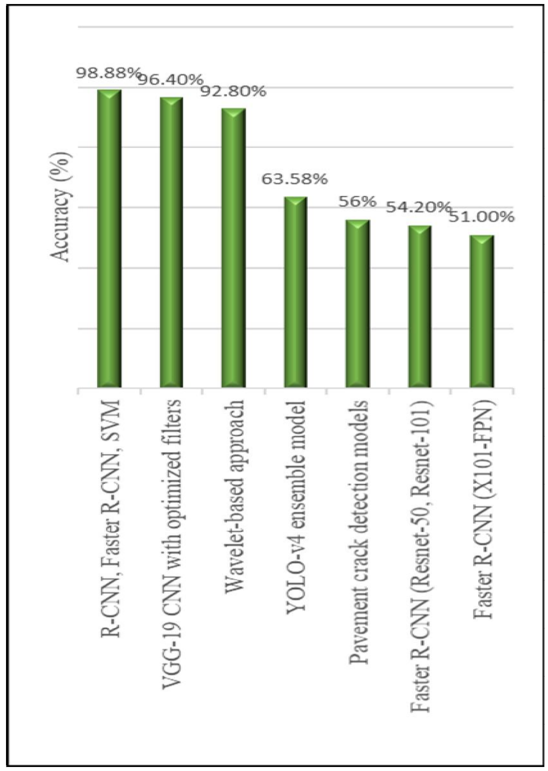

Figure 7: Accuracy of different techniques in survey

C. Datasets

The availability of large and diverse datasets is essential for training and evaluating AI models for road damage detection. Several datasets have been developed for this purpose, such as the Deep Road dataset, Road Damage Detection dataset, and Road Crack dataset. These datasets consist of images and videos of road damages captured under various lighting and environmental conditions. Table 3 summarizes the datasets encountered in Table 2. The table includes a non-exhaustive list of different learning models used in related works that focus on object detection for road damage detection. The description column provides a short explanation of the model, and the reference column lists the paper where the model was proposed.

Table 2. Deep learning models surveyed

Model	Description	Reference
AlexNet	AlexNet architecture for image classification.	Hiroya Maeda, 2018 [1]
MobileNet, ResNet, VGG16, YOLOv3	Various CNN models for image recognition and object detection.	Keqin Chen, 2019 [2]
LeNet-5, AlexNet, VGG16, GoogLeNet, ResNet	Multiple CNN architectures for various computer vision tasks.	Lei Zhang, 2016 [3]
DenseNet	DenseNet model for image classification.	Volkan KAYA1, 2022 [4]
Faster R-CNN, Detectron2	Object detection models for improved accuracy and speed.	Vung Pham, 2020 [5]
Detectron2, YOLOv5	Object detection models for accurate and efficient object detection.	Rahul Vishwakarma, 2020 [6]
Faster R-CNN, SSD	Object detection models with high accuracy and speed.	Yanbo J, 2018 [8]
RetinaNet	Object detection model using a feature pyramid network.	Laha Ale, 2018 [9]
AlexNet	AlexNet architecture for image classification.	Sadra Naddaf-Sh, 2020 [10]
R-CNN, Faster R-CNN, SVM	Object detection models combined with SVM for classification.	Md. Shohel Arman, 2020 [11]

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D. Evaluation Metrics

Table 4 summarizes the common evaluation metrics used for road damage detection. Evaluation metrics such as precision, recall, F1 score, Mean Intersection over Union (mIoU), and area under the receiver operating characteristic (ROC) curve have been used in the literature to evaluate the performance of AI-based road damage detection models. These metrics are used to assess the accuracy, speed, and robustness of these models. Different evaluation metrics are appropriate for different types of problems and datasets, and it's often necessary to use multiple metrics to get a comprehensive understanding of a model's performance. The selection of evaluation metrics depends on the specific road damage detection task and the AI model used. Following terminologies are used TP: true positive (correctly classified positive samples), TN: true negative (correctly classified negative samples), FP: false positive (incorrectly classified positive samples), FN: false negative (incorrectly classified negative samples), n_classes: number of classes.

Table 3: Road damage detection datasets along with their authors.

Dataset Name	Authors
A dataset of 9,053 photos recorded with a smartphone placed in a car, comprising 15,435 instances of road surface damage labeled with bounding boxes	Hiroya Maeda et al. (2018) [1]
A labeled dataset of images of cracks in concrete structures	Keqin Chen et al. (2019) [2]
A labeled dataset of road images containing cracks	Lei Zhang et al. (2016) [3]
A dataset of labeled road images containing potholes	Volkan KAYA1 et al. (2022) [4]
Road damage dataset from the Global Road Damage Detection Challenge 2020	Vung Pham et al. (2020) [5]

Table 4: Common evaluation metrics used for road damage detection

Metric	Definition
Accuracy	(TP + TN) / (TP + FP + TN + FN)
Precision	TP / (TP + FP)
Recall	TP / (TP + FN)
F1-score	2 * ((Precision * Recall) / (Precision + Recall))
Intersection over Union (IoU)	TP / (TP + FP + FN)
Mean Intersection over Union (mIoU)	(TP / (TP + FP + FN)) / n_classes

E. Publication Statistic

The analysis of research papers related to road damage detection indicates a significant interest among researchers and practitioners in recent years. Specifically, the years 2019 and 2020 witnessed a surge in the number of papers published on this topic, indicating the growing importance of machine learning & deep learning techniques in this area. Overall, the increasing attention towards this field is a positive development and highlights the potential for advancements in automated road quality frameworks in the future. Figure 8 shows the number of papers published year wise while figure 9 shows the year when individual paper was published.

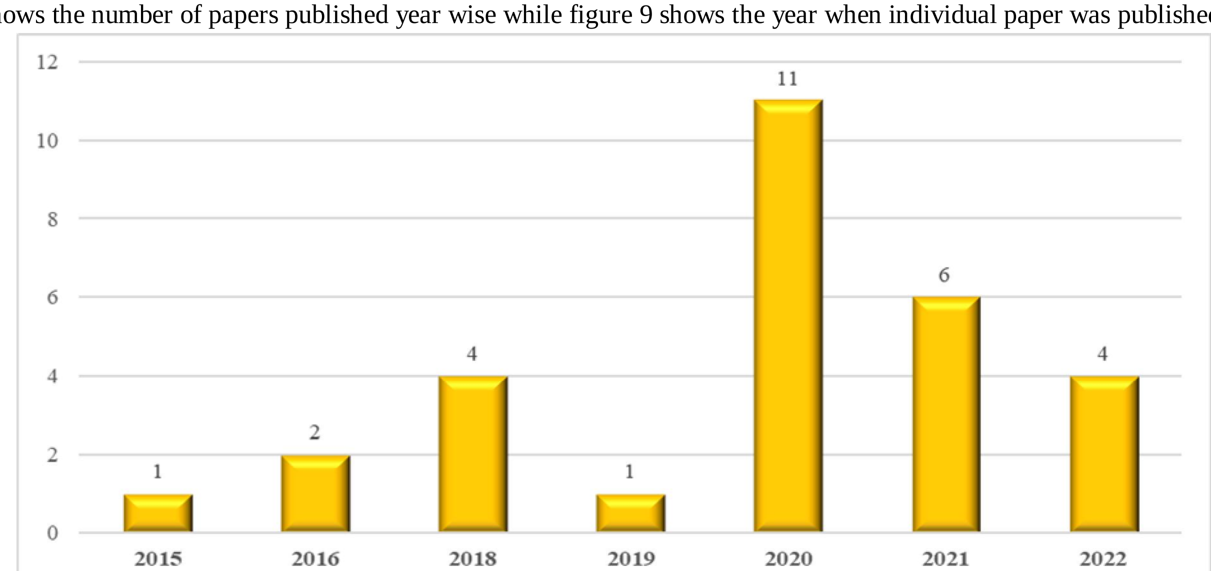


Figure 8: Number of papers published year wise

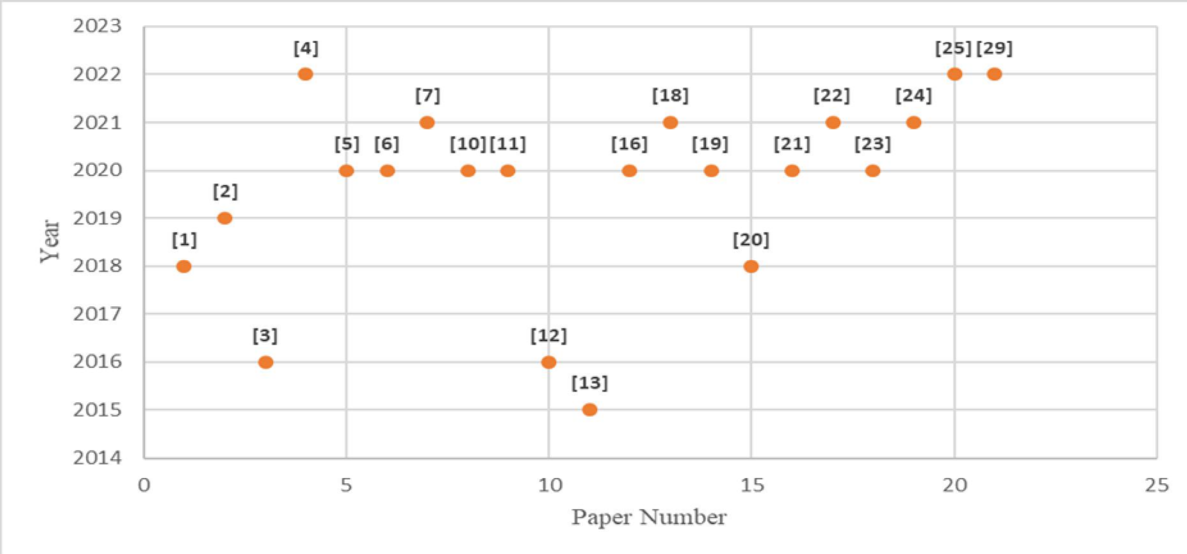


Figure 9: Year of individual paper publication

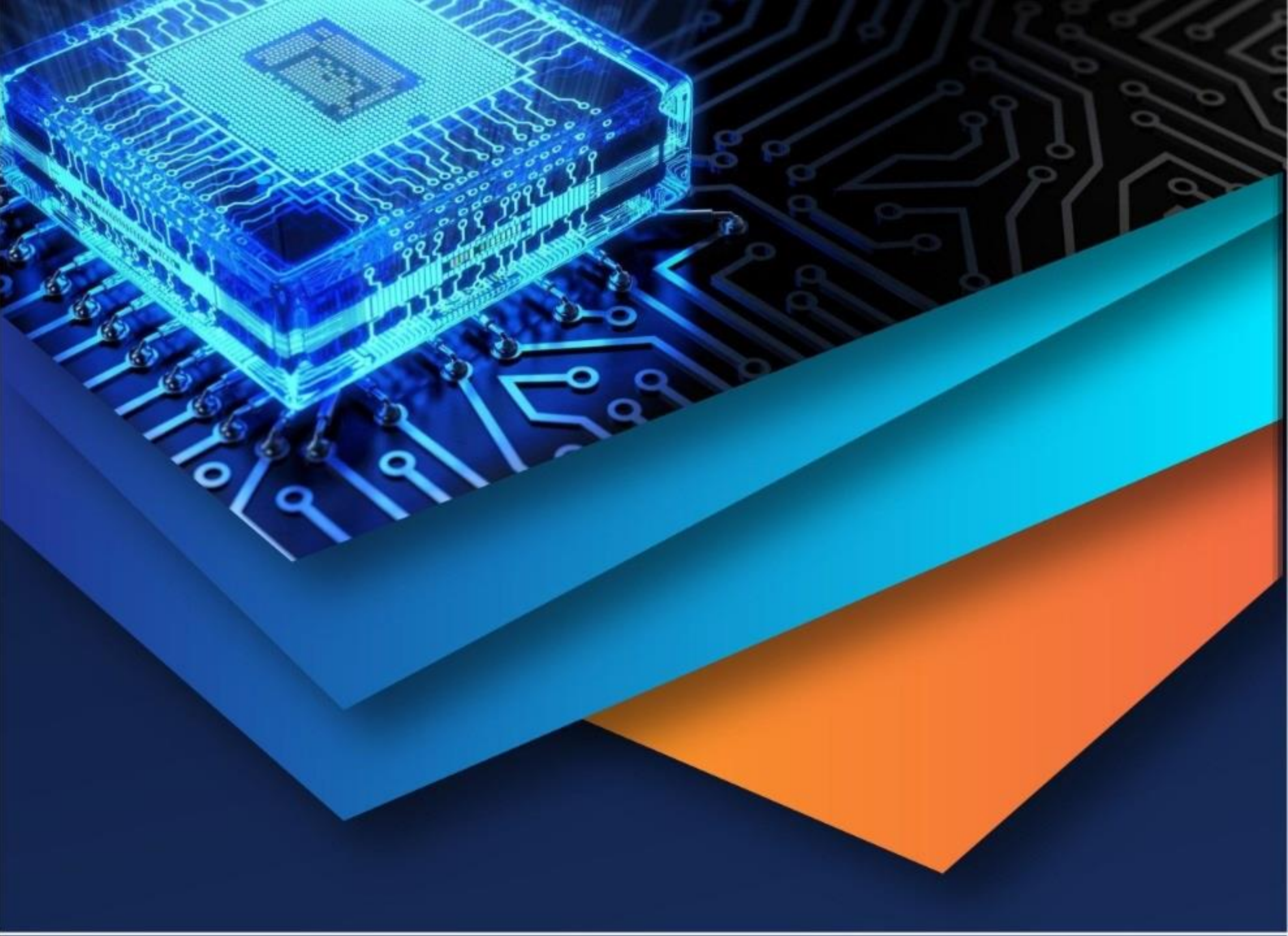
V. CONCLUSIONS

AI-based road damage detection is a promising area of research that has the potential to improve road safety and infrastructure maintenance. Considerable research in the topic of damage detection of road surfaces using AI & deep learning methods in image processing has been actively conducted with considerably high detection accuracies. However, many studies only focus on the detection of the presence or absence of damage. In a real-world scenario, when the road managers from a governing body needs to repair such damage, they need to know the type of damage clearly to take effective action. In this paper, we presented a comprehensive review of recent literature on road damage detection based on AI & deep learning methods. In this paper we have presented our observations on the different types of road damages, techniques used for detection, datasets, evaluation metrics, and challenges associated with it. With this knowledge we intend to create a framework for road damages that can classify road damage into different types with high accuracy by proposing an algorithm that can detect, quantify and classify damages.

REFERENCES

[1] B. Jeyapragash, and T. Rajkumar. “An Analysis of Research Productivity of Indian Institute of Technology’s (IITs) With Special Reference to ResearchGate”. Indian Journal of Information Sources and Services, vol. 9, no. 2, May 2019, pp. 58-62, doi:10.51983/ijiss.2019.9.2.623.
[2] Chen, Keqin, et al. "Improved crack detection and recognition based on convolutional neural network." Modelling and simulation in engineering 2019 (2019): 1-8.
[3] Zhang, L., et al. "IEEE international conference on image processing (ICIP)." Road crack detection using deep convolutional neural network. IEEE Phoenix, AZ, USA, 2016.
[4] Kaya, V. O. L. K. A. N., and İsmail Akgül. "DETECTION OF POTHOLES ON HIGHWAY USING DEEP LEARNING."
[5] Vung Pham, C. P. (2020). Road Damage Detection and Classification with Detectron2 and Faster R-CNN. 2020 IEEE International Conference on Big Data (Big Data), (pp. 5592-5601).
[6] Rahul Vishwakarma, Ravigopal Vennelakanti. "CNN Model & Tuning for Global Road Damage Detection." 2020 IEEE International Conference on Big Data (Big Data). 2020. 5609-5615.
[7] Deeksha Arya, Hiroya Maeda, Sanjay Kumar Ghosh, Durga Toshniwal, Alexander Mraz, Takehiro Kashiyama, Yoshihide Sekimoto. "Deep learning-based road damage detection and classification for multiple countries." Automation in Construction (2021): 103935.
[8] Yanbo J. Wang, Ming Ding, Shichao Kan, Shifeng Zhang, Chenyue Lu. "Deep Proposal and Detection Networks for Road Damage Detection and Classification." 2018 IEEE International Conference on Big Data (Big Data). 2018. 5224-5227.
[9] Laha Ale, Ning Zhang, Longzhuang Li. "Road Damage Detection Using RetinaNet." 2018 IEEE International Conference on Big Data (Big Data). 2018. 5197-5200.
[10] Sadra Naddaf-Sh, M-Mahdi Naddaf-Sh, Amir R. Kashani, Hassan Zargarzadeh, . "An Efficient and Scalable Deep Learning Approach for Road Damage Detection." 2020 IEEE International Conference on Big Data (Big Data). 2020. 5602-5608.
[11] Md. Shohel Arman, Md. Mahbub Hasan, Farzana Sadia, Asif Khan Shakir, Kaushik Sarker, Farhan Anan Himu . "Detection and Classification of Road Damage Using R-CNN and Faster R-CNN: A Deep Learning Approach." Cyber Security and Computer Science. Cham: Springer International Publishing, 2020. 730-741.
[12] Slamet Riyadi, Fiddin Yusfida A’la, Chayadi Oktomy, Kamarul Hawari Ghazali. "Road Surface Crack Detection using Wavelets Features Extraction Technique." Indian Journal of Science and Technology (2016): 108690.

[13] Moslem Ouled Sghaier, Richard Lepage. "Road damage detection from VHR remote sensing images based on multiscale texture analysis and dempster shafer theory." 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). 2015. 4224-4227.
[14] Adyanata Lubis, Isdaryanto Iskandar, MM Lanny W Panjaitan. "Implementation of KNN Methods And GLCM Extraction For Classification Of Road Damage Level." IAIC Transactions on Sustainable Digital Innovation (ITSDI) (2022): 1-7.
[15] Yachao Yuan, Yali Yuan, Thar Baker, Lutz Maria Kolbe, Dieter Hogrefe. "FedRD: Privacy-preserving adaptive Federated learning framework for intelligent hazardous Road Damage detection and warning." Future Generation Computer Systems (2021): 385-398.
[16] Xiaoguang Zhang, Xuan Xia, Nan Li, Ma Lin, Junlin Song, Ning Ding. "Exploring the Tricks for Road Damage Detection with A One-Stage Detector." 2020 IEEE International Conference on Big Data (Big Data). 2020. 5616-5621.
[17] Yachao Yuan, Md. Saiful Islam, Yali Yuan, Shengjin Wang, Thar Baker, Lutz Maria Kolbe. "EcRD: Edge-Cloud Computing Framework for Smart Road Damage Detection and Warning." IEEE Internet of Things Journal (2021): 12734-12747.
[18] Hussein Samma, Shahrel Azmin Suandi, Nor Azman Ismail, Sarina Sulaiman, Lee Li Ping. "Evolving Pre-Trained CNN Using Two-Layers Optimizer for Road Damage Detection From Drone Images." IEEE Access (2021): 158215-158226.
[19] Minh-Tu Cao, Quoc-Viet Tran Ph.D, Ngoc-Mai Nguyen, Kuan-Tsung Chang. "Survey on performance of deep learning models for detecting road damages using multiple dashcam image resources." Advanced Engineering Informatics (2020): 101182.
[20] Abdullah Alfarrarjeh, Dweep Trivedi, Seon Ho Kim, Cyrus Shahabi. "A Deep Learning Approach for Road Damage Detection from Smartphone Images." 2018 IEEE International Conference on Big Data (Big Data). 2018. 5201-5204.
[21] Vinuta Hegde, Dweep Trivedi, Abdullah Alfarrarjeh, Aditi Deepak, Seon Ho Kim, Cyrus Shahabi. "Yet Another Deep Learning Approach for Road Damage Detection using Ensemble Learning." 2020 IEEE International Conference on Big Data (Big Data). 2020. 5553-5558.
[22] Deeksha Arya, Hiroya Maeda, Sanjay Kumar Ghosh, Durga Toshniwal, Yoshihide Sekimoto. "RDD2020: An annotated image dataset for automatic road damage detection using deep learning." Data in Brief (2021): 107133.
[23] Deeksha Arya, Hiroya Maeda, Sanjay Kumar Ghosh, Durga Toshniwal, Alexander Mraz, Takehiro Kashiyama, Yoshihide Sekimoto. "Transfer Learning-based Road Damage Detection for Multiple Countries." 30 08 2020. arXiv.org. <https://arxiv.org/abs/2008.13101v1>.
[24] Hiroya Maeda, Takehiro Kashiyama, Yoshihide Sekimoto, Toshikazu Seto, Hiroshi Omata. "Generative adversarial network for road damage detection." Computer-Aided Civil and Infrastructure Engineering (2021): 47-60.
[25] Maitry Bhavsar, Abdullah Alfarrarjeh, Utkarsh Baranwal, Seon Ho Kim. "Country-specific Ensemble Learning: A Deep Learning Approach for Road Damage Detection." 2022 IEEE International Conference on Big Data (Big Data). 2022. 6387-6394.
[26] H. Kim, S. Ham, I. Lee. "REAL-TIME DRONE MAPPING BASED ON REFERENCE IMAGES FOR VEHICLE FACILITY MONITORING." Remote Sensing and Spatial Information Sciences (2020).
[27] Keval Doshi, Yasin Yilmaz. "Road Damage Detection using Deep Ensemble Learning." 2020 IEEE International Conference on Big Data (Big Data). 2020. 5540-5544.
[28] Deeksha Arya, Hiroya Maeda, Sanjay Kumar Ghosh, Durga Toshniwal, Hiroshi Omata, Takehiro Kashiyama, Yoshihide Sekimoto. "Global Road Damage Detection: State-of-the-art Solutions." 2020 IEEE International Conference on Big Data (Big Data). 2020. 5533-5539.
[29] Hongwei Zhang, Zhaohui Wu, Yuxuan Qiu, Xiangcheng Zhai, Zichen Wang, Peng Xu, Zhenzheng Liu, Xiantong Li, Na Jiang. "A New Road Damage Detection Baseline with Attention Learning." Applied Sciences (2022): 7594.



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