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Evaluating the Efficacy of Computer Vision in Predicting and Detecting Road Damage for Intelligent Transport Systems

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Abstract: Improving road damage prediction and detection through state-of-the-art technology, especially computer vision, is an exciting new direction in Intelligent Transport Systems (ITS), which places a premium on highway safety. In the framework of Intelligent Transport Systems, this review article assesses the effectiveness of computer vision methods in improving road safety via the precise prediction and identification of road damage. The paper commences with a comprehensive examination of the prevailing obstacles in conventional road damage detection methods, emphasizing the imperative for inventive resolutions to circumvent constraints in present strategies. The next step is to investigate several in-depth approaches to computer vision, including everything from traditional image processing methods to cutting-edge deep learning algorithms. We focus on their merits, limits, and usefulness when predicting and detecting different types of road damage. The review summarizes the progress in computer vision for road damage detection by thoroughly analyzing pertinent literature and case studies. It highlights essential breakthroughs and identifies areas that could use additional improvement. The critical review considers the possible effect on road safety as a whole, as well as scalability concerns and difficulties with actual implementation. In addition, the paper explores the amalgamation of computer vision with other technologies, such as sensor networks and data analytics, to develop all-encompassing and resilient systems for improving road damage prediction and detection. The findings reported in this review enhance our comprehension of the present condition of computer vision within the framework of Intelligent Transportation Systems (ITS), providing valuable insights into its possible impact on defining the future of roadway safety. This study aims to consolidate information to guide academics, practitioners, and policymakers in promoting progress that would ultimately enhance the safety and efficiency of intelligent transportation systems.

Keywords: *Intelligent Transport System, Computer vision, Machine Learning, Deep Learning*

1. Introduction

The domain of Intelligent Transport Systems (ITS) is undergoing a period of profound change characterized by swift technological progressions, primarily aimed at augmenting the safety of roadways. Amid numerous advancements, computer vision has emerged as a crucial technology, providing unparalleled prospects for forecasting and identifying road damage with unprecedented accuracy and efficacy that was hitherto unattainable via conventional approaches. With societies growing dependence on intelligent transportation networks, there is an intensified need to develop resilient and advanced solutions for predicting and detecting road damage.
This review paper explores the pivotal significance of computer vision in advancing road safety as it relates to Intelligent Transportation Systems (ITS). Detecting road damage has encountered significant obstacles that have required a paradigm shift in the direction of novel approaches capable of surmounting current limitations. This comprehensive analysis aims to assess the effectiveness of different computer vision methodologies in tackling the intricate challenge of forecasting and identifying road damage. The detection and prediction of harm intensify.

The expedition begins with an analysis of the intrinsic difficulties associated with traditional approaches to road damage detection, thereby establishing a foundation for investigating computer vision-based alternative solutions. The thorough examination incorporates an array of methodologies, spanning from conventional image processing methods to the most recent advancements in deep learning algorithms. A comprehensive comprehension of these methodologies' practicality, merits, and drawbacks is prioritised, thereby furnishing an intricate viewpoint on their efficacy across various contexts. This review ultimately enhances the dialogue surrounding the influence of computer vision on the trajectory of Intelligent Transportation Systems (ITS) by thoroughly comprehending its potential ramifications for road safety. With the ongoing development of intelligent transportation systems, the synthesis of knowledge provided in this document is an invaluable asset for policymakers, practitioners, and researchers. It facilitates progress that ultimately enhances the safety and efficiency of transport infrastructures. Fig. 1, depicts the formation of potholes on roads..

Fig. 1. Road surface: visual illustration of potholes

2. Review methodology

The review is divided into many sections, as illustrated below.

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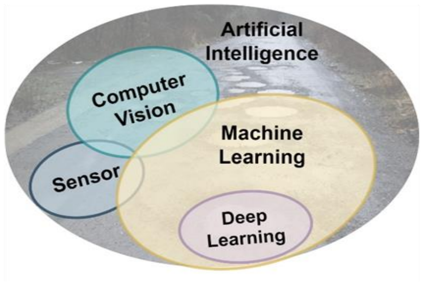
I. A compilation of literary works: We have compiled a collection of literature, including papers, articles, and theses, from reliable and credible platforms such as IEEE Explore, Science Direct, Elsevier, Springer, and others.

II. Literature Review: A comprehensive examination of global research conducted on road damage in Intelligent Transport Systems (ITS) aims to investigate the potential mitigating effects of artificial intelligence (AI), computer vision (CV), machine learning, deep learning, and traditional methods.

III. Identifying the Role of the Computer Science Branches in Intelligent Transport Systems about Road Damage: Following an extensive review of the existing literature, this study aims to identify the specific contributions of several technologies, including "The Internet of Things (IoT)," "Robotics," "Artificial Intelligence (AI)," "Machine Learning (ML)," and "Deep Learning (DL)," in the context of addressing road problems, particularly potholes. Identification of the most often utilized machine learning (ML) and deep learning (DL) methods.

IV. Discussion: A comprehensive examination of the role, relevance, contribution, and concerns associated with the subject matter. This section focuses on the role of artificial intelligence, computer vision, machine learning, and deep learning in identifying road damage.

Fig. 2. The various facets of Artificial Intelligence that are encompassed by ITS.



3. Related Work

Road damage detection can be made possible with the help of emerging technologies of Artificial Intelligence. The work taken up by different authors is depicted in Table 1 as the systematic literature review.

In this research, the above Fig. 2, illustrates how the integration of diverse technologies within the context of Industry 4.0 contributes to the detection of road damage.

Table 1 in this paper presents a comprehensive overview of the primary field of computer science and classifies its notable applications. Table 2 presents a concise overview of the assessment criteria. Table 4 presents three criteria for evaluating the literature survey conducted, showcasing the names of machine learning and deep learning algorithms commonly employed in the detection of road damage. Discussion: a comprehensive examination of their role, notable contributions, and level of concern. The analysis section focuses on the function of AI, ML, and DL in identifying road damage.

Table 1: Illustrates some widely used AI, Computer Vision, ML and DL algorithms

Algorithm	*Title of Paper*	*Authors , Ref & Year*
Convolutional Neural Network	"Road Damage Detection Using Deep Neural Networks with Images Captured Through a Smartphone" [1]	Maeda et al. [1], 2018
	"Detection of Road Potholes by Applying Convolutional Neural Network Method Based on Road Vibration Data" [2]	F. Ozoglu et al [2], 2023.
F-RCNN	"Vision-Based Deep Learning Algorithm for Detecting Potholes" [3]	K. Gajjar et al [3], 2022.
	"Real-Time Road Surface Damage Detection Framework based on Mask R-CNN Model" [4]	B, Kulambayed et al [4], 2023.
	"Application of an Effective Hierarchical Deep-Learning-Based Object Detection Model Integrated with Image-Processing Techniques for Detecting Speed Limit Signs, Rockfalls, Potholes, and car crash" [5],	Y. Chung [5], 2023.
M-RCNN		
	"Performance Evaluation of You Only Look Once v4 in Road Anomaly Detection and Visual Simultaneous Localisation and Mapping for Autonomous Vehicles" [6]	J. Bala et al [6], 2023.
YOLO- V4	"Image-Based Pothole Detection Using Multi-Scale Feature Network and Risk Assessment" [7]	D. Heo, J. Choi et al [7], 2023.
	"Detection of Roads Potholes using YOLOv4" [8]	Omar & Kumar [8], 2020.

	"YOLOv4: Optimal Speed and Accuracy of Object Detection" [9]	A. Bockovskiy, C. Wang et al [9], 2020.
YOLO- V5	"Augmented Reality Maintenance Assistant Using YOLOv5" [10]	A. Malta et al [10], 2021.
Transfer Learning	"RoadScan: A Novel and Robust Transfer Learning Framework for Autonomous Pothole Detection in Roads" [11]	G. Parasnis, A. Chokchi et al [11], 2023.
VANET	"Edge AI-Based Automated Detection and Classification of Road Anomalies in VANET Using Deep Learning" [12]	R. Bibi et al [12], 2021.
SVM	"In-Vehicle Data for Predicting Road Conditions and Driving Style Using Machine Learning" [13]	G. Al-refa et al [13], 2022.
Stereo Vision	"An efficient algorithm for pothole detection using stereo vision" [14]	Z. Zhang, X. Ai et al [14], 2014.
Global Positioning System (GPS)	"A Deep-Learning-Based GPS Signal Spoofing Detection Method for Small UAVs" [15]	Y. Sun, M. Yu et al [15], 2023.
	"Road Condition Monitoring Using Vehicle Built-in Cameras and GPS Sensors: A Deep Learning Approach" [16]	C. Ruseruka et al [16], 2023.
Perspective Transformation	"Rethinking Road Surface 3D Reconstruction and Pothole Detection: From Perspective Transformation to Disparity Map Segmentation" [17]	R. fan, U. Ozgunalp et al [17], 2021.
2D Technique	"Image Features Selection Based on Computer Vision Techniques to Detect Potholes for Intelligent Transport System" [18]	Omar & Kumar [18], 2021.
3D Technique	"Pyramid Stereo Matching Network" [19]	J. Chang, Y. Chen [19], 2018.
	"PT-ResNet: Perspective Transformation-Based Residual Network for Semantic Road Image Segmentation" [20]	R. Fan, Y. Wang et al [20], 2016.
LiDAR	"Highway and airport runway pavement inspection using mobile LiDAR" [21]	R. Ravi, D . Bullock et al [21], 2020.
VIDAR	"VIDAR-Based Road-Surface-Pothole-Detection Method" [22]	Y. Xu, T. Sun et al [22], 2023.
Computer Vision	"Computer Vision for Road Imaging and Pothole Detection: A State-of-the-Art Review of Systems and Algorithms" [23]	n. Ma, J. Fan et al [23], 2022.

Table 2: Summary of the evaluation criteria.

Criteria	***Definition***	***Function***
Detection A1	Detection is the use of technology or observation to identify an entity, occurrence, or event in a specific context.	The role of detection is to identify, recognize, or sense specific items, phenomena, or events in a context or environment.

Classification A2	Classification is the act of sorting items into distinct groups or categories according to their specific features or qualities.	Classifying entities or data points by shared features or attributes simplifies the organization, analysis, and interpretation of complicated information.
Management A3	Methodologies and strategies that are designed to effectively oversee and improve the performance of a model constitute management techniques.	Management comprises planning, organizing, coordinating, directing, and regulating resources to meet goals, maximize resource utilization, guide staff, and adapt to internal and external changes.

Table 3: Summary of the literature review.

Fields	***Papers***	***Contribution***	***Criteria***		
			A1	**A2**	**A3**
Traditional Techniques	GPS	GPS aids in pothole detection by providing precise location data that can be efficiently integrated with sensor technology to identify road surface irregularities.	✓	✓	✗
	3D	3D technology enhances pavement assessment for pothole detection by providing detailed spatial information, enabling more accurate and efficient identification of road surface irregularities.	✓	✓	✓
	VIDAR	VIDAR utilizes advanced sensor technology and data analysis algorithms to accurately and efficiently detect potholes in roads.	✓	✗	✗
	LiDAR	LiDAR technology aids in pothole detection by providing high-resolution 3D mapping, enabling precise identification and monitoring for efficient road maintenance and safety improvement.	✓	✓	✗
	STEREO VISION	STOREO VISION utilizes advanced computer vision algorithms and real-time monitoring systems to enhance pothole detection.	✓	✗	✗
	Computer Vision	Computer vision aids in pothole detection by utilizing image processing algorithms to efficiently and accurately identify and classify road surface irregularities.	✓	✗	✗
Machine Learning	SVM	SVM aids in pothole detection by efficiently classifying road surface data, distinguishing between normal and pothole-indicative conditions, enabling real-time monitoring and maintenance efforts.	✓	✗	✗
	Transfer Learning	Transfer learning improves pothole detection by utilizing pre-trained models' knowledge on similar tasks, reducing the need for extensive labelled data and expediting the training process.	✓	✓	✗

	MLP	MLP (Multilayer Perceptron) contributes to pothole detection through its ability to process complex sensor data and identify patterns indicative of road surface irregularities with high accuracy.	✓	✗	✓
Deep Learning	Mask-RCNN	Mask R-CNN contributes to pothole detection by enabling precise instance segmentation and localization of potholes in road images, aiding in automated road maintenance and safety efforts.	✓	✓	✗
	YOLO	YOLO (You Only Look Once) has significantly contributed to pothole detection by enabling real-time, accurate identification of potholes in road surfaces through its efficient object detection algorithms.	✓	✓	✓
	Multi-Classifier Feature Fusion	Multi-classifier feature fusion enhances pothole detection by combining diverse feature sets from multiple classifiers, improving accuracy and robustness in detecting potholes on road surfaces.	✓	✗	✗
	VANET	VANETs enable real-time identification and notification of road hazards through collaborative sensing and data sharing among vehicles, contributing to pothole detection.	✓	✓	✓

3.1. Traditional Techniques

Road management and autonomous technology depend heavily on automated pothole-detecting systems. In addition to saving manpower, these devices help with planned road management. The study[24] shows the analysis includes three types of automated pothole detection technologies that have been the subject of recent research: vision-based, vibration-based, and 3D reconstruction-based methods. These techniques can be utilized in the management of roads, intelligent transportation systems, car suspension systems, and autonomous driving technology. With advances in accuracy and real-time detection becoming crucial axes in future research trends, the application of deep-learning and machine-learning technologies is growing [24].

The research[22] introduces a VIDAR technology-based method for real-time pothole detection on roadways. The technique integrates visual data with Inertial Measurement Unit (IMU) to identify, label, and outline potholes on level surfaces by employing Maximally Stable Extremal Regions (MSER) to measure the dimensions of potholes. The study also evaluates computer vision models' performance in detecting potholes, with YOLO models showing superior performance and R-CNN models being particularly effective for nighttime detection. This could improve Intelligent Transportation Systems and reduce accidents caused by potholes [22]. This article [25] examines 3D object detection methodologies using RGB images, LiDAR point clouds, and merging data. It compares performance against the KITTI benchmark dataset. LiDAR point clouds are effective, but multimodal information fusion is needed to overcome single-modal limitations. Integrating temporal information reduces uncertainty and enhances detection accuracy (A Review of 3D Object Detection for Autonomous Driving of Electric Vehicles).

The SPFPN-YOLOv4 small 2D pothole detection algorithm is specifically tailored for embedded systems that have restricted processing capabilities. By extracting detailed attributes from photographs using sophisticated approaches, accuracy is improved. The device can detect potholes and anticipate their proportions, which helps to reduce accidents. Its practical driving safety abilities should be confirmed by additional research. (Image-Based Pothole Detection Using Multi-Scale Feature Network and Risk Assessment).
(Sustainable Road Pothole Detection: A Crowdsourcing Based Multi-Sensors Fusion Approach) for roadways and airport runways, the article lays out a method for automatically detecting and quantifying pavement deterioration. Pavement distresses such as wear and tear, missing RPMs, superficial cracking, and pavement repair discontinuities are all easily detected by the algorithm. Using RGB photography to enhance the accuracy of 3D point clouds is the goal of future development.[21]

Sri Lanka's road surface conditions can be tracked via the BusNet, a sensor network integrated into public transportation systems. Costs are reduced and maintenance and security challenges related to large-scale sensor networks are managed by this novel solution. Developing nations can greatly benefit from BusNet because of its potential for various applications that include delay-tolerant sensor networks, even though it does have some latency[26].

This study[27] introduces a pothole identification system that is designed to be efficient, utilizing road disparity map estimation and segmentation techniques. By integrating the stereo rig's roll angle, it is possible to generalize the perspective transformation. Semi-global matching is employed to estimate the discrepancies in road conditions. Subsequently, a disparity map transformation technique is executed to enhance the differentiation of the impaired road regions. Ultimately, employing a straightforward linear iterative clustering technique to categorize the altered disparities into a set of super pixels. The potholes are subsequently identified by identifying the super pixels, which have values below a threshold that is calculated adaptively[27].
The paper describes a new way to find damage on the road that uses automated disparity map segmentation. It reduces an energy function, which makes it work better and more accurately than non-linear optimization methods like GSSDP and GD. The method changes dense disparity maps, tells the difference between damaged and undamaged road areas, and works in real-time with a 97.56% accuracy level at the pixel level[28].
To improve on current techniques, the paper suggests a pothole-detecting system utilizing 2D road photos. Test results reveal an improved accuracy of 73.5% with 80.0% precision and 73.3% recall over the current 45.1%. On the other hand, processing time, stability, and false detection are drawbacks. Real-time pothole identification requires more advancements [29].

3.2. Machine Learning

This paper presents a machine learning (ML) system that utilizes decision trees, random forests, and Support Vector Machines (SVM) in Python to accurately forecast road surface conditions, traffic circumstances, and driving style. Random forests are the most effective for accuracy, precision, recall, and F-score, according to the data. In comparison to more complicated systems, the study also shows that vehicle networks have a wealth of information that can be examined and classified using machine learning (ML). This allows for high accuracy and low implementation costs[13].
The performance of automated road defect and anomaly detection (ARDAD) systems combining conventional machine learning and sensor technology is the main topic of this systematic analysis, which examines 116 peer-reviewed publications on the subject from 2000 to 2023. It emphasizes the rapid expansion of research and the prospects for improvements in IOT, 5G, 6G, swarm drones, satellite images, and GPS in the future [30].
A new acoustic data processing module coupled with vehicle wheel rims for smart city road condition monitoring is presented in the study. It uses ML algorithms to divide road surfaces into four types: smooth, slippery, green, and rough. MLP gives the best accuracy of 98.98%. Cost-effective, accurate, and labor-efficient, this model may save automobile crash victims (Artificial Intelligence for Road Quality Assessment in smart cities: A Machine Learning Approach to acoustic data analysis).
Object-oriented approaches and pattern-based architecture are used to identify, define, and build healthcare software agent applications in this research. The authors examine the compliance monitoring task and employ OOA/OOD notations, such as the Unified Modeling Language, to find similar architectural patterns across numerous agent applications. Architecture has logical and physical parts[31].
The research [32] investigates automatic asphalt pavement pothole detection utilizing GF, SF, and IP image processing. Both ANN and LS-SVM AI methods have good accuracy and CARs. Transportation authorities and traffic inspectors could employ the model with advanced AI and ensemble learning algorithms [32].

3.3. Deep Learning

The study[33] addresses the issues associated with detecting potholes in autonomous vehicles by focusing on improving the quality of training and utilizing embedded edge devices. Two clusters were formed, and a hybrid pipeline was suggested to address the limitations. The hybrid pipeline, which combined all-reduce algorithms and NV-Links, demonstrated encouraging outcomes in terms of training time and epoch size. A strong computer vision model was shown by the model's accuracy, which was higher than 92%. The technique exhibits potential for application in video graphics analysis within smart urban environments [33].
To precisely identify speed limit signs, rockfalls, potholes, and auto wrecks, a novel object detection model (M4) has been built combining YOLOv7 and Mask R-CNN, image-processing techniques, and Gaussian noise. The model demonstrated a fast response time of 6.58% and a mean average precision of 88.20%. Future studies should integrate IoV and 5G networks, conduct experiments under various settings, and increase the number of cameras [5].
Over the course of the research, a CNN-based road anomaly detection model was constructed by utilizing the YOLO v4 object identification model. The model achieved remarkable precision, recall, and F1-score values of 89%, 94%, and 91% respectively. The model performed better than a lot of the methods that were in use, particularly in recognizing three different anomalies. Also created was RA-SLAM, an enhanced visual SLAM method with promising scalability and improved accuracy[6].
In order to identify GPS signal spoofing, the authors of the study [15] used a PCA-CNN-LSTM model in conjunction with a composite-wing UAV and a deception spoofing jammer. The model was trained using grid search and 10-fold cross validation. The simulations showed that the PCA-CNN-LSTM model worked the best, with a score of 99.43% accuracy. In order to enhance computational performance and generalizability, future research will employ flight paths that are more intricate while still utilizing lightweight processing approaches[15].
The project investigates the use of the Mask R-CNN architecture to detect damage to the road surface. The algorithm is adaptable enough to handle complicated scenarios and accurately recognizes different kinds of surface defects. It democratizes the process and demonstrates the possibility for additional innovation and refinement in infrastructure management by using photos and video from smartphones[4].
The article presents a technique for classifying roads into appropriate driving zones utilizing the TLFC-RD approach and several classifiers. It classifies roads and backgrounds using SVM after using LeNet-5, LSTM, and ResNet for feature maps. The solution achieves 99.12% precision on the KITTI dataset and presents deep learning classifiers for detecting objects in safe driving zones[34].
A trained deep learning model-based Edge AI framework detects road irregularities in autonomous vehicles. Automatically recognizing and classifying traffic irregularities minimizes accidents. Further investigation in this area may encompass an increased variety of road anomalies as well as automatic vehicle action control[12].
The study [16]utilized YOLOv5 to train a model to detect and categorize pavement distress states. The model employed visual data sourced from several countries and devices, incorporating hand labeling and image augmentation techniques. The model

attained exceptional precision, recall, F1-score, and mean average precision. The model underwent testing on videos at various speeds, resulting in an 85% precision rate and a 95% recall rate. The efficacy of the approach was validated through testing on the roadways within the campus premises[16].

The study introduces sophisticated deep-learning models designed for the real-time identification of potholes, with a specific emphasis on edge devices. The YOLOv4 model demonstrated superior performance, achieving a remarkable accuracy of 90% and an impressive frame rate of 31.76 frames per second. This technique can assist road maintenance authorities in promptly identifying necessary measures for infrastructure repairs. Furthermore, it can identify additional forms of pavement damage, such as road depressions, and accurately estimate depth [35].

This work introduces state-of-the-art deep learning models designed for real-time pothole identification, with a specific emphasis on edge devices. The YOLOv4 model demonstrated superior accuracy, whereas Tiny-YOLOv4 obtained a 90% accuracy rate. This strategy can facilitate prompt decision-making by road maintenance authorities on infrastructure repairs. A unique Convolutional Neural Network (CNN) model was created by utilizing road data collected from smartphone sensors that are based on vibrations. The model achieved an impressive maximum accuracy rate of 93.24% [2].

The study introduces a road anomaly detection system that utilizes multi-source sensor fusion to identify road potholes. The system gathers data from automobiles using cell phones and cameras, sends it to detection modules, and utilizes a Long Short-Term Memory (LSTM) network and a combination of acceleration and video data for analysis. The solution surpasses conventional machine learning techniques and provides cost efficiencies for local governments [36].

The research introduces a pavement crack segmentation network based on deep learning, which improves accuracy and minimizes the impact of pavement distractors. The model includes a CBAM attention module, weight normalization, multiscale Laplacian residuals, PAN structure, and a well-designed loss function. Subsequent research endeavors to employ the technique in intricate situations [37].

The research examines the creation of a comprehensive dataset called ISTD-PDS7, which is designed to automatically segment pavement distress. The Segformer model, equipped with a multi-layer Transformer-Encoder, is seen as more appropriate for intricate sceneries as it enhances crack extraction and suppresses background noise. Subsequent investigation is scheduled [38].

The paper introduces a dual-network model that combines both coarse and fine networks to enhance fracture segmentation. The coarse network provides a comprehensive perspective of the image, while the fine network concentrates on specific regions to achieve high-resolution segmentation. The efficacy of the algorithm in detecting cracks is showcased through the utilization of two publicly available datasets. Potential future endeavors could encompass the implementation of data augmentation methodologies and the integration of sophisticated sensor systems [39].

The research presents a novel clustering initialization technique employing a deep learning-based object detection model known as YOLO-v5. This solution is lightweight, swift, and sturdy, offering high efficiency. The efficiency of the system has been evaluated using various configurations, confirming its effectiveness in terms of time complexity and resource utilization. Future endeavors involve developing a novel deep learning-based data transformation model tailored for distinct clusters and 3D object detection models [40]. An augmented reality system for maintenance professionals was the target of the study, which trained a deep learning neural network. Two datasets and two iterations of YOLOv5 were generated and then evaluated. The model exhibited exceptional precision and recall in accurately identifying all eight mechanical components of an automobile engine. Subsequent efforts will incorporate the trained model into a CMMS (Computerized Maintenance Management System) to provide real-time guidance for work orders [10].

The YOLOv6, a real-time object detector, outperforms other existing real-time detectors in terms of both accuracy and speed. It provides a tailored quantization technique for the convenience of industrial implementation. The project expresses gratitude to the academic and industry communities for their contributions and efforts.[41]

The detector is a cutting-edge technology that surpasses all other options in terms of speed and accuracy. It is specifically designed to be trained and utilized on a standard GPU with 8-16GB of VRAM. The features enhance the accuracy of both the classifier and detector, making it a benchmark for future investigations [9]. While YOLOv3 is a quick and precise detector, it falls short on the COCO average AP metric, which measures performance between.5 and.95 IOU. The possible misuse of this technology is raised by the fact that humans have difficulty differentiating between IOU of.3 and.5. Scientists should think about the potential harm their work could create and try to lessen it [42].

On a variety of datasets, the real-time detection algorithms YOLOv2 and YOLO9000 provide quicker and more accurate detection. They close the dataset size gap and improve detection outcomes by concurrently optimizing detection and classification using WordTree and ImageNet [43]. Using various finetuning procedures, the FasterRCNN ensemble detected road surface deterioration competitively. Solid-state drives (SSD) were competitive with the model's maximal score of 0.49. Adversarial synthetic datasets are future enhancements[44]. This research suggests a way to reduce road maintenance dependence, especially during a pandemic. YOLOv4 detects potholes more precisely and with fewer errors than YOLOv3. We want to add GPS-equipped surveillance cars to the system for remote pothole monitoring and planning [45].

The system created in MATLAB effectively identifies and monitors items in traffic lanes, including automobiles and pedestrians. It surpasses ACF detectors, as confirmed by 19 brief videos. The camera does its best in bright light, but it falls short when things are busy or the lighting is bad. The system created in MATLAB effectively identifies and monitors items in traffic lanes, including automobiles and pedestrians. It surpasses ACF detectors, as confirmed by 19 brief videos. The camera does its best in bright light, but it falls short when things are busy or the lighting is bad. To develop forward collision warning systems that are more effective, a sensor fusion model is required (Object Detection and Classification for Autonomous Vehicle). An assessment of computer vision models for the detection of potholes in diverse meteorological conditions is conducted in this study. While YOLO models performed best overall, R-CNN models excelled at detecting objects at night. Performance was adversely impacted by lighting. This study has the potential to make valuable contributions to the field of Intelligent Transportation Systems, by enhancing road safety and mitigating accidents resulting from potholes. Subsequent investigations should prioritize the development of weather-specific methods for augmenting data (Comparison of CNN-Based Models for Pothole Detection in Real-World Adverse Conditions: Overview and Evaluation). With a simple height threshold, this work introduces a pothole detection system that achieves high road fitting and pothole identification accuracies utilizing a computationally efficient method and quadratic fitting in the WCS point cloud [14].

With an emphasis on effective SoTA DCNNs, this article examines various road imaging approaches and computer vision algorithms used for pothole detection on roads. We suggest that future studies use hybrid methods that combine stereo matching with semantic segmentation. But it's laborious and needs big datasets to train these networks. We suggest using low-shot learning and unsupervised stereo matching algorithms for semantic road image segmentation [23].

Using a perspective transformation approach to handle stereo images, this paper introduces a deep neural network that can separate road images semantically. With AP at 91.21% and MaxF at 91.19%, the ResNet-based network surpassed competing networks. Future studies should evaluate ResNet's performance against that of other networks to determine if it is indeed the optimal network for learning road semantic segmentation [20].

This study shows a new algorithm for disparity transformation and map modeling that makes disparity map modeling more stable. It can also find gaps with a 98.7% success rate and a 99.6% success rate at the pixel level. The program is going to teach a deep neural network how to find potholes [46].

The study suggests PSMNet, a new CNN design for stereo vision that works from end to end and has two main parts: the SPP module and the 3D CNN. PSMNet does better than other methods and comes in first place on the KITTI 2012 and 2015 leader boards, which means it makes a lot fewer mistakes in poorly defined areas [19]. CNN models for real-time pothole detection are studied in the work. Ten CNNs were utilized, with Faster R-CNN with ResNet50 being the most precise. Ys outperformed the others in speed. Future studies will focus on harsh weather and stereo camera calibration [47]. The method for identifying road damage presented in this research uses RetinaNet and was trained on a real-world dataset derived from cell phones. It shows excellent accuracy in predicting both successful and unsuccessful damage identification [48].In this study, deep learning methods utilizing CNN algorithms for crack identification are presented. It makes use of a 40,000 image public collection; the third method has a greater rate of crack detection. Experiments on the AWS cloud and a variety of datasets boost the system's performance. On the other hand, training time is increased due to the architecture's complexity [49].

4. Discussion

The objective of the scientific community to mitigate road damage through the identification of surface faults and the anticipation of anomalies has been in existence since the inception of high-speed roadways. Fig. 3, depicts the detection of potholes using 3D, feature selection, or object detection techniques through Intelligent Transportation Systems (ITS). An analysis is conducted on the existing proposals by comparing them to other proposals that already exist. Various conventional methods are accessible, such as edge detection, Histograms of Oriented Gradient (HOG), Speed-Up Robust Features (SURF), Support Vector Machine (SVM), Local Binary Patterns (LBP), and others. The progress in sensor technology and the use of computer vision (CV) in conjunction with soft-computing methods like machine learning (ML) and deep learning (DL) have initiated a favourable change in momentum for Road damage.

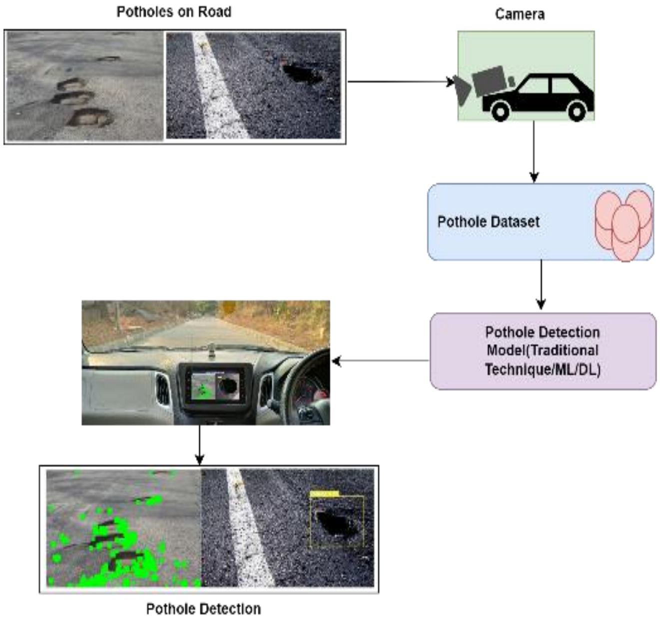


Fig. 3. Flow of Pothole Detection

Intelligent Transportation Systems (ITS) have been extensively employed across various domains to enhance consumer comfort. For instance, contemporary mobile phones are equipped with advanced features like inertial sensors, high-speed video, and additional sensors like light detection and ranging (LiDAR), making them suitable for consumers. In recent years, Intelligent Transportation Systems (ITS) have been extensively employed across various domains to enhance consumer comfort. The literature suggests that deep learning approaches have the potential to effectively address a range of challenges in contemporary Intelligent Transportation Systems (ITS).

5. Conclusion

Road Damage detection is one of the important topics of research in today's time. The state-of-the-art technologies *viz* Artificial Intelligence, Internet of Things is very instrumental in the detection of road damages to prevent accidents. In this paper, we have taken up the review of the work, done by various authors that helps the community in detection of the road damage. The work of road damage detection was taken up with the help of traditional techniques, machine learning, and deep learning. From this paper, it is evident that Deep Learning is one of the best techniques for the detection of objects such as road damages etc.

Author contributions

Mohd Omar: Conceptualization, Visualization and Writing **Pradeep Kumar:** Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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