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Improving Road Safety with AI: An Automated Pothole Detection based on Vision-based Approaches

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ABSTRACT
Efficient road infrastructure is pivotal for ensuring the safety and smooth operation of urban environments. Potholes, often caused by natural or human-induced factors, pose significant threats to vehicular safety and traffic flow. Timely detection of potholes is crucial for proactive maintenance and prevention of accidents. In recent years, computer vision techniques have emerged as promising tools for automated pothole detection. This research focuses on enhancing existing vision-based methods using a combination of the Scale-Invariant Feature Transform (SIFT) and Principal Component Analysis (PCA) algorithms. SIFT, a cornerstone in feature extraction, is employed to identify distinctive features within images of road surfaces. To streamline subsequent processing and improve accuracy, the complementary PCA is utilized to reduce the dimensionality of the feature descriptors generated by SIFT. The resulting feature vectors are then fed into a Support Vector Machine (SVM) classifier for training and pothole classification. To evaluate the performance of the trained model, a Receiver Operating Characteristic (ROC) curve was plotted. The Area Under the Curve (AUC) was calculated to be 92%. Furthermore, the overall accuracy of the system was found to be 94.7%. Experimental results demonstrate that the combined use of SIFT and PCA outperforms the SIFT algorithm alone in terms of pothole detection accuracy. This finding underscores the efficacy of the proposed approach in addressing the challenges associated with automated pothole detection. The developed system offers a potential solution for cost-effective and timely road maintenance, contributing to safer and more efficient transportation systems.

Keywords
Pothole Detection, Scale-Invariant Feature Transform (SIFT), Support vector machine (SVM), Principal component analysis (PCA), vision-based methods.

1. INTRODUCTION
One of the most significant factors contributing to a country is developed road infrastructure. Such infrastructure has a profound impact on a country's economic landscape [1]. The presence of dilapidated roads can create a cascade of negative consequences. In addition to posing a grave threat to public safety, they also impede access to essential healthcare services. These challenges can significantly hinder a country's progress and development, ultimately affecting the overall well-being of its citizens. These challenges can significantly hinder a country's progress and development, ultimately affecting the overall well-being of its citizens.

The monitoring of road infrastructure is paramount. While traditional methods exist, they are characterized by lengthy data collection and analysis processes and often yield inadequate information [2]. As a result, the timely detection and mitigation of road-related issues remains a significant challenge. The prevailing methods for monitoring urban road infrastructure involve manual visual inspections and regular reporting. Although these methods are straightforward and economical, they are inadequate for comprehensive and timely assessment, necessitating the exploration of more advanced techniques [3] [4].

One of the most prevalent road hazards is the formation of potholes of varying sizes, typically on road surfaces as illustrated in Figure 1. These can frequently lead to accidents resulting in both material and human losses.

Fig 1: A road image exhibiting potholes

Potholes pose a significant safety and ride quality hazard, demanding immediate attention. Their detrimental impact on infrastructure has sparked intense research interest within the civil engineering community [5]. To address this challenge, vision-based systems are being developed to accurately identify potholes using advanced image processing techniques applied to both still images and video footage.

In this paper, we address the problem of automatic pothole detection by automatic analysis of 2D images. We suggest a vision-based approach that places a particular emphasis on the feature extraction stage, recognizing its critical role in subsequent detection steps. By synergistically combining two robust algorithms, we have developed a method that significantly enhances the accuracy and efficiency of our system. First, we extract features from 2D-images using SIFT technique. This approach allows us to capture the essential shape and structural information inherent in the images. Subsequently, we apply the PCA algorithm to the resulting feature vector. This algorithm effectively reduces the dimensionality of the feature vector, thereby mitigating the computational burden of subsequent processing stages. Finally, we employ the powerful Support Vector Machines (SVM) algorithm for binary classification. SVM's ability to handle high-dimensional data and its strong generalization properties make it an ideal choice for our application. Experiments conducted on Pothole Detection Dataset [6] have demonstrated that our proposed system achieves superior classification accuracy compared to state-of-the-art methods.

The remaining sections of this paper are structured as follows: Section 2 provides a comprehensive overview of pothole detection techniques and their underlying principles. Section 3 delves into the proposed methodology, outlining the specific steps involved in our approach. Subsequently, Section 4 presents the experimental results and a detailed analysis of the system's performance. Finally, Section 5 concludes the paper by summarizing the key findings and discussing potential future directions.

2. INVESTIGATING THE POTENTIAL OF AI IN POTHOLE DETECTION

In recent years, various automated techniques have been employed for pothole detection on roads. Among the most prevalent methods are vision-based approaches and those relying on 3D reconstruction.

2.1 vision-based approaches:

The approaches utilize visual data [7], including images and video sequences to extract meaningful information and make informed decisions.

An unsupervised vision-based method for pothole detection is proposed by [8]. Asphalt pavements are extracted through RGB color space analysis and image segmentation. The search area is then limited to detected asphalt regions. The method's effectiveness is evaluated on a dataset of images captured under varying conditions. Results indicate its suitability as a preprocessing step for supervised methods.

Asad et al. [9] presented a study to compare the performance of various deep-learning models for detecting potholes in real-time. The models were tested on image datasets capturing diverse road conditions and on videos recorded from moving vehicles. Tiny-YOLOv4 emerged as the top-performing model.

Gajjar et al. [10] employed diverse techniques for crater detection including Faster R-CNN, SSD, and YOLOv3. Images were trained on these models, and experiments revealed that the YOLOv3 technique outperformed the others. Results also indicated that this technique could be utilized for real-time crater detection using cloud and map services.

vision method and vibration method have been used by Toral et al. [11] to identify potholes. The CNN was employed in vision- base method and it was more effective than the vibration-based method. A total of 50 images of the road surface were captured using a smartphone camera. These images were distributed across five different road sections, with 10 images taken from each section. Another study by Saisree and Kumaran [12] proposed a method to detect potholes in various road conditions using deep learning. Moreover, multiple deep learning models, including YOLO variants, were compared on image and video datasets. VGG19 achieved the highest accuracy in detecting potholes on both muddy and highway roads.

2.2 3D Reconstruction-Based Method

Advanced imaging and 3D reconstruction pinpoint potholes and road defects by creating a detailed 3D road surface model.

This research [13] presented a straightforward 3D point cloud segmentation technique for pothole detection. Binocular stereo vision was utilized to capture 3D point clouds, which were subsequently processed by fitting the pavement plane and removing it from the 3D point clouds of the road scene to roughly eliminate potholes. region growing methods and K-means clustering were employed to precisely extract the potholes.

A pothole detection algorithm based on road disparity map estimation and segmentation was proposed by Fan et al. [14]. Road disparities are efficiently estimated using semiglobal matching. Simple linear iterative clustering groups the transformed disparities into superpixels, and potholes are detected by finding superpixels with intensities below an adaptively determined threshold. The algorithm was created using CUDA programming and run on an NVIDIA RTX 2080 Ti graphics card.

A road pothole extraction technique based on the enhanced normal vector distance was presented in [15]. The distance between the sampled point and the tangent plane of the quadratic surface of the local neighborhood was then used to calculate the normal vector distance of the sampled point, which was used to describe the 3D features of the sampled point. The Douglas-Peucker algorithm was then used to dilute the normal vector distance and extract the features. The pit contour is then further fitted using the Alpha-Shape technique to eliminate internal noise points, and the final pit boundary point cloud collection was obtained by fitting the extracted pit contour's boundary using B-sample interpolation once again.

According to the related works, real-time applications are less viable for sensor-based and 3D reconstruction-based systems due to their sophisticated hardware requirements. Researchers are focusing more on vision-based systems that use inexpensive, sophisticated cameras.

3. MATERIALS AND METHODS

In this study, the vision-based approach has been employed to detect the potholes. Figure 2 illustrated the stages of the proposed system.

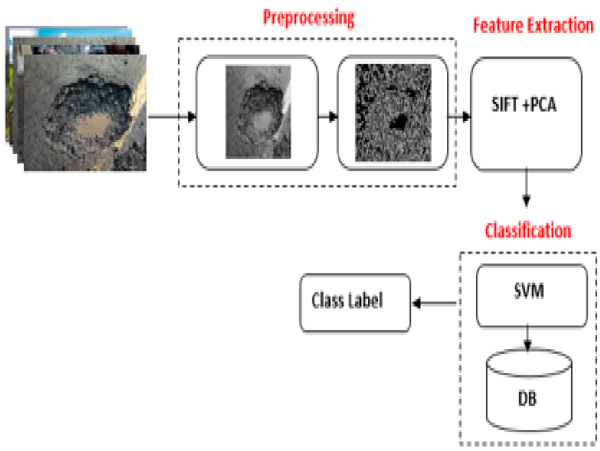

Fig 2: The main stages of potholes detection system

3.1 Data acquisition

For data acquisition, we utilized a reliable dataset sourced from Kaggl (Pothole Detection Dataset) [6]. This dataset is classified into two labels: potholes and normal. Table 1 provides a representative sample of these images.

Table 1: Samples of dataset

3.2 Data Pre-processing

This step includes two steps: image resizing and image segmentation. The training system's images are taken in different sizes, which affects the model's training process to identify potholes on roads. Therefore, some steps will be applied to standardize the image size for all data, as well as converting the data from colored images to grayscale images to facilitate the process of extracting features and classification later [16].

The next step is edge detection, a Canny edge detector [17] is applied to the isolated road surface, creating a black and white image that emphasizes the edges. The Figure 3 shows an example of using the Canny edge detector. The first image shows an example of a road without potholes where external borders have been created for the road, and the second image shows an example of a road image containing potholes where edges have been created for those potholes.

3.3 Feature extraction based on SIFT and PCA

Accurate feature extraction from images is crucial for achieving high accuracy in pothole detection. The SIFT algorithm [18] is one of the most important computer vision algorithms widely used for extracting features from images. Figure 4 shows the model of SIFT and PCA to extract the features.

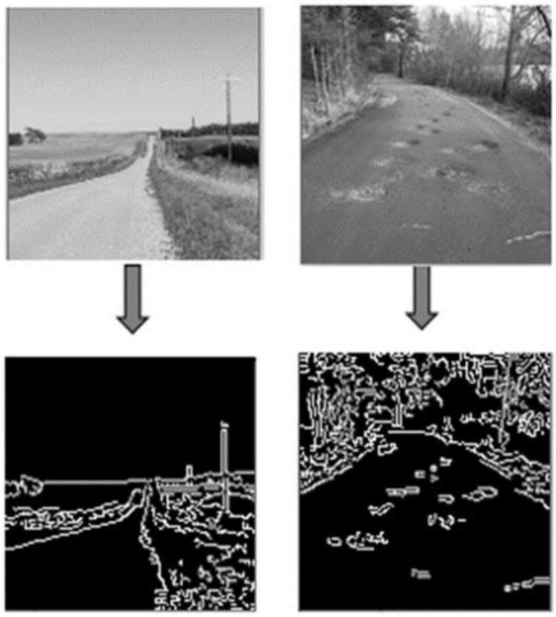

Fig 3: Example output of Canny Edge algorithm

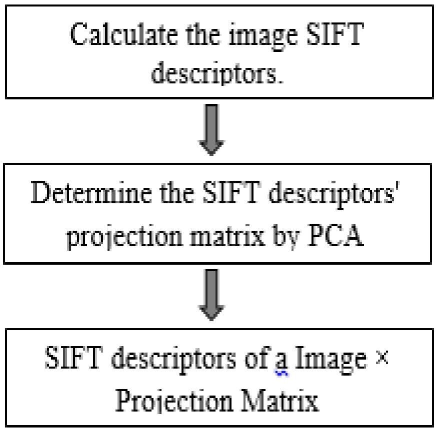

Fig 4: The model of proposed system for extracting features

Accurate feature extraction from images is crucial for achieving high accuracy in pothole detection. The SIFT algorithm [18] is one of the most important computer vision algorithms widely used for extracting features from images. Figure 5 shows the model of SIFT and PCA to extract the features.

The SIFT algorithm detects keypoints in the image edges [19]. These points represent corners, edges, and other distinctive shapes in the image. Then, it computes a description for each keypoint. The description is a numerical vector that represents the appearance of the area surrounding the keypoint. After that, the PCA algorithm is applied to reduce the SIFT descriptors. The SIFT algorithm typically produces high-dimensional feature vectors (128 elements). PCA can help reduce these dimensions to a smaller number of principal components that retain as much of the variance in the data as possible. This reduces the computations needed in later stages and improves the efficiency of the algorithm.

3.4 Support vector machine (SVM)

SVM is a machine learning technique based on statistical learning theory [20] and was used to detect the potholes in this work. In the feature extraction step, the SIFT technique is used to extract distinguishing features from images. Each image is then represented as a numerical vector using these attributes. These feature vectors are then used to train an SVM classifier, which subsequently learns to distinguish between images with and without potholes. The most appropriate hyperplane to divide the data points into two classes of images with and without potholes is found using the SVM. Once trained, the SVM may be used to categorize fresh images by assigning them to one of these classes based on their feature vectors.

4. IMPLEMENTATION AND RESULTS

An accuracy analysis was performed to verify the effectiveness of the SVM classification algorithm based on the SIFT descriptors with PCA in the detection of potholes. In this analysis, 658 images have been utilized. Data division training and testing data are separated into two groups. The complete collection of data must be divided into proportions. Twenty percent has been utilized for dataset testing, and the remaining eighty percent has been used for training. A portion of the bigger dataset that is utilized to train the model is designated as the training dataset. The computation of the proposed system was performed by Google Colab.

4.1 Evaluation metrics

In order to evaluate classifier performance and prevent bias, the was receiver operating characteristic (ROC) [21] used to evaluate the training model. It is an essential tool in evaluating the performance of binary classification models in machine learning. It provides a comprehensive view of the model's ability to distinguish between positive and negative classes and helps in making informed decisions about choosing the optimal model. Moreover, it helps determine the optimal balance between precision and recall based on application requirements. Figure 5 presents the ROC curve of the proposed system.

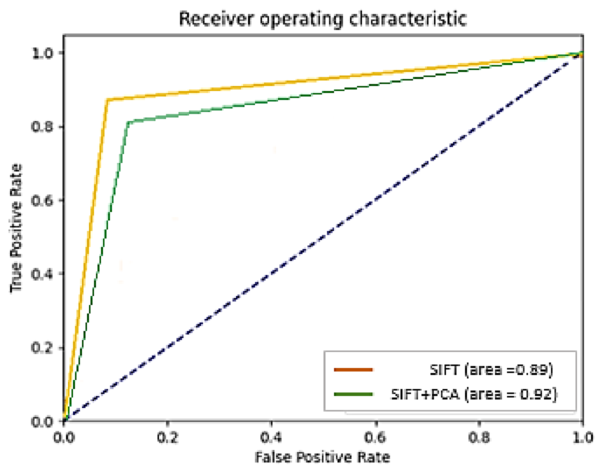

Fig 5: ROC curve of the proposed system

Figure 6 illustrates the relationship between True Positive Rate (TPR) and False Positive Rate (FPR) as the classification threshold varies. The true positive rate represents the ratio of true positives (TP) to the sum of true positives and false negatives (FN) as shown in formula 1, and it quantifies the proportion of actual positive cases that are correctly identified by the model.

$$TRP = \frac{TP}{TP + FN} \tag{1}$$

In the same way, the false positive rate is the proportion of observations that are incorrectly predicted to be positive out of all negative observations as illustrated in formula 2.

$$FRP = \frac{TN}{TN + FP} \tag{2}$$

The x-axis represents the FPR, denoting the proportion of negative instances incorrectly classified as positive. Conversely, the y-axis displays the TPR, indicating the proportion of positive instances correctly identified.

Table 2: Performance Metrics for SIFT-Based Classification with and without PCA

Expression	Method	
	SIFT +SVM	SIFT+PCA+SVM
AUC	89%	92%
Precision	90.71%	93.81%
Recall	89.67%	92.92%
Accuracy	89.31%	93.7%

Table 2 shows the performance of two different methods used in our research to classify data using the SVM algorithm. The first method uses SIFT with SVM directly, while the second method adds a PCA step before applying SVM. We can see from the results presented above that the second method (SIFT+PCA+SVM) achieved a higher AUC value (92%) compared to the first method (89%). This indicates that the second method has a better ability to distinguish between positive and negative classes for pothole detection in images.

4.2 Evaluation metrics

Detecting potholes on roads remains a formidable challenge for researchers, and numerous solutions have been proposed in recent years. Three well-known methods have been presented in recent years [22],[8],[11], and these were utilized to evaluate the performance of the proposed method. The results obtained from the proposed approach using the dataset from Kaggle are scheduled in Table3.

Table3: a comparison of our work with existing approaches

Author	Dataset	method	Accuracy%
[22]	Total dataset 2665 images	Tiny-YOLOv2 YOLOv3 YOLOv4	74.8 78.8 72.7
[8]	Total dataset 80 images	Otsu thresholding + image processing techniques	82
[11]	50	CNN	90

Proposed system	Total dataset 658 images	SIFT+PCA & SVM	93.7

5. CONCLUSION

In this paper, an innovative and cost-effective vision-based approach for detecting potholes has been presented. A system capable of precisely locating and detecting potholes on roadways has been created by utilizing the SIFT algorithm to extract distinguished features from the image. Subsequently, PCA has been implemented to reduce the SIFT descriptor vectors. Finally, the SVM classifier has been employed for pothole detection on roads.

From the experimental results, it was noted that combining SIFT and PCA can be a powerful approach for many computer vision tasks, especially when dealing with high-dimensional feature spaces. To evaluate the training of the system model, the ROC curve was used. While our results are promising, there are still opportunities for further improvements. Future work could focus on expanding the dataset, exploring different deep-learning architectures, and developing a real-time implementation.

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