COMPREHENSIVE POTHOLE DETECTION SYSTEM FOR ROAD MAINTENANCE AND SAFETY USING IMAGE PROCESSING AND STEREO VISION

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ABSTRACT

This paper introduces a systematic approach to pothole detection, emphasizing its significance in road maintenance and safety. The proposed system is comprised of meticulously designed modules that collectively contribute to achieving accurate and effective results. Commencing with data collection through cameras capturing road areas of interest, the images undergo manual cropping and resizing for standardization. The core principle of the system revolves around image enhancement, involving grayscale conversion, application of blurring techniques, and adjustments to brightness and contrast. Automatic thresholding extracts essential information encoded within pixels, paving the way for precise edge detection refined through morphological operations. The focus then shifts to pothole detection, incorporating a stereo camera setup to calculate depth and disparity of road surfaces. Critical steps, including image rectification, correspondence matching, and disparity calculations, contribute to the accurate identification and delineation of potholes using depth thresholds. Subsequent modules employ K-Means clustering to segregate regions of interest from the image background, and post-processing steps, including filtering, masking, and refinement, fine-tune the images. Utilizing the HSV color space for grayscale image refinement and the connected component method to isolate white pixel objects further enhance the system's capability. The final step involves the addition of bounding boxes around identified potholes, streamlining their identification process. This comprehensive methodology ensures effective image processing, precise pothole detection, and contributes significantly to road safety and maintenance efforts.

Keywords: Pothole detection; Road maintenance; Image enhancement; Stereo camera setup; Depth and disparity calculation; Automatic thresholding; Edge detection

1.0 INTRODUCTION

Road safety and efficient maintenance have become top priorities in modern times. With the ever-growing volume of road traffic and the continuous expansion of road networks, potholes have become a significant and persistent challenge. Potholes not only pose dangers to drivers, leading to accidents and vehicle damage, but they also burden infrastructure maintenance budgets. To mitigate these issues and ensure safer, well-maintained roads, timely detection and accurate identification of potholes are critical steps. The system presented here offers a comprehensive solution for detecting potholes in road images. It comprises distinct modules, each serving a specific role in the overall process. Identifying and repairing potholes early is crucial for road maintenance and safety management. The integrity of road surfaces directly impacts the safety and well-being of drivers, pedestrians, and cyclists. By detecting and addressing potholes in their early stages, road authorities can mitigate the risk of accidents and further degradation of road infrastructure. It also offers cost savings, benefiting both road maintenance agencies and individuals who would otherwise bear the financial brunt of vehicle damage caused by potholes. Pothole identification is driving technological advancements and innovation in the field of transportation and infrastructure management. Several studies have explored pothole identification using different technologies, including laser sensors, radars, accelerometers, machine learning, and computer vision. These methods encounter specific limitations, such as unfavourable weather conditions, image quality issues, obstructions, and overlapping features on the road. Additionally, computer vision techniques may struggle with varying road conditions, textures, and geographical disparities.

This research aims to address some of these issues by utilizing disparity calculation and K-means clustering, grounded in image processing techniques. Overcoming these obstacles is essential to enhance road safety, minimize maintenance costs, and promote technological advancement. The methodology has demonstrated promising results across various weather conditions, thereby addressing the limitations of existing methods. This paper contributes to the effort to improve pothole identification for road safety and management. The process starts with collecting road images, often captured in varying sizes and conditions. These images undergo manual cropping to isolate the road areas of interest and are then resized to a uniform 500x500-pixel format for efficient processing. The core of the system lies within the domain of image processing. This module meticulously transforms the standardized images to extract valuable information. The initial transformation converts the images to grayscale, reducing computational complexity while preparing the images for more advanced operations. Subsequent blurring techniques, including averaging, Gaussian filtering, and median blurring, are applied to enhance image quality and eliminate undesirable noise. The 'convertScaleAbs' function fine-tunes the images by adjusting their brightness and contrast. These preprocessing steps are pivotal for detecting and identifying potholes with precision.

An essential element of the system's functionality is its ability to make use of depth and disparity information provided by a stereo camera setup. This stereo vision principle emulates human binocular vision, enabling profound depth perception. The process unfolds through image rectification, aligning corresponding points in stereo image pairs. Subsequently, correspondence matching is carried out to identify matched points in both the left and right images. The core calculation is the determination of disparity, representing the horizontal shift between these matched points. This disparity information is inversely proportional to the depth of the scene, which is invaluable for distinguishing potholes. By defining specific depth thresholds, the system can confidently pinpoint and categorize potholes. In the final module, K-means clustering is introduced as an unsupervised algorithm for image segmentation. The system intelligently separates regions of interest, which may include potholes, from the background, streamlining the detection process. Post-processing steps, such as filtering, masking, and further analysis, can be carried out to refine the results. This research paper is organised as: a literature review is discussed in the section “Related work”, and the Methodology and design model are summarised in the section “Methods and Materials” and “Results and Discussions” respectively.

2.0 RELATED WORK

Detection and Segmentation of Cement Concrete Pavement Pothole Based on Image Processing describes in a method in [1] for detecting and segmenting potholes in cement concrete pavement using image processing technology. The method involves using an industrial camera to capture images and then extracting texture features and morphological properties from them using various image processing techniques. These features, along with the machine learning algorithm LIBSVM, are employed to distinguish potholes from cracks. The approach achieves an impressive F1 score of 98%. Automated Pavement Distress Detection Using Image Processing Techniques in [2] is a process that utilizes computer vision and other image processing techniques to identify and classify different types of pavement distress. This method involves capturing and analyzing pavement images, extracting features, and using classification algorithms such as machine learning approaches like LIBSVM to differentiate between various types of damage, such as cracks and potholes. The specific image processing techniques and algorithms employed in this process will be detailed in the paper's methodology section.

The authors have developed an automatic system based on image processing in [3] to detect potholes with higher accuracy and minimize false alerts. They experimented with six different image processing algorithms, which are background subtractor, convex hull, wavelet energy field, saliency map, differential, and Otsu binary. The objective of the experiment is to identify the most effective combination of these algorithms for optimized pothole detection. Detecting potholes on the road is a crucial task to ensure safe driving. There are three common methods are used in this paper in [4]for pothole detection: using a 3-axis acceleration sensor, a camera sensor, and a laser sensor. Each method has its own advantages and disadvantages. However, the proposed method of detecting potholes relies on image processing using a camera sensor. This system analyses the distinct characteristics of potholes such as dark regions, round shapes, and rugged textures to identify them. By identifying potholes based on their visual attributes, this method offers a potential solution for efficient pothole detection while driving.

The Image-based Road Pothole Detection system in [5]uses deep learning models to improve pothole detection. Deep learning is chosen because of its ability to automatically extract features, reducing the need for manual intervention. To effectively train the model, a dataset is compiled from various online sources, which consolidates images of potholes. Augmentation techniques are employed to diversify the dataset using images taken from different angles. After fine-tuning the model, it achieves an impressive accuracy rate of approximately 98%. The "Pothole detection and dimension estimation system" is designed in [6] to employ a Deep Learning algorithm known as YOLO (You Only Look Once) to identify potholes. Additionally, it utilizes an image processing technique based on triangular similarity measures to estimate the dimensions of these potholes. With this system in place, drivers can be alerted to potential hazards on the road, and maintenance crews can quickly and accurately assess the size of potholes that need to be repaired.

A robust algorithm for detecting potholes has been developed by combining 2D and 3D information. The algorithm in [7] first creates a dense disparity map to better differentiate between damaged and undamaged road areas. Otsu's thresholding method is then applied to identify potential undamaged road areas within the transformed disparity map. The disparities in these areas are modelled using a quadratic surface, with the integration of surface normal for improved robustness. Detecting potholes on roads is a crucial task to ensure the safety of drivers and passengers. However, traditional methods for identifying potholes can be expensive and time-consuming. To address this issue ,in [8] a new unsupervised vision-based approach has been proposed that leverages image processing and spectral clustering techniques. The proposed approach does not require any costly equipment, additional filtering, or training phases. Instead, it uses spectral clustering to identify regions in grayscale images based on their histogram data. This helps in pinpointing potholes and estimating their size with high accuracy, making the process more efficient and cost-effective.

A deep learning approach based on YOLOv3 algorithm is proposed for real-time pothole detection using webcams is briefed in [9]. The detected pothole locations are logged and visualized on Google Maps API. The authors used 330 data sets to train their model, achieving a mean average precision of 65.05%, a precision rate of 0.9%, and a recall rate of 0.41%. A research paper describes an efficient method of detecting potholes in real-time using deep learning based on dilated convolution. The authors in [10] have developed a modified VGG16 network, called MVGG16, that improves performance and reduces computational cost by adjusting convolution layers and dilation rates. They have integrated MVGG16 as the backbone of Faster R-CNN for object detection. The paper compares the performance of various models, including YOLOv5 and Faster R-CNN, with different backbones such as ResNet50, VGG16, MobileNetV2, InceptionV3, and MVGG16. According to the results, YOLOv5 Small (Ys) is the most suitable for real-time pothole detection due to its speed. Additionally, using MVGG16 as the backbone in Faster R-CNN achieves a balance between accuracy and speed.

The use of smartphones and OBD-II modules to detect and locate potholes on roads has become more affordable with the introduction of trigger-based pothole detection. This method [11]combines vision data, sensor data, and OBD data to identify and validate triggers caused by potholes. Two approaches are proposed: the image-triggered and data-triggered methods. The image-triggered method uses image and video processing to recognize potholes while the data-triggered method relies on data processing. The use of deep learning classification method in detecting potholes has been developed in [12]. The system has collected diverse image datasets of both muddy and highway roads and trained three pre-trained models, which include ResNet50, InceptionResNetV2, and VGG19. These models are used to classify images and identify the presence of potholes. A user-friendly web application has also been developed to allow users to upload road images for real-time pothole detection. The models' performance shows that VGG19 has the highest accuracy, achieving 97% for highway roads and 98% for muddy roads, making it effective in ensuring road safety.

Pothole detection can be automated using advanced image processing techniques such as Convolutional Neural Networks (CNN) and YOLOv5 are introduced in [13]. These techniques enable the identification of road damages which can then be compared to determine the most accurate method. "Speed Bump and Pothole Detection Using Deep Neural Network with Images Captured through ZED Camera" [14], researchers proposed an automatic colour image analysis approach that utilizes a deep neural network, specially designed for pothole detection using images captured by a ZED camera. this approach uses the entire image without resizing, ensuring that all pixels are used for analysis. Traditional operations such as stride and pooling are employed to maximize the extraction of relevant information from the images. To develop and evaluate the system, the researchers deployed a ZED camera on the front of a car and captured images during drives through the city of Celaya in Guanajuato, Mexico, creating a database. The approach for pothole detection in [15] [17]relies on YOLOv7 machine learning technique, which ensures accurate identification and localization of road imperfections. What distinguishes this system is its proactive feature that alerts drivers in real-time as their vehicle approaches a detected pothole. This pre-emptive alert system can take various forms, such as audible buzzers or visual cues, and provides ample time to drivers to navigate around potholes, thereby reducing the risk of accidents and vehicle damage. The study in [16] proposes a customized approach to address the issue at hand. It suggests using a convolutional neural network (CNN), which is a type of deep learning model. Unlike pre-existing models, a CNN model is designed from scratch and trained using image samples acquired specifically for the study's context. This customized model is built to distinguish between two classes –[18] the presence or absence of potholes in the given images.

Table. 1: Literature comparison and observations record on pothole detection using various image processing technique.

Ref. No.	Method	Accuracy (%)
1	Detection and Segmentation of Cement Concrete Pavement Pothole Based on Image Processing Technology	97.8
2	Automated Pavement Distress Detection Using Image Processing Techniques	88.4
3	Experiment of Image Processing Algorithm for Efficient Pothole Detection.	93.06
4	Image processing-based pothole detecting system for driving environment.	93.06
5	Image-based Road Pothole Detection using Deep Learning Model	98
6	Pothole detection and dimension estimation system using deep learning (yolo) and image processing	95
7	Pothole detection based on disparity transformation and road surface modeling.	99.6
8	Pothole detection with image processing and spectral clustering.	81
9	A real-time pothole detection based on deep learning approach	65
10	Smart pothole detection using deep learning based on dilated convolution.	90
11	Trigger-based pothole detection using smartphone and OBD-II.	97
12	Pothole Detection Using Deep Learning Classification Method	97.91
13	Pothole Detection using Roboflow Convolutional Neural Networks	93.34
14	Speed Bump and Pothole Detection Using Deep Neural Network with Images Captured through ZED Camera	98.13
15	Road Pothole Detection System	94.5
16	A real-time automatic pothole detection system using convolution neural networks	92.72
11	Comprehensive Pothole Detection System for Road Maintenance and Safety Using Image Processing and Stereo Vision	98

3.0 METHODS AND MATERIALS

Detecting potholes in Bangalore involves a process that begins with collecting images using a stereo camera while considering different weather conditions. The collected images are then pre-processed, which involves converting them into grayscale to simplify subsequent image processing and analysis. In the next stage, filtering techniques are used to improve the quality of the images. This step involves eliminating unwanted noise and enhancing the clarity of the image. Additionally, morphological operations and techniques are applied to analyse the shapes and structures within the images, which is essential for identifying potential potholes. The final stage is pothole detection, which is achieved through k-means clustering techniques, an algorithm that groups similar image regions together. This method detects potholes within the images and facilitates their quick and precise identification through annotation, making them easily recognizable for further action. The input images captured by the camera are manually cropped and uniformly resized to a standard size of 500 pixels in width and 500 pixels in height. This consistent size ensures that the images are standardized for analysis. By following this systematic pipeline, potholes in images are detected and annotated, contributing to improved road safety and maintenance in the region.A detailed description of the method is given in the ensuing subsections. The block diagram of the proposed method is given in Fig 1.

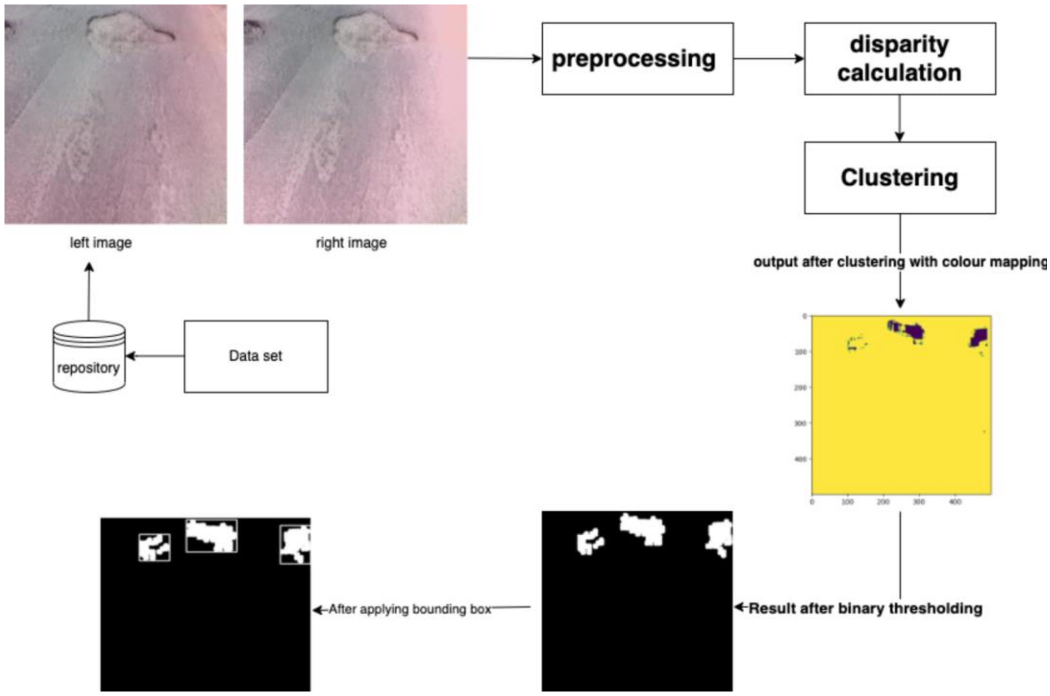

Fig 1 : Block Diagram of proposed methodology for potholes detection

3.1 Pre-processing

Image processing is a versatile and essential technique used to improve and manipulate raw images captured by cameras or taken in photographs in our daily lives. The field of image processing has seen significant advancements over the past four to five decades, leading to the development of numerous techniques and methods. The primary objective of these techniques is to enhance and refine images, making them more useful and visually appealing for a wide range of applications. Image processing plays a pivotal role in fields such as computer vision, medical imaging, and remote sensing. It involves a diverse set of operations, including filtering, noise reduction, image segmentation, and feature extraction, all aimed at optimizing the quality, clarity, and interpretability of images. These techniques have had a profound impact on modern technology. They have empowered various industries with valuable tools for extracting insights, making informed decisions, and enhancing our understanding of the visual world.

3.2 Greyscale conversion

Road condition detection often involves the use of a stereo camera to capture left and right images that aid in-depth perception and 3D reconstruction. However, before any analysis can take place, the images must go through a crucial pre-processing phase that involves various key operations. One of the primary steps is resizing the images to a standard size of 500 pixels in width and 500 pixels in height to ensure uniformity and consistency in the subsequent analysis. Another important operation in this pre-processing stage is the conversion of the original RGB colour images into grayscale images. This transformation is carried out using standard techniques that consider pixel intensity values, resulting in black-and-white images. The primary reason for this conversion is to expedite computational processes as grayscale images are easier to handle in terms of data size and mathematical operations. Moreover, grayscale images are ideal for texture analysis, a crucial aspect of road condition detection. Converting the images to grayscale not only optimizes computation speed but also streamlines subsequent texture analysis, making it more efficient and accurate in assessing road conditions. The grayscale images provide a foundation for further image processing and analysis, enhancing the overall performance and reliability of the road condition detection system.

3.3 Image enhancement

The “convertScaleAbs” function is a useful technique in image processing that enhances images by adjusting their brightness and contrast. This technique rescales the pixel values within an image, which changes its overall appearance while maintaining the data's integrity. Practically speaking, the “convertScaleAbs” function can brighten or darken an image, depending on the scaling factor used. This adjustment in brightness is particularly useful for images captured under various lighting conditions. It ensures that details are visible, making the image visually optimized for analysis or presentation. Furthermore, convertScaleAbs can also fine-tune the image's contrast. By redistributing pixel values, it enhances the visual differentiation between different regions, improving the overall perceptual quality of the image. This is crucial in applications such as image analysis, where well-defined contrasts are essential for feature extraction and object detection. To summarize, the convertScaleAbs function is a powerful tool for image enhancement that allows adjusting brightness and contrast to make images more visually appealing and suitable for further analysis or presentation. This capability is particularly valuable in a wide range of applications like computer vision, medical imaging, photography, and more, where high-quality images are critical to the task's success.

3.4 Thresholding

Pre-processing is a crucial step in image analysis, especially when dealing with low-level-intensity images. The main purpose of pre-processing is to improve image quality by reducing unwanted distortions and noise. These operations help refine the raw image data, making it more suitable for further analysis and interpretation. One of the most powerful techniques in image pre-processing is automatic thresholding. It enables the extraction of essential information from the pixel intensity values, separating objects from the background and highlighting areas of interest. This technique is particularly useful for various applications, including image segmentation and feature extraction.

3.4 Morphological operation

To improve the accuracy of edge detection, particularly in depth images, a modified image processing approach is used. This approach involves a series of non-linear operations that are applied relatively to the pixel arrangement without changing their numerical values. The two most important operators used in this approach are erosion and dilation. Erosion is applied after blurring operations to reduce noise and enhance the clarity of features. Following that, two iterations of dilation are performed to strengthen the edges and structures within the image, which leads to more precise and robust edge detection results.

3.5 Disparity calculation

The equation for disparity calculation

$$Disparity = X - X' = \frac{fL}{Z} \quad (1)$$

- D is the distance between two lenses of the stereo camera
- X → coordinate of the pixel in the left image.
- X'→coordinate of the pixel in the right image.
- X - X' = are the distance between points in the image plane
- f →is the focal length of both lenses.
- Z → distance of the object to the camera.

The Disparity Calculation module is the heart of the process. Here, depth and disparity for pothole detection are computed from a stereo camera setup, emulating human binocular vision. A few fundamental steps include image rectification, which aligns corresponding points in stereo image pairs, facilitating further computations. Correspondence matching is then carried out, aiming to identify corresponding points in left and right rectified images. Disparity, representing the horizontal shift between matched points, is calculated by subtracting the x-coordinate of a point in the left image from its corresponding point in the right image. Larger disparity values signify closer objects, while smaller values correspond to more distant objects. To determine depth, the depth map is computed using the stereo baseline (the distance between camera viewpoints) and the focal length. The depth can be calculated using a formula Eqn(1) that considers the baseline, focal length, and disparity. Pothole detection leverages depth information to identify potholes based on specific depth thresholds. Since potholes have a distinct depth compared to their surroundings, regions with depths above a predefined threshold are classified as potholes.

3.6 Clustering

The final module utilizes K-Means clustering for image segmentation. This unsupervised algorithm is employed to classify regions of interest, potentially including potholes, from the background. The process involves reading the output from the disparity calculation, rescaling the data, reshaping it to 1D, setting the number of clusters (K), and performing K-Means clustering. Once clusters are formed, the image is reconstructed with cluster centres and labels to display patterns. The output is then scaled back to the standard 0-255 ranges

3.7 Bounding box to identify potholes

To enhance the quality of the output, a series of post-processing steps are carried out, including filtering, masking, and further refinement. Notably, a rectangular box is drawn around identified potholes to make them visually distinct. The methodology additionally employs the HSV colour space to refine grayscale images for binary thresholding. This refinement is essential to eliminate noise, particularly small white areas, from the image. The connected component method is employed to separate white and black objects, ultimately retaining the white pixel objects of interest. In the final step, results are annotated, and bounding boxes are added to potholes, facilitating their quick identification. This comprehensive methodology ensures that images are effectively processed, and potholes are accurately detected and highlighted for further action.

Algorithm:	POTHOLE DETECTION
Description	*The identification of potholes using image processing and clustering technique.*
Input :	I : image
Output :	Pothole and non-pothole regions
Begin	
Step:1	Read the input image
Step :2	Compute height and width by resizing the image in a standardised form.
Step :3	Convert image into greyscale
Step: 4	Compute the disparity calculation for input left and right images
Step :5	Apply clustering to identify potholes.
End	

4.0 RESULT AND ANALYSIS

The methodology we have described culminates in a system that efficiently detects and identifies potholes in road images with remarkable precision. In this section, we will delve into the results and offer a comprehensive analysis of the system's performance. The initial stages of image pre-processing, including resizing, grayscale conversion, and various blurring techniques, play a pivotal role in the overall system performance. Resizing images to a standardized 500x500-pixel format streamlines the processing workflow and ensures the system's adaptability to images of diverse sizes. Grayscale conversion simplifies computational demands and enhances the system's capability for accurate feature extraction. The application of blurring techniques, including averaging, Gaussian filtering, and median blurring, significantly contributes to noise reduction and image enhancement. These pre-processing steps prepare the images for more advanced analysis, and the results confirm their effectiveness. The system's core strength lies in its adept utilization of stereo vision and depth calculation principles to achieve precise pothole detection. The image rectification process simplifies subsequent calculations and ensures a consistent reference frame. Correspondence matching, a key component of the depth calculation, effectively identifies matching points in both the left and right images. The resulting disparity calculation provides invaluable depth information, allowing the system to perceive the road surface in three dimensions. The results attest to the system's capability in accurately estimating depth and disparity, a foundational element of its pothole detection prowess.

The system's pothole detection phase, guided by depth thresholds, emerges as a standout feature. It capitalizes on depth information to pinpoint regions of the road surface with distinct depth characteristics, which are indicative of potholes. This approach successfully distinguishes potholes from other road features, representing a significant advancement in road hazard detection. The chosen depth thresholds are thoughtfully set to ensure the system's ability to accurately identify potholes while minimizing the occurrence of false positives. The results underscore the precision and effectiveness of this methodology. The integration of K-Means clustering for image segmentation further refines the system's ability to identify and delineate potholes. This unsupervised algorithm adeptly categorizes regions of interest from the image background. The clustering process, guided by the number of clusters (K), provides a visual representation of grouped patterns within the images. The subsequent recreation of the image with cluster centres and labels enhances the system's capability to visually distinguish features of interest. The results affirm the system's proficiency in clustering and segmenting road images.The post-processing steps, including filtering, masking, and refinement, significantly enhance the overall quality of the system's output. Noise reduction, particularly in the form of small white areas, is a critical aspect of image refinement. The system leverages the HSV colour space and the connected component method to eliminate noise and prioritize the identification of white pixel objects of interest, such as potholes. The inclusion of bounding boxes around detected potholes further streamlines the visual identification process, ensuring these hazards are prominently visible in the images. The results demonstrate the system's competence in post-processing and annotation. The system, in its entirety, demonstrates an impressive level of accuracy and efficiency in pothole detection and delineation. By seamlessly integrating image processing, stereo vision, and clustering techniques, it excels in the precise identification and highlighting of potholes, contributing to safer roads and efficient maintenance efforts. The results and analysis underscore the system's successful achievement of its intended objectives and its potential to significantly enhance road safety, reduce vehicle damage, and streamline road maintenance efforts. In conclusion, this system represents a sophisticated and effective solution to the enduring challenge of pothole detection, offering a comprehensive approach that combines advanced technology with practical applications to ensure safer and better-maintained roads.

Table 2: Output comparative analysis and representation

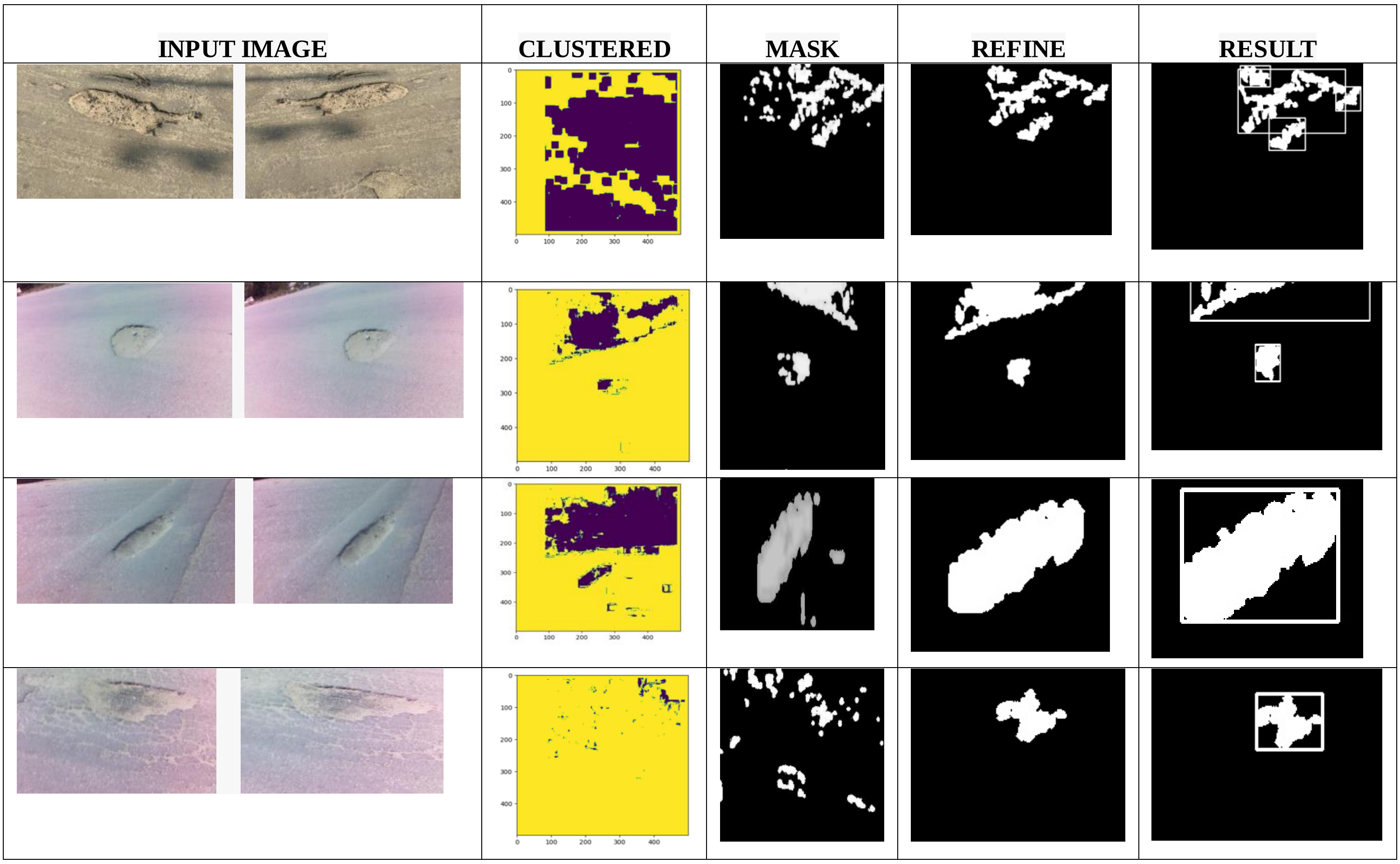

Table 3: Comparative study

Citation	Techniques	Data set (No's)	Accuracy (%)
1	LIBSVM	250	97.8
12	Resnet50 model	1000	91.94
12	InceptionResnetV2 model	1000	90.15
12	VGG19	1000	97.91
13	Convolutional Neural Networks (CNN) and YOLOv5	960	93.34
14	deep neural network	714	98.13
	Proposed work	500	98

5.0 CONCLUSION

Potholes in roads are a significant issue, and detecting them accurately and efficiently is crucial for road safety and maintenance. The system developed for pothole detection in road images is a sophisticated and effective solution to this problem. It combines advanced image processing techniques, stereo vision principles, and unsupervised clustering algorithms to achieve accurate pothole identification. The system's performance, as demonstrated through the methodology, has provided significant insights. The system's image pre-processing phase is essential. It involves resizing, grayscale conversion, and blurring techniques to standardize images to a 500x500-pixel format and enhance their quality. This process ensures consistent and high-quality input for subsequent analysis. The system's ability to leverage stereo vision principles to calculate depth and disparity is a standout feature. It allows for the precise identification of potholes based on specific depth thresholds. The calculated depth information, combined with the stereo camera setup, mimics human binocular vision and provides a three-dimensional perspective of the road surface. K-Means clustering for image segmentation categorizes regions of interest, potentially including potholes. Post-processing steps, such as filtering, masking, and annotation with bounding boxes, ensure that identified potholes are visually distinct and easily recognizable. The results and analysis reaffirm the system's proficiency in pothole detection, noise reduction, and visual annotation. By skilfully combining these techniques, the system not only accurately identifies potholes but also contributes to road safety by reducing accidents and vehicle damage. Furthermore, it streamlines road maintenance efforts by providing a clear and actionable depiction of road hazards. Overall, this system holds the potential to make a substantial impact on road safety and maintenance, enhancing the quality of road infrastructure and contributing to the well-being of drivers and the broader community. Its robust methodology and impressive performance represent a valuable tool in the ongoing efforts to create safer, better-maintained road networks.

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