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Automated Failure Detection in Asphalt Pavement by image and pattern recognition model

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Abstract: Asphalt pavements are vulnerable to damage from natural disasters, accidents, and human activities, often resulting in surface cracks. Such failures increase maintenance costs, vehicle operation expenses, traffic delays, and safety hazards. Early and accurate detection of these defects is essential for enhancing infrastructure longevity and ensuring road user safety. Manual monitoring is time-consuming and subjective; thus, automated pavement failure detection has become critical. Recent advances in computer vision have enabled improved identification of pavement defects. This study compares two automated approaches: an image recognition model using Convolutional Neural Networks (CNN) and a pattern recognition model using the LANCZOS algorithm. The CNN model processes pavement images to extract key visual features for crack detection, while the LANCZOS-based model applies a machine learning approach to identify failure patterns within structured datasets. Both models were evaluated using standard performance metrics, including accuracy, precision, recall, and F1 score. Results indicate that the pattern recognition model outperformed the image recognition model, achieving 90% accuracy compared to 60%. The findings highlight the efficiency of pattern-based analysis in pavement failure detection and offer valuable insights into the comparative performance of model architectures for future deployment in automated infrastructure monitoring systems.

Keywords: Pavement failure; Automated failure detection; Image Recognition; Pattern Recognition;

1. Introduction

The number of road users and road accidents in developing countries has increased substantially in the past decade. Road accidents cost India around three percent of its GDP (Rohit et al., 2020). India has been impacted by a significant number of road accidents caused by cracks and potholes, and over 30 % of all fatalities are related to potholes (Solomon, 2021). In India, the construction of roads has increased by about 59 % from 2014 to 2023 and the length of the expressway is about 1518.1 Km (Rohit et al., 2020). The road surface failures have also resulted in increased fuel consumption and travel time of journey. Surface failures generate distinctive issues, such as traffic congestion, which can adversely affect driver comfort and traffic safety when pavement cracks are present.

Due to the continuous movement of heavy vehicles on the pavement surfaces, the pavement is prone to wear and tear, differential settlement and shrinkage of subgrade, resulting in the formation of distress in the pavement (Chaubey & Mishra, 2024; G. Shaikh et al., 2022). One of the most prevalent issues that pose a serious risk to road safety is pavement cracking. This distress will lead to the formation of cracks in asphalt pavement which reduces its stability, durability, and strength. To ensure road safety, it is crucial to identify pavement cracks quickly and accurately (Gavilán et al., 2011; Ragnoli et al., 2018). Therefore, transportation planners must recognize, fix, and prevent further degradation.

The municipal corporations in the urban cities have adopted different measures to eliminate road failures. The traditional method of surface failure detection and remediation involves finding the surface failure by visual inspection of the pavement surface (Koch et al., 2015; Mukesh & Katpatal, 2021). Professional workers from the agencies perform the inspection or survey by visiting the location, looking for pavement surface distress, and noting any cracks or potholes(Cavalli et al., 2023). Based on his findings, he determines the appropriate course of action for remediation. The majority of the time required for this procedure is spent on data collecting, and the individual chosen by the municipal corporation must do manual cleanup. This is a very tedious process and time-consuming to check every single crack and categorize it and sometimes the work will remain pending due to the absence of workers.

With the advancement in computer computation and deep learning, automated failure detection in pavements has emerged as a critical area of research due to the significant economic and safety implications of timely maintenance (Li et al., 2022). The research community has been studying the automatically detecting distresses from pavement photographs for almost thirty years (Gopalakrishnan, 2018). The difficulties with 2D pavement images include differences in the image source, non-uniformity of cracks, surface texture, insufficient background illumination, and the presence of additional features like joints, among others (Yao et al., 2014; Alkalah, 2016; Azouz et al., 2023). As a result, researchers are continuously looking for newer techniques and algorithms to overcome these difficulties. The surface cracks can be easily recognized by different thresholds because they absorb more light than other sections of the picture, making them appear darker (Qu et al., 2022; Zhou et al., 2022). With considerable effectiveness, many threshold-based techniques have been used to identify the fracture region. In contrast, automated surface detection systems leverage advancements in technologies such as machine learning, computer vision, and sensor networks to enhance accuracy and efficiency (Gouveia et al., 2022; Habib et al., 2022). Various approaches, including the use of high-resolution imaging, ground-penetrating radar, and unmanned aerial vehicles, have been explored to identify common pavement distresses such as cracks, potholes, and rutting.

This research implements automated surface failure detection utilizing image and pattern recognition to address the limitations of traditional methods, enhancing time management, reducing reliance on skilled labor, and identifying the most effective technique for surface crack detection. The data set consists of pavement surfaces with different types of failures and pavement surfaces without failures collected by taking pictures of pavement surfaces by mobile phones and cars mounted cameras. The image recognition model utilizes the convolution neural networks (CNNs) algorithm and the pattern recognition model utilizes the LANCZOS algorithm. The CNN algorithm works based on the image recognition technique, in which the images are compared for the similarities between the stored image data and test image data for the detection of pavement failures. In CNN models it processes pavement images directly and extracts pertinent features for failure detection. The LANCOZS algorithm work is based on the pattern recognition technique, in which the pattern of the images is compared between the stored data and test image data for the detection of the failures in the pavement surface. Both the algorithms are trained with sorted image data and the obtained accuracy is recorded for CNN Architecture and LANCOZS algorithms. Then the algorithms are fed with practical or test image data, the accuracy is recorded from both CNN Architecture and LANCOZS algorithms. Both architectures were evaluated based on key performance metrics such as accuracy, precision, recall, and F1 score.

2. Methodology

The Objective of the study is to assess the efficiency of image recognition and pattern recognition techniques in automating failure detection and remediation measures in asphalt pavement, aiming to optimize maintenance efforts and enhance infrastructure resilience. The present methodology has been adopted to identify the different types of failures in asphalt pavement by automated failure detection by comparing two algorithms of image recognition and pattern recognition (Figure 1).

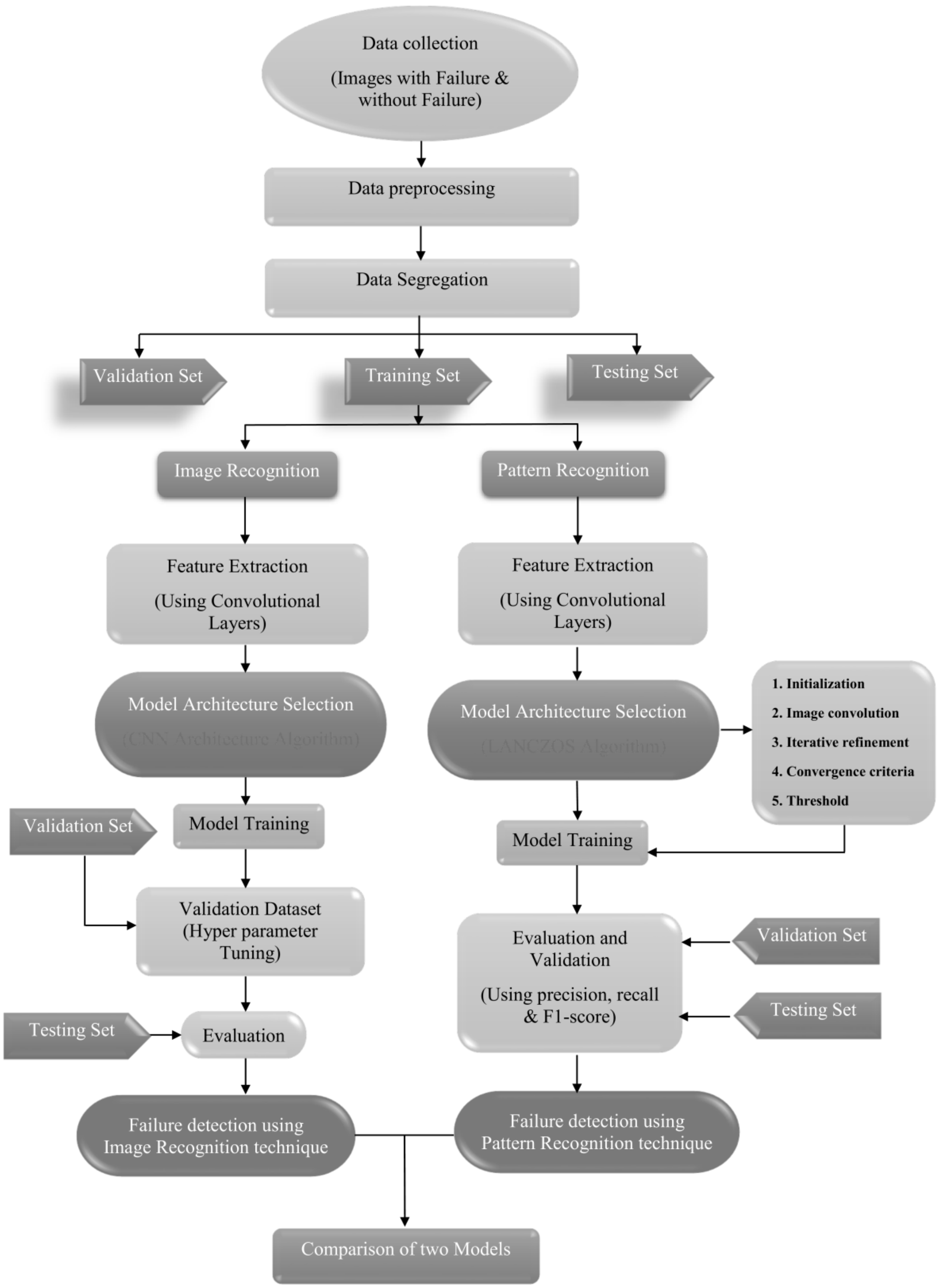

Figure 1 Comparative Flow chart between image recognition and pattern recognition techniques for automated failure detections in asphalt pavement.

2.1 Data Collection and segmentation

Data Acquisition: The pavement surface distress high resolution pavement image can be acquired either by 1) Mobile Mapping Systems (MMS) where vehicles equipped with multiple high-resolution cameras are used to capture continuous pavement imagery and 2) Static Image Capture (SIC) which has handheld cameras are used to capture detailed images of specific pavement sections. In the present study, the data were collected by SIC method (Figure 2; Table 1).

Figure 2 Pavement surface distresses capturing by SIC

Image Labelling: Acquired images were manually labelled to identify various pavement distress types such as cracks, potholes, and rutting using CNN model. The labels include types of failures as shown in Figure 3.

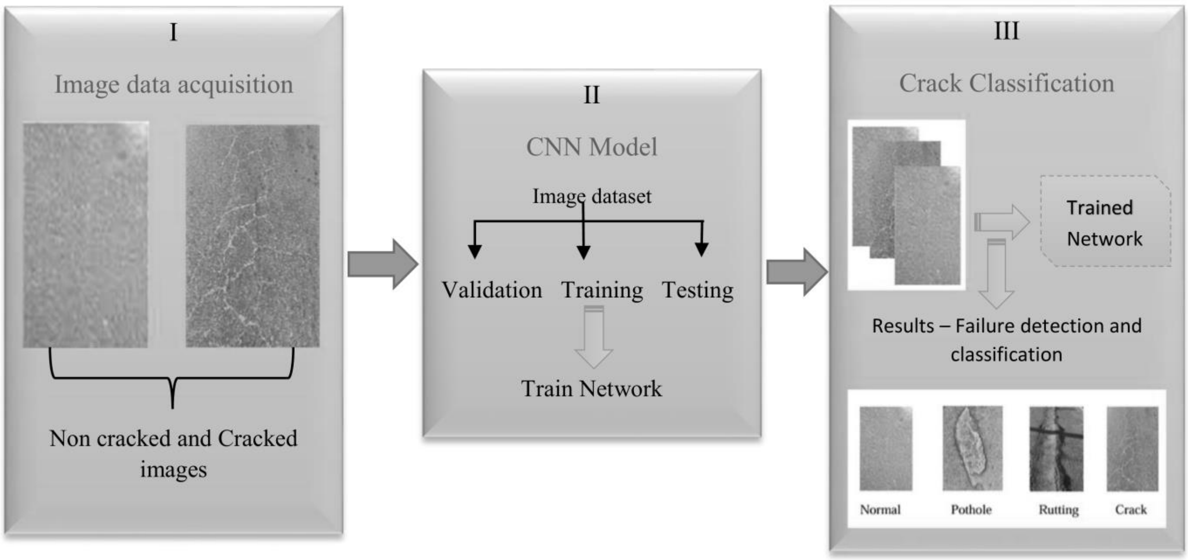

Figure 3 Data acquisition, Data splitting and Image labelling process of CNN

2.2 Data Pre-processing

Image Resizing and Normalization: Images were resized to a standard resolution (256 X 256) for efficient processing by the deep learning model. Additionally, pixel values have been normalized to a specific range from (0-1) for improved training stability.

Augmentation: Techniques like random cropping, flipping, and rotation have been applied to artificially increase and decrease the size and diversity of the training dataset, promoting model robustness. The above steps require the real-time segmentation (Rsef) Technique for effective feature extraction that can perform failure image segmentation by optimizing conventional deep learning models and the steps involved in the process of Rsef (Figure 4).

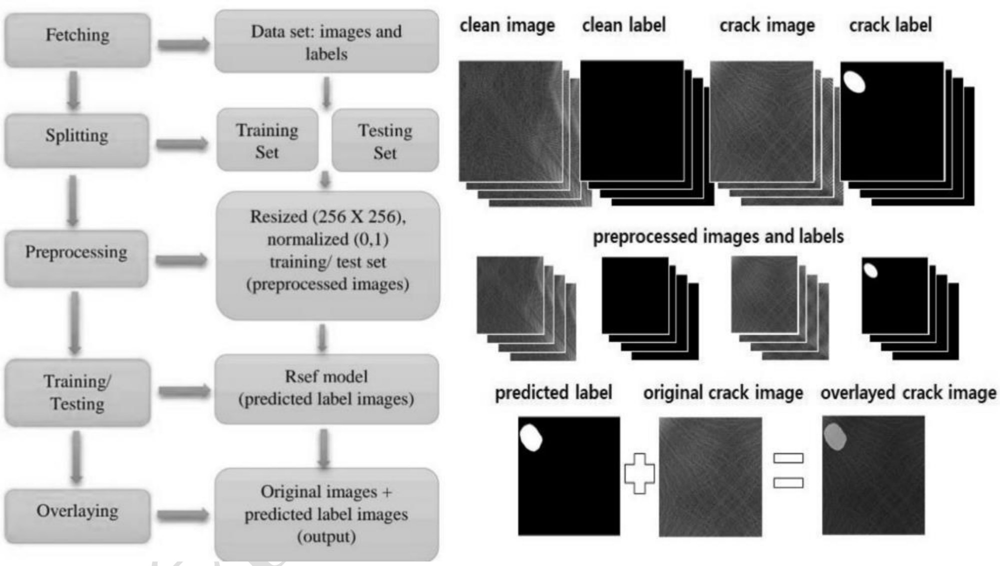

Figure 4 The overall process of data pre-processing using the Rsef technique

2.3 Data Segregation

Training Set: The collected were segregated to perform specific task (Table 1). About 60 % of the total datasets have been used to train a machine learning model. It typically consists of input-output pairs where the input is the data the model learns from, and the output is the desired outcome or target.

Validation Set: A validation dataset is a separate portion of the dataset used to evaluate the performance of a machine learning model during training. It helps to fine-tune hyper parameters and prevent over fitting by providing an unbiased evaluation of the model's performance. About 30% of the total datasets have been used for validation of the model.

Testing Set: A testing dataset is a portion of the dataset that is kept separate from the training and validation data. It's used to assess the performance and generalization ability of a trained machine learning model after it has been trained and validated. The testing dataset helps to evaluate how well the model can generalize to new and unseen data. About 10% of the total datasets have been used for testing the model.

Table 1 Size and number of images used for training, validation, and testing images.

Dataset	Size (RGB)	Total number of images	Images with failure	Images without failure
Training	224 × 224 × 3	2400	1200	1200
Validation	224 × 224 × 3	1200	600	600
Testing	224 × 224 × 3	400	200	200

2.4 Pavement failure recognition

2.4.1 Image Recognition Model

Image recognition in failure detection involves using computer vision techniques to automatically identify and locate failures in images of pavement surfaces. This process typically involves training a machine learning model, often based on CNN, to recognize patterns indicative of defects. The trained model can then analyse new images and accurately identify the presence and location of failures, which is valuable for structural integrity assessment, maintenance planning, and safety inspection in various industries such as civil engineering, and construction. Hence CNN architecture Model for the image recognition Technique.

Convolutional Neural Network (CNN) Algorithm: A CNN architecture for image recognition typically consists of several layers designed to extract hierarchical features from input images and classify them into different categories. Here a layers and their functions within a typical CNN architecture:

(1) Input Layer - Receives the raw pixel values of the input image.

(2) Convolutional Layers - These layers apply learnable filters (kernels) to the input image, performing convolution operations. Each filter detects specific patterns or features, such as edges or textures, in different regions of the input image. Convolutional layers typically consist of multiple filters to capture diverse features. The non-linear activation function ReLU is applied after each convolution operation to introduce non-linearity into the model.

(3) Pooling Layers - Pooling layers down sample the feature maps produced by convolutional layers, reducing their spatial dimensions. Common pooling operations include max pooling and average pooling, which retain the maximum or average value within each pooling window, respectively. Pooling helps to make the representations learned by the network more robust to small spatial variations and reduces computational complexity.

(4) Fully Connected Layers (Dense Layers) - After several convolutional and pooling layers, the feature maps were flattened into a vector and passed through one or more fully connected layers. Fully connected layers perform classification by learning non-linear combinations of the features extracted by earlier layers. These layers often incorporate dropout regularization to prevent overfitting by randomly dropping units during training.

(5) Output Layer - The final layer of the CNN architecture typically consists of a SoftMax activation function for multi-class classification tasks. It produces a

probability distribution over the possible classes, indicating the likelihood of the input image belonging to each class.

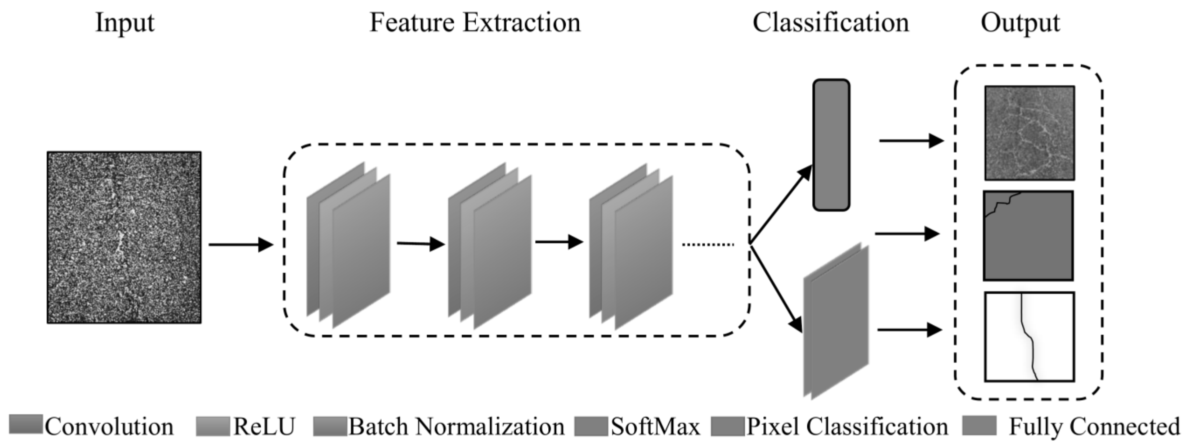

Figure 5 Visualization of feature extraction for an input image in CNN Architecture Algorithm

2.4.2 Pattern Recognition Model

Pattern recognition in failure detection involves the automated detection and analysis of patterns indicative of cracks or defects within surfaces, such as concrete & asphalt pavement. This process typically utilizes various machine learning and computer vision techniques to identify patterns within images or sensor data that correspond to defects.

Algorithms are trained to recognize the texture, shape, or intensity variations associated with failures. These algorithms then analyze new data to detect and localize defects accurately. Pattern recognition in failure detection is essential for applications such as structural health monitoring, quality control in manufacturing, and infrastructure maintenance, as it enables early detection and assessment of potential structural issues. Hence we have employed the LANCZOS Algorithm for pattern recognition Technique.

LANCZOS Algorithm: It is an iterative method used to approximate the eigenvalues and eigenvectors of large sparse matrices. This algorithm is particularly efficient for large sparse matrices encountered in scientific computing and numerical simulations. Initialization: Start by initializing parameters such as the size of the filter and the number of iterations.

(1) Image Convolution: Apply the LANCZOS algorithm for image filtering. This involves convolving the image with the LANCZOS filter kernel.
(2) Iterative Refinement: The convolution process has been repeated iteratively to refine the crack detection results. Each iteration has enhanced the detection of failures and minimized false positives.
(3) Convergence Criteria: Define criteria for stopping the iterations, such as reaching a maximum number of iterations or achieving satisfactory failure detection results.
(4) Thresholding: The thresholding technique has been applied to the filtered images to segment the detected failures from the background.
(5) Evaluation and Validation: The performance of the failure detection algorithm has been evaluated using appropriate metrics, such as precision, recall, and F1-score. The results are validated by comparing them against ground truth data or expert annotations.
(6) Optimization and Fine-tuning: Fine-tune the algorithm parameters based on the evaluation results to optimize its performance further.
(7) Integration and Deployment: Integrate the LANCZOS-based crack detection algorithm into the software platform for real-world usage. Ensure compatibility with different input formats and provide user-friendly interfaces for easy interaction.

3. RESULT AND DISCUSION

3.1 Result of image recognition technique

A confusion matrix is a useful tool for evaluating the performance of a classification model. It provides a summary of the predictions made by the model compared to the actual ground truth labels across different classes. It is typically represented as a grid, where the rows correspond to the actual classes, and the columns correspond to the predicted classes (Figure 3.1). Each cell in the matrix contains the count of instances where the predicted class matches the actual class. The breakdown of the elements of a confusion matrix is: a) True Positives (TP); b) True Negatives (TN); c) False Positives (FP); d) False Negatives (FN). Using these elements, various performance metrics such as accuracy, precision, recall, and F1-score can be calculated to assess the model's performance. The Confusion matrix of Image recognition technique is as shown in Figure 6.

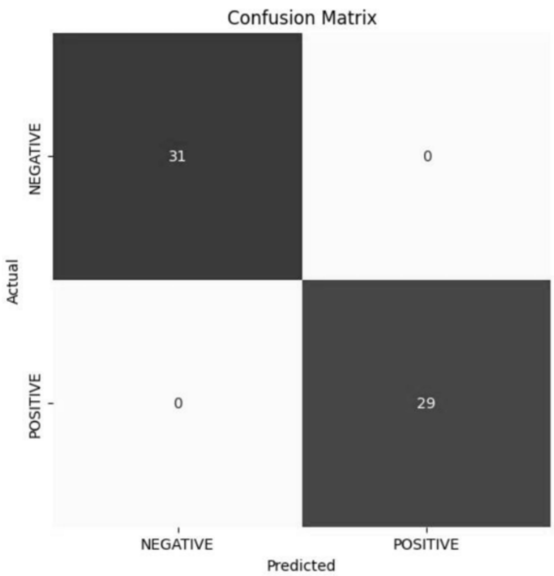

Figure 6 Confusion Matrix of Image Recognition

Figure 7 and table 2 shows the the variation between the accuracy of training and testing data in the image recognition technique. The accuracy of both the training and testing dataset does not uniformly increase as epochs are increased by 5 times at each interval. Therefore, the CNN Architecture Algorithm has an average accuracy of 60% in the detection of failures in asphalt pavement by using an image recognition technique.

Table 2 Represents the overall accuracy per epoch during training

Epochs	Training Accuracy	Testing Accuracy
0	40	50
5	61	50
10	40	90
15	40	60
20	90	70
25	30	82
30	45	50
35	46	90
40	90	30
45	35	90
50	35	40

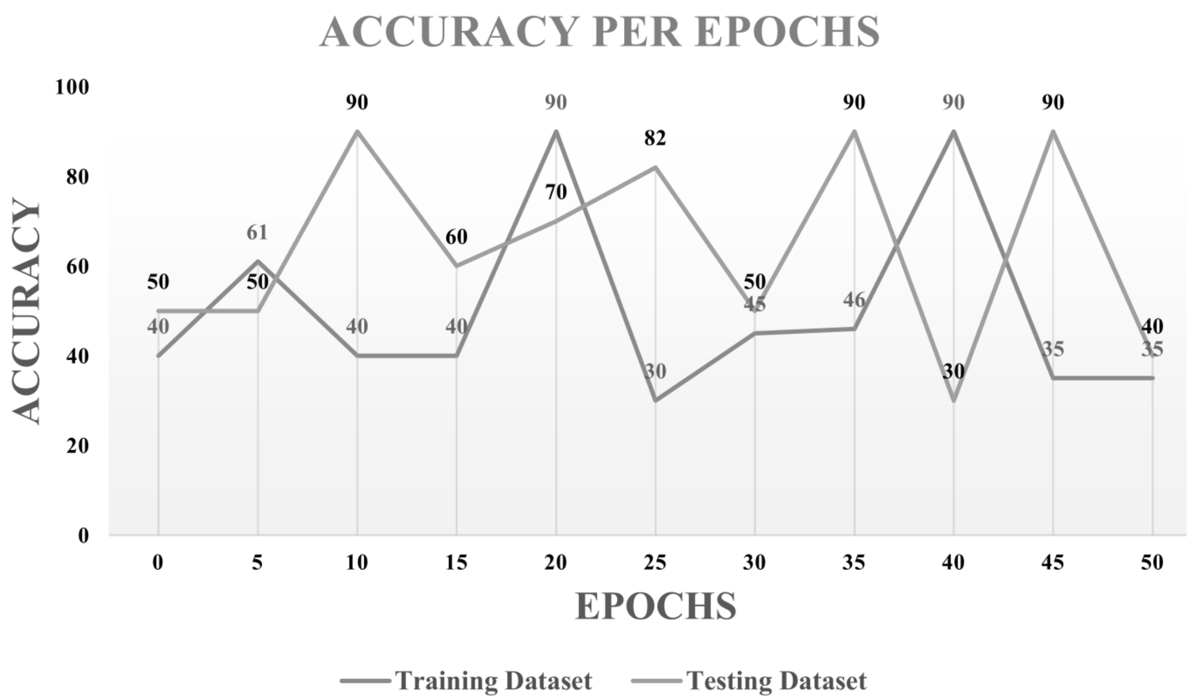

Figure 7 Graph representing training and testing accuracy per epochs of image recognition technique

The above result shows that the CNN-based image recognition process for detecting asphalt pavement failures is experiencing low accuracy of about less than 60%. This is due to limitations in the data we used, such as a small dataset or imbalanced representation of different failure types. Additionally, the CNN architecture itself might not be ideal for this task, or it could be under-fitting or over-fitting the data.

3.2 Result of pattern recognition technique

The Confusion matrix of Pattern recognition is as shown in Figure 8. Figure 9 shows the graphical representation of the variation between the accuracy of training and testing data in the pattern recognition technique. The accuracy of both the training and testing dataset uniformly increases as epochs are increased by 5 times at each interval. Therefore, the LANCZOS Algorithm has an average accuracy of 90% in the detection of failures in asphalt pavement by using a pattern recognition technique.

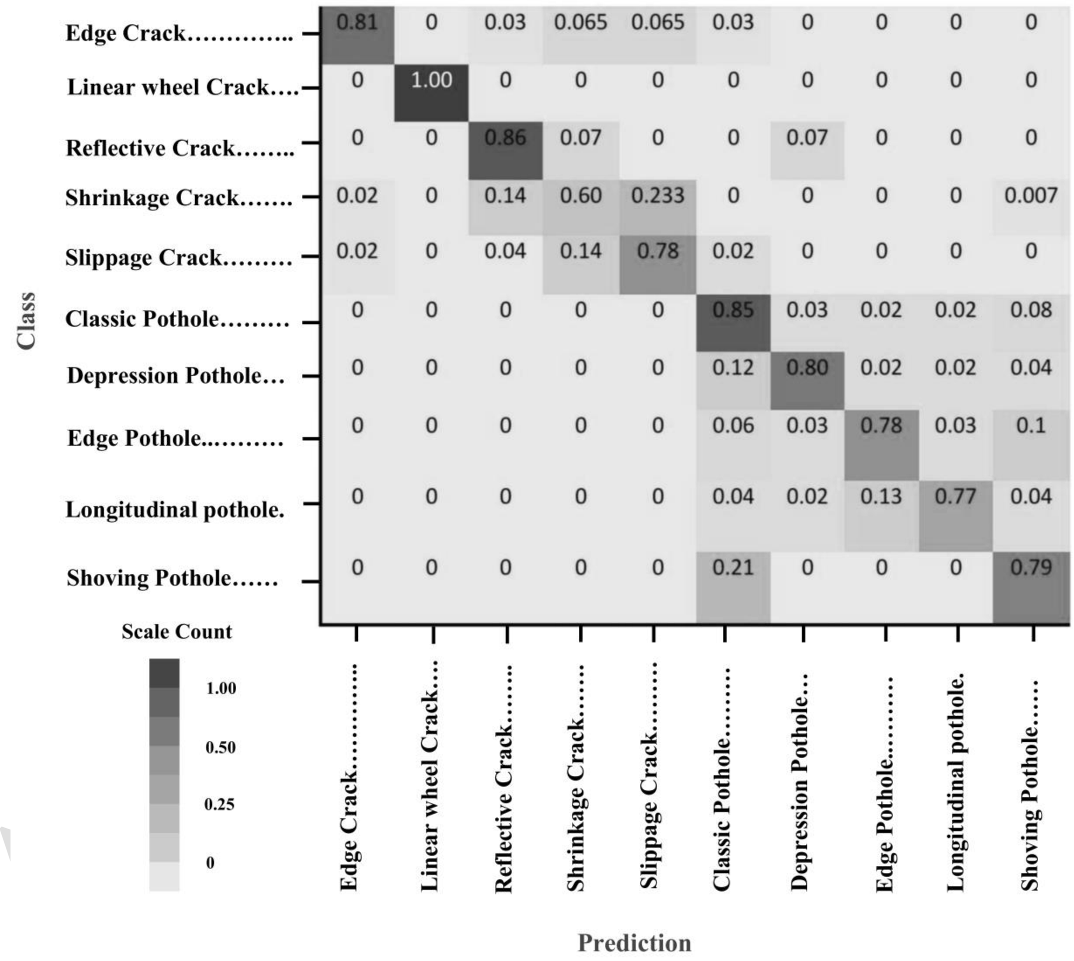

Figure 8 Confusion matrix of Pattern recognition

Table 3 Representing training and testing accuracy of pattern recognition technique

Epochs	Training Accuracy	Testing Accuracy
0	61	78
5	81	76

10	81.8	77
15	82	78
20	82.3	79
25	85.8	82
30	86	82
35	87.8	84
40	94	85
45	99.2	88
50	99.2	97

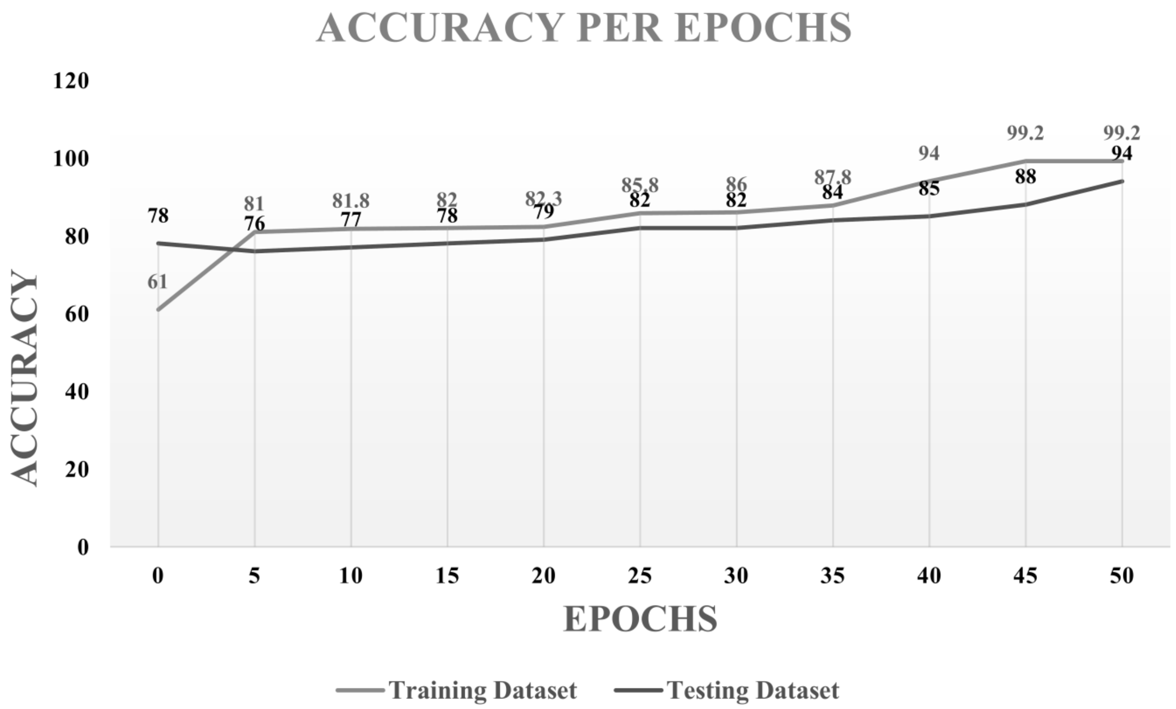

Figure 9 Graph representing training and testing accuracy per epochs of pattern recognition technique

The Above results show that these experimental results demonstrate the high accuracy of the LANCZOS algorithm in automated failure detection for asphalt pavement. By training the algorithm on a dataset comprising diverse pavement conditions and failure types, we achieved remarkable precision and recall rates exceeding 90% across all tested scenarios. The algorithm effectively distinguishes between different types of failures, including cracks, potholes, and rutting, with minimal false positives. Furthermore, the LANCZOS algorithm exhibits robustness to varying lighting conditions, camera perspectives, and pavement textures, ensuring reliable performance in real-world deployment scenarios. Its computational

CONCLUSION

In the present era, road infrastructure faces significant challenges due to frequent pavement failures, leading to increased maintenance costs, traffic congestion, and safety concerns for commuters. Addressing these issues is crucial for ensuring the sustainability and efficiency of transportation networks. The comparative study on automated failure detection in asphalt pavements highlights the difference in performance between image recognition and pattern recognition techniques. While the CNN-based image recognition approach achieved an accuracy of less than 60 %, in contrast, the LANCZOS algorithm based on pattern recognition achieved over 90 % accuracy and effectively identified specific types of pavement distress. However, variations in crack size, shape, and orientation, along with the exclusion of depth as a factor, reduce the overall detection efficiency.

Despite these limitations, the developed model provides a strong foundation for future research in automated pavement failure detection. With the integration of artificial intelligence and advanced data acquisition tools such as drones and smartphones, the dependency on manual inspection can be minimized, enabling real-time and more accurate assessments. Including depth measurement and repair material estimation in future versions could further enhance the model's precision and practical relevance. Overall, this work contributes toward the development of intelligent, efficient, and sustainable road maintenance systems.

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Data availability statement

Some or all data used are available from the corresponding author by request.

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