Impact of Image Enhancement Filters on Road Defect Detection Using Deep Learning

Gabriel T. de Melo Freitas†
Department of Computer Science
Instituto Federal do Ceará - IFCE
Boa Viagem, Ceará, BR
gabriel.tavares@ifce.edu.br

Gabriel G. Carneiro Mota
Department of Computer Science
Instituto Federal do Ceará - IFCE
Boa Viagem, Ceará, BR
ep.gabrielguerreiro@gmail.com

Ernesto F. Nobre Júnior
Department of Transport Engineering
Universidade Federal do Ceará - UFC
Fortaleza, Ceará, BR
nobre@ufc.br

Victor H. C. de Albuquerque
Department of Teleinformatics Engineering
Universidade Federal do Ceará - UFC
Fortaleza, Ceará, BR
victor.albuquerque@lesc.ufc.br

ABSTRACT

The maintenance of road pavements is essential to ensuring the safety and efficiency of land transportation. With advancements in artificial intelligence and deep learning, new possibilities have emerged for automating pavement defect detection. However, the quality of the images used to train these models plays a crucial role in their performance, as variations in lighting or high contrast can compromise the precise identification of defects. In this study, we analyzed the impact of image preprocessing techniques on defect detection using a deep learning model. The CLAHE (Contrast Limited Adaptive Histogram Equalization), LIME (Low-Light Image Enhancement), and gamma adjustment methods were applied, along with unprocessed images. The experiments revealed that the LIME method achieved the best performance, with 78,8% mAP, 91,1% in Precision, 86% in Recall, and an F1 Score of 74%. This study highlights that preprocessing techniques are promising tools for improving the accuracy and reliability of deep learning models applied to the automated detection of defects in asphalt pavement surfaces, significantly contributing to the development of more efficient and accessible pavement management systems.

KEYWORDS

Road Defects, Image Filters, Deep Learning

1 INTRODUCTION

The maintenance of road pavements is a critical task to ensure the safety and efficiency of land transportation. Defects such as potholes and patches compromise the structural integrity of roads, leading to economic losses and increased safety risks for users. In this context, traditional inspection methods, typically involving visual evaluations performed by technicians, present limitations in terms of time, cost, and subjectivity.

Advancements in artificial intelligence and deep learning have opened new possibilities for automating and enhancing the process of identifying pavement defects. Deep neural networks have demonstrated high efficiency in computer vision tasks, such as image detection and segmentation, enabling faster and more accurate analyses. However, the quality of images used for training these models plays a pivotal role in their performance. Images captured under adverse conditions, such as low lighting or high contrast, can hinder the ability of the models to correctly identify defects.

To address this challenge, image preprocessing techniques emerge as a promising approach to improve input quality and, consequently, the performance of deep learning models. Methods such as CLAHE (Contrast Limited Adaptive Histogram Equalization), LIME (Low-light Image Enhancement), and gamma adjustment are widely used across various applications to enhance relevant image features. However, the application of these techniques in the context of road defect detection still lacks systematic studies that evaluate their impact on model performance.

In this study, we propose a comparative analysis of the impact of different image enhancement techniques on the detection of road defects using deep neural networks. Our goal is to investigate how preprocessing filters influence performance metrics such as precision, recall, and inference time, and to identify combinations that optimize segmentation and defect identification. By doing so, we aim to contribute to the advancement of automated pavement management systems, promoting greater efficiency and reliability in the inspection and maintenance of road infrastructure.

2 RELATED WORKS

2.1 Road Defect Detection Using Deep Learning

In recent years, the real-time detection of road pavement defects has been widely applied in Pavement Management Systems (PMS). Deep learning methods have garnered significant interest, with numerous studies exploring their potential in the field of computer vision.

The use of deep learning techniques, particularly Convolutional Neural Networks (CNNs), enables the simultaneous extraction and classification of relevant image features. For instance, [1] proposed a method for detecting eight different classes of pavement defects using a publicly available dataset. Images were collected using a low-cost smartphone in municipalities across Japan, resulting in 9,053 images containing 15,435 defects. The performance of SSD MobileNet and Inception V2 models was compared, and the main contribution of the authors was the implementation of an accessible road inspection system via a mobile application.

Another notable study was conducted by [2], who developed a method for detecting potholes, patches, and cracks in pavements using deep learning. Images were captured by an action camera mounted on the external windshield of a vehicle, totaling 360 images with approximately 500 defects per class. The authors analyzed the impact of image size and iteration numbers on YOLOv3 and YOLOv4 models, highlighting the efficiency of the approach in identifying road defects.

Similarly, [3] developed a pavement defect detection system using YOLO. The study involved capturing images through four different devices mounted on a vehicle, allowing for a comparative analysis of camera positions to determine the best setup for identifying defects. The system achieved impressive results, with the best configuration reaching 99.89% accuracy for pothole detection and 95.91% for patch detection. These results were integrated into an inventory support software, which organizes and presents data through a graphical interface to assist decision-making by pavement managers, researchers, and technicians.

Although many studies in the literature utilize deep learning to identify road pavement defects, most focus solely on the direct application of these models without considering how image preprocessing techniques might influence their performance. This article proposes an innovative approach by investigating the impact of applying image enhancement filters such as CLAHE, LIME, and gamma adjustment prior to training a convolutional neural network. The objective is to determine whether these filters can improve the accuracy and efficiency of detecting defects, such as potholes and patches, compared to using unprocessed images. This study offers a significant contribution both to methodological advancements and to the practical implementation of pavement management systems.

2.2 Image Enhancement

Image enhancement is a fundamental step to improve the visual quality of digital images, facilitating the extraction of relevant information for subsequent analyses. This technique involves applying methods that make images more visually appealing or optimize data extraction processes.

Image enhancement techniques can be classified into two main domains: spatial and frequency [4]. In the spatial domain, pixel values are directly manipulated, while in the frequency domain, the image is transformed into its frequency spectrum using methods such as Fourier transforms, allowing for the manipulation of its frequency components.

Commonly used methods include brightness and contrast adjustment, histogram equalization, noise reduction, sharpening, and color correction. These techniques can be implemented manually using editing tools or automatically through custom algorithms. Image enhancement is widely applied in various fields, including photography, medical imaging, satellite imagery, and video processing [5].

2.3 Contrast Stretching

Contrast Stretching (CS) is a simple image processing technique used to enhance the contrast of an image by expanding the dynamic range of pixel intensities. The goal of contrast stretching is to improve the brightness and contrast of an image, making it clearer and more vibrant. Also known as normalization, contrast stretching employs a piecewise linear transformation to extend gray levels [6], [7].

2.4 Histogram Equalization (HE)

Histogram Equalization (HE) is a technique used in image processing to enhance the contrast of an image. The primary idea behind HE is to transform the pixel values of an image so that they are more uniformly distributed across the entire range of possible values [8]. In HE, the histogram of the image is first computed, representing the frequency of occurrence of each pixel value graphically [9]. Then, the histogram is equalized by redistributing the pixel values to achieve a more uniform distribution across the entire range [10].

The HE process involves two main steps: (1) calculating the Cumulative Distribution Function (CDF) of the image and (2) mapping the pixel values to a new range using the CDF [11]. The CDF is obtained by summing the histogram values from the leftmost bin to the rightmost bin. Then, the pixel values are mapped to the new range by multiplying the CDF value by the maximum pixel value and rounding to the nearest integer.

HE can be applied to both grayscale and color images. However, it may not be suitable for all types of images, particularly those with a narrow range of pixel values or extreme variations in brightness or contrast. In such cases, alternative image enhancement techniques may be more appropriate.

2.4 Adaptative Histogram Equalization (AHE)

Adaptive Histogram Equalization (AHE) is a variation of the histogram equalization technique used to enhance the contrast of an image, particularly in areas with low contrast or uneven illumination [12]. Unlike traditional histogram equalization, which applies the same equalization function to the entire image, AHE uses different equalization functions for different regions of the image based on the local statistics of each region.

The AHE process involves dividing the image into small regions or blocks, computing the histogram for each block, and equalizing each block's histogram independently. This ensures that contrast enhancement is applied only to the regions that require it, rather than affecting the entire image. One of the main advantages of AHE is that it preserves the local contrast of the image while improving overall contrast, making it particularly useful for images with complex textures, such as medical or satellite imagery [13].

However, AHE has certain limitations. It may introduce artifacts in regions where the local histogram is very narrow, such as in uniform areas of the image. This can result in a visible grid-like pattern in the output image, commonly referred to as the "halo effect." Several modifications of AHE have been proposed to overcome this limitation, including Contrast Limited Adaptive Histogram Equalization (CLAHE), which restricts contrast enhancement in each block to avoid the halo effect.

2.6 Contrast Limited Adaptative Histogram Equalization (CLAHE)

Contrast Limited Adaptive Histogram Equalization (CLAHE) is a modification of the Adaptive Histogram Equalization (AHE) technique designed to enhance image contrast while avoiding artifacts such as the "halo effect" that can occur with AHE [14]. In traditional AHE, contrast enhancement can be excessive in image regions with narrow histograms [15]. This can lead to the over-amplification of noise and artifacts in these regions, resulting in a visible grid-like pattern around edges, commonly referred to as the "halo effect."

CLAHE addresses this limitation by restricting the contrast enhancement in each image block. This is achieved by clipping the histogram at a predefined value known as the "clip limit." This ensures that contrast enhancement is not excessive in regions with narrow histograms, thereby preventing the exaggerated amplification of noise and artifacts.

The CLAHE process involves dividing the image into small regions or blocks, computing the histogram for each block, and clipping the histogram at the clip limit. The clipped histogram is then equalized, and the resulting pixel values are used to reconstruct the image. The clip limit is empirically chosen based on the characteristics of the image and can be adjusted to achieve the desired level of contrast enhancement.

CLAHE has been widely used in medical imaging, particularly in X-rays and CT scans, where it enhances image contrast and reveals subtle details that may be missed by the human eye. It is also useful in other domains, such as satellite imagery and computer vision.

2.7 Low-Light Image Enhancement (LIME)

The Low-Light Image Enhancement (LIME) method is widely used to improve the quality of images captured under low-light conditions. It is based on the premise that the illumination at each pixel of an image can be modeled as the product of the intensity of the incident light and the reflectance of the object. The algorithm aims to estimate an illumination map to adjust brightness intensities and enhance the overall visibility of the image [16].

The technique begins with the estimation of an initial illumination map by using the maximum intensity across the RGB channels at each pixel, representing the most illuminated areas of the image. This illumination map is then smoothed to reduce noise and improve uniformity by applying gradient-based regularization methods. Finally, the pixel values of the image are adjusted according to the corrected illumination map, resulting in a final image with enhanced visibility and detail preservation.

LIME is widely applied in domains requiring the enhancement of images captured under adverse lighting conditions, such as surveillance, nighttime image processing, and photography enhancement. Its main advantage lies in enhancing details in underexposed regions without overexposing already well-lit areas, making it a robust tool for improving low-light images.

2.8 Gamma Correction

Gamma correction is an image processing technique that adjusts the nonlinear relationship between pixel intensity and the perception of brightness by the human visual system [17]. In image capture and display systems, such as digital cameras and monitors, the recorded brightness levels may not accurately reflect visual perception, especially under extreme lighting conditions. To address this issue, gamma correction applies an exponential transformation to pixel values, balancing intensities to enhance the visual quality of the image.

3 MATERIALS AND METHODS

3.1 Research Workflow and Experiment Setting

In this experiment, the dataset was organized into four distinct groups: Dataset 1, Dataset 2, Dataset 3, and Dataset 4. The dataset consists of a total of 428 images, with 388 allocated for training and 40 for validation. The images were captured under favorable weather conditions, during the day and without rain, in accordance with DNIT guidelines.

Additionally, the dataset presents significant diversity, including different lighting conditions, environmental variations, and a wide range of pavement defects, ensuring a realistic scenario for model evaluation. The considered defect types include Pothole and Patch.

Dataset 1 consists exclusively of original images without any enhancement techniques applied. Dataset 2 includes both the original images and those enhanced using the Gamma Adjustment technique. Dataset 3 combines the original images with those processed using the LIME (Low-Light Image Enhancement) technique. Finally, Dataset 4 consists of original images enhanced using the CLAHE (Contrast Limited Adaptive Histogram Equalization) technique. This structure enables a comprehensive comparative analysis of the impact of different image enhancement methods on pavement defect detection.

An overview of the system approaches is presented in Figure 1, which illustrates the research workflow. After preparing the dataset with the image enhancement techniques, training was conducted using a convolutional neural network. The LabelImg tool [18] was used to create bounding boxes for all object classes. The labeling process was performed individually for each class, allowing multiple boxes to be assigned to a single image.

The deep learning model architecture used in this study is detailed in Figure 1, comprising four main components: input, backbone, neck, and output. The backbone identifies significant elements in the input images, employing structures such as Cross Stage Partial Networks (CSP) and Spatial Pyramid Pooling (SPP) to extract rich attributes. These structures enable the model to generalize effectively, recognizing objects at various scales. The neck network was developed based on feature pyramid architectures, such as Feature Pyramid Network (FPN) and Path Aggregation Network (PANet), optimizing the combination of semantic and localization features across different levels of the hierarchy.

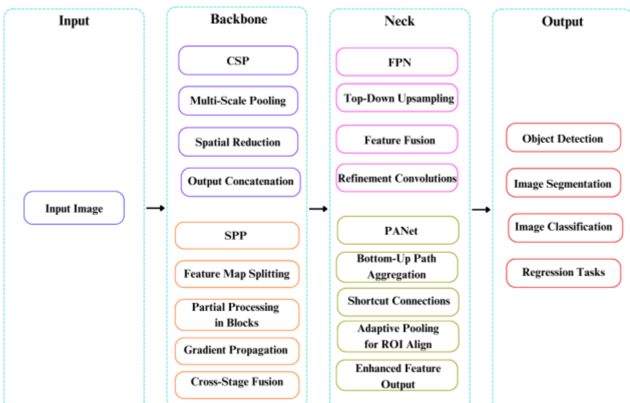

Figure 1: CNN architecture.

The training parameters for the CNN were as follows: the batch size was set to 16, limited by memory constraints; the number of epochs was determined experimentally and set to 100; and the model was trained using images with a resolution of 512 × 512 pixels, optimizing the number of parameters and precision.

The hardware specifications for the experiments included a computer equipped with an Intel Core i7-11700 processor with 8 cores, an RTX 5000 GPU, and 32 GB of DDR4-3200 RAM. This configuration was critical to meeting the computational demands of the CNN and ensuring the efficient execution of the experiments.

3.2 Image Enhancement Result

Although the images used in this study were captured during the day and under favorable weather conditions, factors such as the position of the sun and vehicle shadows introduced lighting variations, resulting in images that were overly bright or dark. These variations posed challenges for the precise identification of pavement defects. To address these issues, the original images were preprocessed using image enhancement techniques prior to training and recognition, aiming to standardize lighting conditions and highlight relevant details.

The results of the adjustments, using three distinct image enhancement techniques, are presented in Figure 2. The primary objective of this experiment was to evaluate the impact of these processing techniques on the detection of road pavement defects and identify the most effective approach. The applied techniques include: (1) Gamma Correction, which adjusts the relationship between pixel intensity and perceived brightness, shown in Figure 2(b); (2) LIME (Low-Light Image Enhancement), which enhances darker regions while preserving details in brighter areas, as presented in Figure 2(c); and (3) CLAHE (Contrast Limited Adaptive Histogram Equalization), which improves local contrast without introducing visual artifacts, illustrated in Figure 2(d).

Figure 2: Example of the image enhancement methods.

4 RESULTS AND DISCUSSION

4.1 Results Analysis

The analysis of the results obtained for each model, using different datasets, provides insight into the impact of preprocessing techniques on the detection of potholes and patches in road pavements. Below is a detailed description of each scenario:

The model trained on the dataset without filters achieved 63 favorable cases, including true positives (TP) and true negatives (TN), for pothole and patch classes. It identified 30 false positives (FP) and 41 false negatives (FN), with a Recall Confidence Curve value of 0.95. The Precision-Recall Curve yielded a mean Average Precision (mAP) of 0.594 for all classes, with 0.551 for potholes and 0.638 for patches. The Precision Confidence Curve showed a confidence value of 0.852, while the F1 Confidence Curve obtained an F1 score of 0.57, with a decision threshold of 0.474.

For the dataset processed with the CLAHE (Contrast Limited Adaptive Histogram Equalization) method, the model recorded 43 favorable cases of TP and TN, 14 FP, and 49 FN. The Recall Confidence Curve reached 0.79. The Precision-Recall Curve registered a mAP of 0.617 for all classes, with 0.477 for potholes and 0.758 for patches. The Precision Confidence Curve achieved a confidence value of 0.683, while the F1 Confidence Curve obtained an F1 score of 0.58, with a decision threshold of 0.254.

The model trained on the dataset processed with the Gamma Correction method achieved 49 favorable cases of TP and TN, 44 FP, and 16 FN. The Recall Confidence Curve recorded a value of 0.90. The Precision-Recall Curve yielded a mAP of 0.741 for all classes, with 0.667 for potholes and 0.815 for patches. The Precision Confidence Curve showed a confidence value of 0.700, and the F1 Confidence Curve reached an F1 score of 0.69, with a decision threshold of 0.175.

The model trained on the dataset processed with the LIME (Low-Light Image Enhancement) method delivered the best results, with 70 favorable cases of TP and TN, 23 FP, and only 11 FN. The Recall Confidence Curve showed a value of 0.86. The Precision-Recall Curve achieved a mAP of 0.788 for all classes, with 0.738 for potholes and 0.838 for patches. The Precision Confidence Curve recorded a confidence value of 0.911, and the F1 Confidence Curve achieved an F1 score of 0.74, with a decision threshold of 0.207.

These results highlight the differences in performance for each model and preprocessing technique. For a clearer and more comparative visualization, Table 1 presents a detailed, organized, and easy-to-interpret summary of the results for each model and dataset.

	Confusion matrix			F1 Confidence		Precision-Recall				
	TP/TN	FP	FN	F1	limiar	ALL	Pothole	Patch	Recall	Precision
CLAHE	43	14	49	0.58	0.254	0.617	0.477	0.758	0.79	0.254
Gamma	49	44	16	0.69	0.175	0.741	0.667	0.815	0.90	0.700
LIME	70	23	11	0.74	0.207	0.788	0.738	0.838	0.86	0.911
Original	63	30	41	0.58	0.474	0.594	0.551	0.638	0.95	0.852

Table 1: Summary Metrics.

4.2 Discussions

From the comparative analysis of the model results with different image processing methods, it was concluded that the LIME method stood out the most. Its results demonstrated consistency, ranging from median to excellent values. The superior performance of LIME compared to the Original dataset can be attributed to the increased contrast level and the enhanced edge definition, which facilitated the detection of pavement defects. This visual enhancement allowed the CNN to more accurately identify the affected regions, reducing classification errors. This method achieved the best performance in metrics such as True Positives (TP), True Negatives (TN), False Negatives (FN), F1 Score, Precision-Recall for all classes (ALL), and Precision Confidence. Additionally, even with intermediate performance in Threshold and Recall Confidence, the metrics were sufficient to maintain the overall balance of the model. These factors highlight LIME as the most effective method for detecting potholes and patches, exhibiting lower error rates and higher reliability and safety indicators.

In contrast, the CLAHE (Contrast Limited Adaptive Histogram Equalization) method delivered the lowest overall performance. Despite achieving the lowest rate of False Positives (FP), indicating fewer misclassifications in this respect, its performance was consistently inferior across other metrics compared to the remaining methods. The consolidated analysis suggests that CLAHE could not match the effectiveness of the other models, making it the least competitive approach in the evaluated set.

The Gamma Correction and Original methods can be classified as intermediate. Both showed True Positive (TP) and True Negative (TN) results that fell between those of LIME and CLAHE. However, the Original method demonstrated a slight advantage over Gamma, standing out with its higher Recall Confidence value, which is crucial for applications prioritizing the reduction of False Negatives. Conversely, the Original method recorded the lowest F1 Score, indicating less harmony between Recall and Precision, limiting its efficiency in scenarios requiring a balanced trade-off between these metrics.

These results reinforce the importance of carefully selecting the most suitable image processing method, considering specific demands for precision, balance, and reliability in road defect detection applications.

5 CONCLUSIONS

The findings of this study demonstrate how image preprocessing techniques can significantly enhance the performance of CNN-based models in detecting road pavement defects, contributing directly to the field of Pavement Management. The detection of defects such as potholes and patches is crucial for mapping road conditions, making it an indispensable step in prioritizing repairs and allocating resources within maintenance departments. In this context, the Digital Image Processing (DIP) techniques evaluated in this study—including Gamma Correction, CLAHE, and LIME—proved to be valuable tools for increasing the accuracy and reliability of automated road image analysis.

Among the methods analyzed, LIME (Low-Light Image Enhancement) delivered the best results, excelling in key metrics such as Precision-Recall (0.788 mAP), Precision Confidence (0.911), and F1 Score (0.74). These outcomes reflect LIME's ability to correct lighting variations and enhance defect detection robustness. Conversely, the CLAHE method exhibited inferior performance, with significantly lower metrics, especially in Recall and F1 Score. The Gamma Correction and Original methods showed intermediate performance, with Gamma standing out for its Recall Confidence (0.90), indicating fewer false negatives—a critical factor for applications emphasizing the detection of all possible defects. These results highlight that selecting appropriate

DIP techniques not only improves system efficiency but also ensures greater reliability in practical applications.

Additionally, the use of accessible tools, such as action cameras and smartphones, for capturing pavement images demonstrates the feasibility of implementing low-cost road monitoring systems, expanding their applicability in financially constrained scenarios. The comparative analysis of image enhancement methods conducted in this study contributes to the development of automated solutions that can be integrated into Pavement Management programs, providing engineers and managers with more informed and data-driven decision-making capabilities. This study thus underscores the potential of integrating advanced DIP techniques and deep learning as essential tools for the efficient and sustainable management of road infrastructure.

6 FUTURE WORK

In the future, we aim to expand the scope of this work to include other types of road pavement defects, such as cracks, depressions, and deformations, enabling a more comprehensive and robust analysis of pavement conditions. Additionally, we plan to investigate other image enhancement techniques to gain deeper insights into how preprocessing impacts CNN performance in defect detection.

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