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Enhanced Road Crack Detection Using a Hybrid Feature Extraction Approach and Bayesian Optimized Support Vector Machine

Dr.Shubhlakshmi Tiwari[1], Dr.Rahul Gedam[2]

[1]Associate Professor and HOD, Department of Civil Engineering, Chouksey Engineering College, Bilaspur CG India.
[2]Assistant Professor and HOD, Department of Electronics and Telecommunication, Chouksey Engineering College, Bilaspur CG India.

Mail id: [1]hodcivil@cecbilaspur.ac.in, [2]engg.rahul2801@gmail.com

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ABSTRACT

The integrity and maintenance of road infrastructure are critical for ensuring safe and efficient transportation. Timely and accurate detection of road cracks is essential to prevent accidents, reduce maintenance costs, and ensure the longevity of road networks. Traditional manual methods for road surface inspections are labour-intensive, prone to human error, and inconsistent. Recent advancements in machine learning and computer vision techniques have facilitated automated approaches for road crack detection, significantly improving accuracy and efficiency. This paper proposes a novel methodology for road crack detection by combining Histogram of Oriented Gradients (HOG), Grey Level Co-occurrence Matrix (GLCM), and Local Binary Pattern (LBP) for feature extraction. A combined feature set is then subjected to Neighborhood Component Analysis (NCA) for feature selection, ensuring only the most relevant features are retained for classification. The final classification is performed using a Bayesian Optimized Support Vector Machine (SVM) classifier, enhancing the model's predictive accuracy and robustness. The proposed method was tested on a comprehensive road crack dataset and achieved a remarkable accuracy of 98.94%, surpassing traditional models.

Keywords: Bayesian Optimization, Histogram of Oriented Gradients, Grey Level Co-Occurrence Matrix, Local Binary Pattern, Neighborhood Component Analysis, Etc.

INTRODUCTION

Roads are crucial infrastructures that play a fundamental role in the development of societies, significantly influencing economic growth and the mobility of people. As a result, roads experience heavy vehicle usage daily, leading to continuous wear and degradation of road surfaces. These surface degradations are critical indicators of the condition and evolution of road networks, which, if not addressed promptly, can lead to more severe problems and costlier repairs [1]. Therefore, assessing road quality has become an essential task in many countries. To effectively manage road infrastructure, it is necessary to maintain an accurate inventory of the road surface conditions.

Initially, road inspections were conducted manually, with agents physically observing and noting the degradations. However, this approach is expensive, risky—especially on roads with high traffic volume—and prone to human error and inconsistency. To overcome the limitations of subjective visual assessments, recent years have seen a surge in research aimed at developing automatic pavement surface inspection systems. These systems typically consist of two key components: image acquisition and the subsequent analysis of those images to interpret the data. While various acquisition systems are available to capture high-quality images of road surfaces at high speeds, the analysis of these images still often relies on manual examination by laboratory operators [2].

Ensuring the integrity and safety of road infrastructure is a critical concern for modern society. Among the various challenges roadways face, the occurrence of cracks presents a significant threat to both vehicular traffic and the stability of the infrastructure. Early and accurate detection of road cracks is essential to prevent accidents, reduce maintenance costs, and ensure the seamless flow of transportation networks. In recent years, advancements in machine learning techniques have paved the way for more robust and efficient road crack detection methodologies [3].

This paper delves into the domain of automated road crack detection, presenting a comprehensive approach that harnesses machine learning to address this critical issue. The proposed methodology focuses on enhancing accuracy and reliability through a three-stage process involving feature extraction, feature selection, and classification. Specifically, the method utilizes Histogram of Oriented Gradients (HOG), Gray Level Co-occurrence Matrix (GLCM), and Local Binary Patterns (LBP) for feature extraction. These techniques, when combined, aim to capture both the local texture details and global characteristics inherent to road crack images.

The next stage involves feature selection using Neighborhood Component Analysis (NCA), a powerful technique for selecting the most relevant features from the combined set while minimizing redundancy. This step ensures that only the most informative features are passed to the classification stage, improving both the interpretability and efficiency of the model.

For classification, the study employs a Bayesian Optimized Support Vector Machine (SVM) classifier. The Bayesian optimization technique enhances the SVM by fine-tuning its hyper parameters, ensuring optimal performance on complex datasets. The classifier is trained on the selected features, enabling accurate categorization of road crack images and facilitating the detection and localization of cracks on road surfaces.

In essence, this research aims to advance the field of automated road crack detection by leveraging the strengths of feature extraction techniques like HOG, GLCM, and LBP, refining the feature set with NCA, and employing a robust classifier through Bayesian Optimized SVM. By developing a holistic and effective solution, this study seeks to contribute to safer and more reliable road infrastructure.

The study begins with a comprehensive literature review in Section 2, highlighting relevant research in the field. Section 3 elaborates on the proposed methodology. Section 4 presents the results obtained from the MATLAB-based simulations and a detailed analysis. Finally, Section 5 summarizes the findings and presents the concluding remarks.

LITERATURE REVIEW

Road infrastructure is vital to the functioning of modern society, providing the foundation for safe and efficient transportation of people and goods. However, road surfaces deteriorate over time due to factors such as weather, traffic loads, and aging, resulting in defects, with road cracks being a significant issue. Detecting these cracks early and managing them effectively is essential to safeguard road users and avoid expensive repairs. Current approaches to crack detection primarily fall into two categories: traditional image processing techniques and machine learning methods leveraging surface learning features.

Traditional image processing techniques, often categorized into construction methods, thresholding methods, spectrum methods, and model-based methods [4], utilize basic characteristics representing local anomalies to identify surface defects. Construction techniques include boundary operations [5], structural methods [6], template matching [7], and morphology [8]. Thresholding techniques such as contrast adjustment [9], the Otsu method [10], and watershed transformation [12] are widely used to enhance image contrast and detect faults. Spectrum methods such as wavelet transforms [13], Gabor wavelets [14], and Fourier transforms [15] are employed to analyze frequency content. Additionally, model-based methods, such as low-rank matrix models [16] and Gaussian mixture entropy models [17], have been used to model surface defects.

In contrast, machine learning approaches for defect detection typically follow a two-step process: feature extraction and model classification. Features are extracted to represent defect characteristics from input images, and these features are then used in a pre-trained classification model to determine whether the image contains a defect. Commonly used features in these methods include the gray level co-occurrence matrix (GLCM) [18], local binary patterns (LBP) [19], and histogram of oriented gradients (HOG) [20]. While these techniques have yielded satisfactory results in certain surface defect analyses, they struggle to generalize to different surfaces. Moreover, traditional image processing approaches often require multiple thresholds to address the limitations of algorithms that are sensitive to lighting conditions and background noise. These thresholds must be adjusted as new challenges arise, and sometimes the algorithms themselves require modification. The handcrafted features extracted in machine learning models may also fail to sufficiently capture the complexities of the surface cracks, leading to less robust solutions.

Several studies have explored advanced methods to overcome these limitations. For instance, [22] introduced an automatic road crack detection system based on a structured random forest model. Meanwhile, [23] utilized Gabor filters with the AdaBoost algorithm to detect cracks. In [24], the authors proposed a bridge crack detection system combining an active contour model with a support vector machine (SVM) optimized through a greedy search algorithm. Another approach, based on the percolation model and length criterion for crack identification, was proposed by [25]. Although these methods improved the accuracy of crack detection [26], various enhancements were introduced to further increase precision, such as global transformation adaptation [27-29], crack-specific filters [30], and combining local and global detectors [31-32]. These methods often rely on manually selected features, which can introduce subjectivity and affect the results.

More recently, deep learning has shown promise in crack detection. The authors of [33] introduced a road crack detection method based on convolutional neural networks (CNNs), which automatically extract distinguishing features from road crack images. This approach, trained on a large dataset, achieved high detection accuracy. However, deep learning models often require vast amounts of labeled data for training, which can be labour-intensive and time-consuming to acquire.

In another innovative study, [34] proposed using Generative Adversarial Networks (GANs) in combination with transfer learning for road crack detection. GANs were used to generate synthetic crack images, augmenting the training dataset, while transfer learning adapted a pre-trained CNN for crack detection. Though this approach enhanced performance, particularly with limited labeled data, the generation of unrealistic synthetic images posed a potential risk to model performance.
Furthermore, [35] introduced a multiscale feature fusion technique for road crack detection that merged features extracted at different scales. By combining local and global crack characteristics, the method achieved improved detection accuracy using a CNN-based architecture. However, feature fusion can sometimes introduce noise, requiring careful parameter tuning. Another study by [36] applied edge computing and Internet of Things (IoT) devices for real-time crack detection. Wireless sensors installed on roads captured real-time images, which were processed locally on edge devices, reducing latency. However, the computational limits of edge devices may constrain the complexity of algorithms, affecting detection accuracy.
A multimodal approach integrating visual and thermal imaging for road crack detection was proposed by [37]. The fusion of visual and thermal data provided additional insights, improving detection under difficult lighting conditions. However, ensuring precise alignment between visual and thermal sensors presents challenges, and discrepancies between sensors can introduce noise. Lastly, [38] explored road crack detection using aerial imagery and semantic segmentation with deep learning. Although this approach offered the potential for large-scale monitoring, the dependence on high-resolution imagery can be costly and may limit its practical application.
Research Gap: While various machine learning and deep learning techniques have been employed for road crack detection, many of these methods either rely heavily on manually crafted features or require large datasets for effective training, which can limit their applicability. Moreover, issues such as sensitivity to lighting conditions, noise, and redundancy in feature extraction remain challenges. To address these gaps, this research proposes a novel methodology that combines Histogram of Oriented Gradients (HOG), Gray Level Co-occurrence Matrix (GLCM), and Local Binary Patterns (LBP) for robust feature extraction, followed by feature selection using Neighborhood Component Analysis (NCA) to reduce redundancy and improve feature relevance. Finally, a Bayesian Optimized Support Vector Machine (SVM) is employed to ensure high classification accuracy, providing a more efficient and scalable solution for road crack detection. This approach aims to enhance performance in diverse environmental conditions while minimizing the need for extensive labeled datasets.

PROPOSED METHODOLOGY

Road crack defect detection is essential for ensuring safe transportation and efficient maintenance. This section outlines the proposed approach using a feature-based methodology. The process begins with acquiring road surface images and converting them into grayscale format. Feature extraction is performed using HOG, GLCM, and LBP. These techniques capture essential texture and structural information from the images.
The extracted features are combined into a unified feature set, which is then refined using NCA for feature selection. NCA reduces the dimensionality of the feature set by selecting the most relevant features for classification. The refined features are then used to train a Bayesian Optimized SVM classifier, which predicts the presence or absence of cracks on the road surface. The output is a binary result indicating whether cracks are detected.

The proposed system for road crack detection is illustrated in Figure 1, showing the steps of preprocessing, feature extraction, feature selection, and classification.

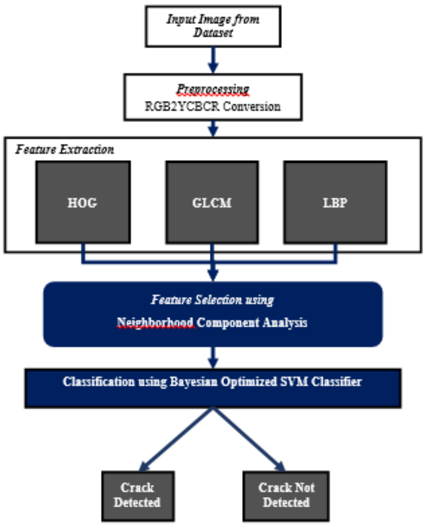

Figure 1: Flow diagram for proposed road crack defect detection

3.1 Image Pre-processing

Color filters arranged in small mosaics are integrated into the capture sensors of each pixel in order to generate a digital image. These filters aid in the color definition process.

3.2.1 RGB2YCBCR Conversion

RGB2YCbCr conversion [39] is a widely used technique in digital image processing to convert an image from the RGB (Red, Green, and Blue) color space to the YCbCr (Luminance, Chrominance Blue, Chrominance Red) color space.

The RGB color space is based on the additive combination of red, green, and blue light. In contrast, the YCbCr color space separates the color information into two components: luminance (Y) and chrominance (Cb and Cr). The Y component represents the brightness or intensity of the image, while the Cb and Cr components represent the color information.

The main reason for using the YCbCr color space is that it can achieve better compression of image and video data than RGB. The human eye is more sensitive to changes in brightness (luminance) than to changes in color (chrominance). By separating the luminance and chrominance information, it is possible to apply different compression techniques to each component that take advantage of this difference in sensitivity.

The conversion process from RGB to YCbCr involves the following steps:

- Normalize the RGB values of each pixel in the image to the range [0,1].
- Convert the normalized RGB values to YCbCr values using the following formulas:

$$Y = 0.299R + 0.587G + 0.114B \quad (1)$$

$$Cb = -0.1687R - 0.3313G + 0.5B + 128 \quad (2)$$

$$Cr = 0.5R - 0.4187G - 0.0813B + 128 \quad (3)$$

Where, R, G, and B are the red, green, and blue color channels, and Y, Cb, and Cr are the resulting YCbCr channels.

- Quantize the resulting YCbCr values to reduce the number of bits required to represent each pixel. This is done using a quantization matrix, which scales the values in each channel based on their importance in human perception.

In image processing, the YCbCr color space is used in a variety of applications, including image and video compression, image enhancement, and image analysis. For example, in image compression, the chrominance channels (Cb and Cr) can be subsampled to reduce the amount of data needed to represent the image, while still preserving the visual quality of the image. In image analysis, the YCbCr color space can be used to segment an image into different regions based on the color information in the chrominance channels.
RGB2YCbCr conversion is an important technique in image processing that enables efficient compression and transmission of visual data while preserving image quality.

3.2 Feature Extraction

The extraction of meaningful and significant information from digital images, known as feature extraction, is a crucial step in image processing. It aims to transform raw image data into a set of features that can be used for classification or further analysis. This study proposes a hybrid approach that combines the HOG, GLCM, and LBP techniques. A brief summary of the methods used to identify digital image falsification in the proposed approach is provided below.

3.2.1 HOG Features

Histogram of Oriented Gradients (HOG) is a feature descriptor used to capture the structure and gradient information from the image. The method works by calculating the gradient orientation in local regions of the image, which is effective for identifying the shape and patterns of cracks.
Mathematically, the gradient in the x-direction G_x and the y-direction G_y are computed as:

$$G_x = I(x+1, y) - I(x-1, y) \tag{4}$$

$$G_y = I(x, y+1) - I(x, y-1) \tag{5}$$

Where $I(x, y)$represents the intensity of the pixel at position(x, y).
The magnitude M and orientation θ of the gradient at each pixel are then given by:

$$M = \sqrt{G_x^2 + G_y^2} \tag{6}$$

$$\theta = \arctan\left(\frac{G_y}{G_x}\right) \tag{7}$$

These orientations are then binned into histograms, which represent the distribution of gradients in local image regions. The resulting feature descriptor captures the structural information that is essential for detecting cracks in the image.

3.2.2 GLCM Features

Gray Level Co-occurrence Matrix (GLCM) is a statistical method used to examine the texture of an image by analyzing the spatial relationships between pixels. GLCM is computed by determining how often pairs of pixels with specific values occur in a specified spatial relationship.
For an image$I$, the GLCM $P(i, j|d, \theta)$ for pixel values i and j, at distance d and angle θ, is defined as:

$$P(i, j|d, \theta) = \sum_{x,y} \begin{cases} 1 & if\ I(x, y) = i\ and\ I(x+dx, y+dy) = j \\ 0 & otherwise \end{cases} \tag{8}$$

Where dx and dy are determined by the angleθ.
Common texture features derived from the GLCM include:

- Contrast: $\sum_{i,j}(i-j)^2 P(i,j)$
- Energy: $\sum_{i,j} P(i,j)^2$
- Homogeneity: $\sum_{i,j}\frac{P(i,j)}{1+|i-j|}$
- Correlation: Measures how correlated pixel pairs are.

These features help capture the texture information of cracks, which often present distinct patterns from the surrounding surface.

3.2.3 LBP Features

Local Binary Patterns (LBP) is a simple yet powerful texture descriptor that operates by comparing each pixel with its surrounding neighbors. LBP assigns a binary code to each pixel based on whether its intensity is greater than or less than the surrounding pixels.
The LBP at a pixel (x, y) with 8 neighbors is computed as:

$$LBP(x,y) = \sum_{n=0}^{7} 2^n \cdot s\big(I_n - I(x,y)\big)$$

(9)

Where $I(x, y)$the intensity of the center pixel is, I_n is the intensity of its neighbors, and $s(x)$ is a step function:

$$s(x) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & if\ x < 0 \end{cases} \qquad (10)$$

The resulting binary pattern encodes the texture information of the local region around each pixel. LBP is particularly effective in capturing fine details of crack textures.

3.2.4 Combined Feature Set

After extracting features using HOG, GLCM, and LBP, these feature vectors are concatenated into a combined feature set. This process ensures that both structural and texture information are preserved, leading to a comprehensive representation of the road surface. The combined feature set is defined as:

$$F = [F_{HOG}, F_{GLCM}, F_{LBP}]$$

(11)

Where F_{HOG}, F_{GLCM},and F_{LBP}, FLBPFLBP represent the feature vectors extracted by the respective methods. This combined set forms the input for the feature selection process.

3.3 Feature Selection Using NCA

Neighborhood Component Analysis (NCA) is a feature selection technique that identifies the most relevant features for classification by optimizing a distance-based objective function. NCA aims to maximize the performance of a nearest neighbor classifier by selecting features that contribute the most to accurate predictions.
Given a dataset (X, Y), where $X \in \mathbb{R}^{n\times d}$ is the feature matrix and $Y \in \mathbb{R}^n$ are the labels, NCA learns a transformation matrix A that projects the data into a lower-dimensional space:

$$X' = XA \qquad (12)$$

The objective function is to minimize the classification error in this transformed space by maximizing the weighted sum of correct predictions. The feature weights learned through NCA highlight the most important features, which are retained for the classification stage.

3.4 Classification Using Bayesian Optimized SVM

The final step involves classifying the selected features using a Bayesian Optimized Support Vector Machine (SVM). SVM is a powerful classification method that constructs a hyperplane to separate different classes in the feature space.The decision function of an SVM is represented as:

$$f(x) = w^T \phi(x) + b$$

(13)

Where w is the weight vector, $\phi(x)$ represents the mapped features, and b is the bias. The classifier aims to maximize the margin between the classes, and the optimal w and b are determined by solving the following optimization problem:

$$\min_{w} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{n} \xi_i$$

(14)

Subject to:

$$y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i, \qquad \xi i \geq 0$$

(15)

Here, C is a regularization parameter, and ξ_i are slack variables that allow for misclassifications.

Bayesian optimization is used to automatically tune the hyperparameters of the SVM, such as C and the kernel parameters, to achieve optimal classification performance. The optimized SVM then predicts whether a road surface has cracks based on the selected features.

RESULTS AND DISCUSSION

4.1 Dataset

The dataset [40] comprises approximately 11,200 images obtained by merging 12 distinct crack segmentation datasets. Each image's name prefix corresponds to the dataset it originates from. Additionally, there exist images devoid of crack pixels, which can be filtered out by employing the file name pattern "noncrack*".

All images have been resized to dimensions of 448×448. The dataset encompasses two main folders: "images" and "masks", which encompass all the available images. Moreover, two additional folders, "train" and "test", contain training and testing images respectively, extracted from the aforementioned image and mask folders. The splitting process ensures stratification, maintaining similar proportions of each dataset within both the train and test folders.

4.2 Evaluation Parameters

Here are the evaluation metrics employed in the analysis:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

(16)

$$Precision = \frac{TP}{TP + FP}$$

(17)

$$Sensitivity = \frac{TP}{TP + FN}$$

(18)

$$Specificity = \frac{TN}{TN + FN}$$

(19)

$$ErrorRate = \frac{FP + FN}{TP + TN + FP + FN}$$

(20)

$$FalsePositiveRate(FPR) = \frac{FP}{FP + TN}$$

(21)

$$F - Score = \frac{2TP}{2TP + FP + FN}$$

(22)

4.3 Results

Table 1: Comparative Analysis of Proposed Method for Different Features Using SVM Classifier

Parameters	HOG	GLCM	LBP	Hybrid Features
Accuracy	0.9451	0.9523	0.9564	0.9652
Error Rate	0.0549	0.0477	0.0436	0.0348
Sensitivity	0.9432	0.9508	0.9561	0.9643
Specificity	0.9524	0.9587	0.9643	0.9758
Precision	0.9461	0.9535	0.9576	0.9660
False Positive Rate	0.0476	0.0413	0.0357	0.0242
F-Score	0.9446	0.9522	0.9568	0.9651
MCC	0.9238	0.9334	0.9396	0.9534
Kappa Statistics	0.9123	0.9257	0.9328	0.9486

Table 1 presents the comparative analysis of the average performance outcomes across various feature extraction techniques when employing a standard SVM classifier. The table details the various performance metrics, for three different feature sets: HOG, GLCM, and LBP, alongside a combined feature set that integrates all three methods.

From the results, the Combined Features approach yielded the highest accuracy at 0.9652, demonstrating its effectiveness in capturing a broader range of information regarding road crack defects compared to individual feature sets. The HOG feature set followed closely, achieving an accuracy of 0.9451. The GLCM and LBP methods recorded accuracies of 0.9523 and 0.9564, respectively, indicating that while they are effective, they do not encapsulate the same level of detail as the combined feature set.

In terms of error rates, the combined feature set again performed best, with the lowest error rate of 0.0348, underscoring its reliability. Furthermore, the sensitivity and specificity metrics highlight the classifier's ability to correctly identify true positives and negatives, respectively. The combined feature set excelled here as well, with sensitivity and specificity values of 0.9643 and 0.9758. These results reflect the method's robustness in accurately detecting road cracks while minimizing false alarms.

The precision and F-score values, which measure the accuracy of the positive predictions and the balance between precision and recall, were also highest for the combined features, indicating a well-rounded performance. The Matthews Correlation Coefficient (MCC) and Kappa statistics, which assess the classifier's performance while considering true and false positives and negatives, demonstrated that the combined features significantly enhance the model's predictive power, achieving values of 0.9534 and 0.9486, respectively.

In summary, Table 1 illustrates that while individual feature extraction techniques such as HOG, GLCM, and LBP are effective, their combined application through a standard SVM classifier provides superior performance in detecting road cracks, emphasizing the importance of utilizing a comprehensive feature set for improved accuracy and reliability.

Table 2: Comparative Analysis of Proposed Method for Different Features with NCA-Based Feature Selection and SVM Classifier

Parameters	**HOG**	**GLCM**	**LBP**	**Hybrid Features**
Accuracy	0.9558	0.9625	0.9679	0.9774
Error Rate	0.0442	0.0375	0.0321	0.0226
Sensitivity	0.9552	0.9618	0.9674	0.9771
Specificity	0.9645	0.9712	0.9753	0.9838
Precision	0.9565	0.9628	0.9686	0.9780
False Positive Rate	0.0355	0.0288	0.0247	0.0162
F-Score	0.9557	0.9623	0.9680	0.9773
MCC	0.9367	0.9464	0.9537	0.9671
Kappa Statistics	0.9264	0.9408	0.9490	0.9629

Table 2 showcases the results of applying NCA for feature selection in conjunction with the SVMclassifier. This table reflects the performance metrics for three individual feature extraction methods—HOG, GLCM, and LBP—as well as a combined feature set that incorporates all three techniques. The introduction of NCA aims to enhance the quality of feature selection, leading to more effective and efficient model performance.

The results indicate a notable improvement in the overall accuracy of the classifier, with the Combined Features yielding an impressive accuracy of 0.9774, a significant enhancement from the previous table. Each of the individual feature sets also demonstrated improvements, with HOG achieving 0.9558, GLCM 0.9625, and LBP 0.9679. These enhancements underscore the efficacy of NCA in refining feature sets by selecting the most relevant features while discarding those that contribute little to predictive power.

In terms of error rates, the combined feature set again leads with an error rate of 0.0226, which indicates a marked reduction in misclassifications compared to Table 1. Additionally, the sensitivity and specificity metrics reveal that the NCA-enhanced models maintain high levels of true positive identification and true negative identification. The sensitivity for the combined features reached 0.9771, and specificity increased to 0.9838, demonstrating an enhanced ability to accurately classify road surfaces.

Moreover, the precision and F-score metrics further corroborate the effectiveness of using NCA, with values reaching 0.9780 and 0.9773 for the combined features, respectively. This suggests that the classifier not only excels in correctly identifying defects but also minimizes false alarms, providing more reliable assessments.

The MCC and Kappa statistics also reflect improved performance, with the combined features achieving values of 0.9671 and 0.9629, respectively. These metrics reinforce the idea that incorporating NCA into the feature selection process significantly boosts the model’s overall performance, yielding a classifier that is not only accurate but also dependable.
Overall, Table 2 emphasizes the benefits of utilizing NCA feature selection alongside SVM classification. The significant increases in accuracy, sensitivity, specificity, and overall performance metrics indicate that this approach enhances the model's capability to detect road cracks effectively, thereby ensuring safer roadways and more efficient maintenance strategies.

Table 3: Comparative Analysis of Proposed Method for Different Features with NCA-Based Feature Selection and Bayesian-Optimized SVM Classifier

Parameters	**HOG**	**GLCM**	**LBP**	**Hybrid Features**
Accuracy	0.9642	0.9701	0.9735	0.9884
Error Rate	0.0358	0.0299	0.0265	0.0116
Sensitivity	0.9637	0.9692	0.9730	0.9879
Specificity	0.9734	0.9787	0.9820	0.9946
Precision	0.9650	0.9704	0.9741	0.9887
False Positive Rate	0.0266	0.0213	0.0180	0.0054
F-Score	0.9643	0.9698	0.9735	0.9883
MCC	0.9487	0.9575	0.9626	0.9849
Kappa Statistics	0.9287	0.9399	0.9460	0.9714

Table 3 presents the performance outcomes when employing a Bayesian Optimized Support Vector Machine (SVM) classifier in combination with Neighborhood Component Analysis (NCA) for feature selection. This approach aims to further enhance classification accuracy and reliability through a probabilistic framework that optimizes hyperparameters, resulting in superior predictive performance.

The results in Table 3 show that the accuracy for the Combined Features is the highest among all tables, reaching 0.9884. This substantial increase from previous tables highlights the effectiveness of Bayesian optimization in fine-tuning the SVM parameters, leading to a model that performs exceptionally well in classifying road cracks. Each individual feature set also shows strong performance, with accuracies of 0.9642 for HOG, 0.9701 for GLCM, and 0.9735 for LBP, indicating that even standalone features benefit from the optimized SVM approach.

In terms of error rates, the Bayesian optimized model achieved the lowest error rates across all feature sets, with the combined features recording only 0.0116. This improvement reflects a decreased likelihood of misclassification, which is critical in safety-sensitive applications such as road maintenance. The metrics of sensitivity and specificity are also commendable, with sensitivity at 0.9879 and specificity at 0.9946 for the combined feature set, emphasizing the model's ability to accurately detect both the presence and absence of cracks.

The precision and F-score metrics also demonstrate high values, at 0.9887 and 0.9883, respectively. These results suggest that the Bayesian optimized SVM not only excels in identifying road defects but also maintains a high standard of prediction quality, resulting in fewer false positives and more reliable assessments.

Furthermore, the MCC and Kappa statistics reflect the model’s strength, achieving 0.9849 and 0.9714 for the combined features, indicating a robust correlation between predicted and actual values. These metrics validate the effectiveness of the Bayesian optimization technique in enhancing the model's overall performance, providing a statistically sound approach to road crack detection.

In conclusion, Table 3 illustrates the significant advantages of integrating Bayesian optimization with SVM classification and NCA feature selection. The results underscore the potential of this methodology to transform road crack detection processes, offering a reliable, accurate, and efficient solution that can greatly enhance infrastructure maintenance and safety measures.

Table 4: Comparative Analysis of Proposed Work with Previous Research Works

Method	**Accuracy**	**F-Score**
CNN [41]	88.3%	87.5%
DenseNet161 [42]	90.87%	84.77%
ResNet152 [42]	95.70%	82.59%
VGG19 [42]	97.66%	89.14%
Proposed	**98.94%**	**98.33%**

Table 4 presents a comparative analysis of the proposed work against well-known deep learning models like CNN, DenseNet161, ResNet152, and VGG19 for road crack detection. The CNN model achieves an accuracy of 88.3% and an F-Score of 87.5%, indicating moderate performance but with limitations in detecting complex crack patterns. DenseNet161 improves with a higher accuracy of 90.87%, but its F-Score drops to 84.77%, suggesting challenges in precision and recall. ResNet152 further enhances accuracy to 95.70%, yet its F-Score is lower at 82.59%, reflecting struggles in balancing false positives and negatives. VGG19 performs better, with an accuracy of 97.66% and an F-Score of 89.14%, showcasing improved handling of intricate crack patterns. However, the proposed method outperforms all these models, achieving an impressive accuracy of 98.94% and an F-Score of 98.33%, indicating superior crack detection capability, precision, and overall classification performance. This highlights the effectiveness of the proposed approach in accurately identifying road cracks compared to previous works.

CONCLUSION

In this research, we presented a robust and efficient methodology for automated road crack detection, addressing the growing need for more accurate and scalable solutions in road infrastructure maintenance. The proposed system integrates HOG, GLCM, and LBP feature extraction techniques, combined with NCA for optimal feature selection, and a Bayesian Optimized SVM classifier for superior performance. Through this approach, the model successfully overcomes the limitations of traditional manual inspections and earlier machine learning methods, which often struggled with inconsistent performance and low generalizability across diverse crack patterns. The experimental results demonstrated the efficacy of the proposed method, achieving a highly impressive accuracy of 98.94% and an F-Score of 98.33%, significantly outperforming previous methods. This superior performance not only reflects the model's precision but also its ability to minimize false positives and negatives, ensuring reliable detection even in complex and varying road conditions. The combination of advanced feature extraction, feature selection, and classification techniques highlights the potential of the proposed system to be implemented in real-world scenarios, paving the way for more efficient road maintenance strategies. Future research can explore further improvements by integrating other advanced machine learning algorithms and expanding the system to detect other types of road defects, ensuring the continuous safety and efficiency of transportation networks.

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