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A Hybrid CNN-SVM Classifier for Automated Pavement Performance Monitoring

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Abstract

This research introduces a new hybrid CNN-SVM classifier for autonomous pavement performance monitoring, combining Convolutional Neural Networks (CNNs) for deep feature extraction with Support Vector Machines (SVMs) for accurate classification. In contrast to isolated models, this hybrid model attains better computational efficiency and real-time adaptability, obviating the constraints of time-consuming manual inspections. Measured using the San Francisco Streets dataset, it achieved a stunning 97.8% accuracy, surpassing conventional approaches through optimised feature extraction and classification. Further testing on heterogeneous datasets such as Google images and the Pune-Mumbai expressway confirmed its performance across different environmental conditions. The scalable, fast solution minimises human effort, maximises real-time monitoring, and raises the bar for pavement management with its dependence on large training data.

Major Findings: *The hybrid CNN-SVM classifier achieved 97.8% training and 96.4% testing accuracy, outperforming standalone models in pavement defect detection. With optimal SVM settings (gamma = 0.1, degree = 3), it ensures robust, scalable performance across diverse conditions. This approach enhances real-time monitoring and maintenance strategies for road infrastructure.*

Keywords: *Automated Pavement Monitoring, Hybrid CNN-SVM, Machine Learning for Infrastructure, Pavement Defect Detection, Road Condition Assessment*

Abbreviations

- CNN: Convolutional Neural Network
- SVM: Support Vector Machine
- PMS: Pavement Management System
- PCI: Pavement Condition Index
- ASTM D6433: Standard guidelines for pavement distress evaluation and PCI calculation
- Distress Index (II): Measure of severity and extent of distress type I in pavement
- Weight (Wi): Importance factor assigned to distress type i in PCI calculation
- n: Total number of distress types considered in the PCI calculation
- Hybrid Approach: Integration of CNNs for feature extraction and SVMs for classification
- Alligator Cracking: Interconnected cracks forming a series of small blocks resembling an alligator's skin
- Block Cracking: Cracks that divide the pavement into rectangular pieces
- Potholes: Bowl-shaped depressions in the pavement caused by surface layer loss
- Defect-Free State: Pavement condition without visible distress

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- Remote Sensing: Acquisition of pavement data using aerial or satellite imagery
- GIS: Geographic Information System, used for spatial analysis of road data
- Lidar: Light Detection and Ranging, used for high-precision surface mapping
- Full-Depth Repair: Complete removal and replacement of distressed pavement layers
- Deep Learning: A Subset of machine learning focusing on neural network-based models
- Feature Extraction: Process of identifying significant patterns or attributes in data
- Classification: Assigning data points to predefined categories based on their features
- Hybrid CNN-SVM Classifier: A machine learning model that combines CNN and SVM capabilities for improved performance.

1.0 Introduction

Roads are vital lifelines for societies worldwide, enabling the efficient movement of goods and services and serving as critical enablers of economic and social development. In India, where road transportation forms the backbone of passenger and cargo movement, maintaining road networks ensures seamless connectivity and fosters regional development. These networks represent significant public assets that require meticulous maintenance and management to remain functional and safe. Road authorities' strategic role in overseeing these assets' well-being is indispensable, particularly in the current global economic landscape, which demands prudent resource allocation amidst challenges such as the ongoing pandemic[1]. A brief overview of Pavement Management Systems (PMS) and automated monitoring methods is tabulated in Table 1.

This study proposes an advanced hybrid CNN-SVM classifier to revolutionise pavement quality assessment. Designed to categorise pavement images into four distinct classes—alligator cracking, block cracking, potholes, and defect-free states. The classifier also computes the Pavement Condition Index (PCI), a critical metric for prioritising maintenance and resource allocation.

The American Standard for Testing of Materials (ASTM) D6433 standard provides the framework for PCI calculation by systematically evaluating various distresses and their severity levels within a pavement section. By integrating these guidelines, the proposed model ensures that its output aligns with established practices, offering actionable insights for road authorities.

1.1 Research Gap and Innovation

Even with advancements in pavement surveillance, there remain vital gaps. Conventionally, manual inspections are time-consuming, tedious, and unreliable due to subjective human perception, while prevalent autonomous techniques, including standalone CNNs or SVMs, are challenged with robustness under varying pavement conditions, as well as environmental conditions like changing lighting or weather. This research fills these gaps with a hybrid CNN-SVM classifier, the first to integrate CNNs' deep feature learning with SVMs' high-dimensional classification ability. Designed specifically for assessing pavement quality, it provides more accuracy, flexibility, and effectiveness, with the weakness of its manual and automatic predecessors.

Novelty: Unlike prior studies that rely on individual machine learning models, this research integrates CNNs and SVMs, combining the former's ability to extract intricate features from images with the latter's strength in handling high-dimensional classification tasks.

Impact: The hybrid approach improves accuracy, robustness, and adaptability, making it a reliable tool for road authorities to optimise maintenance strategies and resource allocation.

Paper Structure:

The paper is structured as follows:

- **Section 2** reviews related literature, highlighting gaps and challenges.
- **Section 3** details the hybrid CNN-SVM methodology.
- **Section 4** presents the experimental configuration, results, and their implications.
- **Section 5** concludes with insights and potential directions for future research in this domain.

2.0 Literature Review

Road infrastructure serves as a cornerstone of societal development, supporting economic growth, regional connectivity, and the seamless movement of goods and services[2]. Roads are particularly significant in densely populated countries like India, where they are the primary

Table 1. Overview of Pavement Management Systems (PMS) and automated monitoring methods.

Section	Description	Critical Elements/ Methods	Advantages	Challenges
Pavement Management Systems (PMS)	Essential tools in road infrastructure management, operating at the network and project levels to optimise resource allocation based on road-related data, ensuring sustained road quality and cost-efficiency.	1. Diverse User Groups: Must address the needs of stakeholders (e.g., planners, engineers). 2. Timely Decision-Making: Supports informed and prompt decisions for efficient execution. 3. Technology Integration: Incorporates modern/ emerging tech for relevance and effectiveness.	- Optimises resource allocation. - Enhances road quality and cost-efficiency. - Supports diverse stakeholders and timely decisions.	Requires integration of varied user needs. Dependent on effective technology adoption.
Automated Monitoring Methods	Various techniques are employed for pavement performance monitoring, each with unique characteristics.			
- Image Processing Techniques	Straightforward methods are efficient for large datasets, relying on manual feature extraction and thresholds.		- Efficient for large datasets. - Relatively simple to implement.	- Labour-intensive due to manual intervention. - Prone to inconsistencies in feature extraction.
- Machine Learning Algorithms	Automate feature extraction and classification, improving accuracy and scalability.		- High accuracy. - Scalable for diverse applications.	- Requires substantial labelled training data. - May falter under diverse conditions or variations.
- Hybrid Approaches	Combine CNNs (feature extraction) and SVMs (classification) for enhanced performance.		- Robust and accurate. - Leverages the strengths of multiple techniques.	- Demands careful design and parameter tuning. - Increased computational complexity.
- Remote Sensing and GIS	Facilitate large-scale monitoring using aerial/satellite imagery.		- Enables large-scale monitoring. - Useful for broad geographic analysis.	- Limited resolution and accuracy. - Less effective compared to ground-based imaging.

mode of transportation due to their accessibility and cost-effectiveness[3,4]. Ensuring the durability, safety, and efficiency of road networks requires robust systems for maintenance and management[5]. This section reviews key studies on PMS, infrastructure maintenance, and the integration of machine learning techniques for automated pavement assessment, with a focus on how these advancements address contemporary challenges in road management[6,7].

2.1 Pavement Management Systems and Infrastructure Maintenance

PMS are critical tools for optimising the maintenance and management of road networks. PMS integrates engineering principles with economic and strategic planning, enabling authorities to assess pavement conditions, predict future deterioration, and develop

cost-effective maintenance strategies[8]. These systems have evolved to become indispensable for resource optimisation, helping authorities allocate limited funds effectively while extending the functional life of road networks.

Accurate data acquisition is a cornerstone of PMS. Pavement inventory data, such as type, structure, and traffic volume, is combined with condition data on cracking, rutting, and surface wear to formulate comprehensive maintenance plans. Effective PMS relies on advanced data analysis techniques to prioritise interventions and ensure sustainable road management[9,10].

2.2 Challenges and Context-Specific Considerations

The implementation of PMS varies significantly across regions due to differences in environmental, economic, and traffic conditions. For example, in densely populated regions like India, road networks must withstand heavy traffic loads, diverse climatic conditions, and rapidly evolving urban landscapes. These challenges necessitate dynamic PMS frameworks tailored to local conditions. Studies have highlighted the importance of adaptable approaches to address financial constraints and regional idiosyncrasies in prioritising road maintenance[11,12].

Additionally, the lack of uniform data collection methods and reliance on manual inspections in many regions hinder the widespread adoption of PMS. Transitioning to automated, data-driven systems is critical to overcoming these limitations[13].

2.3 Machine Learning Applications for Pavement Assessment

Recent advancements in machine learning have transformed pavement assessment, offering automated solutions for distress detection and classification. CNNs, a subset of deep learning, have proven highly effective in image recognition tasks, making them suitable for detecting surface distresses such as cracks, potholes, and delamination. Studies have demonstrated that CNNs can identify intricate patterns in pavement images, significantly improving the accuracy and efficiency of assessments[14,15].

SVMs complement CNNs by serving as robust classifiers, particularly effective in scenarios involving high-dimensional data. Research shows that integrating CNNs for feature extraction with SVMs for classification enhances the overall accuracy and robustness of pavement assessment models[16,17].

Hybrid approaches that combine CNNs and SVMs leverage the strengths of both algorithms. CNNs excel in feature extraction, capturing the intricate texture and structural details of pavement images, while SVMs ensure precise classification even with limited training data. This synergy addresses challenges such as variations in pavement types, environmental conditions, and imaging quality, making hybrid models a promising solution for automated pavement assessment[18].

2.4 Pavement Condition Index (PCI)

The PCI is a standardised metric for evaluating road pavement conditions, widely adopted by road authorities to guide maintenance and rehabilitation decisions. PCI provides a quantitative assessment of pavement distress, enabling data-driven prioritisation of repair efforts. It is calculated following guidelines such as ASTM D6433, which outline systematic steps for data collection, distress identification, and severity assessment[19,20].

2.4.1 Steps in PCI Calculation

1. **Data Collection:** Visual surveys or automated systems collect data on distress types (e.g., cracks, potholes, and rutting) and their severity. Advances in imaging technologies have improved the efficiency of this process[21].
2. **Distress Identification and Severity Assessment:** Distresses are categorised by type and severity, with automated systems reducing human error and increasing consistency[22].
3. **Distress Quantification:** Distress extent, severity, and spatial distribution are quantified. These metrics are used to calculate individual distress indices[23].
4. **Pavement Condition Rating:** The distress indices are weighted and aggregated to compute the overall PCI for a pavement section, providing a standardised measure of condition:

$$PCI = \frac{\sum_{i=1}^{n}(I_i \times W_i)}{\sum_{i=1}^{n}(W_i)}$$

Where:

- Ii is the distress index for Type III,
- Wi is the weight assigned to Type III,
- n is the total number of distress types.

2.5 Relevance to the Study

The proposed hybrid CNN-SVM classifier automates distress identification and severity estimation, contributing directly to the PCI calculation process. By accurately categorising pavement distresses and quantifying their severity, the model provides road authorities with reliable data for informed decision-making. This integration of machine learning into PCI computation represents a significant step forward in pavement management, offering scalability, accuracy, and adaptability across diverse conditions[24,25].

3.0 Proposed Methodology

This study introduces an innovative hybrid CNN-SVM model to address the challenges of road condition categorisation and the calculation of the PCI, utilising the well-known Kaggle San Francisco Street dataset. By leveraging the complementary strengths of CNN and SVM, the proposed model achieves high accuracy in pavement condition assessment and defect classification.

3.1 Overview of the Hybrid CNN-SVM Model

CNN, known for its exceptional image analysis capabilities, form the foundation of the proposed hybrid model. With their multi-layered architecture and supervised learning capabilities, CNN efficiently extract hierarchical patterns from raw pavement images. These extracted features are subsequently classified by SVM, which excels in separating complex, multidimensional datasets. By replacing the traditional SoftMax layer of CNN with an SVM classifier, the hybrid model achieves a notable improvement in classification accuracy and robustness, particularly in handling imbalanced datasets. Figure 1 illustrates the architecture of the hybrid CNN-SVM model, highlighting the seamless integration of feature extraction and classification stages.

3.2 CNN Architecture and Feature Extraction

CNN are pivotal for extracting localised features from pavement images. The model begins with a 128×128 grayscale input image from the SF Street dataset. Using a 5×5 convolutional filter (kernel) with a stride of 2, the CNN progressively reduces the spatial dimensions while capturing meaningful features.

The convolution operation applies the kernel m×m to the input image n×n, producing outputs of dimensions:

$$(n - m + 1) \times (n - m + 1)$$

Key architectural components include:

1. Feature Maps: Generated by convolutional layers, these capture distinctive attributes such as cracks, potholes, or defect-free patterns.
2. Receptive Fields: Focus on effective sub-areas of the input image to extract localised features, mimicking human visual processing.
3. Hierarchical Layers: N1 and N2 layers progressively refine features, ensuring that the CNN captures both high-level and low-level characteristics of pavement images.

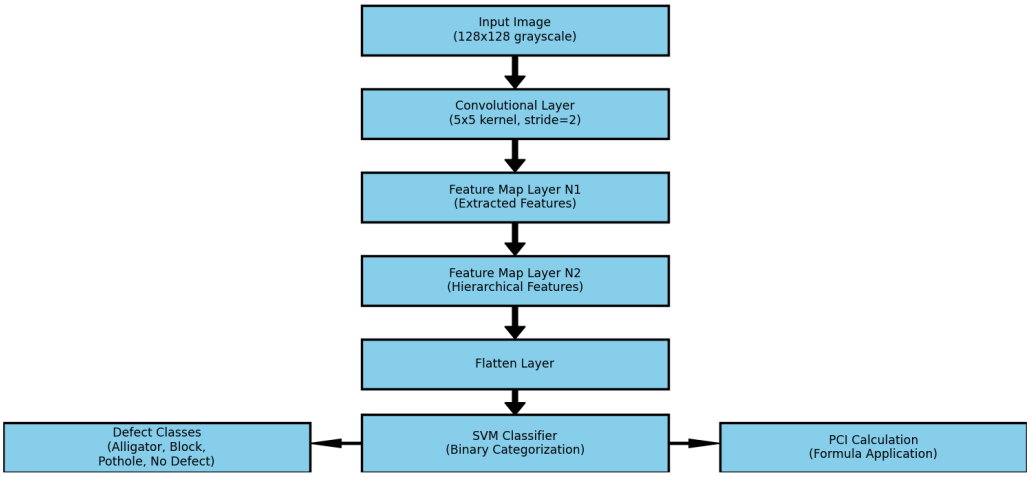


Figure 1. Architecture of the hybrid CNN-SVM model, illustrating feature extraction via CNN layers and classification via SVM.

The CNN undergoes iterative training across multiple epochs to optimise weights and extract robust features for downstream classification.

3.3 SVM Classifier for Final Categorisation

The SVM replaces the SoftMax layer of the CNN, leveraging its strength in binary classification. SVM create optimal hyperplanes in the feature space to separate classes effectively, even in high-dimensional datasets.

Key features of the SVM in this model:

- **Binary Classification:** Handles two-class problems, which can be extended for multi-class categorisation using one-vs-all or one-vs-one strategies.
- **Generalisation:** Minimises overfitting by focusing on maximising the margin between classes.
- **Input Features:** Takes the output of the CNN's N3 layer as input, ensuring that classification benefits from automatically generated, high-quality feature representations. Hyperparameter tuning for the SVM was conducted systematically. The Radial Basis Function (RBF) kernel was selected for its flexibility in handling nonlinear data. Key parameters- gamma (G) and degree (D)-were optimised via grid search over a range of values (G: [0.01, 0.1, 1], D: [1, 3, 5]). Gamma, which controls the influence of individual training points, was set to 0.1 to balance model generalisation and prevent overfitting, while degree, defining the polynomial kernel's complexity, was set to 3 to optimise classification accuracy without excessive computational cost. These values were chosen based on their consistent performance across training and testing phases, as detailed in Section 4.8.

During training, the SVM algorithm learns to classify pavement defects into four categories: alligator cracking, block cracking, potholes, and defect-free pavement. In the testing phase, it assigns each test image to a class and computes the corresponding PCI value.

3.4 PCI Calculation

The calculated PCI is based on defect type, severity, and extent. The steps include:

1. **Defect Detection:** The hybrid model identifies pavement defects and classifies them into predefined categories.
2. **Severity Assessment:** The SVM evaluates the severity level of each defect.
3. **PCI Formula Application:** The identified defects are weighted and aggregated to compute the PCI value for each test image. This output provides actionable insights for road authorities to prioritise maintenance.

3.5 Addressing Dataset Imbalance

Dataset imbalance, a common challenge in real-world applications, can impair the model's ability to generalise across underrepresented classes. To mitigate this, the following strategies were implemented:

1. **Balanced Dataset Curation:** The dataset was curated to ensure proportional representation of defect types, focusing on the three most prevalent and impactful categories-alligator cracking, block cracking, and potholes- along with defect-free pavement. This ensured a comprehensive understanding of pavement conditions. The process of balancing the dataset involves:
   a. **Initial Analysis of the Dataset:** The dataset was first processed to assess the distribution of the types of defects. The aim was to count how many images fell into each class (alligator cracking, block cracking, potholes, and defect-free pavements).
   b. **Threshold-Based Selection:** For balance, a threshold for the class with the lowest sample count was determined.
   c. **Class Balancing Methods:** When a class was over-represented, random sampling was applied to reduce the count.
   If a class was underrepresented, additional samples were obtained from external sources or synthetic samples were created using augmentation. Underrepresentation Criteria: A class was considered underrepresented if its sample count was significantly lower than the majority class (e.g., less than 70% of the most frequent class).
   d. **Final Dataset Validation:** The updated dataset was checked to ensure that all classes were balanced while the integrity of the data was preserved.
2. **Data Augmentation:** Techniques such as rotation, flipping, cropping, and scaling were applied to artificially expand the dataset, particularly for underrepresented classes.
3. **Oversampling and Under sampling:** Synthetic oversampling techniques (e.g., SMOTE) were used

to generate additional samples for minority classes, while undersampling reduced overrepresented classes to achieve balance.

These measures significantly reduced biases and enhanced the model's performance, ensuring it accurately represents diverse pavement conditions.

3.6 Workflow Summary

1. **Preprocessing:** Grayscale conversion, resizing, and augmentation of input images.
2. **Feature Extraction:** CNN processes images to generate hierarchical features.
3. **Classification:** SVM categorises defects into predefined classes.
4. **PCI Calculation:** The model computes PCI values based on classified defects and their severity.
5. **Evaluation:** Performance metrics (e.g., accuracy, precision, recall) are used to assess the model.

By combining the robust feature extraction capabilities of CNNs with the classification precision of SVMs, the proposed hybrid model provides a scalable and accurate solution for road condition assessment and PCI calculation. This approach empowers road authorities to prioritise interventions and optimise resource allocation, ensuring durable and safe infrastructure.

4.0 Experimental Configuration

The suggested experiment evaluates the proposed hybrid model for the SF Streets dataset. Below are the procedures and configurations used in the experimental setup.

4.1 Dataset Utilised

The SF Street dataset was utilised to train and test the suggested classification scheme. The dataset contained 18,480 images taken across varied environmental settings, ranging from sunny (daytime, dusk) to rainy (rainy, fog) weather conditions and city traffic situations. Add-on images taken along the Pune-Mumbai Expressway between December 2022 and December 2023 using a high-resolution smartphone camera added more variety to the dataset, ranging from monsoon-caused wet roads to hot, dry season and extreme car wear. This variety guarantees the model's strength under real-world pavement conditions, ranging from city streets to busy expressways.

4.2 Implementation of CNN for Pavement Problem Detection

The CNN component is tailored to detect pavement defects efficiently. The implementation follows these steps:

1. **Data Preprocessing**:
   - Resize images to a uniform 128×128 resolution.
   - Normalise pixel values to the range [0, 1].
   - Apply augmentation (e.g., rotations, flips) to enhance data diversity.
2. **CNN Architecture**:
   - Custom architecture designed to integrate with SVM.
   - Inspired by popular models like ResNet and VGG, with modifications to handle pavement patterns.
3. **Training**:
   - Trained on labelled datasets with distinct categories: cracks, potholes, deterioration, and defect-free.
4. **Hyperparameter Tuning**:
   - Optimised parameters: learning rate, batch size, dropout rate, and filter size.
5. **Evaluation**:
   - Validated on separate test data to measure generalisation.
6. **Deployment**:
   - Integrated into real-world systems for automated pavement inspection.

4.3 Implementation of SVM for Pavement Problem Detection

The SVM component complements the CNN by classifying extracted features into distinct categories.

1. **Feature Extraction**: Features extracted using CNN (or methods like HOG and LBP for standalone SVM).
2. **Data Preparation**: Features organised into vectors for SVM input, with corresponding class labels.
3. **Kernel Selection**: The RBF kernel is employed for flexibility and accuracy.
4. **Training**: Optimises the hyperplane separating defect categories.
5. **Evaluation**: Validates accuracy on unseen data, ensuring robustness.
6. **Integration**: Deployed with CNN for hybrid classification.

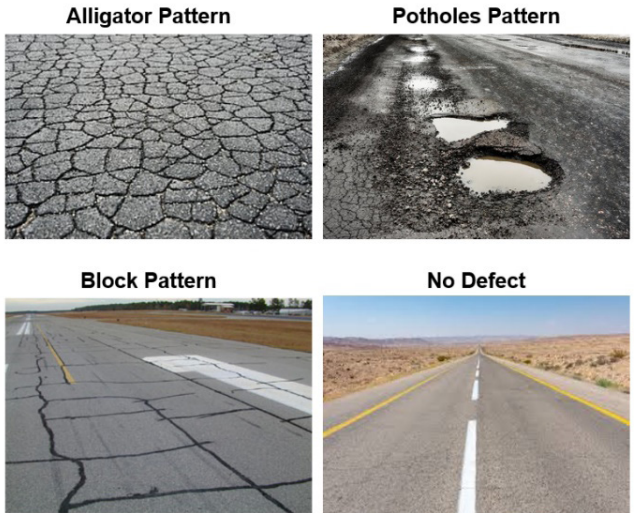


Figure 2. Sample Images as fed input for the proposed hybrid CNN-SVM classifier.

4.4 Data Preprocessing

Data preprocessing is crucial for effective feature extraction, which is shown in Figure 3. Key steps include:

- Noise suppression and resizing to 128×128 pixels.
- Image centring to standardise features.

This ensures that improperly processed images do not hinder feature extraction or classification.

4.5 Data Splitting Methodology

A random selection method partitions the SF dataset into training (80%) and testing (20%) subsets, ensuring:

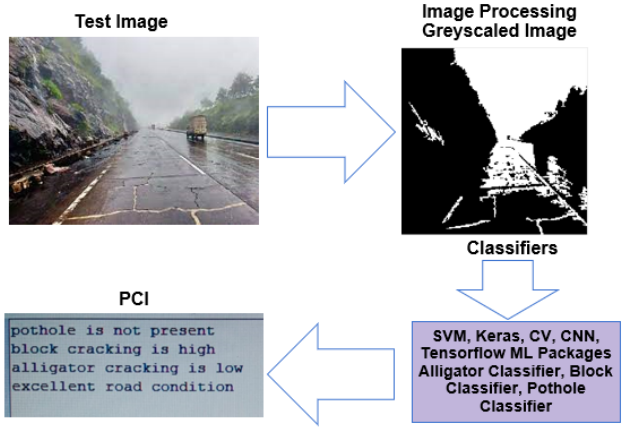


Figure 3. The suggested hybrid CNN-SVM classifier's workflow.

1. **Randomisation**: Minimises biases for real-world simulation.
2. **Balanced Representation**: Maintains diversity in pavement conditions.

   Mathematical representation:
   - Training Data T:
     $T = \{x_1, x_2, \ldots, x_{0.8N}\}$
   - Testing Data V:
     $V = \{x_{0.8N} + 1, \ldots, x_N\}$

This split ensures the model generalises well and is tested on unseen data.

4.6 Feature Extraction (FE)

The CNN component extracts hierarchical features across multiple convolutional layers, using N1, N2, and N3 nodes in three layers:

- **N1** and **N2**: Set to 50.
- **N3**: Set to 100.

Using a Sigmoid activation function, the CNN outputs a one-column feature vector for SVM input. This ensures:

1. Feature extraction accuracy.
2. PCI computation in the CNN's output layer.

4.7 Classifiers and Workflow

The hybrid CNN-SVM classifier integrates feature extraction (CNN) and classification (SVM):

1. **CNN**: Extracts features from input images.
2. **SVM**: Classifies defect patterns (e.g., cracks, potholes).
3. **Output**: Final classification and PCI calculation.

4.8 Discussion on Results

In SVM, Gamma (G) and Degree (D) are crucial hyperparameters that influence the classifier's performance. Gamma controls the influence of individual training points on the decision boundary, with lower values leading to smoother and more generalised boundaries, which helps reduce overfitting. On the other hand, the degree determines the complexity of the polynomial kernel, with higher values creating more intricate decision boundaries but increasing the risk of overfitting.

Table 2 presents the effects of input parameters (gamma and degree) on the performance of different

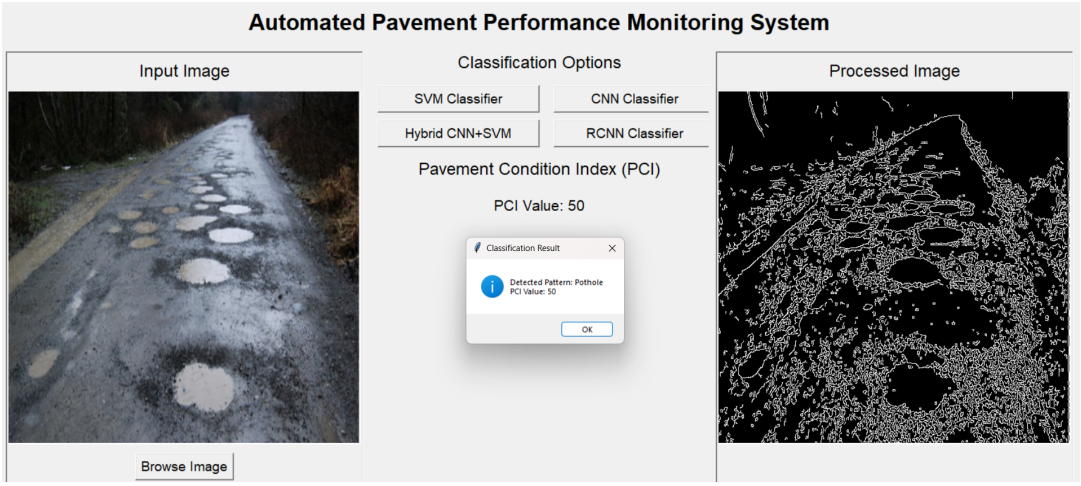


Figure 4. Raw photograph (left) and grayscale segmented image (right) of a pothole sample, processed for PCI calculation.

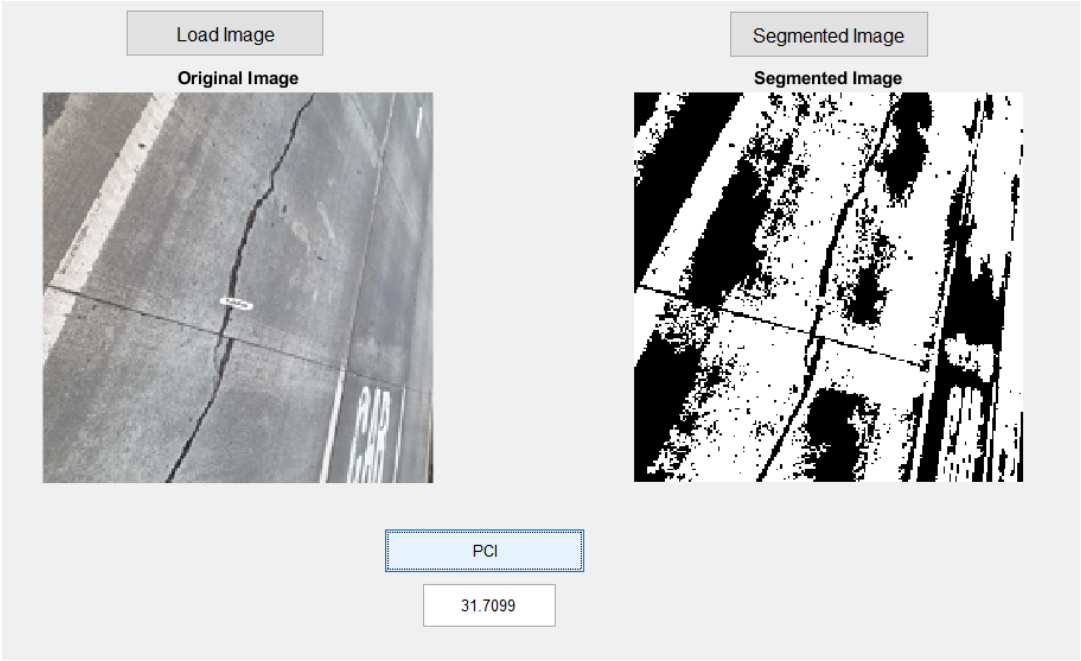


Figure 5. Original (left) and grey-scaled segmented image (right) used for processing the PCI value for Pune-Mumbai express highway, having a PCI of 31.7%.

classifiers across various defect patterns. As shown in the table, the classifier's accuracy tends to decrease when the Classification Function (CF) is switched between alligator, block, pothole, and no defect. Rows 1 and 9 indicate that the classifier performs better when Gamma (G) is set to 0.1 rather than 1. Moreover, accuracy decreases as the Degree (D) increases. However, an unexpected trend emerges where the training accuracy improves when the degree is set to 5 and gamma is 0.1, though test accuracy decreases under these conditions. Specifically, the hybrid CNN-SVM model achieves the highest training accuracy of 97.8% for the pothole pattern when D = 5, G = 0.1. For testing, the highest accuracy of 96.4% is achieved when G = 0.1, D = 3, and the CF is set to alligator. In this study, the hybrid CNN-SVM model demonstrated optimal performance with G = 0.1 and D = 3, balancing generalisation and complexity for accurate pavement defect classification.

The selection of G = 0.1 ensures a smooth decision boundary, reducing overfitting while maintaining

Table 2. Performance analysis of SVM, CNN, and hybrid CNN-SVM classifiers across pavement defect patterns, showing training (Tr) and testing (Te) accuracies with varying gamma (G) and degree (D) parameters.

Sr.	Input			%A for SVM		%A for CNN		%A for CNN-SVM	
	G	D	Pattern	Tr	Te	Tr	Te	Tr	Te
1	1	3	Alligator	92.8	90.3	94.1	94	95.6	95.1
2	1	3	Block	91.7	91.2	93.8	93.7	95.8	95.5
3	1	3	Pothole	93.8	93.6	94.5	94.2	96.1	96
4	1	3	No Defect	93.2	93.3	94.5	94.2	96.1	96
5	1	5	Alligator	90.1	90	95	94.8	96.1	96
6	1	5	Block	91.45	91.1	91.9	92	95.9	95.4
7	1	5	Pothole	90.36	90.5	92	91.7	97.1	96.3
8	1	5	No Defect	91.1	91	93.1	93	96.7	96.1
9	0.1	3	Alligator	93.2	92.5	93.8	93.6	96.8	96.4
10	0.1	3	Block	92.56	92.5	93.4	93.6	95.9	95.7
11	0.1	3	Pothole	94	93	94.6	94.2	96.6	96.3
12	0.1	3	No Defect	93.1	93	94	93.5	97	96
13	0.1	5	Alligator	93.4	93	94.7	94.1	97.2	95.8
14	0.1	5	Block	93.5	93.4	94.3	94	97.2	96.2
15	0.1	5	Pothole	93.97	93.6	95.7	95.5	97.8	96.3
16	0.1	5	No Defect	92.8	93	94.8	94.6	97.5	96.25

Here, %A = %Accuracy

sensitivity to pavement defect patterns. D = 3 strikes a balance between model complexity and generalisation, avoiding the overfitting observed at D = 5 (where training accuracy peaks but testing accuracy drops). This configuration optimises the hybrid model's performance across all defect categories, as evidenced by the highest testing accuracy of 96.4% for alligator cracking.

In the context of pavement defect classification, these findings demonstrate the hybrid CNN-SVM model's ability to achieve superior performance. The CNN-SVM classifier consistently outperforms both the SVM and CNN classifiers across all defect categories, showcasing its potential for precise pavement problem detection.

Figure 6 presents a graphical comparison of the performance of the SVM, CNN, and CNN-SVM classifiers. The hybrid CNN-SVM model consistently outperforms the other classifiers, particularly in terms of classification accuracy. This visual comparison underscores the effectiveness of the hybrid approach in addressing pavement pattern recognition tasks.

Table 3 presents key performance metrics, including Precision, Recall, and F1-Score, for the SVM, CNN, and hybrid CNN-SVM classifiers. These metrics offer a more nuanced view of the classifiers' effectiveness, where:

- **Precision** measures the proportion of true positive predictions among all positive predictions.

- **Recall** measures the proportion of true positives correctly identified out of all actual positive instances.

The **F1-score**, the harmonic mean of precision and recall, provides a balanced measure of performance.

The table highlights the superior performance of the hybrid CNN-SVM classifier across all metrics, demonstrating its capability to more accurately identify pavement defects compared to standalone SVM and CNN classifiers. These results confirm that the hybrid approach is more reliable and effective in pavement condition assessment.

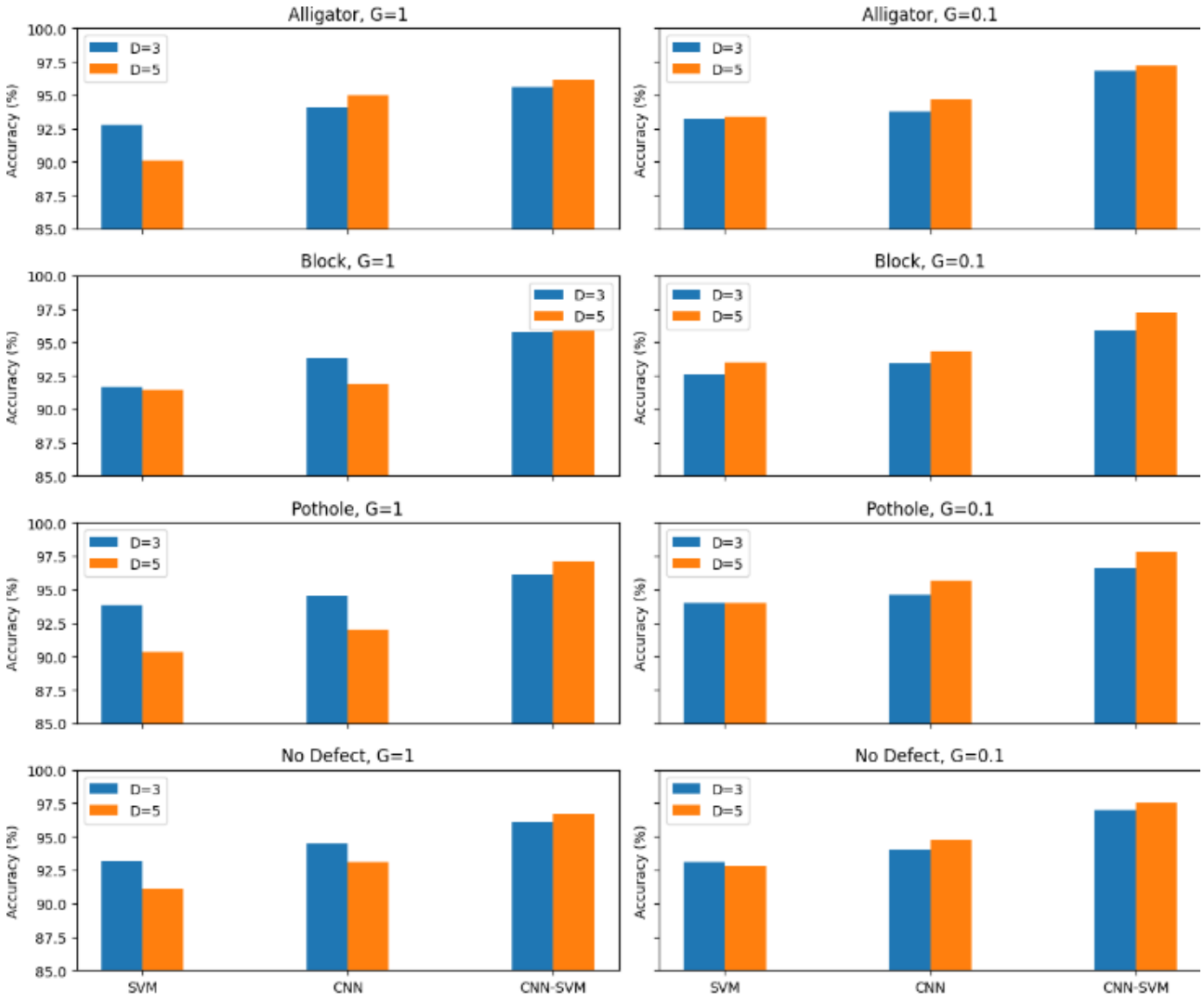


Figure 6. Performance analysis of the algorithms.

False Positive (FP) and False Negative (FN) analysis even better clarifies the model's consistency. With alligator cracking, FP at 2.1% erroneously classified unpaved defective areas as cracked and FN at 1.5% overlooked delicate cracks. There was a lower FP of 1.2% but a higher FN of 2.3% for potholes, occasionally missing tiny depressions. These rates indicate the model's robustness in reducing false alarms but uncover a weakness in identifying small defects, possibly due to dataset imbalance or feature extraction sensitivity. Correcting this by using larger training data may also improve reliability.

Figure 7 shows the confusion matrix for the hybrid CNN-SVM classifier, which visually represents the classifier's performance across different defect categories. The diagonal elements indicate the number of correctly classified images for each defect type, while the off-diagonal elements highlight misclassifications. The matrix confirms that the hybrid model is highly effective in distinguishing between various pavement defects, further validating its robustness and accuracy in real-world scenarios.

Table 3. Comparative performance metrics (Precision, Recall, F1-Score) of SVM, CNN, and hybrid CNN-SVM classifiers for pavement defect detection

Metric	SVM (%)	CNN (%)	CNN-SVM (%)
Precision	93.5	94.2	96.1
Recall	93.2	94.0	96.0
F1-Score	93.3	94.1	96.1

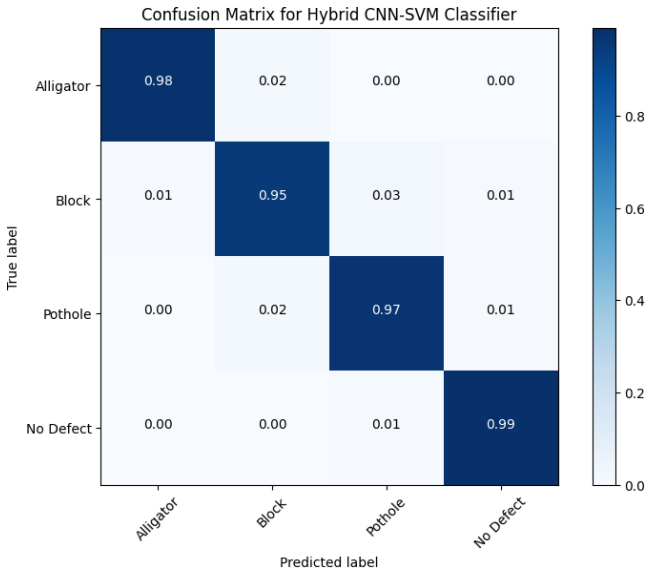


Figure 7. Confusion matrix for a hybrid CNN-SVM classifier.

5.0 Conclusion

This research successfully combines CNNs and SVM to build a hybrid CNN-SVM classifier, resulting in an excellent training accuracy of 97.8% and testing accuracy of 96.4% for pavement condition rating. By harnessing the strong feature extraction capability of CNNs and the accurate classification ability of SVMs, this method forms a robust, autonomous tool for infrastructure management that is superior to conventional manual examination and isolated machine learning models in both accuracy and scalability. The model's flexibility was tested on various datasets, such as the San Francisco Streets dataset and additional images from the Pune-Mumbai Expressway, proving its capability to improve road maintenance decision-making under different environmental conditions.

Despite its advantages, the hybrid CNN-SVM classifier has significant limitations. Its accuracy is dependent on big, well-stationed training datasets, and it has lower sensitivity to small faults, like tiny cracks or initial-stage degradation, as reflected in false negative rates (e.g., 2.3% for potholes). These limitations are due to dataset imbalance and the model's feature extraction susceptibility, potentially missing minor patterns. Also, the computational complexity, although tolerable in controlled environments, raises issues with real-world use on devices with limited resources.

Subsequent studies might overcome these limitations by broadening the model's capabilities to identify a wider variety of pavement defects, including rutting, ravelling, or surface delamination, beyond the existing alligator cracking, block cracking, potholes, and defect-free categories. Broadening the dataset to cover rural or low-traffic roads would also challenge its generalisability, as these types of roads often have different pavement conditions compared with urban or expressway settings. In addition, further optimising the model architecture—perhaps by using light-weighted CNN variants or leaner SVM kernels—could make computational processing more efficient, allowing real-time use in field environments, like mounting on pavement inspection trucks or drones. Such developments would extend the model's practical application, making it scalable and effective in a variety of infrastructure environments.

Through ongoing refinement of the hybrid CNN-SVM method, this study opens doors to more accurate, efficient, and responsive pavement management systems. These enhancements will benefit road agencies globally, enabling the creation of safer, more sustainable transport networks essential for economic and social advancement.

6.0 Contributions

Conceptualisation: A.R.C. and S.S.P.; **Methodology:** A.R.C. and S.S.P.; **Software:** A.R.C.; **Validation:** A.R.C. and S.S.P.; **Formal Analysis:** A.R.C.; **Investigation:** A.R.C.; **Resources:** S.S.P.; **Data Curation:** A.R.C.; **Writing—Original Draft Preparation:** A.R.C.; **Writing—Review and Editing:** A.R.C. and S.S.P.; **Visualisation:** A.R.C.; **Supervision:** S.S.P.; **Project Administration:** S.S.P.; **Funding Acquisition:** S.S.P.

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