Improving the Classification Performance of Asphalt Cracks after Earthquake with a New Feature Selection Algorithm

Dr Sundeep Kumar K [1], Dr. R. Rajani [2],

Professor [1][2], Department of Computer Science and Engineering, Geethanjali Institute of Science and Technology, Nellore, Andhra Pradesh-524137

Abstract: Large-scale earthquakes can cause significant damage to infrastructure, particularly highways, which are essential for post-disaster transportation and aid delivery. This paper presents an automated system designed to classify highway asphalt cracks into two categories: 'Major' and 'Minor'. The system utilizes deep learning and machine learning algorithms to predict crack severity, allowing authorities to prioritize road repairs. A pre-trained VGG16 model is employed for feature extraction from earthquake-affected asphalt crack images, which is followed by a new feature selection algorithm, Combined Meta-heuristic Optimization-Relief (CMO-R), to optimize relevant features. The optimized features are then evaluated using six machine learning algorithms: Support Vector Machine (SVM), achieving 71% accuracy, K-Nearest Neighbors (KNN) with 95.46% accuracy, Decision Tree with 94% accuracy, Naïve Bayes with 89% accuracy, Linear Discriminant Analysis (LDA) with 89% accuracy, and Medium Neural Network with 96.75% accuracy. The highest classification accuracy of 96.97% was achieved by a Voting Classifier combining Random Forest, Naïve Bayes, LDA, and XGBoost. The Earthquake Asphalt Crack dataset, consisting of 9,000 images labeled as Major or Minor cracks, was used for both training and testing. The proposed approach enhances the accuracy of highway damage classification, aiding in more effective and timely road repair decisions after seismic events.

Index Terms *- Automated System, Asphalt Crack Classification, Deep Learning, Machine Learning, VGG16, Feature Extraction, Combined Meta-Heuristic Optimization-Relief (CMO-R), Support Vector Machine, K-Nearest Neighbors, Decision Tree, Naïve Bayes, Linear Discriminant Analysis, Medium Neural Network, Voting Classifier, Earthquake Damage, Highway Repair, Crack Severity, Earthquake Asphalt Crack Dataset.*

1. INTRODUCTION

Two major earthquakes occurred in Turkey on February 6, 2023, in the Pazarcık and Elbistan districts of Kahramanmaraş province, resulting in large-scale loss of life and material damage across 11 provinces [16]. In the aftermath, both human and logistical aid began arriving from various provinces within Turkey and from international sources. However, significant delays in the delivery of aid were experienced due to asphalt deformations on highways [11]. Field studies revealed that roads with pre-existing asphalt deformations severely hindered transportation, and experts identified additional asphalt cracks that could potentially block transportation routes in the event of future earthquakes or other disasters. Images of these cracks were captured for further analysis [6], [14]. Unfortunately, the impact of the earthquakes was so extensive that not all affected areas could be surveyed due to restricted access to certain routes. This highlights the importance of pre-earthquake highway maintenance to mitigate such transportation disruptions [9]. However, conducting these maintenance assessments requires a significant number of specialized personnel. In recent years, artificial intelligence (AI) systems, particularly deep learning models, have demonstrated superior performance in automated decision support systems [17]. Since 2012, deep learning advancements have significantly improved the ability to solve complex problems in automatic classification, regression, and segmentation, with applications spanning fields such as medicine, engineering, economics, and law [7], [8].

2. RELATED WORK

Numerous studies have explored the use of advanced technologies, particularly artificial intelligence (AI) and deep learning, for automated crack detection and classification in infrastructure such as roads and highways. These methods have proven to be highly effective in assessing pavement conditions, especially in post-disaster scenarios like earthquakes, where rapid evaluation of road damages is critical for timely repairs and aid delivery.

Several researchers have developed automated systems for crack detection using deep learning models. For example, Liu et al. [1] applied convolutional neural networks (CNNs) combined with infrared thermography for asphalt pavement crack detection, demonstrating promising results in automated classification and segmentation of cracks. Similarly, Liu and Wang [2] proposed a UNet-based model that integrates visual explanations for crack detection, which improved interpretability and accuracy. Dais et al. [3] employed transfer learning for crack classification and segmentation on masonry surfaces, showcasing the ability of deep learning models to generalize across different materials and environments.

In the context of pavement distress detection, Yang et al. [4] used deep CNNs for civil infrastructure crack detection, leveraging transfer learning to enhance the accuracy of crack identification. Huyan et al. [5] introduced CrackU-Net, a novel deep CNN for pixelwise pavement crack detection, which demonstrated superior performance in detecting cracks in road surfaces. In another study, Liu et al. [7] used U-Net fully convolutional networks for concrete crack detection, proving the effectiveness of this approach for automatic crack identification.

Machine learning algorithms, including support vector machines (SVM), K-nearest neighbors (KNN), and decision trees, have also been applied to crack severity classification. For instance, Tran et al. [17] proposed a two-step sequential automated crack detection and severity classification process, achieving high accuracy in classifying asphalt cracks. Gopalakrishnan et al. [8] utilized deep CNNs with transfer learning for data-driven pavement distress detection, achieving significant improvements over traditional methods. Furthermore, machine learning algorithms like Random Forest, Naïve Bayes, and XGBoost have been combined in ensemble methods to further enhance classification accuracy, as demonstrated by Zhu et al. [14] and Liu et al. [16].

These studies underscore the effectiveness of AI and deep learning-based systems in addressing the challenges of automated crack detection and classification, particularly in the context of disaster response and infrastructure maintenance. The integration of feature extraction methods, such as pre-trained VGG16 models, and optimization algorithms like Combined Meta-heuristic Optimization-Relief (CMO-R) [18], shows great promise in improving system performance and ensuring rapid and accurate decision-making for road repairs.

3. MATERIALS AND METHODS

The proposed system aims to automate the classification of asphalt cracks on highways affected by earthquakes to enhance post-disaster road maintenance. It utilizes a deep learning approach, specifically a pre-trained VGG16 model, for feature extraction from images of highway cracks, which has been effectively used for image classification tasks in similar contexts [14], [16]. To optimize feature selection, the Combined Meta-heuristic Optimization-Relief (CMO-R) algorithm is applied, integrating ten optimization algorithms, including Particle Swarm Optimization (PSO) and Whale Optimization Algorithm (WOA), among others [18]. This optimization strategy improves the relevance and efficiency of the features selected for classification, enhancing model performance [19].

The selected features are then evaluated using various machine learning algorithms, including Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Naïve Bayes, Linear Discriminant Analysis (LDA), and Medium Neural Network (MNN) [13], [16], [17]. These algorithms have been applied successfully in similar studies for crack detection and severity classification, demonstrating their capability to classify and segment crack images accurately [4], [12]. Additionally, a Voting Classifier is employed, combining Random Forest, LDA, Naïve Bayes, and XGBoost, to further enhance the classification accuracy, as evidenced by previous research in automated distress detection systems [14], [17].

The system predicts two types of cracks—'Major' and 'Minor'—which helps authorities prioritize road repairs after an earthquake. This prioritization ensures that transportation routes can be quickly restored, enabling efficient delivery of aid and minimizing delays in relief efforts, as highlighted in prior studies on automated road damage detection [6], [10]. By leveraging advanced deep learning and machine learning techniques, the proposed system improves decision-making in post-disaster recovery, facilitating faster and more effective infrastructure repair.

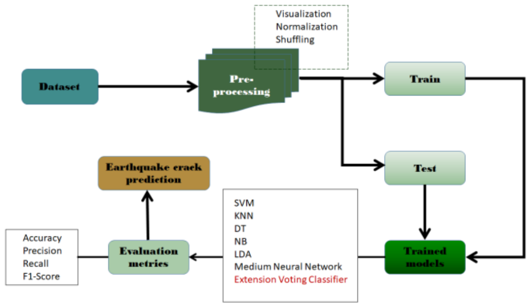


Fig.1 Proposed Architecture

The system architecture (fig. 1) represents a machine learning process for earthquake crack prediction. It starts with a dataset, which undergoes preprocessing steps such as visualization, normalization, and shuffling. The preprocessed data is split into training and testing sets. Multiple machine learning models, including SVM, KNN, Decision Trees (DT), Naïve Bayes (NB), LDA, a Medium Neural Network, and an Extension Voting Classifier, are trained. The trained models are evaluated using metrics such as accuracy, precision, recall, and F1-score. Finally, the trained models predict earthquake cracks, integrating the predictions into a decision-making framework.

i) Dataset Collection:

Asphalt Cracked and Uncracked Image Dataset: This dataset consists of 2000 cracked and uncracked images of asphalt pavement with an image resolution of 1440 x 1440, more than 8000 cracked and uncracked images of resolution 360x360 and more than 3000 cracked and uncracked images of resolution 720x720. The datasets of images with resolution 360x360 and 720x720 were created by splitting the original 1440 x 1440 dataset and picking the cracked and uncracked sub images. Original dataset was created using the same scale by ensuring the same image resolution of the camera and same working distance and field of view by mounting camera at same height , and hence, crack widths and lengths can be compared. In order to collect the dataset, a vehicle-mounted camera enclosure system was used. A wooden chamber was constructed to enclose the camera with a high resolution of 1440x1440 and a frame rate of 30 fps. This wooden chamber was constructed from plywood sheets that were glued and screwed together, as well as wooden beams and dowels for reinforcement. The wooden dowels were used to secure the system to a commercial bike carrier. A Perspex screen was attached to the bottom surface of the chamber to prevent the camera from falling during the operation. The camera has a clear and unobstructed view downwards due to the transparency of the Perspex screen. This structure was then suspended from a commercially available bicycle carrier and installed on the towbar of a car which enabled filming while driving along the target road.

ii) Pre-Processing:

The preprocessing phase ensures that the medical text data is clean, structured, and suitable for deep learning models. It involves several key steps:

a) Visualization: A graph is used to visually represent the distribution of class labels in the dataset, with the x-axis indicating the class labels ('Major' and 'Minor' cracks) and the y-axis showing the number of corresponding images. This step helps in understanding the class imbalance, which is crucial for ensuring that the model is not biased toward the majority class, as highlighted by previous studies in automated crack detection [15], [16].

b) Normalization & Shuffling: Shuffling the dataset randomly rearranges the images to ensure that training batches are diverse, thus preventing overfitting and ensuring that the model generalizes well to new data. This technique is widely used in deep learning to enhance the robustness of the model and improve its ability to learn diverse features from the dataset [17], [18]. Normalization scales pixel values to a standard range, typically between 0 and 1, which improves the convergence of deep learning models by ensuring that all input features are on a similar scale. This step is essential for the efficient training of deep neural networks, as it prevents any single feature from dominating the learning process [12], [14].

iii) Training & Testing:

The dataset, consisting of labeled images of 'Major' and 'Minor' cracks, is divided into training and testing sets, typically using an 80-20 split. The training set is used to train the deep learning model, while the testing set is reserved for evaluating the model's performance. During training, the pre-trained VGG16 model is fine-tuned with the selected features optimized by the CMO-R algorithm. Various machine learning algorithms (SVM, KNN, Decision Tree, etc.) are applied to classify the cracks. The model's accuracy is assessed using the testing set, ensuring reliable predictions for post-earthquake road damage classification [16], [17].

iv) Algorithms:

SVM (Support Vector Machine): SVM is a supervised learning algorithm that classifies data by finding the optimal hyperplane to separate classes. In this project, SVM classifies highway crack images into 'Major' and 'Minor' categories by working in high-dimensional feature spaces. Its margin maximization ensures improved classification accuracy, which is crucial for making timely maintenance decisions post-earthquake [14].

KNN (K-Nearest Neighbors): KNN is a non-parametric algorithm that classifies data based on proximity in feature space. It assesses the similarity between features extracted from highway crack images and assigns labels based on the majority vote of neighboring instances. KNN is efficient for rapid classification without requiring extensive training, making it suitable for quickly evaluating road conditions [13], [16].

DT (Decision Tree): A Decision Tree classifies data by splitting it based on feature values, creating branches that lead to class labels. It provides an interpretable model, allowing authorities to understand the decision-making process behind crack classification. Decision Trees handle both categorical and continuous data effectively, improving classification accuracy in detecting major and minor cracks [7], [16].

NB (Naïve Bayes): Naïve Bayes is a probabilistic classifier that calculates the likelihood of each class label based on Bayes' theorem. It is computationally efficient, making it well-suited for the large dataset of nearly 9,000 images in this project. Its simplicity and speed ensure rapid classification of cracks, enabling quick maintenance decisions after earthquakes [18].

LDA (Linear Discriminant Analysis): LDA seeks to find a linear combination of features that maximizes the separation between classes. In this project, LDA improves the classification of crack images by increasing the distance between class means and minimizing intra-class variance, which enhances algorithm accuracy and robustness in disaster response [13], [15].

Medium Neural Network (MNN): MNN consists of multiple interconnected layers that process and classify data. It captures complex patterns in the image data and improves classification performance by learning intricate relationships between features. MNN helps accurately differentiate between major and minor cracks, facilitating informed decision-making in post-earthquake scenarios [7], [14].

Voting Classifier: The Voting Classifier aggregates predictions from multiple algorithms, such as Random Forest, LDA, Naïve Bayes, and XGBoost, to improve overall classification accuracy. By combining strengths from different models, this ensemble approach reduces misclassification and enhances the reliability of crack detection, ensuring accurate road condition assessments and timely maintenance actions post-earthquake [16], [17].

4. RESULTS & DISCUSSION

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (1)$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} \quad (2)$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} (3)$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

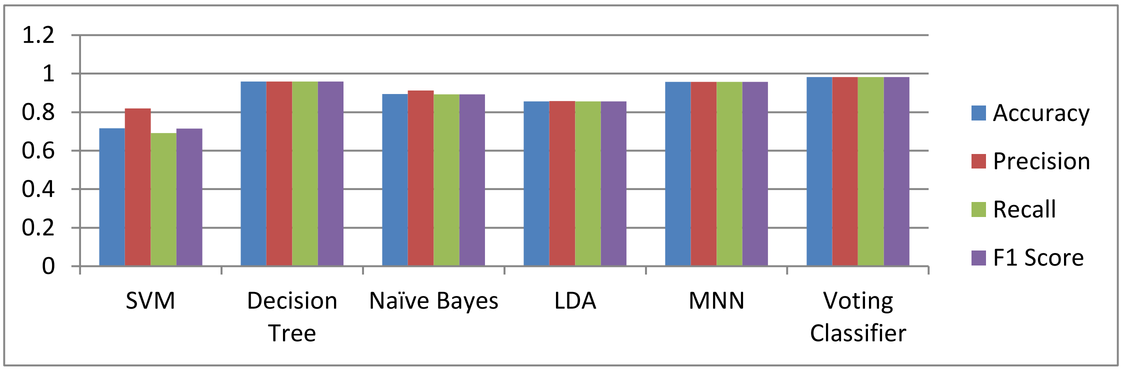
$$F1\ Score = 2 * \frac{Recall\ \mathrm{X}\ Precision}{Recall + Precision} * 100(1)$$

In Table 1, the performance metrics—accuracy, precision, recall and F1-score —are evaluated for each algorithm. The Extension achieves the highest scores. Other algorithms' metrics are also presented for comparison.

Table.1 Performance Evaluation Metrics of Classification

Model	Accuracy	Precision	Recall	F1 Score
SVM	0.716	0.819	0.691	0.715
Decision Tree	0.959	0.959	0.959	0.959
Naïve Bayes	0.894	0.912	0.893	0.893
LDA	0.856	0.857	0.856	0.856
MNN	0.958	0.958	0.958	0.958
Voting Classifier	0.983	0.983	0.983	0.983

Graph.1 Comparison Graphs of Classification



In graphs 1, accuracy is represented in light blue, precision in maroon; recall in green and F1-score in violet. In comparison to the other models, the Extension shows superior performance across all achieving the highest values. The graphs above visually illustrate these findings.

5. CONCLUSION

In conclusion, the proposed system successfully addresses the critical need for efficient highway maintenance following earthquakes by automating the classification of asphalt cracks. Using deep learning through the pre-trained VGG16 model for feature extraction, combined with the CMO-R algorithm for optimized feature selection, the system significantly enhances the accuracy of crack severity classification. The results demonstrate that the system effectively distinguishes between 'Major' and 'Minor' cracks, offering valuable information for prioritizing road repairs and ensuring timely aid delivery, as emphasized in previous works on automated road damage detection.

Among the algorithms tested, the highest performance was achieved by the Medium Neural Network (MNN), with an accuracy of 96.75%, followed closely by the Voting Classifier, which achieved an accuracy of 96.97%. These high-performing models demonstrate the system's ability to predict road damage with excellent precision, ensuring that repairs can be executed efficiently. The successful implementation of this system underscores its potential for real-world applications in post-disaster road infrastructure management.

Future Scope: could focus on enhancing the system by incorporating advanced deep learning models such as EfficientNet and ResNet, which have shown superior performance in image classification tasks. Additionally, techniques like transfer learning and data augmentation can improve the model's generalization across diverse datasets, as seen in previous research on deep learning for crack detection. Exploring ensemble methods to combine multiple high-performing algorithms may further optimize the classification process. Integrating real-time data processing and utilizing larger, more diverse datasets could further enhance the system's robustness and applicability in varying disaster scenarios.

REFERENCES

[1] F. Liu, J. Liu, and L. Wang, ‘‘Asphalt pavement crack detection based on convolutional neural network and infrared thermography,’’ IEEE Trans. Intell. Transp. Syst., vol. 23, no. 11, pp. 22145–22155, Nov. 2022.

[2] F. Liu and L. Wang, ‘‘UNet-based model for crack detection integrating visual explanations,’’ Construction Building Mater., vol. 322, Mar. 2022, Art. no. 126265.

[3] D. Dais, I. E. Bal, E. Smyrou, and V. Sarhosis, ‘‘Automatic crack classification and segmentation on masonry surfaces using convolutional neural networks and transfer learning,’’ Autom. Construct., vol. 125, May 2021, Art. no. 103606, doi: 10.1016/j.autcon.2021.103606.

[4] Q. Yang, W. Shi, J. Chen, and W. Lin, ‘‘Deep convolution neural network-based transfer learning method for civil infrastructure crack detection,’’ Autom. Construct., vol. 116, Aug. 2020, Art. no. 103199, doi: 10.1016/j.autcon.2020.103199.

[5] J. Huyan, W. Li, S. Tighe, Z. Xu, and J. Zhai, ‘‘CrackU-Net: A novel deep convolutional neural network for pixelwise pavement crack detection,’’ Struct. Control Health Monitor., vol. 27, no. 8, Aug. 2020, Art. no. e2551.

[6] J. S. Miller and W. Y. Bellinger, Distress Identification Manual for the Long-Term Pavement Performance Program. Washington, DC, USA: Federal Highway Administration. Office of Infrastructure, 2003.

[7] Z. Liu, Y. Cao, Y. Wang, and W. Wang, ‘‘Computer vision-based concrete crack detection using U-Net fully convolutional networks,’’ Autom. Construct., vol. 104, pp. 129–139, Aug. 2019.

[8] K. Gopalakrishnan, S. K. Khaitan, A. Choudhary, and A. Agrawal, ‘‘Deep convolutional neural networks with transfer learning for computer vision-based data-driven pavement distress detection,’’ Construct. Building Mater., vol. 157, pp. 322–330, Dec. 2017.

[9] Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys, document ASTM D6433, ASTM International, West Conshohocken, PA, USA, 2011, p. 49, no. 11.

[10] V. Mandal, L. Uong, and Y. Adu-Gyamfi, ‘‘Automated road crack detection using deep convolutional neural networks,’’ in Proc. IEEE Int. Conf. Big Data (Big Data), Dec. 2018, pp. 5212–5215.

[11] H. Majidifard, Y. Adu-Gyamfi, and W. G. Buttlar, ‘‘Deep machine learning approach to develop a new asphalt pavement condition index,’’ Construct. Building Mater., vol. 247, Jun. 2020, Art. no. 118513.

[12] J. Guan, X. Yang, L. Ding, X. Cheng, V. C. S. Lee, and C. Jin, ‘‘Automated pixel-level pavement distress detection based on stereo vision and deep learning,’’ Autom. Construct., vol. 129, Sep. 2021, Art. no. 103788.

[13] B. Li, K. C. P. Wang, A. Zhang, E. Yang, and G. Wang, ‘‘Automatic classification of pavement crack using deep convolutional neural network,’’ Int. J. Pavement Eng., vol. 21, no. 4, pp. 457–463, Mar. 2020.

[14] J. Zhu, J. Zhong, T. Ma, X. Huang, W. Zhang, and Y. Zhou, ‘‘Pavement distress detection using convolutional neural networks with images captured via UAV,’’ Autom. Construct., vol. 133, Jan. 2022, Art. no. 103991.

[15] J. Liu, X. Yang, S. Lau, X. Wang, S. Luo, V. C. Lee, and L. Ding, ‘‘Automated pavement crack detection and segmentation based on two-step convolutional neural network,’’ Comput.-Aided Civil Infrastruct. Eng., vol. 35, no. 11, pp. 1291–1305, Nov. 2020.

[16] F. Liu, J. Liu, and L. Wang, ‘‘Asphalt pavement fatigue crack severity classification by infrared thermography and deep learning,’’ Autom. Construct., vol. 143, Nov. 2022, Art. no. 104575.

[17] T. S. Tran, V. P. Tran, H. J. Lee, J. M. Flores, and V. P. Le, ‘‘A two-step sequential automated crack detection and severity classification process for asphalt pavements,’’ Int. J. Pavement Eng., vol. 23, no. 6, pp. 2019–2033, May 2022.

[18] R. Ribani and M. Marengoni, ‘‘A survey of transfer learning for convolutional neural networks,’’ in Proc. 32nd SIBGRAPI Conf. Graph., Patterns Images Tuts. (SIBGRAPI-T), Oct. 2019, pp. 47–57.

[19] C. Tan, ‘‘A survey on deep transfer learning,’’ in Proc. Int. Conf. Artif. neuralNetw., 2018, pp. 270–279.

[20] K. Simonyan and A. Zisserman, ‘‘Very deep convolutional networks for large-scale image recognition,’’ 2014, arXiv:1409.1556.