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Classification of Earthquake-Induced Asphalt Cracks with a Transfer Learning-Based Hybrid Strategy

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Abstract: One of the most popular modes of transportation is the highway. Highways that receive timely maintenance avoid future increases in maintenance expenses. It is crucial to identify highway damage brought on by significant earthquakes. because roadways are used to deliver logistical and humanitarian relief to earthquake-affected areas. Consequently, system applications that automatically identify asphalt deterioration are required. Images of asphalt cracks that appeared in five major Turkish cities following two consecutive severe earthquakes in the Elbistan region were examined in this study. The construction department experts classified these fissures as serious and small. In the following phase, a novel deep learning-based model was used to classify asphalt fractures. In the implementation phase of the proposed model, features were extracted using transfer learning models. These features extracted from different models were combined to create a large feature set. The ReliefF algorithm was used to select the most discriminative features from the extracted features. Popular machine learning algorithms such as SVM, KNN, Naive Bayes, and Decision Trees were used in the classification phase. The best classification results were achieved with the SVM algorithm.

Keywords: Earthquake, Asphalt cracks, Deep learning, Transfer learning models, Classification

Introduction

2023, in the districts of Pazarcık and Elbistan in the Kahramanmaraş province. Eleven Turkish provinces experienced substantial material losses and casualties. As soon as the earthquakes struck, aid started to come in in the form of people and supplies from other countries and Turkish districts. However, this help was delayed significantly due to the warped asphalt of the roads. The field tests showed that roads with previously warped asphalt hindered road movement. Furthermore, experts on the ground found and documented defects in the asphalt that would hinder transportation in the case of the next earthquake or other calamity. However, the effects of the recent earthquakes were so severe that not all places could be evaluated for the state of the highways because access to some earthquake-affected routes was barred.

In order to prevent such disruptions in mobility, pre-earthquake highway maintenance measures are essential (Miller & Bellinger, 2003; Systems & Management, 2011). However, it takes a lot of skilled people to detect these maintenance chores. In automated decision support systems, artificial intelligence systems have lately started to perform better. Since the development of deep learning models in 2012, significant progress has been made in addressing problems related to automatic classification, regression, and segmentation. These models have been applied in many fields, such as engineering, economics, law, and medicine. The proposed approach employs a unique deep learning-based technique to determine the urgency of highway maintenance based on asphalt crack pictures taken after the February 6 earthquakes in Turkey. Automatically classifying asphalt cracks is one of the most prevalent computer vision issues (Dais et al., 2021). Convolutional Neural Networks (CNNs) are growing in popularity and effectiveness for crack detection, according to numerous empirical research (Liu

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et al., 2022a; Liu & Wang, 2022; Liu et al., 2019). In a study by Gopalakrishnan et al. (2017), pavement cracks were binary classified as "crack" or "no crack" using a pre-trained VGG-16 CNN model.

The U-net model was altered by Huyan et al. (Huyan et al., 2020) in order to identify asphalt cracks in a database that contained 3000 photos. Video frames captured from car arches were examined by Mandal et al. (2018). It was estimated that the YoloV2 architecture detected about 9000 pictures. Majidifard et al. (2020) introduced a comprehensive approach to asphalt crack classification, utilising YOLO net for crack detection and U-Net for fracture segmentation. Guan et al. (2021) presented a computerised system that uses a mix of image processing and deep learning techniques to locate asphalt cracks at the pixel level while taking into account the images' depth and colour characteristics. The need for a system that can distinguish and classify crack intensity levels is highlighted by the fact that most research in this field focusses on locating asphalt cracks rather than assessing their severity. Li et al. (2020) created a novel deep learning-based system that can automatically identify different kinds of cracks on asphalt surfaces. They gathered a large dataset with five different fracture patterns, with fatigue fractures being a primary focus. Liu et al. (2020) suggested a two-tiered method for pavement crack identification and delineation based on CNN implementation, with a focus on identifying four distinct fracture types, most notably fatigue cracks. Liu et al. (2022b) employed Grad CAM-based models for three distinct image categories in order to improve the interpretability of the CNN model's outputs. This made it possible to identify multiple classifications of crack severity. Finally, a two-step automatic crack identification system that predicts linear fracture severity levels using image processing approaches was proposed by Tran et al. (2022). Materneh et al. (2024) classified asphalt fractures using a customised DenseNet model. The model was optimised using the Grey Wolf Optimisation technique. Ten CNN models that had already been trained were compared to the suggested model. With an accuracy of 98.73 percent, the cracks were categorised as longitudinal, horizontal, and diagonal. A lightweight deep-learning model was created by Liang et al. (Liang et al., 2024) to categorise asphalt cracks. Furthermore, this model was expanded to include residual blocks. About 83% classification accuracy was attained with this model. Generally speaking, the current research has been done to either identify asphalt cracks or complete the segmentation assignment. A few research have tried to categorise crack directions. This is due to the fact that crack classification is done using ASTM D6433 and FHWA standards, which do not contain any classification guidelines according to crack direction (Chen et al., 2024; Farahmand-Tabar et al., 2024). The fracture width is the most fundamental information on the significance of cracks in these standards. In conclusion, a thorough investigation into the importance of asphalt fractures like the one in our study has not yet been completed.

Dataset

Large earthquakes with magnitudes of 7.7 and 7.6 struck the Turkish province of Kahramanmaraş on February 6, 2023, in the districts of Pazarcık and Elbistan. Following these earthquakes, five distinct provinces near Elbistan saw significant asphalt fractures, both large and tiny. Some of these cracks were so large that they made transportation by road impossible. Even while some of the fractures weren't very large, they were sufficient to create large cracks whenever a heavy vehicle or new tremor passed. Because of this, the building department's experts surveyed the area and classified these cracks as either major or minor.

Figure 1. Samples of images from the field research dataset

A professional camera with a 24 MP resolution was used to take 518 JPEG pictures from a fixed overhead position at a 90-degree angle at a distance of one metre. For every piece of data, this image capture criteria was met. To improve the artificial intelligence systems' dependability, all of these photos were taken from the same distance. The Department of Construction experts classified 293 of the total data as significant and 225 as minor. Samples from both groups are displayed in Fig. 1. Provinces susceptible to earthquakes were visited for labelling. In these provinces, the crack widths of the roadways that were subjected to cracks were measured and documented in centimeters. ASTM D6433 is the standard taken into consideration during the dataset creation process because it offers details on crack widths for crack classification.

Method

The proposed methodology is generally implemented in three steps. In the first step, training and validation were performed using the transfer learning strategy with pre-trained models such as VGG16, VGG19, AlexNet, ResNet50, GoogleNet, and MobileNetV2. Then, features were extracted using the final 1000-dimensional layer of the MobileNetV2 model, which provided the best classification performance. In the second step, the ReliefF algorithm was chosen to select the features with high inter-class discrimination. The ReliefF algorithm was used because it has both a low computational load and has yielded good performance results in the literature. In the final step, popular classification algorithms in machine learning were tested using these selected features. These classifications were performed using SVM, KNN, Decision Trees (DT), Naive Bayes (NB), Logistic Regression (LR), and Random Forest (RF) algorithms. The SVM algorithm, which provided the best classification result, was included in the proposed methodology. A representative illustration of the proposed approach is given in Figure 2.

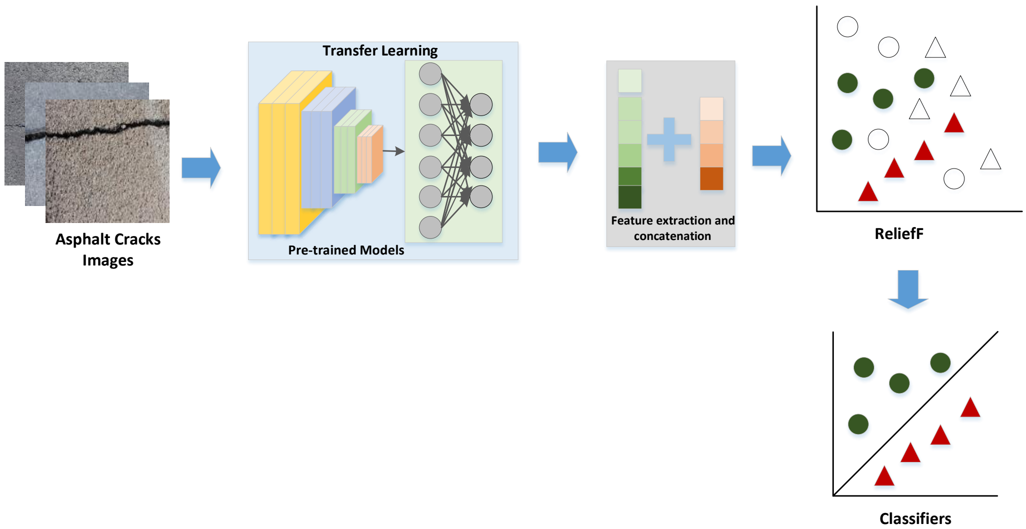

Figure 2. Representative illustration of the proposed methodology

Results and Discussion

A laptop computer with a 12th generation i9 processor, 32GB DDR5 memory, and a 12GB graphics card (RTX3080Ti) was used to conduct experimental studies. All coding was done in MATLAB. During the training process, the Mini-Batch number was set to 32, the Epoch was 100, the Initial Learning Rate was 0.001, and the Validation Frequency was 30. SGDM, which is frequently used in deep learning models, was used as the optimization solver. 10-fold cross-validation was used as the validation technique, thus increasing the overall validity of the model. Figure 3 shows the classification results of the pre-trained models after transfer learning in the form of a confusion matrix.

Among the pre-trained CNN models, the MobileNetV2 model gave the best performance with 84.7%, while the GoogleNet model gave the worst performance with 76.83%. Therefore, the MobileNetV2 model was selected for use in the proposed methodology. In the next step, 1000 features were extracted from the last connected layer of the MobileNetV2 model, named Logits. Of these extracted features, 150 were selected based on the importance weights of the ReliefF algorithm.

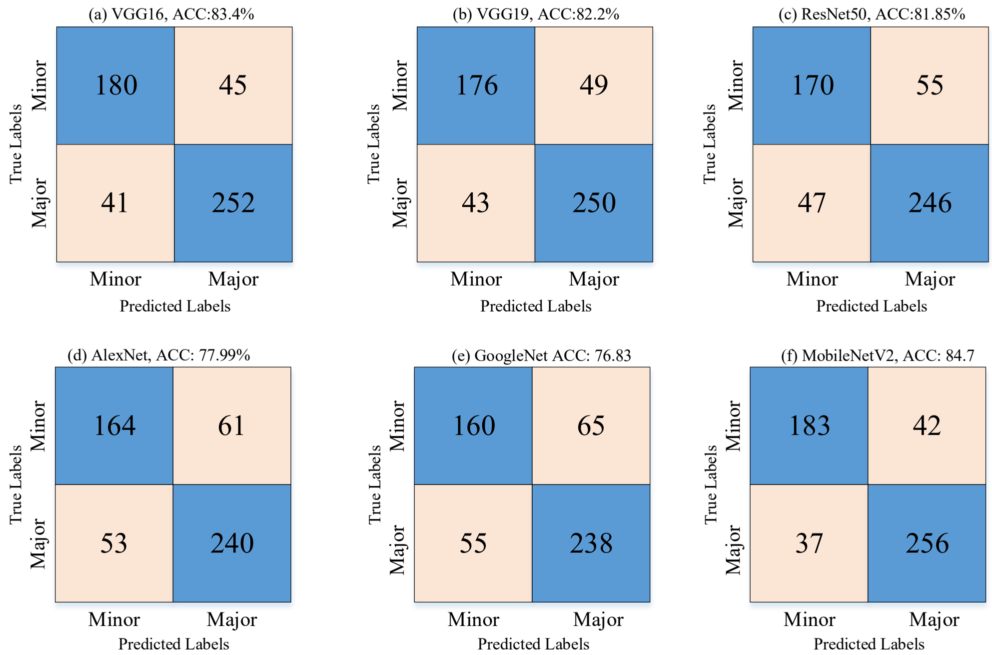

Figure 3. Confusion matrix results of pre-trained CNN models

The importance weights calculated by the ReliefF algorithm are shown in Figure 4. 150 features with importance weight values above 0.001 were selected. With this feature selection process, the computational cost in the classification process is reduced. Six popular machine learning algorithms were used to classify the extracted features. The classification accuracy was 86.3% for SVM, 82.2% for KNN, 81.85% for LR, 81.66% for DT, 82.62% for NB, and 84.16% for RF. The confusion matrix results of these six classification algorithms are given in Figure 5.

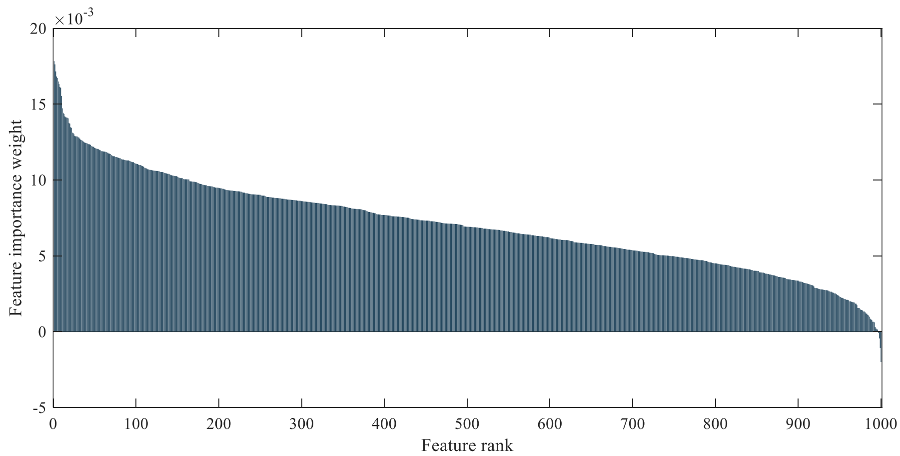

Figure 4. Importance weights of features with the ReliefF algorithm

Conclusion

Major earthquakes cause significant loss of life and property in cities. Rapid aid delivery is essential after such major earthquakes. Highways are a key factor in this transportation. This study examines the deformation data on highways following two consecutive major earthquakes in the Kahramanmaraş region of Turkey. The deformation data was labeled as major and minor by experts in the construction industry. Classification was performed on this dataset using pre-trained CNN models. MobileNetV2 yielded the best classification performance among the six models. To further improve classification performance, features were extracted in this model. Efficient features were selected using the ReliefF algorithm. Using these selected features, the SVM algorithm yielded the best classification performance. While this classification performance is satisfactory, it still has room for improvement. Classification performance can be further improved with new deep learning models in the future.

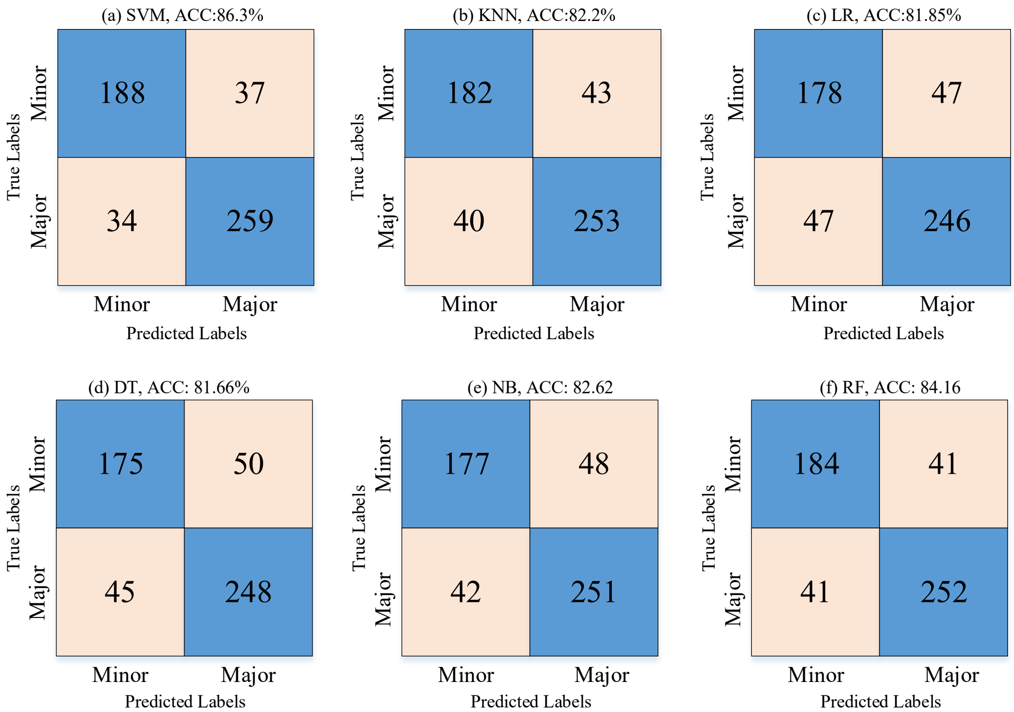

Figure 5. Results of confusion matrices of classification algorithms

Scientific Ethics Declaration

*The authors declares that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Conflict of Interest

*The authors declare that they have no conflicts of interest

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