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ENHANCING THE CLASSIFICATION EFFICACY OF ASPHALT CRACKS POST-EARTHQUAKE VIA AN INNOVATIVE FEATURE SELECTION ALGORITHM

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ABSTRACT

Novel imaging and AI approach, DeepCurvMRI, enhances AD diagnosis. Over 50 million individuals globally are impacted by AD, and that number is projected to increase. It is absolutely critical to detect the disease early and accurately. De-stigmatizing Alzheimer's disease diagnosis, DeepCurvMRI employs Curvelet Transform to extract characteristics from MRI scans. The basic study showed that DeepCurvMRI, which employs a CNN architecture specifically built for AD detection, attained an accuracy rate of 98%. This research takes a look into Xception and DenseNet deep learning models, together with Decision Trees and Voting Classifier. Preliminary research suggests a 99%+ accuracy rate. Numerous implications stem from this research. Doctors are able to intervene earlier when diagnostics are more precise, which benefits patients and their families. Improvements in AD diagnosis also help society with optimal resource allocation and reduced healthcare costs.

INTRODUCTION

On February 6, 2023, the districts of Pazarcık and Elbistan in Kahramanmaraş province in Turkey were hit by two powerful earthquakes. Eleven provinces in Turkey saw heavy casualties and property damage. Many Turkish regions and nations began to arrive with humanitarian and logistical aid following the disasters. Nevertheless, this assistance was severely delayed due to asphalt deformations on roadways. Damaged asphalt on roadways impeded vehicle transportation, according to field studies. Scientists photographed and identified asphalt cracks that could limit mobility in order to be ready for future earthquakes and disasters. The severity of the earthquakes prevented the examination of all sites in order to avoid traffic disruptions [1], [2]. Finding maintenance operations requires a large number of specialised individuals. In automated decision support systems, AI systems have recently demonstrated enhanced performance. Automatic classification, regression, and segmentation problems have been greatly improved by deep learning models since 2012. Many fields make use of these models, including medicine, engineering, economics, and the legal system. Due to the closure of routes impacted by the earthquake, traffic conditions were negatively impacted. Hence, it is essential to maintain highways prior to earthquakes.

In the aftermath of the earthquakes that struck Turkey on February 6, a deep learning-based approach was proposed for determining the criticality of asphalt crack photographs taken during highway repair.

The following are some of the main benefits of the proposed method:

- A new dataset on the condition of asphalt cracks was generated through field study conducted after the earthquake.
- By putting five transfer learning algorithms and six classifiers through their paces, we can analyse their baseline classification performance in great detail.
- Built a feature selection algorithm utilising the ReliefF algorithm, index matching, and ten metaheuristic approaches.

LITERATURE SURVEY

2.1 Distress Identification Manual for the Long-Term Pavement Performance Program

Distress Identification Manual for the Long-Term Pavement Performance Program (Fifth Revised Edition)

ABSTRACT: To ensure that distress evaluation surveys are accurate, consistent, and repeatable, the Long-Term Pavement Performance Program has developed the Distress Identification Manual. Distresses in asphalt concrete-surfaced, jointed (plain and reinforced), continuously reinforced concrete, and portland cement concrete pavement are shown in colour images and drawings. Signs of distress can be represented visually to assess its level. How to quantify pain and rate its intensity is detailed in this article. Distress surveys and the assessment of pavement cracks are also covered in the manual. Here you can find some sample forms for capturing and reporting data. The operation and calibration of defect measurement equipment is covered in the manual.

2.2 Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys:

[D6433 - Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys | GlobalSpec]

ABSTRACT: To evaluate the state of roads and parking lots, this method employs visual surveys that make use of the pavement condition index (PCI). Pavement condition indicators (PCIs) including roughness and structural integrity (rather than capacity) are determined by pavement maintenance engineers. Do not rely on PCI as a substitute for riding, structural capacity, or friction tests. The values in SI are often used. For informational purposes only; they are not standard. The conversions to inch-pound units are enclosed in brackets. There are still some potential dangers that this standard does not cover. Safety, health, and environmental procedures, as well as regulatory limits, must be defined before this standard can be used.

2.3 Deep convolution neural network-based transfer learning method for civil infrastructure crack detection:

[A Deep-Convolutional-Neural-Network-Based Semi-Supervised Learning Method for Anomaly Crack Detection]

ABSTRACT: Finding cracks is an important part of keeping an eye on the condition of a structure. Because of their powerful image processing capabilities, deep convolutional neural networks (DCNN) are able to perform accurate and efficient picture classification. For the purpose of identifying anomaly cracks, we present a DCNN-based semi-supervised learning method. Despite using a small sample size of normal, non-crack images for network training, the proposed technique achieves remarkable detection accuracy. The trained model also holds up well when exposed to crack difference and varying lighting conditions. The proposed method achieves detection accuracies of 99.48%, 92.31%, and 97.57% when applied to images of walls, bridges, and pavement, respectively. It is also possible to illustrate the operation of the neural network by visualising its features. For engineering purposes, this approach shows promise.

METHODOLOGY

a) Proposed Work:

The technique that has been suggested is illustrated graphically in Figure 2. In general, there are four main steps to the suggested method. In the first step, we use the VGG16 model and a transfer learning strategy to assess the dataset. Because the dataset was somewhat tiny, the transfer learning approach was employed.

The suggested system automates the crack classification of asphalt, which will greatly enhance the upkeep of roadways affected by earthquakes. Pictures of cracks in highways are processed using a deep learning algorithm and a VGG16 model that has already been trained. The ten optimisation methods that make up Combined Meta-heuristic Optimization-Relief (CMO-R) work together to improve feature selection. These methods include Particle Swarm Optimisation and the Whale Optimisation Algorithm. Various machine learning methods such as SVM, KNN, Decision Tree, Naïve Bayes, Linear Discriminant Analysis (LDA), and Medium Neural Network (MNN) utilise evaluation of chosen attributes. In order to enhance the accuracy of classification, a Voting Classifier integrates Random Forest, LDA, Naïve Bayes, and XGBoost. To ensure effective relief distribution and minimise delays, the approach estimates 'Major' and 'Minor' cracks. This helps authorities prioritise road repairs following an earthquake.

b) System Architecture:

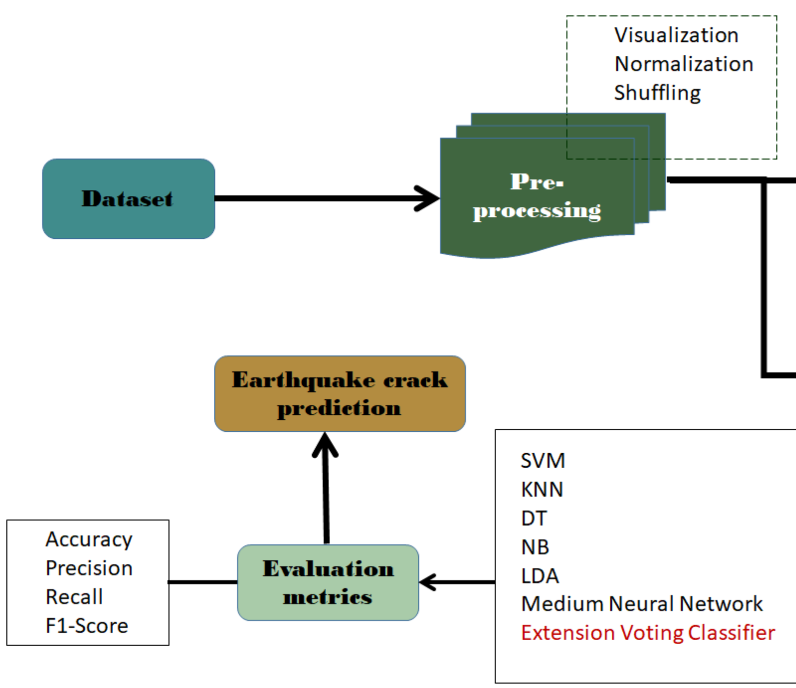

Fig 1 Proposed Architecture

The author's algorithm, CMO-R, optimises features using ten different algorithms: GNDO, EO, ASO, HGSO, HHO, MPA, MRFO, PSO, Slime Mould, and Whale Op. After the aforementioned ten algorithms have optimised the features index, it will be passed on to the RELIEF algorithm, which will choose valid features with an index value of 1 and ignore features with an index value of 0.

To increase prediction performance, the author used highway road photographs and the pre-trained CNN model VGG16. Optimising and selecting suitable features from the VGG16-trained model is the job of the Combined Meta-heuristic Optimization-Relief (CMO-R) method. Naïve Bayes, SVM, KNN, MNN, Decision Tree, and LDA are the six Machine Learning algorithms that will be used to evaluate the CMO-R features. The confusion matrix, FSCORE, AUC-ROC, recall, precision, and accuracy of each approach are evaluated. When it comes to algorithms, MNN is first.

c) Dataset Collection:

Images of asphalt cracks seen in areas hit by earthquakes are part of the collection. The photographs illustrate various fracture patterns, warping, and fissures that could impact the use of the roadway. The dataset depicts the asphalt damage caused by earthquakes using a combination of high-resolution images from field surveys and internet sites.

The author used Earthquake Asphalt Crack dataset (download link) to train and test each algorithm.
https://data.mendeley.com/datasets/88kdyyc73h/1

area_assesed	building_id	district_id	has_geotechnical_risk	has_geotechnical_risk_fault_crack	has_geotechnical_risk_flood	has_geotechnical_risk_land_settlement	has_geotechnical_risk_landslide	has_geotechnical_risk_liquefaction	has_
Both	a3380c4f75	7	0	0	0	0	0	0	
Both	a338a4e653	7	0	0	0	0	0	0	
Building removed	a338a4e6b7	7	0	0	0	0	0	0	
Both	a33a6eaa3a	7	0	0	0	0	0	0	
Building removed	a33b073ff6	7	0	0	0	0	0	0	
Both	6604e4896c6	7	0	0	0	0	0	0	
Both	a33b07430f	7	0	0	0	0	0	0	
Building removed	a33c386cf3	7	0	0	0	0	0	0	
Both	a33c386ee7	7	0	0	0	0	0	0	
Both	a33c38700f	7	0	0	0	0	0	0	
Both	a33c387079	7	0	0	0	0	0	0	
Both	6627e911d56	7	0	0	0	0	0	0	
Both	a3730e8420	7	0	0	0	0	0	0	
Both	a373a71a3d	7	0	0	0	0	0	0	
Both	a3743fb055	7	0	0	0	0	0	0	
Both	a3743fb121	7	0	0	0	0	0	0	

Fig 2 Dataset

d) Data Pre-Processing:
To get raw images ready for machine learning, pre-processing is necessary. Scaling, normalisation, and contrast adjustment are used to keep the image quality. In order to make the model more generalisable to different crack patterns and environmental conditions, data augmentation techniques such as flipping and rotation increase dataset variability.

e) Feature Extraction
A novel feature selection technique is employed to identify and rank asphalt fracture features. Focus on damage type and severity trends and remove irrelevant data to reduce the dataset's complexity. Selecting relevant features enhances the accuracy of classification models while reducing computational complexity.

f) Algorithms:
CNN - DeepCurvMRI Model: Using Curvelet Transform, our CNN architecture, DeepCurvMRI, retrieves MRI features. To boost accuracy, our CNN-based system for Alzheimer's diagnosis employs CNN image analysis and enhanced feature extraction.[28] in Using convolutional neural networks (CNNs) and enhanced feature extraction methods, DeepCurvMRI offers a potential approach to classifying Alzheimer's illness.

VGG16: One straightforward and powerful deep convolutional neural network (CNN) architecture is VGG16. The sixteen convolutional and fully linked layers that make up VGG16[60] make it an excellent picture classifier. Because of its deep design, which learns complex hierarchical structures, it is able to detect subtle patterns in medical imaging, such as MRI images of Alzheimer's disease.

CMO-R: To begin, qualities are ranked according to their accuracy in asphalt crack classification using belief, with important attributes being distinguished from less important ones. The goal of meta-heuristic optimisation is to improve classification accuracy with little computational cost by refining the feature subset. In order to improve the efficiency and precision of asphalt crack categorisation after an earthquake, this hybrid technique enables the model to concentrate on important markers of the asphalt deformation pattern.

SVM: Classification and regression are handled by the robust supervised learning method SVM.[61] in It determines the best hyperplane for data classification. When it comes to high-dimensional picture categorisation, SVM shines. In our study, we compare the performance of deep learning models using SVM.

KNN: KNN is a simple but effective classifier that uses training samples that are near to the feature space to make predictions. To categorise asphalt cracks and detect fundamental fracture patterns, KNN compares a test picture to its dataset neighbours. Feature selection methods, such as CMO-R, are necessary since KNN's sensitivity to irrelevant characteristics makes it underperforming on big or noisy datasets.

MNN: An MNN strikes a good compromise between model complexity and computing performance with its moderate hidden layers and neurones neural network topology. Using hierarchical picture attributes, this project classifies crack patterns using MNN. When collecting intricate patterns of asphalt cracks, it outperforms KNN in terms of accuracy and flexibility. While MNN might have trouble with high-dimensional data in the absence of optimised feature selection, CMO-R's feature refinement solves that problem.

4. EXPERIMENTAL RESULTS

Precision: The accuracy rate of a classification or number of positive cases is known as precision. The formula is used to calculate precision:
Precision = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: The ability of a model to identify all pertinent instances of a class is assessed by machine learning recall. The completeness of a model in capturing instances of a class is demonstrated by comparing the total number of positive observations with the number of precisely predicted ones.

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

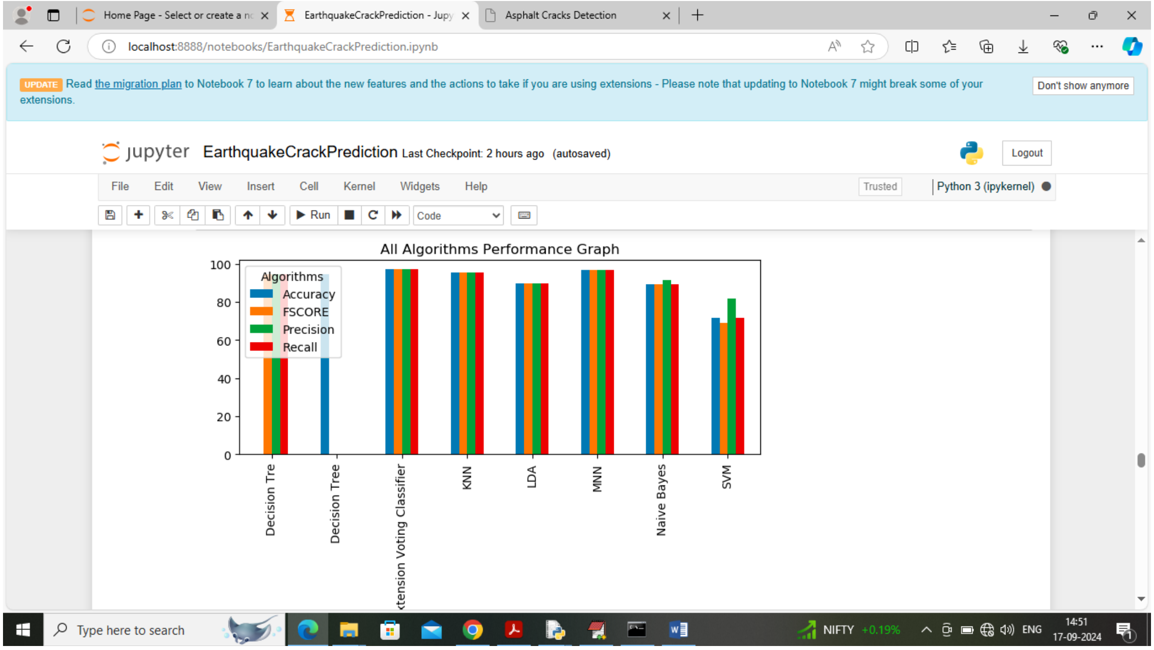

Fig 3 Comparison Graphs

CONCLUSION

Finally, the issue of earthquake-related road maintenance is resolved by automating asphalt crack classification. This technique improves the accuracy of crack severity classification by employing deep learning to extract features using the VGG16 model and the CMO-R algorithm to choose features optimally. The findings demonstrate that the technology is capable of differentiating between "Major" and "Minor" cracks, which expedites the process of prioritising road repairs. In terms of accuracy, the Voting Classifier comes in at 96.77% while the Medium Neural Network (MNN) comes in at 96.75%. These effective models demonstrate the system's ability to foresee road deterioration and facilitate timely repairs. The successful implementation of the technology demonstrates its potential for managing road infrastructure after a disaster.

FUTURE SCOPE

For future research, more advanced DL models such as ResNet and EfficientNet can enhance the accuracy of feature extraction and classification. To make models more generalisable across datasets, data augmentation and transfer learning are useful tools. Classification could be improved by ensemble approaches that combine multiple high-performing algorithms. Larger, more diverse datasets and real-time data processing can increase system resiliency.

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