DEEP LEARNING ASSISTED VISION-BASED PAVEMENT CRACK DETECTION

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Abstract

Cracks in pavements are common distresses affecting the safety and longevity of transportation infrastructure. Automated pavement monitoring for cracks is a pliable solution with access to high-performance computing and memory resources. Vision-based deep learning (DL) solution-oriented techniques promise economic and automated results using commercially available cameras. To maximize the advantage of DL methods, this article proposes a vision-based method employing an optimized and regularized *RetinaNet* convolutional neural network (CNN) for detecting concrete cracks in pavements. The designed CNN is trained on a subset of the SDNET2018 dataset with an F1 score of 94%. The evaluation metrics of the model promise a realistic solution in detecting cracks in concrete pavements.

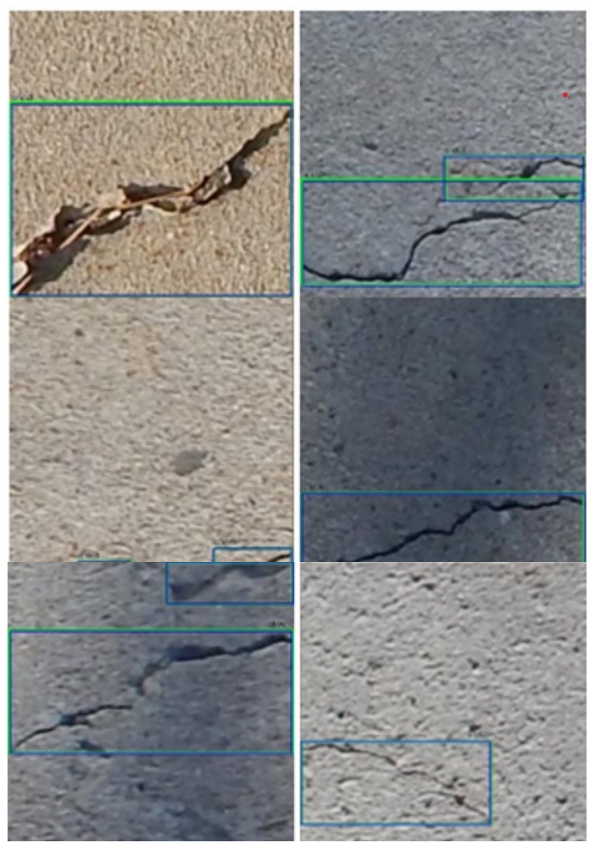

Figure 1. Crack detection in pavements

Project Objective

- To automate the pavement crack detection system.
- Develop a crack classification and localization technique using a computationally feasible and lightweight single-stage convolution neutral network (CNN) to detect cracks in pavements.

Methodology

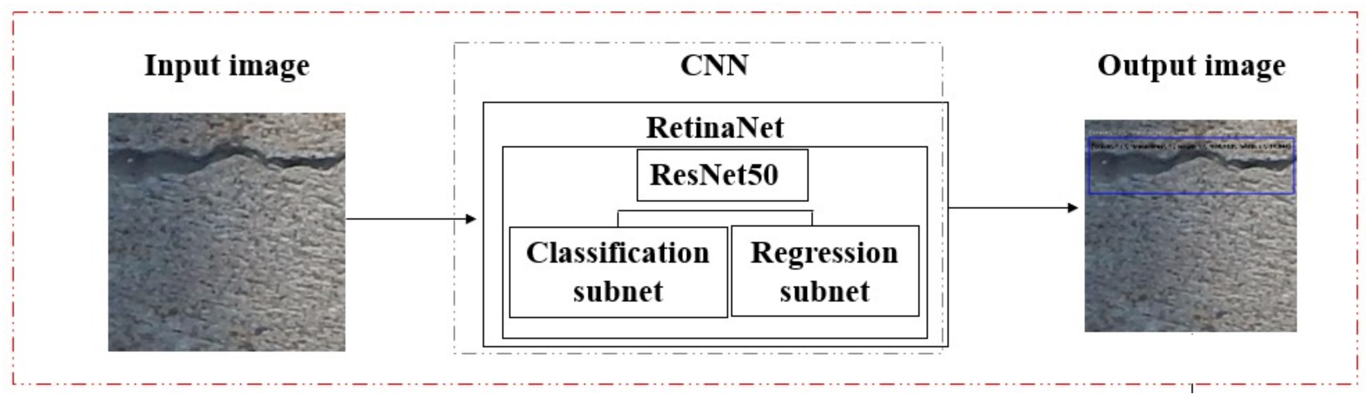

Figure 3. Overall workflow of methodology adopted

Background Information

- Pavements are vulnerable to distresses as a result of harsh climatic conditions, unexpected overloading, heavy traffic, ageing, poor maintenance, error in design etc.
- Distresses in pavements occur when surface degradation of pavement takes place in the form of material disintegration.
- Commonly occurring pavement distresses are cracks, potholes, surface disintegration such as scaling, spalling, blow-ups and surface distortions such as pumping, faulting etc.
- Conventional methods of monitoring involve manual survey followed by repair, which is limited by human expertise, biases and is time consuming.
- Automated pavement monitoring methods can expedite the process of surveying and identification of distresses in pavements, ensuring timely actions.
- Deep learning methodologies involve automated feature extraction and are used to detect distresses using vision based techniques.
- Trained deep learning models can be deployed for real time road monitoring and evaluation.

Implementation Details

Databank generation

- Subset of SDNET2018, a concrete pavement image dataset of crack and non-crack images is used in this study.
- Data acquisition is done through 16 MP Nikon digital camera.
- 1K images are used in this study, each 256 x 256 pixel in size.
- Images of varying textures and taken under different light conditions are selected to ensure an unbiased dataset.
- Image annotation is done using *LabelImg* graphical annotation tool.
- A total of 1046 crack instances are annotated.
- The entire dataset is distributed into training, validation and test datasets with 60% images in training dataset and 20% each in validation and test dataset.

Implementation details

- Training is carried out on a workstation with Core i7-8700k @3.2 GHz CPU, 32 GB DDR4 memory, and 16 GB NVIDIA GeForce GTX 1070 graphics processing unit (GPU).
- Open source *RetinaNet* library with Python 3.8.11, CUDA10.2, CUDNN 7.0 is used.
- Adam optimizer, with a learning rate of 1e-5 for 27,600 iterations is implemented, in batches of 4, for a total of 200 epochs.
- Optimization by hyper-parameter tuning via trial-and-error is performed

RetinaNet Architecture

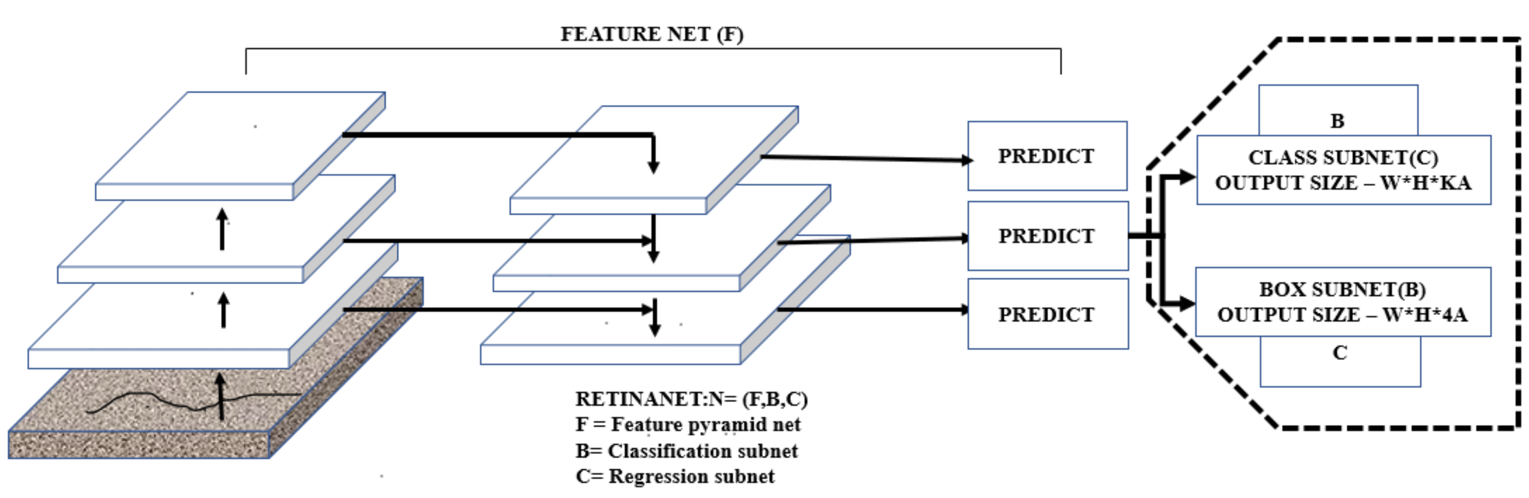

Figure 2. *RetinaNet* Network framework

- Pavement image acts as input to the *RetinaNet* architecture.
- ResNet50 the backbone framework of *RetinaNet* calculates multi-scale feature maps of the image.
- The obtained feature maps are laterally connected to feature pyramid network, which up-samples the generated feature maps and merge the corresponding layers with same spatial size.
- Classification subnet predicts the probability of a crack.
- Regression subnet regresses the offset of the bounding box based on the prediction by the classification subnet.

Results

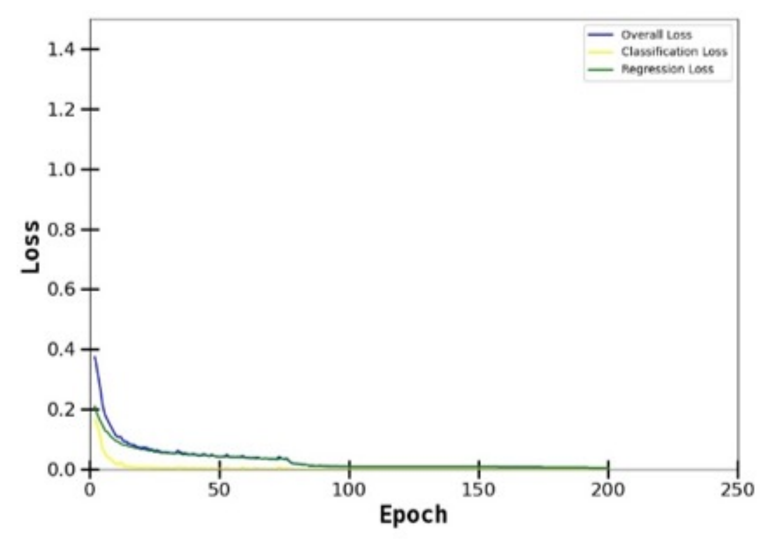

Figure 4. Loss vs epoch

Table 1. Overall classification loss metric.

Loss	@epoch 1	@epoch 250
Classification	0.682	0.005
Regression	0.268	0.00
Overall	0.951	0.005

Table 2. Evaluation metrics of the hypertuned model.

Precision			Recall			F1-Score		
Train	Val	Test	Train	Val	Test	Train	Val	Test
0.98	0.93	0.95	0.90	0.88	0.93	0.94	.90	0.94

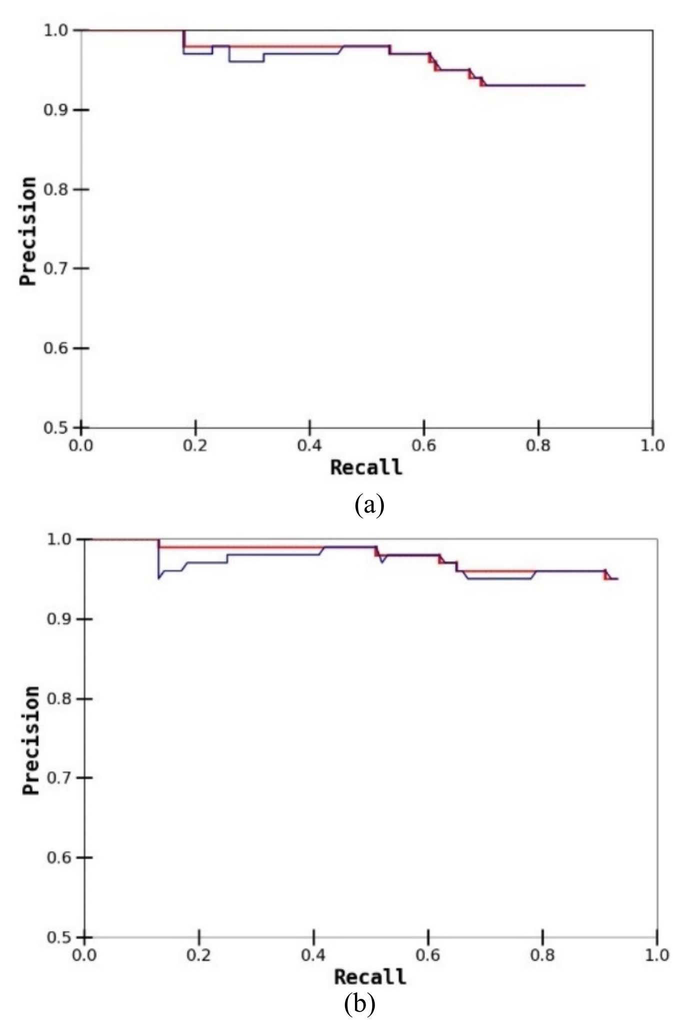

Figure 5 Precision vs recall (a) validation dataset (b) test dataset.

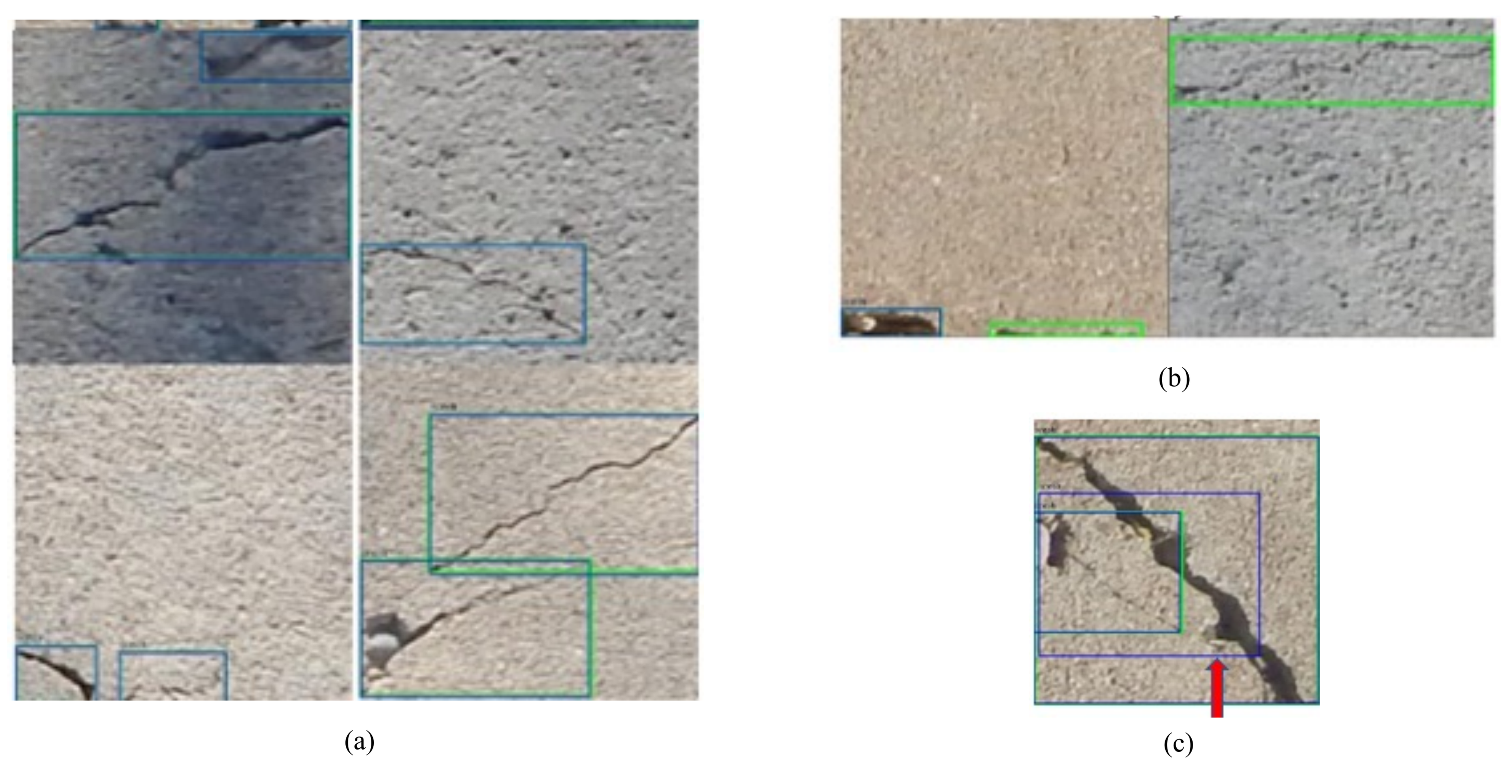

Figure 6. Samples of detection on the test dataset (a) True positives (b) False negatives (c) False positives

Conclusion and Future Scope

An optimized and regularized CNN is implemented to successfully detect cracks in concrete pavements, with the following conclusions-

- Commercially available cameras are effective in pavement crack inspections and offer an inexpensive solution to monitor long pavement stretches.
- The proposed model performs exceptionally well with a high F1-score of 94% on unseen data, thus promising usability in automating the pavement distress detection process.
- The proposed model is not limited to data bias, as is justified by the model's performance on an impartial and random distribution of 1k images in training, validation, and test datasets.

In the future, methods to assess the crack severity will be explored to extract meaningful information, in integration with the proposed model by measuring crack width and length.

Acknowledgments

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