Surface Crack Detection Using Deep Convolutional Neural Network

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Outline

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Introduction

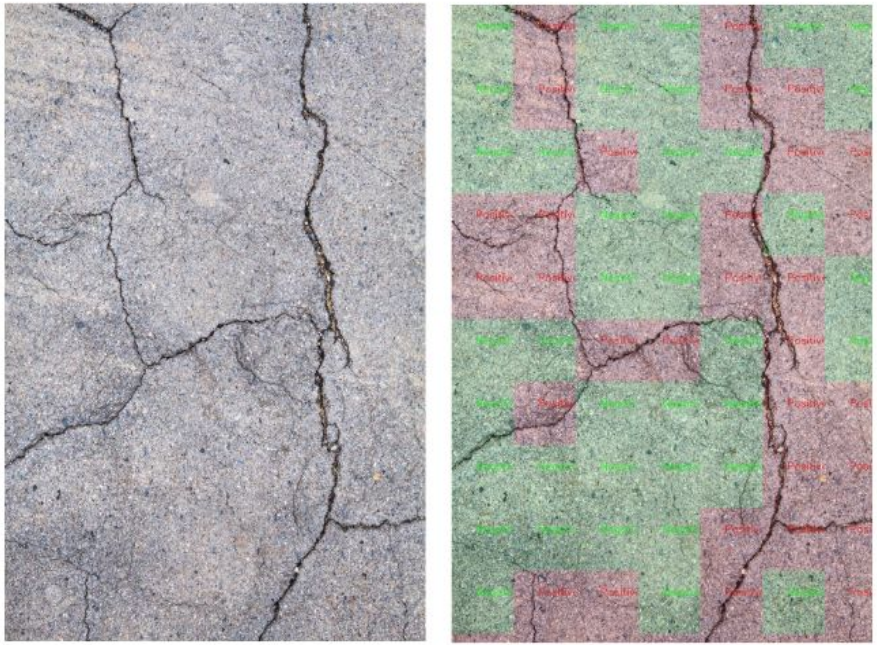

Fig 1: Surface Crack [1]

Measurement of the extent of cracks on the surface of a material (usually a solid material such as metals, plastics and ceramics).

Motivation

1. Concrete surface cracks are major defect in civil structures
2. Detecting Crack of surfaces more accurately
3. More accuracy ensures less accident in highway
4. Inspecting, finding the cracks and determining the building health

Literature Review

1. Autonomous concrete crack detection using deep fully convolutional neural network [2]

   Applied Method - VGG16, Inception V3, ResNet50

   Dataset - 40,000

   Accuracy - 0.998, 0.997, 0.975

Literature Review

2. Road Crack Detection Using Deep Convolutional Neural Network [3]
   Applied Method - ConvNets

   Dataset - 40,000

   Accuracy - 0.8965

Dataset

Fig 2: Crack Image [3]

Fig 3: Non Crack Image [3]

- The dataset is created from 458 (4032x3024 pixel) high-resolution images using the method proposed by Zhang et al (2016) [3]
- Consists of 40,000 images of 227 x 227 in RGB
- 20,000 positive images (Crack)
- 20,000 negative images (Non Crack)

Methodology

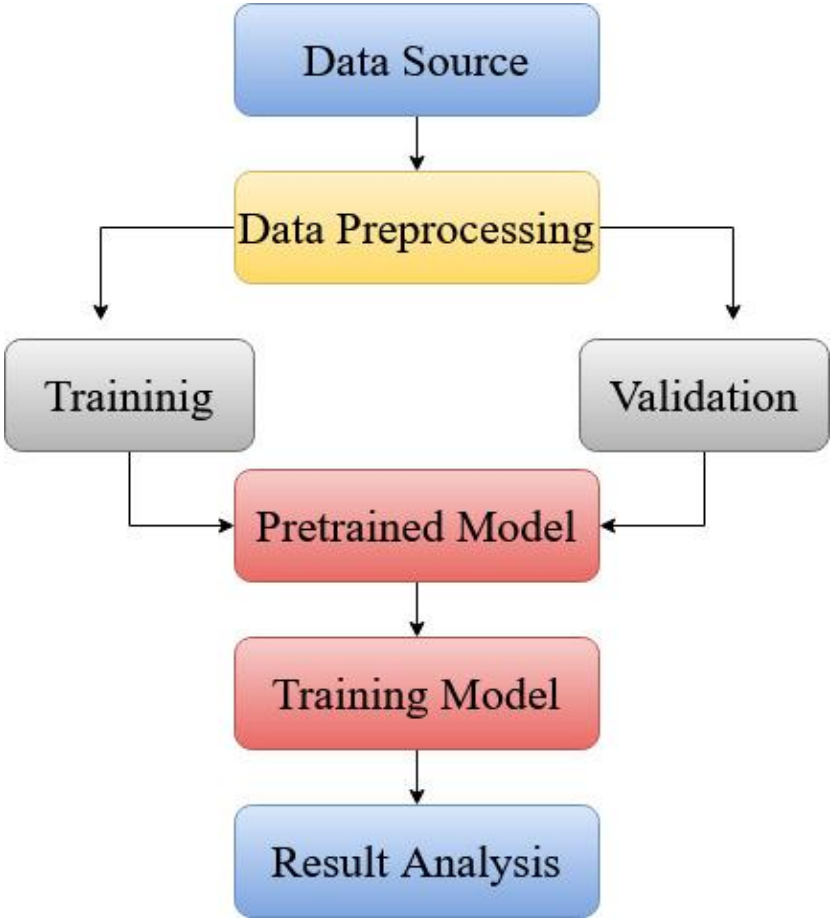

Fig 4: Workflow

Implementation

1. **Data Preprocessing:**

(a) Image Resize: Images are resized into 150 x 150 (RGB) to make all image size uniform for VGG16 model [4] (pretrained model)

(b) Normalization: Images are rescaled between 0 to 1 by dividing each pixel value by 255

2. **Data Split:**

Datasets are splitted into ‘Training’ and ‘Validation’ (30 percent randomly) sets

Implementation

3. Model Architecture:

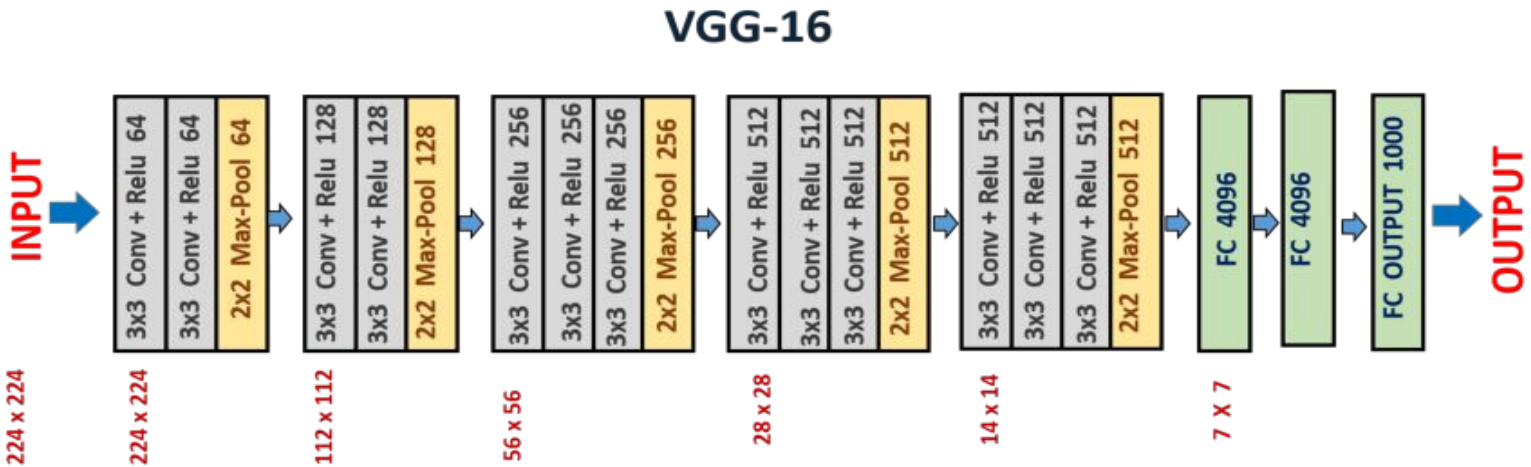

Fig 5: VGG16 Model [4]

Implementation

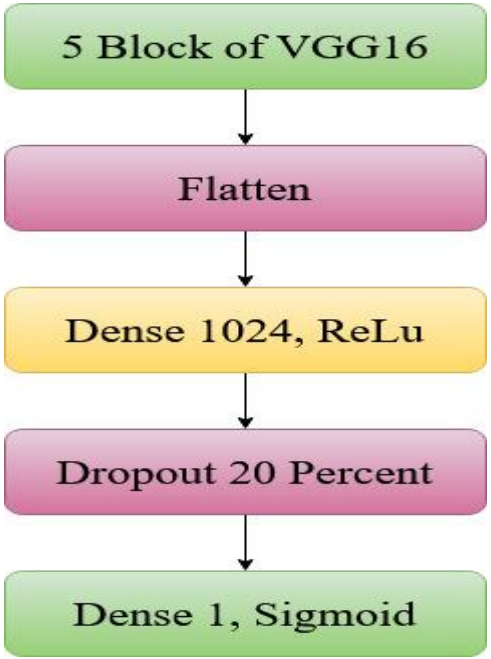

Fig 6: Model Architecture

Parameters:

Epoch: 20

Batch Size: 64

Optimizer: Adam [5]

Loss Function: Binary Crossentropy [6]

Dropout: 20 percent

Result Analysis

```
Epoch 19/20
438/438 [==============================] - 71s 162ms/step - loss: 0.0044 - accuracy: 0.9986 - f1_m: 0.9986 - precision_m: 0.9987 - re
call_m: 0.9986 - val_loss: 0.0161 - val_accuracy: 0.9973 - val_f1_m: 0.9972 - val_precision_m: 0.9975 - val_recall_m: 0.9971
Epoch 20/20
438/438 [==============================] - ETA: 0s - loss: 0.0017 - accuracy: 0.9994 - f1_m: 0.9994 - precision_m: 0.9994 - recall_m:
0.9993
Reached 99.9% accuracy so cancelling training!
438/438 [==============================] - 70s 160ms/step - loss: 0.0017 - accuracy: 0.9994 - f1_m: 0.9994 - precision_m: 0.9994 - re
call_m: 0.9993 - val_loss: 0.0161 - val_accuracy: 0.9974 - val_f1_m: 0.9974 - val_precision_m: 0.9977 - val_recall_m: 0.9972
```

Fig 7: Model Accuracy

Result Analysis

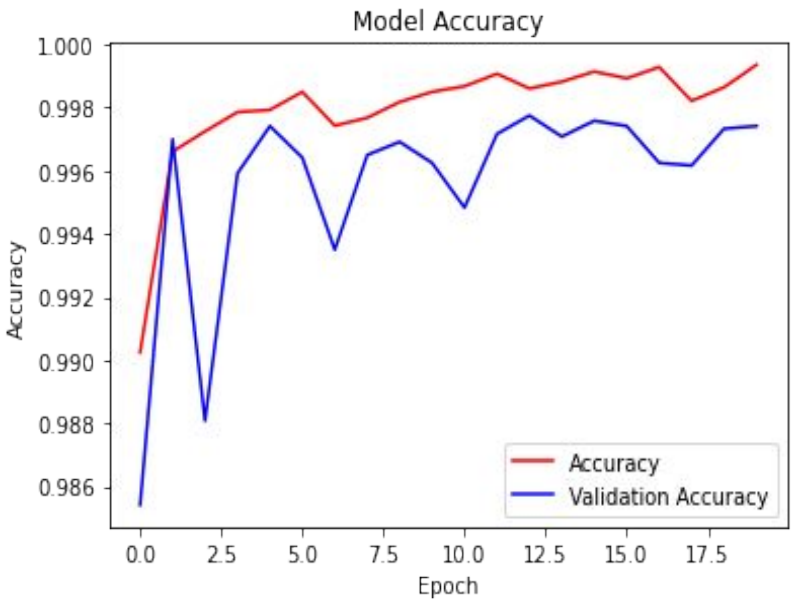

Fig 7: Accuracy vs Epoch Curve (lr=0.001)

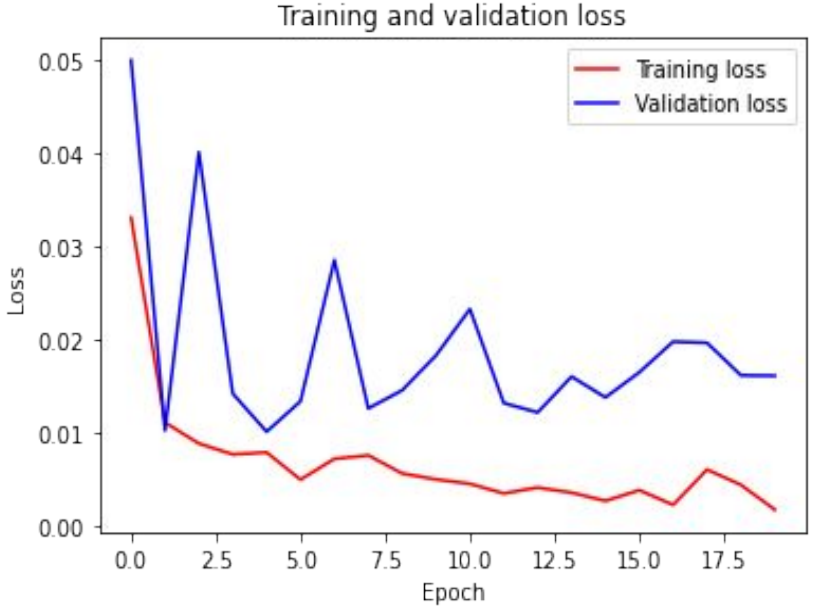

Fig 8: Loss vs Epoch Curve (lr=0.001)

Result Analysis

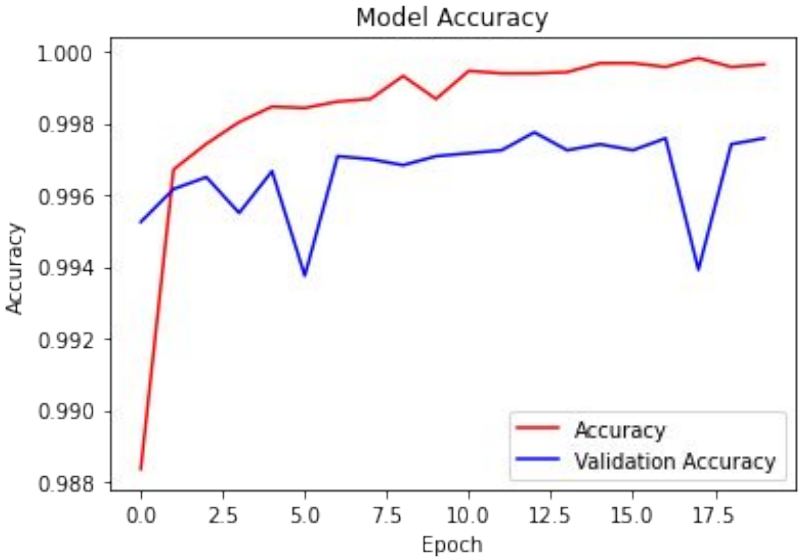

Fig 7: Accuracy vs Epoch Curve (lr=0.0001)

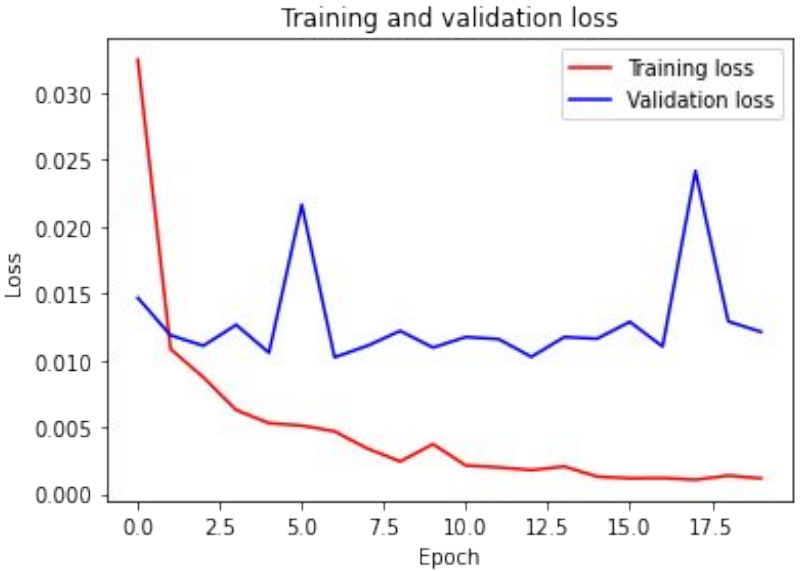

Fig 8: Loss vs Epoch Curve (lr=0.0001)

Result Analysis

Performance of Different Methods:

Method	Accuracy	Recall	Precision	F1 Score
VGG16 [2]	0.998	0.999	0.998	0.998
Inception V3 [2]	0.997	0.997	0.998	0.997
ResNet [2]	0.975	0.945	0.994	0.968
Proposed VGG16	0.999	0.9993	0.999	0.999

Table 1: Performance of Different Methods

Conclusion

1. The dataset was preprocessed before feeding the network
2. VGG16 was successfully implemented and validated
3. Performance analysis was done

Future Works:

1. Extend the dataset using augmentation
2. Performance comparison of different neural network models

References

[1] https://deeplearninganalytics.org/detection-of-surface-cracks-in-concrete-structures-using-deep-learning.
[2] Dung, C.V., 2019. Autonomous concrete crack detection using deep fully convolutional neural network. *Automation in Construction*, *99*, pp.52-58.
[3] Zhang, L., Yang, F., Zhang, Y.D. and Zhu, Y.J., 2016, September. Road crack detection using deep convolutional neural network. In *2016 IEEE international conference on image processing (ICIP)* (pp. 3708-3712). IEEE.
[4] https://medium.com/towards-artificial-intelligence/the-architecture-and-implementation-of-vgg-16-b050e5a5920b
[5] https://towardsdatascience.com/adam-latest-trends-in-deep-learning-optimization-6be9a291375c
[6] https://keras.io/api/preprocessing/image/

THANK YOU