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A Deep Learning Paradigm for Railway Bridge Assessment with CNNs

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Abstract: The key issue for the railway department has been to examine and monitor railway bridges, as urbanization expands, the availability of railways grows, and the railway system has greatly expanded throughout the nation. The expense of maintaining railroad bridges and associated costs with personnel have been a burden on the railroads. To ensure transportation safety, concrete bridge crack detection is critical.

Deep learning technology has made it possible to automatically and accurately detect faults in bridges. The present methods are not accurate and they require a large size of dataset for model training and they require a high computational power model training. The proposed model is a convolutional neural network (CNN) based end-to-end crack detection model. The proposed model achieved a 95% detection accuracy.

Keywords: Deep Learning, CNN, Remote sensing, OpenCV, Keras, TensorFlow.

I. INTRODUCTION

With technology such as remote sensing, it is now possible to monitor bridges even without physically present and receive results promptly. The analysis focuses mainly on model-based finite element update techniques, non-model-based (data-driven) defect detection techniques such as artificial neural networks, and structural health monitoring techniques based on Bayesian belief networks. The main focus is on issues related to bridge cracking. Cracks on concrete surfaces are one of the earliest signs of structural degradation, which is crucial for maintenance. Continued exposure can lead to significant environmental damage. The review provides analysis based on image processing techniques, objectives, accuracy levels, error levels, and image datasets. Finally, this paper present various research issues that can be useful for future research on crack detection.

Origin of the Problem Railways play a crucial role in the GDP of the Indian economy. It has been identified that the Indian Railways recently mentioned a problem in their portal, which included both technical and non-technical requirements. Previously, such problems were solved using various methods and technologies outside of India.

CNN (Convolutional neural networks) is a deep learning algorithm used to identify the image by comparing with the other related images or previous images. The algorithm used here is the CNN sequential model. Different layers will be added to the model and then the model will be trained with the labelled data.

II. LITERATURE REVIEW

The literature review focuses on the materials that helped understand the image processing and classification techniques research field. The research articles discussed the use of various algorithms and frameworks for data classification. This section focuses on research publications, including the main details of each paper, and presents the findings and conclusions from each study.
A fracture detecting model was described by the authors. For the purpose of detecting cracks, they put forth an RCNN model. Three main stages of the methodology— data gathering, 3D construction, damage detection, and analysis—are suggested for studying bridge damage. The newly created deep learning crack segmentation model and toolbox have proven useful for UAV-assisted bridge inspection. They achieved an accuracy of 90% [1].

This study illustrates the viability of applying InSAR to railway track changeover zones. InSAR measurements were taken in transition zones close to a steel bridge. The results that have been given have shown that InSAR can be utilized to monitor transition zones' health conditions [2].

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The authors presented a methodology for identifying bridge cracks using remote sensing. For training, they used satellite image data. In order to find usable, quantitative indicators of bridge condition, remote sensing technologies are helpful. The data gathered in this way can be included into an approachable, web-based DSS created using free software tools that operate with Pontis data structures, providing a framework that any state transportation agency can employ. The DSS presented in this study is meant to serve as an illustration of a cuttingedge asset management tool for bridge condition evaluation [3].

The authors proposed a deep learning model for automatic crack detection in concrete bridges. The model is based on Convolutional Neural Networks (CNNs) and uses techniques such as atrous convolution, Atrous Spatial Pyramid Pooling (ASPP) and depth wise separable convolution to improve performance. The proposed model was found to have a detection accuracy of 96.37% without pre-training and to perform better than other classification models. It can also be used as an effective feature extraction structure in other CNNs [4].

In this study the researchers provide different automatic crack detection using various image processing methodologies. The automatic crack detection helps to replace the slower traditional human inspection processes. The various convictions faced in the image detection are the irregularity in the size of cracks and illuminating conditions, shading in the images. The image processing methodology provides accurate results in comparison with traditional processes. The crack quantification model and the image acquisition pre-processing are some of the methods. The above methods detect the cracks with the curvature evaluation and mathematical morphology techniques. The methods with hybrid sy stem are got an accuracy 96% [5].

For maintaining the structural health of a bridge, it is important to detect the structural damages of the bridge over time to time. In this study they created an algorithm for crack detection. They developed a STRUM classifier model for crack detection. They used robotic imaging for collecting the data about the bridge deck. W ith STRUM classifier they got 95% accuracy in detection of cracks and many typical image-based approaches only got 69% accuracy [6].

III. PROPOSED WORK

- DESIGN METHOLOGY

The model is trained using pre-processed photos from bridge image and other datasets with a 6:1 training to test dataset ratio. The architecture includes three convolutional layers, optional batch normalization, two max pooling layers, and ReLU activation functions. The channel count in the first convolution layer is increased from 1 to 64, and the second layer's channel count is raised to 128. The pooling layer helps in summarizing the features generated by the convolution layer.

The next step is to determine the point where a steady increase in epoch values leads to a rise in loss value and stop training the model. The model is then created and trained with increasing epoch values and adjusting the checkpoints as needed. To assess the model's accuracy, the number of correct predictions is counted and the percentage of accurate predictions is calculated. The metrics used for model analysis are precision, recall, f1- score, and support. The accuracy measures the frequency of correct predictions, while recall measures the number of positive samples the model can identify. ReLU and Dense layer activation functions are commonly used in CNN models.

- SYSTEM ARCHITECTURE

A CNN model is used for railway bridge inspection to detect cracks in images. The model is trained using an image dataset available on GitHub. In data preprocessing, the images will be resized to a width of 224 and a height of 224.

The preprocessed data will be used for training the model. During image processing, the image is divided into smaller parts with a width of 224 and height of 224. If the image size is too large, it will be compressed. The parts of the original image are passed to the model, which detects cracks in the image. If any part contains a crack, the output will be labeled as "cracked." The parts that contain cracks are displayed in the output along with the corresponding negative image. The original image is also displayed in the output with its corresponding negative image.

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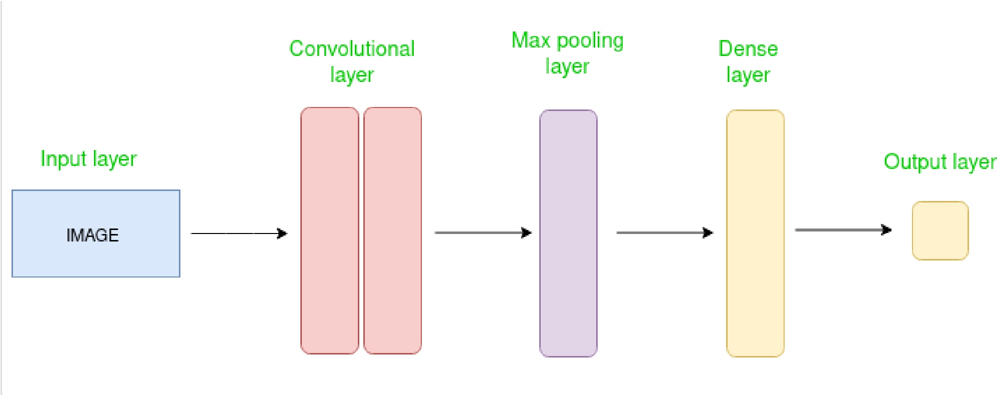


- DESCRIPTION OF CNN ALGORITHMS:

- CNN is a deep neural network algorithm. It is most widely used to classify the images.
- CNN model is trained with a labeled data. It is trained by using image dataset. It extracts the feature of every image in the dataset.
- In a Convolutional Neural Network (CNN), features of an image are extracted through a series of layers that process the input image.

1. Input Layer:

The input layer gets the raw pixel values of the input image. The size of the input layer is determined by the shape of the input image.

2. Convolutional layers:

Convolutional layers are many filters (kernels) that slide across the input image, performing convolutional operations to extract features such as edges, corners, and textures. Each filter is combined with the input image to generate a feature map, which gives a spatial representation of different features. Collection of multiple convolutional layers to detect more complex features from image input.

3. Activation Function:

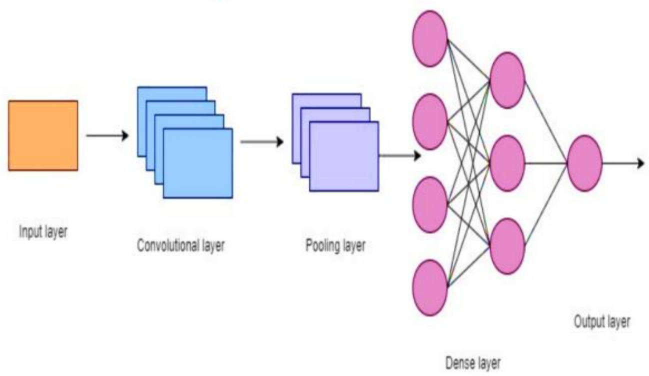
After each convolutional operation, an activation operation such as ReLU (Rectified Linear Unit) is applied elementwise to introduce nonlinearity into the network so that complex patterns can be identified.

4. Pooling Layers:

Pooling layers downsample feature maps obtained from convolutional layers, reducing spatial dimensions while preserving important features. Normal pooling operations include max-pooling, where the maximum value in the area is held, and average pooling, where the average value is calculated.

5. Fully connected layers:

Fully connected layers handle features extracted by convolutional layers and make predictions about the presence and nature of traffic signals.



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- Algorithm steps :-

• Pre-processing of Image dataset (Image to array and image is resized to (224,224)). And splitting the data into trained and testing data.

• Creating a convolutional base with 3 convolutional and 3 pooling layers.

• A convolutional base is a component of a Convolutional Neural Network (CNN) that performs convolution operations on input image data.

• It consists of multiple convolutional layers, activation functions, and pooling layers.

• The convolutional base extracts feature from the input image through the convolutional layers and applies activation functions to produce feature maps.

• The pooling layers then reduce the spatial dimension of the feature maps to reduce computational complexity.

• The extracted features are then passed on to the fully connected layers for classification or regression.

• The image is passed to the convolutional layer.

• The output when the image passes through a Convolutional layer: - Convolution Output dimension = [(I - F +2 *P) / S]+1 x D where I->dimensions of the image F->size of the kernel/filter S->Strides P->Padding D->Depth
• Next the image is passed to the pooling layer.

• The output when an image passes through a Pooling (Max) layer: -
For a pooling layer, one can specify only the filter/kernel size (F) and the strides (S). Pooling Output dimension = [(I - F) / S] + 1 x D
• Next image is passed to relu layer.

• The output when an image passes through a relu dense layer: - ReLU formula is: f(x) = max (0, x)

• Model is compiled with loss sparse_categorical_crossentropy, optimizer adam, metrics accuracy. To get the accuracy the training and testing of the model is fitted using batch size and validation data.

CONCLUSION

This comprehensive review of a deep learning model for traffic signal recognition using a convolutional neural network emphasizes the significant advances and contributions made in computer vision and intelligent navigation systems. Extensive research, testing, and applications have demonstrated that Convolutional Neural Networks (CNNs) provide an effective framework for accurately detecting and classifying traffic signals in real-world scenarios.

By the end of this work, we aim to have a model that can accurately detect cracks in bridges with high accuracy and low cost. The proposed model will make it easy to detect cracks in bridges.

- Real-time Applications of Proposed work

1. Railway bridge inspection provides a clear picture about the problems that they occur in the railway bridges. And it also helps to provide a solution for that problem.

2. Human efforts can be a waste of money and the time during the times/conditions like floods because cracks can’t be identified by the cameras etc.

3. Some of them proposed a decision supported system to monitor the railway bridge condition.

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