**1. Crack Detection and Classification in Asphalt Pavement Images Using Deep Convolution Neural Network [2018]**

This paper is about study proposed a deep convolution neural network (DCNN) as a detection of asphalt pavement crack that capable to detect and classify the pavement crack robustly when dealing with complexity background image.

A method to detect and classify asphalt pavement crack using deep CNN is proposed. This proposed deep CNN architecture composed of eight layers consist of three convolution layer, three pooling layer and two fully connected layer. The network is trained using stochastic gradient (SGD) training algorithm.

Crack detection and classification comprises steps – 1) Image acquisition, 2) image processing and labeling 3) crack detection and 4) crack classification. In order to explore how the size of input image affects deep CNN with respect to detection and classification performance, different sizes and grid scale are adopted in the architecture. The network achieved overall recall, precision and accuracy on the 1000 testing images are 98.0%, 99.4% and 99.2% respectively.

**2. An Extraction and Classification Algorithm for Concrete Cracks Based on Machine Vision [2017]**

To solve the problem of large errors in extraction and the difficulty in classifying crack images in health monitoring of civil engineering structures, a new classification algorithm of concrete crack extraction based on machine vision is proposed in this paper.

Nonlinear grayscale transformation, improved OSTU threshold segmentation and then bifurcation points are all used in algorithm. . The obtained features are used as input to train a support vector machine classifier, which is then used to perform crack classification This algorithm had a good ability to extract cracks with obvious contours, but had difficulty with fine cracks, used a multiscale linear filtering approach based on the Hessian matrix to enhance the crack area and then determined the threshold interval according to the maximum entropy of the image histogram to obtain the crack binarization segmentation result.

3. **Crack and Noncrack Damage Automatic Classification from Concrete**

**Surface Images using Broad Network Architecture [2019]**

In this paper, an automatic crack damage classification method using broad network architecture, it extracts feature nodes from input raw data by convolution function or other mapping transformation, flatted enhancement nodes are combined with feature nodes to construct broad network architecture, finally a decision threshold is set to obtain a binary classification output.

Methodology -The Principle of Broad Learning Algorithma broad network is flatted in the width instead of the deep structure by multiple feature nodes and enhancement nodes.

Dataset – It consists of 40000 concrete images with crack (positive) and noncrack (negative) .Each class has 20000 images with 227×227×3 RGB pixels [L. Zhang, F. Yang, and D. Zhang, et, al. Road crack detection using deep convolutional neural network. In 2016 IEEE International Conference on Image Processing (ICIP)., 2016:3708-3712.]

This method avoids hyper parameter adjustment and complicated deep structure

**4. Application of Internet of Things Technology and Convolutional Neural Network Model in Bridge Crack Detection [2018]**

This paper defines the damage structure of the bridge structure as a comprehensive perception of the damage situation of the structure through the information sensing equipment, the ubiquitous interconnection of structural security impact factors (load, displacement, service life, use environment,etc.).

Methodology – Convolution neural Network (CNN) the set of small neurons in the convolution neural network is connected with a small region of the input image. Application of convolution neural network in classification of bridge cracks consist image preprocessing, the establishment of convolution neural network model, and the example analysis.

Studied a digital and intelligent bridge crack detection method to improve the efficiency of bridge safety diagnosis and reduced the risk factor. Firstly, the collected bridge crack pictures were preprocessed, the bridge crack convolution neural network classification model was established, and the model was simulated and trained using MATLAB. The bridge crack classification was obtained. This method could effectively solve the problems of low fracture diagnosis efficiency and high risk factor in domestic fractures

**5. A Deep Convolutional Neural Network for Semantic Pixel-Wise Segmentation of Road and Pavement Surface Cracks [2018]**

In this paper propose a deep fully convolutional neural network to perform pixel-wise classification of surface cracks on road and pavement images. The network consists of an encoder layer which reduces the input image to a bank of lower level feature maps. This is followed by a corresponding decoder layer which maps the encoded features back to the resolution of the input data using the indices of the encoder pooling layers to perform efficient up-sampling.

This paper presents an algorithm for semantic segmentation of road and pavement surface cracks using a Convolutional Neural Network, namely U-Net.The algorithm is trained, validated and tested on the publicly available CrackForest. Dataset which consists of 118 images of surface cracks on pavement and road surfaces, taken with a hand-held camera. The patch based training method proposed here will be extended to include augmentations of the input data in an attempt to equally represent cracks running at multiple angles.

**6. Road Crack Detection Using Deep Convolutional Neural Network and Adaptive Thresholding [2019]**

Crack detection is performed by either certified inspectors or structural engineers. This task is, time-consuming, subjective and labor-intensive. In this paper, a novel road crack detection algorithm which is based on deep learning and adaptive image segmentation is proposed.

Dataset [http://dx.doi.org/10.17632/5y9wdsg2zt.1]. In this experiments, the proposed deep neural network is trained on an NVIDIA GTX 1080 Ti GPU1, which has 3584 CUDA cores and 11 GB GDDR5X memory. The GPU memory bandwidth is 484 GB/s. The dataset utilized for training the proposed network was created by the researchers from Middle East Technical University. The dataset contains 40000 RGB images (resolution: 227\*227). The number of positive and negative images are both 20000.

The experimental results illustrate that our network can classify images with an accuracy of 99:92%, and the cracks can be successfully extracted from the images using our proposed thresholding algorithm.

**7. Design Application of Deep Convolutional Neural Network for Vision-Based Defect Inspection [2018]**

**I**n this paper, a design application of DCNN (Deep Convolutional Neural Network) is considered and developed for vision-based defect inspection. As a trial test, three kinds of DCNNs are designed, implemented and tested to inspect small defects, such as, crack, burr, protrusion, chipping and spot phenomena seen in the manufacturing process of resin molded articles. An image generator is also implemented to systematically generate range of relevant deformed version of similar images for training.

The DCNN based design application is described to evaluate the usefulness for image defect detection. Setting parameters for the training of the DCNN. The training was conducted using single PC with a Core i7 CPU and a GPU (NVIDIA GeForce GTX 1060).

The designed DCNNs are trained using the generated images and then evaluated through classification experiments. The proposed DCNN design application is planned to be applied to actual physical inspection processes.

**8. A Bridge Crack Image Detection and Classification Method Based On**

**Climbing Robot [2016]**

Develop a bionic climbing robot which can climb on rough surface due to its smart structure and bionic design. After loading simple camera, wall images can be acquired wirelessly in real time, which is suitable for health detection of bridge structure. But, due to the small load of the robot, both the size and precision of its camera are limited, which leads to the lower quality of obtained pictures. The goal of this system is to obtain crack pictures of bridge surface, use algorithms to make up for the deficiency of hardware precision through a series of image processing methods, divide complete crack samples. Based on the visual and geometrical characteristics, a decision-tree-based multiclass support vector machine algorithm is applied to classify crack target.

**9. Grid-based Pavement Crack AnalysisUsing Deep Learning [2017]**

In this paper segment the pavement crack images into different scales of grids. We choose suitable scale of grids to segment image. We design the structure of CNN to detect pavement crack. To classify the type of crack, we utilize principal component analysis (PCA) to calculate the distribution of grids. After analysis the distribution of grids, we achieve the pavement crack classification An image is cut into many non-overlapping grids, and then we use CNN to detect the existence of crack. We only keep the grids that containing crack so that the skeleton of crack can be preserved.

The pavement images are collected by author along the Youyi Avenue in Wuhan city. There were 510 pavement images which including three kinds of crack pictures and non-crack pictures. Took 30000 grid images as training set images. The rest of images were testing set images. The correct rate of classification is increased compared with pavement crack classification using neural network.

**10. A Genetic Algorithm for Convolutional Network Structure Optimization for Concrete Crack Detection [2018]**

GA has been applied to a variable depth CNN. This means that in the proposed method, the GA evolves the network depth, the layer size, and the hyper parameters of the network. The size of layers in the CNN affects the level of details that are recognized by the CNN, a case where GAs have excelled previously.

The proposed method utilizes a GA for CNN structure optimization. This method evolved several parameters that dictate the structure of a CNN, including: number of convolution layers, size of convolution filters, and number of convolution filters used in each layer. Evolving CNN structures produces high-performance networks that have higher classification accuracy than the state-of-the-art network when tested on images of concrete containing cracks. This process allows for a small training set, since mass training data is sometimes difficult to obtain in real-world applications. The process also performs the search for network structures automatically, which removes the need for a deep knowledge of the features being described and the neural network design process. Visual results indicate that the generated networks perform