Automatic Detection Of Sewer Defects Via Hierarchical Deep Learning

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Abstract

One of the biggest problems we are facing nowadays is sewer pipeline damages. A sewer pipeline damage can cause many issues such as traffic discomfort due to the spoiling of road with the leaked sewer water and spread of the waste water on the roads and surroundings. Also these untreated sewer damages cause many other problems such as they make the water impure to use when the waste water mixes with the drinkable and usable water and also cause threat to the aquatic animals and marine life. The leakage releases bad odour into the atmosphere. This also leads to the cause of many diseases due to the use of the impure water and also the bacteria and other life threatening human pathogens that are carried by the sewages includes cholera, typhoid, dysentery and many other diseases causing germs and viruses.

Most of the sewers with lifespan of 25-30 years and older are getting damaged easily also the sewer damages are mostly due to the impose of overweight on the sewer pipelines and underground pressure on the pipelines are causing cracks, fractures, gouges and corrosion to the sewer pipelines.The pipelines of more lifespan should be replaced .So early detection of sewer damages and replacement of sewer pipelines is very important.Thus we can overcome the above mentioned problems and effects of sewer damages.

1. Introduction

Sewer pipe systems form an important component of civil infrastructure which is designed to collect and transport wastewater, stormwater and groundwater to treatment facilities.. Over 50% of the reports sewer sanitary overflows are attributed to pipe cracks.Considering the serious consequences caused by those defects such as cracks, it is important to detect the defects at an early stage such that further pipe deterioration can be avoided, and existing defects can be repaired to maintain normal sewer operations

Currently, visual inspection techniques such as closed-circuit television (CCTV) have been commonly utilized for underground sewer pipe inspection. inspection, the inspector needs to watch the A CCTV usually consists of a camera and an illumination device mounted on a tractor. When encountering a pipe defect or pipe lateral, the inspector would stop the unit and zoom the camera into the abnormal part to check if there are potential defects. After the captured images or videos to identify the defect type and location. Such manual interpretation of the inspection images or videos is time-consuming, labor intensive and the results can be subjective and inaccurate.The automatic detection of sewer damages can be helpful reducing the time and manpower. The results provided by the automatic detection method are also more accurate than the manual interpretation.

2. Problem Statement

Sewer damages or cracks on sewer pipelines caused many effects. As most of the sewer pipe lines are not placed underground any minimum leakages and damages will cause the surrounding areas stinky and huge discomfort for transport and to the public and also releases bad odour into the atmosphere. The sewer pipeline damages can be caused mostly due to the corrosion, cracks, fractures, dents, gouges. Generally homes are experiencing a large wave of sewer pipe line damages due to 25-35 years of life span of pipes. If your sewer pipe lines are 25 years old or older, they could fail at any time.

The draining lines can also get damaged by tree root intrusion, cracks, channeling, or misaligned connections before you experience complete sewer line failure. By this life threatening human pathogens carried by sewage include cholera, typhoid and dysentery. Untreated sewage gets into rivers and canals which cause a huge threat to aquatic life and spoils drinking water which causes an effect to human life. So early detection of sewer damages will help us to overcome the mentioned effects.

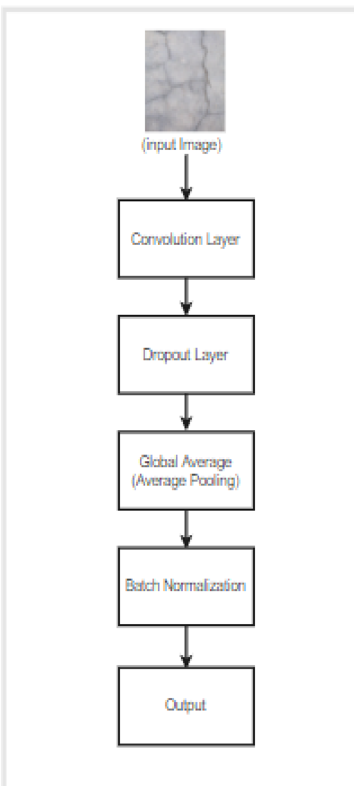

Fig1: Architecture of Inception V3

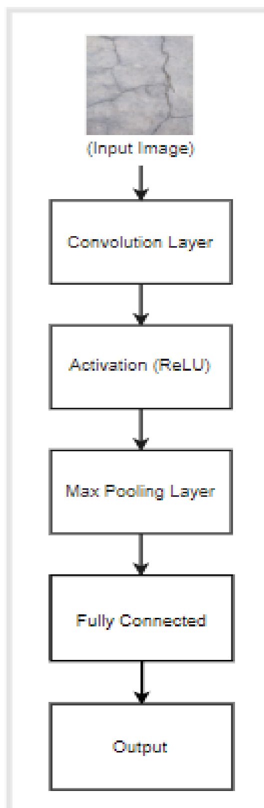

Fig 2: Architecture of VGG 16

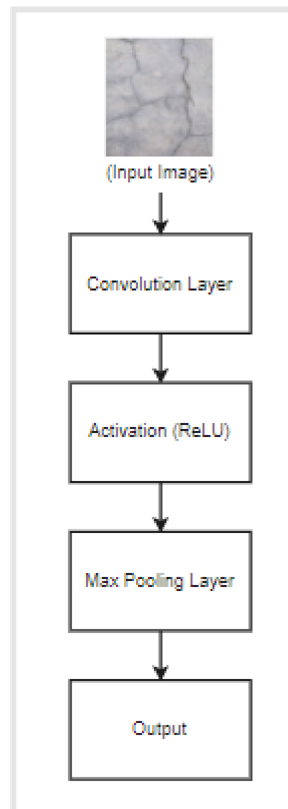

Fig 4: Architecture of ResNet50

Inception v3:

Inception v3 is a convolutional neural network architecture that contains 48 layers in it. We can pretrain the model containing more than one million images. Inception v3 network has multiple blocks, in which each block has different groups like convolution layer, dropout layer, average pooling, Batch normalization and output layer. The input image is sent to the convolution layer where the filters are applied to the image and then the image is sent to the dropout layer. Dropout layer is used to prevent the neural network from overfitting. This layer is used when the training is set to True so that no inputs are dropped during training. Average pooling used to calculate the average patch value from the image. Next batch normalization is applied on the image such that the process is reduced and also epochs required to train the model is also reduced. Output image contains the positive or negative based on the crack detection. Each patch contains positive or negative such that positive represents crack detected and negative represents no crack detected.

VGG 16:
VGG 16 is a convolutional neural network which contains 16 layers in it in which 13 layers are convolutional layers and 3 layers are fully connected layers. Network is so large and contains 138 million parameters. The image dataset contains images of fixed size 224 x 224 so the output image contains 224 x 224 x 3 as size. The input image is sent to a convolution layer in which filters are applied to images. Next Image sent for ReLu activation function. Rectified linear activation function(ReLu) is used to give output to the input image as it is positive if it has crack or zero if it has no crack. It allows models to train the model in a faster way and perform in a better way. In the max pooling layer maximum value in each patch is calculated from each image. Next image is sent to a fully connected layer in which input from one layer is connected to output of previous convolution layers. Output images contain positive or negative in each patch based on crack detection such that positive represents crack detected and negative means no crack detected.

Resnet50 :
ResNet 50 is a convolutional neural network which contains 50 layers in which 48 are convolution layers, one max pool layer and one average pool layer. The Resnet 50 network is so large and contains 23 million trainable parameters. The input image is sent to a convolution layer in which filters are applied to images. ReLu activation function is used to directly give the output to the given input image as it is positive if crack is present and zero if the crack is not present. In the max pooling layer the maximum value in each patch is calculated from each image. Output image contains positive or negative in each patch where positive represents crack is detected and negative represents no crack detected.

Technical flow diagram:

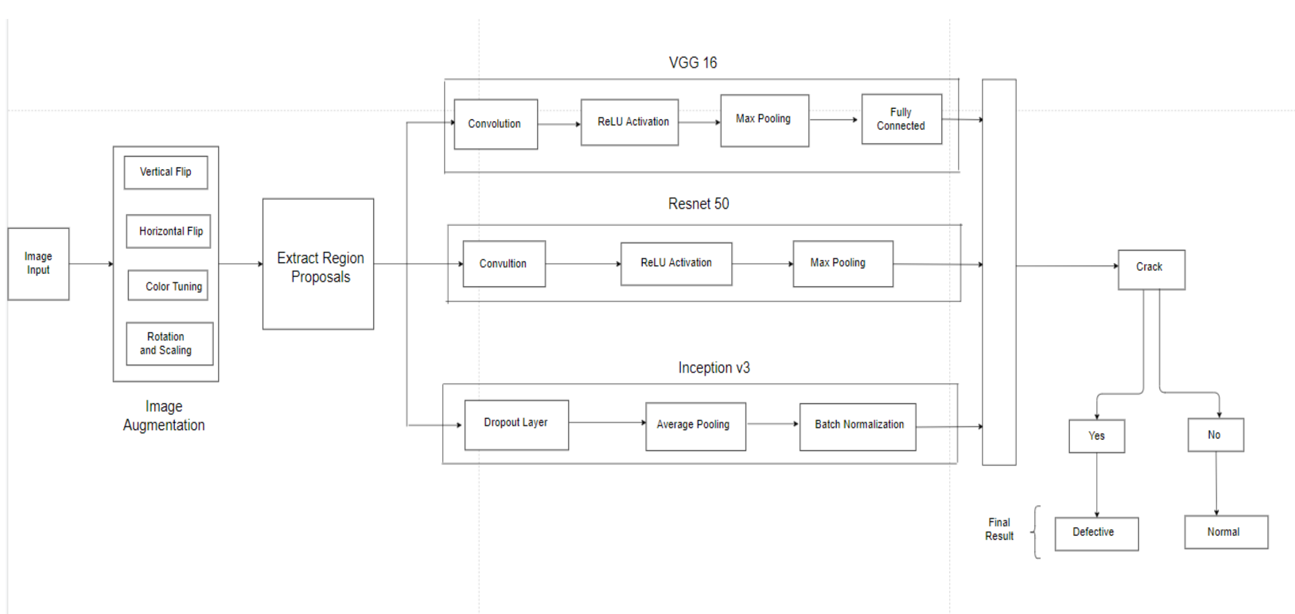

Fig 5:Technical Flow Diagram

The Architecture of the Model carried out in the following way. First the image data set with positive and negative images are loaded. All the required functions are imported such as torch, numpy, matplotlib etc. Now the no of crack images and non-crack images are counted from the dataset. These images are visualized using some random images of crack and non-crack from the dataset. Now the Training dataset is created and the val datasets with the positive and negative images is created. By using pytorch data loader and transforms mean and standard deviation for the dataset are computed. Data augmentation and transforms are defined and the data loader is created. Now some images are visualized by grabbing some of the training data and a grid is constructed from the batch. Now the images are given to different models such as Resnet50, Inception V3, VGG16. Now the input is compared with these models and the model with the best accuracy is taken for the implementation of the Crack detection. Finally testing is performed by providing several raw input images.

Methodology :

Deep learning approach for Crack Detection and Image Classification

2.2.1. Image classification using Deep Learning

Crack detection using Image classification can be done mostly using Deep learning CNN techniques.We have many techniques and methods in deep learning for image classification.Some of the Convolution Neural Networks for the image classification are ResNet50, VGG16 and Inception v3 .There are many other deep learning CNN models for image classification.The process of Convolution neural network is mainly done in two steps namely feature extractions which has the convolution process, activation and pooling and then image classification.The input real time raw input images are collected through CCTV or other sources.The process of convolution is carried out in different layers for different models. Each layer of convolution has different functionalities which classifies the image by applying different filters repeatedly which results in an activation and passes the result to the next layers. Pooling is done on the resultant filtered images which combines the output by forming clusters of neurons in one layer into a single neuron in the next layer. This is the extraction of features from an image. In image classification Fully connected layers connect all the neurons from one layer to all the neurons of the next layer. Finally the output is predicted as positive or negative based on the detection of the cracks when filters are applied on the image in multiple layers to get the optimized result.

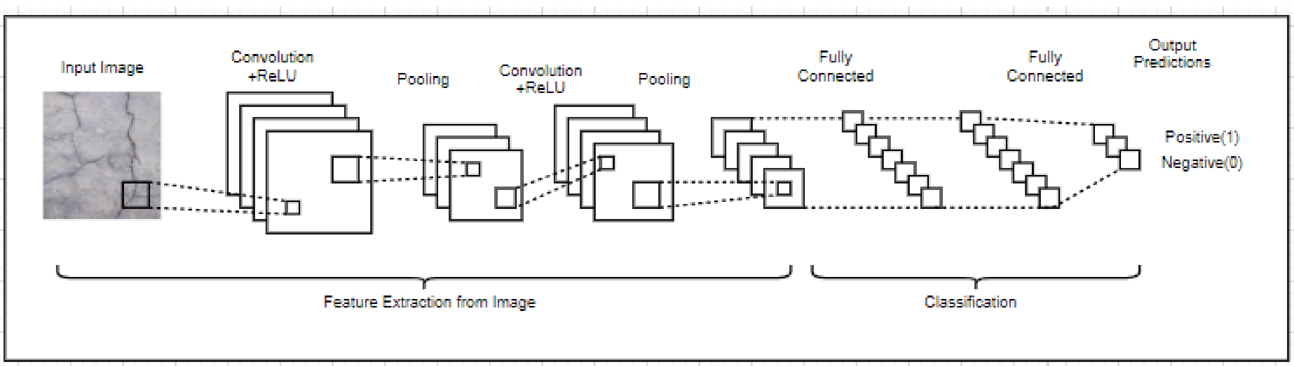

Fig 6: Architecture of CNN mode

Object detection using Deep Learning:

Object Detection is an automated method to detect, classifying or locating any objects such as root, crack or deposit by comparing the image with respect to the background in an image.The objects are detected by extracting the features from raw input images using convolution techniques such as Fast R-CNN, Histogram of oriented gradients(HOG), Single shot detector(SSD), Spatial Pyramid pooling(SPP-net) for the purpose of object detections by applying different filters.

The raw input image is divided into different regions and each region is wrapped for the extraction of features of each region.Each block of region is computed using CNN features by classifying regions for the detection of cracks, root or deposits .

The region-based convolutional neural network (R-CNN) is one of the typical deep learning approaches for object detection and to classify images.

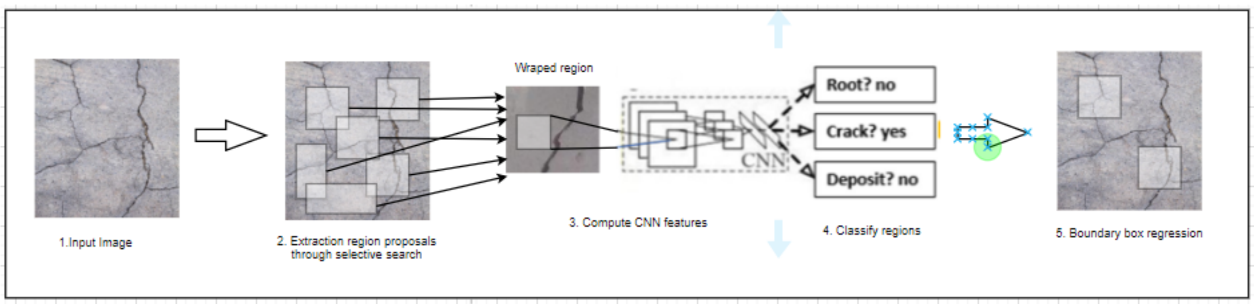

Fig 7: Architecture of R-CNN

4. Experiments and results:

It was reported that the main causes of pipe incidents such as pipe cracks and leakage of water due to the severity of cracks.Therefore the proposed method identifies the cracks and also identifies the part where the crack is present. In this experimentation the algorithms used are ResNet50, VGG16 and Inception V3. The experimental results of the algorithms VGG16, Resnet50 and Inception V3 are shown in Figure 8, Figure 9 and Figure 10 respectively.

VGG16:

```
Epoch 1/7
438/438 [==============================] - 74s 169ms/step - loss: 0.0337 - accuracy: 0.9904 - val_loss: 0.0174 - val_accuracy: 0.9942
Epoch 2/7
438/438 [==============================] - 73s 167ms/step - loss: 0.0133 - accuracy: 0.9962 - val_loss: 0.0152 - val_accuracy: 0.9951
Epoch 3/7
438/438 [==============================] - 74s 170ms/step - loss: 0.0101 - accuracy: 0.9971 - val_loss: 0.0139 - val_accuracy: 0.9958
Epoch 4/7
438/438 [==============================] - 73s 168ms/step - loss: 0.0088 - accuracy: 0.9976 - val_loss: 0.0180 - val_accuracy: 0.9947
Epoch 5/7
438/438 [==============================] - 73s 166ms/step - loss: 0.0075 - accuracy: 0.9982 - val_loss: 0.0203 - val_accuracy: 0.9944
Epoch 6/7
438/438 [==============================] - 74s 168ms/step - loss: 0.0068 - accuracy: 0.9979 - val_loss: 0.0147 - val_accuracy: 0.9958
Epoch 7/7
438/438 [==============================] - 73s 167ms/step - loss: 0.0060 - accuracy: 0.9982 - val_loss: 0.0128 - val_accuracy: 0.9967
```

Fig8 : Output of VGG16 model

ResNet 50:

```
Epoch 1/7
438/438 [==============================] - 161s 366ms/step - loss: 0.0211 - accu
racy: 0.9932 - val_loss: 0.0059 - val_accuracy: 0.9983
Epoch 2/7
438/438 [==============================] - 160s 365ms/step - loss: 0.0046 - accu
racy: 0.9989 - val_loss: 0.0043 - val_accuracy: 0.9987
Epoch 3/7
438/438 [==============================] - ETA: 0s - loss: 0.0036 - accuracy: 0.
9991
Reached 99.9% accuracy so cancelling training!
438/438 [==============================] - 152s 348ms/step - loss: 0.0036 - accu
racy: 0.9991 - val_loss: 0.0040 - val_accuracy: 0.9987
```

Fig 9: Output of ResNet50 Model

Inception v3:

```
Epoch 1/7
438/438 [==============================] - 233s 533ms/step - loss: 0.0707 - accuracy: 0.9847 - val_loss: 0.0097 - val_accuracy: 0.9971
Epoch 2/7
438/438 [==============================] - 74s 170ms/step - loss: 0.0232 - accuracy: 0.9952 - val_loss: 0.0218 - val_accuracy: 0.9958
Epoch 3/7
438/438 [==============================] - 75s 171ms/step - loss: 0.0170 - accuracy: 0.9967 - val_loss: 0.0085 - val_accuracy: 0.9980
Epoch 4/7
438/438 [==============================] - 75s 170ms/step - loss: 0.0176 - accuracy: 0.9970 - val_loss: 0.0179 - val_accuracy: 0.9976
Epoch 5/7
438/438 [==============================] - 74s 170ms/step - loss: 0.0087 - accuracy: 0.9981 - val_loss: 0.0158 - val_accuracy: 0.9974
Epoch 6/7
438/438 [==============================] - 75s 171ms/step - loss: 0.0073 - accuracy: 0.9986 - val_loss: 0.0124 - val_accuracy: 0.9982
Epoch 7/7
438/438 [==============================] - 75s 171ms/step - loss: 0.0066 - accuracy: 0.9987 - val_loss: 0.0127 - val_accuracy: 0.9980
```

Fig 10: Output of Inception v3 model

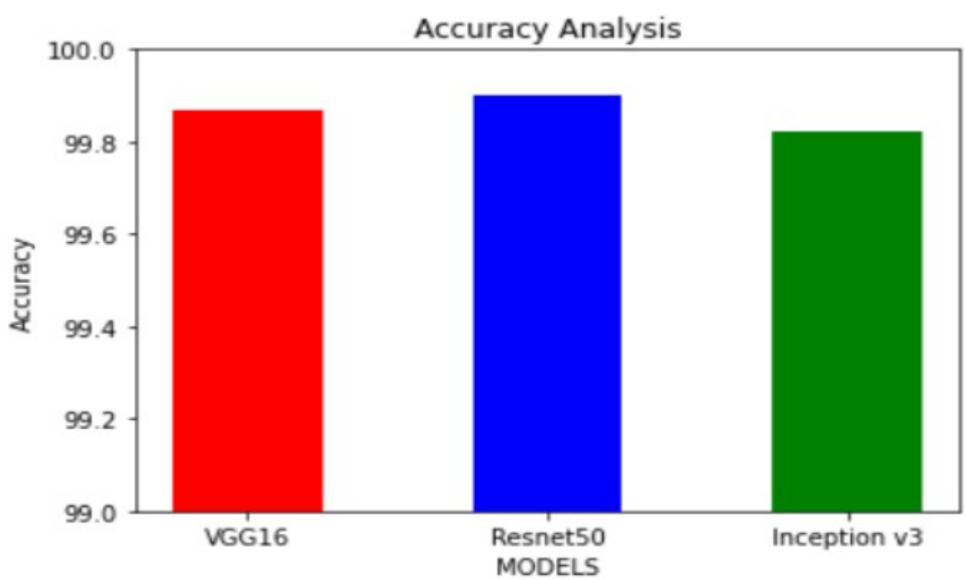

Fig 11: Accuracy comparison graph for VGG16. Resnet 50 and Inception v3 model

Inception v3:

Fig 12: Training and validation accuracy for Inception v3

Fig 13: Training and validation loss for Inception v3

VGG16:

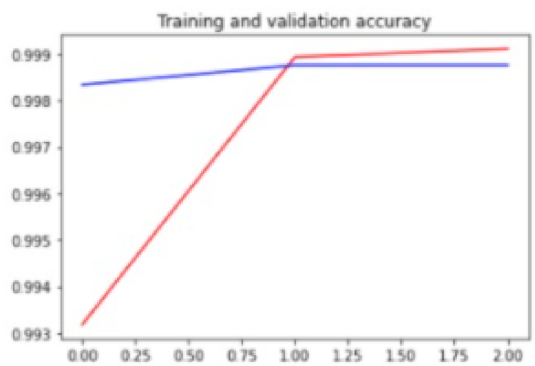

Fig 14: Training and validation accuracy for VGG 16

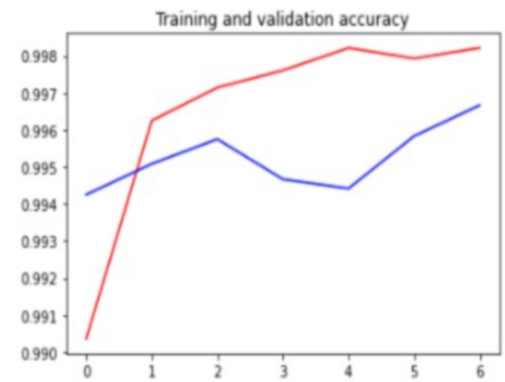

Fig 15: Training and validation loss for VGG 16

ResNet 50:

Fig 16: Training and validation accuracy for Resnet50

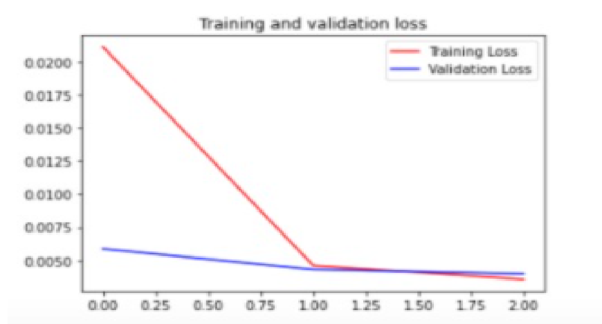

Fig 17: Training and validation loss for Resnet50

Final Result:

After building the model the images are provided and the result gives an image identifying the cracks as displaying positive and negative on the image. In each cell of the original image based on the pixel value it is represented with a tag either positive or negative. Positive cell is represented in red color and the negative cell is represented in green color. The cell containing defect is represented in red color and the cell with no defect is represented in green color.

Fig 18: Crack detection Input Image

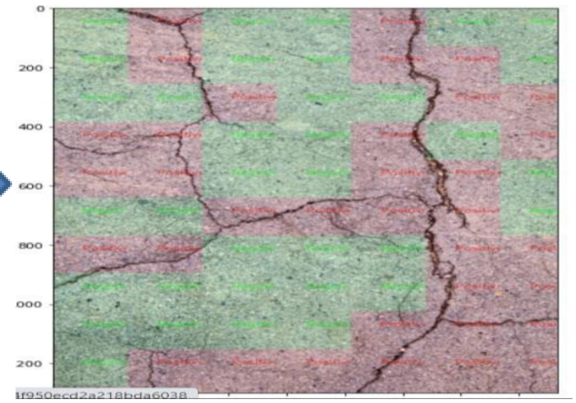

Fig19: Crack detection Output Image

Conclusion:

Sewer pipelines are one of the essential services that we have. Many pipelines as they are over-age and are getting defects such as interior cracks due to tree root intrusions, over pressure imposed on the pipelines and corrosion, leads to serious consequences.

Early detection and replacement of these sewer pipelines is very essential.For early detection images are collected through CCTV as it is one of the dominant techniques to inspect sewer pipelines. As manual inspection of images is very tough due to more time consumption and the current approach works for static images.And also this process needs experience and expertise.

Considering all the backlogs deep learning based techniques are used for the automatic inspection and detection of cracks on sewer pipelines using time series frames. In this way using CNN models such as Resnet50, VGG16, inception v3 and many other CNN models we can automatically inspect and detect sewer damages and cracks.

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