



Big Data Principles for Identifying Product Review Spammers

Mrs.MaruthiKrishna.K

Department of Mca
Dhanalakshmi College of
Engineering and Technology

Ms.Sumaiya.R

Department of Mca
Dhanalakshmi College of
Engineering and Technology

Abstract: Techniques for identifying potholes on road developing strategies for real-time or offline identification of potholes, to support real-time control of a vehicle (for driver assistance or autonomous driving) or offline data collection for road maintenance. For these reasons, research around the world has comprehensively explored strategies for the identification of potholes on roads. This paper starts with a brief review of the field; it classifies developed strategies into several categories. We, then, present our contributions to this field by implementing strategies for automatic identification of potholes. We developed and studied two techniques based on stereo-vision analysis of road environments ahead of the vehicle; we also designed two models for deep - learning-based pothole detection. An experimental evaluation of those four designed methods is provided, and conclusions are drawn about particular benefits of these methods

I. INTRODUCTION

We present a novel deep learning framework named the Iteratively Optimized Patch Label Inference Network (IOPLIN) for automatically detecting various pavement distresses that are not solely limited to specific ones, such as cracks and potholes. IOPLIN can be iteratively trained with only the image label via the Expectation-Maximization Inspired Patch Label Distillation (EMIPLD) strategy, and accomplish this task well by inferring the labels of patches from the pavement images. IOPLIN enjoys many desirable properties over the state-of-the-art single branch CNN models. It is able to handle images in different resolutions, and sufficiently utilize image information particularly for the high-resolution ones, since IOPLIN extracts the visual features from unrevised image patches instead of the resized entire image. Moreover, it can roughly localize the pavement distress without using any prior localization information in the training phase. In order to better evaluate the effectiveness of our method in practice, we construct a large-scale Bituminous Pavement Detection dataset named CQU-BPDD consisting of 60,059 high-resolution pavement images, which are acquired from different areas at different times. Extensive results on this dataset demonstrate the superiority of IOPLIN over the state-of-the-art image classification approaches in automatic pavement distress detection.

Disadvantage Of Existing System

- It has not used on Deep Neural network in keras and TensorFlow as classifier.

- They are not using CNN and OpenCV computer vision technique.
- It has not focused on increasing the recognition rate and classification of road pothole.

Proposed System:

We are proposing road pothole using Deep CNN (convolutional neural network) for deep learning technique. After collecting a suitable amount of data containing the images of potholes under various conditions and weather, and implementing CNN approach of deep learning has been adopted, that is a new approach in this problem domain using pothole imaging. Also, a comparison between the self-built convolutional neural model and some of the pre-trained models has been done. The proposed method for this project is to train a Deep Learning algorithm capable of road pothole classification. This particular classification problem can be useful for road pothole detection. The using Deep Learning with the help of Convolution Neural Networks based on TensorFlow and Keras. we proposed a deep learning (dl) based road pothole dataset to build classification method to prevent the pothole. the deep learning method used in the study is the Convolutional neural network (CNN). it is predicted that the success of the obtained results will increase if the CNN method is supported by adding extra feature extraction methods and classify successfully road pothole.

Advantages Of Proposed System

- To classify road pothole image used on artificial neural network.



- It is best model for deep learning technique to easily road pothole.

4.5 Module Description

List Of Modules

1. Manual Net
2. AlexNet
3. LeNet
4. Deploy

IMPORT THE GIVEN IMAGE FROM DATASET:

We have to import our data set using keras preprocessing image data generator function also we create size, rescale, range, zoom range, horizontal flip. Then we import our image dataset from folder through the data generator function. Here we set train, test, and validation also we set target size, batch size and class-mode from this function we have to train using our own created network by adding layers of CNN.

POTHOLE ROAD:

Trained data for potholes:

```
===== Images in: data/train/pothole
Images count: 367
min_width: 160
max_width: 3840
min_height: 120
max_height: 3840
```



PLAIN ROAD

Trained data for plain:

```
===== Images in: data/train/plain
Images count: 367
min_width: 160
max_width: 3840
min_height: 120
max_height: 3840
```



TO TRAIN THE MODULE BY GIVEN IMAGE DATASET:

To train our dataset using classifier and fit generator function also we make training steps per epoch's then total number of epochs, validation data and validation steps using this data we can train our dataset.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 75, 75, 32)	896
max_pooling2d (MaxPooling2D)	(None, 37, 37, 32)	0
conv2d_1 (Conv2D)	(None, 12, 12, 128)	36992
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 256)	1179904
dense_1 (Dense)	(None, 4)	1028
Total params: 1,218,820		
Trainable params: 1,218,820		
Non-trainable params: 0		

CNN Model Summary details

WORKING PROCESS OF LAYERS IN CNN MODEL:

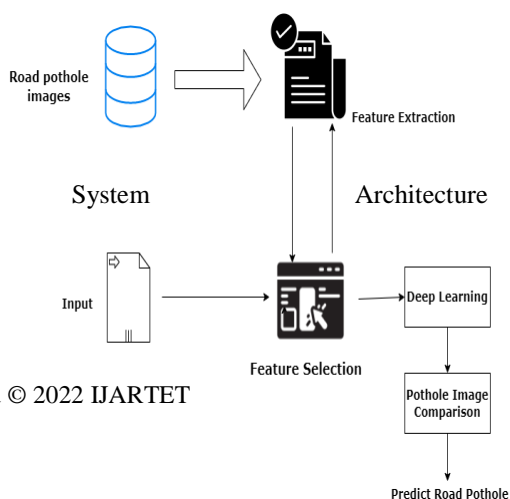
A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. Their network consists of four layers with 1,024 input units, 256 units in the first hidden layer, eight units in the second hidden layer, and two output units.

Input Layer:

Input layer in CNN contain image data. Image data is represented by three dimensional matrixes. It needs to reshape it into a single column. Suppose you have image of dimension $28 \times 28 = 784$, it need to convert it into 784×1 before feeding into input.

SYSTEM DESIGN

6.1 System Architecture:





SYSTEM TESTING AND MANINTANENCE:

Black Box Testing

Black Box Testing is testing without the knowledge of the internal workings of the item being tested. When black box testing is applied to software engineering, the tester selects valid and invalid input and what the expected outputs should be, but not how the program actually arrives at those outputs. Black box testing methods include equivalence partitioning, boundary value analysis, all-pairs testing, fuzz testing, model-based testing, traceability matrix, exploratory testing and specification-based testing. This method of test design is applicable to all levels of software testing: unit, integration, functional testing, system and acceptance.

White Box Testing

White box testing (glass box testing) strategy deals with the internal data structures and algorithms. The tests written based on the white box testing strategy incorporate coverage of the code written, branches, paths, statements and internal logic of the code etc. These testers require programming skills to identify all paths through the software.

Types of white box testing includes code coverage (creating tests to satisfy some criteria of code coverage.), mutation testing methods, fault injection methods, static testing.

Acceptance testing

- Testing with customer data to check that the system meets the customer's needs.

Testing Methods and Comparison

8.4 Black Box Testing

Black Box Testing is testing without the knowledge of the internal workings of the item being tested. When black box testing is applied to software engineering, the tester selects valid and invalid input and what the expected outputs should be, but not how the program actually arrives at those outputs. Black box testing methods include equivalence partitioning, boundary value analysis, all-pairs testing, fuzz testing, model-based testing, traceability matrix, exploratory testing and specification-based testing.

This method of test design is applicable to all levels of software testing: unit, integration, functional testing, system and acceptance.

8.5 White Box Testing

White box testing (glass box testing) strategy deals with the internal data structures and algorithms. The tests written based on the white box testing strategy incorporate coverage of the code written, branches, paths, statements and internal logic of the code etc. These testers require programming skills to identify all paths through the software.

Types of white box testing includes code coverage (creating tests to satisfy some criteria of code coverage.), mutation testing methods, fault injection methods, static testing.

CONCLUTION AND FUTURE ENHANCEMENT

9.1 CONCLUSION

It focused how image from given dataset (trained dataset) in field and past data set used identify road pothole using CNN model.

This brings some of the following different gestures prediction. We had applied different type of CNN compared the accuracy and saw that LeNet makes better classification and the .h5 file is taken from there and that is deployed in Django framework for better user interface.

APPENDICES

Sample Screens



Input image



Output

image

