POTHOLE CLASSIFICATION WITH DATA AUGMENTATION

A Project Report

submitted by

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Abstract

Image classification projects deal with multiple problems, such as knowing how much data is sufficient for our project and which algorithm with what kind of parameters will work better in the project. While debugging such projects, we need to isolate various parameters and test them in a systematic manner to optimize our solution.

Size of the dataset is one central aspect of an image classification project. We can use data augmentation to increase the dataset size and train the model with this dataset for good performance. We can use several data augmentation techniques such as rotation, zoom, vertical flip, width shift, horizontal flip, and height shift on the dataset to check which method has the higher accuracy.

We took pothole detection as a case study to experiment with various data augmentation techniques on a single algorithm. Potholes and road anomalies are the primary cause of road accidents. Potholes affect road quality, driver safety, vehicle structure, and fuel consumption. Thus to avoid

potholes and maintain roadways, we need to detect them first, which calls for pothole image classification. We built a machine learning-based pothole detection model to detect potholes in images. With our primary focus to study the effect of various image transformations, we took a single convolutional neural network and tested the effects of augmented datasets of various sizes on it.

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Introduction

With the increase in population, the number of vehicles and traffic on roads are increasing too. With increasing vehicular traffic and pollution on roads, managing such an amount of traffic has become very tough. Potholes and road surface anomalies are the primary cause of road accidents. In India, 70 percent of road accidents are because of poor road conditions. Road conditions such as potholes, cracks, etc., should be identified to prevent road accidents and significant injuries.

Potholes are a type of road damage caused by climate changes, vehicular traffic, road aging, and low-quality construction materials. The major reason for formation of potholes is due to fatigue of the road surface, insufficient pavement thickness, and heavy rainfall. In India, many people are killed or injured every year due to potholes.

A pothole can put the life of a driver and fellow passengers in danger. It is a severe risk factor. Potholes also create problems for drivers as these can lead to a lot of damage to their vehicles. Due to this, it is crucial to have information about the road surface through which the vehicle travels. Thus to avoid accidents and vehicle damage, we need first to detect potholes, which calls for pothole image classification. Detection of road distress such as cracks, potholes, etc., is mainly performed manually, which is time-consuming and labor-intensive.

Many researches have been carried out across the world to develop systems that can automatically identify road anomalies, especially potholes. There are mainly three parts into which these researches can be classified i.e., vibration-based, 3D reconstruction-based, and vision-based methods. Many automated systems are there to identify road damage through sensors, but this process is costly. Conventional monitoring methods collect data from expensive sensors mounted on vehicles. Due to high cost, such methods cannot be used to regularly check for the need for repairs on a large-scale road network.

As we took pothole detection as a case study to experiment with various data augmentation techniques on a single algorithm, this paper will work on pothole classification using convolutional neural network, which is a low-cost intelligence system. A Convolutional Neural Network (CNN) is the class of deep neural networks. In recent years, the area of deep learning has gained remarkable results and has shown great effectiveness in many areas of research. In this study, we apply convolutional neural network algorithms for pothole classification.

What is a Pothole ?

A pothole is a cavity on the road surface, generally asphalt paved roads, where traffic congestion has shifted damaged pieces of the paved roads. Usually, it is the consequence of water pouring into the soil composition and the traffic which is passing over this area. Potholes are areas in the surface of the roadway that have cracked, worn away, and where a segment of the road surface material has broken-away, eventually forming a hole. They start out as small cracks. If they're not repaired right away, they can grow. Potholes can be anywhere from a few inches broad and deep to a few feet broad and several inches deep.

Motivation

Classification problems deals with many problems and choosing data size is one of the important problem. We took pothole case study because increasing economic growth has increased urbanization, Traffic congestion in India, and a high increase in the number of vehicles. The number of reported road accidents is growing exponentially due to poor road conditions. With more usage, the roads are deteriorating, and maintenance of road surface is little. Drivers face difficulty to identify the potholes, bumps, etc., due to the poor road conditions, which leads to severe accidents. Potholes get filled with water in the rainy season, and drivers are unable to recognize its presence or depth, which leads to life-threatening accidents. The prime motivation behind building a pothole classification method is to help drivers in many aspects and thus helping them to avoid a possible accident.

Objective

The objective of this project is to study the effect of various image transformations like rotation, zoom, vertical flip, width shift, horizontal flip, and height shift on the dataset using a convolutional neural network. In this project, we to build a model to classify potholes and normal images to avoid potholes on the road. Convolutional neural networks (CNN) are widely used for image classification tasks. These neural networks provide better accuracy in classification than other methods. This paper proposes a model using Convolutional neural networks to classify potholes with better accuracy.

Literature Review

The methods used for the detection of potholes can be categorized into vision-based, 3D reconstruction based and vibration-based methods. Vibration variations are recorded in vibration-based methods when a vehicle passes over a pothole or any road surface anomaly. An accelerometer is used to collect the vibration of the vehicle. In vibration-based methods, the main disadvantage is passing a vehicle over a pothole to collect vibrations. 3D reconstruction based method is a type of method thats captures the geometric shape, depth, and featues of real world entities. 3D laser, Kinect sensors or stereo vision cameras are usually used to obtain 3D surface of the region of interest in 3D reconstruction methods. We do not apply 3D reconstruction methods when a vehicle is in moving state; instead, this method is applied on stable vehicles. Vision-based methods use camera as a sensor. Video data or 2-dimensional (2D) images that are captured by a digital camera are used in Vision-based methods. It processes the collected data through video or 2D image processing techniques. After applying image processing techniques, classification methods are implemented to determine the presence of a pothole.

Vibration based methods

Fatjon Seraj, Berend Jan van der Zwaag, Arta Dilo, Tamara Luarasi, Paul Havinga proposed a machine-learning approach to classify road anomalies. The proposed system used support vector machine (SVM) to classify the potholes. For road surface anomalies detection, they used mobile phones(Samsung galaxy) equipped with inertial sensors i.e., accelerometers and gyroscopes. They obtained 90 percent accuracy in detecting road surface anomalies.

Manjusha Ghadge, Dheeraj Pandey, Dhananjay Kalbande investigated on approach of Machine learning to predicting bumps on the road surface in 2015. This paper used an accelerometer and GPS system to monitor road conditions. They used a approach based on machine learning, by using K-means clustering algorithm on training dataset, and random-forest classifier algorithm for testing dataset to detect the location of potholes and bumps. In this paper, when severity is included and clusters are of different sizes, clustering does not perform well.

Artis Mednis, Girts Strazdins, Reinholds Zviedris, Georgijs Kanonirs, Leo Selavo proposes a method for pothole detection with Android smartphones and accelerometers in real-time. This paper uses a mobile sensing system to detect road surface anomalies with smartphone based on the Android operating system. Preliminary data were collected from an accelerometer on the road with many potholes by using a transformed LynxNet collar device.

3D Reconstruction based methods

Truman Shen, Gregory Schamp, Mario Haddad explored Stereo vision-based road surface preview in 2014. This paper proposes the method using stereo-vision system of Takata to accomplish a road surface viewing along with the host vehicle. The video data is recorded by using the compact stereo vision sensor (reference 16.5 cm) and is monitored by an embedded system, which is already been checked on many vehicles. This system gives satisfactory accuracy and a low performance for cases when there is a flare on the road surface.

Kiran Kumar Vupparaboina, Roopak R. Tamboli, P. M. Shenu and Soumya Jana presents a Laser-based detection approach. This paper presents a method to determine potholes depth by using a physics-based geometric method. The depth of the dry pothole is related to measure optical deviation applying simple ray optics. Moreover, to obtain a quartic equation, they used Snell's law of refraction and it's suitable real roots to relate the depth of pothole filled with water to the corresponding optical deviation. But this system does not perform well on water-filled potholes or wet roads.

Abdullah Rasheed et. al. proposed a method stabilizing 3D road images using the Kalman filter with affine transformations as a state space model. The vibrations of the image platform are captured by using a simulated accelerometer and it is used as a prominant feature to measure the affects of instability in road images.

Vision-based methods

Seung-Ki Ryu et. al. proposed an approach for pothole detection for asphalt or concrete pavement. They gathered 2 Dimensional images through an optical device mounted on the vehicle. This method has three stages, i.e., image segmentation, extracting candidate region, and decision. This method will be inappropriate in detecting potholes for cases where roads are covered by the shadow of objects.

Lucy Powell and K G Satheeshkumar proposed a method for automated road distress detection. This proposed method first segments images into non-defected or defected regions. Then texture data is extracted from both defected areas and non-defected areas, and then the results are compared. Since the presence of shadow of objects on the road degrades the system performance, this method aims to remove shadow effects from the system with a shadow removal algorithm to improve the system performance. The system is incapable of functioning in rainy weather. This approach was tested on 2D images, so authors inferred that it should further continue to perform on video data.

Learning-based methods

Zhang et al. about the detection of road damage presents a CrackNet that predicts the class score of every pixel. Unlike CNN, CrackNet does not have a pooling layer, so there is a possibility that the output of the previous layer will decrease. CrackNet input data is a feature map generated by feature extraction using the proposed line filters in different directions, widths and lengths. The CrackNet output is a group of predicted class scores for all pixels. Various efficient learning techniques are used to train CrackNet, including Cross-Entropy, Mini-batch Gradient Descent, Normalized Initialization, Momentum, and Dropout. Then, from the image library, 200 images used for testing processed by the trained CrackNet.

The model proposed by Vosco Pereira, Satoshi Tamura, Satoru Hayamizu, and Hidekazu Fukai uses CNN model to detect potholes, and this model has been trained on CPU. Their experiment illustrates that using CNN approach has better accuracy than using the conventional SVM-based approach. But this method can not perform well or unable to detect potholes under lightening conditions. The results of this approach proves that using deep learning techniques has better solution than traditional algorithms. The model is trained on images from different places and has images in various conditions such as wet, shady, and dry.

Proposed System

In this, we present the method used for pothole classification. We have used convolutional neural network-based VGG16 architecture to classify potholes and normal images. VGG16 architecture is a \gls{CNN} architecture that has 16 layers. It has five blocks, and each block has a max pooling layer. VGG16 has a fixed input size of 224×224 for its first convolutional layer. Firstly the dataset is collected from kaggle, and input images are in two folders, i.e., normal and pothole. The input images are then preprocessed for better training of the model and performance. After this, several data augmentation techniques like zooming, rotation, rescaling, horizontal flip, vertical flip, shear, width shift, and height shift are used on the dataset.

The dataset is split into three parts, i.e., train, test, and validation. Splitting of the dataset is vital in building a robust model. If we do not split our data, then we can not know whether our model will correctly predict new image data or not. Test and validation datasets are used to calculate the performance of models. The division of the dataset is in the ratio of 80:20. The pre-trained model is first trained on the downloaded dataset, and the accuracy is recorded. Then the model is trained on the dataset preprocessed with any one augmentation technique. After training and testing the model on test data, the result of various models is analyzed and compared. Figure \ref{fig:workflow} shows the workflow of the proposed model. The steps involved in the proposed model are data acquisition, data preprocessing, and then training the model with pre-trained CNN based architecture and then comparison of results.

Requirements and Analysis

Cost and Features:

Using vibration and 3D reconstruction based methods have high setup and equipment cost with low accuracy but using Convolutional neural network architecture provides high accuracy at nil cost since it uses open source software. The Convolutional neural network is well suited for detecting complex features of an image. In conventional image classifiers, we obtain features like edge detection, but in Convolutional neural network, it has trainable feature extractor and classifier that extracts features like edge at the first layer, and the object is classified at the last layer.

High Level Requirements:

ID	Description	Status
01	Image Dataset	Implemented
02	Augmented Dataset	Implemented
03	CNN Model	Implemented
04	Confusion matrix	Implemented
05	Images with location in database	Future
06	Alert on mobile	Future

Low level Requirements:

ID	Description	Status
01	Pothole image Dataset	Implemented
02	Non-Pothole image Dataset	Implemented

03	Horizontal-flipped image dataset	Implemented
04	Vertical-flipped image dataset	Implemented
05	Zoom image dataset	Implemented
06	Rescale image dataset	Implemented
07	Rotation image Dataset	Implemented
08	Shear image Dataset	Implemented
09	Width-shift image dataset	Implemented
10	Height-shift image dataset	Implemented
11	VGG16 Architecture	Implemented
12	Pothole images with location on cloud	Future
13	Vehicle GPS tracking	Future
14	Pothole warning on mobile	Future

Design

System Workflow:

The pre-trained model is first trained on the downloaded dataset, and the accuracy is recorded. Then the model is trained on the dataset preprocessed with any one augmentation technique. After training and testing the model on test data, the result of various models is analyzed and compared. Figure below shows the workflow of the proposed model.

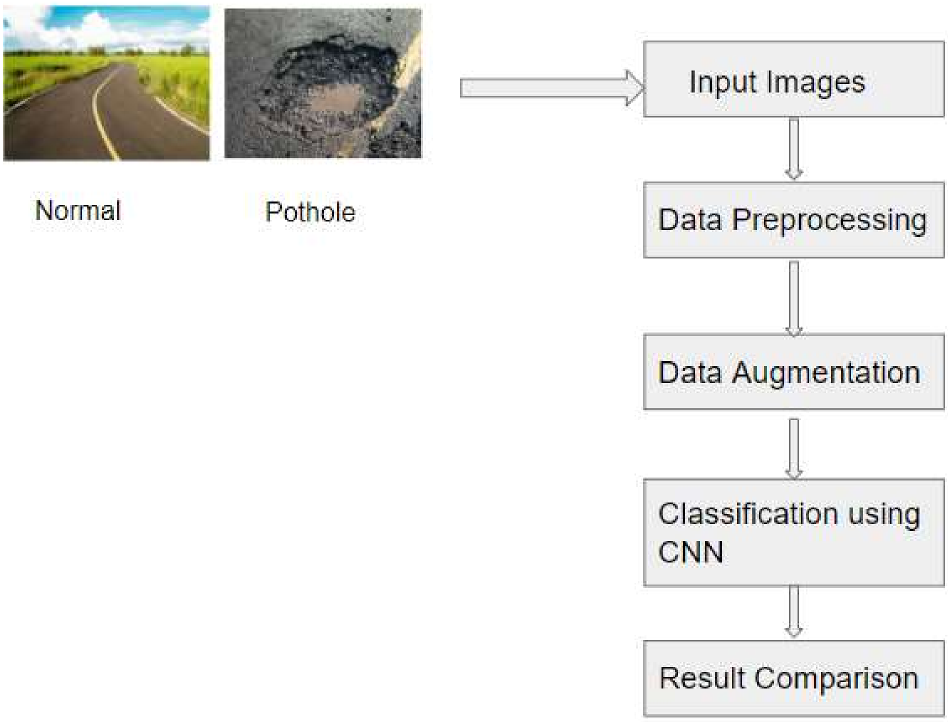
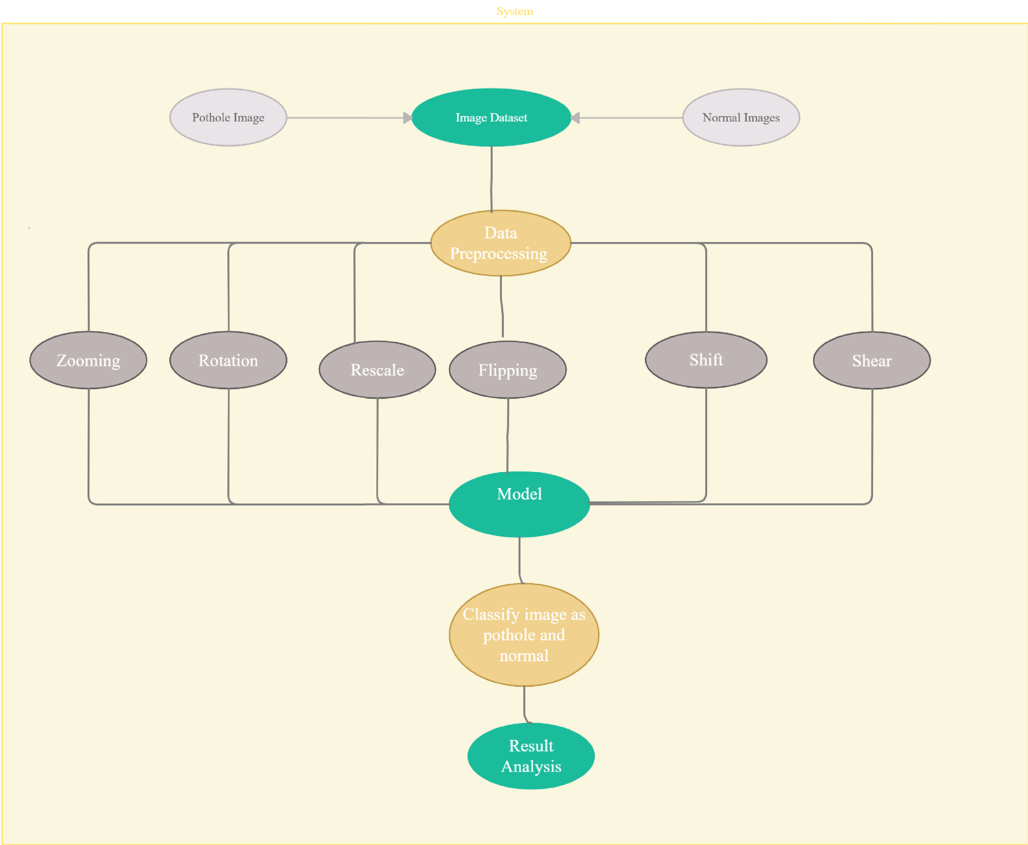


Fig: High level diagram

Firstly the dataset is collected from kaggle, and input images are in two folders, i.e., normal and pothole. The input images are then preprocessed for better training of the model and performance. After this, several data augmentation techniques like zooming, rotation, rescaling, horizontal flip, vertical flip, shear, width shift, and height shift are used on the dataset.



Behaviour Diagrams

User uploads an image and the trained model classifies the image as pothole or normal.

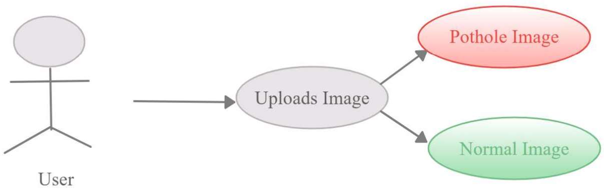


Fig: High level behaviour Diagram

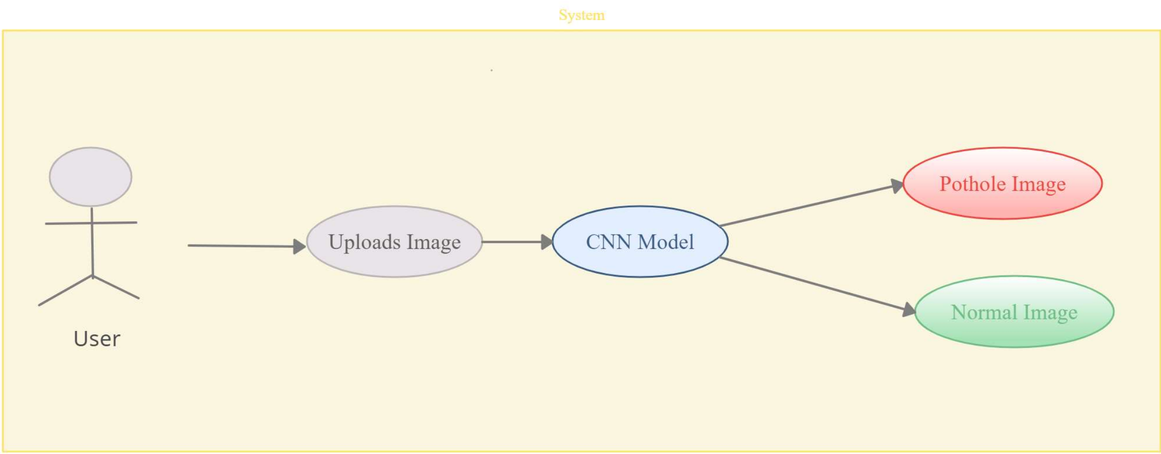


Fig: Low level behaviour diagram

System Diagrams

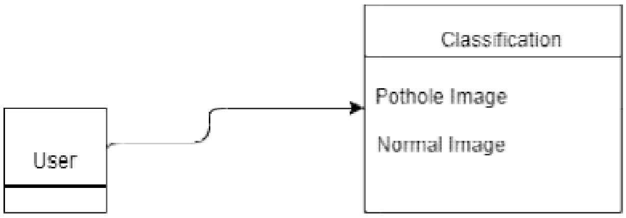


Fig: High level system diagrams

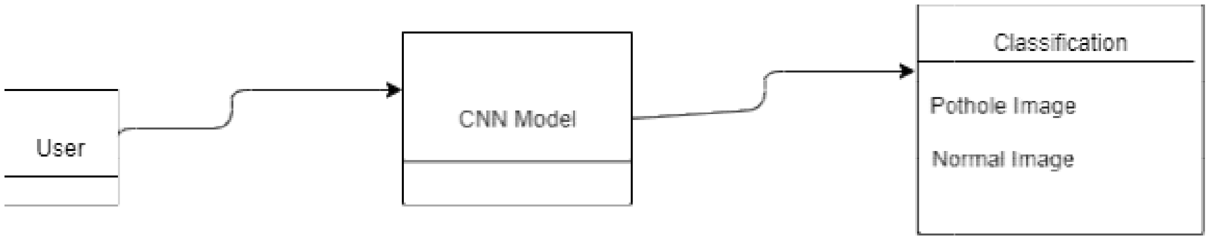


Fig: Low level system diagrams

Implementation

The applied CNN architecture in this project is VGG16 architecture, and it is a convolutional neural net architecture. VGG stands for Visual Geometry Group, and 16 means it has 16 layers. It has five blocks, and each block has a max pooling layer. VGG16 has a fixed input size which is 224×224 for its first convolutional layer. This has total of around 138 million parameters. For all the layers in this architecture, the size of filter is 3x3, and size of pooling is 2x2.

The dataset collected from kaggle, and input images are in two folders, i.e., normal and pothole. The input images are then preprocessed for better training of the model and performance. After this, several data augmentation techniques like zooming, rotation, rescaling, horizontal flip, vertical flip, shear, width shift, and height shift are used on the dataset. The dataset is split into three parts, i.e., train, test, and validation. Splitting of the dataset is vital in building a robust model. If we do not split our data, then we can not know whether our model will correctly predict new image data or not. Test and validation datasets are used to calculate the performance of models. The division of the dataset is in the ratio of 80:20.

System Testing

System testing is a type of software test performed on a fully integrated system to assess the system's compliance with respective requirements. In system tests, components that pass the integration test are taken as input. The objective of integration tests is to detect any anomaly between the units being integrated. System tests detect faults both in the integrated unit and in the entire system. The result of system testing is the observed behaviour of a component or system when it is tested.

Integration test

Model trained on Dataset and classifies pothole or normal images - Requirement based test – Passing

Unit Test

- Data pre-processing - Requirement based test - Passing
- Dataset by performing various data augmentation techniques - Requirement based test - Passing
- Loading various augmented dataset to train model - Requirement based test - Passing
- Is Model Trained - Requirement based test - Passing
- Classifying pothole and non-pothole images - Requirement based test - Passing

Experimental Results and Discussions

This section studies the effect of various image transformations, and we took a single convolutional neural network and tested the effects of augmented datasets of different sizes on it. The dataset used in this project is in two folders i.e., normal and potholes. As VGG16 has a fixed input size thus for this model the image size is 224x224. Then the data is divided into train, test and validation. the ratio of train and validation dataset is 80:20.

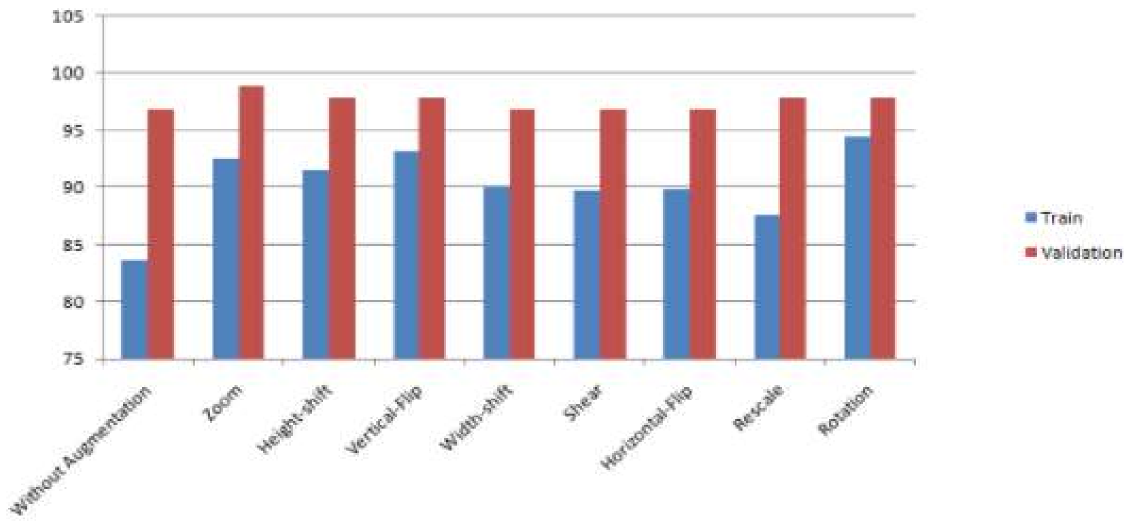


Fig: Comparison of Train and Validation Accuracy.

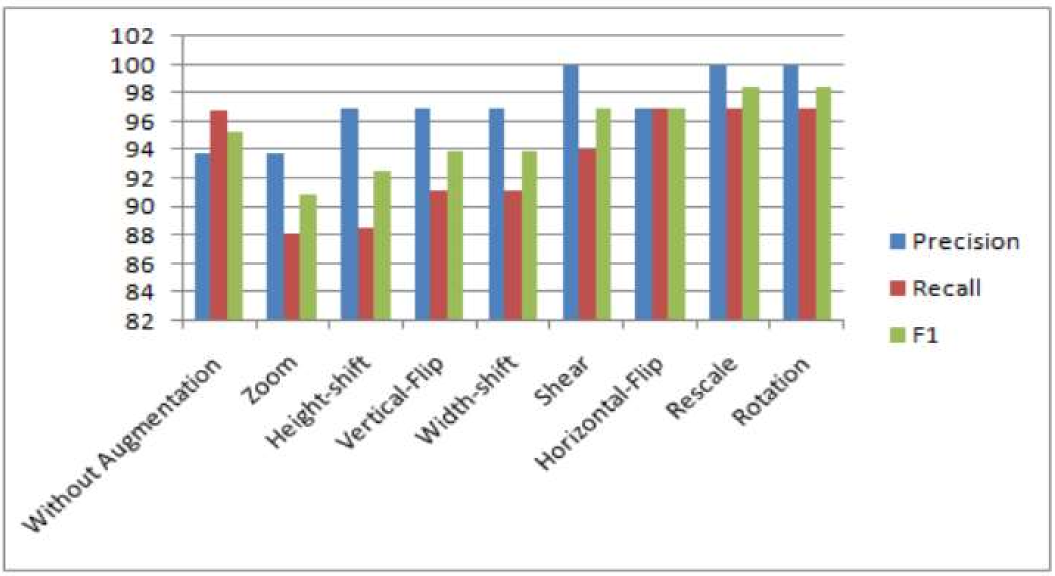


Fig: Comparison of Precision, Recall and F1 scores.

Conclusion and Future Work

In developing countries where resources are limited, using artificial intelligence methods to detect and classify potholes can help to improve road conditions. For this purpose, the proposed method based on convolutional neural networks has the potential to compete with the existing techniques of pothole classification. We took pothole detection as a case study to experiment with various data augmentation techniques on a single algorithm. As the dataset size is one central aspect of an image classification project, we have used a dataset and computed its accuracy. Then we increased our dataset with various augmentation techniques such as rotation, zoom, vertical flip, width shift, horizontal flip, shear, and height shift and then evaluated its train, validation, and test accuracy. Data augmentation techniques have higher accuracy than the model using normal dataset.

The future work can be collecting pothole images with location and storing it in cloud database and with the help of mobile application and GPS tracking of vehicle, driver can get warning or alert on mobile for potholes.

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