REAL-TIME POTHOLE DETECTION USING DEEPLEARNING

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Abstract— As we all know how potholes play a role in causing most of the minor and some major accidents across the globe, having potholes on the roads are very dangerous in any climate. Since it can cause a very serious damage to vehicle's and even the drivers which can make the vehicle fall apart and causing serious injuries. So, here is a Pothole detection project which allows us to solve the problem of avoiding potholes where the model which we have generated using transfer learning i.e., Resnet50 is used to detect whether there are any Potholes or not on the roads, this Pothole Detection model can be integrated with autopilot vehicle modes which allows the vehicle to avoid potholes. We evaluate our model on a publicly available pothole dataset and compare its performance with other state-of-the-art pothole detection models. The results show that our model achieves high accuracy and outperforms other models in terms of both precision and recall. In conclusion, our proposed pothole detection model based on transfer learning is effective and efficient for detecting potholes in road images. This model can be used as a tool for road maintenance and safety and can potentially be extended to other object detection tasks as well.

Keywords: Potholes, Resnet50, CNN, Deep Learning

I. INTRODUCTION

Pothole detection refers to the process of identifying and locating potholes on roads, using various technologies and methods. Potholes are depressions or holes that develop on the surface of roads due to various factors such as wear and tear, extreme weather conditions, heavy traffic, and poor road maintenance. These potholes can cause serious accidents and damage to vehicles, making their detection and repair an important aspect of road safety and maintenance.

inspecting the road surface and identifying potholes through physical observation. This method is time-consuming and can be prone to errors due to the subjective nature of human perception Automated pothole detection systems use various sensors and technologies such as cameras, laser scanners, and accelerometers to detect potholes on roads. These sensors capture data about the road surface, such as its texture, roughness, and height variations, and analyze this data using computer algorithms to identify potholes. Machine learning algorithms are often used to analyze the data and detect patterns that indicate the presence of potholes. Pothole detection systems have several advantages over manual inspections, including higher accuracy, faster detection, and the ability to cover a larger area in a shorter amount of time. These systems can also be integrated with road maintenance systems, allowing for timely repairs and improved road safety. In summary, pothole detection is an important aspect of road maintenance and safety. Automated pothole detection systems using sensors and computer algorithms are becoming increasingly popular due to their accuracy and efficiency in identifying and

locating potholes on roads. Potholes are a significant problem for road users worldwide, causing damage to vehicles, reducing safety, and increasing the cost of maintenance. Detecting potholes early can help prevent accidents and save on costly repairs. However, manual inspections are time-consuming and costly. To address this issue, machine learning has been applied to detect potholes automatically. Transform learning is a subset of machine learning that allows models to leverage pre-trained models' knowledge to perform specific tasks without requiring extensive training data. In the context of pothole detection, transform learning can be used to develop models that accurately identify and classify potholes based on existing data

Link of github source code: https://github.com/manishankar321/project

II. MOTIVATION

Potholes on roads pose a great danger to lives and this is why it is an important issue to be addressed. Since the root cause of pothole formation is water logging and due to the presence of water in cracks and crevices, the temperature of potholes is normally expected to be less than the surrounding road. Thus, it is easy to differentiate between pothole and non-pothole using the thermal imaging technique. Also, normal vision cameras can miss potholes at night but since thermal cameras detect heat and not light, this disadvantage is overcome. There are many other advantages of using thermal cameras such as:

- High response time as compared to vibration-based sensors. There is no need to pass through a pothole to sense the presence of the pothole.
- Less energy consumption – These can be charged using the car battery.
- Cheaper than the existing night-time detection techniques like laser-based techniques.
- Not affected by visual occlusions and lighting conditions, thus, they can be used during day as well as night.
- Image processing techniques used in vision-based cameras can be used for thermal imaging too.

Deep learning is a subfield of machine learning that is inspired by the structure and function of the human brain, particularly the neural networks that allow the brain to learn and process information. It involves training artificial neural networks to perform tasks such as image recognition, natural language processing, and speech recognition. Deep learning models are trained using large amounts of data, and they can learn to recognize patterns and make predictions based on that data. Deep learning models typically have multiple layers of neurons, which allow the to learn more complex representations of the input da These layers are typically organized in a hierarchic manner, with lower layers learning basic features a higher layers learning more abstract representations.

The training process involves adjusting the weights of the neurons in the network so that the network produces the desired output for a given input. Deep learning has been applied to a wide range of fields, including computer vision, speech recognition, natural language processing, and robotics. It has led to significant advances in areas such as image and speech recognition and has also enabled the development of self-driving cars and other automated systems. However deep learning can also computationally expensive to train and require large amount of data.

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III. MAIN CONTRIBUTIONS AND OBJECTIVES

1. Development of a deep learning model specifically tailored for pothole detection, leveraging convolutional neural networks (CNNs) and optimization techniques.
2. Implementation of the trained model on a real-time platform, enabling efficient detection of potholes from images or video streams.
3. Integration of the pothole detection system with existing navigation systems or smartphone applications, providing real-time alerts to drivers about upcoming potholes.
4. Extensive testing and evaluation of the system's accuracy, robustness, and real-time performance under various conditions.
5. Iterative improvement of the system based on user feedback, prioritizing usability and effectiveness in real-world scenarios.
6. Pretrained models in deep learning have become a widely used technique for transfer learning.
7. They allow for the reuse of previously trained models for a new task, reducing the need for large amounts of data and computational resources.

IV. RELATED WORK

Pretrained models in deep learning have become a widely used technique for transfer learning. They allow for the reuse of previously trained models for a new task, reducing the need for large amounts of data and computational resources. In this report, we will discuss pretrained models in deep learning, including their benefits, popular models, and applications.

A neural network is structured like the human brain and consists of artificial neurons, also known as nodes. These nodes are stacked next to each other in three layers:

- The input layer
- The hidden layer(s)
- The output layer.

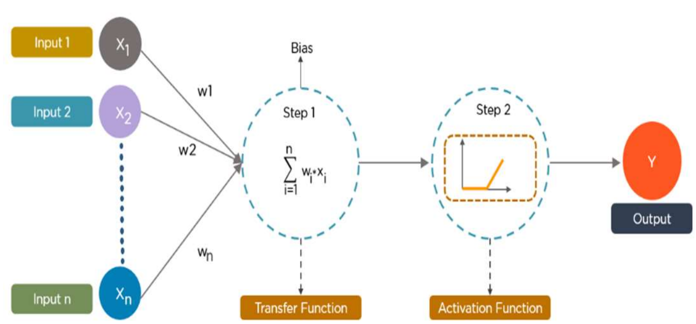


Fig.1 Structure of Neural Networks

Types of Algorithms used in Deep Learning

Here is the list of top 06 most popular deep learning algorithms:

1. Convolutional Neural Networks (CNNs)
2. Long Short Term Memory Networks (LSTMs)
3. Recurrent Neural Networks (RNNs)
4. Generative Adversarial Networks (GANs)
5. Radial Basis Function Networks (RBFNs)
6. Multilayer Perceptrons (MLPs)

In the past few decades, Deep Learning has proved to be a very powerful tool because of its ability to handle large amounts of data. The interest to use hidden layers has surpassed traditional techniques, especially in pattern recognition. One of the most popular deep neural networks is Convolutional Neural Networks in deep learning.

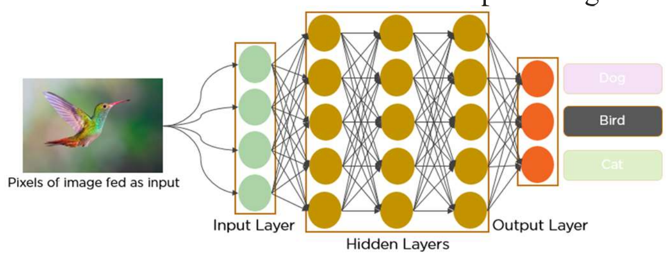


Fig.2 Example for classification of image

Since the 1950s, the early days of AI, researchers have struggled to make a system that can understand visual data. In the following years, this field came to be known as Computer Vision. In 2012, computer vision took a quantum leap when a group of researchers from the University of Toronto developed an AI model that surpassed the best image recognition algorithms and that too by a large margin.

The AI system, which became known as AlexNet (named after its main creator, Alex Krizhevsky), won the 2012 ImageNet computer vision contest with an amazing 85 percent accuracy. The runner-up scored a modest 74 percent on the test. At the heart of AlexNet was Convolutional Neural Networks a special type of neural network that roughly imitates human vision. Over the years CNNs have become a very important part of many Computer Vision applications.

Background of CNNs

CNNs were first developed and used around the 1980s. The most that a CNN could do at that time was recognize handwritten digits. It was mostly used in the postal sectors to read zip codes, pin codes, etc. The important thing to remember about any deep learning model is that it requires a large amount of data to train and also it requires a large amount of data to train and also requires a lot of computing resources This was a major drawback for CNNs at that period and hence CNNs were only limited to the postal sectors and it failed to enter the world of machine learning.

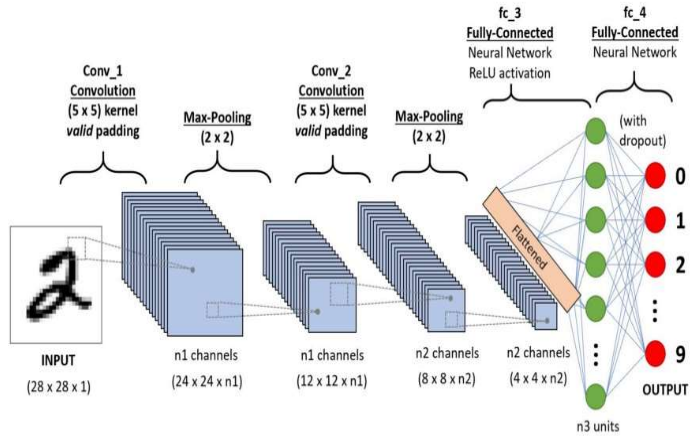
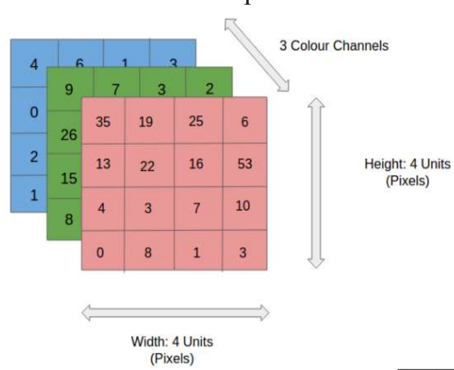
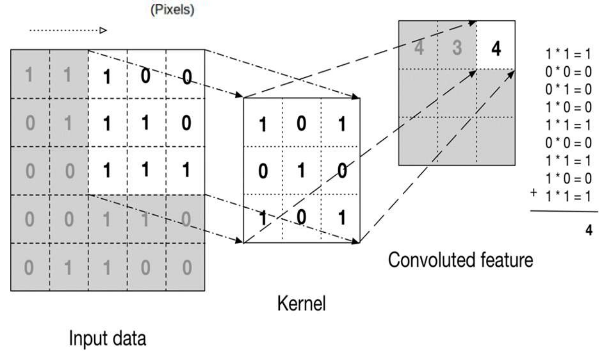


Fig.3 Background of CNN

Before we go to the working of CNN's let's cover the basics such as what is an image and how is it represented. An RGB image is nothing but a matrix of pixel values having three planes whereas a grayscale image is the same but it has a single plane. Take a look at this image to understand more For simplicity, let's stick with grayscale images as we try to understand how CNNs work. The above image shows what a convolution is. We take a filter/kernel(3×3 matrix) and apply it to the input image to get the convolved feature. This convolved feature is passed on to the next layer.





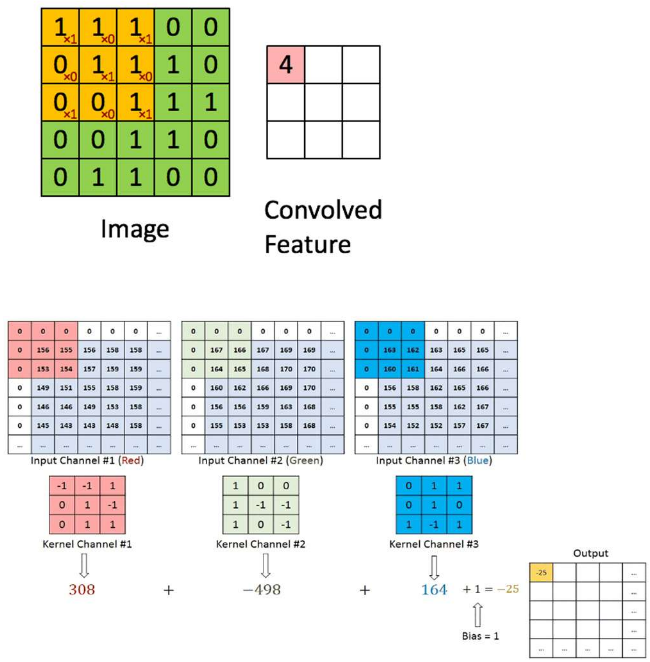


Fig.4 Process of convolution

V. PROPOSED FRAMEWORK

The proposed system for pothole detection using ResNet50 transfer learning is a valid and effective approach to pothole detection. The use of transfer learning can significantly reduce the time and resources required to train a model for pothole detection, and ResNet50 is a well-known architecture that has been proven to be effective in computer vision tasks.

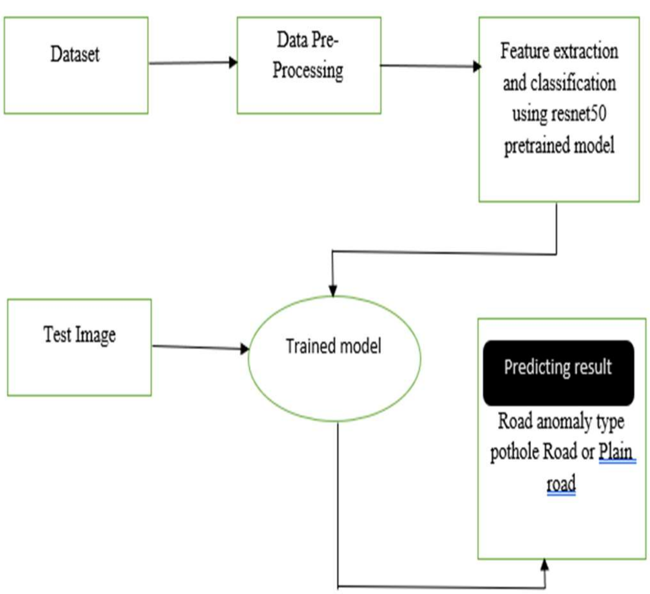


Fig.5 Working of the system

System involves using a pre-trained model on a large dataset to identify potholes in images or videos. The process involves several steps:

Dataset collection: Collect a dataset of images or videos of roads and pavements with and without potholes. The dataset should include a significant number of images with potholes to train the model accurately.

Pre-processing: The images should be pre-processed to make them compatible with the pre-trained model. This may involve resizing, normalization, or any other necessary adjustments.

Fine-tuning: The pre-trained model is then fine-tuned on the pothole dataset to recognize potholes accurately. Fine-tuning involves retraining the model's last few layers on the new dataset to recognize potholes.

Model evaluation: The trained model is then evaluated using a test dataset that contains images with and without potholes. This step is crucial to ensure that the model can accurately detect potholes in a real-world scenario.

Choosing a pre-trained model: When choosing a pre-trained model, it is essential to select a model that is trained on a similar domain. For example, a pre-trained model trained on road scenes or outdoor images can be useful for pothole detection.

Data augmentation: Data augmentation techniques can be used to increase the size of the dataset and improve the model's ability to generalize to new data. Techniques such as rotation, flipping, and changing brightness can be used to create new images from the existing dataset.

Hyperparameter tuning: The performance of the model can be further improved by fine-tuning the hyperparameters such as the learning rate, batch size, and number of epochs. Hyperparameter tuning involves testing different combinations of hyperparameters and selecting the optimal values based on the performance on a validation dataset.

Handling class imbalance: Since potholes are relatively rare, there may be a class imbalance problem in the dataset. This can be addressed by using techniques such as oversampling the minority class, under sampling the majority class, or using techniques such as SMOTE to generate synthetic samples.

Real-time detection: For real-time pothole detection, the model can be integrated with cameras or drones to detect potholes as they occur. This can help to alert authorities or road maintenance teams quickly and prevent accidents or damage to vehicles.

System Architecture

The ResNet50 architecture is a variant of the Res-Net (Residual Network) architecture, which is a deep convolutional neural network (CNN) architecture designed for image classification tasks. ResNet50 is a pre-trained model that has been trained on the ImageNet dataset and can be used for transfer learning in various computer vision tasks. The ResNet50 architecture consists of 50 layers, including convolutional layers, batch normalization layers, activation functions, and fully connected layers. Here is a brief overview of the ResNet50 architecture:

Input Layer: The input layer takes the input image and preprocesses it to make it compatible with the ResNet50 architecture.

Convolutional Layers: The convolutional layers perform convolution operations on the input image to extract features such as edges, shapes, and textures.

Batch Normalization Layers: The batch normalization layers normalize the output of the convolutional layers to improve the training process and prevent overfitting.

Activation Functions: The activation functions introduce non-linearity to the model, allowing it to learn complex relationships between features.

Residual Blocks: The ResNet50 architecture uses residual blocks, which allow the network to learn from the residual (or error) of the previous layer. This allows the model to learn deeper representations and reduces the vanishing gradient problem.

Fully Connected Layers: The fully connected layers take the output of the convolutional layers and produce a probability distribution over the different classes in the classification task.

Output Layer: The output layer produces the final classification output, indicating the class of the input image.

Overall, the ResNet50 architecture is a deep neural network that is capable of learning complex features from images and can be used for various computer vision tasks, including object detection, image segmentation, and pothole detection.

VI. DATA DESCRIPTION

Deep learning relies heavily on large datasets for training and testing of the models. Here are some commonly used datasets in deep learning: **ImageNet**: It is a large-scale image database with over 14 million images belonging to 1,000 classes It is commonly used for object recognition and image classification tasks.

ImageNet is a large-scale dataset of labeled images, commonly used for object detection and image classification tasks in deep learning. The dataset contains over 14 million images belonging to 1,000 classes, with each image labeled with a class from one of the categories.

The dataset was introduced in 2009 and has since become one of the most widely used datasets in deep learning research. It is commonly used to pretrain deep neural networks, such as the popular ImageNet models like VGG, Res-Net, and Inception. The dataset is organized into a training set and a validation set. The training set contains 1.2 million images, and the validation set contains 50,000 images, with each image labeled with a class from one of the 1,000 categories.

ImageNet has played a significant role in advancing the state-of-the-art in computer vision, and many research papers have been published using the dataset. The annual ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is a popular competition that evaluates the performance of different computer vision models on the dataset. While ImageNet has been a critical dataset for advancing computer vision research, some concerns have been raised about the ethics of using large datasets without sufficient consideration for data privacy and bias.

ImageNet was created by Fei-Fei Li and her team at Stanford University in 2009. The project was aimed at improving computer vision algorithms by providing a large-scale dataset of labeled images. The dataset consists of images from various sources, including Google Images and Flickr. The images were manually labeled with one of the 1,000 categories by crowd workers.

The categories in ImageNet range from animals and plants to objects and scenes. Each category has a varying number of images, with some categories having thousands of images and others having just a few. Image-Net has been used as a benchmark dataset for evaluating the performance of deep learning models in object recognition and image classification tasks. The models are trained on the training set of ImageNet and tested on the validation set.

The introduction of the ImageNet dataset led to a significant improvement in the accuracy of object recognition models. The accuracy of the best models in the annual ImageNet Large Scale Visual Recognition Challenge (ILSVRC) increased from 70.5% in 2012 to 85.4% in 2017 the image-net led to significant accuracy while ImageNet has been a useful tool for advancing computer vision research, some researchers have criticized the dataset for its lack of some researchers have criticized the dataset for its lack of diversity and potential biases. Some categories in ImageNet, such as "maillot" and "tobacco shop," have been criticized for their cultural and gender biases. In 2020, the creators of ImageNet announced that they would be retiring the dataset and encouraging researchers to use other datasets that are more diverse and inclusive. Data Used in this project is collected from Kaggle website created by author Viren. EXTC Engineer at DJSCE.

Some of the images from dataset are shown below:

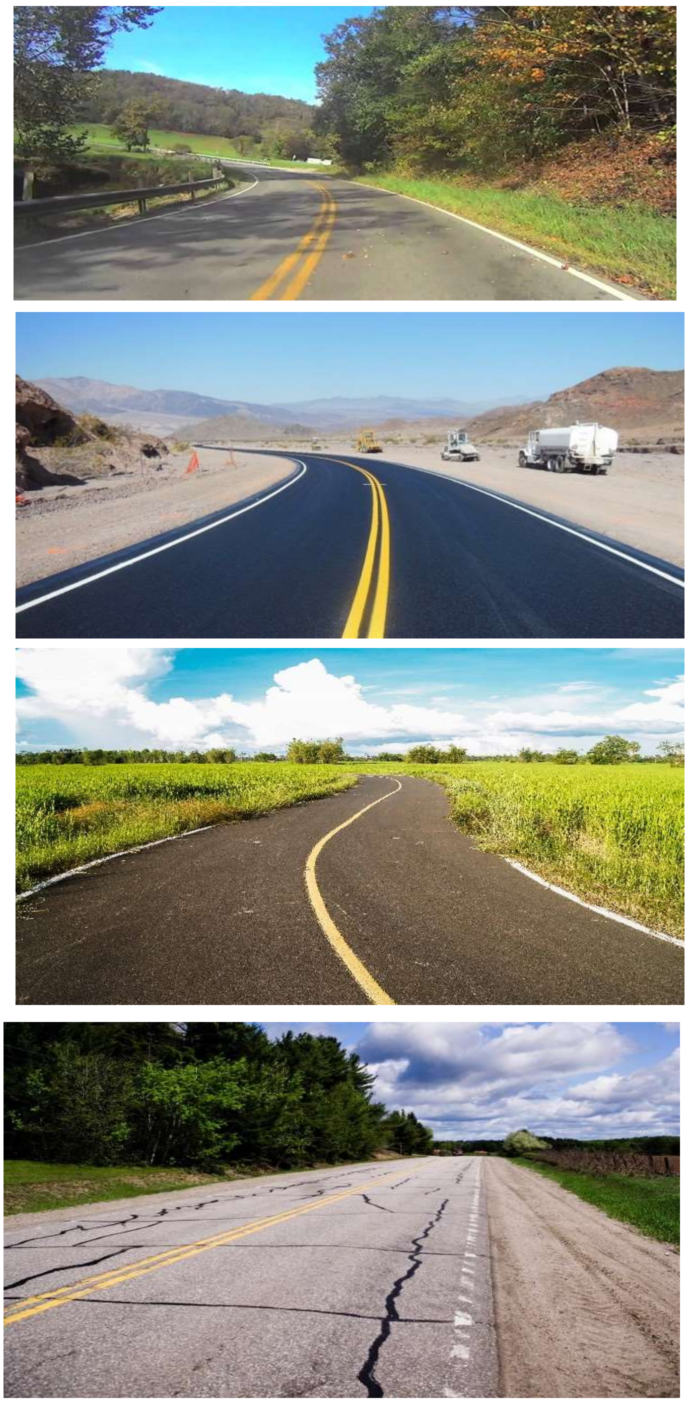


Fig.7 Image of plain roads from dataset

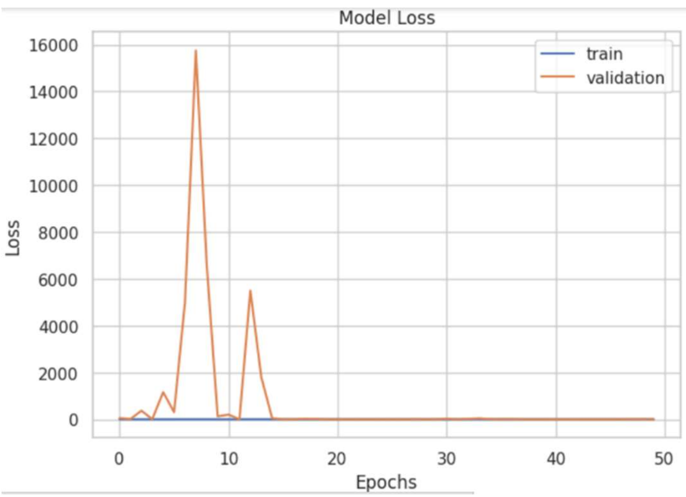
Fig.8 Image of pothole roads from dataset

VII. RESULT

Steps involved in getting results for the model which we have done is shown below :

In the first step we have to import all the required libraries for the model which we are going to do then followed by, selection of the dataset. The dataset which have selected have to divide it into two parts Testing and training. Then Display all the training data with labels.Next step is to Split the data into training and Validation data

The next step is to Build the CNN model Using Resnet (Pretrained model). In this building the CNN model,we have to save the model which is trained. Model Training purpose We have Given 50 epochs. For that record or Plot the Model Accuracy, Model Loss as shown in the Figure below.



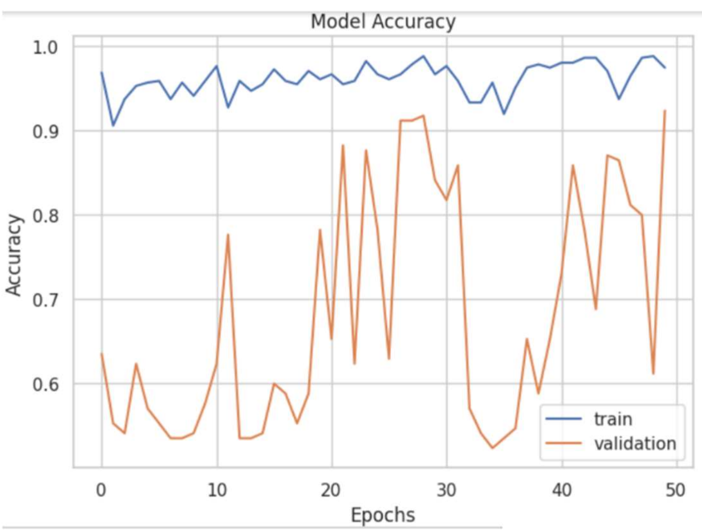
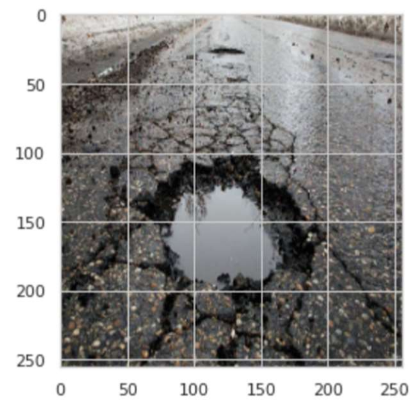
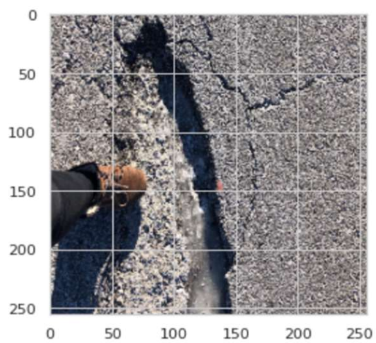


Fig 9 Graph of Model loss And accuracy.

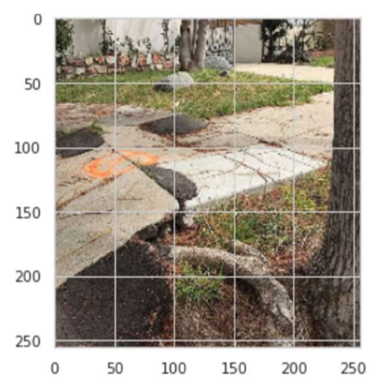
To get the model loss we have to plot the graph Epochs vs Loss similarly For the accuracy We have to plot Epochs vs Accuracy. The next step is to testing the trained model, here we have to test both type of images as potholes and normal road images. First we have tested pothioles images to the trained model we have given Six images as input these six images shown output as pothole road as shown below in the figure.



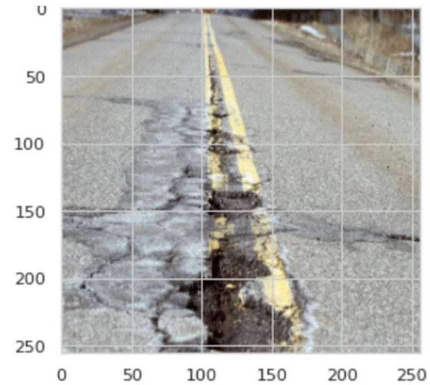
```
1/1 [==============================] - 1s 1s/step
 17%|██         | 1/6 [00:02<00:12,  2.43s/it]Pothole Road
```



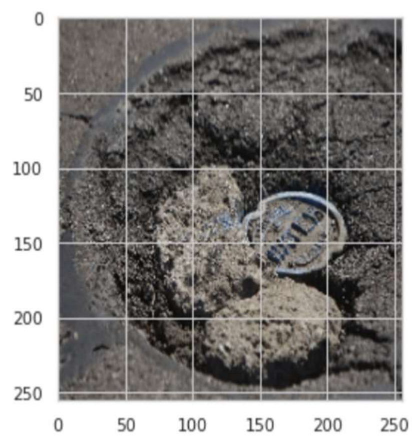
```
1/1 [==============================] - 0s 36ms/step
 33%|███        | 2/6 [00:03<00:07,  1.91s/it]Pothole Road
```



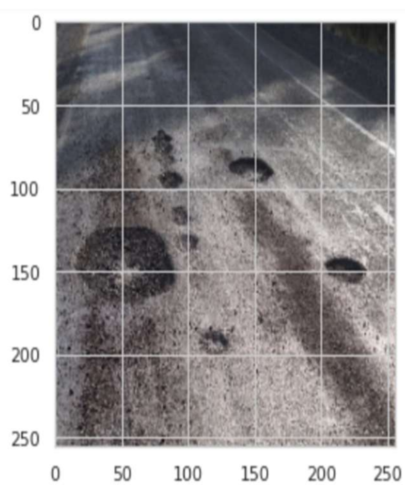
```
1/1 [==============================] - 0s 27ms/step
 50%|█████      | 3/6 [00:04<00:04,  1.46s/it]Pothole Road
```




```
1/1 [==============================] - 0s 26ms/step
 67%|██████    | 4/6 [00:05<00:02,  1.24s/it]Pothole Road
```



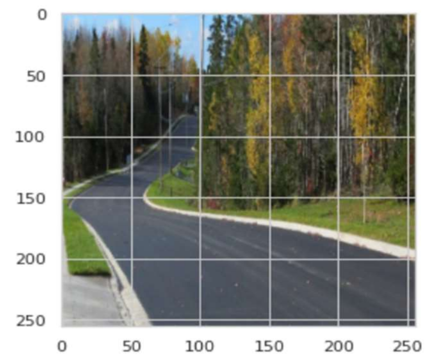

```
1/1 [==============================] - 0s 27ms/step
 83%|████████  | 5/6 [00:07<00:01,  1.34s/it]Pothole Road
```




```
1/1 [==============================] - 0s 25ms/step
100%|██████████| 6/6 [00:08<00:00,  1.40s/it]Pothole Road
```

Fig 10 Images of Pothole Roads from result.

After testing the Pothole Images Then we have to Test the Normal Road images for testing the normal road images Again we have given six different Types of images of different background. After testing these images We have to save the total model and load the model and evaluate the overall accuracy. We got overall accuracy as 92.6% for the Resnet model we have built.




```
1/1 [==============================] - 0s 28ms/step
 17%|█▋        | 1/6 [00:00<00:04,  1.06it/s]Plain Road
```


```
1/1 [==============================] - 0s 58ms/step
 33%|███▎      | 2/6 [00:02<00:04,  1.21s/it]Plain Road
```

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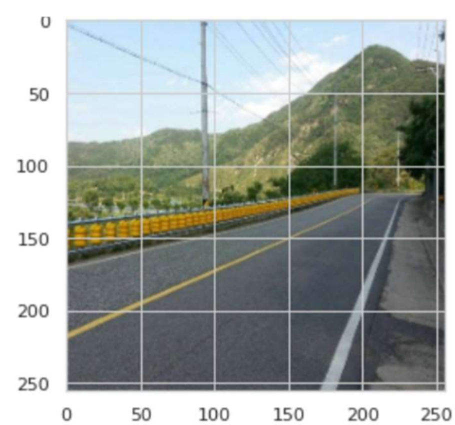


```
1/1 [==============================] - 0s 88ms/step
 50%|█████     | 3/6 [00:04<00:04,  1.56s/it]Plain Road
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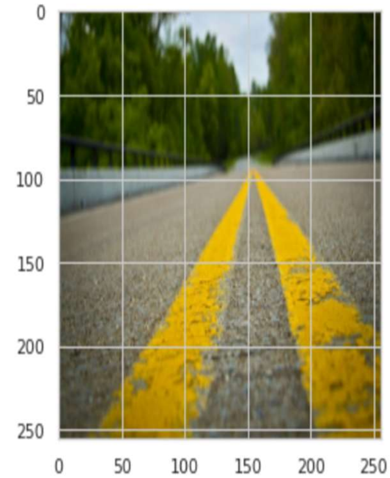
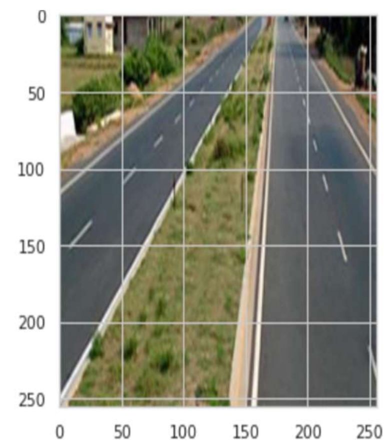
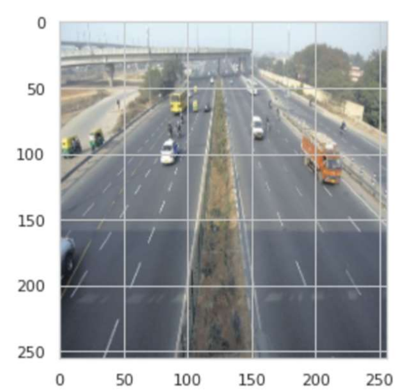


```
1/1 [==============================] - 0s 45ms/step
67%|██████▋   | 4/6 [00:05<00:02,  1.37s/it]Plain Road
```



```
1/1 [==============================] - 0s 44ms/step
83%|████████▎ | 5/6 [00:06<00:01,  1.28s/it]Plain Road
```



```
1/1 [==============================] - 0s 62ms/step
100%|██████████| 6/6 [00:07<00:00,  1.27s/it]Plain Road
```

Fig.11 Images of normal Road from results

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