M.KUMARASAMY
COLLEGE OF ENGINEERING
NAAC Accredited Autonomous Institution
Approved by AICTE & Affiliated to Anna University
ISO 9001:2015 & ISO 14001:2015 Certified Institution
Thalavapalayam, Karur – 639 113.

A Minor Project Report

On

ROAD IRREGULARITIES DETECTION

Submitted in partial fulfilment of requirements for the award of the degree

of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

Under the guidance of

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

M.KUMARASAMY COLLEGE OF ENGINEERING

(Autonomous)

KARUR – 639 113

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(Autonomous Institution affiliated to Anna University, Chennai)

KARUR – 639113

BONAFIDE CERTIFICATE

Certified that this minor project report **"ROAD IRREGULARITIES DETECTION"** is the bonafide work of **"NAVEENA M (20BCS4068), SHARMI K (20BCS4085), SRINITHI B (20BCS4089), YOGI N (20BCS4107)"** who carried out the project work during the academic year 2022-2023 under my supervision.

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

VISION OF THE INSTITUTION

To emerge as a leader among the top institutions in the field of technical education

MISSION OF THE INSTITUTION

- Produce smart technocrats with empirical knowledge who can surmount the global challenges.
- Create a diverse, fully-engaged, learner-centric campus environment to provide quality education to the students.
- Maintain mutually beneficial partnerships with our alumni, industry, and Professional associations

VISION OF THE DEPARTMENT

To achieve education and research excellence in Computer Science and Engineering.

MISSION OF THE DEPARTMENT

- To excel in academic through effective teaching learning techniques
- To promote research in the area of computer science and engineering with the focus on innovation
- To transform students into technically competent professionals with societal and ethical responsibilities

PROGRAM EDUCATIONAL OBJECTIVES (PEOs)

PEO 1: Graduates will have successful career in software industries and R&D divisions through continuous learning.

PEO 2: Graduates will provide effective solutions for real world problems in the key domain of computer science and engineering and engage in lifelong learning.

PEO 3: Graduates will excel in their profession by being ethically and socially responsible.

PROGRAM OUTCOMES (POs)

Engineering students will be able to:

1. **Engineering knowledge:** Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
2. **Problem analysis:** Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.
3. **Design/development of solutions:** Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
4. **Conduct investigations of complex problems:** Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data,and synthesis of the information to provide valid conclusions.
5. **Modern tool usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.
6. **The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.
7. **Environment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.
8. **Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
9. **Individual and team work:** Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.
10. **Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

11. **Project management and finance:** Demonstrate knowledge and understanding of the engineering and management principles and apply these to one’s own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.
12. **Life-long learning:** Recognize the need for, and have the preparation and ability to engaging independent and life-long learning in the broadest context of technological change.

PROGRAM SPECIFIC OUTCOMES (PSOs)

- **PSO1: Professional Skills:** Ability to apply the knowledge of computing techniques to design and develop computerized solutions for the problems.
- **PSO2: Successful career:** Ability to utilize the computing skills and ethical values in creating a successful career.

ABSTRACT

Poor road conditions are one of the major causes for road accidents. Developing countries in particular are witnessing increased accident rates due to these poor road conditions. Potholes, deep ridges, missing pitches, improper speed breakers, poorly constructed manhole covers and slabs all combine to greatly increase the probability of serious accidents thus transforming roads into obstacle courses. Road defects, such as potholes and cracks, are becoming an increasingly significant problem for roads around the world. They present a hazard for all road users, causing considerable vehicle damage. Road surface monitoring and maintenance are essential for driving comfort, transport safety and preserving infrastructure integrity. Traditional road condition monitoring is regularly conducted by specially designed instrumented vehicles, which requires time and money and is only able to cover a limited proportion of the road network. In light of the ubiquitous use of smartphones, this project proposes an automatic pothole detection system utilizing the built-in vibration sensors and global positioning system receivers in smartphones. We collected road condition data in a city using dedicated vehicles and smartphones. A series of processing methods were applied to the collected data, and features from different frequency domains were extracted. In this project we propose a method where we use the Tensorflow pre-trained model and CNN algorithm (Convolution Neural Network) to detect the potholes, deep ridges and speed breakers. Our experimental results demonstrate high accuracy although there are many obstacles on the road.

ABSTRACT WITH POs AND PSOs MAPPING

ABSTRACT	POs MAPPED	PSOs MAPPED
Poor road conditions are one of the major causes for road accidents. Developing countries in particular are witnessing increased accident rates due to these poor road conditions. Potholes, deep ridges, missing pitches, improper speed breakers, poorly constructed manhole covers and slabs all combine to greatly increase the probability of serious accidents thus transforming roads into obstacle courses. Road defects, such as potholes and cracks, are becoming an increasingly significant problem for roads around the world. They present a hazard for all road users, causing considerable vehicle damage.	**PO1(1)** **PO2(2)** **PO3(3)** **PO4(2)** **PO5(2)** **PO6(1)** **PO7(3)** **PO8(2)** **PO9(3)** **PO10(3)** **PO11(2)** **PO12(2)**	**PSO1(3)** **PSO2(2)**

Note: 1- Low, 2-Medium, 3- High

SUPERVISOR **HEAD OF TH DEPARTMENT**

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CHAPTER 1

INTRODUCTION

Potholes, deep ridges, missing pitches, improper speed breakers, poorly constructed manhole covers and slabs all combine to greatly increase the probability of serious accidents thus transforming roads into obstacle courses. Road defects, such as potholes and cracks, are becoming an increasingly significant problem for roads around the world. They present a hazard for all road users, causing considerable vehicle damage. Road surface monitoring and maintenance are essential for driving comfort, transport safety and preserving infrastructure integrity.

Figure 1.1 : Road Irregularities

1.1 OVERVIEW

The goal of this project is to create a CNN-based system capable of detecting and classifying various forms of road imperfections using pictures recorded by cameras placed on cars or drones. The system will educate a CNN model to detect and discriminate between several forms of road imperfections, including such cracks, potholes, even speed bumps, using annotated visual data. The project will be divided into multiple parts, including data gathering and preprocessing, model construction and training, and performance evaluation of the trained model.

During the data collecting phase, photos of various sorts of road imperfections will be captured from various places and under varied lighting situations. The data will be preprocessed to eliminate noise and improve picture quality before being used to train the CNN model. During the model creation and training phase, a CNN architecture suited for the road abnormality detection job will be designed and implemented. This system will be trained utilizing annotated picture data, with each image tagged based on the kind of road irregularity observed. The learning algorithm will next be tested against a different set of test pictures to determine its accuracy of the system.

1.2 DOMAIN INTRODUCTION

DEEP LEARNING

Deep learning has aided image classification, language translation, speech recognition. It can be used to solve any pattern recognition problem and without human intervention. Deep learning models are capable enough to focus on the accurate features themselves by requiring a little guidance from the programmer and are very helpful in solving out the problem of dimensionality. Deep learning algorithms are used, especially when we have a huge no of inputs and outputs.

HOW DEEP LEARNING WORKS?

Neural Networks are layers of nodes, much like the human brain is made up of neurons. Nodes within individual layers are connected to adjacent layers. The network is said to be deeper based on the number of layers it has. A single neuron in the human brain receives thousands of signals from other neurons. In an artificial neural network, signals travel between nodes and assign corresponding weights. A heavier weighted node will exert more effect on the next layer of nodes. The final layer compiles the weighted inputs to produce an output. Deep learning systems require powerful hardware because they have a large amount of data being processed and involve several complex mathematical calculations. Even with such advanced hardware, however, training a neural network can take weeks.

Deep learning systems require large amounts of data to return accurate results; accordingly, information is fed as huge data sets. When processing the data, artificial neural networks are able to classify data with the answers received from a series of binary true or false questions involving highly complex mathematical calculations. Deep learning takes this one step ahead. Deep learning automatically finds out the features which are important for classification because of deep neural networks, whereas in case of Machine Learning we had to manually define these features.

WHY DEEP LEARNING IS POPULAR?

The first advantage of deep learning over machine learning is the needlessness of the so-called feature extraction. Long before deep learning was used, traditional machine learning methods were mainly used such as Decision Trees, SVM, Naïve Bayes Classifier and Logistic Regression. These algorithms are also called flat algorithms. Flat here means that these algorithms cannot normally be applied directly to the raw data (such as .csv, images, text, etc.). We need a pre-processing step called Feature Extraction. The result of Feature Extraction is a representation of the given raw data that can now be used by these classic machine learning algorithms to perform a task. Feature Extraction is usually quite complex and requires detailed knowledge of the problem domain.

1.3 PROBLEM STATEMENT

To ensure safe and effective transportation, the condition of the roads is essential. However, due to a number of factors like weather, frequent use, loads, and old infrastructure, roads are subject to deterioration over time. These elements can lead to abnormalities like potholes, cracks, and other irregularities that can be dangerous for people walking and driving, causing major monetary losses and safety issues. Traditional road damage monitoring methods rely on qualified inspectors to manually locate and analyse damage, which is time-consuming, expensive, and subjective.

This method, which frequently only allows for the diagnosis of obvious defects like cracking, is not viable for broad road networks. Consequently, there is a need for an automated system that can quickly and accurately identify different types of road anomalies. Convolutional Neural Networks (CNN) have demonstrated promising results in a variety of image processing applications in recent years. Therefore, the goal of this project is to investigate how CNN may be used to identify and categorise road anomalies, which can aid with better road upkeep and safer mobility.

1.4 OBJECTIVE

Utilizing techniques to automatically identify and categories different sorts of road surface problems, such as cracks, potholes, bumps, and other abnormalities in the pavement, is a computer vision challenge known as "detection of road irregularities using deep learning." By detecting problems with the road surface that could cause an accident or damage to cars, the main goal of this activity is to increase road safety. Deep learning allows the system to distinguish between several sorts of imperfections and learn to adapt to changing road surface conditions. Large datasets of road photos or videos that have been annotated with data about the numerous road abnormalities shown in the photographs can be used to train deep learning algorithms. The overarching goal of employing deep learning to identify anomalies in the road network is to increase road safety, lower maintenance costs, and enhance everyone's driving experience.

CHAPTER 2

LITERATURE SURVEY

TITLE: ROAD ANOMALY DETECTION THROUGH DEEP LEARNING APPROACHES

AUTHOR NAME: DAWEI LUO

This study attempts to solve the classification problem of road anomaly detection using deep learning techniques. From a vehicle's point of view, extra road abnormalities are introduced in addition to the more common ones. The research pays particular attention to pattern representation in order to speed up the learning process and suggests three sets of numerical features for describing road conditions. Three deep learning methods are also taken into consideration to address the classification issue: Deep Feedforward Network (DFN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN). The detectors are trained and assessed using data gathered from a test car driven under various road anomaly settings, with respect to the three deep learning algorithms. Key hyper-parameters are set to a set of predetermined values in order to conduct a comparison research on the detection performances. Additionally, a comparison analysis of the abilities of each detector in relation to various pattern representations is carried out. The outcomes demonstrate the potency of the suggested methods and the effectiveness of the suggested feature representations in identifying road anomalies.

DISADVANTAGES

It can be challenging to comprehend and interpret.

TITLE: A REVIEW OF ROAD SURFACE ANOMALY DETECTION AND CLASSIFICATION SYSTEMS BASED ON VIBRATION BASED TECHNIQUES

AUTHOR NAME: ERICK AXEL MARTINEZ-RÍOS

Sources of deterioration for road surfaces include the weather, regular use, loads, and the infrastructure's age. These decay-causing factors produce anomalies that could endanger pedestrians and those using vehicles, as well as a large expense to fix the irregularities The creation of systems that automatically detect and categorise road irregularities was spurred on by these drawbacks. This article includes a narrative review that is centred on the identification and classification of anomalies in road surfaces using vibration-based methods. Threshold-based procedures, feature extraction techniques, and deep learning techniques were examined. Also discussed are datasets, signals, preprocessing procedures, and feature extraction methods. The findings of this review demonstrate that vibration-based approaches for road surface anomaly detection and classification have attained quite good performance. The limited testing circumstances, sample size, and absence of publicly accessible datasets, however, have an impact on the difficulties in reproducing and variability of the stated results. Finally, it is possible to analyse and compare the various settings of time-frequency approaches used for feature extraction and signal representation, as well as to standardise the features computed through the time or frequency domains.

DISADVANTAGES

The outcomes of the research under consideration may change due to variations in testing conditions and feature extraction methods.

TITLE: REAL-TIME MACHINE LEARNING-BASED APPROACH FOR POTHOLE DETECTION

AUTHOR NAME: OCHE ALEXANDER EGAJI

Potholes are signs of a badly maintained road and indicate a structural problem underneath. In addition to making for a bumpy ride, a vehicle's collision with a pothole can result in costly repairs to the wheels, tyres, and suspension system of the vehicle. This study compares various machine learning methods for spotting potholes. Multiple Android devices, routes, and automobiles were used to collect the data, which was then pre-processed to extract the necessary statistical features for a binary classifier's training using a 2-second non-overlapping moving window. The Training dataset underwent a stratified K-fold cross-validation, and the Validation dataset was completely separated from the Test dataset. With an accuracy of 0.8889, the Random Forest Tree and KNN performed the best on the Test dataset. When the Random Forest Tree model's hyper parameters were optimised via random search, the model's performance improved. After hyper parameter optimization, the Random Forest Tree model performed 0.9444, 1.0000, 0.8889, and 0.9412 for accuracy, precision, recall, and F-score, respectively.

DISADVANTAGES

Understanding the significance of particular features for pothole detection may be hampered by the complexity of machine learning models like Random Forest and KNN.

TITLE: A REVIEW ON NEGATIVE ROAD ANOMALY DETECTION METHODS

AUTHOR NAME : JIHAD DIB

Negative road anomalies, which we used to refer to potholes and cracks due to their negative drop from the surface of the road, have been the greatest hurdle to obstacle avoidance in the modern era. Because they come in a variety of random and stochastic shapes, this has long been a restriction. Since the latter exceed the sensor's capabilities and cause the sensing approach to be erroneous, modern technology lacks sensors that can detect negative road irregularities efficiently. The identification of negative road anomalies has been the subject of extensive investigation because it is currently a popular area of study. Detection of negative road anomalies is very important in order to facilitate road maintenance, provide a better experience in automatic driving, reduce the risk of accidents (collisions, falls etc.) for the disabled wheelchair users etc. It contributes immensely in widening the spectrum of automation of vehicles' navigation and in decreasing the different risks resulting from neglecting the presence of negative road anomalies such as the effect of the vibrations resulting by driving through negative anomalies which could pose some risks to the driver/user's health, the damage which could be done to the tires of the vehicle . The currently used methods will be reviewed in this essay. Their shortcomings will be emphasised, and they will be evaluated using certain newly presented criteria and specific performance indicators.

DISADVANTAGES:

The study only examines a small number of currently employed techniques for locating negative road anomalies, which could not cover all possible strategies.

TITLE: SMART ROAD DAMAGE DETECTION AND WARNING USINGMACHINE LEARNING

AUTHOR NAME: LOKESH THAKARE

The Road transportation networks are essential social and economic elements in all nations. But they are crumbling everywhere, often fatally, as a result of ageing, a lack of regular maintenance, or natural disasters. Poor road conditions have resulted in significant financial losses as well as safety-related worries. The World Health Organization estimates that automobile accidents result in millions of injuries each year, 300,000 of which are serious, and 1.5 percent to 3 percent of all economic losses worldwide. This stochastic irregularity in the nature of these anomalies presents a significant challenge to its detection for many reasons, such as the fact that these anomalies are available in public places throughout the year posing a challenge to many detectors which are limited by certain factors such as the environment surrounding the anomaly (light intensity, fog, rain etc.). In addition to the previous, these anomalies exist in random locations with different patterns and shapes . Car accidents frequently occur as a result of poor road conditions. Despite this, it is difficult to check the state of the roads due to the extensive road network and the bustling outside environment. Certified inspectors do the majority of the current road damage monitoring technique, which is subjective, labor-intensive, expensive, and time-consuming. Furthermore, only a small number of academics have been involved in previous research, which has mainly concentrated on diagnosing road damage (such as cracking).

DISADVANTAGES:

The methods used now to monitor road deterioration are subjective, time-consuming, expensive, and labor-intensive.

2.1 EXISTING SYSTEM

- Road irregularity detection has been tackled using Support Vector Machines (SVMs), a class of machine learning method.
- As a learning algorithm, SVMs are trained to identify patterns in the data that has been annotated with predetermined categories.
- To identify various sorts of surface characteristics, including such potholes, cracks, as well as bumps, SVMs could be trained on annotated datasets of road photos or videos.
- In order to use SVMs for the detection of road abnormalities, mounted cameras on a car or other equipment are often used to take photos or videos of a road surface.

EXISTING SYSTEM ARCHITECTURE

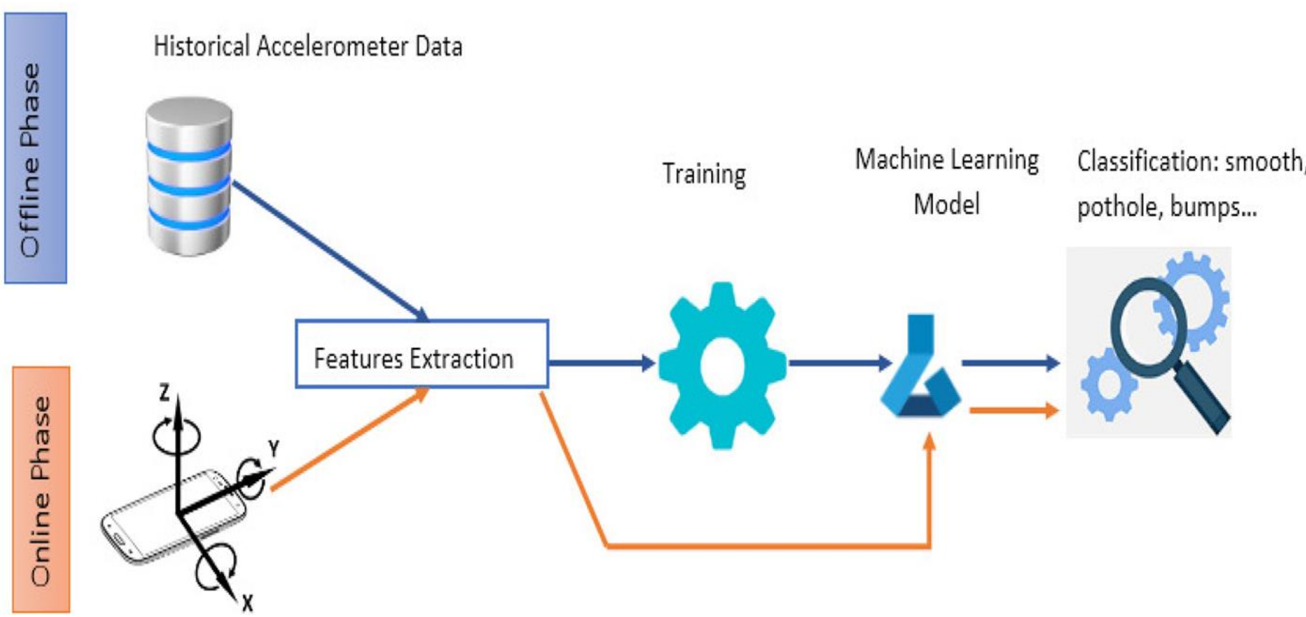

Figure 2.1 : Architecture of Existing System

DISADVANTAGES

- Computationally costly
- Sensitive to the parameters used
- Requires labelled data has trouble with noisy data
- Limited capacity to interpret

2.2 PROPOSED SYSTEM ARCHITECTURE

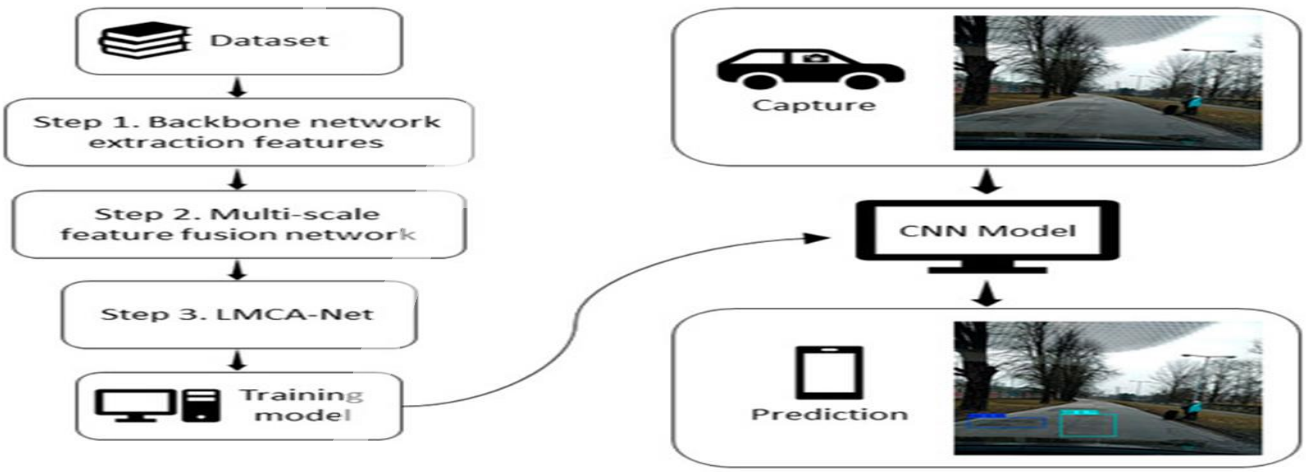

Figure 2.2 : Architecture of Proposed System

The technology is more effective and efficient than conventional machine learning techniques and can manage a variety of road surface conditions. The detection and classification of road irregularities can be automated, allowing maintenance teams to work faster and more productively while conserving time and resources and ensuring the safety of motorists and pedestrians. The suggested approach can enable more effective administration of road infrastructure, save maintenance costs, and dramatically increase road safety.

CHAPTER 3

FEASIBILITY STUDY

Depending on the results of the initial investigation the survey is now expanded to a more detailed feasibility study. "FEASIBILITY STUDY" is a test of system proposal according to its workability, impact of the organization, ability to meet needs and effective use of the resources. It focuses on these major questions:

- What are the user's demonstrable needs and how does a candidate system meet them?
- What resources are available for given candidate system?
- What are the likely impacts of the candidate system on the organization?

During feasibility analysis for this project, events and alerts are to be considered. Investigation and generating ideas about a new system does this.

TECHNICAL FEASIBILITY

A study of resource availability that may affect the ability to achieve an acceptable system. This evaluation determines whether the technology needed for the proposed system is available or not.

- Can the work for the project be done with current equipment existing software technology & available personal?
- Can the system be upgraded if developed?
- If new technology is needed then what can be developed?

ECONOMICAL FEASIBILITY

Economic justification is generally the "Bottom Line" consideration for most systems. Economic justification includes a broad range of concerns that includes cost benefit analysis. In this we weight the cost and the benefits associated with the candidate system and the project is making to the analysis and design phase. The financial and the economic questions during the preliminary investigation are verified to estimate the following:

• The cost of hardware and software for the class of application being considered.

• The benefits in the form of reduced cost.

• The proposed system will give the minute information, as a result the performance is improved which in turn may be expected to provide increased profits.

• This feasibility checks whether the system can be developed with events and alert monitoring does not require the manual work. This can be done economically if planned judicially, so it is economically feasible. The cost of project depends upon the number of man hours required.

OPERATIONAL FEASIBILITY

It is mainly related to human organizations and political aspects. The points to be considered are:

- What changes will be brought with the system?
- What organization structures are disturbed?
- What new skills will be required? Do the existing staff members have these skills? If not, can they be trained in due course of time?

The system is operationally feasible as it very easy for the End users to operate it. It only needs basic information about Windows platform.

SCHEDULE FEASIBILITY

Time evaluation is the most important consideration in the development of project. The time schedule required for the developed of this project is very important since more development time effect machine time, cost and cause delay in the development of other systems. A reliable VM monitoring system can be developed in the considerable amount of time.

LEGAL FEASIBILITY

Determines whether the proposed system conflicts with legal requirements, e.g. a data processing system must comply with the local Data Protection Acts.

CHAPTER 4

PROJECT METHODOLOGY

4.1 BLOCK DIAGRAM

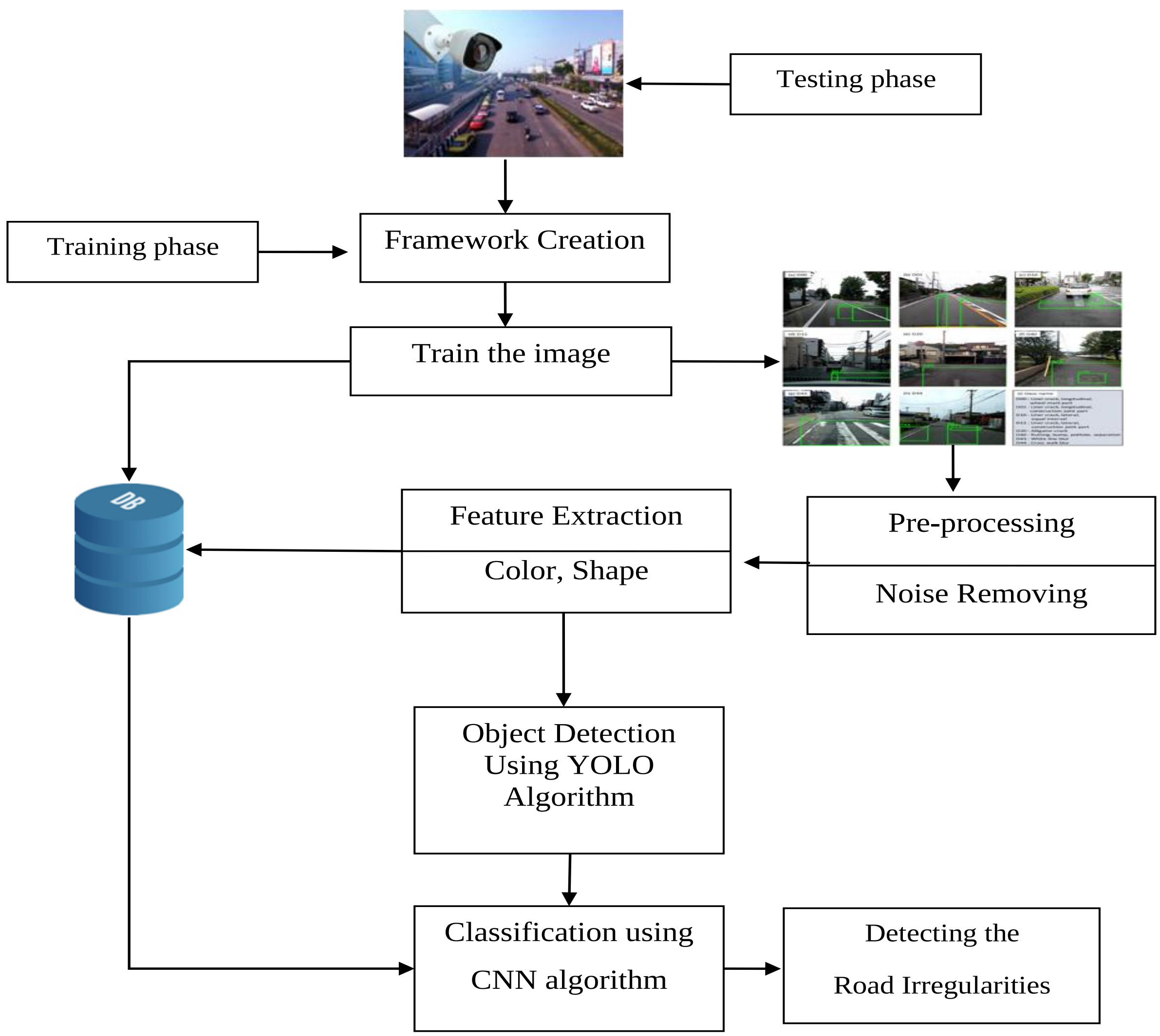

Figure 4.1 : Block Diagram of Training and Testing Phases

4.2 MODULES DESCRIPTION

- Image Acquisition
- Pre-processing
- Feature Extraction
- Classification

MODULE DESCRIPTION

Image Acquisition

Image acquisition is the process of acquiring an image, either by taking a picture of it using a camera. One of the biggest and most significant difficulties facing the government sector is the early diagnosis of road irregularities, which is essential to the security and protection of environmental spaces. Road imperfections are crucial in reducing traffic accidents. This method of detecting road irregularities eliminates the need for human protocols while assisting in the monitoring and protection of challenging-to-protect locations. Regardless of the weather or time of day, the new system is employed to enable the development of systems to allow for detailed monitoring. This module allows us to upload images that have been taken from CCTV footage. This issue has been fixed, and the recommended approach lowers the error.

Preprocessing

Removing any arbitrary variations or oscillations in the image's pixel values, this can be brought on by electrical noise, camera noise, or other sources. Different filtering methods, such median filtering, can be used to accomplish this. Changing the image's brightness and contrast will make it simpler to view the image's details. Histogram equalisation or other image enhancing methods can be used for this.

Feature Extraction

The process of turning an image's raw pixel values into a set of features that may be used to describe the image in a condensed and understandable way is known as feature extraction, and it is a vital step in the image analysis pipeline. The numerous image processing tasks like object detection, picture classification, as well as image recognition also. Edges, corners, blobs, textures, and forms are among the key details that are extracted from a picture during feature extraction and converted into a set of numerical values .

Classification

There are numerous crucial processes involved in the Convolutional Neural Network (CNN) classification process used for road irregularity detection. Data gathering is the first step in the process, where a sizable dataset of photographs of roads with and without anomalies is gathered. In order to make sure that the network is strong and can generalise well to new data, the photos should be taken from multiple locations and under various lighting conditions. By feeding an image into the network after training and evaluating the results, the CNN can be used to detect road irregularities. The network has identified a road irregularity if the "irregularities present" class score is higher than a threshold. This procedure can be repeated for numerous photos, enabling the network to carry out real-time road abnormality identification.

CHAPTER 5

RESULTS AND DISCUSSIONS

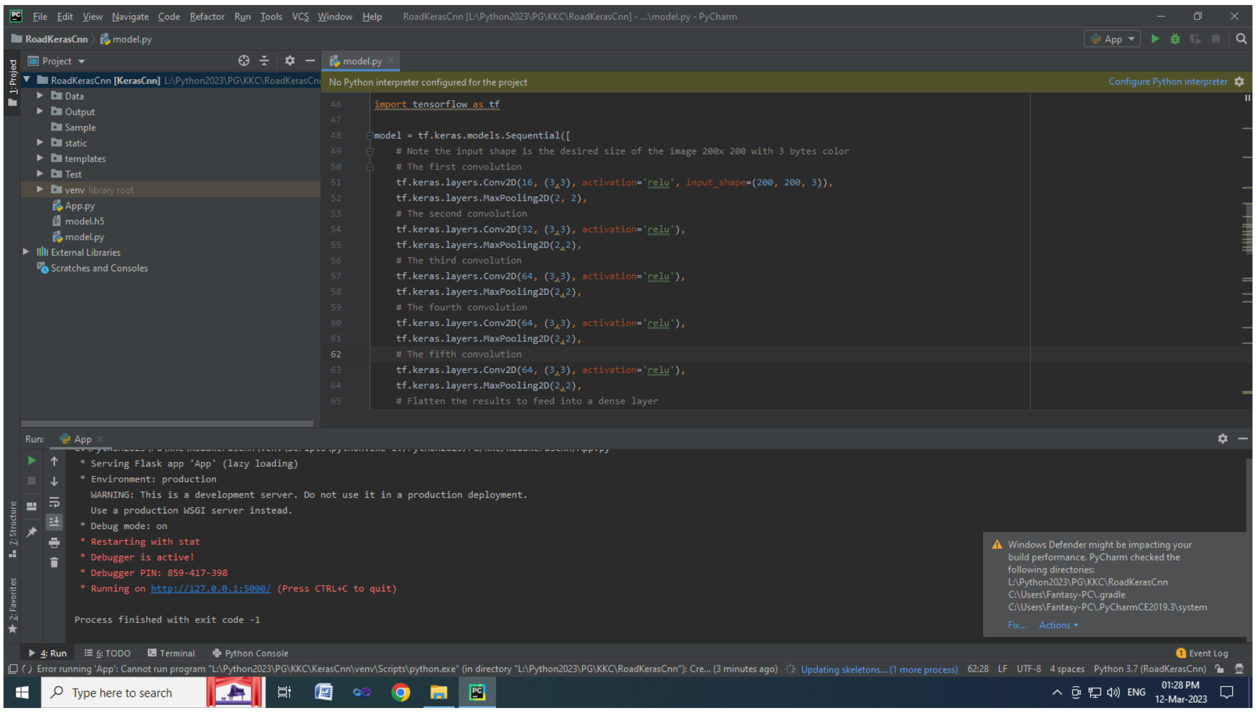

Figure 5.1: Screenshot of train and test code

This figure deals with the entering our details according to the program implemented in Python and helps to understand how to build a simple convolutional neural network(CNN) using the TensorFlow in python .

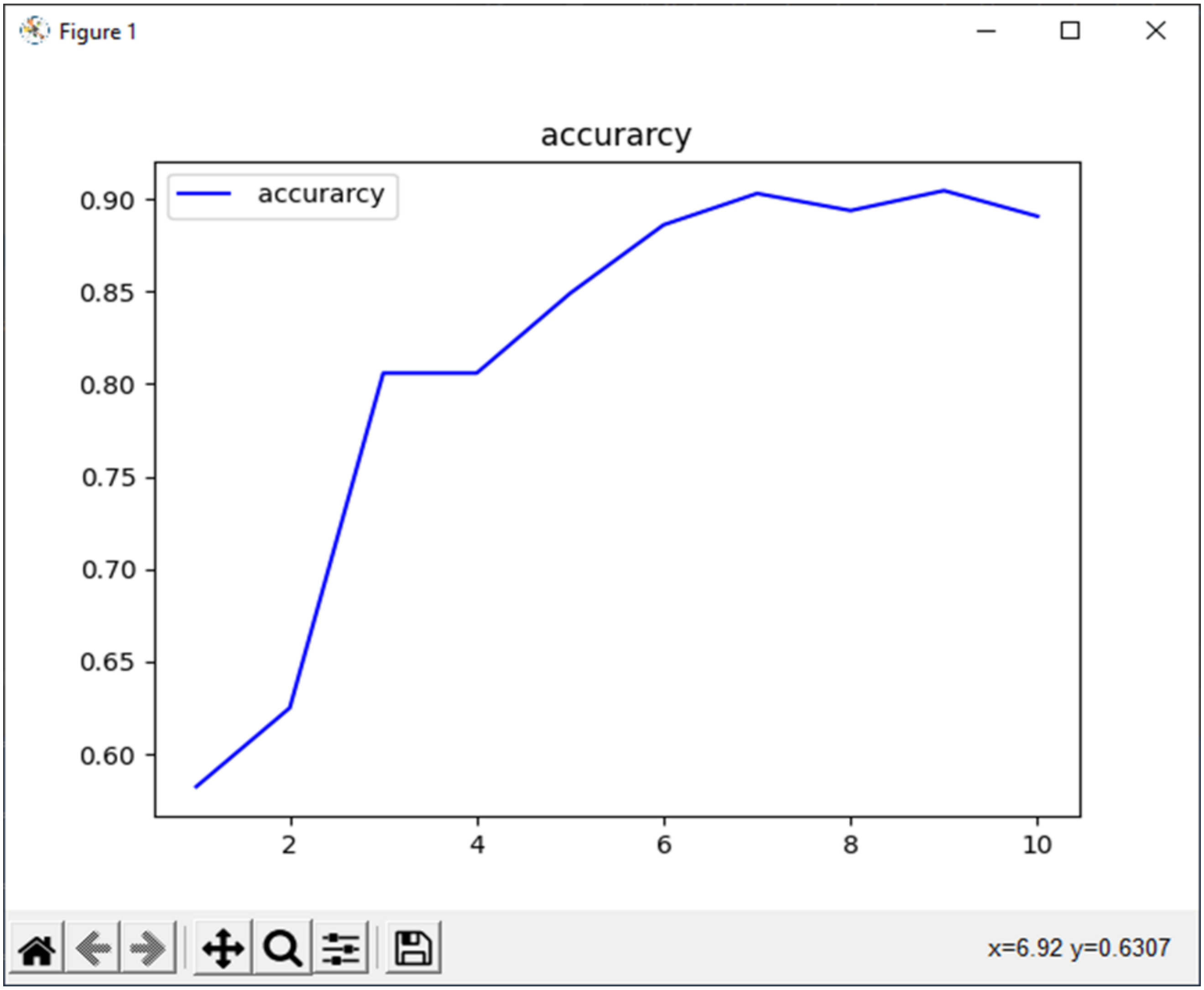

Figure 5.2: Screenshot of Accuracy

This figure shows the screenshot of trained dataset accuracy and futher implementation . The trained model accuracy can also be used for further implementation such as model selection , hyperparameter tuning or comparing of different models.

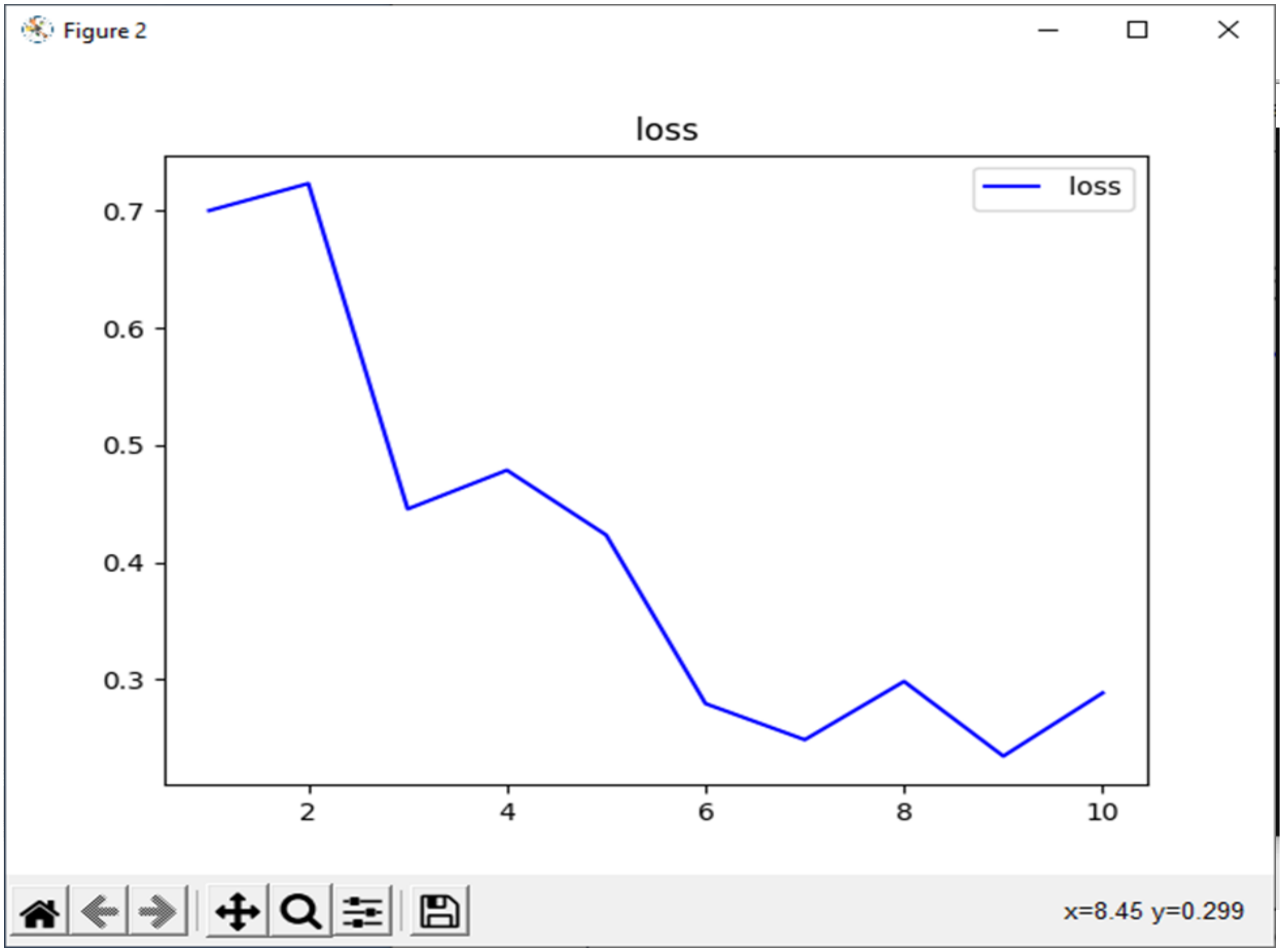

Figure 5.3: Screenshot of Loss

This figure shows the screenshot of trained dataset loss and this can be used to determine which one is the most effective at solving a specific problem on new data.

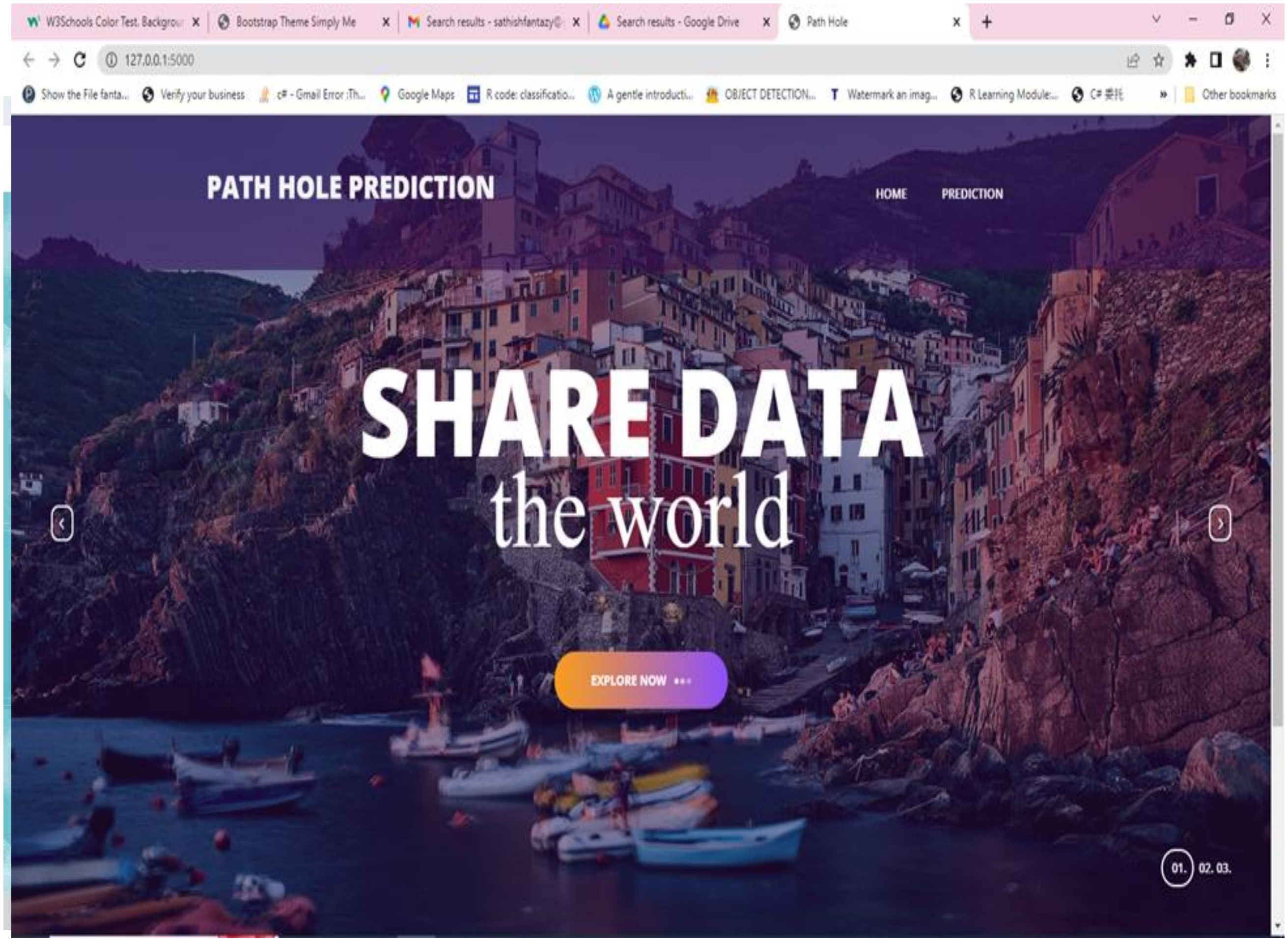

Figure 5.4: Screenshot of Home Page

This Figure shows the home page of a website is the main page that visitors see when they first visit the site. It sets the tone and provides the first impression for visitors . The home page typically includes an overview of the sites purpose , navigation links to other pages on the site .

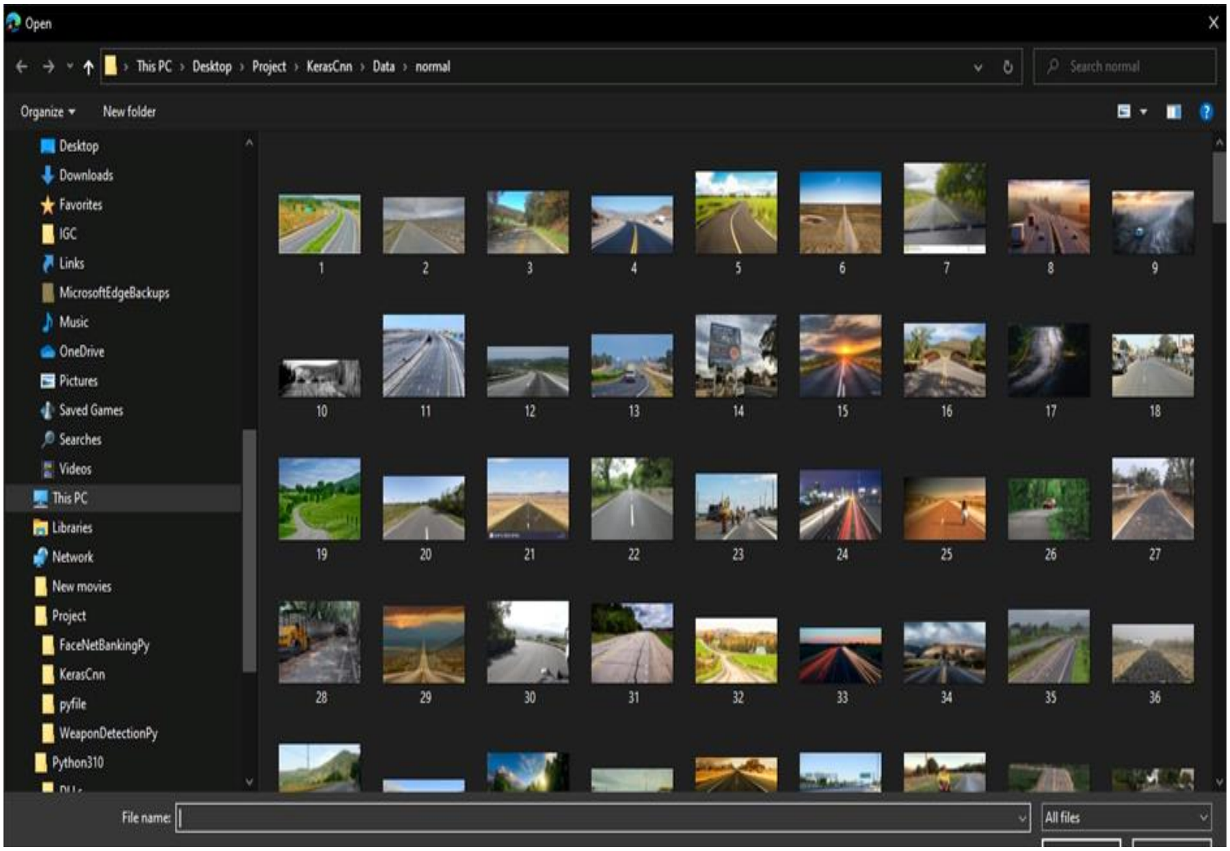

Figure 5.5: Screenshot of Selecting the image

This figure shows that the model learns to recognize patterns in the input images and associate them with the corresponding output labels. When selecting images from the train and test dataset in CNN it is important to ensure that the images are representative of the real world data that the model will be applied to and select the image.

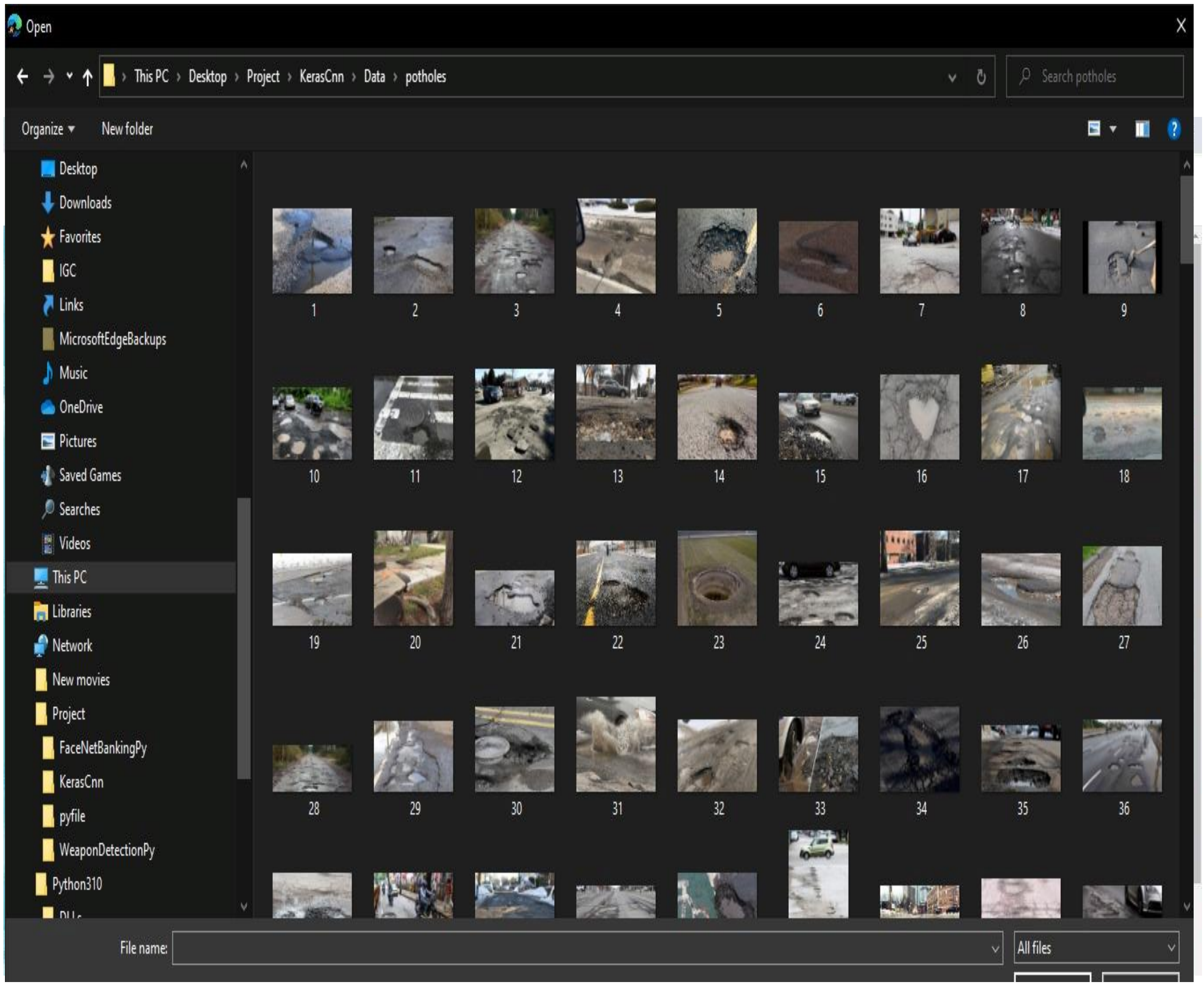

Figure 5.6: Screenshot of potholes image

This Figure shows the image upload of pothole from local folder and also shows that the model learns to recognize patterns in the input images and associate them with the corresponding output labels. When selecting images from the train and test dataset in CNN it is important to ensure that the images are representative of the real world data that the model will be applied to and select the image.

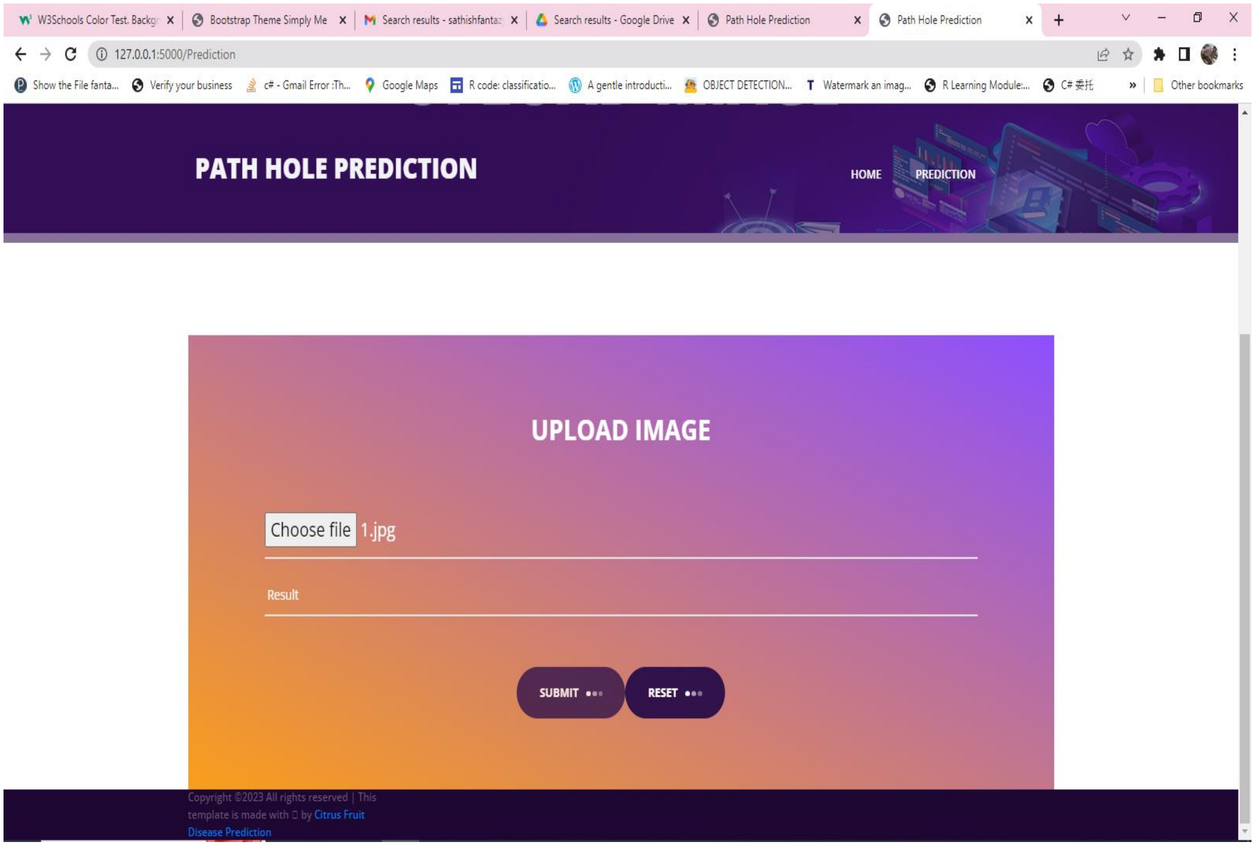

Figure 5.7: Screenshot of Image uploading Page

This figure shows that the uploading image that could include images of various file types(eg.,JPEG,PNG,GIF) , different sizes and aspect ratios and different types of content (eg.,photographs,graphics,screenshots).

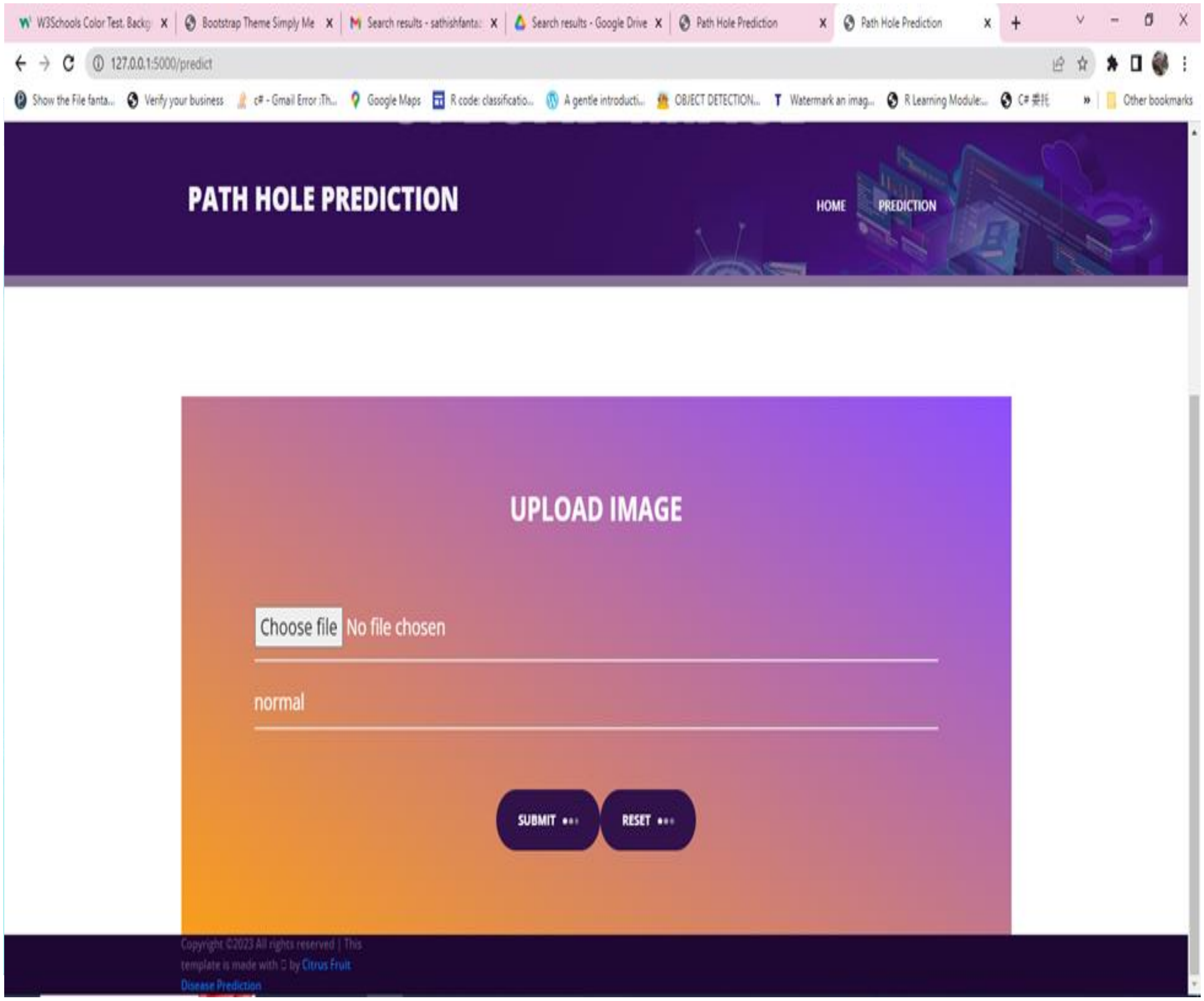

Figure 5.8: Screenshot of output

This figure shows the predicted image of normal road .

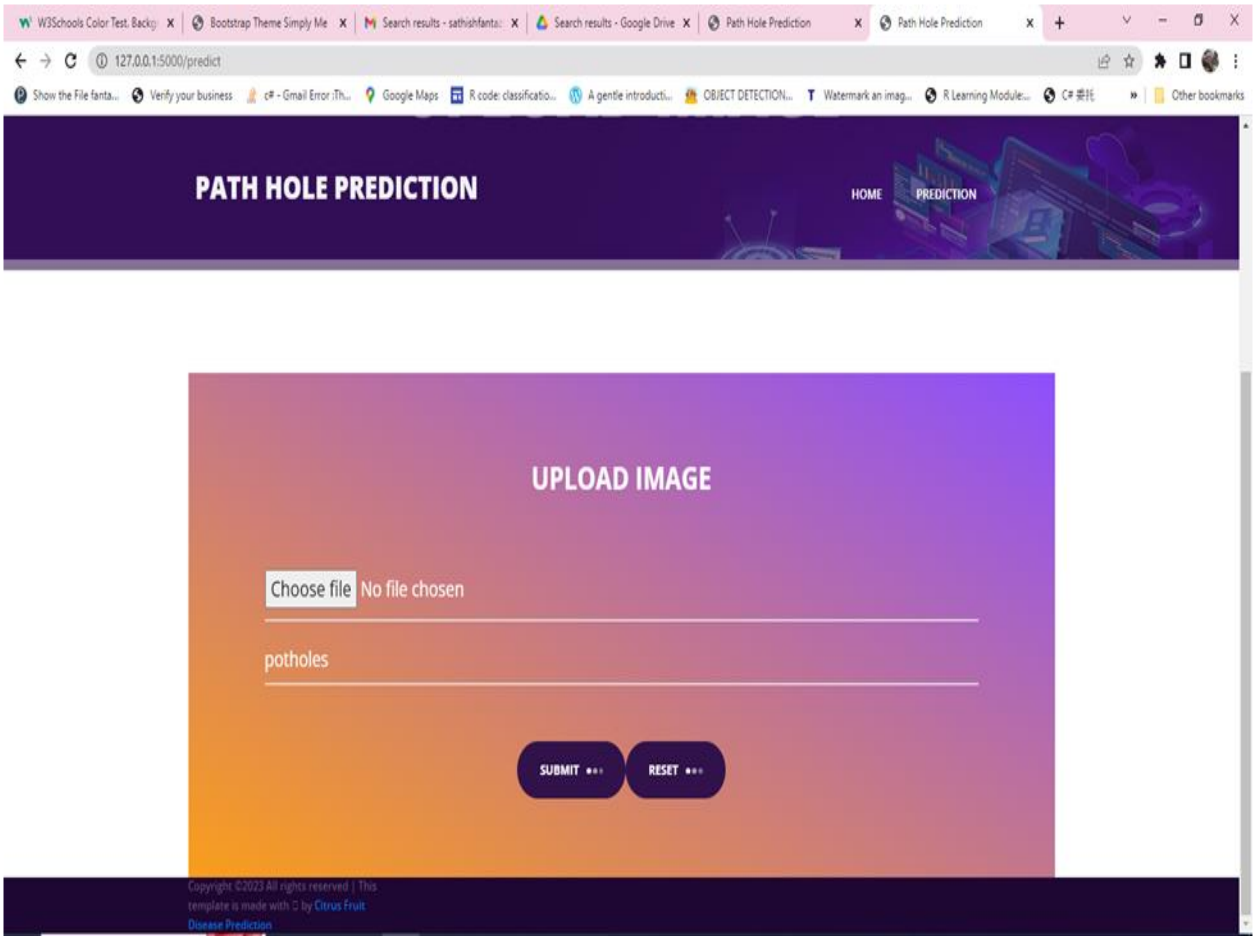

Figure 5.9: Screenshot of output

This figure shows the predicted image of patholes road .

CHAPTER 6

CONCLUSION

In conclusion, deep learning have many advantages over conventional machine learning techniques for the detection of roadway imperfections . The detection and classification of road irregularities can be automated, allowing maintenance teams to work faster and more productively while conserving time and resources and ensuring the safety of motorists and pedestrians . Real-time detection and classification of possible dangers can lessen the need for expensive repairs by enabling timely maintenance, which in turn can help prevent accidents. The system's consumer interface also enables more effective maintenance of road infrastructure by enabling drivers or road repairs crews to locate and assess the severity of identified anomalies on a map or even in a list format. This approach might fundamentally alter how we identify and handle traffic abnormalities, improving the safety and effectiveness of our roads.

FUTURE WORKS

The accuracy can further be increased by using training images that are taken from vehicle cameras in an angle that the model will use later to predict and by adding more variation to the training images. Furthermore, as an extension of this project, the depth of potholes and the distance (in meters) may also be estimated using calibrated stereo cameras.

REFERENCES

BOOK REFERENCES

- Van Rossum, Guido, and Fred L. Drake. The python language reference manual. Network Theory Ltd., 2011.
- Van Rossum, Guido, and Fred L. Drake. The python language reference manual. Network Theory Ltd., 2011.
- Dierbach, Charles. Introduction to Computer Science using Python: A Computational Problem-Solving Focus. Wiley Publishing, 2012.
- James, Mike. Programmer's Python: Everything is an Object Something Completely Different. I/O Press, 2018.
- Reges, Stuart, Marty Stepp, and Allison Obourn. Building Python Programs. Pearson, 2018.

WEBSITE REFERENCES

- https://docs.python.org/3/tutorial/
- https://www.learnpython.org/

APPENDIX

SOURCE CODE

```
from flask import Flask, render_template, flash, request, session
import cv2
app = Flask(__name__)
app.config.from_object(__name__)
app.config['SECRET_KEY'] = '7d441f27d441f27567d441f2b6176a'
@app.route("/")
def homepage():
    return render_template('index.html')
@app.route("/Prediction")
def Prediction():
    return render_template('Prediction.html')
@app.route("/predict", methods=['GET', 'POST'])
def predict():
    if request.method == 'POST':
        file = request.files['file']
        file.save('static/Out/Test.jpg')
        import warnings
        warnings.filterwarnings('ignore')
        import tensorflow as tf
        classifierLoad = tf.keras.models.load_model('model.h5')
        import numpy as np
        from keras.preprocessing import image
        test_image = image.load_img('static/Out/Test.jpg', target_size=(200, 200))
        img1 = cv2.imread('static/Out/Test.jpg')
        # test_image = image.img_to_array(test_image)
        test_image = np.expand_dims(test_image, axis=0)
        result = classifierLoad.predict(test_image)
        print(result)
```

```
 pre = ''
        if result[0][0] == 1:
            pre = "normal"
        elif result[0][1] == 1:
            pre = "potholes"
        #sendmail("","Prediction :"+pre)
        #sendmsg("", "Prediction :" + pre)
        return render_template('Prediction.html', pre=pre)
def sendmsg(targetno, message):
    import requests
    requests.post(
        "http://smsserver9.creativepoint.in/api.php?username=fantasy&password=596692&to="
+ targetno + "&from=FSSMSS&message=Dear user  your msg is " + message + " Sent By
FSMSG FSSMSS&PEID=1501563800000030506&templateid=1507162882948811640")
def sendmail(Mailid, message):
    import smtplib
    from email.mime.multipart import MIMEMultipart
    from email.mime.text import MIMEText
    from email.mime.base import MIMEBase
    from email import encoders
    fromaddr = "sampletest685@gmail.com"
    toaddr = Mailid
    # instance of MIMEMultipart
    msg = MIMEMultipart()
    # storing the senders email address
    msg['From'] = fromaddr
    # storing the receivers email address
    msg['To'] = toaddr
    # storing the subject
    msg['Subject'] = "Alert"
```

```
    # string to store the body of the mail
    body = message
    # attach the body with the msg instance
    msg.attach(MIMEText(body, 'plain'))
    # creates SMTP session
    s = smtplib.SMTP('smtp.gmail.com', 587)
    # start TLS for security
    s.starttls()
    # Authentication
    s.login(fromaddr, "hneucvnontsuwgpj")
    # Converts the Multipart msg into a string
    text = msg.as_string()
    # sending the mail
    s.sendmail(fromaddr, toaddr, text)
    # terminating the session
    s.quit()
if __name__ == '__main__':
    app.run(debug=True, use_reloader=True)
# Part 1 - Building the CNN
# Importing the Keras libraries and packages
from keras.models import Sequential
from keras.layers import Convolution2D
from keras.layers import MaxPooling2D
from keras.layers import Flatten
from keras.layers import Dense
from keras.models import model_from_json
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
batch_size = 32
```

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
# All images will be rescaled by 1./255
train_datagen = ImageDataGenerator(rescale=1/255)
# Flow training images in batches of 128 using train_datagen generator
train_generator = train_datagen.flow_from_directory(
        'Data',  # This is the source directory for training images
        target_size=(200, 200),  # All images will be resized to 200 x 200
        batch_size=batch_size,
        # Specify the classes explicitly
        classes = ['normal','potholes'],
        # Since we use categorical_crossentropy loss, we need categorical labels
        class_mode='categorical')
test_datagen = ImageDataGenerator(rescale=1/255)
# Flow training images in batches of 128 using train_datagen generator
test_generator = test_datagen.flow_from_directory(
        'Test',  # This is the source directory for training images
        target_size=(200, 200),  # All images will be resized to 200 x 200
        batch_size=batch_size,
        # Specify the classes explicitly
        classes = ['normal','potholes'],
        # Since we use categorical_crossentropy loss, we need categorical labels
        class_mode='categorical')
import tensorflow as tf
model = tf.keras.models.Sequential([
    # Note the input shape is the desired size of the image 200x 200 with 3 bytes color
    # The first convolution
    tf.keras.layers.Conv2D(16, (3,3), activation='relu', input_shape=(200, 200, 3)),
    tf.keras.layers.MaxPooling2D(2, 2),
    # The second convolution
    tf.keras.layers.Conv2D(32, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
```

```
    # The third convolution
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # The fourth convolution
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # The fifth convolution
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # Flatten the results to feed into a dense layer
    tf.keras.layers.Flatten(),
    # 128 neuron in the fully-connected layer
    tf.keras.layers.Dense(128, activation='relu'),
    # 5 output neurons for 4 classes with the softmax activation
    tf.keras.layers.Dense(2, activation='softmax')
])
model.summary()
from tensorflow.keras.optimizers import RMSprop
early = tf.keras.callbacks.EarlyStopping(monitor='val_loss',patience=5)
model.compile(loss='categorical_crossentropy',
              optimizer=RMSprop(lr=0.001),
              metrics=['accuracy'])
total_sample=train_generator.n
n_epochs = 10
from sklearn.metrics import classification_report
history = model.fit_generator(
        train_generator,
        steps_per_epoch=int(total_sample/batch_size),
        epochs=n_epochs,
        verbose=1)
```

```
model.save('model.h5')
acc = history.history['accuracy']
loss = history.history['loss']
epochs = range(1, len(acc) + 1)
# Train and validation accuracy
plt.plot(epochs, acc, 'b', label=' accurarcy')
plt.title('accurarcy')
plt.legend()
plt.figure()
# Train and validation loss
plt.plot(epochs, loss, 'b', label=' loss')
plt.title('  loss')
```