Road Condition Rating System

Submitted in partial fulfillment of the requirements for the degree of

Bachelor of Technology

in

CSE With Specialization in Data Science

by

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Under the guidance of

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Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

May, 2023

DECLARATION

I hereby declare that the thesis entitled "Road Condition Rating System" submitted by me, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering with Specialization in Data Science* to VIT is a record of bonafide work carried out by me under the supervision of Anisha M. Lal.

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Akshay

Place: Vellore

Date: 19/05/23

Signature of the Candidate

CERTIFICATE

This is to certify that the thesis entitled "Road Condition Rating System" submitted by **Akshay Syal & 19BDS0010**, **SCOPE**, VIT, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering with Specialization in Data Science* is a record of bonafide work carried out by him under my supervision during the period, 01. 07. 2022 to 30.04.2023, as per the VIT code of academic and research ethics.

The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university. The thesis fulfills the requirements and regulations of the University and in my opinion meets the necessary standards for submission.

Place : Vellore

Date :

Signature of the Guide

Internal Examiner **External Examiner**

Dr. Parveen Sultana H

Computer Science and Engineering with Specialization in Data Science

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I would like to convey my gratitude to my acquaintances, who provided encouragement for me to undertake this undertaking and sustained me throughout the entire process. Finally, I express my heartfelt thanks to all individuals who contributed directly or indirectly towards my prosperous accomplishment of this project.

Place: Vellore — Akshay Syal
Date: 19/05/2023 — Name of the student

Executive Summary

In the era of technology, there is a need for a reliable and easily accessible method to monitor road conditions that is both accurate and cost-effective. I propose the implementation of a Road Condition Monitoring System comprising three main components. The first component is a deep learning model that can effectively identify and segment potholes and cracks from road images. The second component is a rating module that utilizes the segmented masks from the images to calculate the overall rating of the road. Lastly, a video processing module is included to extract individual image frames from road videos for evaluation purposes.

To train the deep learning model, the Pothole Mix dataset used in the SHREC 2022 competition will be utilized. The logic for the rating module will be based on the guidelines outlined in the Code of Practice for Maintenance of Bituminous Road Surfaces, as published in the Indian Road Congress 2015 edition. This ensures that the rating system aligns with established standards and practices.

By implementing this Road Condition Monitoring System, we can establish a consistent and accessible approach to monitor road conditions using advanced technology. This system addresses the need for accurate assessment without requiring extensive financial resources.

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List of Abbreviations

IRC	Indian Road Congress
DL	Deep Learning
SHREC	Shape Retrieval Contest
MoRTH	Ministry of Road Transport and Highways
API	Application Programming Interface

1. INTRODUCTION

1.1. THEORETICAL BACKGROUND

Semantic segmentation is a computer vision task that involves partitioning an image into different meaningful regions or segments and assigning a semantic label to each segment. Unlike traditional image classification, where the goal is to assign a single label to the entire image, semantic segmentation aims to understand the fine-grained details and boundaries within an image.

In semantic segmentation, every pixel in an image is classified into a specific category or class. The classes can vary depending on the application, but common examples include objects like cars, pedestrians, buildings, roads, trees, and so on. The output of a semantic segmentation algorithm is a pixel-wise mask, where each pixel is assigned, a label corresponding to the object or region it belongs to.

UNet3+ is an extension of the original UNet architecture, which is a popular deep learning model used for image segmentation tasks. UNet3+ incorporates skip connections and dense connections to improve the segmentation performance and capture more detailed information.

The UNet architecture consists of an encoder pathway, which gradually reduces the spatial resolution of the input image while extracting high-level features, and a decoder pathway, which upsamples the feature maps to reconstruct the segmentation mask. The skip connections in UNet allow the decoder to receive information from the corresponding encoder layers, which helps in preserving spatial details and enhancing the segmentation accuracy.

In UNet3+, additional dense connections are introduced between the encoder and decoder pathways. These dense connections enable the flow of information between different levels of the encoder and decoder, facilitating better information fusion and feature reuse. This helps in capturing both low-level and high-level features, leading to more accurate and detailed segmentation results.

The "3+" in UNet3+ indicates the usage of three resolutions or scales during the training and inference stages. Instead of using only one resolution, UNet3+ incorporates three different scales of the input image, enabling the network to capture multi-scale contextual information. This improves the segmentation performance, especially in scenarios where objects of different sizes are present in the image.

Overall, UNet3+ combines the benefits of skip connections, dense connections, and multi-scale input to enhance the accuracy and detail of image segmentation. It has been successfully applied in various medical image analysis tasks and has shown promising results in other domains as well.

1.2. MOTIVATION

Roads are the arteries through which the economy pulses. By linking producers to markets, workers to jobs, students to school, and the sick to hospitals, roads are vital to any development agenda.

According to the statistics shared in the Indian parliament, the total number of road accidents due to potholes in 2016, 2017, 2018, 2020, and 2019 stood at 6,424, 9,423, 4,869, and 4,775, respectively.

According to a "Road Accidents in India," report by the Ministry of Road Transport and Highways (MoRTH), roads with sharp curves, potholes, and steep gradients tend to be more accident-prone because successfully negotiating them requires skill, extra care, and alertness.

Considering that the road condition directly and substantially impacts road safety, the roads need to be maintained regularly and monitored exhaustively from time to time.

However, the orthodox methods for road assessment involve a labor-intensive manual inspection of road surfaces which fail to meet the present requirements due to the vast area of road networks to be inspected in a limited time.

Additionally, the monetary shortage restricts many local administrations from conducting the requisite inspections on time. Thus, this project aims to provide a solution for the problems mentioned.

1.3. AIM OF THE PROPOSED WORK

The age of technology necessitates a consistent and accessible Road Monitoring methodology that is both accurate, accessible and doesn't have much monitory requirement. I propose a Road Condition Monitoring System that consists of primarily 3 modules: deep learning model capable of segmenting pothole and cracks from road images, rating module that processes the segmentation masks from the images and calculates the rating of road and a video processing module that extracts the individual image frames from video of the road to be evaluated. The deep learning model will be trained on the Pothole Mix dataset that was used in the SHREC 2022 competition. The rating module's logic is derived from the guidelines of the Code of Practice for Maintenance of Bituminous Road Surfaces published by the Indian Road Congress 2015 edition.

1.4. OBJECTIVES OF THE PROPOSED WORK

My project workflow consists of four major sections, as follows:

1. Semantic Image Segmentation: The deep learning model employs the state of the art, UNET 3+ architecture using Efficient net B3 backbone pretrained with imagenets weights. The model is trained on the pothole mix dataset. The model expects input image of shape (1x400x400x3).
2. Rating Module: The IRC 82:2015 edition Code of Practice for Maintenance of Bituminous Road Surfaces book has guidelines for rating highway, urban, rural and major district roads. It comes with an excel sheet application in which users can enter percentage of road covered with specific road defects and it calculates the rating. I have extracted the formulae in the excel sheet using Python and inferred the rating module.

3. Video Processing: This module expects a video of road as input. The image frames are extracted from the video and stitched together to create a long image of the road. Then that long image is cutup into small images of size of the input size of model. The model then predicts potholes, cracks and road pixels on those small images and the results are added over all the images to produce overall rating of the road.
4. Web Application: The front end consists of basic form that accepts an image or video of road, type of road, geolocation of start and end position of road. The backend part is made using Flask that utilizes the deep learning model, video processing and rating module. The entire project is hosted using Heroku.

2.1. SURVEY OF THE EXISTING MODELS/WORK

1. A Review of Pavement Condition Rating Models for Flexible Pavements (Madhavendra Sharma June 2019): This paper explores several rating models employed to assess the condition of pavement. These models fall into three broad categories: direct panel rating, utility function, and deduct values and weighting factors. The article delves into various models, including the Texas Department of Transportation (Tx DOT) Method, Asphalt Institute Method (Minnesota Asphalt Pavement Association), IRC: 82 – 2015 (a Code of Practice for Maintenance of Bituminous Road Surfaces published by the Indian Road Congress), South Dakota's DOT Surface Condition Index (SCI), and many more.

2. An Exploration of Recent Intelligent Image Analysis Techniques for Visual Pavement Surface Condition Assessment (Waqar S. Qureshi November 2022): The article discusses the importance of assessing the pavement condition of roads for maintenance, asset management, and budgeting purposes. Pavement condition is assessed by measuring pavement characteristics such as roughness, surface skid resistance, pavement strength, deflection, and visual surface distresses. Visual inspection identifies and quantifies surface distresses, and the condition is assessed using standard rating scales. The article analyzes research trends in the academic literature, professional practices, and current commercial solutions for surface condition ratings by civil authorities. The literature indicates experimentation in evaluating different imaging technologies, imaging road views, and developing robust algorithms for detecting distinct instances of distresses in an image. However, current limitations include a lack of a general evaluation matrix to evaluate the robustness of the detecting algorithms for different shapes, sizes, and textures of distinct distresses in different geographical locations. The article highlights the lack of algorithms for quantifying these distresses in images and for rating a stretch of pavement using a sequence of images to develop a real-world automated pavement condition assessment rating. The article concludes by stating that there is no off-the-shelf solution for automated pavement condition rating, and current research tends to focus more on distress identification than distress quantification, which is essential for developing approaches for automated pavement rating.

3. Improving Road Semantic Segmentation Using Generative Adversarial Network (Abolfazil Abdollahi April 2021): The article discusses a new deep learning approach for road segmentation from high-resolution aerial imagery. The approach uses a modified UNet model and a generative adversarial network (GAN) framework to improve the accuracy of segmentation maps and preserve edge information. The proposed GAN-based approach for road network extraction involves four major steps: generation of training and testing samples, pre-processing with LLF-based filtering to enhance image quality, GAN optimization using the

training samples, and extraction of the road network from images in the test set using the generator from the optimized GAN. The GAN framework uses two subnetworks, a generator, and a discriminator. The generator seeks to learn a map that produces a binary segmentation map from the input image based on the distribution seen in the training data, while the discriminator attempts to distinguish true ground truth data from data produced by the generator. The generator and discriminator architectures used in the proposed approach are described in detail.

4. Road surface detection and differentiation considering surface Damages (Thiago Rateke January 2021): The paper discusses the challenges in reliable path and obstacle detection for vehicles and robots on heavily damaged and unpaved roads, and presents an approach using Convolutional Neural Networks (CNN) for road detection that can identify different surface types, damage, and other relevant information for driving safety. The author's approach to train a CNN to perform semantic segmentation is to use a U-NET architecture with ResNet34. Also, they have used transfer learning to improve model's performance. Specifically, they first train a CNN model without using class weights so that the model learns to generalize over major classes like Asphalt, road markings, etc. Then this model is further trained using class weights so that accuracy of predicting under-represented classes like potholes and cracks is improved.
5. Segmentation of Potholes from Road Images (Sai Ram Atluri January 2022): This project developed a system using convolutional neural networks to detect potholes on Indian roads. The system uses a Mask_RCNN pretrained model with a dataset containing over 900 images to classify and generate bounding boxes around potholes. The application can be extended in the future to assist users by locating and noting the coordinates of potholes using Google Maps API. This system could also be used by government authorities for road maintenance, and in the future, integrated into autonomous vehicles. Further work will be done to improve the system to work as an unsupervised learning model and to eliminate the root cause of accidents. The system developed uses a CNN model in two stages for pothole detection. In the first stage, the system assesses the image for pothole objects, while in the second stage, the pothole objects are analyzed and classified. Anchor boxes are used in the system to create bounding boxes around the pothole objects, which are then classified with a unique class ID. The goal of the anchor boxes is to allow for images of different sizes and aspect ratios to be resized to a standard size of 600x600 dimensions. The system uses regression to refine the bounding boxes and make them converge to the ground truth bounding boxes.
6. SHREC 2022 Pothole and crack detection in the road pavement using images and RGB-D data: This paper presents the methods submitted for evaluation to the SHREC 2022 track on pothole and crack detection in road pavement. Seven different runs for semantic segmentation of the road surface were compared, all using deep learning techniques and tested in the same environment. The methods were evaluated on a training set and validation set composed of 3836 image/mask pairs and 797 RGB-D video clips, and then on a test set of 504 pairs and eight video clips. The results showed that the use of RGB-D data is still challenging in this context, and the two methods PUCP-Unet++ and HCMUS-CPS-DLU-Net were found to be the most valuable runs. In the future, it could be interesting to explore the possibility of having a dataset entirely built on RGB-D data to improve the recognition of road damage.
7. UNET 3+: A FULL-SCALE CONNECTED UNET FOR MEDICAL IMAGE

SEGMENTATION (Huimin Huang 2020): The paper proposes a new method for medical image segmentation using deep learning called UNet 3+. The method builds on the popular UNet architecture by incorporating full-scale skip connections and deep supervisions. The full-scale skip connections allow for the combination of low-level and high-level features from different scales, which is beneficial for organs that appear at varying scales. The deep supervision enhances hierarchical representations from the full-scale feature maps. The proposed method also introduces a hybrid loss function and a classification-guided module to improve the accuracy of the segmentation results. The experiments on liver and spleen datasets show that UNet 3+ outperforms all previous state-of-the-art approaches and produces coherent boundaries.

8. Vibration vs. vision: best approach for automated pavement distress detection (Janani Lekshmipathy December 2019): Roads are critical infrastructure that impact people's daily lives by providing connectivity and mobility. Continuous monitoring and repair of roads are crucial for consistent surface quality. Traditional manual and instrumented methods used for pavement distress detection are tedious and time-consuming, leading to the development of automated techniques like Ground Penetrating Radar, Laser-Imaging-Systems, and smartphone-based systems for pavement distress detection. This study compares a vibration-based method using a smartphone accelerometer and gyroscope with a vision-based method using video processing for automated pavement distress detection. The results show that the vision-based method is more effective than the vibration-based method for detailed analysis, while the latter is useful for routine monitoring. Combining both methods could provide more accurate results and improve pavement management. These automated methods can help pavement engineers, policy makers, and planners allocate funds for cost-effective corrective measures. Further research could focus on developing smartphone applications using automated techniques, improving the accuracy of the experiments, and developing GPS navigation systems that forewarn road users of approaching distresses.
9. CODE OF PRACTICE FOR MAINTENANCE OF BITUMINOUS ROAD SURFACES (IRC 2015:82): This book contains specific guidelines regarding maintenance of highways, urban roads and major district roads. It also describes types of pavement distresses, their causes and treatment. It also highlights preventive measures that can be taken to prevent road distress in the first place. It also discusses strategies for periodic renewals of roads. The book also describes the repair theory on how the pothole filing and patching is done, what tools and equipment are used for pothole/patch repairs and modern technologies for pothole filling and road patching.

2.2 SUMMARY/GAPS IDENTIFED IN THE SURVEY

1. A Review of Pavement Condition Rating Models for Flexible Pavements (Madhavendra Sharma June 2019): The most widely used and accepted approach for assessing road conditions is the deduct value method. Within this category, the IRC method stands out as it employs a rating system based on the extent of pavement surface distress. However, this method has a limitation in that it does not take into account the severity of the distress during the rating process. The rating points assigned vary depending on the class of the road, which is a reflection of the fact that different traffic loadings impact the occurrence of specific distress and overall pavement deterioration patterns.

2. An Exploration of Recent Intelligent Image Analysis Techniques for Visual Pavement Surface Condition Assessment (Waqar S. Qureshi November 2022): The main thing that this review paper highlights are that the current research trends tend to focus more on pavement distress identification i.e. presence/absence detection but less on distress quantification which is essential for developing approaches for developing automating road rating system. The paper discusses various deep learning techniques used commonly in this domain like classification, object detection and pixel segmentation. Few research papers were also discussed like in one of the papers the authors create a hybrid model of an object detector and semantic segmentation for classifying and quantifying distress severity on pavements and predicted PASER indices for each road section. However, one of the drawbacks was they were using outdated Google API images and only 2 distresses were taken for rating but in practical scenarios patches, raveling etc. need to be considered too. In one of the papers the authors use Efficient Net V2 image classification to infer PSCI ratings.

3. Improving Road Semantic Segmentation Using Generative Adversarial Network: The article discusses a new deep learning approach for road segmentation from high-resolution aerial imagery. The approach uses a modified UNet model and a generative adversarial network (GAN) framework to improve the accuracy of segmentation maps and preserve edge information. The results show that the proposed GAN framework outperforms prior CNN-based approaches and is particularly effective in preserving edge information. However, the accuracy of the proposed deep learning model is slightly lower, and the method cannot identify roads from complex areas or extract continuous road parts from these images. Future research could address these limitations.

4. Road surface detection and differentiation considering surface Damages: The article discusses the possibility of differentiating label categories in road damage detection to improve accuracy. The authors suggest creating more specific classes for damage types on different surface types, such as AsphaltCracks, Paved Cracks, and Unpaved Cracks, to enable better differentiation. The article concludes that using standard resolution monocular video streams can extract useful information on road surface status, which can be used by intelligent systems to identify threats such as potholes, water-puddles, and other damages and obstacles. However, challenges still exist, such as identifying surface type and variations in different weather conditions and at night.

5. Segmentation of Potholes from Road Images: They have not made their dataset public. This project developed a system using convolutional neural networks to detect potholes on Indian roads. The system uses a Mask_RCNN pretrained model with a dataset containing over 900 images to classify and generate bounding boxes around potholes. The application can be extended in the future to assist users by locating and noting the coordinates of potholes using Google Maps API. This system could also be used by government authorities for road maintenance, and in the future, integrated into autonomous vehicles. Further work will be done to improve the system to work as an unsupervised learning model and to eliminate the root cause of accidents.

6. SHREC 2022 Pothole and crack detection in the road pavement using

images and RGB-D data: In the base line method the dataset was trained on the DeepLabv3+ architecture with a ResNet-101 encoder pre-trained on ImageNet. The training process involved using the Fast.ai library and the progressive resizing technique to augment and accelerate the convergence of the network. Various data augmentations were also used to prevent overfitting. The training process was automated using Fast.ai callbacks for early stopping and saving the best model. Two training rounds were run at different resolutions, with variable numbers of epochs and freeze/unfreeze steps. The batch sizes and learning rates were adjusted accordingly. The network was trained on a set of 3340 image/mask pairs in the training set. This paper presents the methods submitted for evaluation to the SHREC 2022 track on pothole and crack detection in road pavement. Seven different runs for semantic segmentation of the road surface were compared, all using deep learning techniques and tested in the same environment. The methods were evaluated on a training set and validation set composed of 3836 image/mask pairs and 797 RGB-D video clips, and then on a test set of 504 pairs and eight video clips. The results showed that the use of RGB-D data is still challenging in this context, and the two methods PUCP-Unet++ and HCMUS-CPS-DLU-Net were found to be the most valuable runs. In the future, it could be interesting to explore the possibility of having a dataset entirely built on RGB-D data to improve the recognition of road damage.

7. UNET 3+: A FULL-SCALE CONNECTED UNET FOR MEDICAL IMAGE SEGMENTATION: The paper proposes a new deep learning network architecture for semantic segmentation called UNet 3+, which takes advantage of full-scale skip connections and deep supervisions to incorporate low-level details with high-level semantics from feature maps in different scales. The proposed method is designed to improve accuracy for organs that appear at varying scales while reducing the network parameters to improve computation efficiency. Additionally, the paper introduces a hybrid loss function and a classification-guided module to enhance the organ boundary and reduce over-segmentation. The proposed UNet 3+ architecture and methods outperform previous state-of-the-art approaches in experimental results on liver and spleen datasets.
8. Vibration vs. vision: best approach for automated pavement distress detection: This article discusses the importance of monitoring and repairing roads to maintain their quality and ensure mobility and connectivity. Traditional methods of pavement distress detection are often tedious and time-consuming, prompting the development of automated techniques such as smartphone-based vibration and vision-based methods. The study compares the accuracy of these methods and concludes that the vision-based method is more effective but requires artificial lighting at night and is computationally heavy, while the smartphone-based method is suitable for routine monitoring. The article suggests that both methods can complement each other, and the data generated can be linked to a GIS platform for better allocation of funds for corrective measures. The study recommends further research to improve accuracy, develop a user-friendly smartphone application, and implement advanced techniques like Convolutional Neural Networks and ANN-Fuzzy hybrid techniques. Additionally, a GPS navigation system can be developed to warn road users about approaching distresses.
9. CODE OF PRACTICE FOR MAINTENANCE OF BITUMINOUS ROAD SURFACES: The book has various appendix on how to calculate rating of road. It also comes with its own excel sheet application.

3. OVERVIEW OF THE PROPOSED SYSTEM

3.1 INTRODUCTION AND RELATED CONCEPTS

From the IRC 82:2015 book the preliminary rating of Indian roads is calculated in the following way. First it is determined what type of road it is. Highway, Major District Road and Urban Roads are the 3 categories which are taken into account. Rating for all is calculated in slightly different ways. However, the overall idea is to estimate the percentage of the road covered with a particular defect like crack or pothole. The severity of the defect is not taken into account. Then certain calculations are done on that percentage to calculate rating of road. To find the percentage of road covered with cracks or potholes I have trained a semantic segmentation model with UNET 3+ architecture and EfficientNet B3 weights on the Pothole Mix dataset which has 2 classes: pothole and cracks. I have also developed a website. In the front end the user will provide image or video of road to be evaluated along with geolocation of starting and ending position of road. In the backend the model will predict over the image or on around 50-60 images extracted from the video. The number of pixels is used to calculate percentage area of cracks and potholes with respect to background which should be road. So, the background of image or video taken should be road only. After calculating the rating of the road, it will be displayed to the user and will be stored on a MongoDB database along with geolocation. An API endpoint to the database will be created.

Deep learning: Deep learning is a subset of artificial intelligence (AI) that utilizes neural networks with multiple layers to process and learn from vast amounts of data. By hierarchically extracting complex features, deep learning models can recognize patterns and make predictions or decisions. Through an iterative process of training and optimization, these networks autonomously adjust their weights to improve performance. Deep learning has proven effective in various applications, including image and speech recognition, natural language processing, and even autonomous driving, enabling machines to mimic human-like intelligence and achieve remarkable accuracy and efficiency in complex tasks.

Semantic Segmentation: Semantic segmentation is a computer vision technique that assigns labels to each pixel in an image, dividing it into distinct regions based on their semantic meaning. It goes beyond object detection and provides fine-grained understanding of an image. By employing deep learning algorithms, semantic segmentation models can accurately identify and segment different objects or regions, enabling applications such as autonomous driving, image editing, and medical imaging. It has wide-ranging applications, from scene understanding to augmented reality, by enabling machines to interpret visual data and comprehend the context of an image at the pixel level.

Flask Framework: Flask is a lightweight web framework for building web applications in Python. It provides a simple and flexible way to handle web requests and responses, allowing developers to create RESTful APIs, serve web pages, and build web services. With its modular design, Flask offers various extensions for functionalities like database integration, authentication, and form handling. It emphasizes simplicity and minimalism, making it easy to get started and customize as per project requirements. Flask's versatility and ease of use have made it a popular choice for developing small to medium-sized web applications quickly and efficiently.

MongoDB: MongoDB is a popular document-oriented NoSQL database that provides flexible and scalable data storage. It stores data in a JSON-like format called BSON, allowing for dynamic and schema-less data models. MongoDB's flexible document structure makes it easy to handle complex data, and its distributed architecture allows for horizontal scalability. It supports powerful querying, indexing, and aggregation capabilities, making it suitable for a wide range of applications. MongoDB's ability to handle large amounts of unstructured data, scalability, and ease of use have made it a popular choice for modern web and mobile applications.

3.2 FRAMEWORK, ARCHITECTURE OR MODULE FOR THE PROPOSED SYSTEM

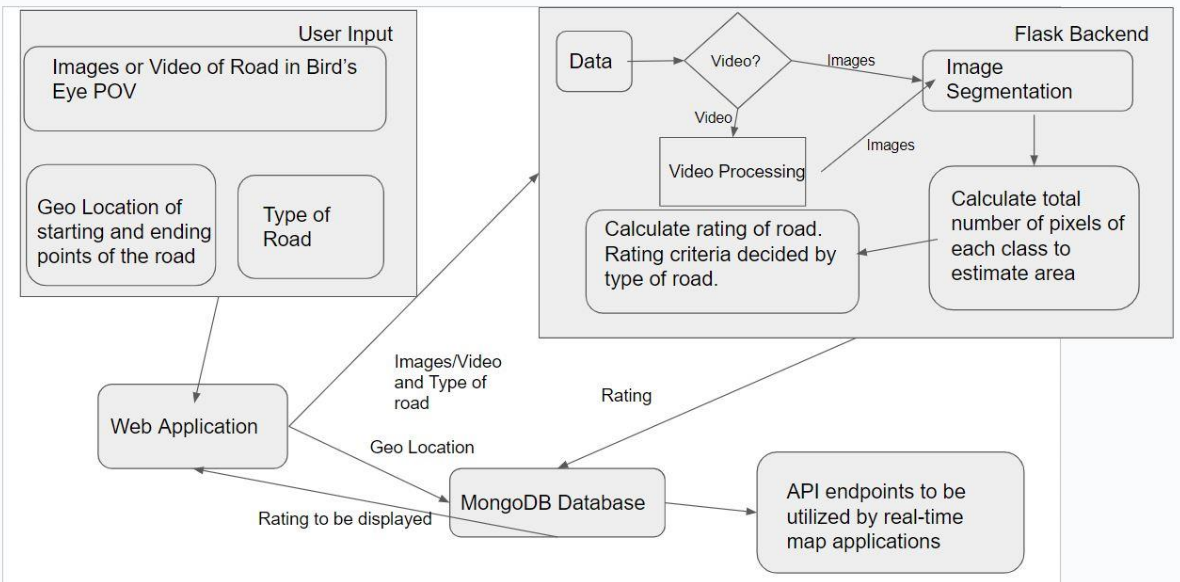

Fig 3.1 Overall Architecture

The IRC 82:2015 book outlines the methodology for determining the preliminary rating of Indian roads. It categorizes roads into three types: Highway, Major District Road, and Urban Roads, and assigns ratings to each category based on the percentage of road coverage by defects like cracks or potholes. The severity of defects is not considered. To calculate the percentage of road coverage, a semantic segmentation model using the UNET 3+ architecture and EfficientNet B3 weights is trained on the Pothole Mix dataset, which includes two classes: pothole and cracks. A website is developed where users can submit road images or videos along with geolocation information. The model predicts the presence of defects by analyzing the images or extracting frames from the videos. The percentage of defects is calculated based on the number of pixels, considering the road as the background. The road rating is then displayed to the user and stored in a MongoDB database along with geolocation information. An API endpoint is created to access the database.

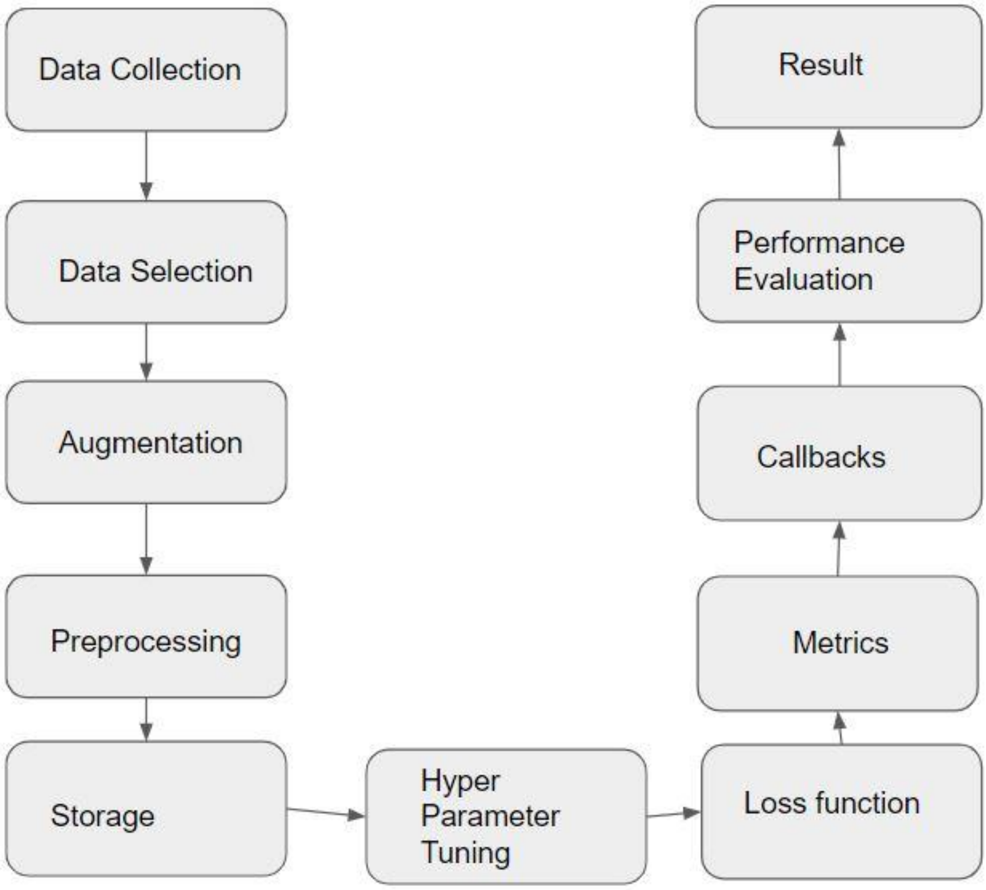

Fig 3.2 Deep Learning Workflow

The following points have been taken into consideration while defining my DL workflow:

- Data Collection: The data was collected from Mendeley Data. It consists of 3 GBs of images and segmentation mask images. The dataset was created by combining five publicly available datasets (Crack500, GAPs384, EdmCrack600, Pothole-600, CPRID, Web Images). Additionally, a small number of segmented images were added to enhance the dataset. The main dataset consists of 4340 pairs of images and corresponding masks at various resolutions. These pairs are divided into training, validation, and test sets with proportions of 3340, 496, and 504 images, respectively, which accounts for approximately 77%, 11%, and 12% of the dataset. This dataset was specifically utilized in the SHREC2022 competition.
- Data Selection: After training a base model I tested it on road images that I took behind my house. I did it for qualitative analysis. I observed that the model was not good at detecting severe potholes. This is due to the fact that the major portion of the dataset is CPRID dataset which doesn't have much severe potholes. Also, the CPRID dataset had very small cracks which were also not severe. Hence for later models a small portion of CPRID dataset was selected for training the model which had severe potholes only along with rest of the dataset. Also, Pothole-600 dataset was not used for training because many images were not annotated properly.
- Data Augmentation: The images were augmented using Roboflow. Three outputs per training example were produced and brightness augmentation (-20% to +20%), exposure augmentation (-5% to +5%), blur (upto 1px) and noise augmentation (upto 1% of pixels) were done. In addition, for a few models, rotation augmentation (90, 180 and 270 degree) augmentation were also done.

- Data Preprocessing: The images were not normalized as Efficient B3 backbone didn’t require images that are normalized. However, the mask images were preprocessed. They were converted to grayscale and were label encoded as 0 for background pixel, 1 for crack pixel and 2 for background pixel. The images were resized to 400x400.
- Dataset Storage: The data is stored on Google Drive. The model is trained on Colab. The drive is first mounted on colab notebook. Then using Image Data Generator, the dataset is supplied to model in batches.
- Hyper Parameter Tuning: The model’s output activation function is Softmax. It is set for deep supervision as it improves model performance. The Efficient Net B3 backbone is pretrained on Imagenet is freezed. The rest of the parameters are set as follows:
    - Filter_num_down: [64, 128, 256,512]
    - filter_num_skip='auto'
    - filter_num_aggregate='auto',
    - stack_num_down=2
    - stack_num_up=1
    - activation='ReLU'
    - freeze_batch_norm=True
- Loss function: The model is initially trained using categorical cross entropy and then it is trained using Focal Loss. The focal loss is also configured to give importance to potholes and cracks more than the background.
- Metrics: To evaluate the model MeanIoU is considered which takes all labels into account. Separate IoUs for crack class (cIoU) and pothole class (pIoU) are also calculated. Categorical Accuracy is also calculated.
- Callbacks: Two callbacks are configured. Earlystop monitors validation loss and has patience of 10 epochs. The checkpoint callback also monitors validation loss and saves the best model in google drive.
- Performance Evaluation: The performance of models are evaluated using model.evaluate function. The image generator is configured with batch size of 1 and the evalute function is configured with steps equal to number of images in the test or validation dataset. This is done to make sure that the evaluations are averaged over single images rather than batches of images.

3.3 PROPOSED SYSTEM MODEL (ER DIAGRAM)

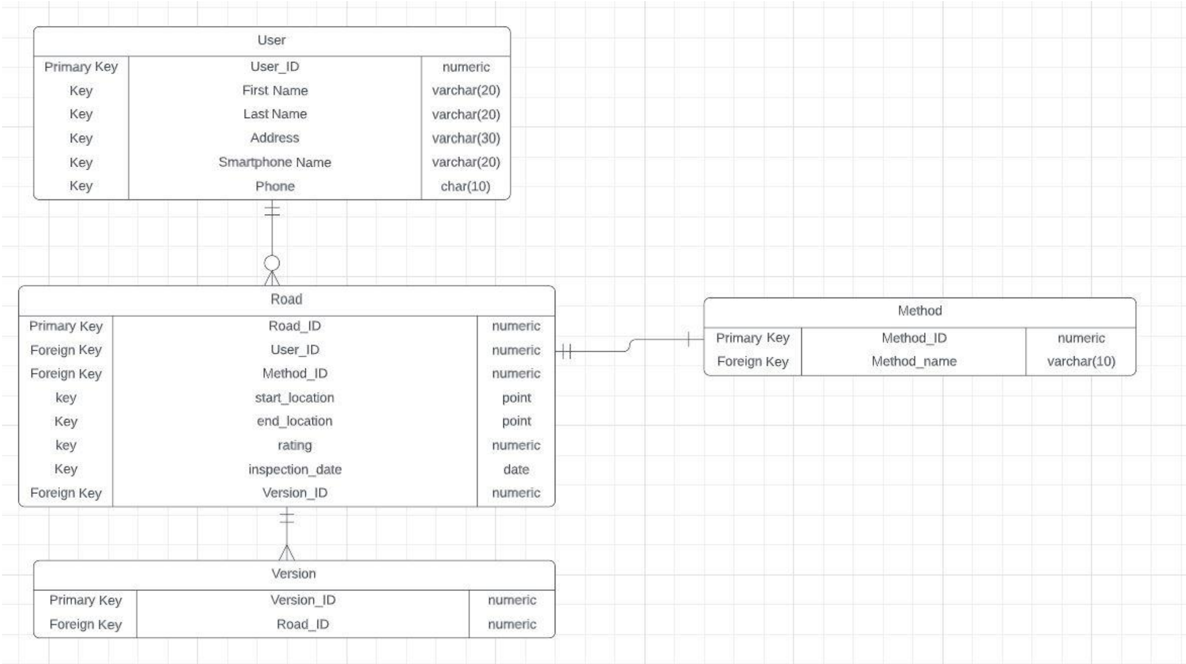

Fig 3.3 ER Diagram

1. User Entity: It contains basic information related to user that evaluates roads.
2. Road Entity: It contains information related to road being evaluated. This information includes the method of taking pictures of road, start and end geolocation, rating of the road, inspection data and it also has a version field to track various versions of road. This can be used for certain analysis like tracking how rating of a particular road changes month wise.
3. Method entity: Intended for storing method name like “on foot”, “by car”, “by 2-wheel vehicle” etc.
4. Version Entity: Intended for storing various version of road for future analysis.

4 Proposed System analysis and design

4.1 Introduction

The Road Condition Rating System comprises of simple front end that takes a few inputs from user like video or image of road to be evaluated, type of road, geolocation of start and end point of road and method of taking pictures (for future analysis purpose). The backend consists of a semantic segmentation model that produces segmentation masks of potholes and cracks detected on road, MongoDB database that stores information provided by user and information derived from model like rating of road etc., and a few modules like video processing module which extracts images from road, rating module which calculates rating of road according to criteria mentioned in IRC 82:2015.

4.2 Requirement Analysis

The Road Condition Rating System accepts video or image of road that has to be evaluated. Video is expected to be taken from smartphone while walking or in car or in a two-wheeler vehicle with the camera facing in downward direction (not exactly Birds eye view, but with a slight tilt). Then, from the video around 60 frames will be extracted. On those images the model will predict crack and pothole mask. Using the masks, the number of pixels of crack and pothole relative to background will be calculated. Percentage area of crack and pothole will be estimated. Then according to the type of road set by the user the evaluation criteria will be set and accordingly the rating of the road is calculated. The rating is displayed on the screen as well as stored in MongoDB database along with other information about the road.

4.2.1 Functional Requirement

4.2.1.1 Product Perspective

The product perspective of this system is that is can be used by anyone to perform a preliminary road evaluation. Local government bodies like municipalities can use the information to plan road maintenance. Further analysis can be done to plan cities, traffic etc. The API endpoint of database can be used in conjunction with Google Maps or a map like app to plan safest or smoothest way from one place to another.

4.2.1.2 Product features

- Semantic Segmentation of cracks and potholes: Produces crack and pothole segmentation mask images
- Video processing: Extracts at most 60 frames from video for analysis
- Road Rating evaluation: Calculates rating of road using the mask images according to criteria set by IRC 82:2015.

4.2.1.3 User characteristics

The product can be used by anyone. The following categories of people are kept in mind:

- Road evaluators: The product can be directly used by road evaluators for quick preliminary evaluation of highways, urban and major district roads.
- Local government or municipalities: They can use this product to plan road maintenance activities.
- Concerned citizens: They are the most important users. If people began to use this product, then the system can be populated with latest version of data. This data can be used to do quicker repairments and monitor condition of roads and how it changes throughout the year.
- Data Scientists: The data produced by the system can be used by data scientists to create various products or do analysis. For example, they can use it for city planning to identify which area has the worst and best roads and correlate it with traffic or material used for making roads to come up with cost saving solutions for making resilient roads or create a route planner for calculating smoothest and safest route between two places.

4.2.1.4 Assumption & Dependencies

- The product assumes that all users have internet access and a compatible web browser.
- The product depends on MongoDB to store data provided by users and Google Cloud Platform for deploying the model.

4.2.1.5 Domain Requirements

- Data privacy and security: The product must adhere to data privacy and security regulations to protect patient information.
- Compliance: The product must comply with industry regulations and standards such as HIPAA.
- Accessibility: The product must be accessible to users with disabilities.

4.2.1.6 User Requirements

- Road Evaluators: Requires good internet connection to upload video file or a compressor to first compress the video file and then upload
- Data Scientist: Requires access API endpoint to make analysis project

4.2.2 Non-Functional Requirements
4.2.2.1 Product Requirements
4.2.2.1.1 Efficiency (in terms of Time and Space)

The Road Condition Rating system is backed up by Google Cloud Platform which has the capability of utilizing Cloud Run, a fully managed environment to run stateless containers that can handle two million requests per month

4.2.2.1.2 Reliability

The Road Condition Rating system is designed to be highly reliable to ensure that road data is always available when needed. The system incorporates a distinct Identity ID assigned to each user, guaranteeing the preservation of data and restricting access to content solely to users with their authorized devices. This safeguard remains intact even in the event of an Identity ID compromise, ensuring data integrity and user content security.

4.2.2.1.3 Portability

The Road Condition Rating system is designed to be easily portable across different users. Since is a web application it is accessible to a large group of users.

4.2.2.1.4 Usability

The users are only required to use their own cameras basic functionality of recoding videos and then uploading them to get rating. But knowledge about APIs is required to leverage API endpoint of the database.

4.2.2.2 Organizational Requirements
4.2.2.2.1 Implementation Requirements (in terms of deployment)

- Google Cloud Platform for hosting deep learning model
- Netlify for hosting website

4.2.2.3 Operational Requirements

- **Economic**

The road infrastructure plays a crucial role in providing essential transportation services worldwide, impacting both people and goods. Potholes, despite being seemingly insignificant, cause significant damage to vehicles and contribute to a significant number of highway fatalities. Several challenges exist when it comes to road assessments:

1. Traditional methods of manually inspecting road surfaces are labor-intensive and cannot meet the requirements of inspecting vast road networks within limited timeframes.
2. Many local administrations face financial constraints that hinder timely inspections.
3. Neglecting the repair of hazardous potholes can lead to costly lawsuits for municipalities, particularly when it poses a threat to bicyclists.

Implementing this project successfully would save time, reduce maintenance costs, and ensure safer roads for everyone. In the United States, the impact of potholes is further highlighted:

1. Approximately 24 million school children rely on 450,000 school buses for transportation, resulting in significant exposure to road conditions.
2. With 60 million annual trips, ambulances heavily rely on well-maintained roads.
3. The transportation of 32 million tons of goods daily relies on sturdy road

infrastructure.

4. Pothole damage to vehicles can amount to significant repair costs, yet 63% of Americans lack the necessary funds to cover such expenses.
5. Neglecting Road repairs ultimately incurs higher costs, with $1 of maintenance deferred resulting in $7 of expenses after five years. The cost of rebuilding an entire road is 14 times that of repairs.
6. Personal injury lawsuits due to potholes pose significant financial burdens for public and private property owners.
7. Municipalities may face multimillion-dollar lawsuits if hazardous potholes are not promptly addressed, particularly when they pose risks to bicyclists.

- **Environmental**

Environmentalists and fiscal conservatives in the United States are forming an unexpected alliance centered around the idea of prioritizing road repair over new construction. They share the belief that it is more sensible to fix deteriorating roads rather than investing in building new ones. This convergence of viewpoints on road maintenance creates peculiar political partnerships. Both fiscal conservatives and environmental conservationists advocate for addressing crumbling roads rather than pursuing new infrastructure projects. One contributing factor to this perspective is the decrease in driving habits compared to previous years.

Constructing new roads contributes significantly to carbon emissions, which can further escalate due to increased traffic. Indian Prime Minister Modi's announcement at COP26, stating that India would not aim for net-zero emissions until 2070, indicates a short-term focus on growth. Wealthier nations face challenges in arguing against India's pursuit of a world-class road network.

As a result, India is likely to emphasize the construction of new roads, while repairing existing ones may lead to increased traffic and subsequent carbon emissions.

- **Social**

The application enables continuous monitoring and timely assessment of road damage, allowing the general public to actively contribute by uploading images of any encountered road issues. Road agencies can leverage this data to develop effective maintenance strategies. Involving the public in road assessment fosters a sense of responsibility and control over the surrounding environment. The Ministry of Road Transport and Highways (MoRTH) report, "Road Accidents in India," highlights that roads with sharp curves, potholes, and steep gradients tend to be more accident-prone due to the need for skill, care, and alertness. Implementing a robust and accurate road assessment system can significantly enhance driving safety and enjoyment.

Statistics shared in the Indian parliament reveal the number of road accidents caused by potholes in recent years. In the US, approximately one-third of the 33,000 annual traffic fatalities can be attributed to poor road conditions. Enhancing the current road assessment system has the potential to save numerous lives.

Moreover, improved roads have the potential to attract more tourism, as people become more willing to visit remote and challenging-to-reach locations. This, in turn, contributes to the economic growth and development of these areas.

- **Political**

The overlooked key to China's impressive economic growth in recent decades lies in its extensive road development. China's highway network has more than tripled, expanding from approximately 50,000km in 2000 to around 160,000km by the end of 2020. This means that within a span of just two decades, China has added highways that are 20% longer than the entire US interstate highway system, constituting about 40% of the country's road infrastructure.

In comparison, India has also experienced a three-fold increase in its highway network over the same period, but the quality and scale are considerably less impressive. Indian highways are lower in quality, narrower, less well-maintained, and represent only a small fraction of the overall road system in the country.

This disparity is arguably one of the reasons why India's economy has significantly underperformed compared to China's over the past 20 years. China's GDP has grown twelve-fold, reaching a value of US$14.7 trillion (£10.8 trillion) by 2020, while India's GDP has grown six-fold, reaching US$2.6 trillion over the same period.

On the surface, India appears to have a superior road infrastructure. The cumulative road network spans 5.9 million kilometers, longer than China's 4.6 million kilometers, although slightly smaller than the US's 6.7 million kilometers. The density of India's road network, with 1.62 kilometers of roads per square kilometer of land, is much higher than that of the US (0.68) or China (0.49). However, this is not surprising considering that both the US and China are geographically three times larger than India.

Despite the seemingly extensive road network, the quality of India's road infrastructure is notably poor. Only 3% of the roads are national highways, and 75% of highways are only two-lane roads. Congestion is common, and road maintenance is underfunded. Additionally, 40% of the roads are unpaved, and over 30% of villages lack access to all-weather roads.

Various factors contribute to India's inadequate investment in road infrastructure, including insufficient funds and poor project management. A 2017 Economist article pointed to a litigious system that hampers the government's ability to acquire land and numerous stalled public-private partnerships.

India's political system is another contributing factor. Road construction is a shared responsibility between the central government and each state. The central government tends to reward states aligned with the ruling party, particularly core supporters. Furthermore, road-building necessitates coordination between states and the central government to overcome obstacles such as land acquisition, planning permission, and tender vetting, which often lead to project delays and significant cost overruns.

Therefore, by developing a system that makes road assessment more cost-effective, accessible, and user-friendly, it would be easier to address challenges such as these. Initially, the project could focus on a local level, collaborating with panchayats (village councils) and local municipal bodies. Subsequently, the project could be expanded to involve the central and state governments, facilitating more effective road infrastructure management.

- **Ethical**
  My system prioritizes user privacy and data security, ensuring that sensitive user information is not shared without their consent. The overall project is designed to keep people safety in mind my improving condition of roads and highways. The project aims to reduce incidents related to vehicle breakdown, accidents and reducing carbon footprint by improving condition of roads.
- **Health and Safety**
  The primary objective of the project is to prioritize public safety by enhancing the state of roads and highways. The project aims to minimize vehicle breakdowns, accidents, and carbon emissions by improving the overall condition of the road infrastructure.
- **Sustainability**
  The project idea is based on the fact that road assessment takes lot of time, resources and manpower. By reducing these needs my project becomes a sustainable solution to the problem of road assessment.
- **Legality**
  The system complies with all legal requirements related to data privacy, security and regulations. The project is made using datasets freely available to public.
- **Inspectability**
  The project can be expanded to have a human in loop. This means that the quality of segmentation should be monitored. The project right now exists as a minimum viable product. However, it needs to include a human element to verify the quality of segmentation and notifying machine learning engineers about the shortcomings of the model.

4.2.3 System Requirements

4.2.3.1 H/W Requirements (details about Application Specific Hardware)

It’s a web application so it requires a smartphone having camera to record videos and internet connection to upload images or videos. To train the model google colab was used. To train the deep learning model the following hardware was utilized:

- Tesla V100 16.3 GB GPU
- Intel Xeon CPY 2 GHz
- Tesla T4 15.3 GM GPU

4.2.3.2 S/W Requirements (details about Application Specific Software)

- Google Colab: The deep models were trained on google colab. Tensoflow 2.12 was used.
- Jupyter Notebook: It was used to perform testing of model, data augmentation, data splitting, data preprocessing before uploading the dataset on google drive on my personal laptop. These operations didn’t

require use of internet.
- Google Drive: It was used to store train, validation and test data. It stored the images, label masks and the best versions of models that were trained.
- Roboflow: This application was used to augment the dataset.

5 RESULT AND DISCUSSION

I trained my models in two different ways:
- Using entire dataset (No_Aug model)
- Using a subset of dataset augmented using Roboflow (Lim_DS model)

The qualitative performance of No_Aug model i.e., its prediction on a few images that I took behind my house was not good. That model was not good at predicting severe potholes. Hence, I decided to train a model on images of severe cracks and potholes only. I augmented those images with help of Roboflow.

The following metrics were calculated:
- MeanIoU (taking into account all three classes)
- cIoU (crack IoU)
- pIoU (pothole IoU)

The following datasets were evaluated:
- Validation dataset (consists of 496 images)
- Test dataset (consists of 504 images)
- Limited Validation dataset (A subset of validation dataset was selected to train the Lim_DS model)

The results are compiled in the following table along with prediction of both models on the qualitative assessment images:

5.1 Evaluation on validation, test and limited validation datasets

No_Aug Model	Validation Dataset	Test Dataset	Limited Validation Dataset
MeanIoU	0.54	0.61	0.53
cIoU	0.33	0.43	0.52
pIoU	0.31	0.44	0.10
Lim_DS Model	Validation Dataset	Test Dataset	Limited Validation Dataset
MeanIoU	0.50	0.51	0.63
cIoU	0.30	0.41	0.50
pIoU	0.22	0.19	0.41

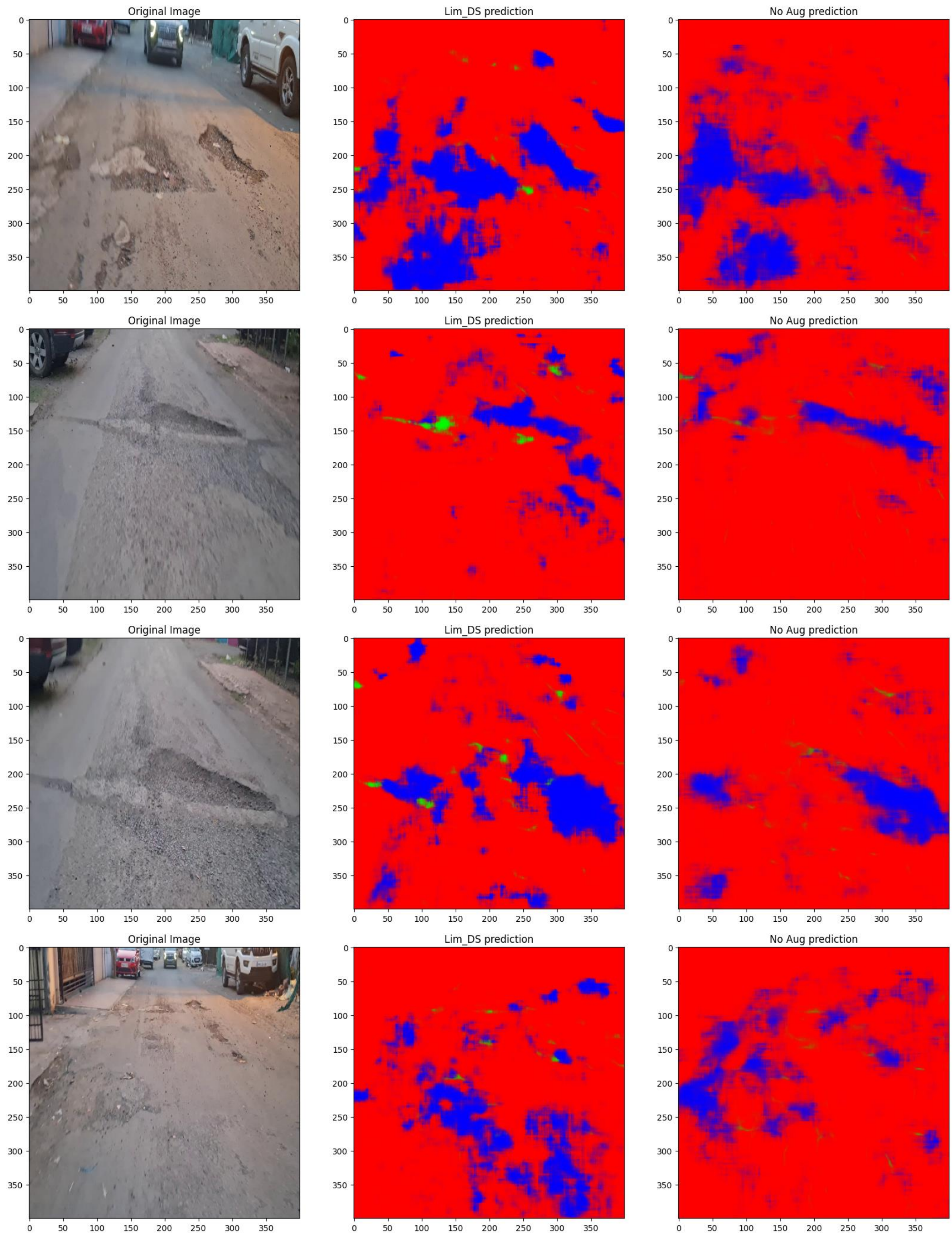

Fig 5.1 Qualitative Analysis

```
ratingOneImage(lim_ds,'/content/frame_0023.jpg')
```

```
1/1 [==============================] - 8s 8s/step
{'Crack Area': 0.11624999999999999,
 'Pothole Area': 18.619374999999998,
 'Pothole Rating': 0.5,
 'Pothole Condition': 'Poor',
 'Crack Rating': 3.0,
 'Crack Condition': 'Good',
 'Overall Rating': 1.8,
 'Overall Condition': 'Fair'}
```

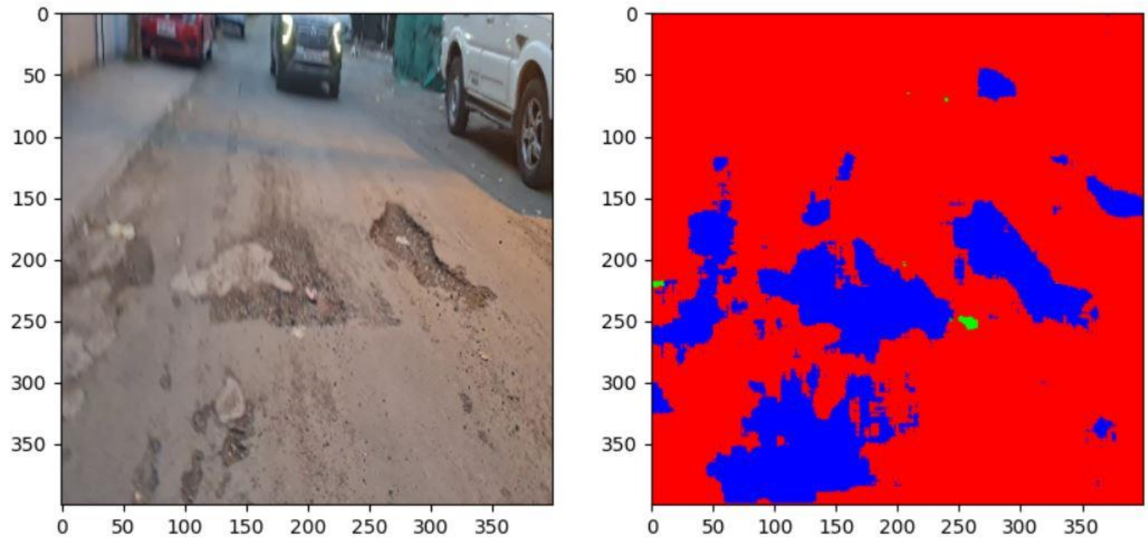

Fig 5.2 Rating of single image

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