Road Surface Assessment: Road Abnormalities Detection using Neural Networks in Dakshina Kannada Region

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Abstract:

The safety and quality of our nation's highways and roads is of utmost importance, since these networks of pavement carry more people than every other mode of modern transportation combined. Although the use of Image Processing for transportation-related maintenance and detection has grown in popularity over the past fifty years due to advances in technology, there is still room for improvement since Image Processing is not yet being used to its full potential in this industry. The purpose of this research was to deals the many applications of Image Processing to the highway and road maintenance industries. This research begins with an overview of Image Processing, then moves on to explain how it is put to use in the identification and repair of potentially dangerous road defects such potholes, cracks, and irregularities. Furthermore, the efficacy of these techniques is investigated and assessed by analysis and comparison of the available machine learning techniques, with a special focus on precision and accuracy. The findings gave cause for optimism for the application of computer vision in these areas, as it was seen as a simple and cheap solution. Each section with a unique circumstance or set of methods at hand has its own discussion and comparison of results.

Keywords: *Crack, pothole, threshold, CNN, Deep learning, precision, recall*

Introduction:

Travelling to and from different locations has been simpler in recent decades due to advancements in transportation technology. These days, we expect nothing less than the best from our modes of transportation. They are the most common and reliable mode of transportation, and they serve an important role in linking communities of all sizes and even whole nations. Since wear and tear is inevitable due to normal use and environmental factors, regular inspections and maintenance are crucial to ensuring the continued reliability of these transportation networks. These heavily used thoroughfares were built by humans and are therefore imperfect.

When roads start to show indications of wear and tear, including cracks and potholes, it might mean there is underlying pavement or structure deterioration. They are useful for gauging the health of transportation networks. Traffic delays and safety hazards can be caused by pavement flaws. Additionally, our transportation network has to be extensively upgraded so that autonomous cars may use it in the context of smart cities. Manual inspection is still widely used for road surface surveys, despite its drawbacks, which include high costs and limited efficiency. Such fissures often go unrepaired for a long period.

In the absence of regular maintenance, the roads in question may deteriorate to the point where they pose a major hazard to drivers and pedestrians. For efficient, cost-effective, and risk-free maintenance and detection of these dangers in the workplace, an automated system may be the ideal option. Accordingly, the term "Image Processing" pops into my head. Multiple scenarios involving the upkeep and detection of a road network can benefit from the application of Image Processing methods. Because of advancements in computer-vision technology, recent advances in Image Processing have made the identification and upkeep of such risks a simple and inexpensive process, requiring only a small number of workers. Since this is the case, Image

Processing is a viable option for the existing highway maintenance and danger detection responsibilities.

Road abnormalities utilising camera acquired photos is becoming more possible because to the rapid development of deep learning technologies in computer vision sector. In challenging scenarios, CNN algorithms like regions-based convolutional neural network have shown performance levels on par with those of humans. There have been attempts to use deep learning algorithms for detecting road imperfections [3, 12, and 13]. However, unlike conventional objects, road imperfections have no consistent shape and typically have very high aspect ratios, making the identification of road irregularities a highly distinct challenge.

In order to evaluate the state of the roads, this article uses a dataset culled from the Mangalore, Karnataka area following the monsoons. A regional dataset of photos of cracks, potholes, and other imperfections was compiled. The road tests yield information in the form of a collection of around 600 photos with various anomalies. To find these anomalies, a new approach is suggested that makes use of deep neural networks.

Related work:

2.1. Rule-based Techniques:

Rule-based, machine learning-based and deep learning-based methods are the three most common approaches to spotting anomalies in visual data. In rule-based approaches, anomalies in pictures are detected using a variety of filtering and image processing techniques. A strategy incorporating many methods of image processing was presented by Gavilán et al. [15]. For starters, the picture was pre-processed to bring out the linear features, and then non- irregularities feature identification was done to get rid of the potentially confounding areas like pavement seams and cracks that had been filled in. The CrackTree approach, created by Zou et al. [16], consists of three stages. By employing a geodesic-based approach, they were able to first eliminate the shadow cast by the object. In comparison with other methods already in use, theirs performed better in their article. Overall, rule-based techniques benefit from a simpler implementation and verification of performance due to the lack of an annotation or training procedure requirements. They can't account for every possible difference in real-world photos, and the methods often have limited applicability.

2.2. Machine Learning-based Techniques:

Researchers have been looking for machine learning based methods for abnormalities identification since the beginning of this decade. This is due to the complexity of pavement surface textures, variations in lighting, and the irregular forms of cracks. In contrast to more conventional rule-based methods, the anomalies that may arise during training can be taken into account implicitly by algorithms based on machine learning. To determine if a certain location has decent roads or not, support vector machines were employed. Self-organizing map, an unsupervised learning technique, was used by Mathavan et al. [19] to address picture distortions. The self-organizing map was enhanced with the ability to differentiate anomalies from the backdrop by including texture and colour features. Shi et al. [20] suggested a random structured forests-based approach for detecting road imperfections. Integral channel characteristics were incorporated in their approach to provide a more systematic means of learning the crack tokens. The tokens were then processed using a random structured forest to identify road defects.

2.3. Deep Learning-based Techniques:

In recent years, deep learning as a subfield of machine learning has garnered a lot of interest due to its impressive results in object identification and semantic segmentation [11, 21]. By 2016 [22], they were being used for the first time in a crack detecting assignment. There are two main types of deep learning-based algorithms for spotting anomalies in data: region-based and pixel-based. More than one researcher has looked into the region-based approach since it requires less processing power. In order to transfer learn from photographs of hot-mix asphalt and Portland cement concrete pavements, Gopalakrishnan et al. [24] used a pre-trained deep CNN model. Their method is able to determine whether or not a picture contains a crack. When evaluating an edge detection technique, Hoang et al. [25] compared one that was tuned for a CNN model. They demonstrated that CNN outperformed an edge detector by a wide margin. However, depending on the size of areas, the information provided by region-based approaches is limited to the occurrence of anomalies and their approximate shape and position.

There is promising early evidence that deep learning-based systems can resolve fracture identification issues on pavement surfaces. According to the author, the scarcity of high-quality, demanding datasets with comprehensive annotations is a major barrier to the rapid development of innovative algorithms. Studies [13, 23–26] and [3] used either researchers' own datasets for testing, or very basic publically accessible datasets for testing.

3. POTHOLES AND CRACK DETECTION USING IMAGE PROCESSING TECHNIQUES:

Troublesome potholes arise when regular road inspections are neglected. If they are not stopped, they can cause serious damage to vehicles and even accidents. Understanding their formation is necessary before moving on to the method of how they might be recognised via image processing. The bowl-shaped malformation known as a pothole can have internal causes like pavement deterioration from water access, exterior causes like poor manufacturing and high traffic volumes, and climatic causes like heavy rainfall [6, 7]. Here, in Figure 1, is an illustration of a crater.

These potholes are annoying since they are hard to spot when driving, as the image shows. Thus, their discovery is crucial to the procedure of upkeep and repair. However, there is a procedure involved in image processing, the first of which is picture segmentation. To begin detecting pavement deterioration, image segmentation is a necessary initial step. Multiple approaches, such as thresholding, clustering, transform, and texturing, are listed in [8] for doing picture segmentation. They go on to note that histogram-based thresholding, which works on the assumption that a picture is made of varying shades of colour and grey, is the simplest of these approaches. In Figure 1 we see a Block Diagram for locating cracks and holes.

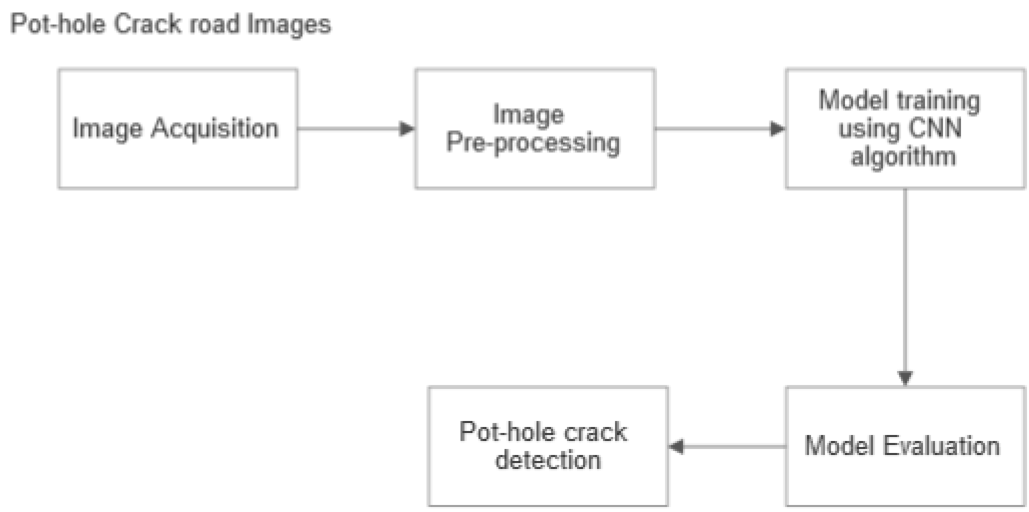


Figure 1: Block Diagram for Pot-hole and crack detection

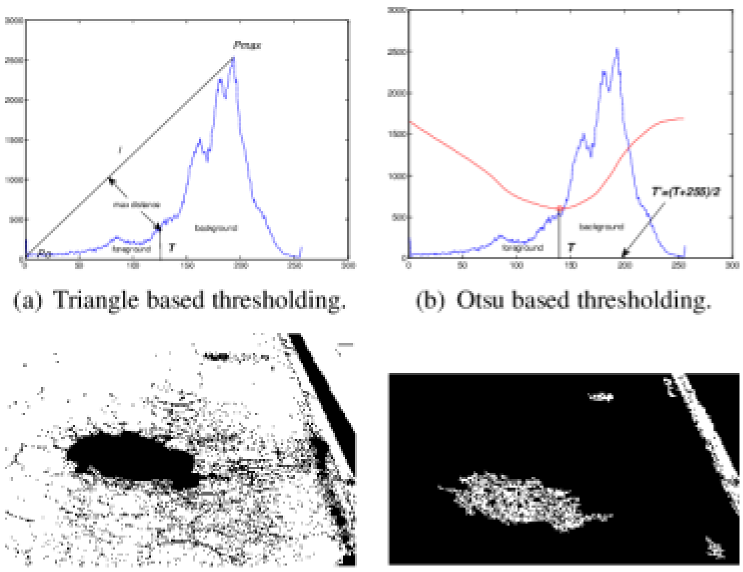
Data Acquisition: 600 images of damaged roadways make up the dataset. These photographs were taken in Mangalore, Karnataka, India, with the intention of locating road defects. The collected data set will be divided into two distinct types: training data and test data.

Image Augmentation: In order to increase the size of our data collection, we apply image augmentation. Additionally, we adjusted the images by cropping, rotating, and flipping using the image enhancement settings.

In order to locate and count these potholes, picture segmentation must first be performed. Identifying potholes can be challenging since some of them seem like fissures, have jagged edges, or are filled with water, sand, or other material that obscures their true nature. Pothole identification is a prime application of image processing, as even a straightforward approach using a regular camera and no machine learning shows encouraging results. A research done in this fashion is shown in Table 1 below; the authors of this study, [9], claim that their study demonstrates an accuracy of 85.4% and a recall of 82.65%. Their research also boasts that a single optical camera can effectively spot potholes at a range of 1-10 metres.

Figure 2: Dataset for potholes in Mangalore

These potholes are annoying since they are hard to spot when driving, as the image shows. Thus, their discovery is crucial to the procedure of upkeep and repair. A sample of the data set used to develop a pothole detection system for the Mangalore area is displayed in Figure 2. In this context, image processing becomes useful. In recent years, image processing has become a practical tool for locating these hazards. However, there is a procedure involved in image processing, the first of which is picture segmentation. To begin detecting pavement deterioration, image segmentation is a necessary initial step. They go on to note that histogram-based thresholding, which works on the assumption that a picture is made of varying shades of colour and grey, is the simplest of these approaches. Check out the comparison of two thresholding techniques applied to the same pothole image in Figure 3.



(a) Triangle based thresholding.

(b) Otsu based thresholding.

(c) The result of binary image calculated with threshold T.

(d) The result of binary image with threshold T'.

Figure 3: Two different methods image segmentation for the pothole image

Table 1: Pothole detection system accuracy matrices

True Positives	False Positives	False Negatives	Precision (%)	Recall (%)
78	18	15	85.4	82.65

Here, the efficacy of image processing for pothole identification can be seen, even with a rudimentary system including only a single optical camera. While this approach is only useful in specific scenarios, it shows promise as a straightforward and efficient technique to employ Image processing in the identification of potholes. Finally, the performance of these distinct approaches should be examined to assess the efficacy and aid in the selection of the method to be utilised in order to put all this knowledge about Image processing to use.

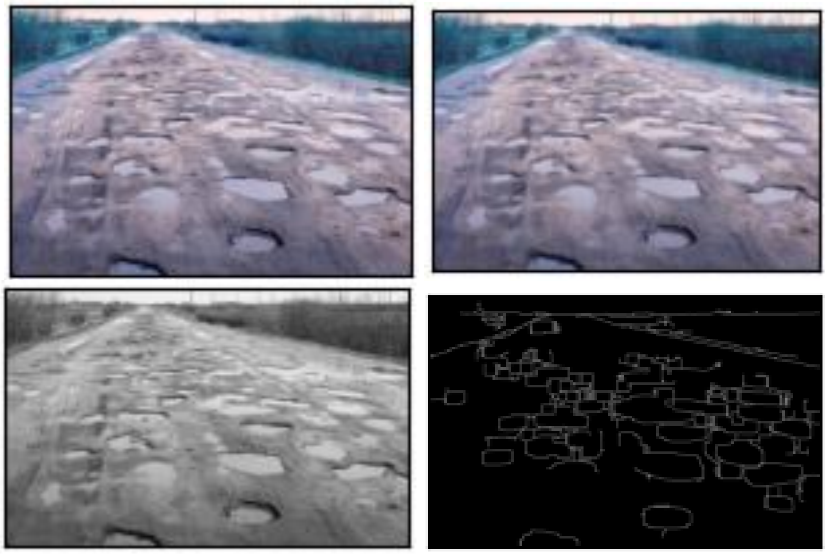


Figure 4: Potholes Detection image set 1

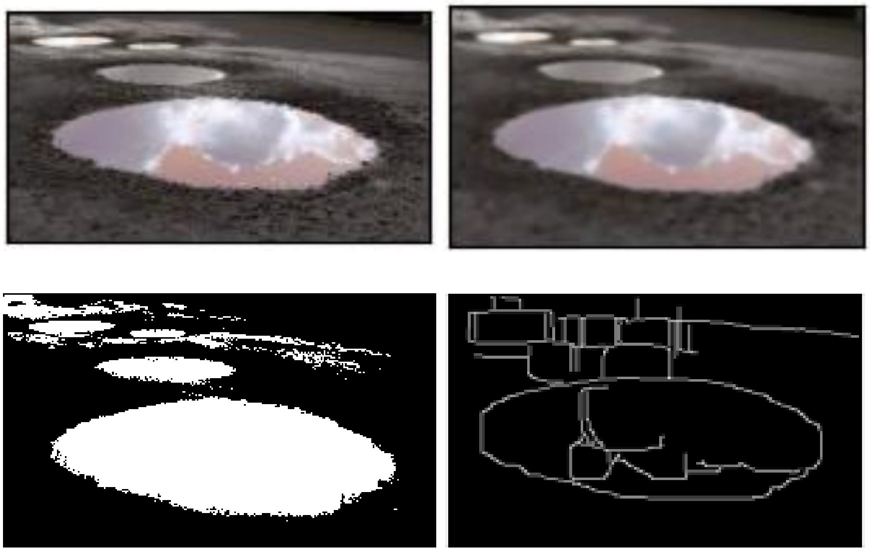


Figure 5: Potholes Detection image set 2

Table 2 below displays the findings of their investigation. [10] Justify these findings by noting that both edge segmentation and k-means perform well in single-pothole scenarios, while edge segmentation outperforms k-means in multiple-pothole detection. In addition, they note that k- means facilitates quick computations and increased sensitivity. The identification and extraction of potholes on roadways in the Mangalore region using edge detection, thresholding, and K-means approaches are depicted in Figures 4 and 5.

Table 2: Comparing performance measures

Samples	Segmentation method	Accuracy	Sensitivity	Specificity	Computation Time
55	Thresholding	72.54	68.70	71.68	1.52
55	Edge Detection	87.42	74.58	89.21	0.62
55	K-means	80.70	81.20	82.40	0.24

Ultimately, potholes are a serious problem that must be addressed, but because to advancements in image processing, we now have a variety of options for spotting them. With each passing day, we go one step closer to a world where these potholes may be spotted and avoided with the use of image processing.

3.1 PAVEMENT CRACKING DETECTION:

The predominant distress type of all pavement distress kinds is surface crack, making detection of pavement distress an important part of highway maintenance and restoration. This is why high-quality roadway maintenance necessitates crack detection [16]. Additional information from 2018 suggests that the recurring severity of cracks might create a hazardous atmosphere that can disrupt highway users was provided by [17]. Therefore, a powerful computer algorithm plays a crucial part in the development of analytical tools for the automated identification of cracks. It has taken a lot of time and effort, as reported by [18], to develop standards for evaluating pavement conditions consistently. The supervisor is also put in danger by the inherent hazards of working on roadways. Based on the findings, it makes perfect sense to employ automated procedures employing computer vision and image processing technology. In recent years, crack detection has seen a surge in the use of digital image processing. Many different methods exist for using image processing to spot pavement damage.

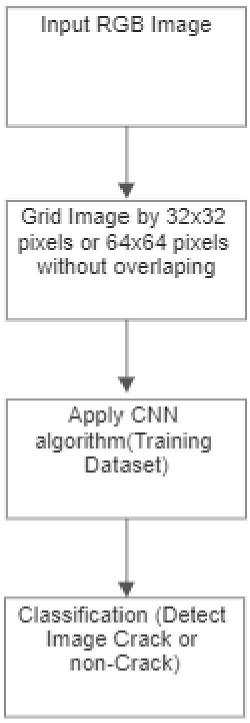


Figure 6: Procedure for Crack detection

Digital image processing methods were used to identify the presence of various fractures in the pavement surface after thresholds and noise had been removed from the photos. Additionally, a neural network pattern recognition algorithm was specifically created to take into account the angle and length of the cracks, so that this information could be captured automatically.

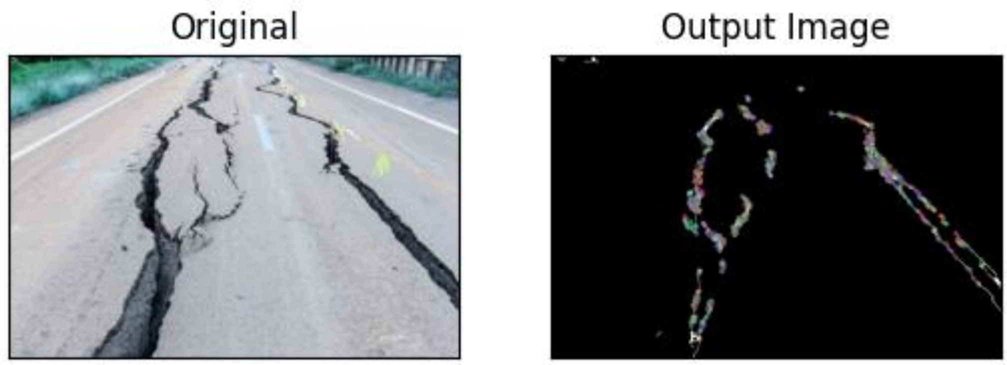


Figure 7: Crack Detection

Crack extraction using a Neural Network has been tried and tested with positive results. Many different designs and depths of concealment were tested. The results demonstrated that a combination of image processing techniques and a neural network successfully identified pavement fractures. Road crack identification and extraction is seen in Figure 7.

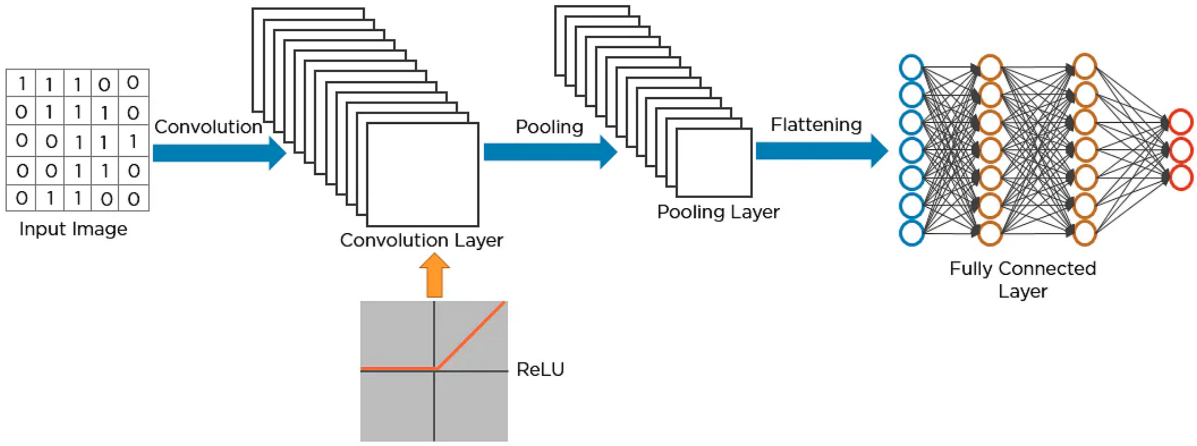


Figure 8: Architecture of CNN

Figure 8 depicts the suggested CNN architecture. As a means of detection, it devised a deep convolutional neural network (CNN). Digital photography was utilised to record the pavement fracture. The digital camera's raw data is then sliced into 32x32 and 64x64 grids, respectively, and fed into the initial stage of a deep convolution neural network. The importance of a convolutional neural network (CNN) in fracture identification on asphalt pavement can be demonstrated in all of the illustrative instances.

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288/626 [============>................] - ETA: 0s - loss: 0.1919 - accuracy: 0.9201
320/626 [==============>..............] - ETA: 0s - loss: 0.1890 - accuracy: 0.9219
352/626 [===============>.............] - ETA: 0s - loss: 0.1934 - accuracy: 0.9176
384/626 [=================>...........] - ETA: 0s - loss: 0.1965 - accuracy: 0.9115
416/626 [==================>..........] - ETA: 0s - loss: 0.1967 - accuracy: 0.9111
448/626 [====================>.........] - ETA: 0s - loss: 0.1929 - accuracy: 0.9129
480/626 [======================>.......] - ETA: 0s - loss: 0.2122 - accuracy: 0.9042
512/626 [=======================>......] - ETA: 0s - loss: 0.2159 - accuracy: 0.9023
544/626 [=========================>....] - ETA: 0s - loss: 0.2122 - accuracy: 0.9062
576/626 [==========================>...] - ETA: 0s - loss: 0.2124 - accuracy: 0.9045
608/626 [============================>.] - ETA: 0s - loss: 0.2278 - accuracy: 0.8997
626/626 [==============================] - 1s 2ms/step - loss: 0.2435 - accuracy: 0.8946 - val_loss: 0.5078 - val_accuracy: 0.7857
```

Figure 9: Model training with 15 epochs

Thus, it is crucial for image processing to put emphasis on convolution neural network. Methods for crack identification and classification are described in [17], which includes gathering relevant images, labelling them, processing them with deep convolutional neural networks (CNNs), and finally classifying them. The training of the suggested model is depicted in Figure 9. After receiving a raw picture as input, images are gridding by 32x32 pixels or 64x64 pixels without overlap, the CNN process operates, the image is detected as a crack or non-crack, and the procedure concludes with the calculation of the network [17]. Check out Figure 6 to view the schematic.

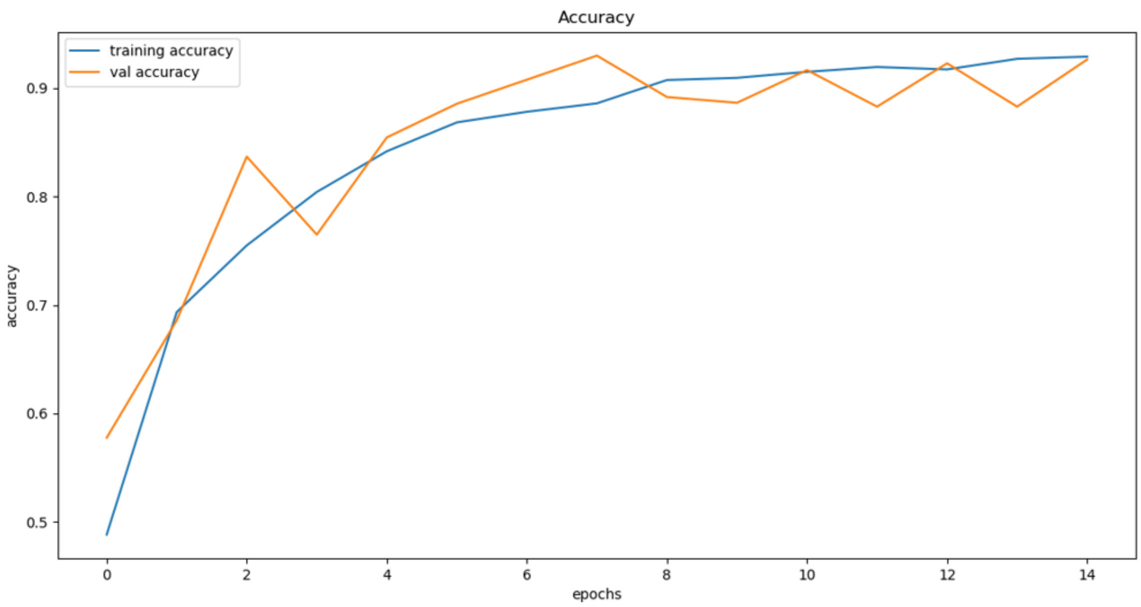

Figure 10: Proposed Model Accuracy Plot for 15 epochs

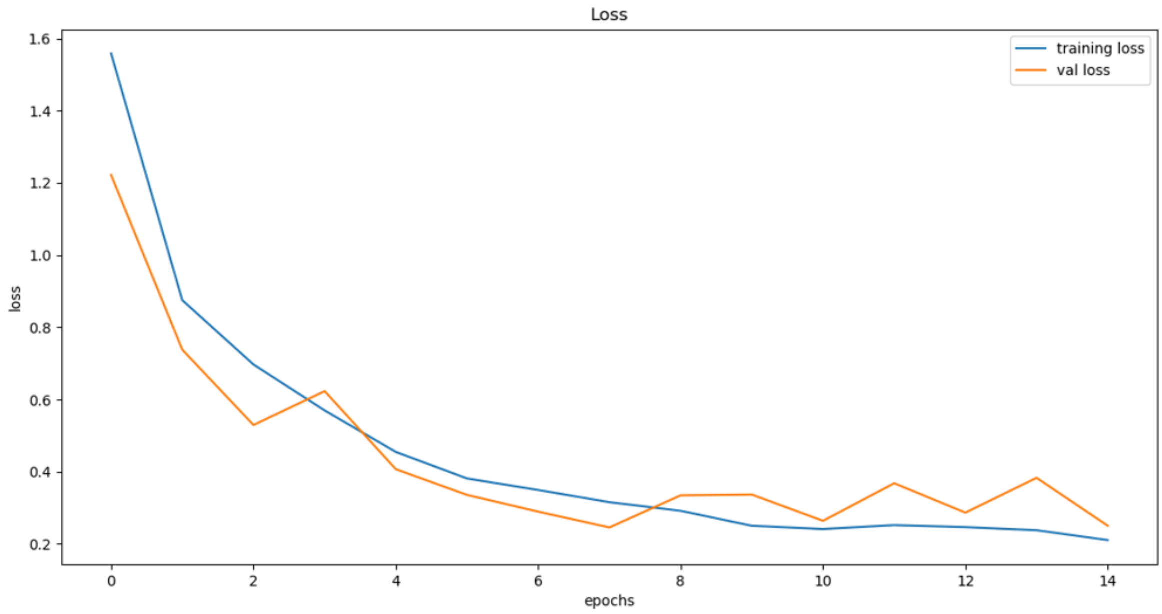

Figure 11: Proposed Model loss graph for 15 epochs

Precision and accuracy percentages provide further insight into the experimental findings of the investigations. According to [17], the accuracy and precision for 32x32 pixels is 96.70% and 96.10%, respectively, whereas for 64x64 pixels, these values drop to 90.30% and 91.50%, respectively. See Table 3 for the data. The accuracy and loss graphs after 15 epochs of training are displayed in Figure 10 and Figure 11, respectively.

Table 3: Accuracies of different pixel grid images

Grid Image	Recall	Precision	Accuracy
32x32	95.42	96.70	96.10
64x64	90.30	92.80	91.50

Table 4: Proposed model matrix

Parameter	Result %
Sensitivity	92.54
Specificity	86.20

Accuracy	88.90
Precision	90.52

According to Table 4, the findings of the investigations appear to be promising. The research' results are comparable despite the fact that they collect raw photos in a variety of ways, such as using digital cameras and other hand-held devices. The distance between the cameras and the asphalt surface is a potential point of criticism for the two outcomes above.

Thus, the research employ slightly diverse approaches to their work, but they all share the use of a convolution neural network (CNN), which is central to the studies' respective approaches and yields effective outcomes.

Conclusion:

Roadway roughness is really bad situation that a transportation engineer can face, and tests of roughness are hard in old-fashioned way. However, new applications are showing up to ease the job of engineer and to increase accuracy. For example, straight edge measurement is an old-fashioned method which is done with less accuracy since it is done by human eye but not with technology. On the other, hand in both application reports, it was mentioned that these methods were cheaper than other ways. Another thing to consider in this is how these methods help prior detection of these defects could contribute significantly to reducing road accidents. From the applications, it can be observed that computer vision with deep learning is applicable in real-life scenarios. Both applications give an applicable solution which shows that these image processing methods were ready to use if substructure is ready.

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