Road Crack Detection and Segmentation Using Two-phase Convolutional Neural Network

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CANDIDATE DECLARATION

I JAYA GPUTA hereby certify that the work which is being presented in the thesis entitled **Road Crack Detection and Segmentation Using Two-phase Convolutional Neural Network** in partial fulfillment of the requirements for the award of the Degree of Master of Technology submitted in the Department of Software Engineering, Delhi Technological University in an authentic record of my work carried out during the period from August 2022 to May 2024 under the supervision of Dr. Abhilasha Sharma.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

Jaya Gupta

This is to certify that the student has incorporated all the corrections suggested by the examiner in the thesis and the statement made by the candidate is correct to the best of our knowledge.

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iv

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CERTIFICATE BY THE SUPERVISOR

I hereby certify that **Jaya Gupta (Roll no 2K22/DSC/07)** has carried out their research work presented in this thesis entitled **"Road Crack Detection and Segmentation using Two-phase Convolutional Neural Network"** for the award of **Master of Technology** from the Department of Data Science, Delhi Technological University, Delhi under my supervision. The thesis embodies results of original work, and studies are carried out by the student herself and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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Road Crack Detection and Segmentation using Two-phase Convolutional Neural Network
Jaya Gupta

ABSTRACT

With the extensive development in the infrastructures, road crack maintenance has become a critical issue in our day-to-day life. Specially, in concrete-structured constructions like roads, monuments, and bridges, cracking is a typical issue. Letting it to grow will increase the danger of accidents and cause considerable financial losses. numerous methods have been developed in these directions (road crack detection and segmentation) but there isn't a proven technique for dealing with noisy, poor-quality real-world road crack photos. In this research paper a deep-learning based method has been proposed namely, Two-phase Convolutional Neural Network at pixel-level for road crack detection and segmentation. The first phase aids to remove noise and separate the small cracks whereas second phase labels the crack detected area and learn the actual context of crack. Hence, it shows higher impact on learning over the original noise image. The experiments have been performed done on two-publicly accessible benchmarks i.e., CFD dataset and Crack500 dataset. There are many methods and algorithms that are satisfactory in pavement crack applications, but there is no standard until today. Therefore, in order to know the developing history and the advanced research, we have collected a number of literatures in this research topic for summarizing the research artwork status, and giving a review of the pavement crack image acquisition methods and 2D crack extraction algorithms. The results on these datasets demonstrates that the two-phase CNN method outperform better results as compared to existing approaches, particularly for noisy and imbalanced datasets. Our analysis gives the precision of about 97.82% for the crack image detection and in pixel-level segmentation accuracy comes out to be approx. 95.40%.

Keywords: CNN, RNN, DNN, RMDL, DLR

TABLE OF CONTENT

LIST OF TABLE(S)

LIST OF FIGURE(S)

LIST OF ABBREVIATION(S)

NLP	Natural Language Processing
RNN	Recurrent Neural Network
CNN	Convolutional Neural Network
SVM	Support Vector Machine
AI	Artificial Intelligence
ML	Machine Learning
DNN	Deep Neural Network
RMS	Root Mean Square
DL	Deep Learning
GPU	Graphics Processing Unit
MLP	Multilayer Perceptron
Re-LU	Rectified Linear Unit
GRU	Gated Recurrent Unit
LSTM	Long Short-Term Memory

CHAPTER 1

INTRODUCTION

This research work addresses the usages of various deep learning models in the surface pavement Crack Identification, Detection and Segmentation. Also, emphasis on findings of our research emphasize the value of multi-model fusion and imply that integrating several learning modalities can have positive effects in the computer vision.

1.1 BACKGROUND

Retrieving Pavement cracks are a prevalent and common form of road damage. Infrastructure such as, bridges, street organizations, extensions, highways, and dams, are the general public pavements in which cracks may occur. The timely repairing of these cracks requires an accurate method of their early detection. Due to the complex qualities of cracks' images such as multi-surface, multi-objective, contrast, brightening changeability, colour cluttering etc., it becomes a difficult task to recognize them in pavement images. Maintenance tasks for roads crack include a visual examination and evaluation of its state to guarantee their serviceable and actual uprightness of sample images. Crack detection is an extremely laborious work whenever conducted through manual visual examination. This may lead to bring situations where cracks remain undetected. Therefore, the need arises for execution of crack detection in foundation to guarantee its viability and unwavering quality. Even a small harm might show up as minor or significant cracks, presents bit by bit spreading which leads to extreme breakdown of the construction. Road construction constitutes the main proposals for pavement maintenance. Cracks may also exist in other artificial and natural things like dams, metal surfaces, bones, and so on. Over a period of time, crack extension prompts critical decay in road structure and its function [1]. Since the cracks and their surrounding region are brittle, it is possible for holes to get form in certain circumstances within the pavement. The more confusing features of the road are shadows on pavement created via shrubs, pedestrians or a few fake items on the sides of the road. Nowadays, image-based approaches are in trend for the detection of cracks even for small patches. These strategies include capturing the sample images of target area, detecting it automatically and classify the types of cracks. These techniques are very quick, affordable, and robust in nature and are categorized in two types i.e., image-processing techniques. The image processing strategies don't need a model training procedure but consist of various channels uses, morphological classification and its strategies, and a proper detection technique for cracks [2,3]. Figure 1 depicts the overall outline for crack detection & its segmentation on any pavement i.e., the essential design of an image processing-based strategy for crack recognition.

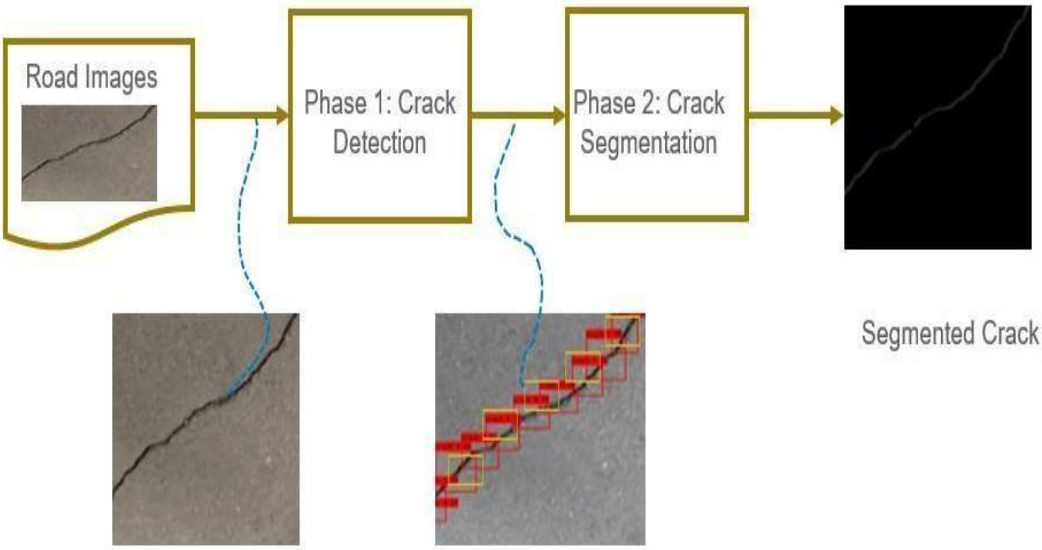


Fig.1.1 Outline Diagram for Pavement Crack Detection and its Segmentation.

On additional side, machine learning (ML) methods incorporate a variety of dataset samples that are given to the selected ML approaches for training. Previously, different ML approaches like support vector machines (SVM) model, convolutional neural network (CNN), which have utilized for surface crack detection [4]. After forming the loss optimization function, the next way to diminish the loss during model training. One effective approach is to utilize a weighted cross-entropy loss function [5][7-8]. With the extensive use of cameras and cell-phones, image-based methods are thought to be more economical [9]. Deep-learning is the actually subset of artificial intelligence and machine learning where neural NN layers are utilized for the extraction of feature and the framework talks about the relevance of feature [10]. The epoch of big data has been ushered by advancements in digital technology and its significant usages over internet, and thereby accelerating the progress in deep learning [12]. Hence NN can directly learn about the sample images and easily reconstruct the segmented sample images [13]. A CNN is the subset for an ANN that utilizes the applications deep learning [14]. It comprises of input layer (IL), hidden layers

(HL) and output layer (OL) and fully connected (FC) layers. The FC layers in CNN are swapped out for partly associated convolutional layers followed by pooling layer, which is identified by bias weight allocation and sparse associates. Since it is simpler than a traditional neural network, a CNN uses fewer training restrictions and uses less computation. The author Cha et. al. [15] introduced a recognition technique employs on the Faster Region Convolutional Neural Network (Faster-RCNN) to differentiate between specific types of pavement damage with accuracy rate approx. of 87.8%. As compared to a traditional convolutional neural network, the proposed model can detect the crack more rapidly. Using Faster RCNN, Song et. al. [16] implemented an approach for identifying pavement damage. In finding cracks, a faster RCNN outperformed a CNN and a K-value model. On the basis of YOLO v2, Mandal et al. [18] worked on an automated pavement detection network system. This system is capable of spotting corruption and other cracks having F1 score around 87.8%. Tong et al. [19] created a technique to automatically calculate pavement crack length using a DeepCNN with an accuracy of 94.36%, demonstrating the effectiveness of a training method that combine two techniques: orthogonal coding with stochastic gradient descent. A very precise automatic feature categorization technique was created by Li et al. [20] utilizing a CNN to convert 3D road surface photos into small image blocks and achieved a higher F1 score.

(a) Crack images (b) No-crack images

Fig.1.2 Example of Crack and Non-Crack Images

1.2 OBJECTIVE

Road crack detection is one of the challenging problems that has examined by various researchers for years. Solutions focusing on top view surfaces are widely explored in research and dominate the market. Nevertheless, an ideal method applicable to any imaging system has not yet been identified. Thus, this thesis aims to devise an effective technique for detecting surface cracks in complete road scene inventory images. The objective of detecting cracks in images containing multiple obstacles is quite ambitious, yet achievable in many instances. The initial challenges include eliminating grass fields and sidewalks. Additionally, shadows on the surface pose a significant obstacle by hindering clear vision.

In conclusion, numerous objects on the surface road, including pedestrians, spare cones, signs, branches, puddles, and oil spills, complicate crack detection due to the presence of dark pixels that computers might erroneously interpret as cracks. Taking all these disruptive elements into account, it is evident that devising a perfect detection method without any manual input is an extremely challenging task. Therefore, a combined solution from a different perspective is proposed. By developing a method that can accurately pinpoint perfect surface areas, the amount of data needing manual inspection could be significantly reduced. This approach aims to streamline the detection process and minimize manual effort. The more the data is reduced, the more human work hours can be saved. Consequently, the key objective of this thesis is to detect pavement areas without any distress, thereby minimizing the total volume of image data that requires inspection. Furthermore, the thesis aims to evaluate the accuracy of classifying undamaged road surfaces. Every year, advancements in computer analysis leads to increasingly sophisticated solutions for crack detection. While traditional step-by-step algorithms heavily depend on chosen methods and coefficients, an alternative approach may exist—one that analyzes entire images without specific instructions. It is within this context that the two methods utilized in the thesis have been developed. The first method takes a more traditional route, employing precisely defined clipping functions with identifiable detection limits. In contrast, the second method explores a less constrained recognition approach, leveraging large labeled datasets conducive to learning from acquired information, a technique known as deep learning.

1.3 PROBLEM STATEMENT

- Description:

In today's interconnected world, geographical regions spanning areas are linked by various modes of transportation, including all transportations such as air, trains, buses, public transports, metros, and roads. Among these, road transportation stands out and most cost-effective means of connecting origin and destination points. However, the constant use of roads, coupled with factors like hefty snowfall, poor drainage, and the passage of heavy vehicles, can lead to surface degradation and the formation of cracks.

Crack detection entails identifying cracks in road surfaces using a range of processing approaches. By employing visual examination and surveying tools, deficiencies in surface conditions can be assessed. Automated crack detection on roads offers advantages over manual inspection, allowing more efficient and precise identification of road defects.

- Challenges:

1. Traditional low-level image processing techniques are vulnerable to difference changes and may struggle to detect cracks under conditions of low illumination or when cracks are speedily varying objects.
2. Only a few of algorithms are currently accessible for detecting cracks in road images or videos.
3. While the current focus of the project revolves around analyzing recorded videos of roads or surfaces, the transition to real-time crack detection for Autonomous Driving would necessitate further steps. This could entail the development of a mobile application or the deployment of dedicated hardware devices to facilitate on-the-go detection.
4. Limited dataset availability: Should this project struggle to locate a suitably extensive dataset for crack detection, it will be essential to generate its private dataset comprising images of surfaces.

- Scope:

  Road crack detection has extensive applications in identifying deviations from typical road and surface patterns, facilitating timely interventions. Some crucial field where road cracks can be beneficial include:

1. Road examination.
2. Status of roads in unfavourable weather conditions in heavy rain etc.
3. To evaluate the expanse of damage of roads when natural calamities occur such as earthquake, Tsunami.

4. Length, width and direction of the cracks on the roads.
5. Crack detection for autonomous driving cars.
6. Lane Detection, Traffic Light Pole Detection, Buildings, number of adjacent moving cars and distance between adjacent moving vehicles etc. for Autonomous Driving Cars.

1.4 MOTIVATION

Based on a deep learning methodology, two-phase of this task are completed in a single outline. For unbalanced datasets based on pavement crack in which the proportion of crack surface pixels samples is inferior to non-crack surface pixels samples, enhancing the proposed model performs better.

The major contributions are as follows:

- To detect cracks from sample images and then segment the detected images at pixel-level for noisy and unbalanced datasets. Hence, introduces a two-phase architecture based on CNN i.e., detection phase and segmentation phase.
- To compare with the various model's performance for a prior detection and segmentation strategy; The proposed model generates better results.
- To works upon on the standard pavement crack datasets based on road i.e., CFD Dataset [34] and Crack500 Dataset [33] which gives a better result as compared to some existing approaches.

1.5 THESIS ORGANIZATION

The chapter 1 offerings background statistics and road surface detection valuation and road crack evaluation, and find out the objectives of researches. The chapter 2 gives the details of literature survey of recent practices and prevailing revisions. The chapter 3 gives fundamentals of basics approaches of deep learning, followed by the proposed methodology in Chapter 4. The chapter 5 gives the details of datasets used for crack detection. Chapter 6 discuss about the experiential results and analysis. Finally, the chapter 7 discuss about the conclusion with future scope followed by references.

CHAPTER 2

LITERATURE SURVEY

Pavement image detecting technique is more effective and valuable than earlier image-based acquisition techniques and current 3D laser scanning techniques. A number of improved crack-intended connection and recovery technique have also surfaced, and effectively improving the cracks' ability to be detected. Previously, the crack detection technology can be classified into three basic phases:

(i) traditional manual crack detection,
(ii) semi-automated crack detection,
(iii) automatic crack detection.

2.1 RELATED WORK

The traditional manual detection approach indicates a detection technique that only makes use of manual data collection, artificial measurement, and subjective mode for evaluation; the semi-automatic crack detection uses an image sample capture device to preserve the obtained data on equipment such as tape or hard discs. In this, some operators are used which manually marks, assesses, and detect the crack region within the sample image; automatic crack detection uses the image processing approaches as well as the semi-automation technique to analyse and identify the crack. The traditional manual crack detection approaches depend on manual work and hence have some drawbacks like influencing traffic, high cost and low efficiency, unsafety which have the potential to be dangerous; and deprived accuracy or stability. The semi-automatic crack detection focusing to ensure the speed and exactness within the pavement road crack detection. This method significantly enhances work effectiveness and automation levels. It is cost-effective, protected, robust, and good for data storage and analysis. It also helps in shaping a steady and occasional location framework, which causes the crack recognition innovation to turn into an unavoidable consequence of the improvement of present-day identification innovation. Due to the digitization and advancements in technologies it's conceivable to make an automatic system for crack detection. In order to gather pavement photos in real-time, the majority of pavement disease detection systems in todays' market deploy charged coupled device cameras in road crack detection. Recently, the pavement crack detection has been improved, in terms of intelligence and automation, and also succeeding in its related algorithms. Other methods such as neural networks, wavelet transforms, logical and multi-regression, deep learning, and others are also being explored for surface road crack detections. The technology is more developed as a outcome of the expanded uses of road crack detection with its recognition algorithms. Author Shi et al. [23] introduced a process of reconstructing crack formation utilizing integral channel parameters. Mokhtari et al. [24] worked on supervised classification technique for the identification of surface fractures in the same year. Cubero-Fernandez et al. [25] implemented an improved method which prior to extracting cracks and classifying them. The accuracy of crack extraction was 88%, and the accuracy of classification was 80%. Recently for measuring enormous objects, 3D laser scanning approaches has been used in road detection. A 3D laser scanner was employed by Barbarella et al. [26] for stiff airport pavement maintenance. Research on 3D laser profiling technology for automatic pavement flaw detection was conducted by Zhang et al. [27]. 3D laser scanners were used by Tang et al. [28] to find flatness issues on concrete surfaces. Surface roughness characterization using 3D laser imaging was carried out by Mah et al. [29]. Kim et al. [30] worked to locate and count concrete spalling problems on terrestrial algorithm of laser scanning. 3-D laser scanning technology can instantly identify the cracks in 3-dimensional without the impact of illumination or shadow occlusion. It can increase detection accuracy and speed in comparison to existing technologies. The pavement damage image recognition technology will be significantly impacted by deep learning technology. In the research of image recognition in computer vision in deep convolution neural networks (DCNN) and convolutional neural networks (CNN) become the primary tool. In this view, figure 2.1 illustrating the three types of pavements which are primarily focused on this report.

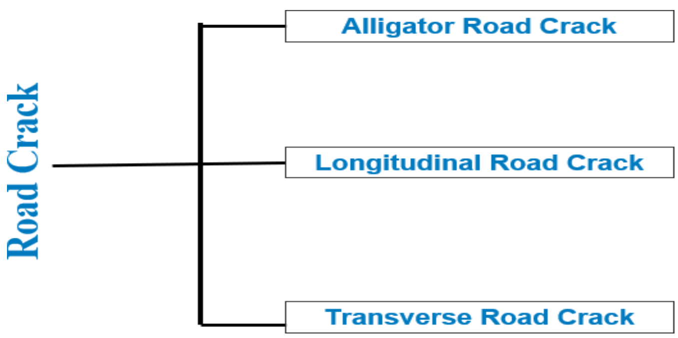


Fig.2.1 Pavement Crack Detection Types

Lins et al. [31] provides the research content on the subject of digital image processing of pavement cracks. They worked on pavement maintenance, monitoring, and crack detection, the furthermost significant index to gauge pavement quality. When it comes to maintenance and management, early crack detection and real-world monitoring permits for timely analysis and restoration, extending the pavements' life and improving its bearing ability along with significant lowering of vehicle fuel consumption and maintenance costs which in turns increases road safety and successfully offer protection for private safety. However, the crack detection and segmentation approaches are still in developing stage specially at pixel level images.

In transport intelligent system, the optical high speed imaging devices are used and positioned at the bottom and at the back of vehicle, which is used to captured images of the road. The images serve as a significant constituent of the image acquisition module that is specifically designed for acquiring crack images. Imaging equipment will be created by a positioning system made up of multiple sensors like global positioning system, pavement road detector, a communication coordination system, and so on. The captured images are sent and then stored in the appropriate storage device like hard drives, tapes, etc. The central component of the entire system is the image processing module, which also does crack extraction and image enhancement for pre-processing. Removal of background noise and crack information processing are the two examples of image enhancement. Image enhancement is the preliminary and crucial task of crack detection since it is tough to directly recognize and extract cracks from images owing to illumination, imaging equipment, features, and the three-dimensional characteristics of the road pavement itself. The pavement detection and its segmentation basically consist of feature extraction and feature morphological analysis. It gives the better accuracy for crack sample images to be detected, and will further help in classification. Table 1 shows the taxonomy of all related worked based on pavement detection and segmentation.

Table 2.1. Taxonomy for Pavement Detection and Segmentation

Author, Year	**Methods**	**Feature**	**Disadvantages**	**Result**		
				Preci--sion	**Re-call**	**F1-score**
Liu et. al.,	Gabor-Filter Method	Crack Detection	Results presented	95%	82.8%	92.90 %

2009			on 5 images only			
Fujita et. al., 2011	AS Operator	Crack Detection & measurement	Without GPS and in a windy environment, UAS are instable.	95.2 %	82.8%	93.70 %
D. Dhital et. al., 2011	FCN	Crack Detection & density assessment	Noise-induced degradation of crack density assessment performance	89.30%	88.7%	89.30 %
Zou. et. al., 2012	Recursive Tree-edge pruning	Crack Detection	extended runtime of 30s	79%	92%	85%
Landstrom et. al., 2012	FPHBN	Crack Detection	Method is not real time	81.0 %	77.2%	79.8%
Baohua Shan, 2015	K-means clustering, Gaussian Methods	Crack Detection, & Characterization & severity assessment	less efficient detection of minor cracks such as 2 mm	96.5 %	96.3%	97%
Koch et. al., 2015	CNN	Crack Detection	does not effectively address stone image cracks			87%
Shi et. al., 2016	Beamlet Transform Method	Crack Detection, Crack measurement & Classification	Crack width cannot be calculated, and manual threshold setting inhibits complete automation.	92.9 %	90.2%	89.9%

Arun Mohan et. al., 2017	Google-Net CNN, FPN	Crack Detection	16 seconds are required to locate cracks in a 6000 x 4000-pixel image.	80.13%	86.09%	81.55%
Feng et. al., 2017	CNN	Crack Detection	Results subject to location variance	91.3%	92.8%	90.9%
Olson et. al., 2018	Random Structured Forests, SVM	Crack Detection & Characterization	Unmeasured crack width; no video testing	96.73%		
Lei et. al., 2018	NB-CNN	Crack Detection	a huge number of training images are necessary; overfitting must be avoided; dependence on GPU	96.8%		
Yang et al., 2019	Shi-Tomasi feature point detection	Crack Detection	A noise-limited camera resolution reduces accuracy			
Sari et. al., 2019	CNN	Crack Detection	Reduced accuracy in finding hairline cracks	90.13%	87.63%	88.86%
Zhou et. al., 2021	Canny algorithm, heuristic decision-tree	Crack Detection & classification	Not tested in real-time	88%	89.3%	87.6%
Wu et al.,	Morphological analysis,	Crack Detection &	Setting parameters is necessary for	Accuracy >		

2021	segmentation,	Classification	images with various resolutions.	90%		
Duo Ma et al., 2022	CNN with multiple feature-layers	Crack Detection		Accuracy =98.217 %		

Problems with asphalt pavement have become a big worry for government bodies that want to keep bad things from happening. Pavements get cracks and holes because of things like bad draining, bad weather, old age, and using low-quality building materials. Potholes are depressions in the road surface that are concave. They need to be fixed because they cause big problems like crashes, bad driving experiences, and car problems. It is important to quickly fill in holes to lessen the damage they can cause [3].

By 2030, the World Health Organization (WHO) says that car crashes will have killed more people than any other cause. Potholes interested people who study civil engineering. Manual checking methods for finding potholes in developing countries are often wrong because they depend so much on personal experience. These manual testing methods need a lot of time and money-consuming human help to be carried out. Potholes can be found using a variety of technologies, such as thermal imaging, computer vision, 3D reconstruction scans, and technologies that use vibration sensors [4].

A system of cameras on public transit buses, called "BusNet," would be used to keep an eye on traffic. Different GPS systems and cheap, quick, and accurate sensors are used. Bad weather could damage the sensor and make BusNet less effective, which makes this way less than ideal. The popularity of computer vision and image processing techniques has grown because more low-cost cameras can quickly find potholes instead of people, which takes a lot of time. Image processing has a hard time finding potholes because of things like different textures, structures, road flaws, manholes, and shadows. In this area, different computer vision methods have been looked at to find and classify craters. Using image processing methods, the researchers came up with an idea for a system that can find errors and rate how bad they are without breaking the bank.

The research presented that the automated technique was more accurate than the manual technique, with an 88.4% success rate [5]. A lightweight camera is suggested as a way to reduce shadow effects. This is an effective answer that doesn't require committee participation. It's not just potholes that can cause discoloration; road signs, shadows, wet roads, manholes, and other things can do it too. With this method, 120 shots of pavement were analyzed in MATLAB. With an accuracy of 86.7%, a precision of 83.3%, and a memory of 87.5%, the method was thought to work. 88.6% of the pavement pothole pictures found match the extracted pothole region, which means that about 85% of them are the same [6].

Oliveira's (2013) research has yielded a comprehensive system utilizing automated techniques for identifying and characterizing fractures in road surfaces. A significant advancement of this approach is the elimination of the need for manually labeled samples.

2.2 Summary

The literature review culminations that previous automatic crack classification methods may not presently aid agencies in conducting pavement surface condition surveys. Key areas of concern identified include:

- Most existing literature simplifies crack types into categories such as longitudinal, transverse, block, and alligator cracking. However, agencies typically utilize more detailed definitions of crack types and severity levels for tasks like pavement performance monitoring, maintenance prioritization, and treatment method selection.

- The definitions of cracks vary widely among different protocols, yet state agencies are often required to adhere to multiple protocols simultaneously. For example, while the Georgia Department of Transportation conducts its pavement condition surveys following the PACES protocol for pavement management. Therefore, an ideal automatic crack classification method should be adaptable to different protocols with minimal modification effort to meet these diverse requirements.

- The majority of existing literature investigates similar crack characteristics, primarily centered on crack orientation and the number of crack pixels. However, these features alone are insufficient to support real-world crack definitions. Previous reviews have highlighted that crack type and severity level definitions involve multiple factors, including crack location, length, width, orientation, intersections, and polygons. There is a critical need to develop an automatic methodology that systematically and comprehensively extracts these crack characteristics, aiming to replicate human perception in the field.

CHAPTER 3

FUNDAMENTALS OF DEEP LEARNING

Nowadays, image-based approaches are in trend for the detection of cracks even for small patches. These strategies include capturing the sample images of target area, detecting it automatically and classify the types of cracks. These techniques are very quick, affordable, and robust in nature and are categorized in two types i.e., image-processing techniques and deep-learning techniques. The image processing strategies don't need a model training procedure but consist of various channels uses, morphological classification and its strategies, and a proper detection technique for cracks [2,3].

3.1 Convolutional Neural Network

A CNN is a generous of deep neural network [46] which is frequently incorporated in CV [47] tasks such as image and video validation. It is a specialized NN [46] architecture that is considered to manage data such as figures, by performing a series of convolutional and pooling operations. The main building blocks of a CNN are convolutional level, pooling level, and fully connected level. Convolutional layers are obliged to isolate features from input data by enforcing a series of filters that slide over the input data and output a set of feature maps. Pooling layers are used to downsample the feature maps and diminish the spatial dimensionality of the data. Fully connected layers are utilized to classify the input data based on the extracted features. During training, the weights of the filters in the convolutional layers are adjusted through backpropagation, which is a pro- cess that involves computing the gradient of the loss function in reference to the network parameters and updating them accordingly. This process is repeated over many iterations until the network learns to recognize patterns in the input data and produce accurate pre- dictions. CNNs have achieved advanced performance on a varied range of CV [47] tasks, including object detection, image classification, and semantic segmentation. They are also commonly used in other domains such as NLP [48] and speech recognition [49], where the input data can be represented as a grid-like structure.

On the additional side, machine learning (ML) approaches incorporate a variety of dataset samples that are given to the selected ML approaches for training.

Previously, different ML approaches such as SVM, CNN, have been utilized for crack detection [4]. With the extensive use of cameras and cell-phones, image-based methods are thought to be more economical [9]. Deep learning (DL) is the subset of ML where neural network layers are utilized for the extraction of feature and the framework talks about the relevance of feature [10]. The epoch of big data has been ushered by advancements in digital technology and its significant usages over internet, and thereby accelerating the progress in deep learning [12]. Hence NN can directly learn about the sample images and easily reconstruct the segmented sample images [13]. A CNN is the subset for an artificial neural network that utilizes deep learning [14]. It contains of input layer, hidden layers and output layer and fully connected (FC) layers. The FC layers in CNN are swapped out for partly associated convolution layers and a pooling layer, which is identified by weight allocation and sparse associates. Since it is simpler than a traditional neural network, a CNN uses fewer training parameters and uses less computation.

Cha et. al. [15] introduced a detection method employs on the Faster RCNN to differentiate between 5 specific types of pavement damage with accuracy rate of 87.8%. As compared to a traditional convolutional neural network, the proposed model can detect the crack more rapidly.

Using Faster RCNN, Song et. al. [16] implemented an approach for identifying pavement damage. In finding cracks, a faster RCNN outperformed a CNN and a K-value model. On the basis of YOLO v2, Mandal et al. [18] worked on an automated pavement detection network system. This system is capable of spotting corruption and other cracks having F1 score around 87.8%. Tong et al. [19] created a technique to automatically calculate pavement crack length using a DeepCNN with an accuracy of 94.36%, demonstrating the effectiveness of a training method that combine two techniques: orthogonal coding with stochastic gradient descent. A very precise automatic feature categorization technique was created by Li et al. [20] utilizing a CNN to convert 3D road surface photos into small image blocks and achieved a higher F1 score.

3.2 **Data Acquisition**

Data acquisition is the procedure of aggregation data from numerous sources and converting it into a digital format that can be managed via systems or other electronic device. These systems are used in various possible implementations, from scientific research to industrial process control. Its process includes three important key mechanisms:

1. Sensors/devices: These devices calculate physical properties of the environment, like voltage, pressure, and temperature.

2. Data acquisition hardware: This equipment is used to connect the sensors or devices to the system or other electronic machines. Data acquisition hardware involves ADCs that transform the analog signals from the sensors into digital signals and can be managed by a system.

3. Data acquisition software devices: This is the software used to manage the data acquisition hardware and to collect, store, and analyze the data which is being acquired. Data acquisition software can involves drivers for the data acquisition hardware, user interfaces to configuring and manage the hardware, and data processing and analyzing tools.

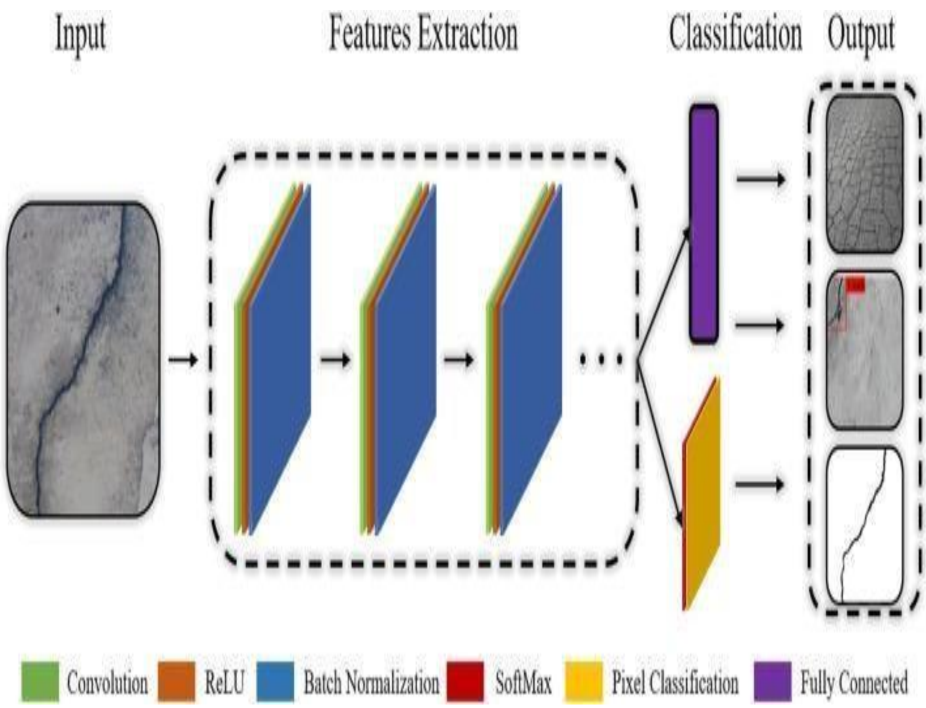


Fig.3.1 Example of Structural Crack detection using Convolutional Neural Network [61]

Data acquisition systems can be fabricated for the widespread series of presentations, from simple data categorization to composite process control and monitoring systems.

Some common uses of data acquisition schemes include:

1. Scientific research: Data acquisition systems are used in scientific research to gather and evaluate data from investigates and clarifications.
2. Industrial process control: Data acquisition systems are used in manufacturing process control to monitor and control developed processes like temperature control in chemical reactions or pressure control in oil drilling.

3. Environmental monitoring: Data acquisition structures are used in environmental monitoring to ration and examine air and water worth, weather conditions, human patterns, and other environmental factors.

In essence, data acquisition helps as a keystone in the gathering and exploration of data from a numerous of sources, allowing enhanced decision-making, process control etc.

3.3. Image Processing

The image processing approaches can apply individually or in combination to attain diverse image processing objectives, ranging from enhancing image quality for visual inspection to extracting quantitative information for further analysis.

There are numerous applications of image processing, like:

1. Medical Images: Image processing is used to analyze medical images, such as X rays, MRI scans, and CT scans, to aid in the diagnosis and treatment of medical conditions.

2. Security-Surveillance: Image processing is used to enhance and analyze surveil- lance camera images, as well as to identify and track objects or people of interest.

3. Robotics-Automation: Image processing is used in robotics and automation systems to provide vision capabilities, such as object detection and recognition.
4. Entertainment-Education: Image processing is used in the creation of visual effects for movies and video games. Education like results OMR sheets etc.

In recent years, deep learning techniques such as CNNs, RNN have also been used in image processing and pattern recognition and also achieving advanced results in various image related tasks which are object recognition, segmentation, and image classification.

3.4. Data Augmentation

This is a method of expanding the range of dataset via employing different transformations or modifications to the original datasets. The primary aim behind data augmentation is to enrich the variety of the dataset, eventually enlightening the performance of deep learning models. This improvement is achieved by mitigating overfitting and enhancing the model's ability to generalize to unseen data. The choice of augmentation techniques depends on the specific characteristics of the data and the requirements of the task at hand.

Some common techniques include:

1. Image augmentation: This involves applying transformations such as rotation, flip ping, scaling, cropping, and color adjustments to images.
2. Text augmentation: This involves applying techniques such as synonym replacement, word deletion, and word swapping to text data.
3. Audio augmentation: This involves spread on transformations such as time stretching, pitch shifting, and noise addition to audio data.

Following are the steps for the data augmentation process:

1. Selection: Firstly, to select the suitable augmentation technique formed on the category of data and the task.
2. Configuration: Each augmentation technique hasseveral parameters that can be configured to control the degree of transformation.
3. Application: The augmentation technique is applied to the original data to generate new augmented data points.

4. Incorporation into the dataset: The augmented data is thenadded to the original dataset to increase its size and diversity.

   The data augmentation can be achieved manually, on the mean time it can also be evaluated by using various libraries of python such as PyTorch, Keras and TensorFlow. Also, these python libraries deliver built in functions for common augmentation techniques.

CHAPTER 4

PROPOSED WORK

This chapter offers the proposed model specifically, *two-phase CNN at pixel-level for road crack detection and its segmentation* which comprises of two-phase i.e., detection phase and segmentation phase individually. Phases one and two of the process are called CNN segmentation and detection, respectively. Firstly, CNN is utilised as a classification detection technique which is trained on image patches to search for any areas that have cracks. In next phase, it covered with the pixel-level in small patches for segmenting road cracks from the original photos. The pipeline of proposed model for detecting road cracks and its segmentation is shown schematically in Figure 4.1, in which each CNN layer likely followed by max-pooling layer and Relu functions for the activation function. We use 2 dropout layers for avoiding the model to be overfitted. In the initial phase, a CNN is employed akin to a detection technique. It undergoes training using sample image patches to identify areas within the images that contain cracks. Furthermore, this phase involves the removal of background noise and extraneous elements present in the images. Subsequently, in the second phase, the segmentation of road cracks occurs at the pixel level, discerning discrete regions within the original images. Finally, the collective process offers advantages in both classification and segmentation processes, resulting in a comprehensive approach to crack detection.

4.1 Crack Detection and Segmentation in CNN Architecture

In this, for feature extraction the convolution function is applied for an input image i.e., $W_{m,n}$ size is m*n. The inputs' image includes kernel $k_{r,s}$ of size r*s. Here, a kernel with a 3×3 pixel size is added to an input image that is 72 × 72 pixels in size. The equation is as given as follow:

$$\boldsymbol{C_{i,j} = f\left(\sum_{r=m}^{M} \sum_{s=n}^{N} W_{i,j} \,.\, k_{(i+p)*(j+q)} + b_{(m,n)} \right)} \quad (1)$$

where $C_{i,j}$ indicates i^{th}, j^{th} element of the convolutional layer. f is called as transfer function, k indicates the kernel, W indicates weight matrix for convolutional input layer, b indicates bias weight matrix to the input layer for m*n. In this, each convolutional layer presents pixel-level feature mapping of the image for i, j. Various number of neural network layer are used, since it helps in upgrading the useful features map and sharpening the weak crack features as well. In these experiments, total six CNN layer are used for feature extraction of the crack images.

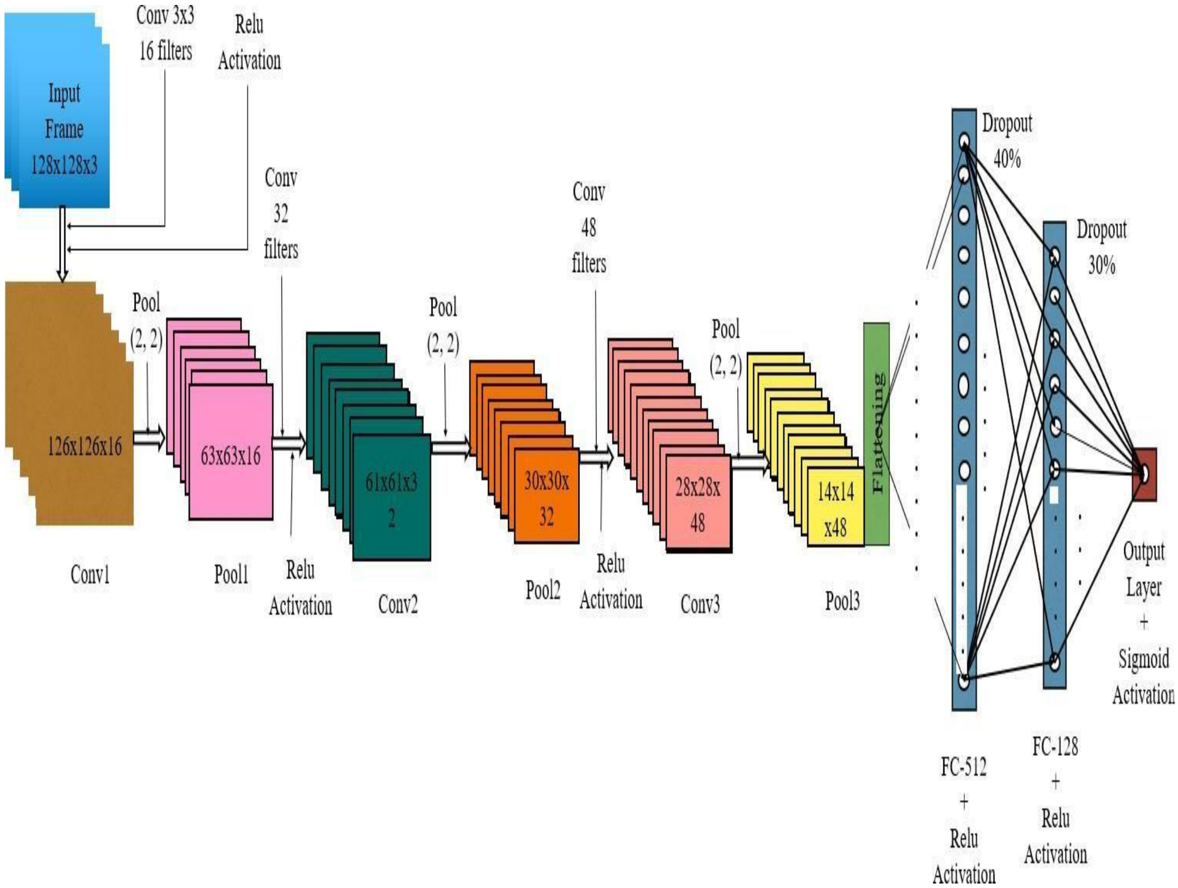


Fig.4.1 Block diagram of 2-phase CNN Model at pixel-level for Road Crack Detection and Segmentation

Large-scale real-world issues including automated image categorization, natural language processing, human action identification, and physics can be effectively resolved by DEEP neural networks (DNNs). With the advancement of DNN training techniques (unsupervised pretraining, dropout, parallelization, GPUs, etc.), DNNs can now gather extraordinarily huge volumes of training data and achieve record results in a wide range of study domains. However, because DNNs are typically thought of as "black box" techniques, users may find this lack of transparency to be a practical disadvantage. Specifically, it is challenging to both statistically and intuitively interpret the outcome of DNN inference, that is, to determine why the trained DNN model arrived at a specific response for a single new input data point. Keep in mind that feature selection asks: Which characteristics are salient for the ensemble of training data on average? This is not the same as feature selection. For broad nonlinear estimators, the transparency issue has just lately drawn increased attention. Numerous techniques have been devised to comprehend the knowledge that a DNN has acquired [36].

Rather than MLP, DNN [37] has an enormous number of stowed-away layers. Following that, the neural network is prepared by the regular backpropagation process. Hubs in the information layer are equivalent to the number of attributes that were removed. For multiclass order, SoftMax fills in as the enactment capability in the result layer, and sigmoid and Re-LU are used in the secret layers. The expectation model is utilized in the outcome layer. How much hubs in the result layer look like how many classes are in the dataset.

CHAPTER 5

DATASETS

In this model, two datasets, CFD dataset [34] and Crack500 dataset [33] have been used for the recommended approach. We are now going to read the in-depth descriptions of the datasets that has been compared in the section below.

In general, pavement surface cracks are categorized into three types: (i) Alligator surface crack, (ii) Longitudinal surface crack, and (iii) Transverse surfaced crack-based pavement structure [35]. For implementation on the pavement road crack, two standard publicly available datasets are used as follow:

4.2 CFD Dataset

CFD [34] is publicly available pavement surface crack dataset. It consists of total 118 sample images including annotations images. It shows the overall road condition in Beijing, China and the contained images varied illumination in 2016, surface-stain, greasy-dirt, and complex background texture. Out of 118 images, 82 samples for training and 36 samples for validation has been chosen and randomly split the training set & validation set at about 70% and 30% respectively.

4.3 Crack500 Dataset

The researcher Yang et al [33] publicly shared the Crack500 dataset, it was recorded at the main campus of Temple University in which total 500 original images were collected having of 2000x1500 pixels via cell phone cameras. Here, each surface includes a pixel-wise annotated binary mapping of crack image. Due to limited number of images, large size of each image, and restricted computation resource, each image was cropped to 16 non- overlapping image regions, and only regions with cracks greater than 1,000 pixels were recorded. Crack500 dataset contains of 224x224 images & a total of 3368 images. In the released dataset, 1896 images are taken for training, 348 images are taken for validation, and 1124 images for testing. For working in model: flip with rotate; contrast; gamma, brightness sets are applied. We also resize each image; annotated around 320 × 640 based on training set for different methods.

Table 5.1: Distribution of Dataset

Dataset Name	**Training Images**	**Testing Images**	**Total Images**
CFD [34]	82	36	118
Crack500 [33]	1896	1124	3368

CHAPTER 6

RESULTS AND DISCUSSION

Four landscapes are castoff to establish performance measurements, such as sensitivity, precision, accuracy, and F1-score: false positive, true negative, true positive, and false negative. This experiment uses performance indicators like sensitivity, F1-score, weighted average-based precision, and accuracy to evaluate the classifier's performance. The evaluation measures are defined as:

- Precision: The percentage of genuine positive predictions to the total of false positives and true positives is measured by the precision performance metric.

  Precision = True Positives / (False Positives + True Positives)

- Recall: Analyzing a model's capacity to prevent false negatives is essential. A high recall score indicates that there is less chance of false negatives because the model is good at identifying a significant percentage of pertinent positive cases.

  Recall = True Positives / (False Negatives + True Positives)

- F1 Score: The F1 score is an average of recall and accuracy that is balanced. It assesses how well an algorithm can identify positive circumstances while reducing false negatives and possible positives.

  F1-Score = 2 * (Recall * Precision) / (Recall + Precision)

6.1 Experimental System Setup

This section defines the implementation detail of whole setup. The model has been executed on two pavement crack datasets which is publicly available i.e., CFD dataset [34], Crack500 [33]. The range of hyper parameters during training is also discussed. The experiments are performed on machine having a Processor: AMD Ryzen-7 series, 5600H- Radeon, having Graphics: 3.30 Gigahertz, RAM: 8 GB, GPU NVIDIA GETFORCE RTX.

6.2 Methods for Evaluation

Accuracy, Precision, and Recall are the three performance measures utilized in this caseto compare the outcomes. These metrics are employed to assess the effectiveness of classification algorithms, particularly CNN-based models for the identification of road crack.

6.2.1. Precision

Precision is the fraction of relevant instances among all retrieved in stances2. It can be calculated by dividing the number of true positives (TP) by thenumber of predicted positives (TP + FP). Precision measures how well a model canavoid false positives, or how accurate its positive predictions are. Let's say a doctorwants to determine whether a patient has a certain disease, and uses a diagnostictest to make the determination. The test results can be positive or negative. Thedoctor performs the test on 100 patients, and the test results show 40 positive resultsand 60 negative results. The doctor knows from previous experience that the trueprevalence of the disease in the patient population is 20%.The doctor is interestedin the precision of the test, which refers to the proportion of positive test resultsthat are truly positive. If the doctor examines the 40 patients who tested positive and finds that 30of them truly have the disease, while 10 do not, then the precision of the test is:

Precision = 30 / (30 + 10)

Precision = 0.75 or 75%

This means that the precision of the test is 75%, meaning that 75% of the patientswho tested positive actually have the disease, while 25% of the positive results were false positives.

6.2.2. Accuracy

A measurement, computation, or forecast is accurate or precise is referred to as accuracy. The number of accurate forecasts or measurements divided by the overall count of accurate predictions or measurements is often stated as a percentage or ratio. In other words, accuracy assesses a model's or system's performance in terms of the accuracy with which it can recognize or categorize data. Accuracy represents the proportion of accurate predictions made by an algorithm among all the predictions it has made. It can be calculated by dividing the number of true positives (TP) and true negatives (TN) by the total number of instances (TP + TN + FP + FN), where FP is false positives and FN is false negatives. Accuracy measures how well a model can classify all instances correctly, regardless of their class. Let's say a company is trying to predict which job candidates will be successful in their role. They use a test to evaluate candidates' skills, and they use the results of the test to make their hiring decisions. The company hires 100 candidates based on their test results. After six months on the job, the company evaluates how well each employee is performing and categorizes them as either successful or not successful based on predetermined criteria. If the company correctly identified 80 out of the 100 successful candidates using the test, and correctly identified 10 out of the 100 unsuccessful candidates, then the accuracy of their test is:

Accuracy = (No. of correct predictions) / (total no. of predictions)

Accuracy = (80 + 90) / 200

Accuracy = 0.85 or 85%

This means that the test had an accuracy of 85%, meaning that it correctly identified 85% of the candidates who would be successful on the job, and incorrectly identified 15% of the candidates who would not be successful on the job.

6.2.3. Recall

Recall is the fraction of relevant instances that were retrieved. It can be evaluated by dividing the number of true positives (TP) by the number of actualpositives (TP + FN)2. Recall measures how well a model can capture positive cases,or how sensitive it is to positive instances. Let's say a company wants to predict which customers are likely to churn (i.e., stop using their services). They use a machine learning model to make these predictions, which outputs a score for each customer indicating their likelihood of churning. The company has a total of 1,000 customers, of which 200 have already churned. The machine learning model predicts that 300 customers are likely to churn in the future. The company is interested in the recall of the model, which refers to the proportion of actual churners that are correctly identified by the model (i.e., the proportion of true positives among all actual positives). If the model correctly predicts 150 out of the 200 customers who have already churned, then the recall of the model is:

Recall = 150 / (150 + 50)

Recall = 0.75 or 75

This means that the recall of the model is 75%, meaning that the model correctlyidentified 75% of the customers who actually churned, while 25% of the actual churners were not identified by the model.

$$\boldsymbol{Recall = TP/(TP + FN)} \tag{3}$$

$$\boldsymbol{F1\ Score = (2 * Precision * Recall)/(Precision + Recall)} \tag{4}$$

$$\boldsymbol{\mu P = \sum \frac{Precision}{N}} \tag{5}$$

$$\boldsymbol{\mu R = \sum \frac{Recall}{N}} \tag{6}$$

$$\boldsymbol{\mu F1 = \sum \frac{F1}{N}} \tag{7}$$

where TP indicates numbers of True-Positive, FP indicates numbers False-Positive and FN indicates numbers False-Negative images. N represents the number of classes for each metrics setting value N=2.

In 1st phase i.e., detection phase: crack present and crack absent images are generated. The crack present image is that area which contains even the small crack whereas the crack absent image is that area which contains no cracks. In 2nd phase i.e., segmentation phase: a crack present image with pixel images and crack absent images with background pixel images are generated as shown in figure 4. During testing, (m × 72 × 72) pixels where m is number of non-crack patches of images in total for non-crack areas and (n × 72 × 72) pixels where n number of crack patches and n are detected as crack areas. The image enhancement result on types of road cracks is represented in figure 5.

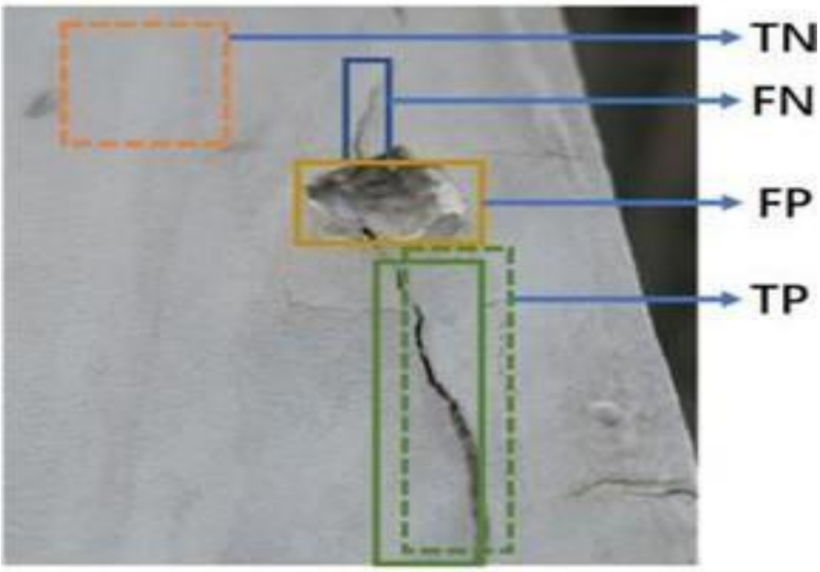
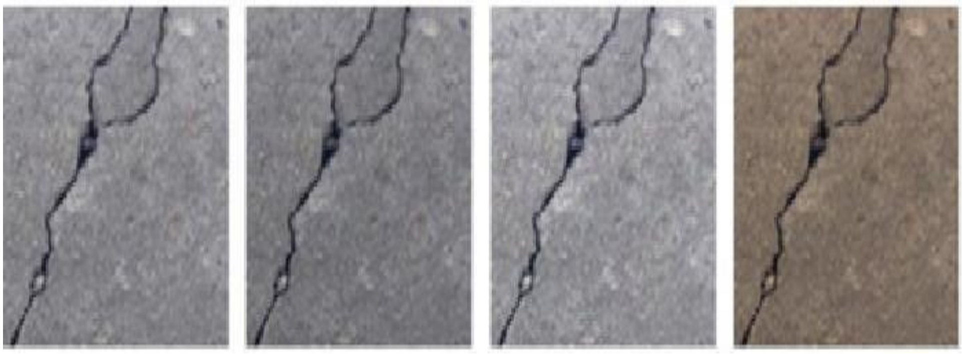
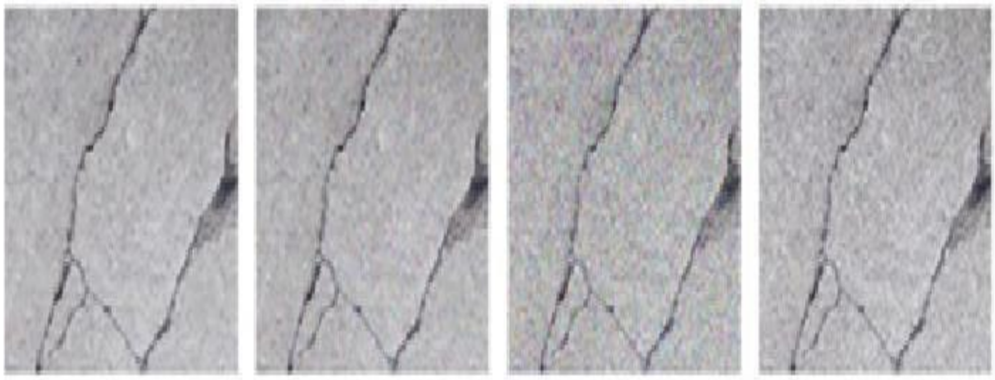


Fig.6.1 Classification of Crack present (Positive sample images) & Crack absent (Negative sample images)

i) Alligator Road Crack



ii) Longitudinal Road Crack



iii) Transverse Road Crack

Fig.6.2 Image Enhancement Results on various Crack

6.3 Results

This subsection shows the comparative results of various methods on the CFD dataset. Table 6.1 listed the result analysis for µF1 score, µPrecision, and µRecall and µRecall of various models, which shows that the proposed model out-perform better results.

Table 6.1. Comparative Results of different methods for CFD Dataset.

Model	**µF1 (%)**	**µPrecision(%)**	**µRecall (%)**
CT [36]	94.6	92.94	96.41
Unet [37]	90.31	94.21	87.06
Unet (ResNet-34 encoder [38]	87.27	91.8	83.65
DeepLabv3-Unet [36]	92.21	89.88	94.85
Proposed model	97.82	92.83	97.88

Table 6.2 represents that the proposed model which attains the best μF1 score among various models for Crack500 dataset. We also resized the samples into 224 × 416.

Table 6.2. Comparative Results of different methods for Crack500 Dataset

Model	**μF1(%)**	**μPrecision(%)**	**μRecall (%)**
CT [36]	88.73	87.45	90.12
Unet [37]	79.04	75.99	83.12
Unet (ResNet-34 encoder [38]	83.07	80.15	86.74
DeepLabv3 [36]	83.19	81.39	85.26
Proposed model	96.23	93.42	96.46

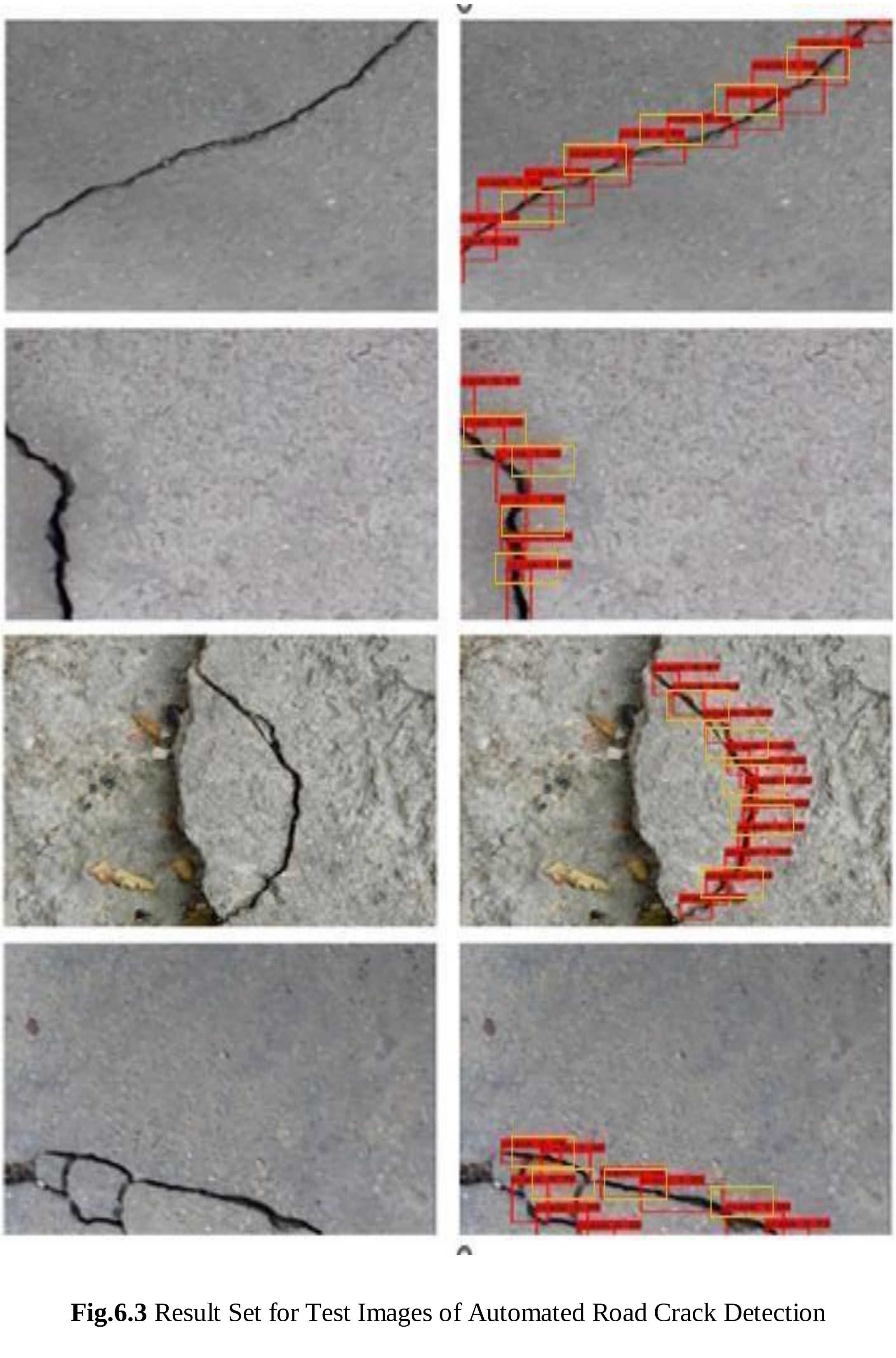


Fig.6.3 Result Set for Test Images of Automated Road Crack Detection

Figure 6 shows the sample images of raw cracks, then via 1st phase of CNN, it detects the crack images with overall ratio. The overall testing results generated automatically by the proposed 2-phase CNN model is depicted in Figure 7, where firstly the original image in taken and then labelling of the image sample is done and then the segmentation result is generated.

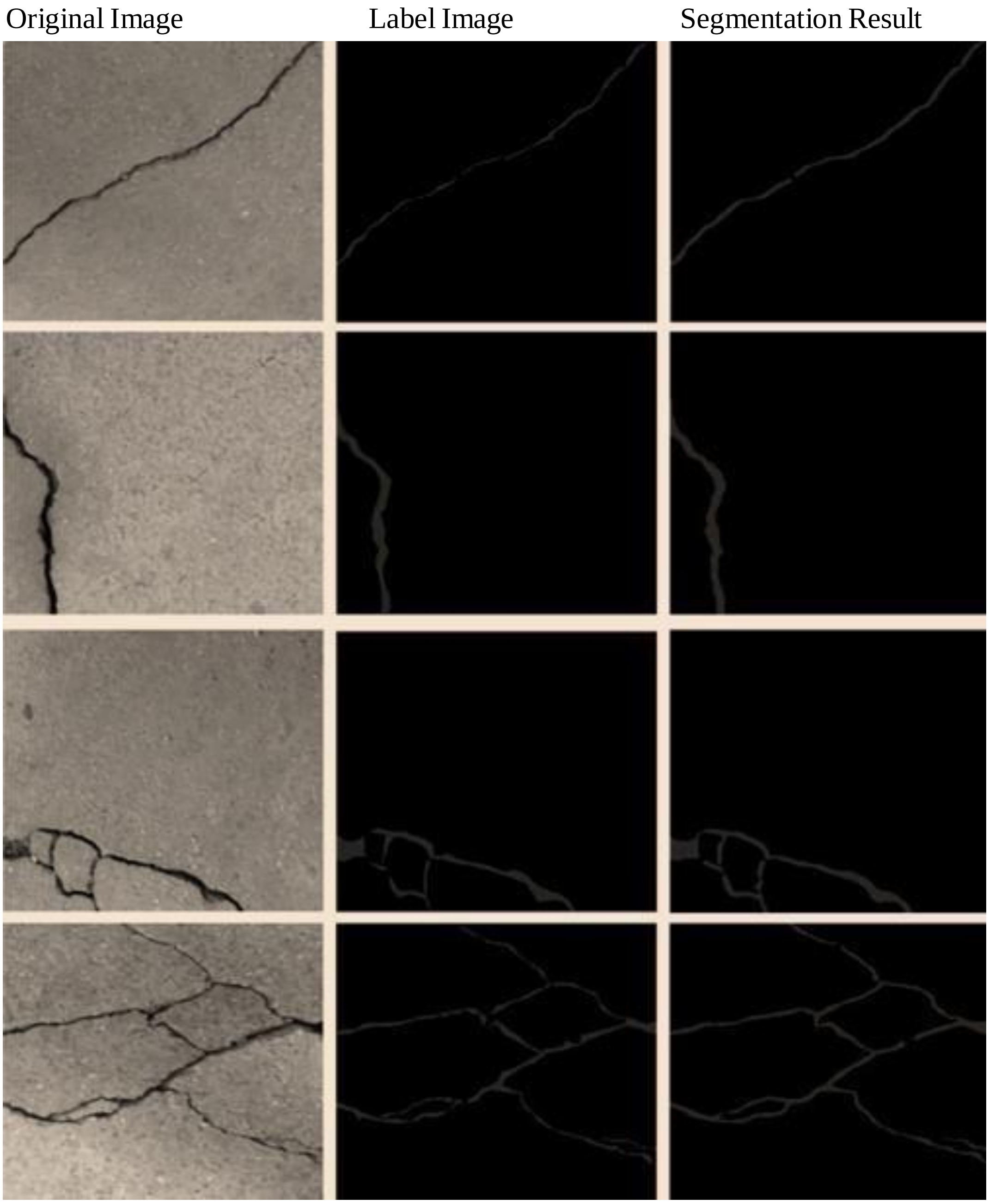


Fig.6.4 Result set for Test images of automated road crack Segmentation

6.4. Model Training, Validation and Testing Results

This section displays the outcomes of proposed models on crack detection and segmentation on both the datasets i.e., CFD and Crack500 dataset by using the weights gained from the trained model. The training vs validation results of model for various epochs are presented accordingly and are visualized in Figure 8. Figure 8 (a) shows the training and validation results for CFD Dataset; Figure 8 (b) represents the same for Crack500 dataset. The comparison of precision, recall on both the dataset is represented in Table 4.

Table 6.3. Summary of proposed dataset's result on the CFD and Crack500 dataset.

Dataset	***Batch Size***	***Epoch***	***Class***	***Precision %***	***Recall %***
CFD	8	200	All crack	0.974	0.964
			Large crack	0.973	0.968
			Small crack	0.972	0.959
Crack500	8	200	All crack	0.975	0.967
			Large crack	0.978	0.988
			Small crack	0.971	0.954

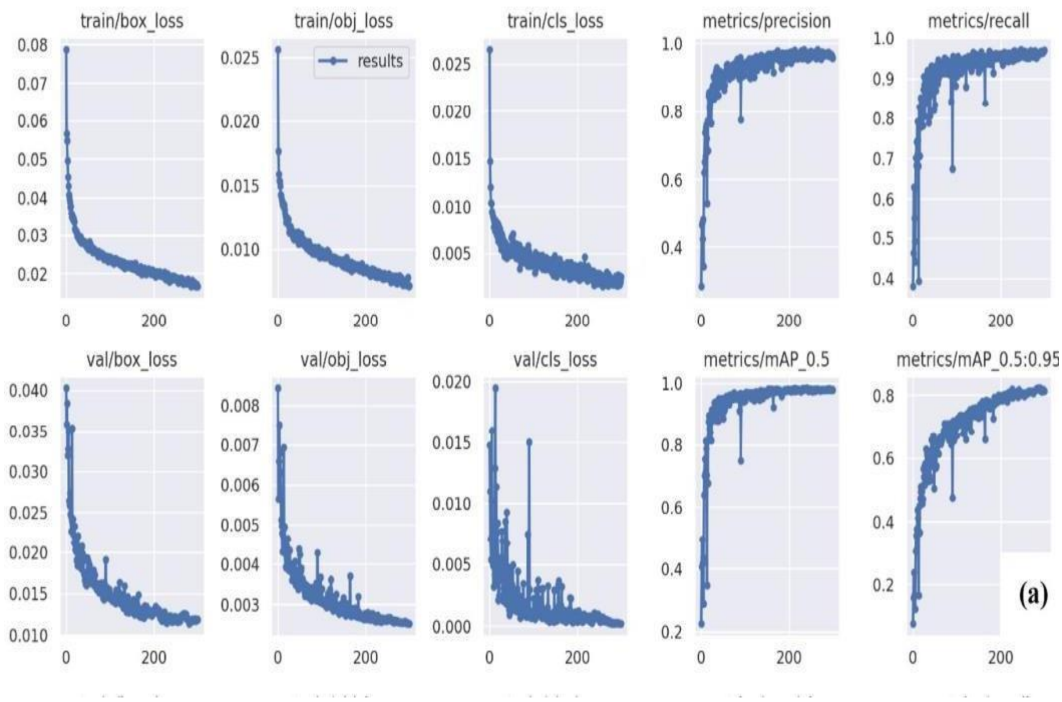


Fig 6.5 (a) Training Vs Validation Results on CFD datasets.

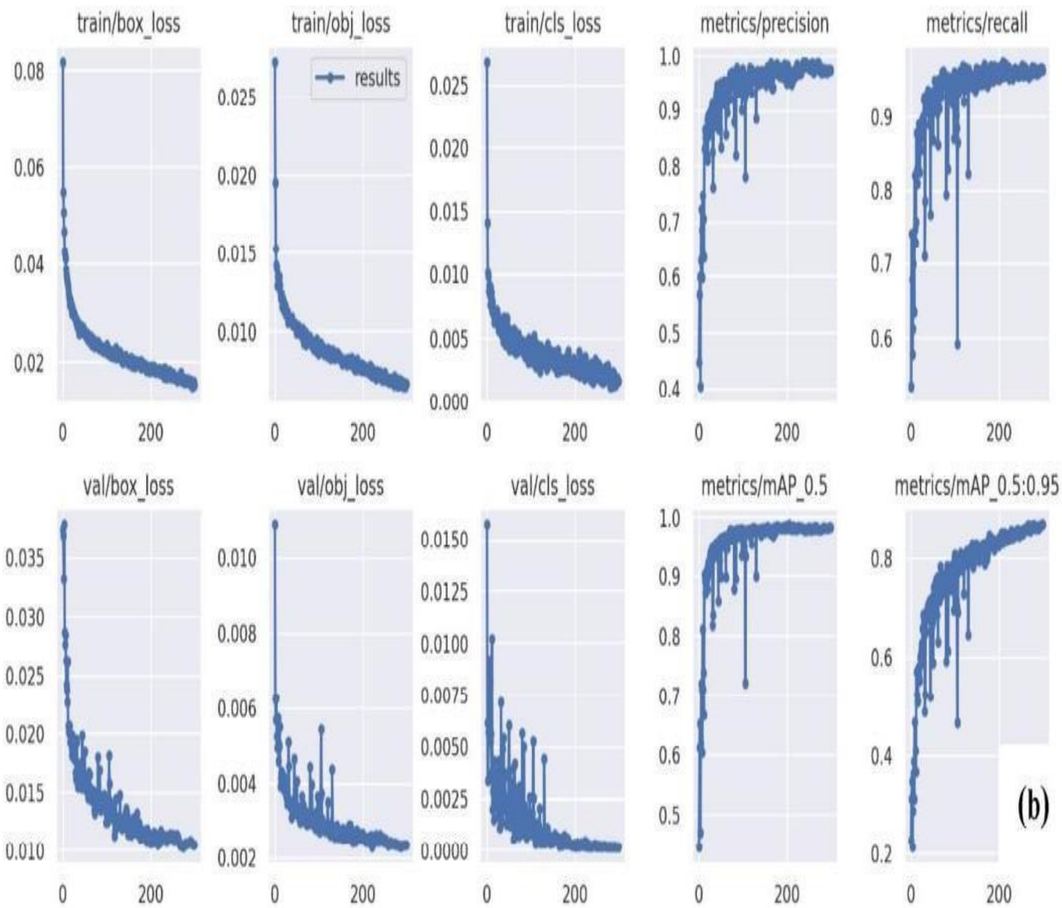


Fig 6.5. (b) Training Vs Validation Results on Crack500 datasets.

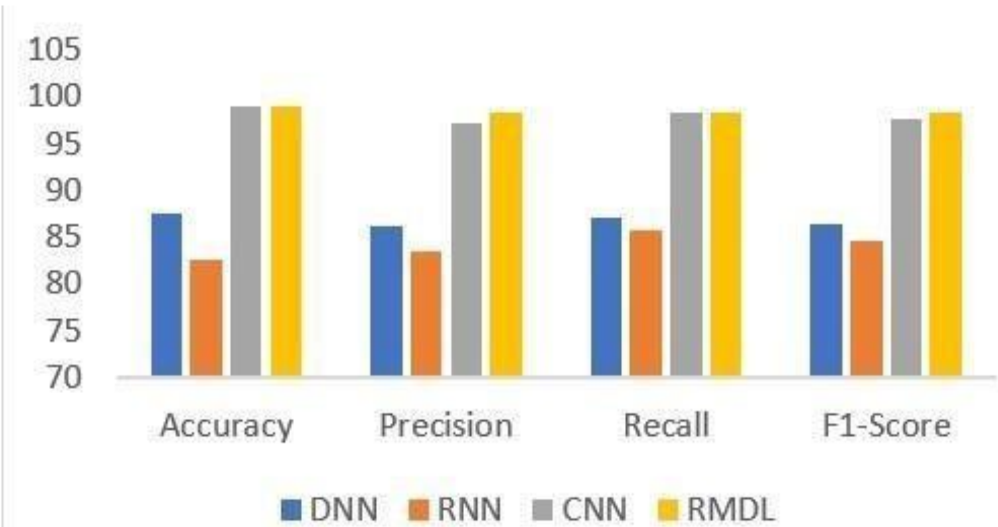


Fig 6.6 Comparison of all Performance Metrics Used

CHAPTER 7

CONCLUSION AND FUTURE WORK

Road crack detection in pavement images is a crucial task for ensuring the safety and reliability of the infrastructure and public. Image-based methods, especially those using machine learning models, have become increasingly popular for crack detection. However, the complexity and variability of pavement images, such as uneven illumination and shadow, make crack detection a challenging task. Nevertheless, with the advancement of technology and machine learning models, researchers continue to develop new and improved methods for crack detection, making it a rapidly evolving field. In our method, firstly the input images are classified into either crack present called positive or crack absent called as negative. The crack sample images were processed via two phase CNN at pixel level, which helps in minimizing the number of noise pixels as well as also worked on unbalanced data among the crack and non-crack areas. Lastly, featured images were down-sampled and cracks is detected by segmentation. Our analysis gives the precision of about 97.82% for crack image detection and in pixel-level segmentation accuracy comes out to be approx. 95.40%. Therefore, for future reference a DNN will be trained to segment the cracked samples in a set cracked region and non-crack regions. Further, we will work on improving the robustness of model.

In this study, test has been conducted to see how well the Multilayer CNN model can recognize PDs. The model performed very well in distinguishing between healthy and sick plants, and also in naming the disease that each plant had. The model learned from a big collection of plant pictures, which helped it to identify the features and patterns that are related to different PDs. Different measures such as accuracy, precision and recall have been used to assess how well the model did, and the results showed that the model was very accurate in all measures.

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ANNEXURE-IV

DELHI TECHNOLOGICAL UNIVERSITY
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PLAGIARISM VERIFICATION

Title of the Thesis Road Crack Detection and Segmentation using two-phase Convolutional Neural Network

Total Pages 42 Name of the Scholar Jaya Gupta

Supervisor (s)

(1) Dr. Abhilasha Sharma

(2)

(3)

Department Software Engineering Department

This is to report that the above thesis was scanned for similarity detection. Process and outcome is given below:

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17

Page 17 of 22

LIST OF PUBLICATION(S)

DECLARATION

We/I hereby certify that the work which is presented in the Major Project-II/Research Work entitled Road Crack Detection and Segmentation using two-phase ... in fulfilment of the requirement for the award of the Degree of Bachelor/Master of Technology in Data Science and submitted to the Department of Software Engineering, Delhi Technological University, Delhi is an authentic record of my/our own, carried out during a period from 2022, under the supervision of Dr. Abhilasha Sharma.

The matter presented in this report/thesis has not been submitted by us/me for the award of any other degree of this or any other Institute/University. The work has been published/accepted/communicated in SCI/SCI expanded/SSCI/Scopus indexed journal OR peer reviewed Scopus indexed conference with the following details:

Title of the Paper: Road Crack Detection and Segmentation using two-phase Convolution Neural Network
Author names (in sequence as per research paper): Dr. Abhilasha Sharma
Name of Conference/Journal: ICOTET 2024
Conference Dates with venue (if applicable): June 14-15, 2024
Have you registered for the conference (Yes/No)?: Yes
Status of paper (Accepted/Published/Communicated): Accepted
Date of paper communication: 27-04-2024
Date of paper acceptance: 11-05-2024
Date of paper publication: –

Jaya Gupta, 2K22/DSC/07 JayaGupta.
Student(s) Roll No., Name and Signature

SUPERVISOR CERTIFICATE

To the best of my knowledge, the above work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere. I, further certify that the publication and indexing information given by the students is correct.

Abhilasha Sharma
Supervisor Name and Signature

Place: Delhi

Date: 27-05-2024

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Acceptance : ICOTET 2024 Inbox

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We are pleased to inform you that **Paper ID 2407** entitled **" Two-phase Convolutional Neural Network at Pixel level for Road Crack Detection and Segmentation "** submitted by you has been accepted by the 2nd International Conference on Optimization Techniques in Engineering and Technology Engineering (ICOTET 2024).

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We/I hereby certify that the work which is presented in the Major Project-II/Research Work entitled Sentimental Analysis using Long short Term Memory (LSTM) Neural Network and Inverse Document Frequency Word Embedding Technique in fulfilment of the requirement for the award of the Degree of Bachelor/Master of Technology in DATA SCIENCE and submitted to the Department of Software Engineering, Delhi Technological University, Delhi is an authentic record of my/our own, carried out during a period from 2022, under the supervision of Dr. Abhilasha Sharma.

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Author names (in sequence as per research paper): Dr. Abhilasha Sharma, Jaya Gupta
Name of Conference/Journal: Hånweis Second International Conference on Compter Science, CCIT.
Conference Dates with venue (if applicable): June 29-30, 2024.
Have you registered for the conference (Yes/No)?: Yes
Status of paper (Accepted/Published/Communicated): Accepted
Date of paper communication: 2 June, 2024
Date of paper acceptance: 6 June, 2024
Date of paper publication: —

2K22/DSC/07, Jaya Gupta, Jayalupta.
Student(s) Roll No., Name and Signature

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To the best of my knowledge, the above work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere. I, further certify that the publication and indexing information given by the students is correct.

Place: Delhi

Date: 27-06-2024

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Consolidated Content review comments	• **Paper should strictly formatted according to the standard format** • **Very less description is provided on proposed system and its related literature review** • **Adequate testing, results and its discussion are required. The paper could be revised with more results**

Sl No	**OVERALL RATING: (5= EXCELLENT, 1= POOR)**	**5**	**4**	**3**	**2**	**1**
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4.	Appropriateness of abstract as a description of the paper			X		
5.	Appropriateness of the research/study methods		X			
6.	Relevance and clarity of drawings, graph and table	X				
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