Asphalt pavement crack detection and classification using deep Convolutional Neural Networks

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Asphalt pavement crack detection and classification using deep Convolutional Neural Networks

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SUMMARY

Asphalt pavements make up a large portion (around 95%) of all roadway surface types in Georgia. These pavements need to be preserved and resurfaced depending on their condition. Among different categories of pavement distresses, pavement cracks are significant and contribute hugely in assessing and predicting the life cycle of pavement in a certain project. This research work deals with automatic classification of Asphalt pavement cracks using convolutional neural networks.

Different transportation agencies such as the Federal and State departments of transportation use varying protocols for rating pavement distresses. This is attributed to varying geographical and climatic conditions across regions in the United States. The Georgia Department of Transport (GDOT) evaluates pavement distresses based on its protocol, Pavement Condition Evaluation System (PACES). An enhanced Computerised Pavement Condition Evaluation System (COPACES) is currently used to either manually or automatically survey sections of roadways in Georgia. A few automated or semi-automated pavement crack detection and classification algorithms have been developed. However, Artificial Intelligence based automated crack detection and classification techniques haven't been implemented so far. This can be mainly attributed to the complicated task of identifying diverse crack patterns and corresponding severity levels adopted by GDOT and unavailability of sufficient pavement crack datasets. Therefore, it is important to note that this research work is possible due to the availability of huge pavement image dataset. Deep Learning based artificial neural networks have proved to work well on automatic detection and classification tasks when sufficient data is available. This has been the primary motivation to implement pavement crack detection and classification using deep learning techniques.

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Object detection based deep convolutional neural networks are most suitable for this task. Many such networks like Single Shot Detection (SSD), YOLO, Fast RCNN are current the state of art for object detection tasks. They have achieved outstanding performance accuracies. Faster RCNN is one among these networks that has consistently performed well on difficult object identification problems and has achieved high performance accuracies on PASCAL VOC and MS COCO datasets. We implement pavement crack detection and classification using the Faster RCNN network model. A pre-processed image dataset is used for training the network to detect and classify pavement cracks. The network achieves a mean average precision of 0.56 in identifying complicated preliminary definitions of pavement crack categories incorporated in accordance with crack types and severity levels defined in PACES. Since different cracks categories appear to be very similar with a few distinguishing features, the Faster RCNN network is trained to identify only those features which are characteristic of a certain category as preliminary detections. These detections are further post processed to develop a complete method to automatically classify cracks according to GDOT's distress classification standards. This proposed method performs reasonably well and achieves good results in comparison to visually rated pavement sections and outcomes of a pre-existing crack classification technique based on the Mutiscale Crack Fundamental Element model. It can serve as a performance baseline for other advanced deep learning methods to be developed in the future.

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CHAPTER 1

INTRODUCTION

GDOT surveys and maintains around 18,000-centerline miles of highway apart from county roadways. Of the total public assets of Georgia, transportation assets make up a whopping 60 percent. The estimated budget needs for the maintenance of highway system from 2011 – 2014 were set at $ 1.3 billion with $135 million available in funding for the maintenance of lump sum category (Transportation Asset Management, 2011). Therefore, it is important to plan and analyze the allocation of maintenance funds among different projects depending on the lifecycle estimates and also by applying “optimization” techniques to achieve a high overall rating post rehabilitation. As is apparent, to carry out such analyzes, it is important to have accurate roadway survey results. The current practice of manual survey is tedious and prone to variations due to differences in analysing a particular distress by Survey Engineers who rate projects across states. In order to achieve consistent survey results, it is important to automate the task. Currently, automated pavement crack classification tools are integrated within COPACES. However, these results need to be re-analyzed and manually checked for any inconsistencies. This research project aims to use artificial intelligence (AI) based techniques to automatically classify pavement cracks accurately to reduce any manual quality checks on the surveyed results.

Pavement crack distresses are classified differently by different transportation agencies depending on varying distress patterns. This variation is due to distinct geographical and climatic conditions across states as well as varying pavement surface types. Asphaltic pavements make up more than 95 percent of all roadways in Georgia. The GDOT uses COPACES as its protocol to classify pavement distress. According to the protocol, Asphalt pavement cracks can be classified into different types and severity levels as Load cracks (Severity Levels 1 - 4) and Block cracks (Severity Levels 1 - 3). Load cracks are formed due to the repeated movement of heavy traffic load on the pavement. They occur along the wheelpath. Block cracks appear in the non-

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wheelpath and spread throughout the pavement. They are caused due to weathering of pavement or shrinkage of the cement treated base material. They are not confined to the wheelpath.

COPACES derives the definitions of the various types of cracks and their severity from PACES protocol for pavement preservation. Load cracks are classified into four severity levels depending on the number of longitudinal cracks and density of the intersecting transverse cracks. Block cracks are categorized into three severity levels depending on the density of the block patterns that appear. These are a few characteristics typically representing a certain crack type and severity. These patterns are efficiently learnt by the neural networks to be able to distinguish between them. Training the deep learning model with sufficient data improves detection accuracy. The features that are detected by the model need to be further analyzed using post processing techniques to identify the type and severity of the crack.

This research develops a complete method to use the detected crack patterns from the image and output the type, severity and extent for pavement cracks. Crack patterns are detected using the Faster RCNN model and they are post-processed to match the crack type and severity definitions in COPACES.

1.1 Proposal Organisation

Chapter 1 outlines the need for the proposed method and briefly mentions the proposed outcome. Chapter 2 elaborates on the current state of art methods for pavement crack classification. It also reviews the crack category definitions defined in COPACES. Chapter 3 presents the methodology for the proposed research work and elaborates on the Deep learning method used for crack classification. This chapter also outlines the post-processing steps for crack severity and extent calculations. Chapter 4 presents a discussion of the outcomes. It elaborates on the methods used for validation and also presents an analysis for validated results. Chapter 5 proposes a recommended technique as future research work to further improve current results. Chapter 6 is a conclusion for the proposed method. A few recommendations for future work are also proposed.

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CHAPTER 2. LITERATURE REVIEW

This section first presents the pavement distress evaluation practices with a special focus on crack type classification, and then reviews the crack detection and classification methods.

2.1 Pavement Condition Evaluation Practices – Crack Type Classification

COPACES defines different pavement distresses and the methods to be followed to identify each distress type and severity. Cracking distresses are classified into three types and each type is further categorized into different severity levels. Among the three crack types, load cracking and block cracking occur frequently across most roadways in Georgia and hence this study focuses on developing a method to classify them.

a) Crack type and Severity

- **Load cracking** typically occurs in the wheelpath and is caused by repeated heavy loads. The cracks are characterized by longitudinal and small intersecting transverse cracks in the wheelpath. As the severity increases, the number of longitudinal cracks and intersecting transverse cracks increase. Level 1 load cracking has a single longitudinal crack bound to the wheelpath with a few intersecting short (0-2ft wide) transverse cracks. Severity Level 2 includes single or double longitudinal cracks that are wider than cracks in level 1. These longitudinal cracks have many transverse cracks that intersect. The number of longitudinal crack bound to the wheelpath increase to 3 or more with many intersecting transverse cracks forming polygons, as the severity increases. This is considered as level 3 and is referred to as alligator cracking as the pattern resembles alligator hide. Severity Level 4 occurs as the pavement condition further deteriorates, crack width increases and pop-outs are visible. Illustrations for these crack categories is show in Figure 1. The wheelpath and non-wheelpath designations are shown in Figure 2.

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Figure 1: Crack Severity levels for load cracking. Level 1 (top left) to Level 4 (bottom right)

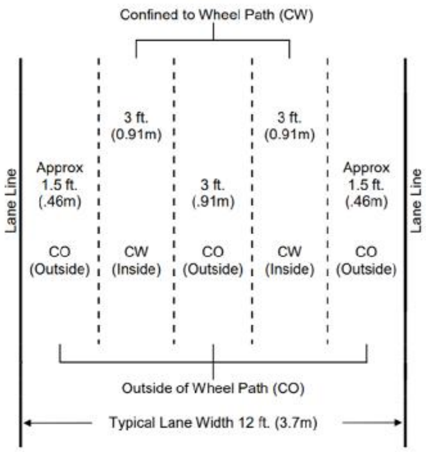

Figure 2: Designation of the Wheelpath as per Florida Department of Transport

- **Block cracking** is caused by shrinkage of the base pavement materials. It is not bound to the wheelpath and occurs across the entire pavement. Block crack level 1 includes

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transverse cracks that are not bound to any single section of the pavement and longitudinal cracks that occur in the non-wheel path. These longitudinal cracks sometimes wonder into the wheelpath. Block cracking severity level 2 typically can be identified by the block patterns that appear. The block pattern occurs across the entire pavement and the area enclosed by these blocks is large. As the severity increases the crack width and density of block patterns also increases. However, the area enclosed by the blocks decreases and a tight crack pattern is visible. This is identified as severity Level 3. Illustrations for these crack categories is show in Figure 3.

- **Reflection cracking** is the third category of pavement cracks defined in COPACES. It is caused when cracks or joints from the underlying PCC pavement reflect on to asphaltic concrete overlay. Level 1 reflection cracking pattern has straight, tight, transverse lines that may not extend across the entire pavement or longitudinal cracks if the underlying concrete pavement is shorter than the overlay.

Figure 3: Crack Severity levels for block cracking. Level 1(top left) to Level 3 (bottom)

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Severity Level 2 is characterized by all cracks and joints being reflected through the pavement as the crack progresses. Longitudinal cracks are formed at the edge of the pavement that are caused by the widening of underlying concrete pavement of the asphaltic concrete overlay. The cracks are wider than in Level 1. Level 3 reflection cracking has much wider cracks and visible spalling. The part of the pavement needs to be resurfaced. Figure 4 is an illustration from COPACES showing all the types of reflection cracking. This research only focuses on classification of load and block cracking.

Figure 4: Illustration of severity levels of reflection cracking (Level1 to Level 3)

b) Crack Extent

Crack extent usually refers to total crack length. In COPACES it is calculated as a percentage of the total length of the pavement section with visible cracking. The following examples illustrate crack extent calculations. The same method is followed for all other severity levels.

- Load cracking extent

  As shown in Figure 5, 150 ft of cracking is seen in the 100 ft sample area. This accounts for 75% of sample area. Thus, load cracking crack extent is recorded as 75%.

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- Block cracking extent

  As shown in Figure 5, 80% of the total sample area shows Level 2 block cracking. Therefore, block cracking the block cracking extent is recorded as 80%.

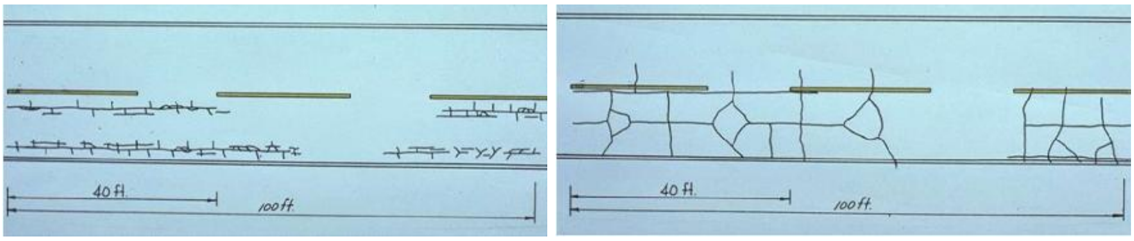

Figure 5: Illustration for Load cracking Level 2 and Block cracking Level 3 showing crack lengths in the sample area

For block cracking severity Level 1, crack extent is the total crack length. If the total crack length exceeds the sample length, then the crack extent is recorded as 100%

2.1.1 Crack Properties

The different crack categories mentioned above possess specific properties. These properties can be divided into high-level properties and fundamental properties.

High-level properties: These properties are specific to a certain type of crack and can be used to distinguish between the two crack types

- Crack location (e.g., wheelpath or non-wheelpath)
- Crack orientation (e.g., transverse or longitudinal)

Fundamental properties: These properties are specific to the severity level. Each crack type can be further classified into different severity levels based on these properties.

- Load cracking
  - o Number of longitudinal cracks
  - o Number of intersecting short transverse cracks
  - o Number of polygons

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- Block cracking
  - Number of blocks
  - Area of the block
  - Coverage range (wheelpath (WP) and non-wheelpath (non-WP))

Crack type and severity level can be determined based on these properties. Table 1 shows the properties that are specific to each category. These properties are necessary for labelling the image and will be discussed in detail in the next section.

Table 1 Crack properties for each crack type and severity

Crack Type	Crack severity	High Level Properties		Fundamental Properties			
		Location of occurrence	Orientation wrt direction of traverse	# Longitudinal cracks	# Intersecting transverse cracks (0-2ft wide)	# Blocks/ #Polygons	Area of block (m^2)
Load cracking (LC)	LC1	WP	Parallel	1	Few	2 or 3	NA
	LC2			2	> LC1	3 or 4	
	LC3			3 or more	> LC2	many	
	LC4			3 or more	> LC3	Many	
Block cracking (BC)	BC1	WP & Non -WP	Perpendicular/ parallel	1 or 0 (non-WP)	NA	NA	NA
	BC2		NA	NA		3 or more	>12.5
	BC3					4 or more	<12.5

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2.2 Review of Automatic Crack Classification Methods

Most of the research work for image-based pavement distress detection has been limited to identifying distresses and there has been considerably less research devoted to distress classification. The existing image-based crack classification techniques can be grouped into two categories as image processing based techniques and machine learning methods. This review discusses the important machine learning methods implemented for crack classification, performance accuracies achieved, and also the types of crack categories considered for classification. Crack feature detection is an important step for crack classification. However, pavement cracks occupy only a small portion of the image and the major portion is the background that increases image noise and complicates the task of detection and classification. Therefore, most research work first deals with de-noising the image which is followed by implementing different feature extraction techniques. Research based on crack classification is mainly focussed on classifying primitive categories like longitudinal, transverse and alligator crack patterns. Cubero-Fernandez A (2017) have used the decision tree C4.5 algorithm to classify these cracks. In order to enhance the range of the darker pixels belonging to cracks, logarithmic operations are performed on the grayscale pavement images. Bilateral filters and Gaussian filters are used to increase the contrast and smoothen the image. This is followed by using canny edge detection to detect the crack patterns. These detected crack patterns in the images are used to obtain projection integrals which are numerical inputs for classification using the decision tree algorithm. This method achieves close to 80% accuracy in classifying crack categories. In another study by Henrique Oliveira et al (2013), clustering algorithms such as k-means method and one class classification strategies like minimum covariance determinant Gaussian (MCDG) classifier are used to detect patches of images that contain cracks. Standard deviations of the pixel values along the rows and column pixels of the detected connected crack components are used as features to further classify the cracks as outlined in the Portuguese distress protocol. This method

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has a few false positive detections in terms of detecting ravelling distresses that are less than 2mm wide but appear similar to cracks. Nhat-Duc Hoang et al (2018) implement laplacian pyramid based image processing techniques for feature extraction. Projection integrals of these images are used as inputs to the Least square Support vector machine (LSSVM) that is tuned using Differential Pollination Algorithm (DFP). This combination of LSSVM and DFP achieves a high, 93.4% classification accuracy. Automatic Pavement Crack Detection and Classification Using Multiscale Feature Attention Network which consists of the Multiscale Dilated attention module (MDA) and Feature Fusion Upsampling (FFU) module was proposed by Weidong Song et al (2019). The MDA module is used to obtain high-level features from the image which are further upsampled to match the input feature resolution using the FFU module. The different crack objects detected are fitted with a minimum enclosing rectangle (MER). The cracks are categorized into different types and severity levels based on the properties obtained by different MER such as the angle, distance between them and length of the diagonal etc. This method performed well with an overall classification accuracy of 91%.

Artificial neural networks simplify the task of crack classification by automatically extracting features from the images. However, most classification tasks are limited to categorising cracks based on their type and very few works incorporate severity classification. Few works like Li Baoxian et al (2018) and Kaseko (1993) have achieved classification of cracks belonging to four different categories, longitudinal, transverse, block and alligator types. Former uses four convolutional neural networks with different sizes of receptive fields. These networks are trained using patches of images and achieve a good classification accuracy of 94%. The latter research work is one of the earliest studies classifying cracks using Multilayer Feedforward network (MLF). This work first carries out image segmentation by automatically selecting the threshold value obtained from training a MLF network. The input to the network include features obtained from the grayscale image histograms such as the global mean and standard deviations for each pixel.

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Another MLF network is used to classify the cracks using properties of segmented crack objects such as the variance, mean number of uninterrupted sequence of object pixels and projected crack length in a certain direction. Anisotropy which is a measure of the probability of a certain pixel being a crack or non-crack depending on the features in a certain orientation is used by Tien Sy Nguyen (2009) to identify crack pixels in the images. These detected crack pixel features are then used as input to the multilayer perceptron network to classify cracks belonging to different categories. N.A.Yusof et al (2018) make use of two deep convolutional neural networks to detect and classify cracks. First stage is used for crack detection and segmentation which is followed by the second stage for crack classification. However, cracks are only classified as longitudinal and transverse. In another recent study by Ronald Roberts et al (2020) several road distresses such as cracking, visco-plastic distresses such as rutting and other distresses such as potholes are classified using object detection based convolutional neural networks like Faster RCNN and Single Shot Detection (SSD) using Inception v2 and MobileNet. Cracking distresses were divided into two categories based on area of cracking. This method achieved an overall accuracy of 90%; however, the categories of cracks considered based on type and severity were limited.

Another research work developed by Tsai, et al (2014) implements a multi-scale crack analysis method based on Crack fundamental element. Multiscale Crack Fundamental Element (CFE) model, is used as a basis to extract mutliscale crack properties which further assist in classifying cracks based on their type and severity. A CFE is defined by clustering cracks based on their proximity using a bounding box. These clusters are further expanded to obtain different crack properties which are mutliscale and represent topological properties of the crack. These properties are divided into three scales namely, fundamental properties, aggregated properties and CFE geometrical properties as shown in the figure 6. The method expands from calculating the fundamental crack properties which are specific to a single crack segment (e.g., crack length), to aggregated crack properties which represent the interactions between cracks with each CFE

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(e.g., Crack intersections) to the final step of calculating clustered CFE properties which focus on the overall crack itself (e.g., CFE orientation). In this way, the model manages to capture all types of properties that can be useful to analyze and classify pavement cracks.

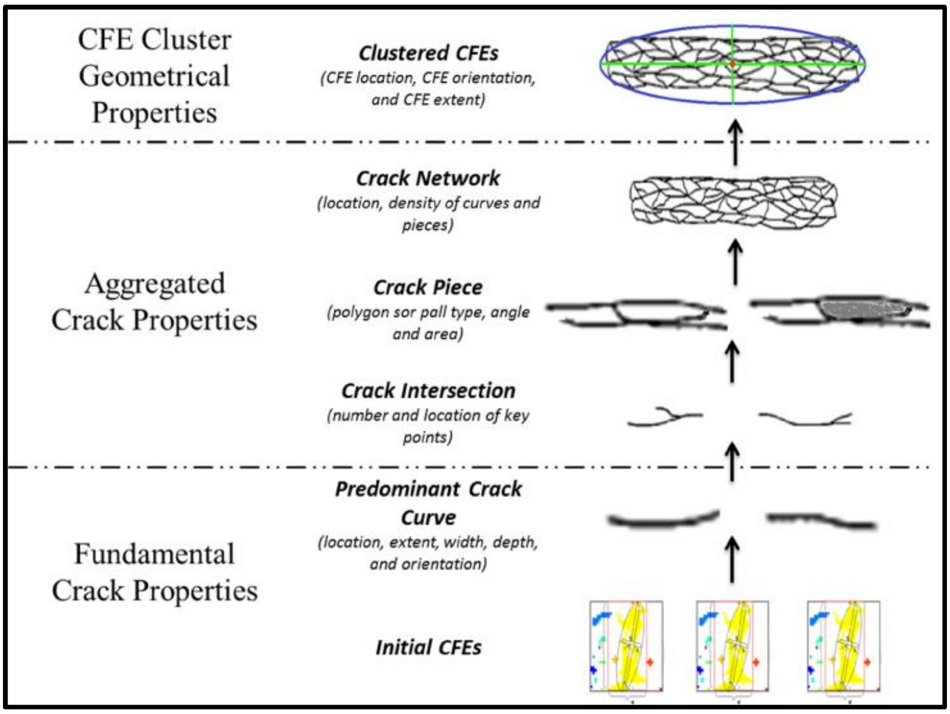

Figure 6: Mutiscale crack properties, Tsai et al, (2014)

These crack properties are intuitively related to the crack type and severity definitions in COPACES. However, directly correlating them to a particular crack category is a complex task. Hence a machine learning technique (Ordered Logistic Regression) combined with heuristic rules is used to automatically classify cracks. This method achieves an overall classification accuracy of 92.2% and 98.1% for load cracking and block cracking respectively. This method is used as a baseline to develop the object detection based crack classification technique. It also serves as a benchmark to validate results.

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From this literature review it is clear that deep learning networks have not been used to classify complex crack structures which represent different crack types and severity levels outlined in COPACES and there is a need to further research and develop novel techniques that can achieve this. Therefore, the objectives of this study is to propose a method that aims to classify these cracks directly using object detection based convolutional neural networks and analyze the performance which in turn addresses the need.

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CHAPTER 3

An Automatic crack classification technique using Convolutional Neural Network and Post-processing techniques

Automatic crack detection and classification is a complicated process because multiple crack properties need to be considered. Therefore, the method proposed for crack classification leverages the robustness of object detection based convolutional neural networks to identify multiple crack properties and applies certain geometrical principles to post-process the obtained detection results to arrive at the final expected outcome. These geometrical principles serve as post-processing techniques to the ML based detection results.

The proposed methodology is composed of

1. **Object detection based Crack Classification technique**
   a) Step 1 – Data Preparation
   b) Step 2 – CNN Model Selection
   c) Step 3 – Training and Testing
2. **Post-processing techniques**
   a) Step 4 - Method for crack type and severity classification
   b) Step 5 - Method for crack extent classification

This chapter provides a detailed description of the steps for object detection based crack classification technique using convolutional neural networks. It also deals with post-processing techniques used for crack classification.

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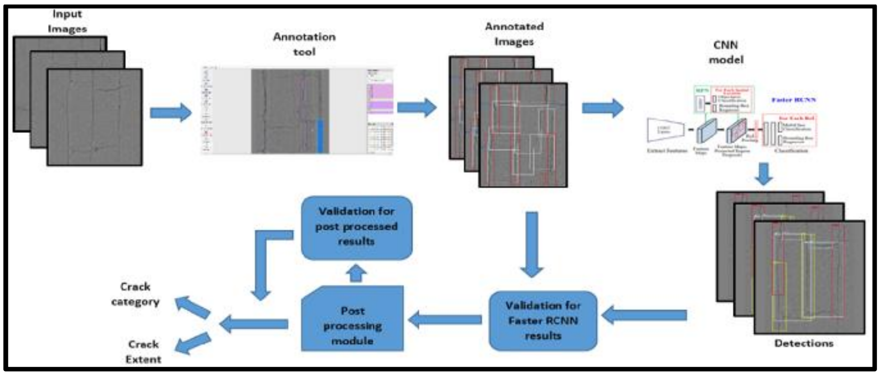

Figure 7: A flow chart presenting the components/steps followed for the proposed method and their relationship.

3.1 Step 1: Data preparation

Convolutional neural networks require huge, diverse datasets in order to produce accurate results. 3D pavement data captured by the GT Sensing Vehicle is processed to obtain 3D Range images. LCMS software outputs an image that corresponds to a resolution of 4mm. The original image size is 1040x1250. LCMS software also records the location of the lane marking for every image. As joints are present at the edges of the lane, images are cropped as shown in Figure 8 to exclude the joints as they appear similar to cracks and can result in false positive detections. These images are annotated to create ground truth.

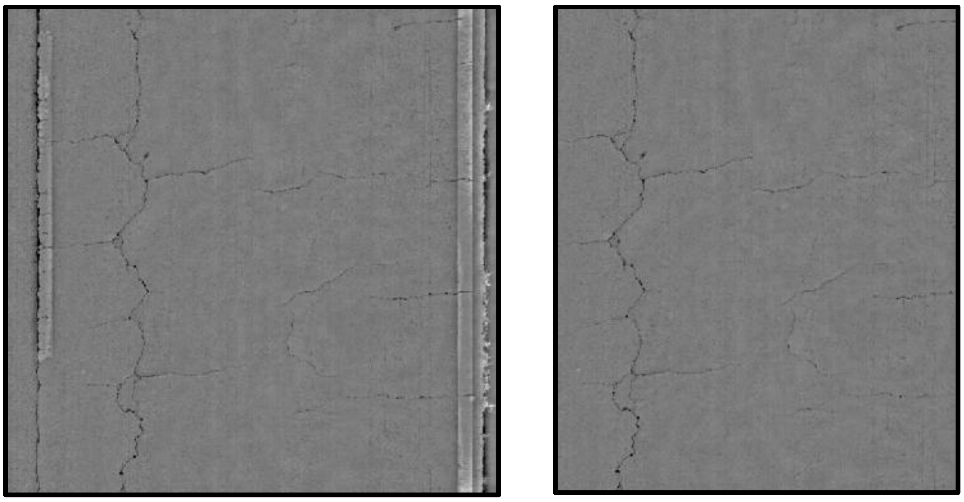

Figure 8: Illustration of the original image and pre-processed image

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3.1.1 Annotation Method

Annotations for Faster RCNN model are created using a labelling tool, LabelImg shown in Figure 9. Bounding box type annotations are created by drawing on the image and also specifying the class label. LabelImg saves these annotations as XML files using the PASCAL VOC format.

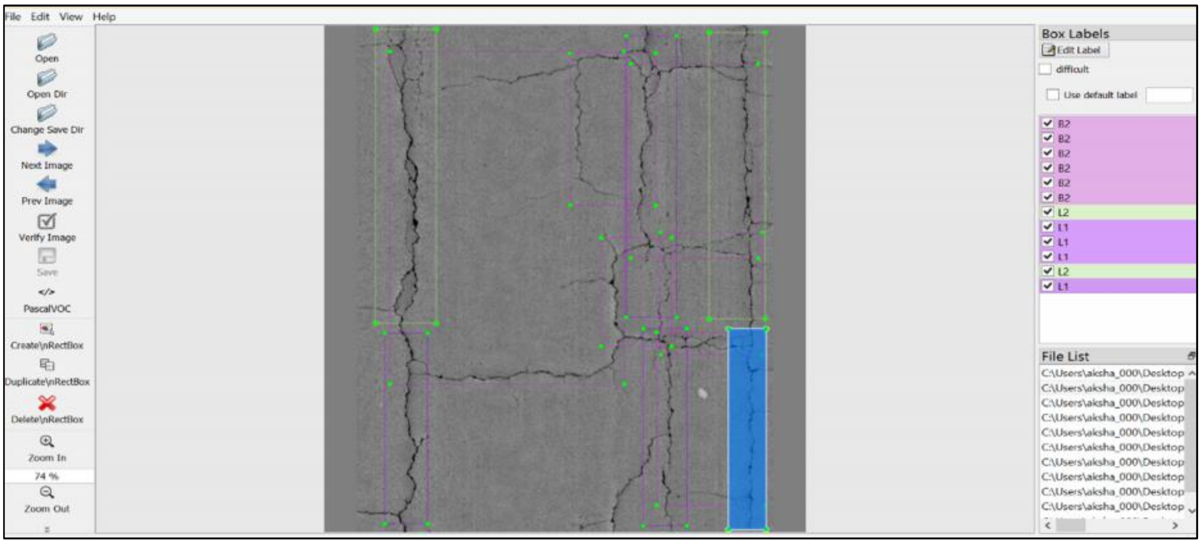

Figure 9: Illustration of the labelling tool used for creating annotations

A single section of the pavement can have multiple combinations of cracks belonging to different types and severity levels. This complicates the process of crack classification. Current GDOT standards require reporting all crack types, severity levels and extent. Different categories considered for annotation are:

Load Cracking – Severity Level 1 (LC1), Severity Level 2 (LC2), Severity Level 3 (LC3) and Severity Level 4 (LC4)

Block Cracking – Severity Level 1 (BC1), Severity Level 2 (BC2) and Severity Level 3 (BC3)

Convolutional neural networks can distinguish between different categories of objects by extracting unique features specific to a certain category. As defined in the literature review

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section, cracks are categorized into different types based on the location of occurrence. It is a task complicated task for neural networks to distinguish between different types based on the location of occurrence. This is due to the absence of any reference that is unique to a certain category in the background that can help differentiate between different sections of the pavement i.e, Wheelpath (WP) and Non-Wheelpath (Non-WP). Hence different categories considered for annotation are based on identifying unique features. To accommodate these features, crack definitions are slightly changed from those defined in COPACES.

1. **Load Cracking:** Different from COPACES, all longitudinal cracks irrespective of the location of occurrence or whether it is forming a block pattern are defined as load cracking with different severity levels. This is done because all longitudinal cracks in both WP and Non-WP or even when they are part of block patterns appear to be similar. Hence the model cannot distinguish between them.
    a. **LC1/BC1:** This category is defined to include all single longitudinal cracks that appear in the image. The image shown below shows all single longitudinal cracks annotated with a label LC1/BC1. Further to distinguish between Level 1 and Level 2, number of polygons formed is an important distinguishing feature. A longitudinal crack having 2 to 3 small polygons is also considered as LC1/BC1 (red).
    b. **LC2:** Cracks belonging to this category have more than 3 small polygons or 2 to 3 large polygons appearing along single or double longitudinal cracks. The image below shows an annotated example belonging to this category and is labelled as LC2 in yellow.
    c. **LC3:** This category includes 3 or more longitudinal cracks forming many polygons. This pattern resembles that of the alligator hide. This crack usually occurs across the entire 5m wheelpath section parallel to the direction of traverse. The image below shows the annotated LC3 category in dark blue

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d. **LC4:** Pavement pop out caused by severe load cracking and aggregate loss is a unique feature of this category. These areas of the pavement appear dark in the images due to the loss of pavement material causing less light to reflect. The image shows the annotated LC4 category in green.

2. **Block cracking:**

   a. **BC1:** Different from COPACES, this category of annotations includes only transverse cracks that are wider than 2ft since all longitudinal cracks are annotated as load cracking as previously mentioned. These transverse cracks can occur either independently across the pavement or they may be intersecting longitudinal cracks. The image below shows these annotated transverse cracks as BC1 (light blue)

   b. **BC2/BC3:** All the block patterns formed in the image are labelled as BC2/BC3. As defined in COPACES, both BC2 and BC3 have block patterns appearing across the entire roadway. Therefore, the task of detecting these categories can be simplified by detecting the block patterns. With the detected block patterns from the model, the classification of BC2 and BC3 is done using the post-processing steps. The image shows the annotated blocks in white with labels as BC2/BC3.

An image can contain combinations of crack categories. Therefore, each image is carefully annotated. All crack combinations in each wheelpath are labelled separately because the patterns are different for different severity levels as mentioned above. Hence the model is trained to identify these specific patterns. For this particular example in Figure 11, a part of the crack in the left wheelpath is labelled as LC3 (dark blue) and bottom part as LC2 (yellow). On the right Wheelpath, both LC2 and LC1/BC1 (red) categories are annotated. All transverse cracks are annotated as BC1 (light blue).

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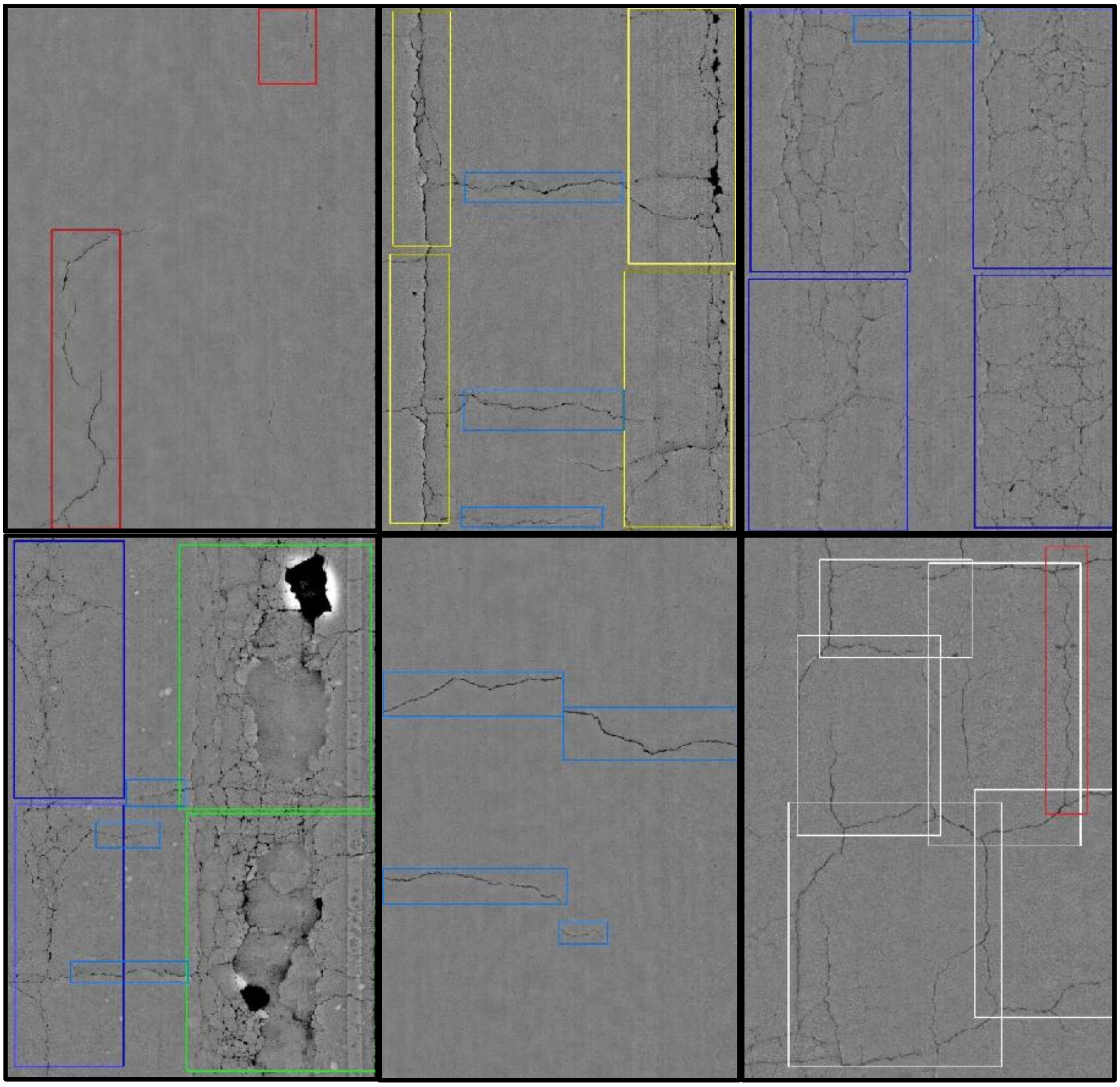

Figure 10: Annotated crack categories

Note that even when the crack in a single wheelpath has consistent severity level, it is labelled as two separate bounding box if the length exceeds a certain minimum threshold (visually decided – crack length is at least half the image length) as shown in Figure 11. This is because the model learns to detect similar number of categories in each wheelpath as it is trained to detect. Therefore, by annotating each wheelpath with two bounding boxes, the model learns to split the detections in each wheelpath. This also helps reduce the number of duplicate detections due to

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inconsistent annotations i.e, labelling a few images with one bounding box in the wheelpath and a few other images with two.

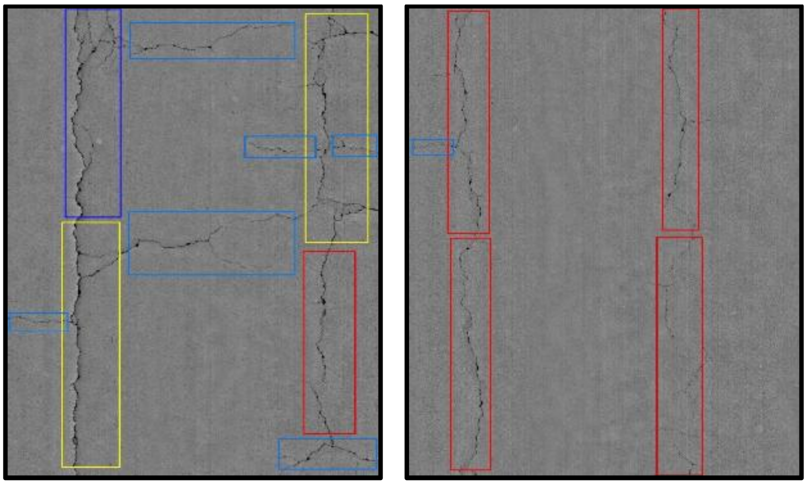

Figure 11: Annotation method

1000 pavement images were used for training the model. The annotation count per category is shown in table 2

Table 2 Annotation count per category

Crack category	Training	Testing
LC1/BC1	1704	155
LC2	501	79
LC3	259	97
LC4	40	4
BC1	2937	231
BC2/BC3	425	62

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3.2 Step 2: CNN - Model Selection

Convolutional Neural Networks (CNN) are a class of deep learning algorithms which take 2D images as inputs. They represent deep neural networks with different layers performing different operations. The convolutional layer performs a convolution operation between the learned filter weights and the input image. This helps reduce the size of the input while preserving important high dimensional features. The output of each convolutional layer is a feature map. The pooling operations such as max-pooling, L2 pooling also help in reducing the dimension of the feature map. This is done by down-sampling the input feature map. This operation helps to create location invariant features. A number of convolutional and pooling layers are stacked together and the output is fed to a fully connected layer which consists of a non-linear activation function that fine tunes the input to adjust the output as required for classification. This entire network is trained and optimised for different classification tasks.

Applications of Object detection according to Zhong-Qiu Zhao et al., (2019) can be divided classified as follows

- **Generic Object detection** – which is based on detection and classification using bounding box regression
- **Salient Object detection** - which deals with pixel level segmentation

Generic Object detection can be further classified based on the type of framework used for detection and classification as follows

- Region Proposal based framework
- Regression and Classification framework

The Region proposal based framework typically starts by selecting regions of interest in an image. This is done either using methods such as selective search, Edge box or using CNNs as in case of Faster RCNN. The generated region proposals act as inputs to the Convolutional Neural

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Networks which further extract high dimensional features. These features are used to train the network for object classification and localization where each object in the image is classified into separate categories and are fitted with a bounding box.

Faster RCNN model which was proposed by R. Girshick et al., (2015) was chosen for this generic object detection task of detecting different crack types in an image. Faster RCNN has proven to achieve high classification accuracies for complex classification problems. This section elaborates on the functional mechanism and model structure for Faster RCNN. The model consists of two modules that share a set of convolutional networks. This helps increase the computational speed. The first module is the region proposal network (RPN). This network takes as input the convolutional feature map generated by the last convolutional layer of the shared network and generates region proposals by sliding a network over each n x n window of the input feature map. This sliding network consists of an n x n convolutional layer which outputs a lower dimensional feature map for every window of the input feature map. This network also has two, 1 x 1 convolutional layer that output a set of predicted anchors (with different size and aspect ratios) and an associated score representing a probability estimate of the object being present or not for every window. The different scales and aspect ratios of an anchor makes the model scale invariant. This helps reduce the model size and also saves computational costs related to rescaling the proposals for the next layer. The loss function used for the RPN network takes into account the errors in predicted objectness probabilities and also the predicted bounding box coordinates. It is trained by back propagation and stochastic gradient descent.

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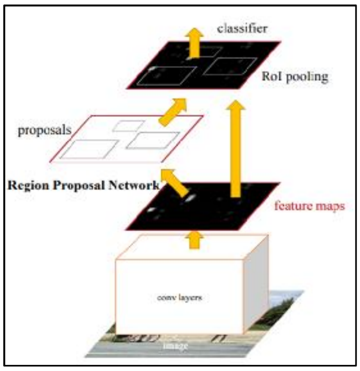

Figure 12: Illustration of the Faster RCNN model, Girshick et al (2015)

Region proposals from the RPN network are inputs to the Fast R-CNN network which was developed by R. Girshick, (2015). Fast R-CNN network first generates a feature map for the entire image and uses the object proposals to extract a fixed length feature vector from the feature map for the region enclosed by the proposal using an RoI pooling layer. This network consists of 5 max pooling layers and 3-15 convolutional layers. The last fully connected layer is split into two sibling layers. One of the layers generates class probabilities for each object proposal and the other outputs the bounding box coordinates for the region proposals. This method makes use of the stochastic gradient mini batches while training that increase the training speed by sharing the computations for proposals from the same image. A multitask loss function that takes into account both predicted class probabilities and locations of the bounding box is proposed for training.

The RPN and Fast R-CNN networks are trained using an alternating optimization approach where RPN is initially trained to generate region proposals. These proposals are further used to train the Fast R-CNN network. The weights for the shared convolutional layers are fixed and only the layers specific to each module are trained and fine-tuned alternately.

3.3 Step 3: Training and Testing

Training and testing was implemented using Google's object detection API which is an open source code repository that provides access to different state of art object detection models. To

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train the model, first a Pascal TF Record file that records the labels and bounding box coordinates for each image was created. This is used as the input to the network. The model was trained on Google Colaboratory GPU using a learning rate of 0.0001 and batch size of 1. The following anchor scales were used (0.25, 0.5, 1.0, 2.0) and aspect ratio were set at (0.5, 1.0, 2.0). Adam Optimizer was used for optimising the network weights. The first and second stage IOU threshold for the model were selected to be 0.7 and 0.6 respectively.

The trained model was tested using 100 pavement images. In order to reduce overlapping detections, non-maximum suppression with an IOU threshold of 0.5 and a bounding box score threshold of 0.4 was used. This technique eliminated many duplicate detections from an initial 300 detected bounding boxes to 10-12 bounding boxes per image. These final detections were considered for model evaluation by comparing with the ground truth.

To simplify the task of obtaining the final crack types and severity levels using post-processing techniques, the number of overlapping detections at this stage were further reduced, as shown in Figure 13, using an Intersection over Area (IOA) threshold of 0.65. This value was chosen by trial and error to obtain the best detection results.

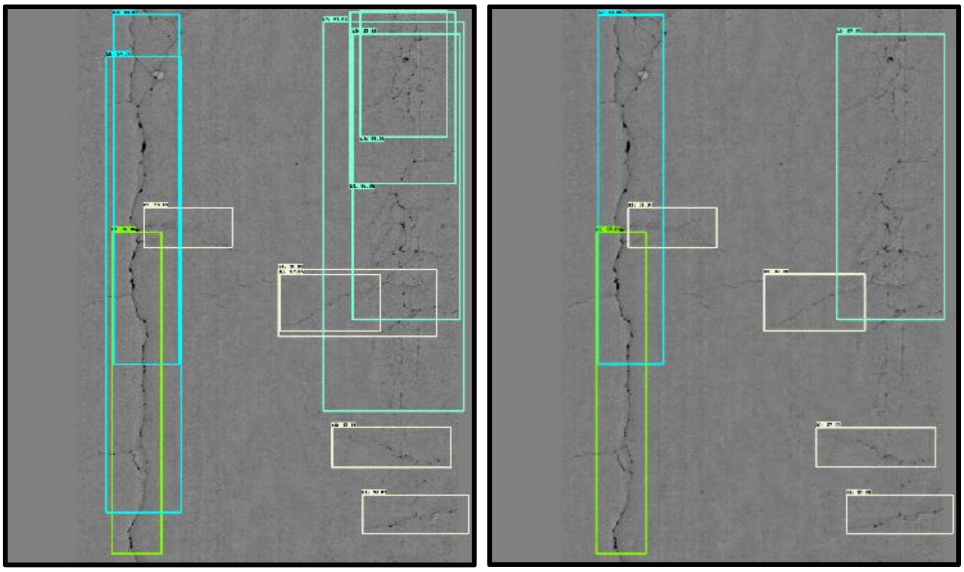

Figure 13: Illustration of overlapping detections before and after post-processing

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3.4 Post-Processing For ML Results

The second part of the methodology involves post processing the results obtained from the first part which is detailed in Chapter 3. Post processing is done to determine crack severity and extent. This is an important step to obtain the final outcome because the crack type and severity definitions were modified from those defined in COPACES during annotation. The techniques used for post processing are described in the next section

3.4.1 Step 4: Crack Type and Severity

The detection results are post processed to determine the wheelpath and non-wheelpath crack type and severity as outlined in COPACES.

The wheelpath, as noted by a GDOT engineer is considered to be approximately 3.25 feet wide. The entire pavement is divided into 5 zones as shown in the Figure 14. These zones are marked based on the location of the lane marking. Lane marking locations are recorded by LCMS software during pavement data acquisition process. Zone 3 which represents the non-wheelpath is approximately 3 feet wide. However, for the purpose of validating the results with the benchmark method, similar approximate measurements for wheelpath – 3.00 feet and Non-wheelpath – 3.05 feet are used.

Two of detection results that need to be post-processed include

1. LC1/BC1 - As mentioned in section 1.1.1, during annotation, all longitudinal cracks are labelled as LC1 irrespective of their location of occurrence. These detections can include longitudinal cracks in the non-wheelpath which could be independent cracks that need to be post – processed to BC1 or they can be part of the block pattern in which case they need to be deleted. This is done as follows:
    a. LC1/BC1 detections in the Non-wheelpath which are not part of the block pattern are detected by checking the region of overlap between the detected bounding box

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and the non-wheelpath using an IOA threshold of 0.8 If the detection, has an IOA value greater than the threshold, the category label for that particular detection is changed to BC1

   b. LC1/BC1 that are part of the block pattern – Since all longitudinal cracks are labelled as LC1/BC1 for training the model, the model will also detect longitudinal cracks that are part of a block pattern as LC1/BC1. The location of wheelpath is also used to decide whether to remove these detections. If the longitudinal crack forming a block pattern is in non-WP, then this detection (bounding box) is removed. On the other hand, if the longitudinal crack is in the WP, then the LC1/BC1 detection (bounding box) of this longitudinal crack is kept. This is done by checking if there is overlap between the detected bounding box for LC1/BC1 and BC2/BC3 categories using an IOA threshold of 0.4 If there is overlap, then this bounding box is removed.

2. BC2/BC3 – This category includes detected blocks on the pavement which are typically part of BC2 or BC3 as mentioned in COPACES. The individual blocks are annotated as BC2/BC3. In order to determine the level of severity, these detections have to be post processed to check if they map to either BC2 or BC3 category as outlined in COPACES. The steps followed to post process these detections are as shown in the flowchart in Figure 15. The important features of these detections that are taken into account for classifying them are:
   a. Number of detected BC2 bounding boxes
   b. Area of each detected bounding box
   c. Coverage range and the location (whether it is in WP or not) of the detected bounding box

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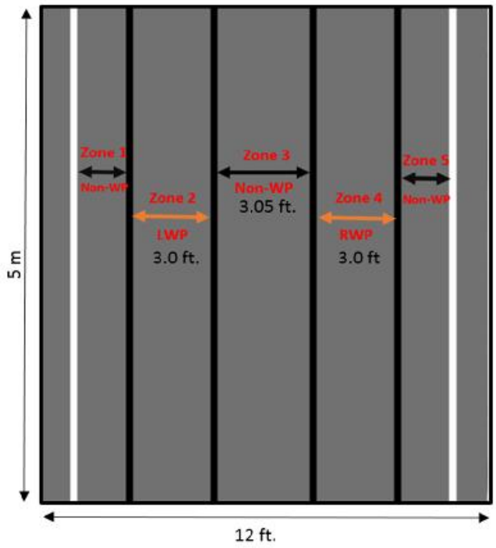

Figure 14: Representation of WP and Non-WP sections

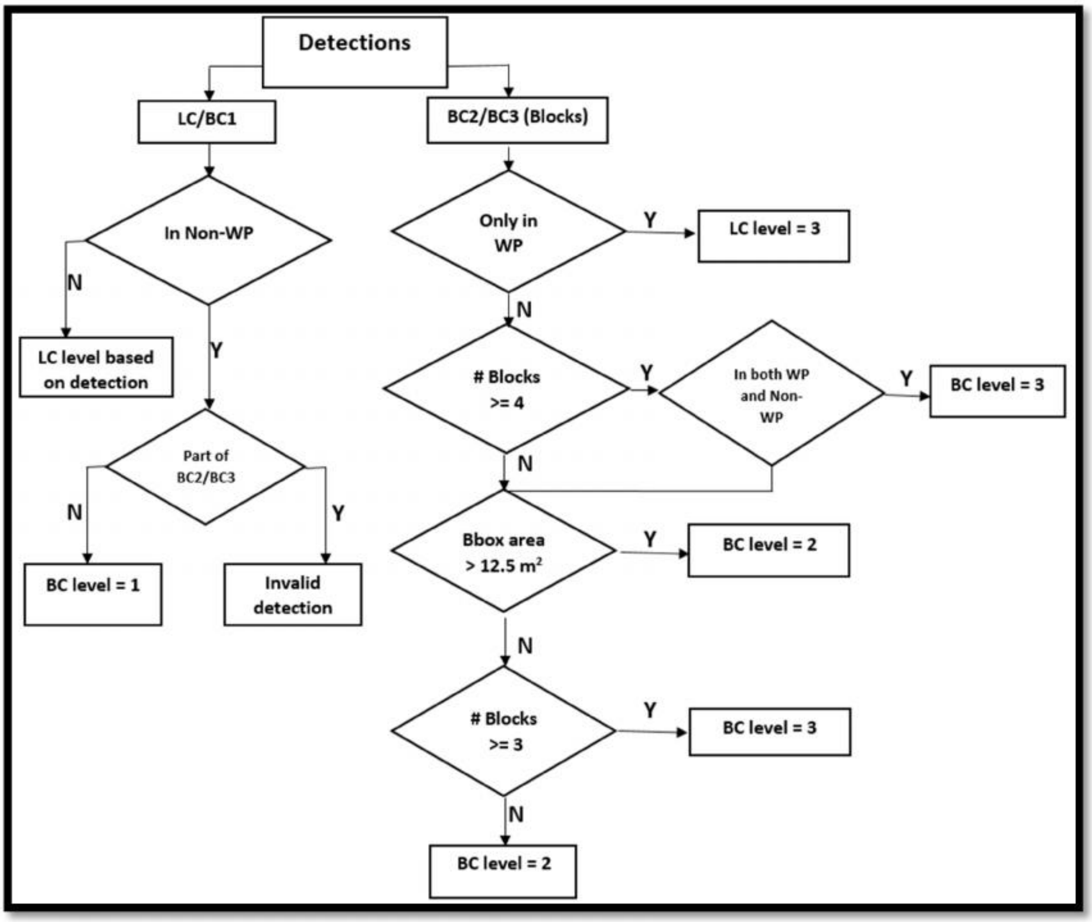

Figure 15: Flowchart of post-processing steps to categorise LC/BC1 and BC2/BC3

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3.4.2 Step 5: Crack Extent

GDOT calculates the extent of the crack based on the longitudinal length for load cracking and total crack length for block cracking. This extent is calculated as a percentage of the pavement section considered for survey. Based on the extent of cracking for each severity level, deduct values are obtained for the surveyed section. The following post-processing technique to calculate crack extents gives an approximate value. The extent calculations for each crack type are as follows

a) **Load cracking** – For each wheelpath, load cracking extent is an approximate value obtained by measuring the lengths of the detected bounding boxes as shown in Figure 16. Overlapping lengths are deducted to get an approximate total crack extent. This is not an accurate value because the detected boxes do not accurately span the entire crack length.

   RWP extent (LC3) = b1 + b2 – b3 > 1180 pixels = 5000 mm

   This value can be converted into percentage extent as required by GDOT by taking the ratio with respect to the entire wheelpath length.

b) **Block cracking** – BC1 extent is calculated by measuring either the breadth or length of the detected bounding box based on the orientation of the bounding box as shown in Figure 16. BC2/BC3 extents are approximate values got by summing the perimeter of each detected block pattern. This method only gives an approximate value because the crack classification algorithm does not need to detect every crack present on the pavement to determine the severity of block cracking. Therefore, many small cracks are not included in these extent calculations.

   BC1 Extent: a1 + a2 = 368.02 pixels * 4 = 1472.08 mm

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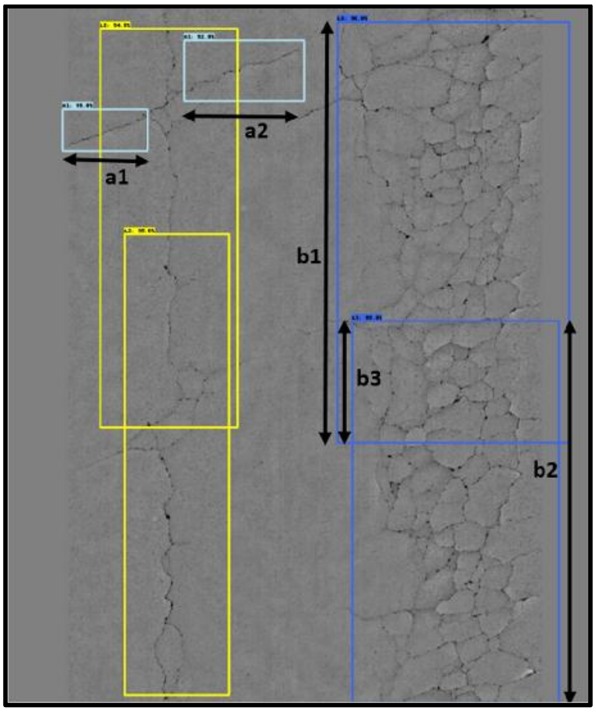

Figure 16: Example showing extent calculations

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CHAPTER 4. VALIDATION

The first section of this chapter presents validation of the results obtained from the first part of the proposed method i.e., Object detection based crack classification. The second section focuses on validation of the final outcomes obtained from the post-processing detection results.

4.1 Validation for ML based crack classification technique

This section elaborates on the dataset and metrics used for validation of Object detection based classification technique. It also presents a discussion for the obtained results.

4.1.1 Dataset and Metrics

For the validation of the trained Faster RCNN model, a test set containing all categories of cracks was used. This dataset contained 100 images with per category annotation count as shown in table 2 in section 1.1.1 The images for train and test sets were chosen separately from the collected pavement image set to include different images with no duplicate images. Annotations were created using the same technique that was adopted to create ground truth data for model training. The model was tested using the trained network weights. The performance was the best for weights obtained from training the model for around 35000-40000 epochs.

The metrics used to validate the model performance were based on the same metrics that have been used for the PASCAL VOC challenge i.e., Average precision and Recall. These metrics are also the most popular for validation of object detection based models. Precision is related to the models prediction accuracy.

$$Precision = \frac{True\ Positive}{True\ Positive\ +\ False\ Positive}$$

Recall is a measure used to determine how well the model performs in detecting all true positives.

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$$Recall = \frac{True\ Positive}{True\ Positive + \ False\ Negative}$$

Average precision is calculated as the average of precision values over recall values ranging from 0 to 1. This basically represents the area under the Precision-Recall curve. The IOU threshold used for detection was set to 0.5.

4.1.2 Validation Results

The model was able to achieve a mean average precision of 0.568 with the average precision and recall values for every category as shown in Table 3.

Table 3: Detection Results

Crack category	Average precision @ 0.5 IOU	Recall
LC1	0.375	0.580
LC2	0.478	0.658
LC3	0.548	0.742
LC4	0.892	1.00
BC1	0.626	0.714
BC2	0.461	0.50

The major issue for low scores related to LC categories was due to overlapping detections as shown in Figure 17. This resulted in a number of false positive detections. These overlapping detections are mostly due to the splitting the annotations for each wheelpath to consider multiple

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combinations of existing crack severity levels. These detections were treated as false positives as the metric considered for evaluation treated only a single matching detection as true positive and all overlapping detections as false positives. Methods that were used to eliminate overlapping detections depending on their confidence score or IOA value did not work because it was difficult to automatically determine which of the detections have to be removed in each wheelpath. The previous statement notes this task as difficult because a few false positives were detected with a high confidence value. The low recall values for the LC1 and LC2 categories is related to the model not being able to distinguish between them because they share similar crack patterns. There were a few cases where LC4 was detected as LC3 as illustrated in Figure 18. Overall the model performed well in identifying LC4 cracks.

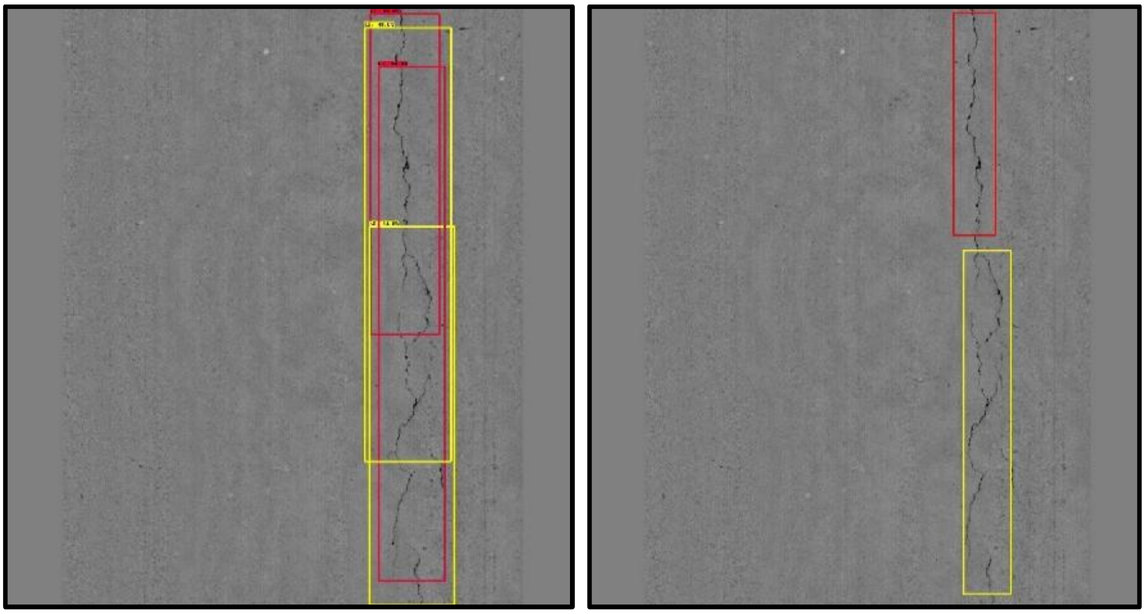

Figure 17: Illustration of crack detections (left) and labels (right)

The model wasn't able to detect all transverse cracks (BC1) which resulted in a low score. This is because to the model fails to detect many short transverse (3ft) cracks. However, all transverse cracks that are wide enough (4-5ft) were detected accurately. There were a few

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cases wherein the model falsely detected transverse cracks which were part of BC2/BC3 category as seen in Figure 19. This justifies the low recall value. Performance for BC2/BC3 category is low in part because the model fails to detect small block patterns and also patterns that are not clearly visible as shown in figure 19.

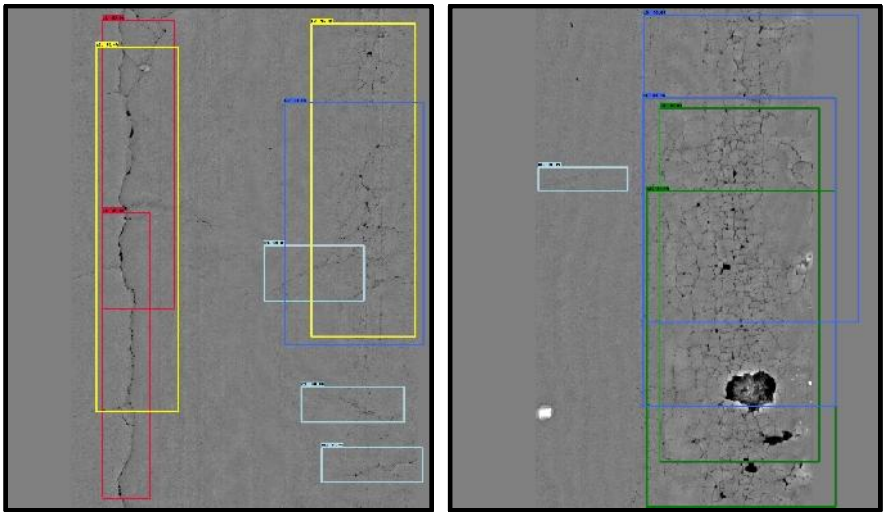

Figure 18: Illustration of false LC1(top left WP) and LC3 (right WP) detections.

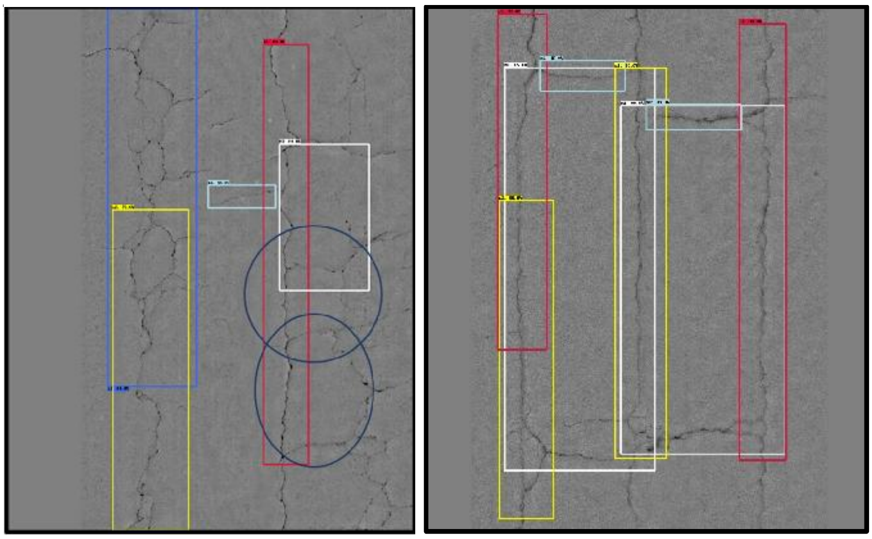

Figure 19: Illustration of missing BC2/BC3 detections (circled) in the first image and false positive BC1 detections in second image

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4.2 Validation for post-processed results

This section elaborates on the dataset and methods used for validating the final outcomes obtained from the post-processed detection results. It also discusses the performance of the proposed method by analysing the validation results for a few images.

4.2.1 Baselines for validation

Traditionally, Pavement Engineers from GDOT have been visually surveying pavement sections and recording this data using a computerised pavement condition evaluation system. These ratings are done for a single survey section (a mile or partial mile) that is considered as a representative for the entire segment that is being rated. These visually classified results based on the crack definitions outlined in COPACES serve as ground truth for validating the results obtained from this method. With the help of an Engineer from GDOT, several complicated cases for pavement cracking images have been resolved and a consistent method is followed for classifying cracks.

Another method that is considered for validation is a research work implemented by Tsai, et al (2014) that has been reviewed in section 1.1.2. This method serves as a baseline for the current object detection based crack classification technique and hence is used as a second method for validating the results.

4.2.2 Validation Results

A set of 10 images consisting of all crack types and severity levels were used for validation using the two techniques mentioned above. A few of the results are shown below in table 4. Figure 20 shows the images used for validation. For the purpose of visual validation, pavement markings along with the Right wheelpath (RWP), Left wheelpath (LWP) and Non-WP sections are drawn for the ease of making better decision. These methods record the crack category and extent values (mm) for each wheelpath (Load cracking) and Non-WP (block cracking).

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The object detection based crack classification technique is able to achieve good classification outcomes that match the visual detection results. However, the accuracy of classification mainly depends on the detection and classification results from the Faster RCNN model. In all the below mentioned cases the model classification results were accurate. This confirms that the post processing techniques used to detect the crack category and extent worked.

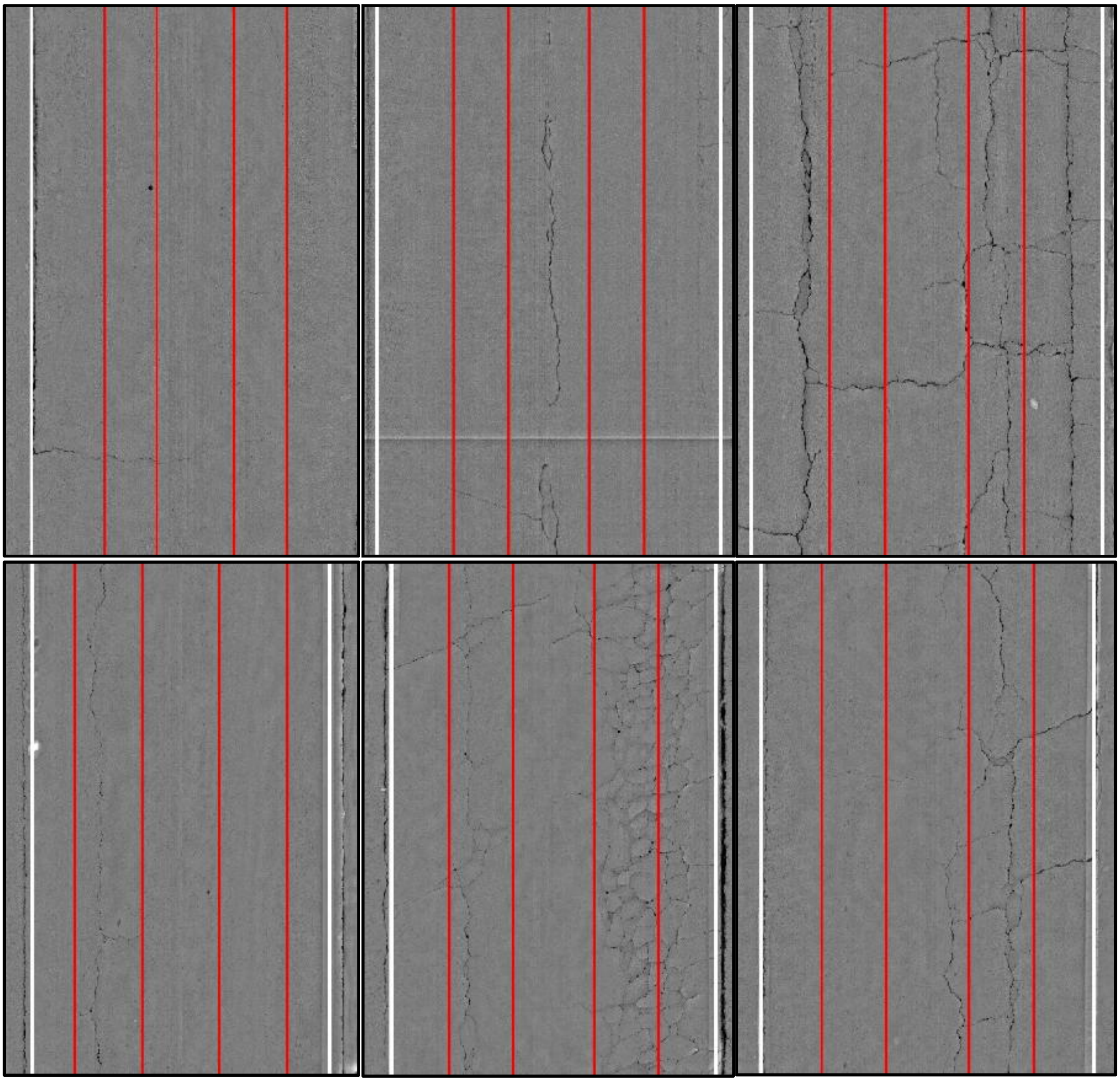

Figure 20: Images used for validation

In the first image in Figure 20, all the results from the three methods classify the crack as BC1. However, the drawback of the proposed technique is that the extent calculations only give an

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approximate value of the crack extent because as seen in the detection result in Figure 21, the width of the bounding box is not equal to the crack length. Another instance of BC1 where the longitudinal cracks appears in the wheelpath is shown in Figure 20, second image (top). Post processing technique used to differentiate between wheelpath and non-wheelpath cracks works well and is able to differentiate between these cracks as seen in the second illustration in Figure 21.

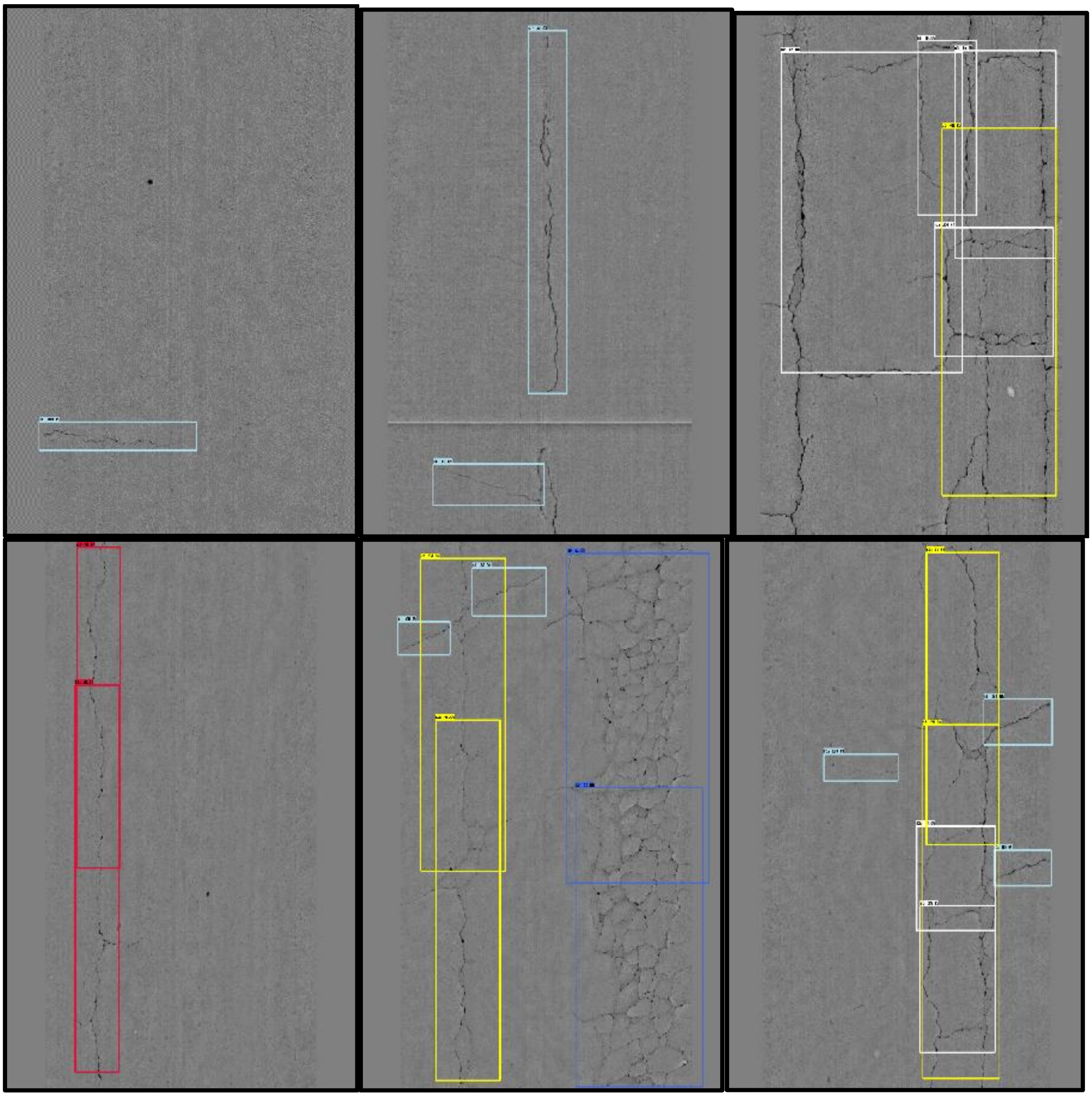

Figure 21: Detection results for validation images

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There is a difference in the crack category result in the fifth image (mid bottom) in Figure 15, where the Multiscale CFE method based classification technique classifies the crack in the left WP as LC1 whereas the actual crack category is LC2. This shows that the proposed algorithm performs well even when the cracks are formed at the edge of the WP.

Table 4: Validation results

		Multiscale CFE based crack classification algorithm			**Object Detection based Convolutional Neural Network**			**Visual detection**		
Image		LWP	RWP	Non-WP	LWP	RWP	Non-WP	LWP	RWP	Non-WP
1	**Level**	0	0	1	0	0	1	0	0	1
	Extent	0	0	2833.20	0	0	1882.97	0	0	-
2	**Level**	0	0	1	0	0	1	0	0	1
	Extent	0	0	6142.16	0	0	4536	0	0	-
3	**Level**	0	1	1	0	2	3	0	2	3
	Extent	0	4944	9967.499	0	3529	26969	0	5000	-
4	**Level**	1	0	0	1	0	0	1	0	0
	Extent	4940	0	0	5000	0	0	5000	0	0
5	**Level**	1	3	1	2	3	1	2	3	1
	Extent	4836	4944	2564.786	5000	5000	1472.08	5000	5000	-
6	**Level**	0	2	1	0	2	2	0	2	2
	Extent	0	4964	6313.95	0	3737	10592.72	0	5000	-

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In the last image (Figure 20), Mutliscale CFE method based crack classification technique classifies the block cracking category as BC1. However, the visual results match the proposed method where the image is classified to have BC2. This difference is in part because of the current updated classification protocol by GDOT which specifies that block cracking exhibits block pattern and these patterns need to overlap either partially or completely with the non-WP. This is also the case for difference in results for the third image where block patterns appear across the entire pavement and hence has been classified as BC3 by the proposed method. These results also explain the difference in block cracking extent calculations.

These results give an overall idea of the performance of this method. The proposed method performs well when the detection results are accurate and can easily detect crack category in certain complicated images where the Mutliscale CFE method based crack classification technique fails to perform well. However, it fails to give accurate crack extent calculations and also does not perform well if the detection results from the CNN are not accurate. As an example, in Figure 22, the crack on the right wheelpath is visually classified as LC4. However, the model fails to classify accurately and misclassifies the crack as LC3. In few other cases, it becomes difficult to use post processing techniques to determine which among the overlapping detections need to be eliminated. As an example in the second image in Figure 22, the left-WP has two categories of overlapping detections i.e, LC1 and LC2. If the overlapping cracks are eliminated based on either the confidence score or length of the bounding box, the detection for the upper portion of the Left-WP would be LC2 which does not match visual detection results.

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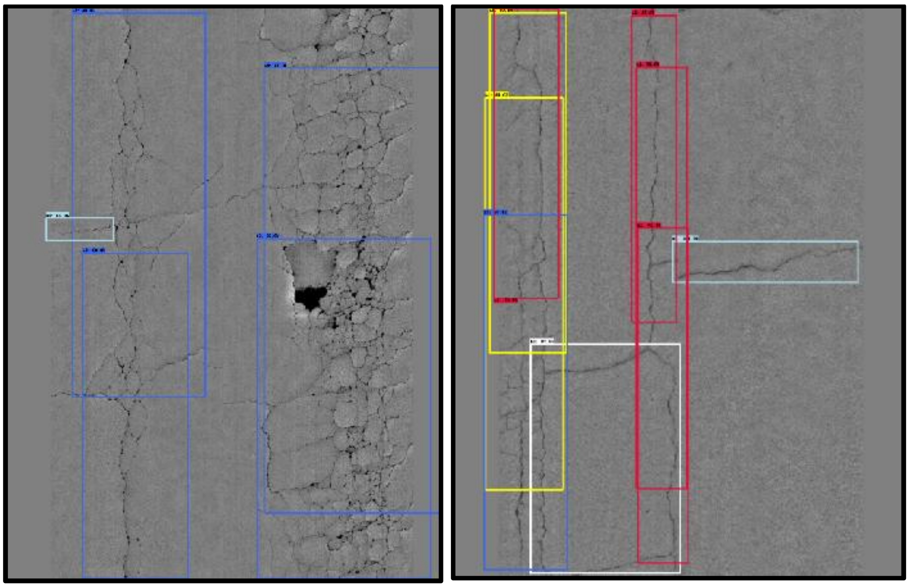

Figure 22: Examples showing a misclassified LC4 crack (left) and a complicated case for eliminating overlapping detections (right)

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CHAPTER 5. Future Research on deep learning method for crack classification

The proposed method can be considered as a baseline for developing future deep learning methods for crack classification. A drawback of the proposed method that uses post-processing steps to categorize the detections is the use of hard-coded thresholds values e.g., number of block patterns detected, area of the block pattern etc. As crack patterns vary across different regions, these thresholds may not hold true for all pavement datasets. Post-processing steps also increase the computational requirements and slow down the process of crack classification. In order to mitigate these issues partially or completely, the process of crack classification must be made fully autonomous using deep neural networks to eliminate post-processing. This recommended method tries to achieve this by automatically classifying the wheelpath and Non-wheelpath cracks thus, eliminating one of the post-processing steps.

This problem can be formulated as one related to spatial location based classification of 2D objects in an image. Most research work in this area is based on using probabilistic models to encode spatial relations between the objects of interest. Southey and Little (2007) developed and trained a maximum entropy model to learn the qualitative spatial relations between objects that can be used to classify objects in a scene. In another research work by Haldekar et al (2017) these spatial relations between objects in an image were used as part of annotations and each image was annotated based on the context as “To left”, “Inside”, “Below” etc. A Multi-layer perceptron was trained to predict these spatial relations.

However, a recent work by Islam et al (2020) shows that convolutional neural networks implicitly encode absolute location information of objects in images. Even though spatial extent of CNN filters is limited to extracting local features specific to an object, this work provides experimental proof showing the extracted feature maps, encoding absolute location information. This

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information is of high value for classification and detection tasks that depend on spatial relationships between different features.

In line with the latter research work, this method recommends enhancing location based information encoded by CNNs and using this information to automatically classify cracks based on location of occurrence.

5.1 Data Preparation

The image dataset that will be used for this method consists of similar 3D range images as used in the proposed method. However, the range images are not cropped and the entire image including the pavement markings is used to train the Faster RCNN model. As mentioned above, this method tries to enhance the location related information. This is done by including the pavement markings in the image. Pavement markings provide reference for locations of the wheelpath and Non-wheelpath boundaries. Hence they can be treated as reference for the model to learn spatial distance relations between lane markings and WP/non-WP boundaries. This can be useful to classify cracks that are region specific i.e, WP cracks (load cracks) and non-WP cracks (Block cracks)

The 3D images capture approximately 5m longitudinal pavement sections. These sections may not always include visible lane markings. This is because double lanes have discontinuous lane markings with gaps of around 10m and bad roadway conditions in certain areas may not have visible pavement markings. To overcome this issue, a white line which is 10 pixels wide is drawn on every image as shown in Figure 23. This line is drawn using the lane marking location information got from the LCMS data and it is slightly offset to align with the center of the lane marking which is approximately 20 pixels wide.

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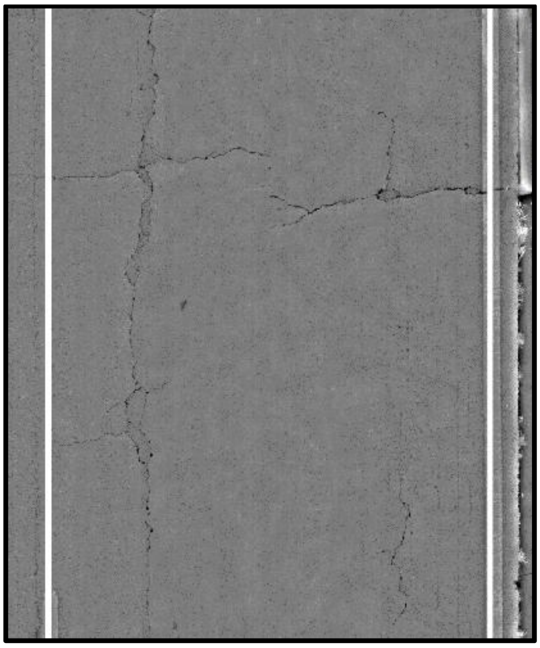

Figure 23: Illustration of white lines drawn on lane markings

5.2 Annotation Method

This method aims to reduce post-processing of the detected cracks to determine their actual crack category. Therefore, annotated crack categories are more aligned to match crack type and severity definitions outlined in COPACES. The class labels considered for annotation are as follows

1. Load Cracking: This category of annotations includes longitudinal cracks in the WP and their definitions match COPACES. Each wheelpath is annotated to include two bounding boxes based on the severity of the load cracking that is present as shown in method 1. This category also includes longitudinal cracks that are part of block patterns.
2. Block cracking: This category is different from that in the previous method that was implemented. It includes 3 types of annotations
    a. BC1-1: All transverse cracks that are wider than 2ft are labelled as BC1-1

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b. BC1-2: All longitudinal cracks in the non-wheelpath are labelled as BC1-2. Longitudinal cracks that are part of block patterns are not annotated. As shown in the Figure 24, this crack category in the non wheelpath is labelled in pink

c. BC2/BC3: Similar to the previous implemented method, this category includes all block patterns that appear in an image. These block patterns as mentioned in section 4.1 are typically part of BC2 and BC3. These detections need to be post-processed to categorize as either BC2 or BC3 using the same post-processing technique as discussed in section 4.1 for BC2/BC3 crack detections.

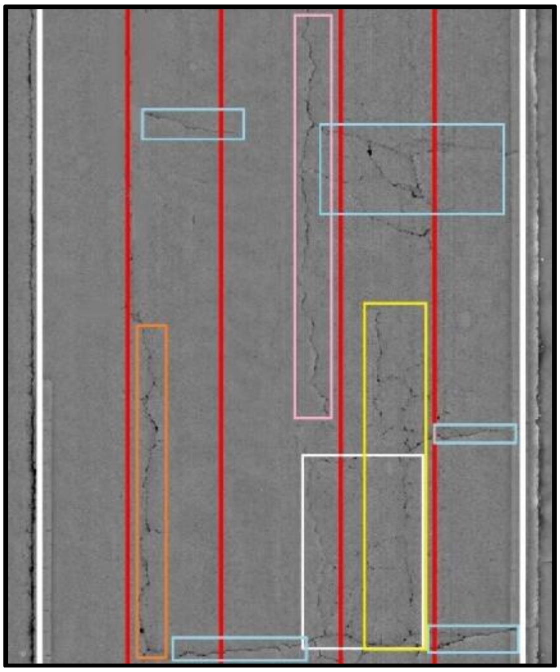

Figure 24: Recommended Annotations for different crack categories

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CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

Current practices followed by many transportation departments for rating pavements mainly depend on manual surveys by engineers or make use of semi-automatic methods. The complexity involved in automatically classifying pavement crack patterns has resulted in less research work in this area and most of the research has been dedicated to developing automatic crack detection techniques. State of art research for pavement crack classification using Convolutional neural networks has been mostly limited to classifying primitive crack categories. This proposed algorithm is among very few projects using object detection based Convolutional Neural Networks to classify complex crack categories.

6.1 Conclusions

A Faster RCNN model was trained to detect different crack types and severity levels based on specific crack properties. The Faster RCNN model was chosen because it has achieved the best classification accuracies for complex object classification problems. Pavement crack images are annotated based on GDOT's crack classification protocol, COPACES. Two methods were proposed for automatic crack classification and one of these methods has been implemented. The first method uses crack definitions that are slightly modified from those defined in COPACES to achieve higher detection accuracy. In doing so it compromises on using rule based post-processing techniques which depend on hardcoded threshold values to classify cracks as per the protocol. This method achieves a mean average precision of 0.56. Considering the complexity of the crack categories, this score is reasonable for crack classification. This algorithm is validated based on visual survey results and crack classification results obtained from a benchmark model based on the Multiscale-CFE method.

A second method is proposed for future research to build on this existing algorithm. This method aims to eliminate post-processing techniques as they make use of fixed threshold values to

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classify different crack categories. These thresholds are not consistent across different pavement datasets thus, can lead to erroneous results. Making use of pavement marking locations in the image, this method aims to exploit the ability of CNNs to encode location information for each crack category and thus, automatically detect WP and Non-WP cracks. Hence this technique helps automate a part of the crack classification process.

6.2 Recommendations

- There is a need to develop novel Machine learning techniques for crack classification problems that can achieve better classification results. Therefore, further research work in this direction is recommended taking into account the time and resources spent annually on maintaining road systems in USA.
- An algorithm to completely automate pavement crack classification using deep learning techniques is recommended. The proposed methods make use of post – processing techniques to classify cracks which are based on using fixed thresholds that may not work for all pavement datasets.
- Pavement crack classification can work well even without high quality 3D images. Hence smartphone images that can be easily acquired are recommended for use in future studies. This also helps reduce the cost associated with acquiring high quality images.
- Developing an algorithm for accurate crack extent measurements depending on the requirements of the transportation departments is recommended.
- Developing an automatic annotation technique is recommended as manually labelling images consumes more time.
- Unsupervised learning or Semi-supervised learning algorithms can reduce time and effort required to annotate thousands of images.

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- Methods to automatically detect joints and other crack-like distresses in an image can improve the performance of the proposed algorithm by eliminating false positive detections.
- Crack classification requires accurate pavement marking location information. Therefore, a method for automatic pavement marking detection is recommended.

6.3 Contributions

- A diverse dataset of 1000 images including all crack categories was annotated using the labelImg tool. These annotations can be further used for future study for improving the results
- A post-processing framework to classify cracks according to COPACES was designed and implemented.
- Code repository for training, testing and post-processing for crack classification is made available.

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