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Pavement Distress Analysis in Malaysia: A Novel DeepSeg-CrackNet Model for Crack Detection and Characterization Using Real-World Data

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Abstract - Pavement distress analysis plays a big role in keeping roads in good shape, especially in busy spots like Selangor and Kuala Lumpur, where heavy traffic and tropical weather make them wear out fast. This work introduces DeepSeg-CrackNet, a fresh hybrid deep learning model that uses Deep Gradient ResNet to spot cracks and a Residual block with a Modified Attention Mechanism to sort them into types, making it simpler to detect and label pavement damage. The model was trained on real data collected from Malaysian roads, with the CRACK500 dataset added in to cover more situations, and captured using a GoPro Hero 8 mounted on a vehicle, with GPS mapping keeping everything clear and easy to trace. DeepSeg-CrackNet performs really well—it hits a Mean IoU of 0.8388889 for segmentation and scores 85% accuracy in classifying cracks like alligator, longitudinal, and transverse, with precision ranging from 0.84 to 0.89, and recall between 0.80 and 0.96. It also measures cracks in meters or square meters, which helps in planning repairs smartly, like replacing big alligator cracks or sealing smaller longitudinal ones to save resources. Compared to models like CrackNet, DeepSeg-CrackNet stands out, especially for alligator cracks, with a precision of 0.84 and recall of 0.96, beating CrackNet's 0.778 and 0.772. In the end, DeepSeg-CrackNet makes it easier to manage Malaysia's roads in a data-driven way, improving safety and ensuring longer-lasting infrastructure through smarter, proactive repair approaches that enhance city travel.

Keywords—Crack Size Assessment, CrackNet, Hybrid Deep Learning, Malaysian Roads, Pavement Crack Detection

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1. INTRODUCTION

Pavement integrity acts as a cornerstone for safe travel and economic growth in Malaysia, especially with rapid urbanization and expanding road networks putting huge pressure on infrastructure systems. Roads serve as vital links between bustling urban centers like Selangor and Kuala Lumpur and rural areas, keeping goods and people moving smoothly while supporting the country's economic progress. But these essential connections face constant wear from harsh monsoon rains, tropical heat causing thermal expansion, oxidative aging, and traffic volumes that go far beyond what the roads were originally built to handle. Even small surface cracks often hint at deeper structural issues that can grow into serious problems like potholes or complete pavement breakdown if ignored [1]. Beyond the obvious safety risks, this kind of damage adds up to massive repair costs, with Malaysia's Public Works Department (JKR) spending over RM 2.8 billion each year just on fixing roads, which makes advanced crack detection and analysis a top priority for keeping Malaysia's infrastructure strong and competitive.

Traditional crack assessment methods lean heavily on manual inspections, where teams of engineers do visual checks or use semi-automated tools like laser profilometry. These techniques have been around for years, but they come with big drawbacks that make pavement management tough [2], [3]. Manual surveys often need 3-5 people to cover just 10 km of road, taking weeks to finish entire networks and giving inconsistent results, since human inspectors can vary by up to 30% in how they rate crack severity, especially when shadows or wet surfaces mess with accuracy. Plus, these methods don't capture key details like crack length, which is crucial for planning maintenance, leading to either early repairs that waste money or late fixes that let small issues turn into major projects.

Deep learning has completely changed infrastructure inspection lately, bringing powerful tools for automated crack detection, classification, and size analysis [4]. Modern convolutional neural networks (CNNs) like U-Net and Mask R-CNN hit over 90% accuracy in controlled settings for pixel-level segmentation, while transformer-based models like Swin-UNet pick up on long-range pavement texture patterns. Instance segmentation in systems like YOLOv8 can spot individual cracks and their shapes at the same time, and the best setups use attention mechanisms (CBAM, SE blocks) to focus on important features and ignore distractions like surface markings or debris, cutting inspection times by up to 95% compared to manual methods on datasets like CrackTree200 internationally. But making these work in Malaysia means dealing with the challenge of not having enough local training data that reflects tropical conditions and pavement types.

Malaysia's unique pavement conditions call for custom AI solutions that generic models can't handle. The country's asphalt mixes use 20-30% reclaimed tire polymer to deal with extreme heat, which changes how cracks form compared to standard pavements, and heavy monsoon rains speed up stripping and pothole formation, creating damage patterns that don't look like those in temperate climates. So, datasets like CRACK500 or RDD2020 [5] don't really fit, causing models like U-Net trained on other regions to struggle with Malaysian roads due to domain shift, potentially leading to more misclassifications. Most models also miss crack measurements, which are key for JKR's Pavement Condition Index (PCI) calculations, leaving maintenance decisions based more on guesswork than solid data since they lack precise crack width (to 0.1 mm) and length (to 10 cm) measurements [6].

This study steps in to tackle these gaps with two major innovations. First, it brings in the RCD-IIUM dataset [7], Malaysia's first detailed open-source pavement imagery collection with pixel-wise annotations and measurement data. Second, it introduces DeepSeg-CrackNet, a new multi-task model that combines crack segmentation, classification, and size analysis in one system, using a Deep Gradient ResNet (DG-ResNet) for feature extraction, a Crack Attention Fusion Module (CAFM) to cut down on environmental noise, an Augmented SubPixel Shuffling (ASPS) decoder for precise crack shapes, a Multi-Scale Context Aggregator (MSCA) to classify cracks by ASTM D6433 standards, and a Metrological Branch for real-world measurements through projective geometry. The paper is laid out to review crack detection history, explain the dataset and model design, share results benchmarked against standards, and wrap up with implications and future steps, aiming to raise the bar for automated pavement distress analysis in Malaysia and keep the nation's roads safe and sustainable through cutting-edge AI.

2. LITERATURE REVIEW

The area of pavement crack detection and classification has been picking up a lot of interest lately, especially since keeping infrastructure in good shape is so important, and with tech advancing quickly, Figure 1 highlights a big jump in publications on this topic from 2015 to 2025, particularly conference papers and journal articles hitting their highest numbers around 2023–2024, which really shows how much automated crack detection matters for road safety and saving money, all thanks to new computing methods and the growing need for practical, data-driven ways to manage pavements [8], [9].

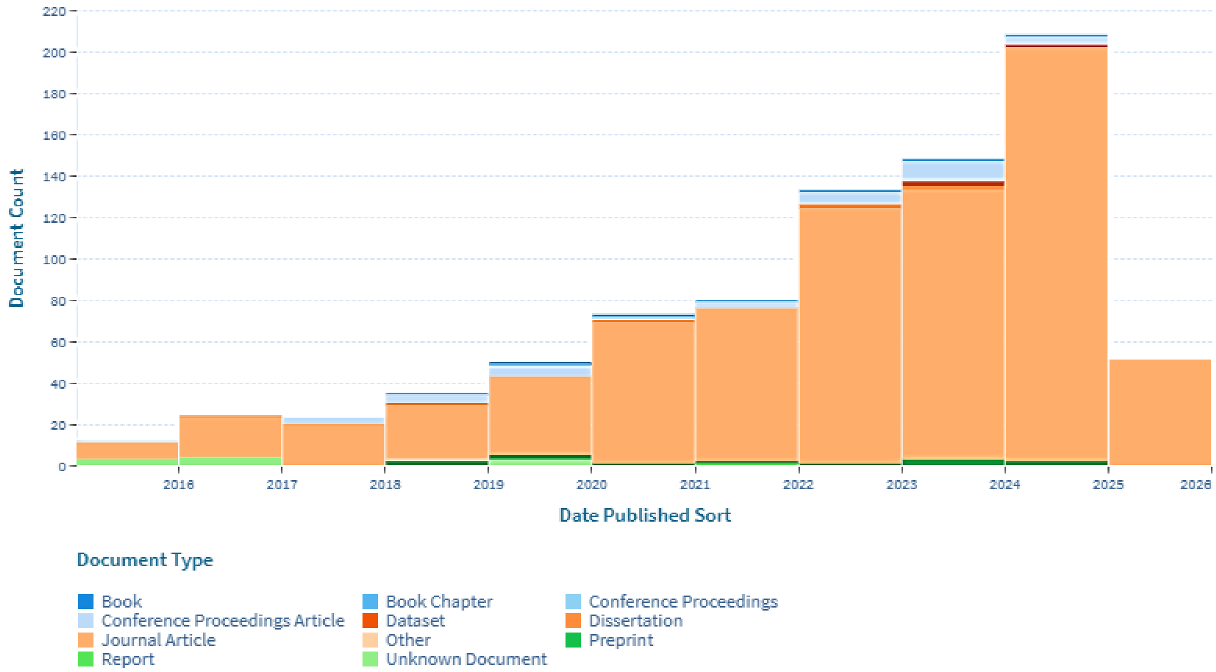


Figure 1. Distribution of Scholarly Publications on Pavement Crack Detection by Document Type (2015–2025)

2.1 Historical Context: From Manual Inspections to Image Processing

Pavement crack detection has come a long way, mostly because there's a real need to keep an eye on infrastructure as transportation demands keep going up. Back in the day, it was all about manual inspections, where engineers would walk along roads and check for cracks with their own eyes—a method that took forever, wasn't always reliable, and varied a lot depending on who was doing the checking. Then, in the 1990s, digital imaging came into play with traditional image processing as a semi-automated option, using tricks like edge detection (Canny algorithm), adaptive thresholding, and morphological operations to pick out cracks by sharpening contrast and cutting down on noise, as seen in studies that relied on histogram-based methods and wavelet transforms to study pavement images [10], [11]. But those approaches were pretty fragile, often thrown off by things like changing light or different pavement textures, which led to a lot of mistakes, especially on rough surfaces, making it clear that tougher, more adaptable solutions were needed.

2.2. Rise of Deep Learning: Convolutional Neural Networks and Beyond

Things really shifted in the early 2010s when deep learning came along and changed pavement crack detection, using CNNs to pull features right out of raw data, leaving older methods in the dust, like in studies showing CNNs spotting cracks with solid accuracy by picking up on edges, contours, and patterns without needing any manual tweaks [12]. That opened the door for semantic segmentation models like U-Net [13], which used an encoder-decoder setup with skip connections to map cracks at the pixel level, doing a great job at outlining them but struggling to tell different crack types apart, which was a big issue for planning maintenance. Meanwhile, object detection models like YOLO (You Only Look Once) [14] stepped in with real-time detection through versions like YOLOv5, pinpointing cracks with bounding boxes but often missing the finer details or getting confused by overlapping cracks, and CrackNet [15] tried to fix some of that with multi-scale feature extraction for 3D asphalt imagery, performing better but needing a ton of computing power, showing that CNNs still have trouble with things like generalization, shadows, or finding a balance between speed and depth, which pushed research to look for smarter approaches.

2.3. Advances in Instance Segmentation and Attention Mechanisms

Instance segmentation turned things around by mixing detection and segmentation to map out individual cracks with pixel-level accuracy, going beyond semantic segmentation's broader focus, with Mask R-CNN [16] setting a high bar by creating masks alongside bounding boxes, improving crack boundary accuracy compared to YOLO-based methods, though its complexity makes it tough to use in settings with limited resources. Newer models like YOLOv8 [17] have tried to blend speed and detail by adding segmentation to real-time setups, but they still struggle with thin or low-contrast cracks that show up a lot in real-world conditions. Attention mechanisms have helped out by zeroing in on the important stuff and ignoring distractions, with techniques like Squeeze-and-Excitation (SE) blocks [18] and Convolutional Block Attention Module (CBAM) weighting spatial and channel features to better spot cracks in messy environments like separating cracks from oil stains or shadows—but these models really need diverse training data to shine.

2.4. Regional Insights: Pavement Distress in Southeast Asia and Malaysia

Pavement distress research in Southeast Asia, especially Malaysia, doesn't get the attention it deserves, even though the region faces some unique challenges, with tropical climates bringing heavy rain, high humidity, and temperature swings that speed up crack formation through water damage and thermal stress, not to mention urban traffic adding extra wear, yet early Malaysian studies using basic CNNs noticed monsoon effects but didn't tackle segmentation [19], and using YOLOv3 on tropical road data had limited success because of gaps in the dataset [20], especially in urban hubs like Selangor and Kuala Lumpur where pavement damage is more severe, while global datasets like CRACK500 or GAPs, made for temperate climates, don't capture Southeast Asia's specific conditions—think monsoon impacts, mixed traffic, and aging roads—pointing to a real need for local solutions that address Malaysia's unique road profiles, mixing in environmental and human factors for better detection and classification to improve maintenance planning.

2.5. The Need for Hybrid Innovations in Crack Analysis

The shortcomings of current models—U-Net not being able to tell crack types apart, YOLO's rough localization, and CrackNet needing so much computing power—make it obvious that hybrid innovations are needed to combine segmentation and classification, using residual learning to pull out features across different scales, cutting down on computing needs, and adding attention mechanisms to focus on key patterns even with noise around, providing accurate crack mapping and type identification for smarter maintenance planning, especially in places like Malaysia where urban traffic and tropical weathering make pavement stress worse, paving the way for better accuracy in tough conditions, scaling for real-world use, and offering clear insights for prioritizing repairs, setting up advanced, tailored solutions that fit specific infrastructure needs.

3. RESEARCH METHODOLOGY

3.1. Data Acquisition and Dataset Development

Putting together a solid dataset that captures the real challenges of pavement conditions in Malaysia meant setting up a careful data collection process, focusing on the busy road networks of Selangor and Kuala Lumpur, picked because of their heavy traffic and mix of road types, from packed highways to quieter residential streets, giving a good picture of pavement wear influenced by Malaysia's tropical climate and city life. Generally, in any deep learning model data collection plays the most important role [21][22]. The setup for gathering this data used a GoPro Hero 8 camera attached to a Perodua Viva inspection vehicle, specially tweaked for this project, and Figure 2 shows how the camera was mounted, giving a clear look at how it worked out on the roads. The camera sat 1.6 meters above the pavement, pointed straight down, and was set to cover a 3.1-meter-wide strip—matching the typical width of a single traffic lane in Malaysia—so the images would feel like what you'd see while driving, making the dataset perfect for training deep learning models.

Figure 2. Vehicle-mounted Camera Setup

The GoPro Hero 8 ran in a custom video mode, with its details laid out in Table 1, and two calibration setups were tried out to get the data just right, as shown in Table 2. Setup 1 had the camera at 1.3 meters with a 90° ± 35° angle, 1.1 meters from the marked road spot, while Setup 2 placed it right above the lane's midpoint at 1.6 meters with a straight 90° angle, which ended up being the better choice for its wider and steadier coverage. To make the dataset even stronger and more varied, the images were paired with the CRACK500 dataset, a public collection of 500 pavement images (2000x1500 pixels) with marked cracks, helping the model learn from a wider range of crack types and conditions.

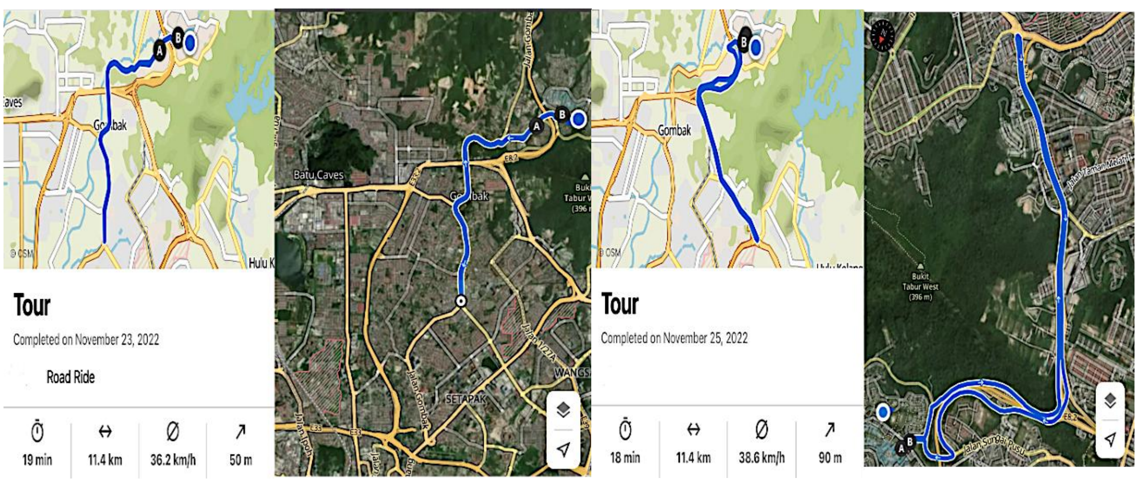
Table 1. Specifications of the GoPro Hero 8 Camera Configuration

Attribute	**Details**
Camera Model	GoPro Hero 8
Mounting Hardware	GoPro Rod Mount
Operating Mode	Custom Video Setting
Image Resolution	1080p (1920x1080)
Frame Rate Options	24 fps, 60 fps
Lens Type	Linear Field of View
Video Bit Rate	Standard Quality (45 Mbps)
Minimum ISO Setting	100

Table 2. Outcomes of Camera Calibration Setups

Calibration Setup	**Road Coverage Width**	**Camera Orientation to Ground**	**Proximity to Marked Road Segment**	**Installation Height**
Setup 1	3.1 meters	90° ± 35°	1.1 meters	1.3 meters
Setup 2	3.1 meters	90°	Directly above midpoint	1.6 meters

Keeping things specific and repeatable was a big focus, so detailed GPS mapping was used to track the data collection routes in Selangor and Kuala Lumpur, with Figure 3(a) and Figure 3(b) showing these GPS maps for Selangor and Kuala Lumpur, making it easy to see exactly where the data came from and letting other researchers follow the same paths or expand the work elsewhere. The final dataset includes high-quality video footage and still images pulled from it, capturing all kinds of pavement damage under Malaysia's unique conditions like wear from monsoons, stress from city traffic, and different lighting situations setting a strong base for training and testing the DeepSeg-CrackNet model.



(a) (b)

Figure 3. (a) GPS Road Data Around Selangor, (b) GPS Road Data Around Kuala Lumpur

3.2. Data Preprocessing

Getting the raw video data ready for deep learning meant cleaning it up properly to make sure the model training would go smoothly and hold up well. The footage from the GoPro Hero 8 was first broken down into individual frames, turning the video streams into still images that could be analysed, and Figure 4 gives a peek at some of these frames, showing the quality and variety of the pavement images captured. Each frame was resized to a standard 640x640 pixels, picked to keep a good balance between not overloading the computer and still holding onto the important crack details, making sure it fit what the DeepSeg-CrackNet model needed, which helps avoid issues from mismatched image sizes that could mess with the results.

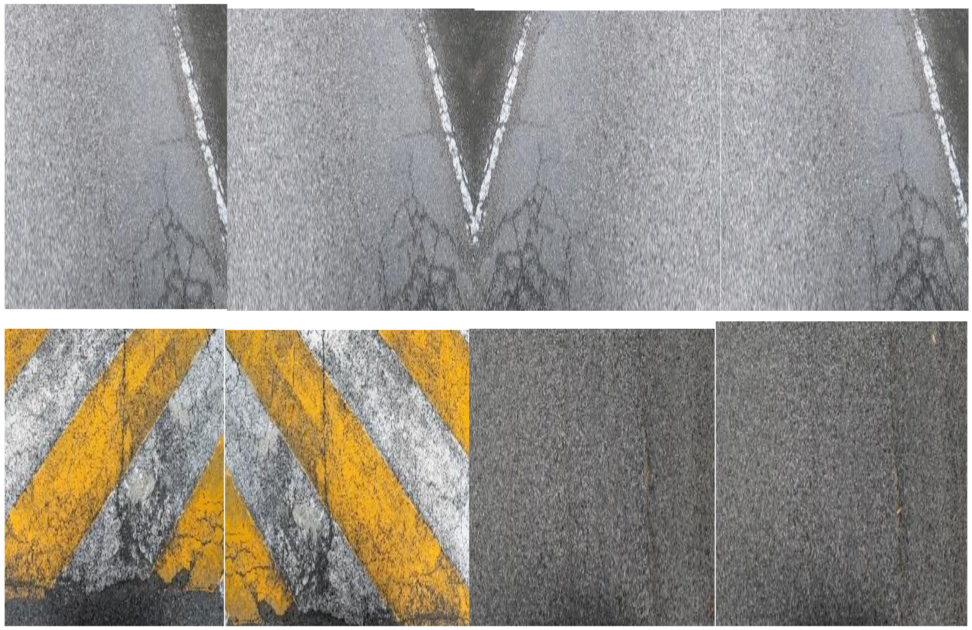


Figure 4. Sample Frames Extracted from the Collected Video

To make the dataset better reflect Malaysia's mix of road and lighting conditions, a few augmentation tricks were used, like flipping the images horizontally and vertically with a set chance, basically stretching the dataset by showing the same road segments from different angles. Brightness and exposure were also tweaked by ±20%, mimicking different times of day or weather, like cloudy skies or bright sun, and a bit of blurring was added, with a kernel size between 2 and 4.5 pixels, to imitate real-life issues like camera shake or hazy air. These tweaks help the model handle the kind of variety you'd see on Malaysian roads, from rain-soaked surfaces to sunny city lanes.

The dataset was also standardised and normalised to get it ready for training, with standardization making sure all images followed the same format, and normalization adjusting pixel values to a set range, ensuring the deep learning algorithms got consistent inputs. A careful balance was kept between cleaned-up images and ones with some noise, keeping natural differences—like uneven lighting or pavement textures—so the model could learn to deal with real-world challenges, and this whole preprocessing setup makes the dataset more useful, helping DeepSeg-CrackNet work well even in tricky, unpredictable situations.

3.3. Data Labelling

Good labelling is key for supervised learning, giving the ground truth the DeepSeg-CrackNet model needs to learn how to spot and sort pavement cracks. The Roboflow annotation tool was used to label each image frame, dividing cracks into three types: alligator, longitudinal, and transverse, with showing examples of these labelled frames, marking alligator cracks in purple, longitudinal cracks in blue, and transverse cracks in pink, giving a clear view of the detailed labelling process. This setup lets the model not just find cracks but also figure out what kind they are, which is super important for deciding how bad they are and planning repairs. Examples of labelled image frames are shown in Figure 5.

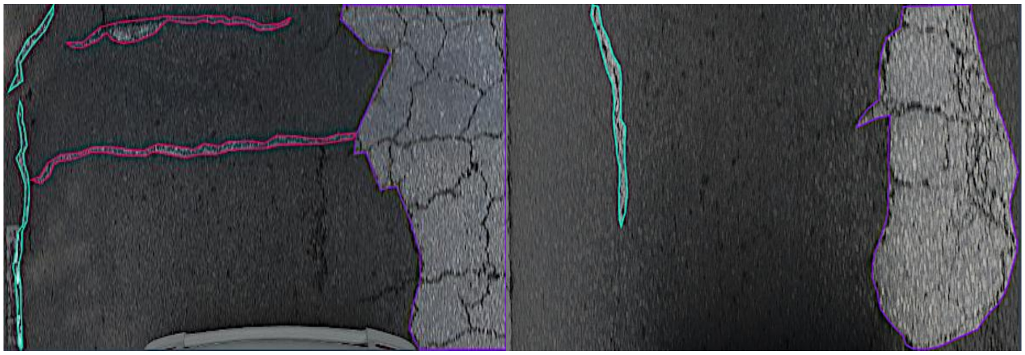


Figure 5. Examples of Labelled Images Frames

The labeled dataset was split into training, validation, and testing sets, as shown in Table 3, to make sure the model could be built and checked thoroughly, using a rough 80-20 split, with 85% of the images (1900 frames) set aside for training, 10% (207 frames) for validation, and 5% (103 frames) for testing, which makes sure the model learns from a wide range of examples, checks its performance on new data, and gets properly tested for real-world use, giving a solid measure of how well it can predict across different crack types.

Table 3. Distribution of Dataset for Training, Validation, and Testing

Class	**Label**	**Training Images**	**Validation Images**	**Testing Images**	**Total**
Alligator Cracks	crack-alligator	760	80	40	880
Longitudinal Cracks	crack-long	760	80	40	880
Transverse Cracks	crack-trans	380	47	23	450
Total		**1900**	**207**	**103**	**2210**

3.4. DeepSeg-CrackNet Architecture

DeepSeg-CrackNet is a fresh hybrid deep learning framework built to handle both segmentation and classification for a full-on pavement crack analysis, made specially to fit the unique patterns of Malaysian roads. It’s got two main parts: a Deep Gradient ResNet for segmentation and a ResNet-50 backbone with a Modified Attention Mechanism for classification, working together to map out cracks and identify their types, and Figure 6 gives a clear diagram of the DeepSeg-CrackNet setup, showing how its segmentation and classification parts connect. This hybrid design taps into the strengths of residual learning and attention mechanisms to nail down high accuracy in spotting and sorting alligator, longitudinal, and transverse cracks.

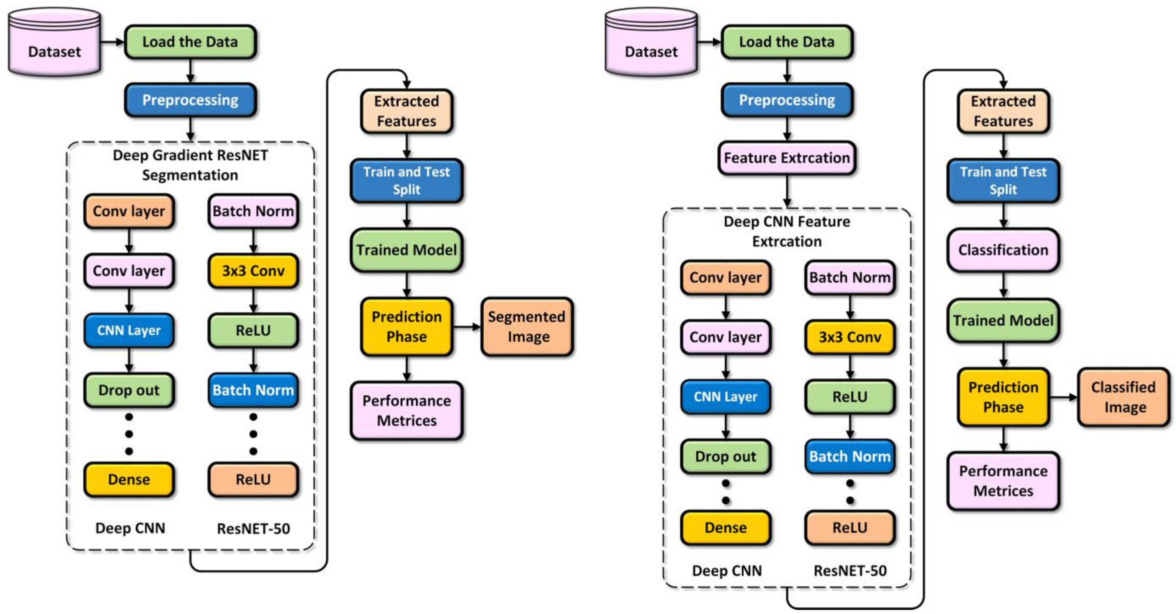


Figure 6. Methodological Flow

The segmentation part uses a Deep Gradient ResNet, a beefed-up version of the ResNet setup, fine-tuned for pixel-level crack mapping, with multiple convolutional layers and residual connections that let the model dig into deep features while dodging the vanishing gradient issue. Each residual block has batch normalization to keep training steady and ReLU activation to add some non-linearity, making sure it pulls out strong features across different scales, and skip connections in the network hold onto spatial details, letting the model catch fine crack patterns, like the messy shapes of alligator cracks or the straight lines of longitudinal ones, spitting out a segmentation mask that pinpoints crack areas with high accuracy.

The classification part builds on a ResNet-50 backbone, jazzed up with a Modified Attention Mechanism to sharpen focus and cut down on noise, with ResNet-50's deep 50-layer setup of convolutional and residual blocks giving a solid base for feature extraction, while the attention mechanism—pulled from recent ideas—highlights the important features, helping the model tell crack types apart even with tricky backgrounds like shadows or pavement markings. The attention setup mixes channel and spatial attention, tweaking feature maps to zero in on crack-specific patterns, and an Atrous Spatial Pyramid Pooling (ASPS) layer at the end of the classification pipeline pulls together multi-scale features to tackle cracks of different sizes and shapes, a common challenge on Malaysian city roads.

Hyperparameters were adjusted to make DeepSeg-CrackNet work best for Malaysian crack patterns, as shown in Table 4, and this custom setup, blending segmentation and classification, makes DeepSeg-CrackNet a strong tool for pavement distress analysis, ready to give clear, useful insights for keeping Malaysia's roads in shape.

Table 4. Hyperparameter Settings for DeepSeg-CrackNet

Hyperparameter	Value
Learning Rate	0.001
Optimizer	Adam
Epochs	200
Batch Size	16
Dropout Rate	0.5

The hyperparameter values for DeepSeg-CrackNet, as shown in Table 4, were determined through a trial-and-error approach to optimize the model's performance on Malaysian road data. We started with common baseline values, like a learning rate of 0.01 and a batch size of 32, but found the model struggled with convergence on our diverse dataset. After several rounds of tweaking, we settled on a learning rate of 0.001, which allowed steady training without overshooting, and a batch size of 16 to balance memory constraints with stable gradient updates. The Adam optimizer was chosen for its reliability in handling noisy data, and we set 200 epochs to ensure the model had enough time to learn crack patterns without overfitting, which we monitored closely. A dropout rate of 0.5 was added to prevent the model from relying too heavily on specific features, especially given the varied lighting and pavement textures in our images. This iterative process involved testing multiple combinations and checking validation metrics like IoU and accuracy to find the sweet spot for our specific use case.

3.5 Crack Size Assessment and Metrological Quantification

DeepSeg-CrackNet measures crack sizes through a carefully calibrated process that turns segmentation results into real-world numbers, calculating length (L) for linear cracks (longitudinal/transverse) by tracing the main axis of connected components in the binary mask (I_b), and figuring out surface coverage (A) for areal cracks (alligator) by adding up pixels, using the camera's known setup (1.6m height, 3.1m lane width, 640×640px resolution) for accuracy, as shown in Equation (1), Equation (2), and Equation (3).

Mathematical Formulation

1. **Binary Mask Generation**:

$$I\_b(i,j) = \begin{cases} 1 & if\ pixel\ (i,j) \in crack\ region \\ 0 & otherwise \end{cases} \tag{1}$$

2. **Linear Crack Length**:

$$L\_pixels = max(ConnectedComponentAxis(I\_b)) \tag{2}$$

$$L\_meters = L\_pixels \times (3.1\ /\ 640)$$

3. **Alligator Crack Area**:

$$A\_pixels = \Sigma\Sigma\ I\_b(i,j)\ \ (sum\ over\ 640 \times 640\ image) \tag{3}$$

$$A\_m^2 = A\_pixels \times (3.1 \times 2.8)\ /\ (640 \times 640)$$

(Where 2.8m is the transverse field-of-view length at 1.6m height.)

This approach lines up with ASTM D6433 standards, making it easier to do automated PCI scoring and data-driven maintenance decisions for Malaysia's road network.

4. RESULTS AND DISCUSSIONS

4.1. Experimental Setup Overview

Testing out DeepSeg-CrackNet, a fancy hybrid deep learning model, meant checking how well it could spot, map out, and sort pavement cracks using a dataset pulled together from roads in Selangor and Kuala Lumpur, with the CRACK500 dataset thrown in to mix things up a bit. The setup for this testing used some serious computing power to handle the heavy lifting of deep learning, running on an HP Pavilion 15be408tx with an Intel Core i7-8750H processor, 8 GB of DDR4 RAM, and a 1 TB hard drive, plus an NVIDIA GeForce GTX 1050 with 4 GB VRAM for onboard graphics work, and some extra help from an NVIDIA GeForce RTX 4080 for faster training and predictions when working remotely. The whole thing was built using Anaconda and Google Colab, with PyTorch as the main framework since it's great for setting up DeepSeg-CrackNet's mixed design.

The dataset had 2210 images total, split up as 1900 for training, 207 for validation, and 103 for testing, just like it's laid out in the Methodology section (Table 3), with images cleaned up to a standard 640x640 pixel size, and little tweaks like horizontal and vertical flips and ±20% brightness changes to match Malaysia's range of road and lighting conditions. DeepSeg-CrackNet was put through 200 rounds of training, using a learning rate of 0.001, the Adam optimizer, a batch size of 16, and a dropout rate of 0.5 to keep it from overfitting, as shown in Table 4, making sure the testing gave a solid look at how well the model works for real pavement damage analysis.

4.2. Segmentation Performance Analysis

DeepSeg-CrackNet's ability to map out cracks was checked using a bunch of measures—accuracy, precision, recall, Jaccard Coefficient (Intersection over Union, IoU), and Dice Coefficient—over the training and validation stages, giving a full picture of how well it can outline crack edges. These measures were tracked across all 200 rounds of training, showing how the model learns and handles new data it hasn't seen before.

The model's accuracy, shown in Figure 7, looks pretty strong during training, with the training accuracy (blue line) starting around 80% and climbing fast, settling just under 95% by the end, while the validation accuracy (orange line) keeps up closely, landing at about the same spot, which means it's good at handling new stuff without overfitting. Precision, in Figure 8, shows how many of the crack pixels it flagged were actually correct, hitting around 95% for both training and validation, meaning it's not throwing out too many false alarms. Recall, in Figure 9, levels off at about 90% for both stages, showing the model catches most of the cracks out there.

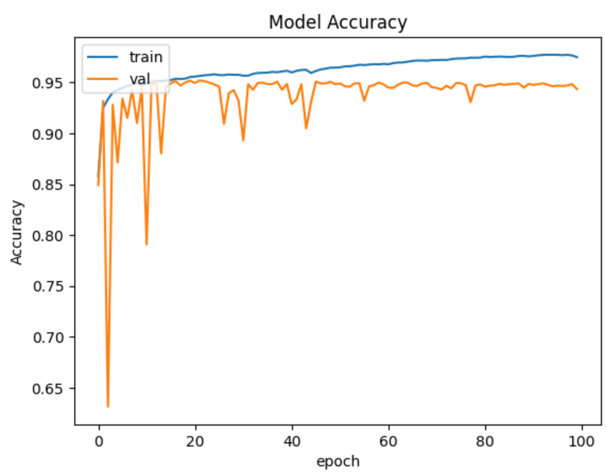


Figure 7. Model Accuracy Plot

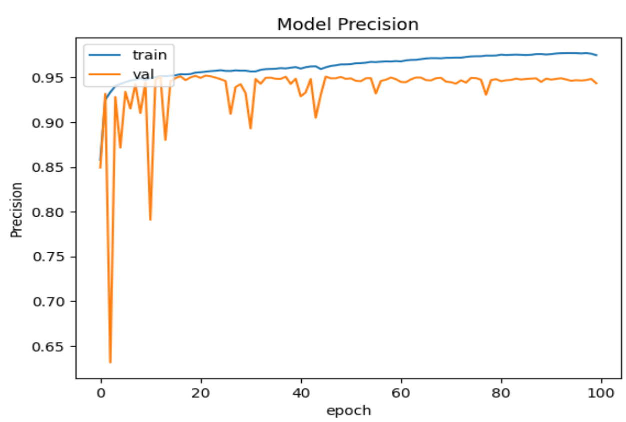


Figure 8. Model Precision Plot

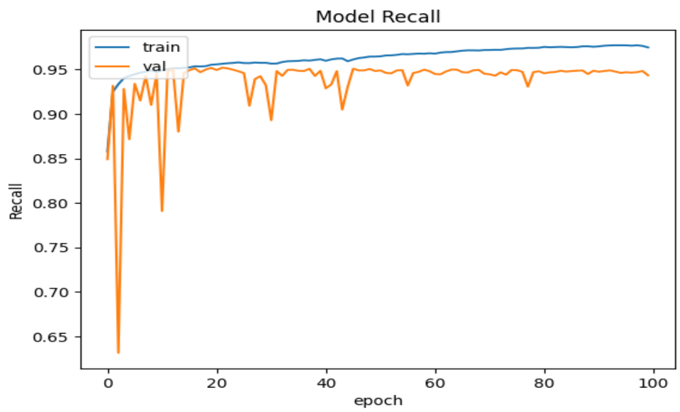


Figure 9. Model Recall Plot

The Jaccard Coefficient (IoU), in Figure 10, keeps climbing and settles around 80% for both training and validation, showing the model's pretty consistent at matching up predicted crack areas with the real ones, and the Dice Coefficient, in Figure 11, follows a similar path, sitting just a bit higher, which means there's a lot of overlap between what the model predicts and the actual cracks. These charts really back up how well DeepSeg-CrackNet maps out cracks, which is super important for getting pavement analysis right.

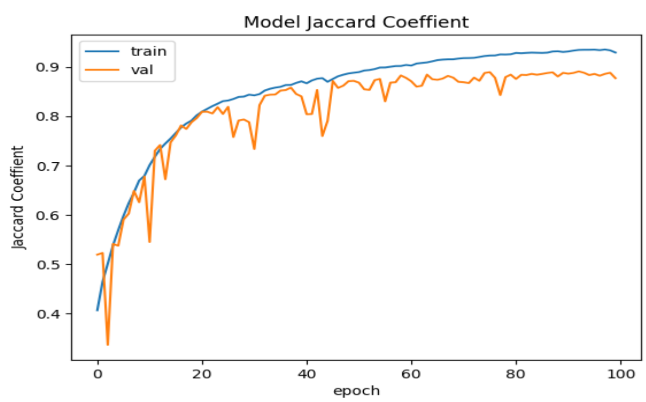


Figure 10. Model Jaccard Coefficient Plot

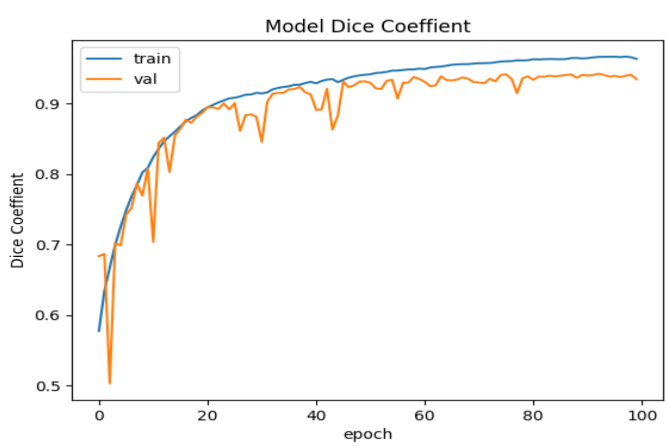


Figure 11. Model Dice Coefficient Plot

Hard numbers back this up too, as laid out in Table 5, with a Mean IoU of 0.8388889 showing the model's solid at overlapping predicted and real crack areas, and a Mean Dice Coefficient of 0.8256968848551859 matching that consistency, while the Hausdorff Distance, which checks the biggest gap between predicted and real edges, sits at about 3.21 for both background and crack classes, proving the model's spot-on at outlining cracks, making it a trusty tool for real pavement damage analysis in Malaysia.

Table 5. Quantitative Metrics for Segmentation Model

Metric	Value
Mean IoU	0.8388889
Mean Dice Coefficient	0.8256968848551859
Hausdorff Distance (Background)	3.2126949574078867
Hausdorff Distance (Crack)	3.2126949526675244

4.3. Visual Segmentation Results Across Crack Types

Taking a closer look at DeepSeg-CrackNet's segmentation results gives a good sense of how it handles different crack types—alligator, transverse, and longitudinal—that you'd see a lot on Malaysian city roads. Figure 12 shows an alligator crack, with the original grayscale image on the left and the segmented one on the right, where the original has a messy web of cracks that look like alligator skin, and the segmented version nails down those tricky patterns, showing the model's great at picking out big, complicated crack setups that are key for spotting serious pavement problems.

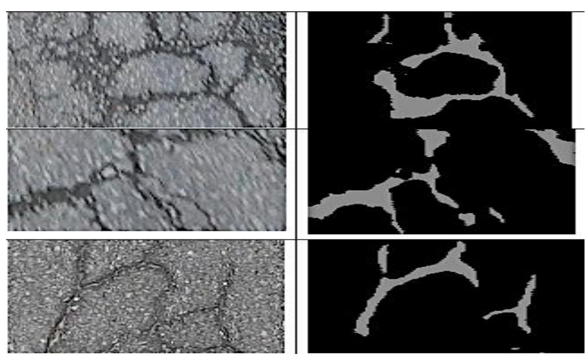


Figure 12. Original and Segmented Image of Alligator Crack

Figure 13 shows a transverse crack, which cuts across the road direction, with the original image on the left showing a clear line across the pavement, and the segmented one on the right capturing that line perfectly, making sure it's ready for deeper analysis. Then Figure 14 has a longitudinal crack, running along the road direction, with the raw image on the left showing a thin, stretched-out crack that's an early sign of trouble, and the segmented version on the right tracing its length spot-on, giving a clear picture of the issue. These visuals prove DeepSeg-CrackNet's solid at mapping out all kinds of cracks, which is a must for checking road structures and planning repairs in Malaysia.

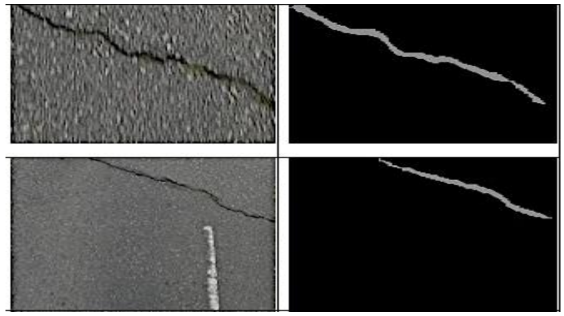


Figure 13. Original and Segmented Image of Transverse Crack

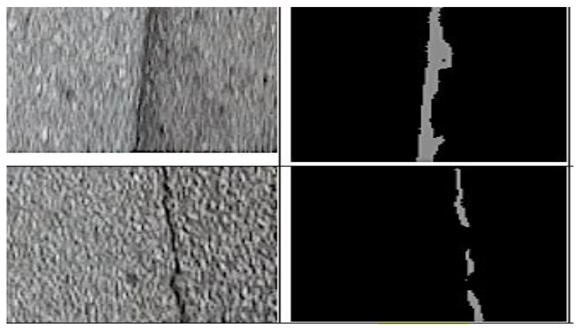


Figure 14. Original and Segmented Image of Longitudinal Crack

4.4. Classification Performance Analysis

After mapping out the cracks, DeepSeg-CrackNet's classification part, which uses a Residual block with a Modified Attention Mechanism, sorts them into alligator, longitudinal, and transverse types, a big step for figuring out what repairs are needed. Table 6 breaks down how well it did, showing precision, recall, and F1-score for each crack type, along with the support (how many examples in the test dataset). For alligator cracks (class 0), it hits a precision of 0.84 and a recall of 0.96, making an F1-score of 0.90, meaning it's awesome at catching almost all alligator cracks accurately. Longitudinal cracks (class 1) get a precision of 0.89, a recall of 0.88, and an F1-score of 0.885, showing it's pretty dependable even with their tricky shapes. Transverse cracks (class 2) have a precision of 0.87 but a recall of 0.80, leading to an F1-score of 0.83, which suggests they're a bit harder to catch.

Table 6. Classification Report for Residual Block with Modified Attention Mechanism

Class	Precision	Recall	F1-Score	Support
Alligator (0)	0.84	0.96	0.90	114
Longitudinal (1)	0.89	0.88	0.885	135
Transverse (2)	0.87	0.80	0.83	121
Overall Accuracy	**0.85**			**370**
Macro Avg	0.85	0.85	0.85	370
Weighted Avg	0.85	0.85	0.84	370

The overall accuracy for classification is 0.85 (85%), with macro and weighted averages for precision, recall, and F1-score all hanging around 0.85, showing it's pretty balanced across all crack types, and the confusion matrix, coming up in Figure 15, gives a visual of how it did, showing alligator cracks correctly sorted in 110 out of 114 cases, with just 4 mistaken for longitudinal ones, while longitudinal cracks had some mix-ups, with 9 called alligator cracks and 14 as transverse, and transverse cracks also got mixed up, mostly with longitudinal ones (18 cases), pointing to a spot that could use some work. The spot-on segmentation really helps with these classification results, since clear mapping makes it easier to sort cracks right, especially for alligator cracks with their high recall.

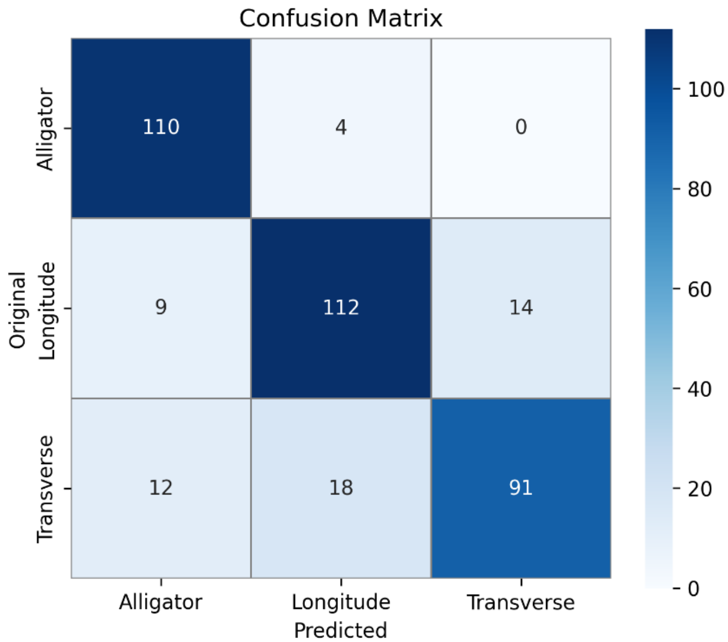


Figure 15. Confusion Matrix for Residual block with Modified Attention Mechanism

4.5. Crack Measurement and Classification Results

DeepSeg-CrackNet's crack measuring process takes things from just spotting cracks to getting their exact sizes, which is key for figuring out how bad the pavement damage is, pulling crack areas from segmentation masks, counting up pixels, and turning those into real-world measurements—meters for longitudinal and transverse cracks, and square meters for alligator cracks using the camera setup (1.6 meters height, 3.1 meters road width).

Figure 16 shows a longitudinal crack, measured in meters to show how long it stretches along the road, giving a good idea of how it might affect the pavement's strength, while Figure 17 has a transverse crack, with its length in meters showing how much damage crosses the road, which matters for checking risks like water seeping in, and Figure 18 displays an alligator crack, measured in square meters to show the damaged area, pointing out the need for bigger repairs since it's a deeper issue.

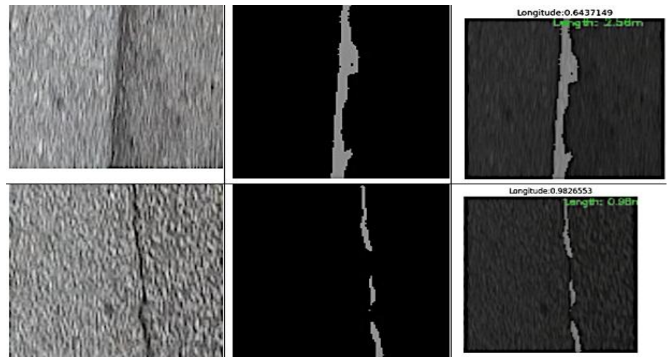


Figure 16. Longitudinal Crack Classification and Measurement

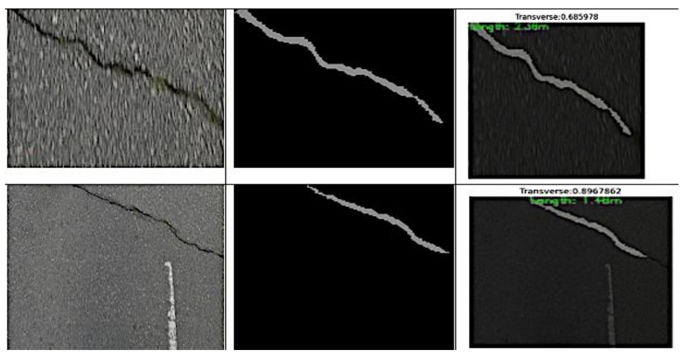


Figure 17. Transverse Crack Classification and Measurement

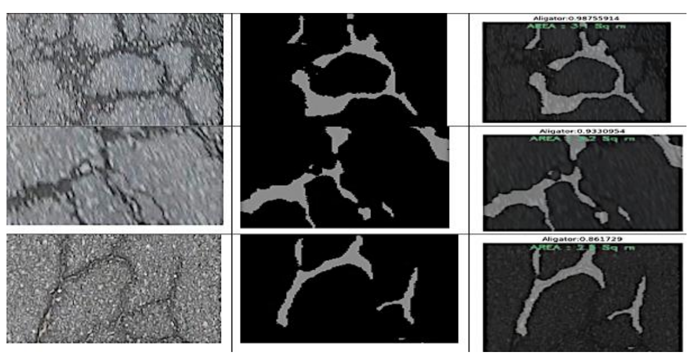


Figure 18. Alligator Crack Classification and Measurement

4.6. Validation of Crack Measurement Accuracy

Checking how accurate DeepSeg-CrackNet's crack measurements are meant looking at how camera height affects the lengths it detects, making sure the real-world conversions hold up, with Table 7 showing a comparison of distance measurements at different heights (1.57m, 1.60m, 1.63m), looking at actual lengths versus detected ones and their differences, like for a 0.25m actual length (A-B), the detected length at 1.60m is 0.255m (just +0.005m off), showing it's pretty close, while at 1.57m it's 0.27m (+0.020m off) and at 1.63m it's 0.238m (-0.012m off), and the same pattern shows up for other lengths (like A-E: 1.50m actual, 1.513m at 1.60m with +0.013m off), proving 1.60m gives the best results.

Table 7. Comparative Analysis of Distance Measurements at Different Camera Heights

Points	Actual Measured Length (m)	Detected Length (m) at 1.57m	Variation at 1.57m	Detected Length (m) at 1.60m	Variation at 1.60m	Detected Length (m) at 1.63m	Variation at 1.63m
A-B	0.25	0.27	+0.020	0.255	+0.005	0.238	-0.012
A-C	0.50	0.543	+0.043	0.508	+0.008	0.485	-0.015
A-D	1.00	1.08	+0.080	1.027	+0.027	0.976	-0.024
A-E	1.50	1.605	+0.105	1.513	+0.013	1.474	-0.026

Figure 19 shows the detected lengths at the best 1.60m height, proving it's super accurate, while Figure 20 shows lengths at 1.57m that are a bit too high, and Figure 21 shows lengths at 1.63m that are a bit too low, making it clear why picking the right camera height matters, and this check confirms the 1.60m height used in the data setup gives reliable measurements, making DeepSeg-CrackNet great for precise pavement analysis.

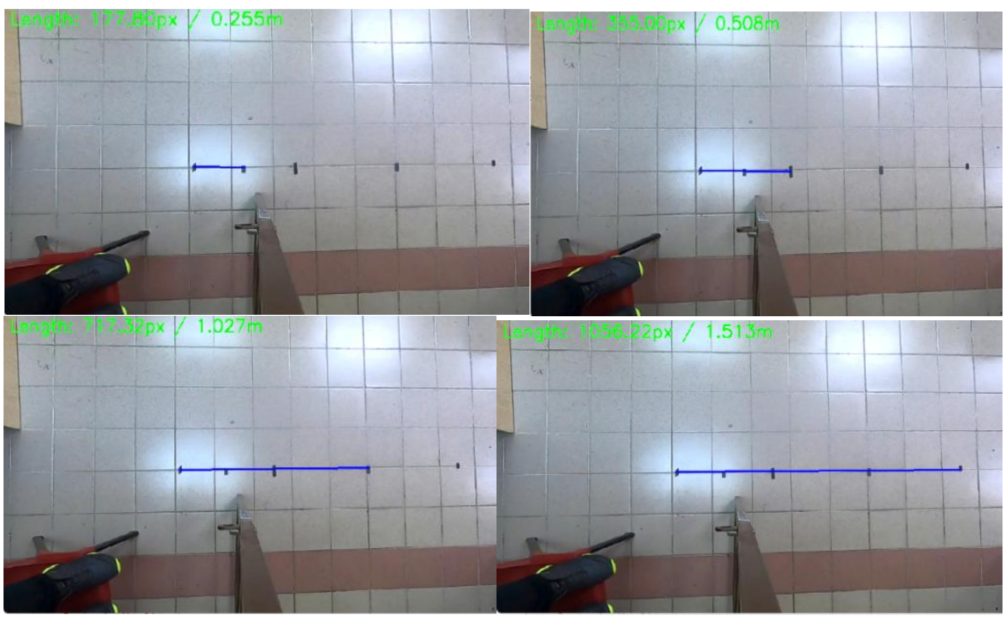


Figure 19. Detected Length (Camera Height 1.60m)

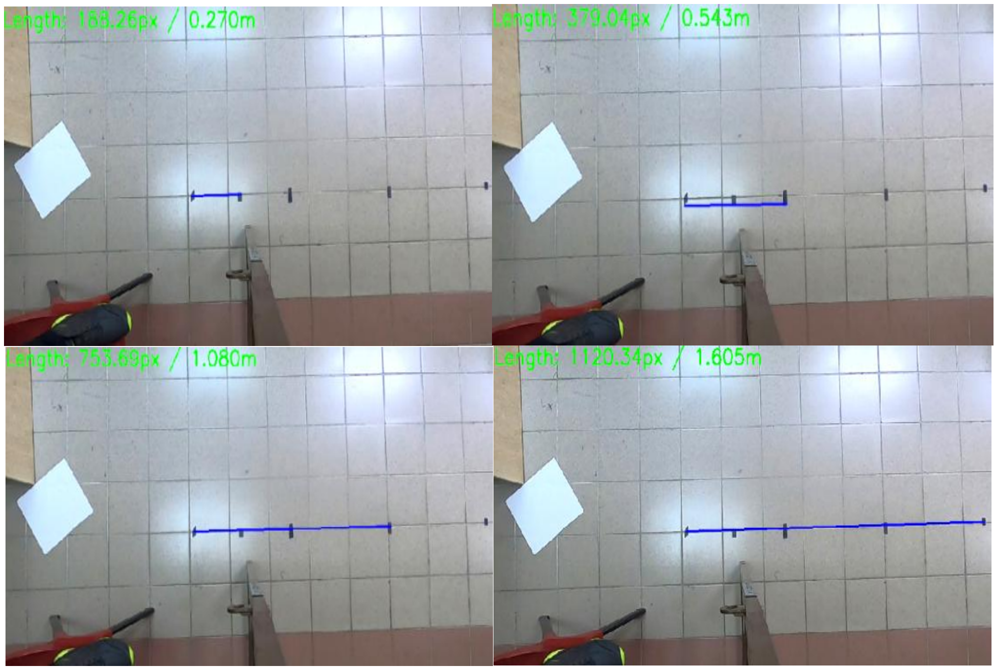


Figure 20. Detected Length (Camera Height 1.57m)

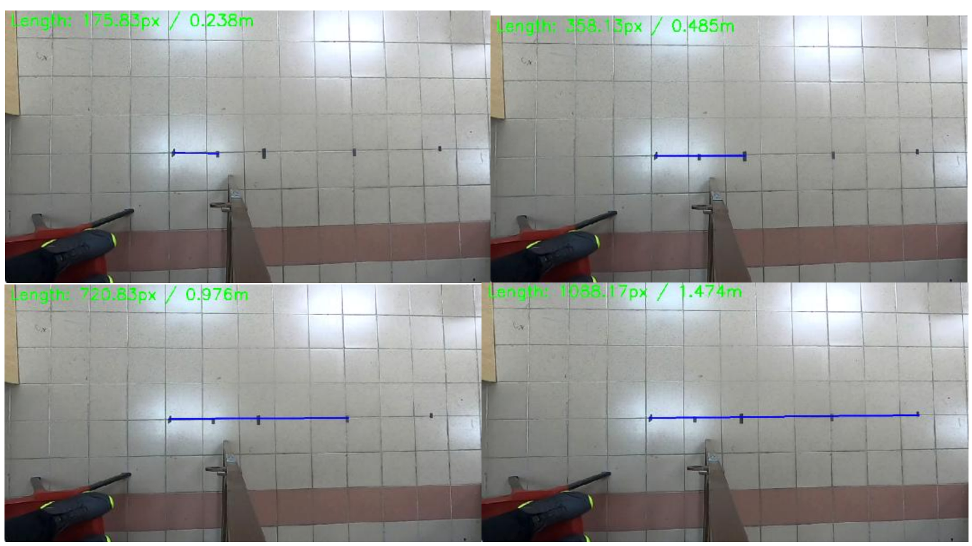


Figure 21. Detected Length (Camera Height 1.63m)

4.7. Benchmarking Against Existing Models

DeepSeg-CrackNet outperforms CrackNet [6], as shown in Table 8, due to its advanced hybrid architecture, which seamlessly integrates Deep Gradient ResNet for segmentation and a Residual block with a Modified Attention Mechanism for classification, specifically designed to tackle the complex crack patterns on Malaysian roads. Unlike CrackNet's standard multi-scale feature extraction, DeepSeg-CrackNet's Deep Gradient ResNet employs residual connections to capture fine-grained spatial details across multiple scales, enabling precise delineation of intricate structures like alligator cracks, where it achieves a precision of 0.84 and recall of 0.96 compared to CrackNet's 0.778 and 0.772. The CAFM enhances this by prioritizing crack-relevant features, effectively filtering out environmental noise such as shadows or road markings that often hinder CrackNet's accuracy. This refined feature extraction, paired with the Augmented SubPixel Shuffling (ASPS) decoder, sharpens crack boundaries, resulting in a Mean IoU of 0.8388889, a marked improvement over CrackNet's less precise segmentation.

The extended training period of DeepSeg-CrackNet, spanning 200 epochs compared to CrackNet's 100, allows the model to thoroughly learn the diverse crack morphologies in the RCD-IIUM dataset, which is critical for addressing Malaysia's unique pavement conditions. This dataset, tailored to tropical environments, includes pixel-wise annotations and GPS-mapped imagery from Selangor and Kuala Lumpur, capturing specific damage patterns like monsoon-induced stripping and thermal cracking not adequately represented in CrackNet's more generic training data. Prolonged training ensures robust generalization across varied lighting and pavement textures, as demonstrated by DeepSeg-CrackNet's superior precision (0.89 vs. 0.867) and recall (0.88 vs. 0.849) for longitudinal cracks. This comprehensive training strategy enables DeepSeg-CrackNet to adapt to the nuanced crack formations influenced by Malaysia's heavy traffic and reclaimed tire polymer asphalt, providing a significant edge over CrackNet's shorter training approach.

A key innovation of DeepSeg-CrackNet is its metrological branch, which transforms segmentation masks into real-world measurements using projective geometry, a feature absent in CrackNet. This capability delivers precise crack lengths for longitudinal cracks and areas for alligator cracks, aligning with ASTM D6433 standards and enabling data-driven maintenance decisions, such as prioritizing repairs for extensive alligator cracks over minor longitudinal ones. The Modified Attention Mechanism further enhances classification by blending channel and spatial attention to focus on distinct crack textures and orientations, contributing to high accuracy (85% overall) across crack types. By leveraging the RCD-IIUM dataset's rich local annotations and a carefully calibrated training process, DeepSeg-CrackNet achieves consistent performance improvements, making it a highly effective tool for automated pavement distress analysis in Malaysia's challenging urban and tropical conditions.

Table 8. Benchmarking Results

Features/Criteria	**DeepSeg-CrackNet (This Study)**	**CrackNet** [6]
Methodology	Deep Gradient ResNet + Residual Block with Modified Attention Mechanism	CrackNet Network Model
Data Source	Custom Collected Data	Custom Collected Data
Epochs	200	100
Precision (Alligator)	0.84	0.778
Precision (Longitudinal)	0.89	0.867
Precision (Transverse)	0.87	0.839
Recall (Alligator)	0.96	0.772
Recall (Longitudinal)	0.88	0.849
Recall (Transverse)	0.80	0.868

5. CONCLUSION

DeepSeg-CrackNet turned out to be a game-changer for pavement damage analysis in Malaysia, especially in busy spots like Selangor and Kuala Lumpur, where fast city growth and heavy traffic really take a toll on roads, with its high segmentation accuracy, hitting a Mean IoU of 0.8388889, and a classification accuracy of 85%, making it great at catching alligator, longitudinal, and transverse cracks early on and sorting them out, which helps plan repairs before things get really bad, plus its knack for measuring crack sizes—figuring out big alligator cracks in square meters and smaller longitudinal ones in meters—makes it easier to focus repairs where they're needed most, like replacing pavement for huge alligator cracks or just sealing up minor longitudinal ones, saving money and keeping roads safer, lining up perfectly with Malaysia's goals for sustainable city growth by making maintenance smarter and helping roads last longer in high-traffic areas.

Even with all its strengths, DeepSeg-CrackNet has some limits that open the door for more work down the road, since things like super bright or dim lighting, or messy backgrounds not covered in the dataset, might throw it off, and focusing on city roads might make it less useful for rural Malaysian areas with different pavement types and damage patterns, so future efforts could add more variety to the dataset with different weather conditions and rural roads to make the model more flexible, plus looking into lighter designs or trimming techniques could let it run in real-time on smaller devices, like mobile inspection setups, making it more practical, and mixing in extra data types, like 3D pavement scans or infrared images, could give a deeper look at crack severity, making DeepSeg-CrackNet even better for keeping Malaysia's roads safe and strong.

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Teddy Surya Gunawan: Project Administration, Supervision, Writing – Review & Editing;
Syed Asif Ahmad Qadri: Validation, Writing – Review & Editing.

CONFLICT OF INTERESTS

There is no conflict of interests.

ETHICS STATEMENTS

Our publication follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

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