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Crack Detection In Surface Pipeline Images Using Deep Learning

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ABSTRACT

Pipeline networks are cost-efficient and secure for gas and fluid conveyance over long distances. Pipeline failure, especially cracks can lead to manifold consequences and detecting cracks is vital for minimizing the impact of pipeline disasters. However, pipeline crack detection remains understudied, especially in Nigeria and existing approaches are tedious and face various challenges. This research, therefore, addresses the challenges of lack of pipeline datasets and consequently a lack of pipeline crack detection systems by developing an enhanced surface pipeline crack detection system using deep learning techniques, achieving high performance with minimal misclassifications. Industrial pipeline videos and images were collected from various sources including water corporations, food, and beverages industries. The video frames were annotated into cracked and non-cracked classes. Preprocessing techniques like Gaussian blur and histogram equalization were applied to improve the image quality prior to classification. The ResNet50 pre-trained model was adapted and finetuned on the curated image dataset to enhance its performance in detecting surface pipeline cracks, achieving 94.05%, 99.38% and 99.84% accuracies on the training, validation, and test splits of the dataset, respectively. To validate its effectiveness, the ResNet-50 model was compared against other standard deep learning models, including MobileNetV2, VGG16, DenseNet121, and a simple CNN. Among these, ResNet-50 consistently achieved superior results which confirms its suitability and robustness for this task.

Keywords: Image classification, Machine Learning, Pipeline Crack, ResNet, Deep Learning, Detection

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1. INTRODUCTION

Pipelines are important infrastructures, likened to human veins, that are used to efficiently transport different commodities like water, natural gases, refined petroleum, sewage and liquid hydrocarbon, which are indispensable resources in our everyday life, industries, and ecosystems [1] [2]. The process of manufacturing pipelines includes the use of quality materials that can lower the rate of deterioration and stand the test of time [3]. However, pipelines' continuous exposure to various environmental conditions makes them prone to some forms of pipeline defects which include cracks, corrosion, and leakage in the pipeline wall and other defects that can cause pipeline failure [4]. Pipeline crack formation depends on prevailing service conditions and can be classified into four different categories: lateral cracks, longitudinal cracks, fractures originating from a specific spot, and inter-angular cracks [5].

Pipeline failure can have severe consequences, including loss of properties, environmental damage, and fatalities [1]. For instance, the Nigeria Oil Spill Monitor reported 1,066 total pipeline incidents since 2021, which is equivalent to about twenty incidents per month [6], while the FracTracker Alliance reported 6,950 pipeline incidents in the U.S. since 2010 which amounted to approximately two occurrences per day [7]. These facts highlight the critical importance of early detection and effective monitoring to prevent such pipeline failures. The advancements in technology have extensively improved pipeline monitoring systems, with many focusing on detecting leaks, the most common type of pipeline failure [8]. However, less attention has been given to detecting cracks before they develop into leaks, which is an important aspect of pipeline monitoring systems. Crack detection in pipeline is crucial for enabling proactive maintenance and repair, minimizing the detrimental impact of pipeline disasters and reducing environmental damage [9].

Recent advancements in Computer Vision have been explored for detecting cracks in pipelines [10]. Computer Vision techniques for crack detection include the extraction of crack-related features from pipeline images, which can be achieved by applying either image processing techniques or deep learning architectures [11]. However, the image processing approaches used in existing works are significantly impacted by image noise interference and the complexity of numerous parameters, limiting their reliability [12]. Additionally, deep learning models, while promising, often suffer from overfitting when not properly tuned, thereby further impacts detection performance [13]. A critical challenge in this domain is the lack of publicly available, large-scale pipeline image datasets for surface crack detection, which are essential for training robust deep learning models. This dataset scarcity hinders continuous research and development, as previous works are often tested on relatively small, non-public datasets.

Therefore, this research focuses on the development of efficient deep-learning models for the detection of cracks in surface industrial pipelines. To achieve this, a new dataset of pipeline images was curated to facilitate robust training and evaluation of the models which enables thorough comparison of multiple model architectures. The evaluation highlights the superior performance of one model demonstrating its effectiveness in accurately classifying pipeline images. Consequently, this work is focused on classifying pipeline images into two classes: cracked and non-cracked. It is important to highlight that this study is limited to surface pipeline cracks detection and does not include buried or submersible pipelines, as well as other forms of pipeline anomalies or defects.

This is due to the technical challenges involved in capturing images of underground pipelines without excavation and the need for specialized equipment like infrared imaging devices. Section 2 of this paper presents a review of previous works with a focus on their methods and results. Section 3 details the methodology used in this work, and Section 4 analyzes and discusses our results and findings. The conclusion is presented in Section 5.

2. LITERATURE REVIEW

There are several approaches used to detect pipeline cracks, and they can be broadly categorized into three: *Inter-Modal Inspection Methods, Traditional Image Processing Approaches, and Convolutional Neural Networks (CNN).*

2.1 The Inter-Modal Inspection Method

This method includes the use of different inspection techniques, such as girth weld inspection, electromagnetic acoustic transducer (EMAT), and thermal imaging to detect and assess cracks in pipelines [14] [15]. According to [15], the common techniques used to detect cracks in pipelines include magnetic field measurement, thermal camera, and acoustic detection (microphone). Magnetic field measurement, being the first approach, is employed for sensing cracks in pipelines during external inspection. The magnetic sensor is used to detect the changes in the magnetic field which are caused by the presence of a crack. However, this method requires a high level of expertise to understand the result and is not suitable for non-magnetic materials.

The use of an acoustic detector is the second approach, which involves the exploitation of stress waves in ultrasound and sound solid. The third approach considered during external inspection is the use of a thermal camera. The heat transfer from the hotspot enables the camera to detect a white spot bounded by a range of low grey values. The thermal camera is regarded as the ideal choice for crack detection because it’s easy to operate, has remote detection capabilities, and has outstanding performance and dependability. However, the performance was still hindered by uneven brightness and noise in the images, the high cost of the specialised equipment and the specialist skill required to use it.

2.2 Traditional Image Processing Approach

This approach involves techniques such as block processing, which separate the image into smaller sections for independent evaluation, and wavelet transforms to extract essential features and patterns associated with cracks at different scales and resolutions, as demonstrated by [16] for pipeline crack detection. Semantic segmentation is another widely used approach, enabling precise identification of cracks by separating them from the background and other non-crack regions in the image [17].

Additionally, methods like local analysis, filtering techniques and histogram-based thresholding have been applied for crack detection, but often result in a high rate of false-positives and incomplete detections [18]. Edge detection and binary image analysis have also been explored, with discussions highlighting their strengths and limitations in handling noisy images, thin cracks and shadow [19].

2.3 CNN-Based Methods

CNN-based methods have also been adopted in crack detection due to the numerous advantages they offer over the previous two approaches. CNN-based approaches eliminate the need for manual designs of sophisticated feature extraction techniques, which require significant image preprocessing. CNNs can automatically extract features through learning, making them more accessible to users without prior experience [13]. With the promising performance demonstrated by CNNs in numerous computer vision tasks, including object recognition, localization, and image classification, these capabilities make them a viable choice for detecting cracks in large datasets [12].

Many researchers have explored the application of deep learning in detecting and segmenting cracks, particularly in civil engineering structures where over 67% of articles between 2010 and 2021 proposed machine learning approaches over traditional image processing techniques [20]. As compared to conventional methods, machine learning models require not only preprocessing, such as contrast adjustments and data augmentation, but also the critical step of annotating defect areas in images to guide the model in distinguishing cracked from non-cracked areas. The choice of a machine learning model plays a pivotal role as the model's architecture directly impacts its accuracy in classifying cracks. The current challenge lies in selecting the optimal model that can generalize across varied datasets while minimizing false positives and false negatives in crack detection.

Building on this trend, [13] presented a deep learning-based method using CNN and crack contour network (CCN) for pipeline crack monitoring. Their model processed high-resolution images captured by drones to detect, identify and classify the shape and type of cracks in the pipeline images. After optimizing the model's threshold, they achieved an F1 score of 84.6%, an accuracy of 91.9% and a recall of 86.1%, which indicates the effectiveness of their approach in identifying cracks. However, despite the promising results, a high false positive rate remains a concern, suggesting that further refinement is necessary for real-world application, mainly in autonomous pipeline monitoring systems.

In [21], the use of a deep CNN classifier was proposed in combination with a sliding window technique for detecting surface-level cracks in teeth. This AI-based system was built on the pre-trained Residual Network (ResNet), which consists of an input layer, convolution layers, residual blocks, and a dense layer. The fine-tuned network was trained and validated on a dataset of 20,000 tooth images, categorized as cracked and non-cracked teeth. The model performance was tested on 100 tooth images, achieving an accuracy of 90.39%, with only two false-positive regions and one false-negative region. These results indicate the AI-based method effectiveness and versatility in detecting cracks in teeth. However, the study only focused on superficial cracks, which are limited to the tooth surface, and the dataset was based on artificially generated images of cracked teeth; hence, the need for further research to address deeper cracks and validate performance on real-world datasets.

The authors of [22] combined CNN with wavelet packet energy (WPE) employing piezoelectric active sensing with time reversal to detect and quantitively assess the interior corrosion condition of pipelines. A CNN is used to convolve the wavelet packet energy, and the pipelines with varying corrosion levels are discovered by examining the output matrix. The proposed approach possesses a minimal cost, easy design, and higher accuracy of 99.40% when compared with the other three models: CNN, WPE-SVM, and WPE-KNN.

Considering the danger caused by leakage in natural gas pipelines, [23] focused on developing a system for detecting, identifying, and evaluating the size of minor leaks from a compressible and dynamic natural gas flow in a pipeline. MATLAB was used to develop and train a shallow neural network classifier (SNNC) using temperature, mass flow rate, and pressure measurements. A case study of a natural gas pipeline of 80km in length was simulated with leak magnitudes of 5%, 2%, and 0% to get the pipeline data. The developed system proved its ability to identify, detect, and calculate the magnitude of the leakage with an extraordinary average accuracy of 99.9%. However, this technique lacks information about the system framework, which suggests that it is likely to mistakenly categorize leaks that are not included in the training data, and the classifier cannot recognize multiple faults concurrently.

With respect to the minimal impact and low generalization capability of traditional image processing techniques on concrete crack image segmentation, [9] proposed an improved fully CNN method based on ResNet101 for concrete crack detection. FCN and U-Net network models make up the enhanced fully CNN known as CrackNet model, which has a shrinking path for acquiring features of the images and an expanding track for identifying and restoring features. Out of the 3000 images of concrete surfaces collected, 2500 were utilized for training the model and the other 500 were used for testing. The proposed model has an average of 96% recall and 95% precision, which indicates better performance when compared with the FCN technique which has an average of 94% and 93% for recall and precision respectively.

Our proposed model utilizes the ResNet-50 architecture, a CNN-based approach chosen for its proven robustness in various deep learning tasks, including crack detection. ResNet-50 is known for its resilience against vanishing gradient, a common issue in deeper networks, as it employs identity shortcut connections or skip connections that bypass layers that could hinder performance [24]. While earlier studies often focused on crack detection in dental and concrete structure, our approach uniquely applies ResNet-50 to surface pipeline images, an area that has not been extensively explored. In addition to outperforming conventional CNN models traditionally used in pipeline cracks, ResNet-50 was also benchmarked against other CNN architectures such as MobileNet V2, VGG16, and DenseNet121, further solidifying its status as the top performer. Unlike previous studies that utilized datasets of images from concrete or teeth or required specialized imaging equipment, our research leverages a newly curated dataset of high-resolution pipeline images for crack detection.

3. METHODOLOGY

In this work, the task of detecting cracks in pipeline images is addressed as a binary (Crack or Non-crack) classification problem. Given that one of the problems of pipeline crack detection is the non-availability of sufficient dataset, a dataset containing 3,044 images of surface pipelines was collected during this research and each image was annotated as either cracked or non-cracked. To enhance the quality of the images, image preprocessing techniques including cropping, and rotation were employed, and the enhanced images were fed into a ResNet50 model fine-tuned for this task. Figure 1 shows a general overview of the methodology adopted in this work. In summary, the pipeline images serve as the input data to the system.

Some preprocessing techniques were applied to images to improve the quality of the images to the model's training for feature extraction and crack detection. The data was split into three; the training set was used to train the ResNet50 model, and the model was evaluated with the validation and test sets. Additionally, other deep learning models such as VGG16, DenseNet121, MobileNetV2 and a simple CNN were also trained and evaluated on the same industrial pipeline dataset. This comparative evaluation helped validate the effectiveness of ResNet50, demonstrating its superior performance in accurately predicting and classifying pipeline surface cracks based on the assigned class labels. The rest of this section discusses in detail each aspect of this methodology.

3.1 Dataset

The newly created Industrial Pipelines Dataset (IPD), specifically for this research contained a total of 3,044 industrial pipeline images gathered from various sources. 500 images were extracted from the oil spill incident report displayed on the online map of the [6], which gives the public access to current official data on oil spills collected by the National Oil Spill Detection and Response Agency. The remaining data was originally collected by us as a video stream of various industrial pipelines recorded in different industries, including water management companies. Image frames were extracted from these videos at 2-second intervals using the OpenCV library, resulting in 2,544 images. These images were then labelled based on the two basic classes considered in this research, which are cracked and non-cracked. Figure 2 shows the data generation and annotation steps described herein as well as some sample images.

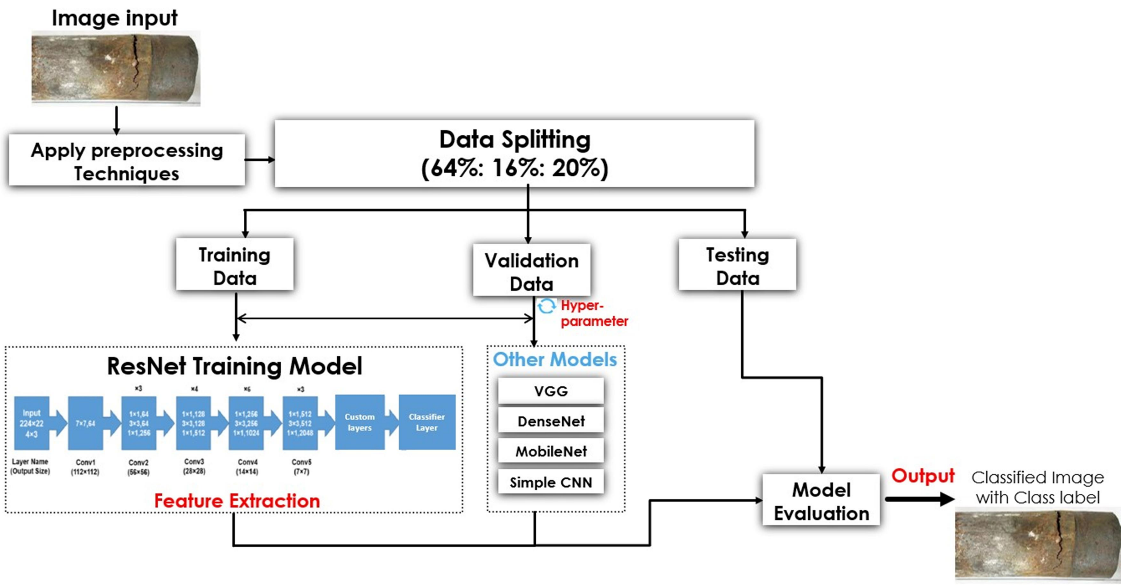

Figure 1: Generic architectural diagram

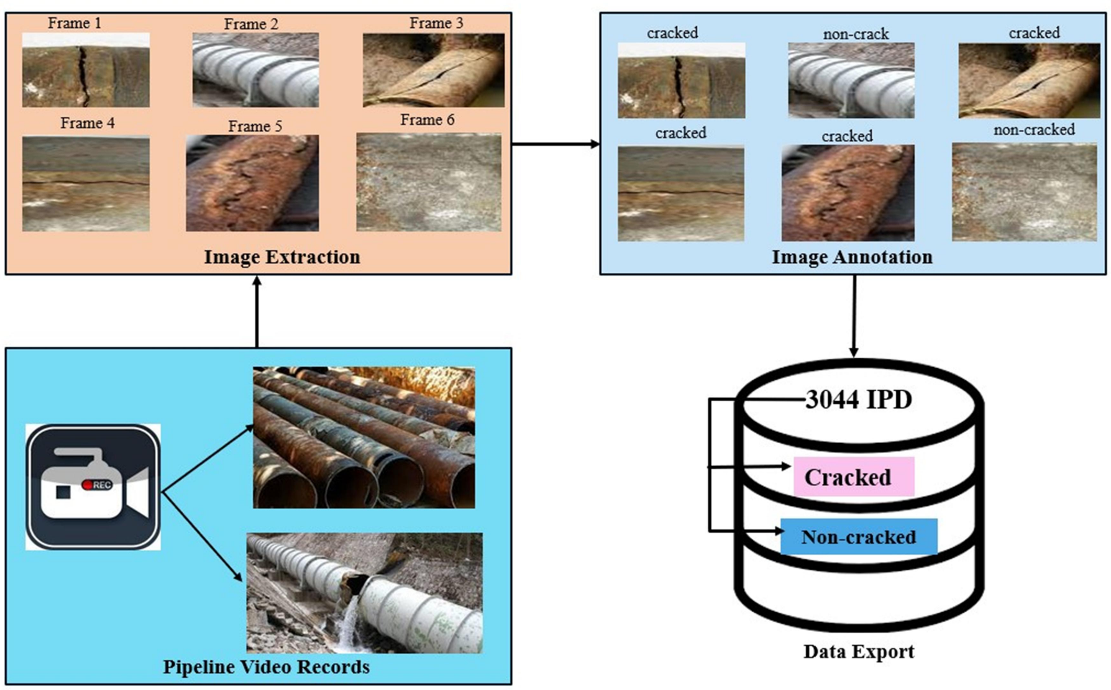

Figure 2: Data generation and annotation steps

3.2 Image Pre-processing

To enhance the quality of the images, some pre-processing techniques were applied to the IPD after data collection, as shown in Figure 3. The images were first cropped to the size of 224 x 224 to remove unwanted sections, then histogram equalization was applied to the cropped images for contrast enhancement and intensity normalization. This was then followed by applying Gaussian blur to reduce the noise and deal with uneven illumination, after which a perspective transformation was applied to correct distortions in the images. The IPD was split into three, with 20% devoted for testing, 16% for validation, and 64% for training the model for feature extraction and crack detection. To further avoid overfitting, data augmentation techniques which include rotation, flipping, and zooming, were applied to artificially increase the size of the training dataset. This resulted in 1,948 images being seen per epoch, with each image augmented differently in each epoch, resulting in a total of 19,480 augmented images over 10 epochs for model training.

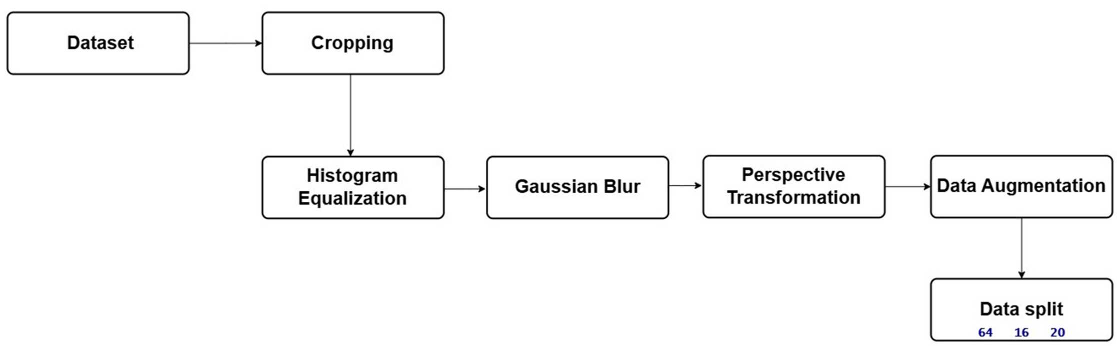

Figure 3: Data Pre-Processing Techniques

3.3 Computer Vision Techniques Based on Deep Learning

This section explores the application of the deep learning model in the context of computer vision techniques for crack detection on surface industrial pipelines. For this research, the ResNet-50 deep learning architecture was adapted for feature extraction and crack detection in pipeline images. ResNet [24] is one of the most popular CNN-based architectures for image recognition, and it is renowned for its precision that exceeds that of human sight based on its success in image classification tasks. Additionally, it can learn and represent complex features and is available as a pre-trained model, which can be fine-tuned for specific tasks like pipeline crack detection. The adapted ResNet-50 architecture, shown in Figure 4, consists of an input layer of size 224 x 224 with three colour channels (R, G, B), which accepts the input image fed into the model for further processing. The input images are processed by the model through multiple convolutional layers, residual blocks, pooling layers, dropout layers and an output layer.

The next layer is the convolutional layer with 64 filters, 7 x 7 kernel size and a stride of 2, the Batch normalization layer to improve performance, and the ReLU activation layer to introduce non-linearity into the model. The max pooling layer has a pool size of 3 x 3 and a stride of 2, which is used to decrease the data size after the convolution process. The model has 16 residual blocks, which can be divided into 4 stages with 3 residual blocks in stage 1, 4 in stage 2, 6 in stage 3 and 3 in stage 4.

Each residual block contains several convolutional layers and a skip connection (identity shortcut) that directly connects the input of a residual block to its output. The skip connection is one of the unique characteristics of the ResNet architecture that makes the network more efficient. It prevents the problem of exploding or vanishing gradient that occurs in most deep neural networks and acts as a gradient super-highway, which allows it to flow without being altered by a large magnitude. To fine-tune the model for our specific task of crack detection, as shown in Figure 4, additional layers like the average pool, dense layer, and dropout layer were added on top of the ResNet-50 base before the output layer. The Global average pooling layer averages the values within each feature map and results in a fixed-length feature vector, which is applied to reduce the spatial dimension of the feature map output.

The first dense layer is a fully connected layer with 128 units that learn complex patterns from the features extracted by the previous layers. To further prevent overfitting, a dropout layer was added after the dense layer, which helps to reduce reliance on specific tasks by randomly setting a fraction of input units to zero during training. There is another fully connected dense layer with 64 units after the dropout layer to further refines the learned features. Finally, the output layer has a single unit dense layer that has 1 neuron applied to perform a weighted sum of the input features and a sigmoid activation function that squashed the output into a range of 0 and 1 which allows it to be interpreted as a confidence score for the binary classification task of cracked or non-cracked.

3.4 Models' Performance Comparison on IPD

To ensure that the best-performing model was used, the performance of four additional deep learning models (VGG16, DenseNet121, MobileNetV2, and a simple CNN) was evaluated on the Industrial Pipeline Dataset (IPD). These models were trained and tested on the same primary dataset used for ResNet-50 each architecture was modified to support binary classification by replacing their default classification layers with a sigmoid-activated output layer.

VGG-16 [25], developed by Oxford's Visual Geometry Group is a deep CNN with 13 convolutional, 5 pooling, and 3 fully connected layers, In this study, custom fully connected layers (2 x 4096 units) were retained before the replacement of the original softmax output with a single-node sigmooid layer to suit binary classification.

DenseNet121 [26] utilized dense connectivity between layers for efficient gradient flow. The architecture includes multiple dense and transition blocks and the final softmax layer was replaced with a fully connected layer followed by a sigmoid activation to enable binary output. MobileNetV2 [27] is designed for efficient computation using depthwise separable convolutions and inverted residuals. The final layer was modified by applying global average pooling, a dense layer and a sigmoid layer, replacing the original multi-class softmax output. Lastly, a simple CNN with a conventional layered architecture was included as a baseline for comparison.

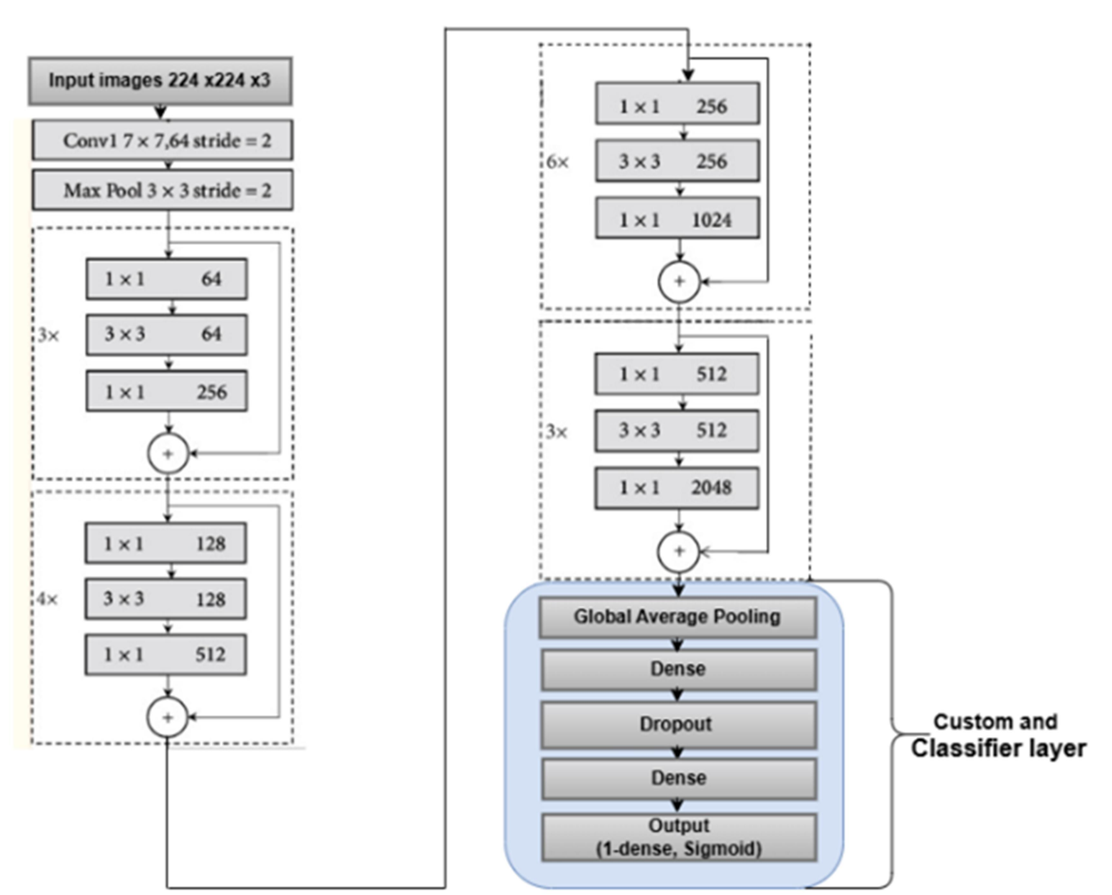

Figure 4: The architecture of the customized ResNet50 model

3.5 Performance Evaluation

The performance of the experimental results obtained from this research were assessed by applying various evaluation metrics, including sensitivity (recall), specificity (precision), accuracy, and F1-score. The formulae used to calculate each metric is listed in equations 1 to 4.

Accuracy calculates the overall correctness of the predictions across all classes.

$$\frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

Precision represents the percentage of the predictions that are correct.

$$\frac{TP}{TP+FP} \tag{2}$$

Recall calculates the percentage of the true positives that are found.

$$\frac{TP}{TP+FN} \tag{3}$$

F1 Score is the harmonic mean of precision and recall.

$$\frac{2 \times (Precision \times Recall)}{Precison + Recall} \tag{4}$$

where TP stands for true positive, TN stands for true negative, FP stands for false positive, and FN stands for false negative.

3.6 Experimental Setup

This research was carried out using the Python programming language, version 3.10. The implementation was done on two platforms that are cloud-based integrated development environments (IDE), which are Google Colab and Kaggle Notebook. These cloud-based IDEs provide access to the required computing resources needed in this research, including GPU and CPU, to write and execute code, build, and train deep learning models and perform necessary visualizations. Some of the Python and machine learning libraries used in this research are NumPy, Matplotlib, OpenCV, Tensorflow and Keras.

4. RESULTS AND DISCUSSION

4.1 Dataset

As earlier noted, one of the main problems in pipeline crack detection research is the non-availability of sufficient datasets. Consequently, a dataset containing a total of 3,044 industrial surface pipeline images was generated during this research, and each image was annotated as either cracked or non-cracked. Figure 5 shows a sample of an image denoted as a cracked pipeline, with the portion of the pipeline that is cracked highlighted, while Figure 6 and Figure 7 represent the visualization of the sample IPD before and after preprocessing, respectively.

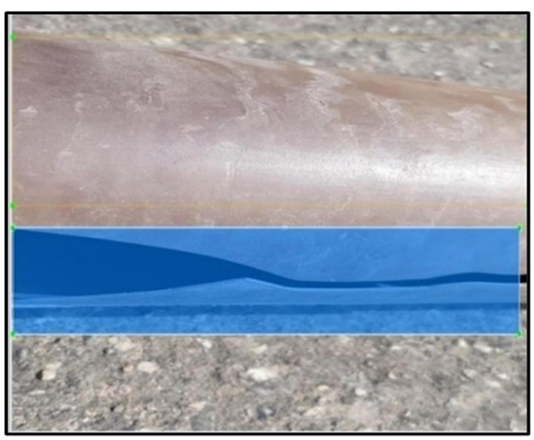

Figure 5: Sample Image with Crack

4.2 Hyperparameters

It has been noted that the choice of hyperparameters has a great effect on a model's training and performance, therefore, the hyperparameters were tuned until the right values for good performance were achieved. The model was trained for 10 epochs, which implies the number of times the model iterates over the entire training dataset. ImageNet was used as the weight to initialize the model with pre-trained weights from the ImageNet dataset, and 0.0001 was used as the learning rate, which determines the step size taken in the optimization process.

The smaller the value, the slower and more stable the model converges. For binary classification tasks of cracked or non-cracked, binary cross-entropy is a suitable loss function and ReLu was used as the activation function to introduce non-linearity. In the output layer, sigmoid activation was used since the research was focused on binary classification, as it squashes the output values between 0 and 1, which represents the class probabilities.

Figure 6: Sample pipeline images with their classes

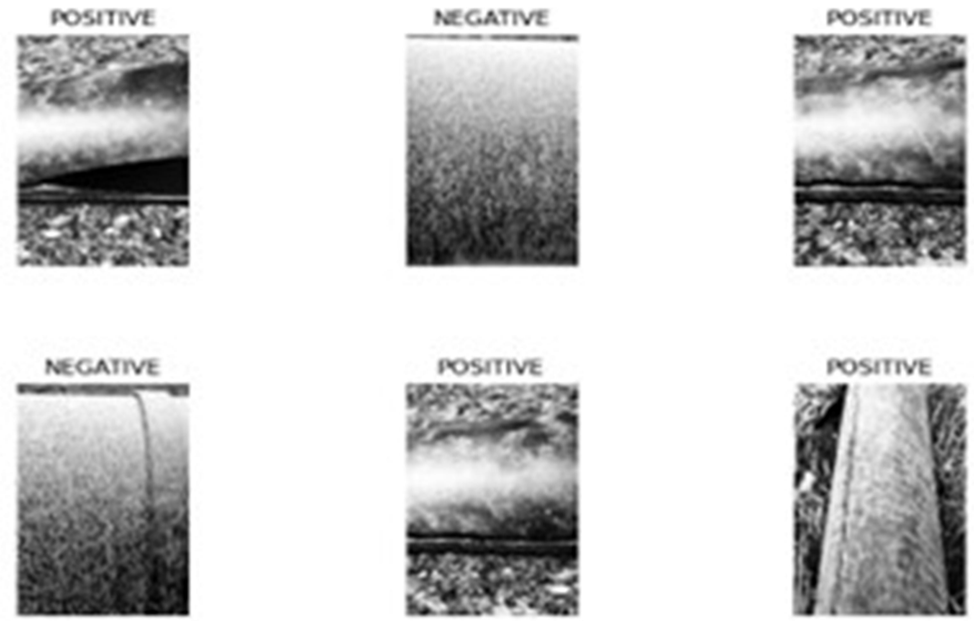

Figure 7: Preprocessed sample dataset

4.3 ResNet50 model training and validation

The customized ResNet50 model used for feature extraction and classification was trained with the training dataset and validated using the validation and test dataset. Figure 8 depicts the graph of training and validation accuracy over time, which shows that as the number of epochs increases, the accuracy also increases and the higher the accuracy, the better the performance. The graph of training and validation loss across time is represented in Figure 9, which implies that the loss reduces as the epoch increases and the lower the validation loss the better the model performance.

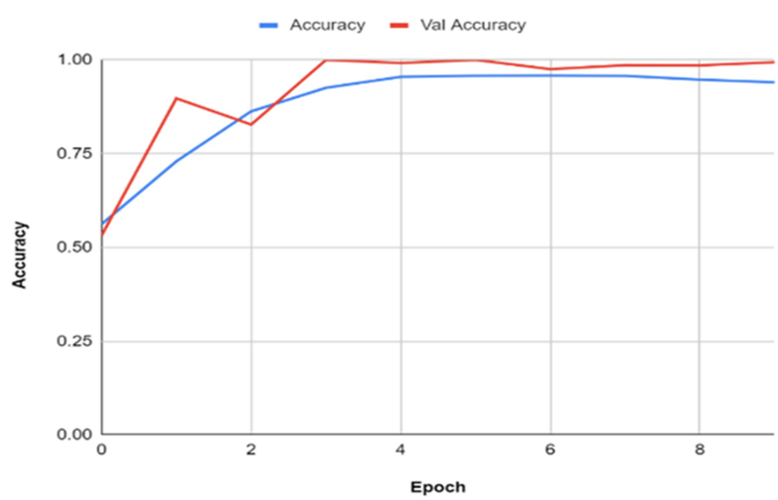

Figure 8: ResNet50 Training/Validation Accuracy over Epoch

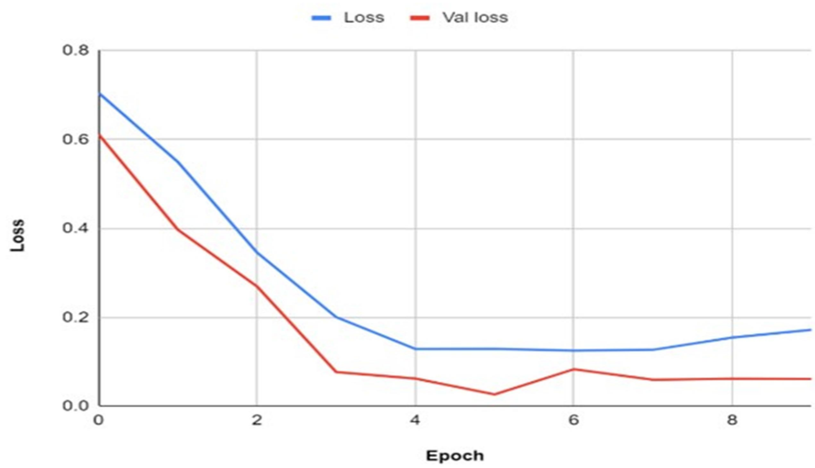

Figure 9: ResNet50 Training/Validation Loss over Epoch

4.4 ResNet50 model evaluation

To evaluate the performance of the model, standard classification metrics of recall, precision, accuracy and F1 score are used. Figure 10 shows the confusion matrix for the test set containing 600 images. The matrix shows that there were no false negatives, 303 images were correctly classified as non-cracked pipeline images, while 293 images were correctly classified as images of cracked pipelines. However, there are three misclassifications of false positives where cracked images are misclassified as non-cracked. This shows that the customized model effectively handled the issue of model overfitting by correctly classified most of the sample images generated for this research with an accuracy of 99.84% and minimal misclassification as compared to existing work. Table 1 shows the summary report of the resulting model with a precision of 99.51%, recall of 99.49%, an accuracy of 99.84%, and f1-score of 99.50 %.

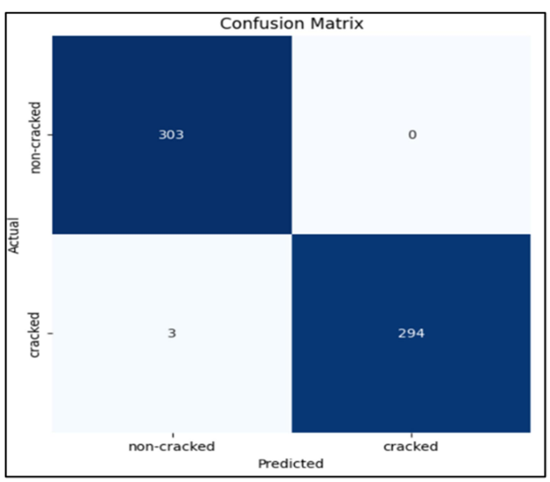

Figure 10: Confusion Matrix of the ResNet50 Model

Table 1: ResNet50 Model Classification Report on the test set

	Precision	Recall	F1-score	Support
Non-cracked	0.9902	1.0000	0.9951	303
Cracked	1.0000	0.9999	0.9949	297
Accuracy			0.9984	600
Macro avg	0.9951	0.9949	0.9950	600
Weighted avg	0.9950	0.9949	0.9950	600

4.5 Performance of other standard models on the IPD

This includes the result of the comparison and investigation of other standard learning models on the IPD. As illustrated in Figure 11, the training patterns and validation accuracy of VGG16, DenseNet121, MobileNetV2 and CNN shows distinctive characteristics. VGG16 showed gradual improvement after initial fluctuation, while MobileNetV2 achieves near-perfect accuracy from the outset and DenseNet121 demonstrates consistent performance with low loss rates. All three models peaked at 98.33% validation accuracy, while the CNN achieved 96.67% with stable loss. This highlights the comparative strength of DenseNet121 and VGG16 in convergence and performance.
The summary of the models' test performance is presented in Table 2, with ResNet50 and VGG16 achieve high precision in their predictions which indicate excellent accuracy. In contrast, MobileNetV2 and DenseNet121 offer competitive accuracy despite differences in model complexity and Simple CNN provides a simpler yet decent performance.

4.6 Discussion of Result

This study conducted a comprehensive evaluation of five deep learning architectures (ResNet50, VGG16, MobileNet12, DenseNet121 and a custom CNN) on a custom developed Image Pipeline Dataset (IPD) for detecting pipeline cracks. The evaluation was based on test accuracy/loss, training time and a visual trends from training/validation plots.

4.6.1 Model Performance Comparison

Table 2 presents a summary of the models' performance. ResNet50 outperformed all other models by achieving the highest test accuracy of 99.84%, indicating a balanced classification capacity with minimal misclassification of cracked and non-cracked samples. This strong performance demonstrates ResNet's robustness and potential for real-world deployment in critical infrastructure inspection tasks.

Table 2: Model Performance Comparison

Model	Test Accuracy	Test Loss
ResNet50	99.84%	0.05830
VGG16	99.80%	0.01585
MobileNetV2	99.40%	0.40169
DenseNet121	99.40%	0.09321
Simple CNN	96.20%	0.11615

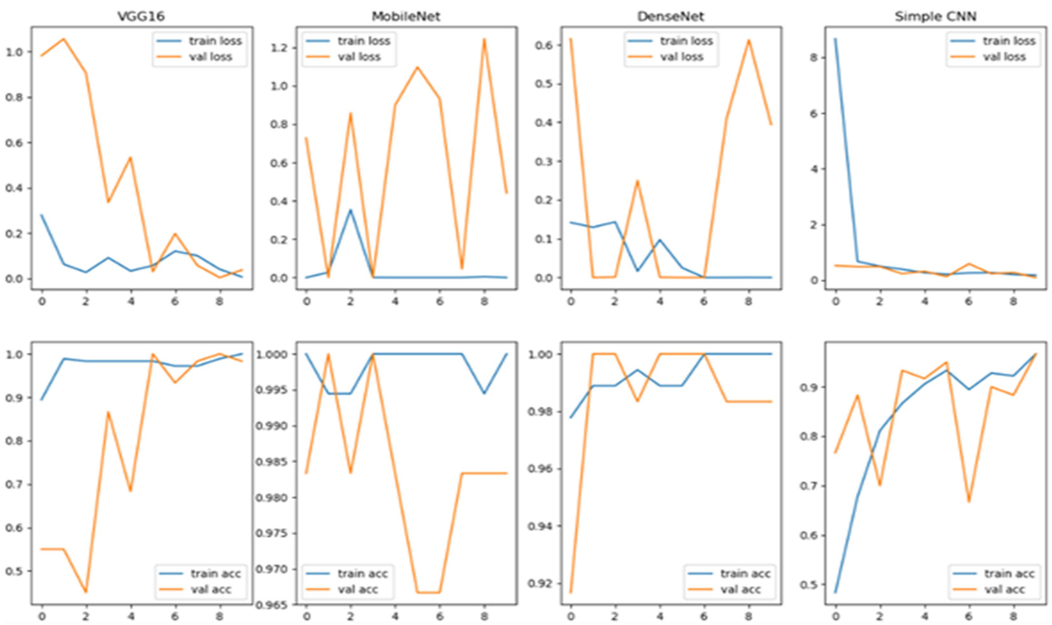

Figure 11: Training/Validation accuracy and loss for each model

VGG followed closely, attaining slightly lower accuracy of 99.80% but outperforming other models in terms of test loss. This low loss suggests a highly stable generalization capability during inference. DenseNet121 and MobileNetV2 achieved identical test accuracy score of 99.40%; however, DenseNet121 exhibited superior generalization through a lower loss value (0.09321) compared to MobileNetV2 (0.40169). MobileNet is a suitable model for resource-constrained or real-time environments despite slight fluctuations observed in its training and validation curves. The custom CNN model, while significantly less accurate than the pretrained model (96.20%), still delivered acceptable performance and low loss, reflecting its suitability for lightweight applications. However, its reduced depth and absence of pretaining constrained its capacity to learn complex features compared to the deeper transfer learning architectures.

4.6.2 Implication of Findings

The findings from this research have practical implication for pipeline monitoring and maintenance systems. Models such as ResNet50 and VGG 16, with their high accuracy and generalization capabilities, are well suited for deployment in high-risk, safety-critical industrial environment where precision is paramount. Their minimal error rates ensured reduced chances of false alarms and undetected faults. In contrast, MobileNetV2 is ideal where speed and resource efficiency are prioritized. CNN is suited for basic offline inference scenarios.

4.6.3 Limitations

Despite the promising results, some limitations were observed. Firstly, although the IPD was carefully collected, its limited size and controlled distribution may constrain the model's ability to generalize to more diverse, real-world scenarios. Future research should consider extensive data collection to enhance robustness.

The exceptional high training accuracy observed in MobileNetV2, raise the possibility of overfitting. Although, test performance remained strong, further investigation using additional regularization technique is recommended. Another limitation pertains to model interpretability, the black-box nature of deep models makes it difficult to explain or trace the basis of their predictions. lastly, training times are dependent on the underlying hardware.

5. CONCLUSION AND FUTURE WORKS

This research developed and evaluated deep-learning models for detection of surface pipeline crack using a custom image dataset. the application of appropriate preprocessing and model customization significantly improved classification accuracy, with ResNet50 achieving the best overall performance with only a minimal number of misclassifications as compared to other models and the existing work. These results demonstrate the effectiveness of the developed system in accurately detecting pipeline cracks, contributing to improved maintenance, and monitoring of pipeline infrastructure. Future work will involve expanding the dataset to improve generalization and incorporating object detection technique (YOLO, Faster R-CNN) to localize cracks and estimate their severity, further enhancing the system's practical utility. Additionally, the application of transformer-based architecture such as Vision Transformer (ViT) can be explored to assess their effectiveness in modeling global features for more accurate and explainable crack detection.

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