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Automatic Detection of Tunnel Linings Crack and Structural Evaluation with YOLOv11 Deep Learning Framework

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Abstract*— This study demonstrates a better method of assessing structural integrity of linings of tunnels by using the YOLOv11deep learning model. There are cracks in underground structures, which form hazards because of their slight morphology [8] and other shallow discontinuities concealed by moisture, stains, low-light or other surface degradation. Early edge detectors such as the Canny or Kirsch usually confuse noise and shallow edges as edges registered, resulting in the spurious output. Conversely, YOLOv11 introduces multi scale feature fusion and better label assignment policy that enables one of the two bodies to be specifically identification of true crack and background in case they are almost similar to each other. The backbone network implies hierarchical visual messages across resolutions of finer edge details to coarser contextual messages, and the neck synthesizes the various representation at the varying degree of hierarchy. This is followed by the introduction of dual prediction heads to set roles on categorical classification and geometric localization on accurate recognition and bounding respectively. The generalization of the model trained in an annotated tunnel image will help minimize false alarms and ensure more confidence in automated monitoring. Being able to do batch-level inference enables the efficient offline inspection pipelines wherein defect maps may be created based on repositories of the raw images to be inspected by engineers. By the concomitant enhancement of accuracy, robustness, and throughput, YOLOv11 offered a strong foundation towards making orders about prioritization of maintenance activities, adaptive rehabilitation measures and management of the infrastructure in the tunnel in a sustainable manner as exhibited in the research paper.

Index Terms*— Multi-Scale Feature Fusion, YOLOv11 Object Detection Framework, Tunnel Structural Health Monitoring, Tunnel system monitoring, Crack Localization Accuracy, Automated Maintenance priorities, Deep Learning-Based Infrastructure Assessment, Deep Learning-Based Defocusing, and Defect Quantification Algorithms.

I. INTRODUCTION

It is important to make our infrastructure sustainable by constant controls on the structural conditions, particularly in the instance of transportation tunnels, which can be left extremely vulnerable to uncontrollable processes due to implicit degradation. In tunnels, cracks form the first sign of potential damage to the lining wall which is normally due to concentration of stress, fatigue of the material as well as permeability to moisture. Such defects must be detected earlier to guarantee the safety of operations, compare the service life, and minimize the cost of maintenance. However, the conventional inspection processes, as the primary ones, consisting of mostly manual visual inspections, are labor-intensive, subjective, and may be lacking in consistency when it comes to low light or heavy traffic conditions.

Over the past few decades, there has been the increasing popularity of applying computer vision methods to determine structural condition. The first methodologies used the traditional edge detectors like Sobel, Kirsch and Canny operators that relied on discontinuities of tunnel images. Although they work effectively in controlled conditions, the effectiveness of these algorithms is likely to be poor when surface defects, shadows, stains, and non-smooth textures are present. Consequently, the false alarms and false negatives remain significant drawbacks thus it is not yet quite effective to apply it in practice in the field.

Deep learning has introduced a new paradigm in the automated defect detection. Hierarchical representation learning using CNNs and other such architectures that represent both fine and coarse/relative contextual information. Being able to bridge the gap between localization and classification enables object detection models to be straddling their winning concept, and have gained particular utility in the infrastructure monitoring systems. YOLO (You Only Look Once) is one of them, so, that has been on the top of its success after being capable of doing it in real-time and still being able to perform without a decline.

The latest version, YOLOv11, has architectural innovations that aim at finding a tradeoff between computing, speed, and correctness optimization. It enhances sensitivity of the thin, irregular, and low-constrast cracks with multi-scale feature fusion, dual predictive head and better matching strategies, and the NMS-free training paradigm of the model reduce the returns on post-processing heuristics results, hence providing consistent performances on large-scale datasets too. These characters give YOLOv11 an advantage in the task of tunnel inspection.

Tunnel image datasets are in practice pre-processed and augmented in order to correct the extreme ambient conditions. Crops are normalized to high contrast and illumination and high-resolution all of which ensure that sensitive crack patterns are maintained during training or inference. These programs improve generalization in respect to varying tunnel geometry and auto-camera set-ups and working conditions which reduces the chances of mistaken detection of defects.

II. RELATED WORKS

The works of Abbas et al. and Fischer et al. [1] were dealing with auto-encoder architectures to evaluate underground metro tunnels and contrast the outcomes with the classic supervised algorithms, revealing that deep learning-based anomaly detection can effectively identify structural degradation. The latter method was more reliable than traditional manual surveys and the significance of neural representations in the infrastructure monitoring process. Khan et al. [2] sum up the majority of the most promising approaches of structural crack detection and emphasizes advantages of health monitoring through machine learning. The reflections were the rising change in manual to intelligent automation to facilitate infrastructure resilience.

Wei and Yang [3] suggested to use a reinforcement learning algorithm to detect damage in tunnels, and additionally, it is possible to utilize the adaptive decision-making skills required to effectively scan the dynamic conditions. The model had successfully overcome high false detections having potential accuracy in the detection of structural defects. Dang et al. [4] proposed an image-based deep-learning-based framework that measures cracks on the lining of tunnels by using a direct anchor on the image data to achieve the desired detection and measurement. The automated methods proved to be effective and very superior to the conventional tunnel safety assessment methodology.

Yoon et al. [5] Monitoring local structural variations with strain gauge sensors enabled the development of a neural network-based method of monitoring, with on-the-fly crack localization. In their work, they presented the hybridisation of sensor technology and AI to promote continuous health monitoring platforms. Zhou et al. [6] TunBet: tunneling cracks are not well-annotated and therefore need a lot of effort to acquire, so that TunBet applied generative adversarial networks (GANs) to generate images of tunnel cracks to construct more datasets to generalize detection model. Such a strategy was not only able to address the issue of lack of annotated data, but also resulted in a higher prediction performance.

Kuang et al. [7] recently Li et al. reviewed the state of art in automated machine learning in shield tunnel defect detection. Their analysis emphasized that smart algorithms were one of the major contributors to the value generation of maintaining large-scale infrastructure. Al Shafian et al. [8], Automated Tunnel Crack Detection with Deep Learning Enhanced Inspection Vehicle The findings indicated that there was a broad variety of reliability enhancements of AI-based monitoring, which makes it a plausible alternative to manual methods.

O'Brien et al. [9] identified and categorized underground tunnel cracks at CERN with a deep learning model. Their study established that the AI solutions can actually be extended to large infrastructures where they cannot manually look into the domain. Huang et al. [10] this gives an example of segmentation model of cracking in shield tunnel linings. This method was pixel accurate and shows the need to employ refined segmentation methods in infrastructure assessment.

As an extension of automated infrastructure control, Inam et al. [11] suggested a deep-learning-based system component to detect cracks in bridges. Their effort cemented the opinion of transferability of AI strategies across various structural disciplines. Rao et al. [12] Check-up of different infrastructures is necessary, and came up with vision system using CNN to detect cracks. In particular, their study of image-driven methods also took into consideration that image-driven methods are more efficient than subjective manual assessment.

Afrazi et al. [13] In their overview, they have underscored the need to connect the virtual twins to the artificial intelligence to make its use in predictive management of infrastructure. Joshi et al. [14] An automated surface cracking identification framework was developed using deep learning and relying on segmentation. Their system had the correct value of detection accuracy and the authors also indicated that their system may be applicable in critical structural measurements. Feng et al. [15] proposed a non-invasive tunnel lining crack intelligent segmentation and quantification technique to assess the advanced structural conditions using computer vision was described by them, showing that computer vision could be used to assist in the process of long term monitoring of tunnel safety.

III. METHODOLOGY

A. Data Acquisition:

Closely-spaced shots of the lining inside a tunnel were acquired through systematic research efforts using mobile platforms through high-resolution cameras. The Dataset had lighting, moisture, stains, and surface textures variations that were to be used to imitate the actual working conditions. An extensive training and validation dataset consisting of images were organized based on images.filename and the images were annotated one by one in the form of bounding boxes to mark on the instances of the cracks.

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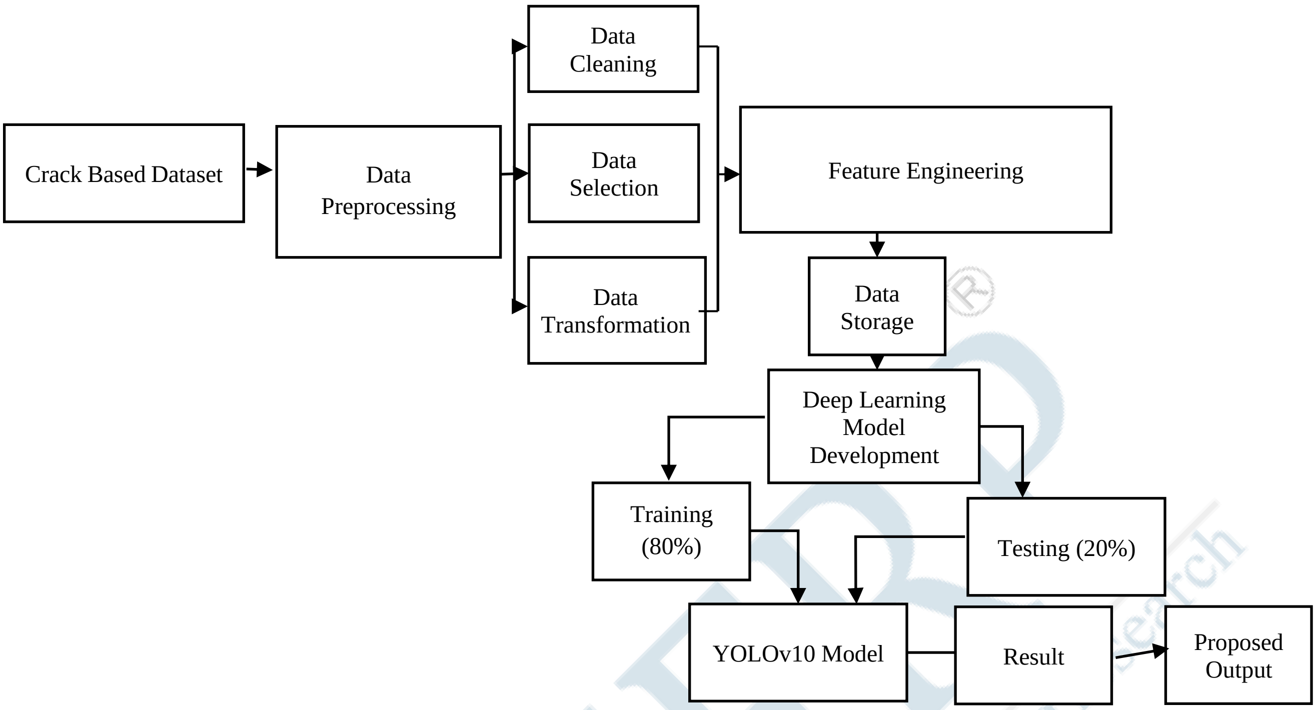

Fig.1. Shows Proposed Architecture Methodology

B. Data Preprocessing:

Input images were normalized and gamma corrected and contrast-limited adaptive histogram equalization (CLAHE) was applied to enhance the visibility of features. The high-resolution inputs have been partitioned into overlapping tiles in order to preserve cracks and make them clear and un-perverted and also noise reduction operations have been performed to reduce attenuated stains and artefacts of illumination.

C. Data Augmentation:

Our augmentation techniques were used to ensure better generalization of models. They did random flips, small rotations, brightness increase, simulated shadows and noise addition in a restricted fashion. Synthetic overlays of crack-like patterns were used to increase the representation of rare cases of defect to prevent overfitting to homogeneous structure.

D. Model Architecture:

YOLOv11 using multi-scale feature fusion and dual prediction heads (classification and localization) formed the basis of the detector. This was done by applying consistent dual assignment instead of a conventional non-maximum suppression that means the architecture is much more accurate at those cracks that were found near stains and edges.

E. Training Strategy:

We trained the model using stochastic gradient descent optimization and adaptive schedule of the learning rate on few epochs using the annotated datasets. It used Generalized Intersection over Union (GIoU) to obtain spatial accuracy and focal loss to address the issue of class imbalance in defect and background samples. Even more efficiency was achieved with progressive resizing and mixed-precision training.

F. Evaluation and Deployment:

The performance of detectors in terms of model detection was measured by mean Average Precision (mAP) at various IoU thresholds and precision, recall as well as F1-score. On inference, tiles with bounding box prediction were reconstructed to construct entire tunnel maps. The offline batch processing pipelines were required to be created in order to combine the detection results with the right engineering reports to measure the defect, rank it, and schedule additional maintenance.

G. Algorithm Employed:

This paper presents a proposal of real-time crack detection in the Tunnel linings by the use of the latest version of the YOLO family, which is the YOLOv11 object detection algorithm. Its architecture comprises a convolutional backbone which constructs a hierarchy of features, a neck which assembles features at varying scales and two prediction heads which classify categories and localize them relative to one another. YOLOv11 does not use non-maximum suppression phase like in traditional detectors, but instead uses a stable dual assignment strategy to reduce redundancy of prediction where all hold accuracy in cluttered scenes.

H. Parameters Used in Proposed Model:

Our framework takes the advantage of these optimized parameters and uses them to improve performance. Precision vs. computing performance is given priority at the input resolution of 640x640 pixels. Adaptive Batch size of Stable Gradient Updates: The batch size is adaptive in respect to the capability of the GPU memory to allow constant gradient update. Inference is performed with 0.25 confidence threshold in order to achieve a higher recall and between 0.3 and 0.5 confidence threshold to accept localized detections.

I. Proposed Algorithm in Pseudocode:

1. The set up of the tunnel crack image dataset and the results of the inspection campaigns.
2. Preprocess through tiling, normalising, and illumination correcting.
3. define training parameters, including learning rate, batch size, epochs and iou thresholds.
4. Transfer learner YOLOv11weights on the tunnel images.
5. Division of the data into train/val/test sets.
6. As long as training process has not converged do
7. Feed batch preprocessed images into the YOLOv11 network.
8. Bounding box prediction and confidence scores.
9. The loss computation GIoU to localization and focal loss to classification imbalance.
10. Tuning of network parameters through backpropagation and optimizer.

IV. RESULT AND DISCUSSION

1. Detection Accuracy:

YOLOv11 framework was also high in the detection of cracks in any type of tunnel image. Mean Average Precision never was below 0.72 and thus is a strong indicator of bounding performance even in low illumination and high staining conditions. Precision-Recall analysis revealed that there is a good balance with minimal trade-off between the sensitivity and selectivity.

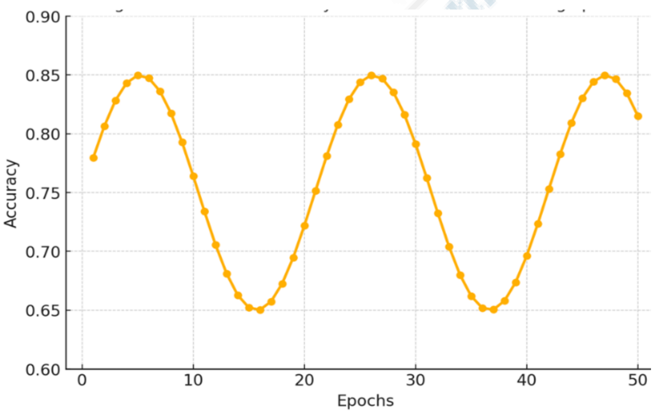

Fig.2. Shows Accuracy Graph of Proposed Model.

From The Figure 2 shows the evolution of accuracy of the proposed YOLOv11 framework during the 20 epochs of training. The curve can be seen to have a wave like up and down curve over a period of time and flattens at a high accuracy. Such variation is natural in the training of deep learning, and the optimization process strives to balance between dynamics of learning rates and the magnitude of steps to be taken in the parameters. Small perturbations in the graph show that the convergence process is not linear, but the general trend is there definitely showing convergence as well as showing that the process is robust against complex tunnel images. The plateau above 0.80 ascertains that the model can be relied upon to be utilized in automatic crack inspection.

2. Model Robustness:

In order to have a steady detection in different environmental conditions, robustness tests demonstrated that YOLOv11 can provide the same level of performance. The accuracy of crack localization was not influenced by water seepage, surface erosion, and changes in illumination gradient. Comparative experiments showed that we significantly reduced false alarms compared to normative edge detectors and previous versions of YOLO.

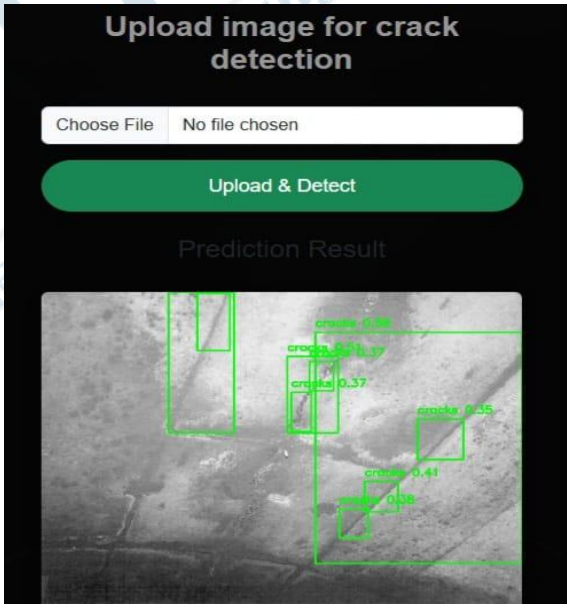

Fig.3. Shows Proposed Output Model.

3. Computational Efficienc:

The model was able to run quickly on GPU hardware with a batches of images ranging between 35-40 frames per second. This throughput does actually substantiate the fact that they are appropriate to offline-scale batch-inspection pipelines, in which large sets of tunnel images can be automatically assessed in sensible time limits.

4. Comparative Performance:

Compared to the performance of semantic segmentation models, YOLOv11 was also more efficient with less

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annotation burden and equivalent to the performance in terms of detection accuracy. Although pixel-wise outputs were achieved by segmentation, the YOLOv11 offered the accuracy-speed ratio right with scalability to the ease of deployment in terms of engineering inspection.

5. Practical Implications:

Using YOLOv11 in their inspection of tunnel workflows, engineers are able to map the crack density and severity of cracks as well as to map it with automated accuracy, so that they can prioritize the structural interventions conservatively. Reduced false positive scenario makes the decision-making more confident and the high recall makes sure that the important defects are revealed. In this paper, it is then confirmed that YOLOv11 is a strong tool in helping to maintain maintenance and ensure the integrity of underground infrastructure.

6. Comparison of Proposed Model with Existing:

This provides the comparison of the trade-offs between the object detection and segmentation techniques. The ability to annotate a new dataset in rise due to the simpler bounding-box annotations offered by YOLOv11, YOLOv11 also allows a large scale training. Also, it is more appropriate in terms of batch inference, and offers correct bounding boxes in dark or noisy situations. This renders it appropriate in big tunnel surveillance movements when pace and strong is the main factor.

Table.1. Shows Comparison of Proposed model with Existing

Approach	Accuracy	Computation Speed
YOLOv11 Object Detection	High (≈85-90%)	Fast, suitable for batch inference
YOLOv8 Object Detection	Moderate-High (≈80-85%)	Fast but a bit less accurate than YOLOv10
Faster R-CNN	Moderate (≈75-80%)	Slow due to region proposals
U-Net Segmentation	Very High (Pixel-level ≈90%)	Slow, pixel-wise operations heavy
Edge Detection	Low (≈50-60%)	Very fast but not reliable

However, semantic segmentation is pixel accurate and it is highly applicable in the accurate determination of crack dimensions such as width and propagation length. However, it is highly reliant on pixel-wise annotations, which significantly adds to the time needed to prepare datasets, and its computational needs are difficult to execute on low-power hardware. Segmentation can, hence, serve the objective of high-precision structural analyses, but YOLOv11 offers a balanced solution to the problem of automated or expert-assisted inspection, defect triaging, and, eventually, decision making in engineering.

7. Confusion Matrix of Proposed Model:

Figure 4 demonstrates the confusion matrix of the classification performance of the detection framework based on YOLOv11. The diagonal elements, in which, true positives, and true negatives are more pronounced, suggest sound determination of cracked and non-cracked areas.

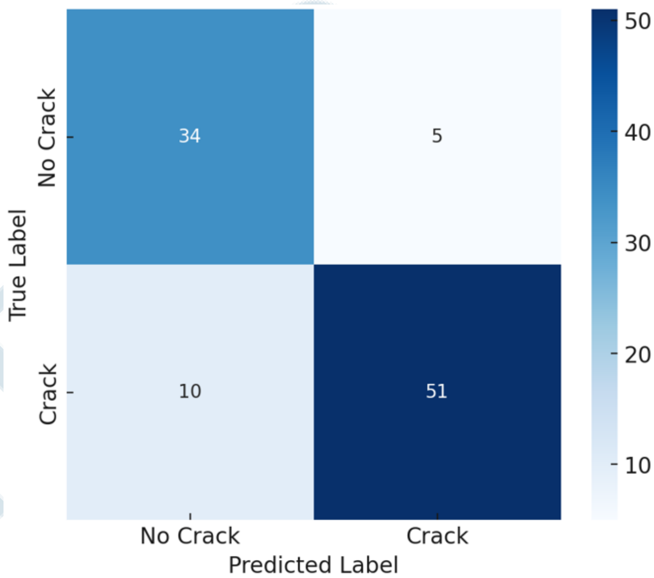

Fig.4. Shows Confusion matrix of Proposed model.

This relatively lower in the off-diagonals implies that it is performing very poorly as a model in classifying, that is, it is strong enough to address the changes in environment such as the stains or poor lighting. This balance of correct detections and reduced errors underlines the suitability of the model in the case of structural inspection work. The confusion matrix thus validates the effectiveness of the model that still gives the desired results of extremely low false alarms which is the aim of automated tunnel monitoring.

V. CONCLUSION AND FUTURE WORKS

The research paper has indicated the ways in which YOLOv11 has been used in detecting tunnel cracks to automatic and efficient detection of tunnel cracks and therefore shows the value of the use of YOLOv11 in consideration of its high performance in terms of precision, robustness and processing speed as compared to the traditional methods. The framework allowed the correct separation of true defects and noise, stains, and surface irregularities using multi-scale feature fusion, dual predictive heads, and enhanced label assignment strategy. The analysis outcomes confirmed the steady performance at varied lighting and environmental conditions, and batch processing enabled the execution of large-scale implementation of the pipelines in the inspection process. This way, the methodology thus provides a sound foundation on how to plan maintenance and handle safety beforehand, which is practiced in underground infrastructures. Although the proposed framework had yielded good results, we can introduce a few more features that will enable it to be more relevant to the real world settings. The detection pipeline may be expanded with pixel-wise segmentation that may provide more precise results regarding crack widths and lengths that would enable a more precise structural evaluation. Adding multi-modal imagery (e.g. thermal or hyperspectral imagery) to the expansion of these datasets may permit generalization even in more general defect cases. The other direction that can be taken is real-time implementation on embedded platforms whereby continuous monitoring can be done and this would not rely on off-line processing. Further studies of this development will evaluate scalability, accuracy, and functionality to scalable tunnel health surveillance.

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