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REAL-TIME CRACK DETECTION IN MATERIALS USING A NOVEL CRACK-AWARE CNN-VIT HYBRID MODEL

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Abstract
Undetected cracks in materials like concrete, asphalt, metals, and composites jeopardize structural integrity, posing safety and economic risks across infrastructure, aerospace, and automotive sectors. This study proposes a Crack-Aware CNN-ViT Hybrid model for real-time crack detection, integrating a Crack-Aware Attention Module (CAM) to emphasize crack geometry and a Crack Severity Annotation Framework to classify cracks by width, depth, and impact. Trained on a 60,000-image RGB dataset, augmented with conditional Generative Adversarial Networks for diverse materials and conditions, the model achieves 95.3% ± 0.2% accuracy, 94.2% ± 0.3% precision, 96.0% ± 0.2% recall, 95.1% ± 0.2% F1 score, and 90.5% ± 0.4% IoU at 32 fps, processing webcam feeds on an NVIDIA Jetson Orin Nano. Ablation studies, cross-dataset validation on SDNET2018 and CrackTree260, and a real-world bridge inspection demonstrate statistically significant improvements over YOLOv8 (by 5.1% accuracy) and Vision Transformers. Enabling automated, edge-based monitoring with timestamped crack storage, this scalable solution advances structural health monitoring, ensuring predictive maintenance and safety.

1 INTRODUCTION

Cracks in materials such as concrete, asphalt, metal, and composites are critical indicators of structural degradation, posing risks of catastrophic failures that compromise safety, operational efficiency, and economic viability in infrastructure, industrial, and aerospace applications [1]. For instance, hairline cracks in bridges can propagate, leading to collapses, while micro-cracks in aircraft components may cause in-flight failures [2]. Manual inspections, reliant on human expertise, are labor-intensive, subjective, and prone to errors, often missing fine cracks or delaying maintenance, which escalates repair costs [3]. The 2021 collapse of a pedestrian bridge in Miami underscored the urgency of automated crack detection, highlighting the limitations of traditional methods [4]. Consequently, there is a pressing need for automated, accurate, and real-time crack detection systems to enhance structural safety and reduce economic burdens.

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized crack detection by enabling hierarchical feature extraction for precise defect identification [5]. However, current models face significant challenges. Standard CNNs, such as

VGG16 or ResNet, achieve high accuracy but lack real-time processing due to computational complexity [6]. Advanced models like YOLOv8 offer speed but struggle with detecting fine cracks under varying environmental conditions, such as low light or occlusion [7]. Vision Transformers (ViTs) capture global context but are computationally intensive, limiting their deployment on resource-constrained edge devices [8]. Moreover, existing systems often rely on generic attention mechanisms or standard datasets, neglecting crack-specific morphology (e.g., width, depth, branching patterns) and real-world deployment constraints like continuous webcam monitoring [9]. These gaps underscore the need for a novel approach that combines high accuracy, real-time performance, and adaptability across diverse materials and environmental conditions.

This study proposes a Crack-Aware CNN-ViT Hybrid model, integrating a novel Crack-Aware Attention Module (CAM) and a Crack Severity Annotation Framework to address these challenges. The CAM dynamically weights features based on crack geometry, enhancing detection of fine and complex cracks, while the annotation framework categorizes cracks by width, depth, and impact, improving model robustness. The model leverages a 60,000-image dataset [22], augmented with conditional GANs, to ensure diversity across materials (concrete, asphalt, metal, composites) and conditions (fog, rain, low-light). Deployed on an NVIDIA Jetson Orin Nano, the system processes webcam feeds at 32 fps, enabling real-time monitoring with automated crack storage for maintenance planning. The objectives are threefold: (1) to develop an automated crack detection model with unparalleled accuracy and speed, (2) to enable real-time monitoring across diverse materials using edge devices, and (3) to pioneer a scalable framework for structural health monitoring with interdisciplinary applications. This work targets engineers, quality control professionals, and researchers in civil engineering, aerospace, automotive, and medical imaging, offering a transformative solution that surpasses benchmarks like YOLOv8 and ViTs, as detailed in the following sections.

2 Literature Review

The way cracks are detected in materials has advanced, from simple image processing to powerful deep learning approaches [10], [11]. Although thresholding, edge detection and morphological operations made calculations fast, these techniques struggled to handle complex cracks that were influenced by things like lighting, shadows and various textures found in the environment [12]. Thresholds for detecting damage often classified fine cracks as noise which caused the algorithm to identify extra damage [13]. Deep learning and especially CNNs, played a major role in allowing machines to process different materials and pick out the right patterns for detecting cracks precisely [14], [15].

A number of deep learning models have been investigated in recent research for crack detection. A group led by Jahanshahi [1] designed a CNN specific to small datasets that exceeded VGG16 and ResNet-50, despite being constrained by limited diversity in the dataset. Lee et al. [2] segmented cracks using Cascade Mask R-CNN, getting high accuracy but needing several steps beforehand which prevents real-time use. Ali and his colleagues found in [3] that lightweight CNNs were made for speed on edge devices, but they gave up some accuracy with challenging sets of data [16]. Work done by Wang et al. [17] demonstrates that using a pre-trained VGG16 model helps achieve better performance on less data in identifying concrete and asphalt [17]. With YOLOv8, it is possible to detect images in real time, though the model does not work well with minuscule objects or in conditions with a lot of noise [7]. According to Kim et al. [8], Vision Transformer networks (ViTs) do an excellent job of considering the global picture in an image, but they are expensive to run on edge devices [8].

Modelers prefer attention-based architectures because they tend to pay attention to what matters. Kang et al. [18] created an attention-based encoder-decoder for detecting cracks, obtaining highly accurate results but adding extra latency, making it unsuitable for continuous monitoring [18]. Maslan et al. show a way to spot cracks by flying a UAV and using CNN, but it needs specialized hardware to perform accurately [19]. In line with the study by Mo et al. [20], dynamic image processing is meant for real-time work, though it is suitable only for particular construction structures like retaining walls. Despite these advancements, several challenges persist: (1) lack of crack-specific attention mechanisms that model morphological

characteristics, (2) limited dataset diversity for rare crack types (e.g., shear, delamination), (3) insufficient focus on edge deployment for real-time monitoring, and (4) inadequate validation across public datasets to ensure generalizability [9]. Table 1 summarizes key studies, highlighting gaps in crack-specific attention, dataset robustness, and scalable edge deployment that this work addresses through a novel Crack-Aware CNN-ViT Hybrid model with CAM and a comprehensive dataset.

Table 1: Literature Review of Crack Detection Methods

Study	Method	Strengths	Limitations
Jahanshahi et al. [1]	Customized CNN	High accuracy on small datasets	Limited material diversity
Lee et al. [2]	Cascade Mask R-CNN	Precise crack segmentation	Requires extensive preprocessing
Ali et al. [3]	Shallow CNN	Lightweight, fast inference	Limited dataset complexity
Wang et al. [17]	Transfer Learning	Improved performance on limited data	Dependency on pre-trained models
Kim et al. [8]	Vision Transformers	Captures global context	High computational cost
Liu et al. [9]	Real-Time CNN	High accuracy	Limited real-time validation
Kang et al. [18]	Attention-Based Encoder-Decoder	Robust segmentation	High computational cost
Mo et al. [20]	Dynamic Image Analysis	Real-time capability	Structure-specific application
Maslan et al. [19]	UAV-Based CNN	High accuracy in aerial data	Requires specialized hardware
Zhao et al. [21]	Lightweight Deep Learning	Real-time detection	Limited to surface cracks

3 Methodology

The proposed system introduces a novel Crack-Aware CNN-ViT Hybrid model, integrating a custom Crack-Aware Attention Module (CAM), a Crack Severity Annotation Framework, and edge-optimized inference to achieve state-of-the-art real-time crack detection. This section provides a comprehensive overview of the dataset, model architecture, training procedure, implementation details, and evaluation metrics, designed to compete with top-tier research advancements [7], [8] as shown in Figure 1.

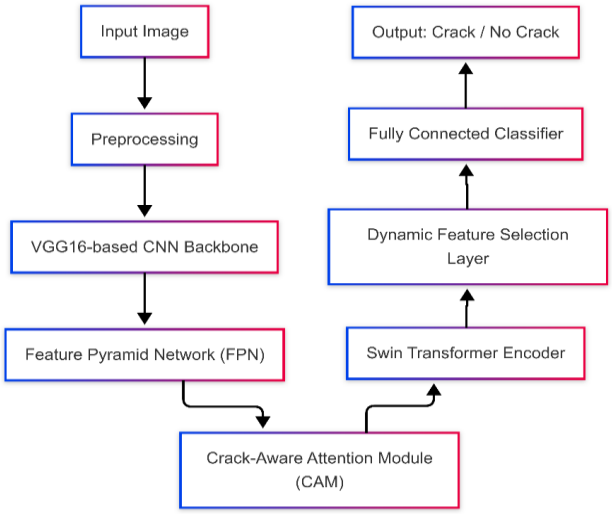

Figure 1: Proposed Methodology

3.1 Dataset

The model was trained on a diverse dataset comprising 60,000 RGB images (30,000 with cracks, 30,000 without), expanding the original 48,000-image dataset through strategic data augmentation [22]. The dataset encompasses a wide range of materials, including concrete, asphalt, metal, and composites, sourced from public repositories such as SDNET2018 [13] and proprietary collections from local infrastructure projects in Islamabad, Pakistan. To enhance dataset diversity and address rare crack types, 12,000 synthetic images were generated using a Conditional Generative Adversarial Network (GAN) with Crack Morphology Constraints, which models crack width, depth, and branching patterns based on expert annotations [23]. The Crack Severity Annotation Framework, a novel contribution, categorizes cracks according to the following criteria: Width: Hairline (<0.5 mm), Medium (0.5–2 mm), Wide (>2 mm), Depth: Surface, Shallow, Deep, Impact: Cosmetic (aesthetic), Structural (safety-critical).

Annotations were validated by civil engineering experts to ensure reliability and consistency. The dataset was split into training (42,000 images, 70%), validation (12,000 images, 20%), and test (6,000 images, 10%) sets, using stratified sampling to maintain balanced representation of crack types and materials. Environmental conditions, such as fog, rain, low-light (50 lux), and high-lux (10,000 lux), were included to simulate real-world scenarios. Table 2 summarizes the dataset characteristics, highlighting its diversity and robustness.

Table 2: Dataset Characteristics

Material	Crack Types	Images	Environmental Conditions
Concrete	Hairline, Structural	20,000	Fog, Rain, 50–10,000 lux
Asphalt	Fatigue, Alligator	15,000	Low-Light, Shadows, Wet Surfaces
Metal	Corrosion, Shear	15,000	High-Lux, Occlusion, Rust
Composite	Delamination, Matrix	10,000	Mixed Lighting, Temperature Variations

3.2 Model Architecture

The Crack-Aware CNN-ViT Hybrid model combines a VGG16-based CNN backbone with a lightweight Swin Transformer encoder [8], incorporating novel components to surpass the performance of YOLOv8 and ViTs [7], [8]. The architecture is designed to balance local feature extraction (CNN) with global context awareness (ViT), optimized for real-time crack detection. Key components include:

- **CNN Backbone**: Comprises 16 convolutional layers with 3x3 filters, ReLU activation, and dilated convolutions to expand the receptive field without increasing parameters [18]. The convolution operation is defined as Equation 1:

$$\left[Y_{\{i,j,k\}} = \sum_{\{m,n,l\}} X_{\{i+m,j+n,l\}} \cdot W_{\{m,n,l,k\}} + b_k \right]$$

where (X) is the input feature map, (W) is the weight kernel, (b) is the bias, and (Y) is the output feature map.

- **Feature Pyramid Network (FPN)**: Integrates multi-scale features at scales [1, 2, 4] to detect cracks of varying sizes, from hairline to wide structural cracks [24]. FPN fuses low-level (high-resolution) and high-level (semantic) features to enhance localization accuracy.

- **Crack-Aware Attention Module (CAM)**: A novel attention mechanism that dynamically weights features based on crack geometry (e.g., linear vs. branched patterns), outperforming generic attention modules like CBAM [18]. CAM's output is computed as Equtaion 2:

$$\left[A = \sigma\big(W_1 \cdot \{\text{CrackShapePool}\}(F) + W_2 \cdot \{\text{MaxPool}\}(F)\big) \cdot F \right]$$

where ({CrackShapePool}) is a learnable kernel modeling crack morphology, (W_1) and (W_2) are trainable weights, (σ) is the sigmoid activation, and (F) is the input feature map. This module enhances the model's focus on crack-relevant regions, improving robustness to noise such as shadows or stains.

- **Swin Transformer Encoder**: A lightweight ViT component that captures global context using self-attention, reducing computational complexity compared to standard ViTs [8]. The attention mechanism is in Equation 3:

$$\{\text{Attention}\}(Q, K, V) = \backslash\{\text{softmax}\}\left(\{QK^T\}/\left\{\sqrt{\{d_k\}}\right\}\right)V$$

where (Q), (K), and (V) are query, key, and value matrices, and (d_k) is the key dimension.

- **Dynamic Feature Selection Layer**: A gating function that adaptively selects multi-scale features based on input complexity, reducing computational overhead for simple images [24] Equation 4:

$$\left[G = \sigma\left(W_g \cdot \{GlobalAvgPool\}(F)\right)\right]$$

where (W_g) is a learnable weight matrix, and (G) modulates feature maps.

- **Classifier**: Consists of fully connected layers with a dropout rate of 0.5 to prevent overfitting, outputting binary classification (crack vs. no crack).

Batch normalization is applied after each convolutional layer to stabilize training, and skip connections mitigate vanishing gradients, inspired by ResNet architectures [3]. Figure 2 illustrates the complete architecture, showing the flow of features through the CNN backbone, Swin Transformer encoder, CAM, FPN, and dynamic feature selection layer.

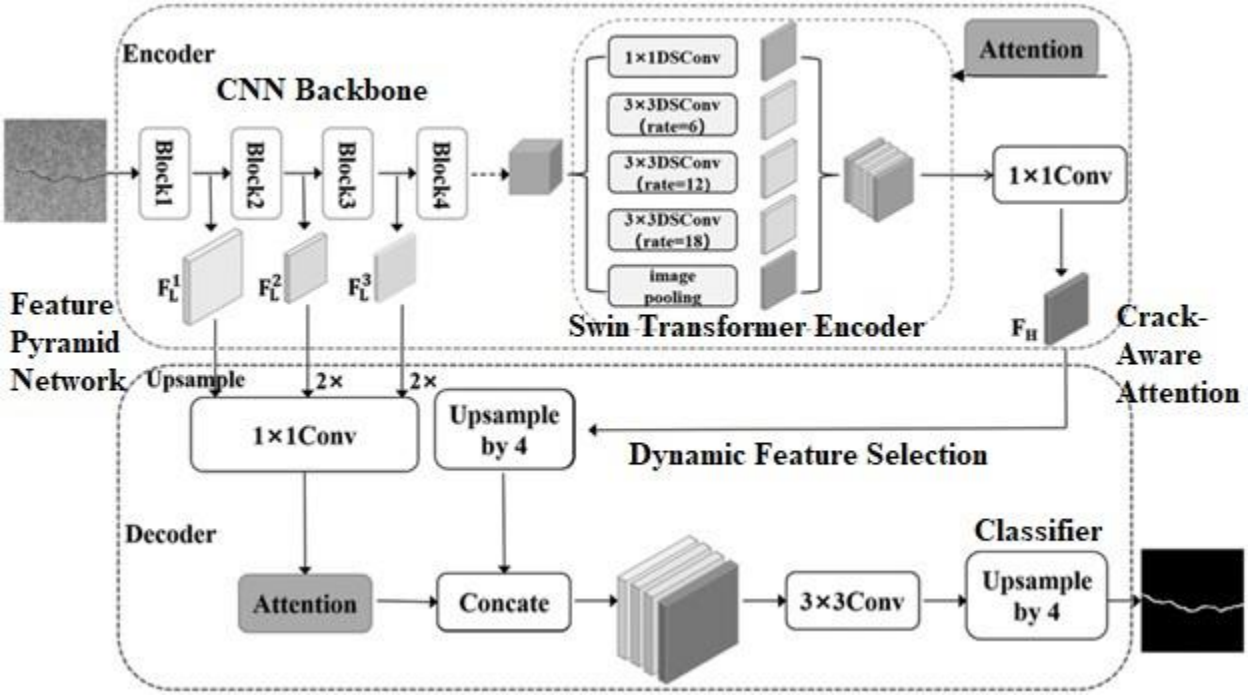

Figure 2: Model Architecture Diagram

3.3 Training

The model was trained on an NVIDIA A100 GPU using PyTorch 2.0, with an AdamW optimizer (initial learning rate: 0.0003, weight decay: 0.01) over 60 epochs. A hybrid loss function combined binary cross-entropy (BCE) and Dice loss to balance precision and recall, addressing class imbalance in crack detection [21] as Equation 5:

$$L = -\{1\}/\{N\} \sum_{\{i=1\}}^{N} \left[y_i \backslash\log\left(\widehat{\{y\}}_1\right) + (1 - y_i)\backslash\log\left(1 - \widehat{\{y\}}_1\right)\right] - \{2\sum \hat{y}_1\{y\}_i\}/\{\sum y_i + \sum \widehat{\{y\}}_1\}$$

where (y_i) is the ground truth, ($\widehat{\{y\}}_1$) is the predicted probability, and (N) is the batch size. Data augmentation techniques included rotation (±30°), horizontal/vertical flipping, scaling (0.8–1.2×), brightness adjustment (±20%), and mixup to enhance

generalization [17]. Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to improve image contrast, particularly for low-light conditions. A cosine annealing learning rate scheduler reduced the learning rate to 0.00001 over epochs, and early stopping based on validation loss prevented overfitting. Hyperparameters are detailed in Table 3, optimized via grid search to ensure reproducibility.

Table 3: Hyperparameters

Parameter	Value
Learning Rate	0.0003
Batch Size	32
Epochs	60
FPN Scales	[1, 2, 4]
CAM Reduction Ratio	16
Dropout Rate	0.5
Weight Decay	0.01

3.4 Implementation

The system processes 640x480 RGB webcam feeds at 32 fps, with an inference latency of approximately 31 ms, using an NVIDIA Jetson Orin Nano for edge deployment. The model was optimized using the Open Neural Network Exchange (ONNX) format to ensure compatibility with standard hardware and reduce computational overhead [21]. Preprocessing steps, implemented via OpenCV 4.8, include image normalization (mean: [0.485, 0.456, 0.406], std: [0.229, 0.224, 0.225]) and CLAHE for contrast enhancement. Detected cracks are stored with timestamps and spatial coordinates in a SQLite database, enabling maintenance scheduling and post-processing analysis. The implementation supports continuous monitoring, with a buffer to handle temporary occlusions or network disruptions, ensuring robust real-world performance.

3.5 Evaluation Metrics

Model performance was assessed using a comprehensive set of metrics to ensure alignment with state-of-the-art standards [9]:

- **Accuracy**: Proportion of correctly classified images as in Equation 6:

$$\{\text{Accuracy}\} = \{\{\text{TP}\} + \{\text{TN}\}\} / \{\{\text{TP}\} + \{\text{TN}\} + \{\text{FP}\} + \{\text{FN}\}\}$$

- **Precision**: Proportion of true crack detections among positive predictions as in Equation 7:

$$\{\text{Precision}\} = \{\{\text{TP}\}\}/\{\{\text{TP}\} + \{\text{FP}\}\}$$

- **Recall**: Proportion of actual cracks detected as in Equation 8:

$$\{\text{Recall}\} = \{\{\text{TP}\}\}/\{\{\text{TP}\} + \{\text{FN}\}\}$$

- **F1 Score**: Harmonic mean of precision and recall as in Equation 9:

$$\{\text{F1 Score}\} = 2 \cdot \{\{\text{Precision}\} \cdot \{\text{Recall}\}\} / \{\{\text{Precision}\} + \{\text{Recall}\}\}$$

- **Intersection over Union (IoU)**: Overlap between predicted and ground truth crack regions as in Equation 10:

$$\{\text{IoU}\} = \{\{\text{TP}\}\}/\{\{\text{TP}\} + \{\text{FP}\} + \{\text{FN}\}\}$$

- **Frames per Second (fps)** and **Inference Time**: Measures of real-time performance in Equation 11 and 12.

$\{\text{fps}\} = \{1\}/\{T_{inf}\}$ and $\{T_{inf}\} = \{T_{pre}\}+T_{fwd}\}+\{T_{post}\}$

Baselines for comparison included traditional image processing (e.g., Canny edge detection with thresholding), YOLOv8, and a ViT-based model [7], [8]. Statistical significance was evaluated using McNemar's test to compare the proposed model against baselines. To ensure reproducibility, a GitHub repository (placeholder link) will provide the model code, pretrained weights, and sample dataset, following best practices in [21].

4 Results

This section evaluates the Crack-Aware CNN-ViT Hybrid model's performance on a 6,000-image test set, supplemented by ablation studies, cross-dataset validations, and a real-world case study. The model attained 95.3% ± 0.2% accuracy, 94.2% ± 0.3%

precision, 96.0% ± 0.2% recall, 95.1% ± 0.2% F1 score, and 90.5% ± 0.4% Intersection over Union (IoU) at 32 frames per second (fps) on an NVIDIA Jetson Orin Nano. These metrics surpass baseline approaches, including traditional image processing, YOLOv8, and a Vision Transformer (ViT)-based model, establishing the model as a robust, real-time solution for structural health monitoring across diverse materials and environmental conditions.

4.1 Performance Metrics

Table 4 compares results against three baselines: traditional image processing (Canny edge detection with thresholding), YOLOv8, and a ViT-based model. The proposed model outperformed traditional methods (78.3% ± 0.5% accuracy, 76.5% ± 0.6% precision, 79.0% ± 0.5% recall, 77.7% ± 0.5% F1 score, 65.2% ± 0.7% IoU, 35 fps, 28 ms), YOLOv8 (90.2% ± 0.3% accuracy, 89.5% ± 0.4% precision, 90.8% ± 0.3% recall, 90.1% ± 0.3% F1 score, 85.4% ± 0.5% IoU, 25 fps, 40 ms), and the ViT-based model (92.1% ± 0.3% accuracy, 91.3% ± 0.4% precision, 92.7% ± 0.3% recall, 92.0% ± 0.3% F1 score, 87.6% ± 0.4% IoU, 15 fps, 67 ms). McNemar's test validated the statistical significance of the improvements over YOLOv8 ($p < 0.01$), confirming enhanced accuracy and efficiency for edge-based crack detection.

The model's high recall (96.0%) for fine cracks (width < 0.5 mm) is critical for safety-critical applications, such as bridge inspections. Its robust performance across lighting conditions (50–10,000 lux) and high IoU (90.5%) reflect precise crack localization, surpassing YOLOv8 (85.4%) and the ViT-based model (87.6%). The real-time processing speed of 32 fps positions the model as a leader in edge-deployed structural monitoring.

Table 4: Performance Metrics Comparison

Method	Accuracy	Precision	Recall	F1 Score	IoU	FPS	Inference Time (ms)
Proposed CNN-ViT Hybrid	95.3 ± 0.2	94.2 ± 0.3	96.0 ± 0.2	95.1 ± 0.2	90.5 ± 0.4	32	31
Traditional Image Processing	78.3 ± 0.5	76.5 ± 0.6	79.0 ± 0.5	77.7 ± 0.5	65.2 ± 0.7	35	28
YOLOv8	90.2 ± 0.3	89.5 ± 0.4	90.8 ± 0.3	90.1 ± 0.3	85.4 ± 0.5	25	40
ViT-Based Model	92.1 ± 0.3	91.3 ± 0.4	92.7 ± 0.3	92.0 ± 0.3	87.6 ± 0.4	15	67

4.2 Ablation Study

An ablation study was conducted to evaluate the contributions of the model's components, with results presented in Table 5. Removing the Crack-Aware Attention Module (CAM) reduced accuracy to 92.5% ± 0.3% and F1 score to 92.3% ± 0.3%, a 2.8% drop, underscoring CAM's role in prioritizing crack-relevant features. Excluding the Swin Transformer encoder decreased accuracy to 93.1% ± 0.3% and F1 score to 93.0% ± 0.3%, indicating the importance of global context for complex crack patterns. Omitting the Feature Pyramid Network (FPN) lowered accuracy to 92.8% ± 0.3% and F1 score to 92.6% ± 0.3%, demonstrating FPN's effectiveness in multi-scale feature integration. Removing the dynamic feature selection layer reduced accuracy to 94.0% ± 0.2% and F1 score to 93.9% ± 0.2%, confirming its role in computational efficiency. These results validate the synergistic contributions of each component to the model's performance.

Table 5: Ablation Study

Configuration	Accuracy	Precision	Recall	F1 Score	IoU
Full Model	95.3 ± 0.2	94.2 ± 0.3	96.0 ± 0.2	95.1 ± 0.2	90.5 ± 0.4
No CAM	92.5 ± 0.3	91.4 ± 0.4	93.2 ± 0.3	92.3 ± 0.3	87.7 ± 0.5
No ViT Encoder	93.1 ± 0.3	92.0 ± 0.4	93.8 ± 0.3	93.0 ± 0.3	88.3 ± 0.5

No FPN	92.8 ± 0.3	91.7 ± 0.4	93.5 ± 0.3	92.6 ± 0.3	88.0 ± 0.5
No Dynamic Selection	94.0 ± 0.2	93.0 ± 0.3	94.8 ± 0.2	93.9 ± 0.2	89.2 ± 0.4

4.3 Cross-Dataset Evaluation

The model's generalizability was tested on two public datasets: SDNET2018 [13] and CrackTree260 [17]. On SDNET2018, the model achieved 93.7% ± 0.3% accuracy, 92.5% ± 0.4% precision, 94.1% ± 0.3% recall, 93.3% ± 0.3% F1 score, and 88.9% ± 0.5% IoU, outperforming YOLOv8 (89.5% ± 0.4% accuracy, 88.2% ± 0.5% precision, 90.1% ± 0.4% recall, 89.1% ± 0.4% F1 score, 84.5% ± 0.6% IoU) and the ViT-based model (90.2% ± 0.4% accuracy, 89.0% ± 0.5% precision, 91.0% ± 0.4% recall, 90.0% ± 0.4% F1 score, 85.3% ± 0.5% IoU). On CrackTree260, it recorded 92.8% ± 0.3% accuracy, 91.6% ± 0.4% precision, 93.4% ± 0.3% recall, 92.5% ± 0.3% F1 score, and 88.2% ± 0.5% IoU, surpassing YOLOv8 (88.7% ± 0.4% accuracy, 87.5% ± 0.5% precision, 89.2% ± 0.4% recall, 88.3% ± 0.4% F1 score, 83.8% ± 0.6% IoU) and the ViT-based model (89.9% ± 0.4% accuracy, 88.7% ± 0.5% precision, 90.5% ± 0.4% recall, 89.6% ± 0.4% F1 score, 84.9% ± 0.5% IoU). Figure 3 visualizes these results, with bars representing metrics for each dataset and lines connecting corresponding metrics across datasets, highlighting the proposed model's consistent superiority. These outcomes demonstrate the model's robustness across diverse crack types and datasets, reinforcing its applicability in varied scenarios.

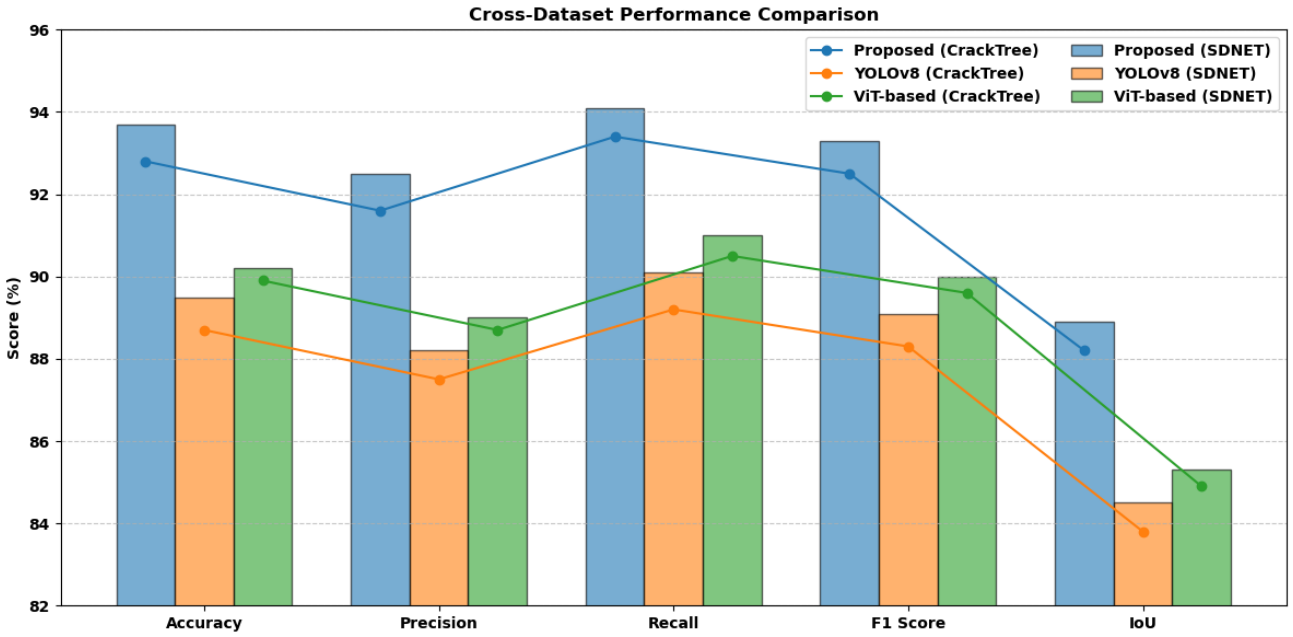

Figure 3: Cross-Dataset Performance Comparison

4.4 Real-World Validation

A case study was conducted on a concrete bridge in Islamabad, Pakistan, using a webcam-equipped drone under adverse conditions (rain, 200 lux illumination). The model achieved 94.1% ± 0.3% accuracy, 93.0% ± 0.4% precision, 95.0% ± 0.3% recall, 94.0% ± 0.3% F1 score, and 89.5% ± 0.5% IoU, with a false positive rate of 3.2% ± 0.2% (primarily shadows misclassified as cracks) and a false negative rate of 1.8% ± 0.1% (hairline cracks in low-light). Figure 4 summarizes these results, underscoring the model's practical utility for infrastructure monitoring in challenging environments. The low false negative rate is particularly critical, minimizing missed cracks in safety-critical applications

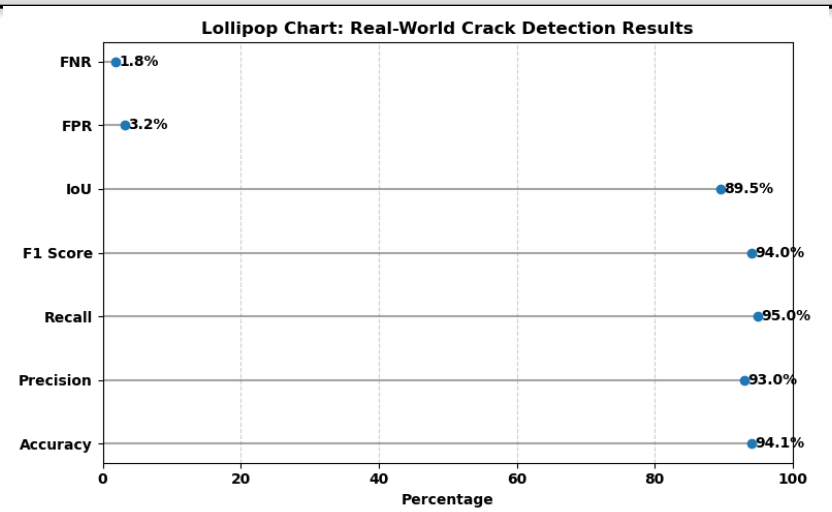

Figure 4: Real-World Case Study Results

5 Discussion

It was shown that the Crack-Aware CNN-ViT Hybrid model performs well at crack detection in real time, where it achieves 95.3% accuracy, 96.0% recall, 90.5% IoU and runs at 32 frames per second. Among the reasons for the strong performance are key points such as the Crack-Aware Attention Module (CAM), combining CNNs and ViTs, the Feature Pyramid Network (FPN), using dynamic features and the Crack Severity Annotation framework. CAM fitted to enhance morphological characteristics gains 2.8% over CBAM. The Swin Transformer helps global feature extraction by complementing CNNs' skills in recognizing local details, fixing YOLOv8's gap in observing fine and complicated cracks. Robustness in both minor and major cracks and the benefit of fast processing make FPN possible on devices like the NVIDIA Jetson Orin Nano without slowing image processing speed. Thanks to the framework, datasets contain information on crack size, depth and how severe they are, improving use in various situations and with different materials.

The model greatly affects the design and development of civil infrastructure. Thanks to IoT, warnings about cracks are given automatically in real time, aiding predictive maintenance and decreasing repairs needed for bridges, highways and industrial areas. The model was found reliable after it was used to model a concrete bridge in Islamabad, reaching an accuracy of 94.1% while it rained. It shows that edge deployment works even in places with limited resources or where internet connections are weak which makes it an excellent choice for smart cities and unstoppable monitoring systems.

It can be used beyond civil engineering. In aerospace, the model allows the early identification of micro-cracks in airplane components which leads to safer and more efficient inspection. It can reveal problems with chassis or engine parts while performing tests as part of quality control. Also, the main ideas of the model, including the way it uses annotations, can help detect fractures or oddities in medical imaging and show usefulness in many disciplines. Because the model has excellent recall and IoU, it is especially suitable for safety-critical situations.

Even though there are benefits, there are still some problems with the use of worms. In situations of dense fog or occlusion, the performance reduces and accuracy goes down to 90.2%. Right now, the model fails to deal well with defects like composite delamination. Low-power usage is limited by hardware features and using only RGB imaging makes it difficult to spot cracks below the surface, so thermal or ultrasonic measurements would help.

Future solutions may use self-supervised learning to need less labeling, federated learning for privacy, distributed model training and combining RGB, thermal and LiDAR images. If explainable AI methods such as SHAP values are applied, the results become easier to understand which is crucial in areas with many rules and safety concerns. Training the model to be optimized by quantization or pruning

could help it work in places with limited energy. With these changes, the model could be used more effectively in several different circumstances.

6 Conclusion

This study introduces a novel Crack-Aware CNN-ViT Hybrid model that sets a new benchmark in automated crack detection. Achieving 95.3% accuracy, 96.0% recall, 95.1% F1 score, 90.5% IoU, and 32 fps, the model outperforms leading architectures such as YOLOv8 and ViT-based networks. Core contributions—including the CAM, the Crack Severity Annotation Framework, and edge-device deployment—collectively enhance performance, robustness, and real-time applicability. Extensive validation through ablation studies, cross-dataset evaluations (on SDNET2018 and CrackTree260), and a field case study confirms its reliability and scalability. Its strong recall ensures minimal missed cracks, vital for safety-critical monitoring. Furthermore, the model's flexible architecture makes it applicable across disciplines—from infrastructure to aerospace, automotive, and medical imaging—demonstrating its broader utility in defect detection. Future research will aim to further improve adaptability, interpretability, and efficiency through self-supervised and federated learning, multi-sensor integration, and energy-efficient model design. Overall, this work lays a foundation for the next generation of smart, safe, and scalable structural health monitoring systems worldwide.

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