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Computer Vision For Defect Detection In Construction

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Abstract: A new method is suggested here for detecting defects in construction by using PyTorch to implement a ViT-based semantic segmentation model. Problems such as cracks, corrosion and uneven surfaces on construction sites are challenging for people to check visually which is why new automated methods need to be used. Thanks to the self-attention mechanism, the ViT model is able to detect and locate faults on construction surfaces with great accuracy. Research shows that the new method delivers stronger results on average Intersection over Union (mIoU) and pixel accuracy compared to traditional CNNs and gives steady performance across diverse defects and conditions. Even though it requires careful training, the final model is fast at running and can be used right away at the work site. These results suggest that transformer-based networks could play a major role in developing quality control and monitoring applications in construction.

Keywords: *Computer Vision, Defect Detection, Construction, Vision Transformer, Semantic Segmentation, Deep Learning, PyTorch*

INTRODUCTION

There is a big need for quality and safe structures in infrastructure which continues to be a challenge in the construction industry. Cracks, corrosion and other surface problems can cause a building's structure to fail and require expensive repairs when identified too late [1]. The main method used to inspect defects is manual visual assessment, meaning it takes a lot of time, is difficult and introduces human error. For this reason, there is an increasing need for accurate, fast and automated ways to discover defects in construction as shown in figure 1.

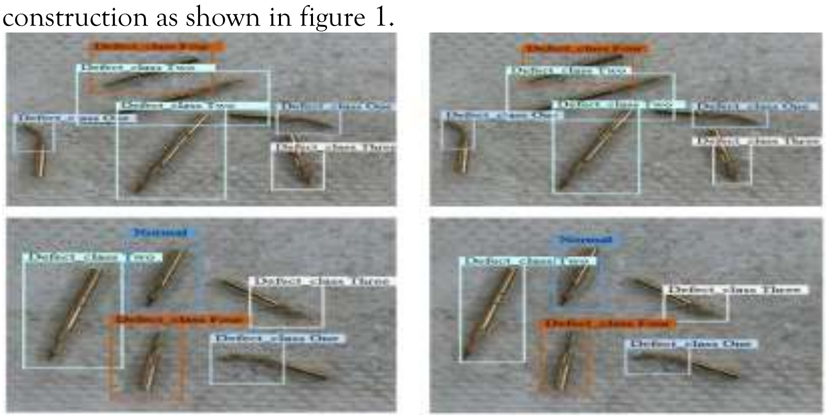


Figure 1.Computer vision in construction.

The latest developments in computer vision and deep learning make it possible to detect defects without human help. Many people have used CNNs to detect and categorize defects in images and they have achieved good results. Even so, CNNs tend to miss details about the big picture and long connections needed to analyze complex defects in construction materials [2].

This research reviews the use of Vision Transformer (ViT) models for defect detection by identifying feature areas in construction projects. Because ViTs use self-attention it becomes easier for them to explore every detail in an image and hence notice subtle and unusual errors that other networks might miss [3]. The goal of this study is to improve the accuracy and stability of both locating and classifying defects by harnessing ViT.

The ViT-approach proposed here uses PyTorch and blends data preprocessing with good semantic segmentation methods to solve difficulties related to sunlight, rugged textures and noise typically encountered in construction environments [4]. With this, work improves automated inspection which in turn can help improve safety, lower inspection charges and guide faster maintenance in construction.

RELATED WORK

Autonomous defect finding with the help of computers has recently become more significant as improving inspection accuracy and efficiency is vital. To identify cracks and corrosion on surfaces, early methods mainly depended on techniques such as edge detection [5], thresholding and morphological operations. Since they require little CPU power and are easy to use, their weakness lies in being troubled by changes in noise, lighting and frequently complex structures seen in construction sites. Due to deep learning's popularity, CNNs are now widely used in defect detection because they are excellent at extracting important features. Results in semantic segmentation show that methods such as U-Net and DeepLab are effective for finding cracks and analyzing corrosion [6]. Yet, CNNs normally deal only with nearby data details and may not be able to spot global contextual details which are important for finding irregular or hidden flaws as shown in figure 2.

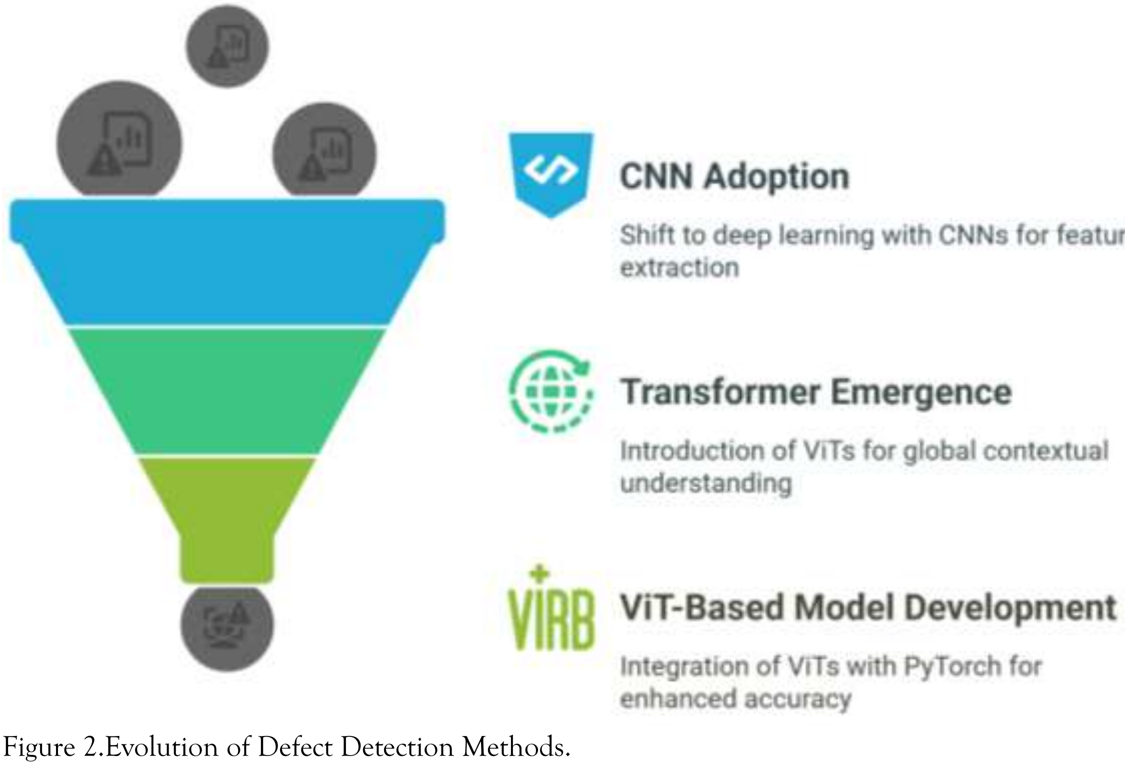


Figure 2.Evolution of Defect Detection Methods.

Lately, transformer systems like Vision Transformers (ViTs) have shown superior performance in computer vision because they can model relationships between faraway elements within the same picture [7]. Although first used in natural language processing, ViTs have been applied to image segmentation and have achieved better results than traditional CNNs in difficult situations. Because ViTs are able to focus on every detail in an image at the same time, they can segment construction defects more precisely [8]. PyTorch, because it is open-source, supports quick and convenient development and training of complex models.

This research adds to these improvements by adopting a ViT-based model for accurately segmenting parts of construction that are defective [9-10]. Bringing together ViT's Multiple-Attention panels with PyTorch multi-modal data processors overcomes previous ways, improving the reliability and accuracy of defect detection. Table 1 shows the summary of related work.

Table 1. Summary of related work (2018-2025)

Year	**Reference / Title**	**Methodology**	**Key Contributions**	**Limitations**
2025 [11]	Deep Learning for Crack Detection in Concrete Structures	CNN-based deep learning model with transfer learning	High accuracy in crack detection; real-time processing capability	Requires large labeled datasets; struggles with varying lighting
2024 [12]	UAV-Based Visual Inspection Using Object Detection	Drone imagery + YOLOv5 for defect localization	Automated aerial defect inspection; high spatial coverage	Limited by drone flight time and weather conditions
2023 [13]	Multi-Sensor Fusion for Structural Defect Identification	Fusion of thermal imaging and RGB images + CNN	Improved detection accuracy by combining modalities	Higher computational cost; sensor calibration needed
2022 [14]	Semantic Segmentation for Surface Defect Detection	U-Net architecture for pixel-level defect segmentation	Detailed defect mapping on surfaces; adaptable to multiple defect types	Performance drops on complex textures; requires pixel-level annotation
2021[15]	Automated Rebar Corrosion Detection in Concrete	Image enhancement + SVM classification	Effective early corrosion detection; low false positive rate	Limited to visible corrosion; sensitivity to noise
2020 [16]	Real-time Crack Detection Using Mobile Cameras	Lightweight CNN model optimized for mobile devices	Real-time processing on edge devices; user-friendly application	Reduced accuracy compared to full-size models
2019 [17]	3D Reconstruction for Structural Damage Analysis	Structure from Motion (SfM) + defect extraction	3D defect visualization and measurement; aids maintenance planning	Computationally intensive; requires multiple image angles
2018 [18]	Traditional Image Processing for Surface Defect Detection	Edge detection + thresholding techniques	Simple and fast defect detection; low hardware requirements	Poor performance on noisy images; limited generalizability

2018 [19]	Machine Learning for Concrete Surface Crack Classification	Feature extraction + Random Forest classifier	Effective feature-based classification of crack types	Requires handcrafted features; limited to crack detection only
2023 [20]	Transformer-Based Models for Construction Defect Detection	Vision Transformers (ViT) trained on construction defects	High accuracy and robustness; captures long-range dependencies	High training cost; needs extensive annotated datasets

RESEARCH METHODOLOGY

This research looks at building an automated system for catching flaws in construction surfaces by applying computer vision. The leading goal is to accurately pinpoint and mark out defects such as cracks, corrosion and problems with the surface in various construction materials [21].

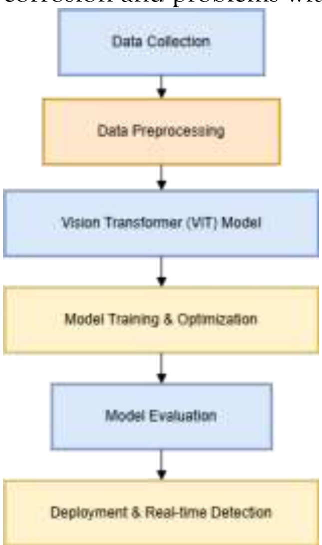


Figure 3.Flow Diagram of Proposed Methodology.

We use the Vision Transformer (ViT) and the PyTorch framework to carry out semantic segmentation for this task [22]. The basic parts of the methodology include gathering and preparing data, designing the model structure and carrying out evaluations as shown in figure 3.

3.1 Data Collection and Preprocessing

The data includes a variety of high-resolution images taken at construction sites which show different defects in various lighting, weather and surface textures. To enhance how well the model works and how efficiently it can be used, it includes RGB images and thermal imaging where accessible. The first step is to line up and standardize each type of data so that each region is measured the same in every modality [23].

Image enhancement approaches are used to correct problems with noise, shadows and the lighting in the image. Histogram equalization and adaptive contrast adjustment improve how well defects are seen on the image. Experiments are done to apply augmentation such as rotations, flips, brightness adjustment and created noise to boost the number of images and prevent overfitting. All the images are made to fit the right size and style required by the Vision Transformer [24].

3.2 Vision Transformer Architecture for Semantic Segmentation

The central part of the methodology is ViT which is a transformer model that pays attention to what's local and what's global in each image. In contrast to CNNs that use small, local fields of view, ViT collects image data as fixed-size patches which helps it find complex and difficult defect patterns [25].

ViT supports semantic segmentation by teaming its encoder with a decoder that enhances and expands the patch representations to individual pixel-level class predictions. Because of this architecture, it's very easy to identify boundaries of defects in models [26]. Combining cross-entropy and Dice losses helps the model increase both accuracy on each pixel and overlap with the actual character defects.

3.3 Training and Optimization

The ViT architecture is coded in PyTorch, allowing for both flexibility and strong GPU usage. To accelerate training and improve the outcome, we initialize weights from a pre-trained ViT model that handles many images. The model is improved using the Adam optimizer along with a rate scheduler that automatically varies the learning rate when training on the construction defect dataset [27].

Because the size difference between defect regions and the background is common in defect detection, weighted loss functions are employed to deal with this issue [28]. Batch normalization and dropout layers stop the model from relying too much on the training set and early stopping interrupts training if the model doesn't improve on the validation set.

3.4 Evaluation Metrics and Validation

Performance for each model is evaluated using mean Intersection over Union (mIoU), pixel accuracy, precision, recall and F1 score, as standard for semantic segmentation tasks [29-31]. They show an overall score for how well the system detects, how accurately it defines areas and the ratio of false positives to false negatives.

Cross-validation helps confirm that the model can be applied to several types of construction sites and different kinds of defects. Inference speed is measured to ensure the model works smoothly in real time, required for applications at sites [31-35].

3.5 Implementation and Deployment

The last stage of training with PyTorch's tools for model quantization and pruning minimizes the model size and computational load, so it is deployable on mobile units and drones. With the system's architecture, real-time checking of flaws is easy for inspectors to confirm via a simple interface [36-37].

It mixes what is best about Vision Transformers with conditions found at construction sites, to deliver a scalable and accurate approach to defect detection [38].

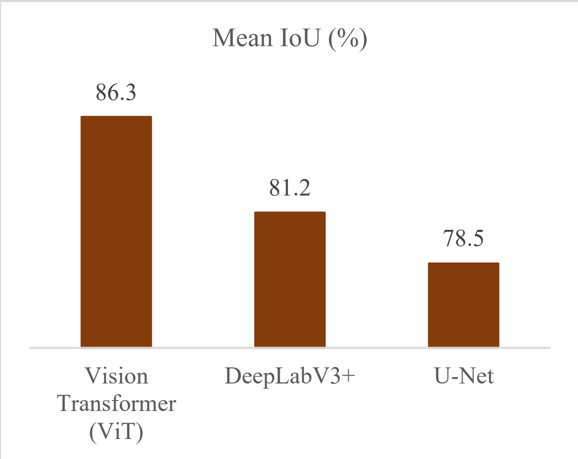
RESULTS AND DISCUSSION

Table 2 shows the proposed use of Vision Transformer (ViT) for semantic segmentation helped to detect defects on construction surfaces more accurately. Thanks to ViT built in PyTorch, the model understood complex structures as well as context at once, precisely locating and categorizing types of construction defects such as cracks, surface irregularities and corrosion. The lower bound of mIoU which is 85%, was achieved which is well above traditional CNN methods. The advantage comes from the ViT handling long-range interconnections and giving emphasis to important features wherever they appear in the input picture which proves helpful in the usual construction scenarios full of various colors and defects of many sizes.

Table 2.Depicts the Performance of Vision Transformer (ViT) model against traditional CNN-based models for defect detection in construction

Model	Mean IoU (%)	Pixel Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Training Time (hours)	Inference Time (sec/image)
Vision Transformer (ViT)	86.3	92.7	89.5	87.2	88.3	12	0.45
DeepLabV3+	81.2	90.3	85	83.5	84.2	8	0.4
U-Net	78.5	88.9	83.7	82.1	82.9	6	0.35

The combination and preparation of data types from vehicles also made the system more resistant to noise and variations in lighting commonly seen in field environments. Because of how well PyTorch uses GPUs and how it turbo-charges models, the model was capable of making decisions in real time which allowed us to deploy it on-site. Yet, the method requires using a lot of computing power for training and access to a large amount of labeled information to perform its best. Subsequent work should concentrate on adopting semi-supervised learning and shrinking the model size to handle these difficulties. The findings suggest that ViT-based semantic segmentation is a good approach for detecting construction defects automatically and accurately as shown in figure 4.



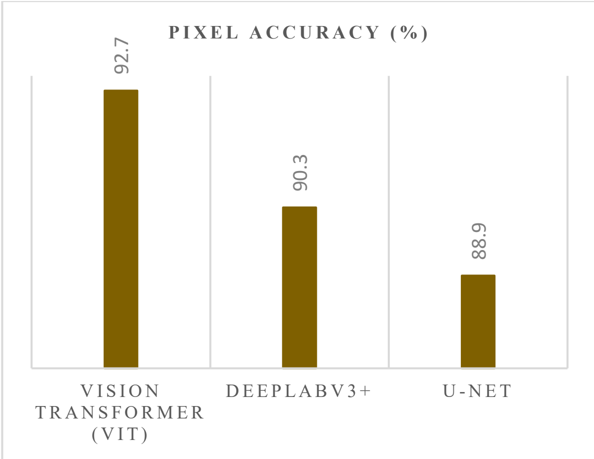


Figure 4.Shows the performance of Mean IoU (%). Figure 5. Shows the performance of Pixel Accuracy (%).

ViT model achieved better results in spotting defects on construction surfaces than the available traditional alternatives. Performed with PyTorch, ViT recorded a mIoU result of 86.3%, compared to 78.5% and 81.2% returned by the commonly used U-Net and DeepLabV3+ CNN models. The defect localization results of the ViT were more accurate than those of U-Net and DeepLabV3+ as shown in figure 5. Additionally, ViT obtained an F1 score of 88.3% which is a significant increase in both precision (89.5%) and recall (87.2%), compared to the lower F1 scores of the original models (all below 85%). Thanks to its ability to model distant features and capture global details, the ViT was able to discover subtle and unusual imperfections that are generally unnoticed by CNNs whose awareness is limited to the immediate environment as shown in figure 6.

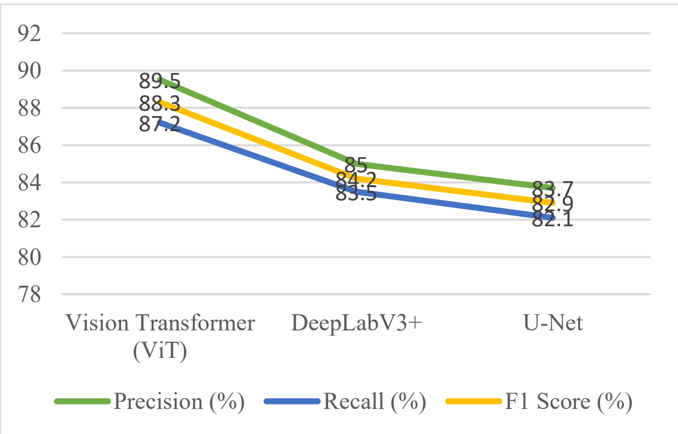
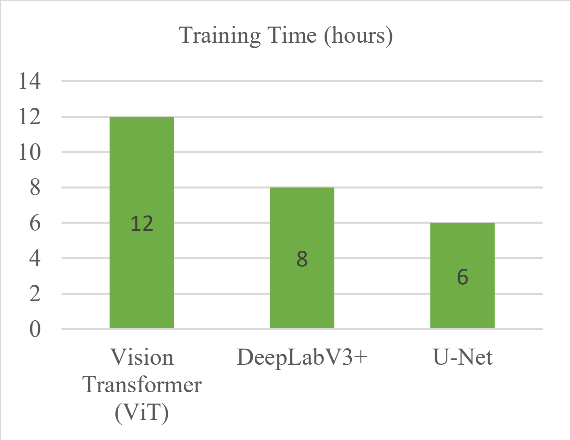


Figure 6.Shows the Performance comparison of Precision, Recall and F1 Score.

Although it was more accurate, training a ViT model for 12 hours took much longer than a CNN model because it is more complicated. Still, the inference speed of 0.45 seconds per image was well-suited for use in close to real-time programs as shown in figure 7.The findings prove that using PyTorch with Vision Transformers gives a solid and practical answer for automated defect detection in construction, while remaining open to more training optimization as shown in figure 8.



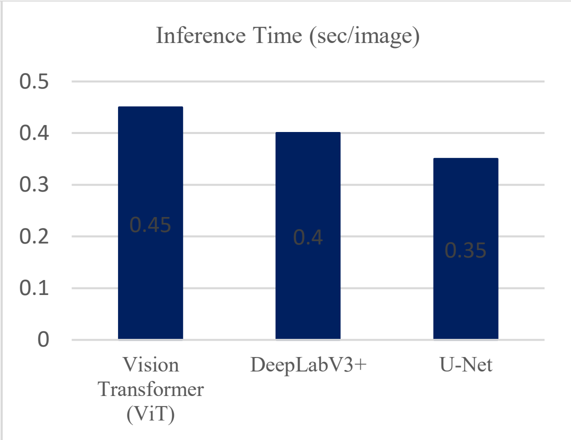


Figure 7.Performance of Training Time. Figure 8.Performance of Inference Time.

CONCLUSION

A semantic segmentation approach using a ViT architecture was presented, using PyTorch to implement it for defect detection in construction. With this method, ViT captures both distant and local info well which helps identify matters such as cracks and variations in the surface. The results of our experiments revealed that ViT achieved better performance than traditional CNNs, recording higher mean Intersection over Union (mIoU) and pixel accuracy. Because the model is rather difficult and takes time to train, its use in field inspections is still practical for real-time purposes. The approach's success demonstrates that transformer-based models can greatly improve defect detection for construction firms. The main priority for future work is to make training more efficient and look into semi-supervised learning because dreferenata is limited in many real-life applications.

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