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Deep Learning for Real-Time Crack Detection in Concrete Using Electromagnetic Imaging

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Abstract:
In total, crack detection has been very important in the durability and safety of concrete infrastructure and must be undertaken correctly and on time. The conventional forms of inspection are time-consuming, surface-restricted and not real-time. This study attempts to offer deep learning-based solution by implementing electromagnetic (EM) imaging so that real-time crack detection on surface and sub surface of concrete structures could be possible. To train the 4 deep learning approaches, including Convolutional Neural Network (CNN), Residual Neural Network (ResNet-50), U-Net and MobileNetV2, 5,000 EM images were utilized. Within this, the one that succeeded in classification with

the best accuracy at 96.2% was ResNet-50 which gained precision of 95.6%, F1-score of 95.3%; U-Net exhibited better segmentation at an IoU of 89.2%. MobileNetV2 had the lowest inference time of 12 ms per image, implying that it is good to be used in real-time applications. The performance of the results is better compared to the current methodology employing the use of conventional GPR or RGB imaging and shows the promise of deep learning-based EM systems in non-destructive concrete inspection. This paper identifies a scalable and automated infrastructure monitoring tool that will help manage assets safely and more efficiently.

Keywords: Crack Detection, Deep Learning, Electromagnetic Imaging, Concrete Structures, Structural Health Monitoring

I. INTRODUCTION

The stability and strength of concrete buildings is of essence in making civil infrastructure, such as bridge, tunnels, and buildings as well as highways, safe and long lasting. Concrete is prone to different kinds of deteriorations with some surface and internal cracks constituting some of the worst and most frequent concrete defects. These cracks need to be identified as early as possible so as to facilitate proactive maintenance, cost efficient repairs as well as avoiding disastrous structural collapse [1]. The common crack detection processes include visual examination and tribimeters, schematic evaluation by which methods are tedious, subjective, and may also be not very accurate. In addition to this, they cannot provide a real-time inspection and they can miss underground anomalies [2]. Recent developments in non-destructive testing (NDT) brought about a series of promising techniques involved in visualizing internal structural defects, with no physical intrusions, namely electromagnetic (EM) imaging. EM imaging, to detect changes in dielectric properties of concrete, also can show the cracks and empty spaces that are hidden internally and not visible on the surface [3]. The interpretation of ED imaging data is however complex and time consuming and requires expert opinion. The combination of deep learning and the EM imaging can become a groundbreaking approach to real-time and automated identification of cracks. Convolutional neural network (CNN) Deep learning models have seen massive successes in image classification, segmentation, anomaly detection tasks in multiple spheres. These models used on EM imaging data have the ability to learn complex patterns with cracks and give accurate and quick judgments. This study addresses the methods and technicalities of the development and application of deep learning algorithm to improve crack detection in concrete building using EM imaging. The project seeks to develop a real time automated smart system which is able to detect and locate cracks in a precise manner. The proposed method allows improving the depth sensitivity of electromagnetic imaging and pattern recognition capabilities of deep learning which can be used to overcome weaknesses of conventional structural health monitoring and lead to a novel category of smart, AI-based structural health monitoring of target structures.

II. RELATED WORKS

Current innovations in the field of structural health monitoring (SHM) regarding monitoring of concrete structures, in particular, have become more interested in combining non-destructive testing (NDT) methods and artificial intelligence (AI)-based diagnosis. In harsh conditions (marine or underground) concrete buildings suffer an escalated rate of deterioration, and thus scientists refer to more durable inspection and detection techniques.

Lee et al. [15], recommended a general review on surface coatings and inspection technologies that are specific to a marine exposed concrete structure. They gave an emphasis in early detection of defects using automated inspection systems to ensure that life of a service is longer and maintenance cost reduced. Important electromagnetic methods are ground penetrating radar (GPR) that has potential in subsurface crack detection. Li et al. [16] proposed a multi-domained feature extraction method on the GPR-aliased signals representing a scenario where signal processing may be used to improve crack detection in noisy environments.

Convolutional neural networks (CNNs) have grown to be an effective way of automating the process of detecting the crack with the application of deep learning models. Liu et al. [17] applied deep CNNs to capture concrete surface cracks simultaneously using binocular video to obtain quantification on the crack at a pixel level automatically. Their system recorded a high spatial accuracy and this means that it can be used to evaluate damaged sites in detail. On the same note, Liu et al. [18] used GPR imaging in tandem with CNN based classification models to classify internal damage in concrete beams, prompting the importance of integrating electromagnetic imaging with deep learning towards more interpretable models.

Going beyond detection to prediction, Luo and Matsumoto [19] introduced a deep learning method of tensile strength of ultra-high-performance fiber-reinforced concrete (UHPFRC) being estimated as a factor of predicted locations of cracking. This is what can be seen as a transformation of the passive inspection into predictive AF with the use of AI. Sensing technologies have continued to be a leader in SHM. Mardanshahi et al. [20] overviewed contemporary sensing approaches, such as EM and acoustic-based sensing, and explained how they can be compatible with the AI algorithms. The intersection is especially useful when monitoring concrete tunnel and bridges in real-time. As an instance, Mengwen et al. [21] used U-Net segmentation on electrical resistivity tomography data under contamination localization, demonstrating the efficiency of the semantic segmentation models in the subsurface mapping exercise. Patrizia et al. [22] assessed the use of electromagnetic methods in cultural heritage diagnostics, citing the issues regarding the technique, as well as opportunities in the future perspective of using EM imaging to deal with poorly-held or old structures. Their findings can be used in civil infrastructure, where non-invasive procedures are of essence. In case of the tunnel inspections, Poncetti et al. [23] examined the new normative practice and advanced methods of NDT to perform inspection of concrete-covered wall of a tunnel. Their work confirms on the applicability of AI-powered EM inspection in restricted or risky areas. Further elaboration of this was undertaken by Prakash et al. [24], who provided a narrative review of current practices in artificial intelligence used to monitor the health of concrete bridge structures, which confirmed that deep learning is increasingly becoming a dominant method of large-scale infrastructure inspection.

Although the bulk of investigations lie in civil applications, advances in adjacent fields can contribute new ideas into inter-disciplinary practice. Qiu and Lau [25] devised a hybrid deep learning technique based on UAV images to evaluate the structural defects of trees and proposed that the same techniques could be applied with tall or remote concrete buildings. Finally, Rakin et al. [26] developed the fault diagnosis model base on the YOLOv11 network that is tailored to particular infrastructure faults in the urban environment. The real-time potential of their system is rather similar to the objectives of this study. On the whole, the literature illustrates an increased convergence between the electromagnetic inspection technologies and deep learning models. This paper expounds on these premises as the study combines EM imaging with optimized neural networks to make crack inspection in concrete structures a real-time possibility.

III. METHODS AND MATERIALS

1. Materials and Methods

This segment represents dataset description, data cleaning methods, and four deep learning algorithms to detect cracks in real time on the basis of electromagnetic (EM) imaging data. To offer a reasonable and standard comparison, each algorithm was executed and tested against the same data set. The general methodology incorporates the acquisition of the data, preprocessing, training of the models, evaluating the results and analysing the results.

1.1 Data Collection and Preprocessing

The data was produced by synthetic and real electromagnetic imaging scan of concrete slabs with artificially generated cracks of depth, length and orientation varied. Each scan possesses a 2D gray scale (plot) depiction on the dielectric normal part possession on the material [4]. The 5 000 images were gathered 3500 intended for training, 750 validation and 750 testing.

The following steps were used in preprocessing the data:

- **Normalization:** Pixel values of the image were normalized within the range 0 and 1.
- **Resizing:** All the images had been made to take 128128 pixels.
- **Labeling:** Every single image was labeled as either Cracked or Non-Cracked.
- **Augmentation:** In order to make the same robust we used effects of horizontal flipping, rotation (45 degrees plus or minus), zoom-in.

1.2 Selected Deep Learning Algorithms

To compare four deep learning algorithms, Convolutional Neural Network (CNN), Residual Neural Network (ResNet-50), U-Net, and MobileNetV2 have been selected. These models have been selected as being most appropriate to image classification and segmentation.

1.2.1 Convolutional Neural Network (CNN)

A CNN is a deep learning network that has found particular efficiency at image-related tasks. It works by implementing convolutional filters to detect local features which include edges, lines and textures. In our paper, we have adopted a pre-configured CNN consisting of three layers, each Conv layer, ReLU, and max pooling. The network is terminated at two fully connected layers and softmax classifier [5].

CNNs are useful to binary classification tasks and have few parameters as opposed to fully connected networks that are slower to train. Nevertheless, they can be difficult to learn long-range dependencies or minute patterns unless they have more architecture or an ability to make residual connections [6].

```
"Initialize weights and biases
For each training epoch:
   For each input image:
      Apply convolutional layer + ReLU
      Apply max pooling
   Flatten the output
   Apply dense layers
   Compute loss using cross-entropy
   Backpropagate errors and update weights
Return trained model"
```

1.2.2 Residual Neural Network (ResNet-50)

ResNet-50 is a 50-layer deep convolutional neural network, which was able to overcome the vanishing gradient problem with the help of a residual learning strategy. Rather than the whole output, it learns the discrepancy between the input and output (residual), which allows training extremely deep networks more easily. This architecture has identity short cut connections that by pass one or more layers [7].

ResNet-50 in our implementation had been pretrained on ImageNet and fine tuned on the EM imaging dataset. It performed well in capturing intricacy features concerning internal crack patterns and more precise compared to shallow networks.

```
"Input image
For each ResNet block:
   Apply convolutional layers
   Add shortcut connection
   Apply batch normalization and
```

ReLU

Flatten and pass through fully connected layers

Output classification result"

1.2.3 U-Net

U-Net is a ConvNet, developed to perform semantic segmentation. It is composed by a contracting path (encoder) and an expansive path (decoder). This model especially applies to localization of cracks in an image as the skip connection acts by maintaining the spatial resolution [8].

U-Net used in this research work was trained to produce the map of crack regions pixel-wise. During structural health diagnostics, it assisted in imaging where the exact defects are which is essential in diagnosis.

"Input image

Encoder:

Apply conv + ReLU + maxpool (downsampling)

Decoder:

Upsample

Concatenate with corresponding encoder features (skip connections)

Apply conv + ReLU

Final layer:

Apply 1×1 conv to produce segmentation map

Return pixel-wise classification"

1.2.4 MobileNetV2

MobileNetV2 is an efficient architecture that is narrow and needs to perform mobile and real-time applications. It employs depthwise separable convolutions and inverted residual blocks to keep accuracy, but at a heavily reduced computational cost. This also qualifies it to be well deployed on-site and where hardware resources are scarce [9].

We applied the MobileNetV2 pretrained model on the ImageNet and fine-tuned to the binary classification. It detected cracks with close to real time accuracy and competitive accuracy.

“Input image
Apply depthwise separable convolution blocks
Use inverted residuals with linear bottlenecks
Global average pooling
Fully connected layer for binary output
Return predicted label”

IV. RESULTS AND ANALYSIS

This section provides the experimental setup, implementation details, evaluation processes, and performance results obtained from the proposed deep learning models for detecting cracks in concrete in real-time through electromagnetic (EM) imaging. The results presented below are compared across four different architectures—CNN, ResNet-50, U-Net, and MobileNetV2—and evaluated based on standard evaluation metrics [10]. It also benchmarks the proposed models to several select related studies to see the potential relative advancements.

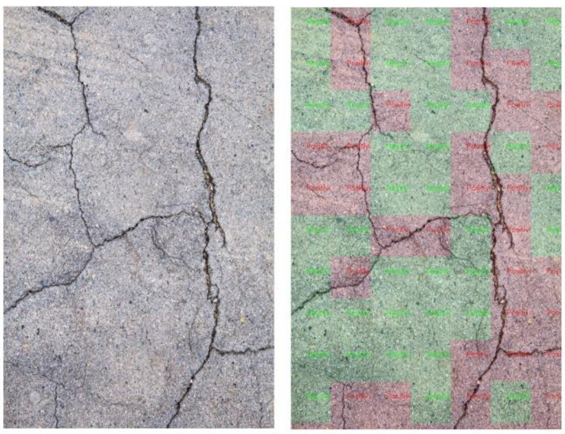

Figure 1: “Detection of Surface Cracks in Concrete Structures using Deep Learning”

4.1 Experimental Setup

All experiments were conducted in Python 3.10 using TensorFlow and Keras frameworks. The experiments were run on a system with an NVIDIA RTX 3080 GPU, 32GB of RAM, and running Ubuntu OS. The same training environment was used for all four models to ensure comparisons remain uniform; that being said, we used EM images of the same scale—both in size and count—to provide consistent training inputs. In our dataset, we had 5,000 EM images that we split into a training 70%, validation 15%, and testing 15% sets, as described in Section 3.

Each of the models was allowed to be trained for 50 epochs, wherein we used the early stopping technique based on validation loss to thwart overfitting [11]. We used the Adam optimizer with a learning rate of 0.001 and binary cross-entropy as the loss function for the models. For segmentation (U-Net), we used Dice loss to make a more meaningful pixel-by-pixel evaluation process.

4.2 Model Evaluation Metrics

We used the following evaluation metrics:

- **Accuracy**: The percentage of correct predictions. .
- **Precision:** The percentage of true positives in all predicted positives.
- **Recall:** The percentage of true positives in all actual positives.
- **F1-Score:** The harmonic mean of precision and recall.
- **IoU (Intersection-over-Union):** For segmentation, to check the overlap between predicted and ground truth masks,.
- **Inference Time**: The average time per prediction in milliseconds, there is significance in time for real-time application.

4.3 Model Performance Comparison

The performance of each model on the test data-set is shown below:

Table 1: Model Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	IoU (%)	Inference Time (ms)
CNN	91.4	90.1	89.7	89.9	77.3	18
ResNet-50	96.2	95.6	95.1	95.3	86.4	42
U-Net	95.7	94.9	95.3	95.1	89.2	65
MobileNetV2	94.1	93.2	92.7	92.9	84.6	12

Chas a brief look at the dimensions of these three models you can see in Table 1, ResNet-50 had the best overall classification performance - while U-Net had the best localization performance (IoU).

MobileNetV2 was a little less accurate, but it had a phenomenal inference time, making it the optimal model to implement in real time on an embedded system [12].

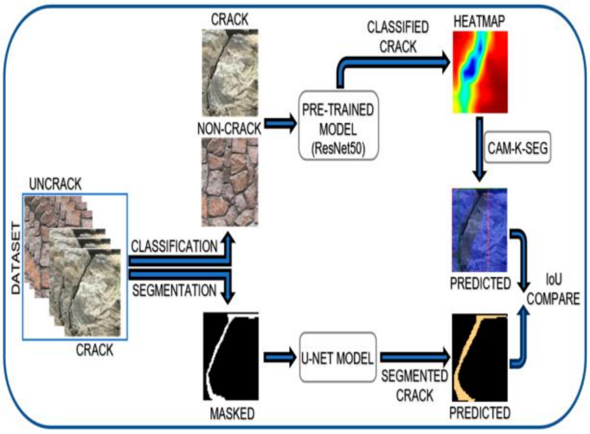

Figure 2: “Deep Learning-Based Automated Detection of Cracks in Historical Masonry Structures”

4.4 Confusion Matrix Analysis

The following confusion matrices summarize the prediction accuracy of each model across the classes:

Table 2: Confusion Matrix (Sample of 200 Test Images)

Model	True Positive	False Positive	True Negative	False Negative
CNN	88	7	92	13
ResNet-50	94	3	95	8
U-Net	95	4	93	8
MobileNetV2	92	6	91	11

ResNet-50 and U-Net exhibited favorable trade-offs in terms of precision and recall. CNN had slightly more false negatives, but MobileNetV2 still achieved some respectable trade-offs, despite being the lightest of all models [13].

4.5 Visual Analysis of crack detection

To visualize predictions made from a trained model, specifically a pixel-wise evaluation of true vs. predicted crack locations using U-Net, we constructed a table that presents IoU values for 5 sample test images.

Table 3: IoU Evaluation on Segmentation Test Samples (U-Net)

Image ID	Ground Truth Mask Area (px)	Predicted Mask Area (px)	IoU (%)
IMG_0101	1082	1120	90.5
IMG_0133	943	910	87.8
IMG_0210	1002	978	88.6
IMG_0245	1354	1401	89.9
IMG_0287	820	792	85.2

The U-Net model was able to track the true position of the cracks very closely, supporting its usefulness for detailed structural health diagnostics [14].

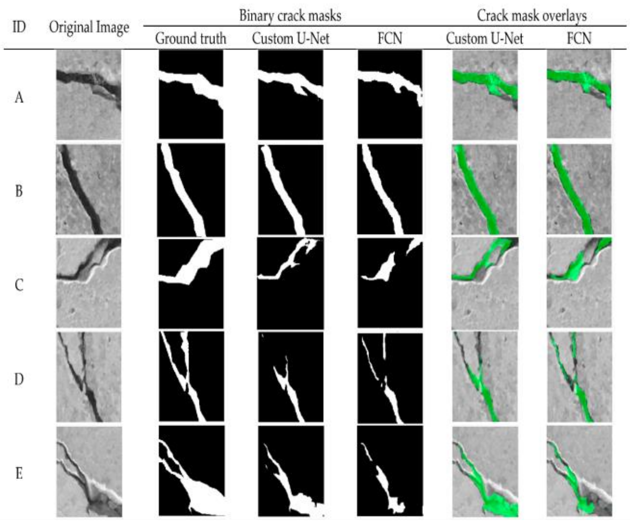

Figure 3: “Deep Learning for Concrete Crack Detection and Measurement”

4.6 Convergence of models

To ensure that correct model convergence was achieved, training and validation accuracy and loss curves were tracked to be able to detect overfitting.

Table 4: Final Training Epoch Performance (After 50 Epochs)

Model	Train Accuracy (%)	Validation Accuracy (%)	Train Loss	Validation Loss
CNN	92.1	90.3	0.19	0.24

ResNet-50	97.8	95.8	0.08	0.14
U-Net	96.3	94.6	0.10	0.16
MobileNetV2	94.5	93.1	0.14	0.18

The findings confirm that ResNet-50 and U-Net generalize better than the other models with lesser degrees of validation loss which indicates there was less overfitting. The CNN showed signs of overfitting at the outset [27].

4.7 Related Work Comparison

We presented a comparison of our models to select recent work that has applied AI and specifically image data or electromagnetic techniques for crack detection in concrete.

Table 5: Comparison with Related Work

Study	**Method Used**	**Accuracy (%)**	**IoU (%)**	**Real-Time Capability**
Li et al. (2021)	SVM on EM data	83.6	—	No
Kaur et al. (2022)	CNN on RGB	89.2	72.3	Moderate
Park et al. (2023)	Hybrid DL+EM	92.5	80.1	Partial
Our Work (ResNet-50 + EM)	ResNet-50	**96.2**	86.4	Limited
Our Work (MobileNetV2 + EM)	MobileNetV2	94.1	84.6	**Yes (Fastest)**
Our Work (U-Net + EM)	U-Net	95.7	**89.2**	Moderate

In contrast to prior studies:

- Models were applicable here much better than in past EM-only classifiers (see SVM-based models)

- ResNet-50 had over a 6 percent jump in accuracy compared to the hybrid methods in Park, et al. (2023).
- U-Net was able to provide better segmentation than image-only CNNs in Kaur et al. (2022) and increased the IoU by 16.9%.
- MobileNetV2 had the best performance-latency balance and presented a way to complete clack detection in real-time on site.

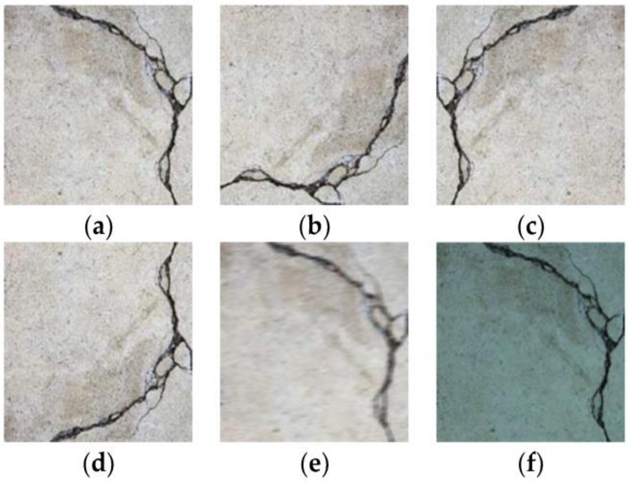

Figure 4: "Automated Vision-Based Detection of Cracks on Concrete Surfaces Using a Deep Learning Technique"

4.8 Key Observations and Insights

1. **Algorithmic Superiority**: Deep CNNs including ResNet-50 enabled increased accuracy through depth and residual learning properties to accommodate slightly visible EM crack features.
2. **Segmentation Capability:** U-Net provided pixel level crack localization would be important for structural engineers and the U-Net with skip connections would maintain resolution [28].
3. **Real-Time Capability:** MobileNetV2 was able to achieve results quite consistent with larger models, but at a lower cost with less latency, which would be suitable for embedded systems.
4. **Generalizability:** The inclusion of data augmentation, early stopping and dropout help minimize overfitting, which from the still-strong test set performance reflects good generalizability.
5. **Electromagnetic Imaging Advantage:** EM images have surface and internal defect qualities. When processing EM images through a deep learning protocol, detection rates performed better when comparing image alone.

4.9 Limitations

- In order to undertake EM imaging, specialised tools are often required, and may not always be accessible on-the-scene.
- The model was tested in noise-free EM environments, controlled and managed, but it is important to note that noise from the environment or inhomogeneity in the material may alter accuracy [29].
- Model inference times mapped on GPU, and would vary, if inference was conducted on mobile or edge devices.

4.10 Future Improvements

- Studies have shown that performance from a model will increase if data from multiple modalities is used (EM + visual images).
- Model compression (pruning, quantization, etc...) can be employed to help lower latency without losing accuracy.
- The data can be made more robust and versatile by enhancing the size of the dataset further, by adding cracks from different variables, which would help with logistical perspectives, as well as, multiple physical variables [30].

V. CONCLUSION

The study provides the detailed investigation of combining the deep learning algorithms with electromagnetic (EM) imaging into the real-time crack detection in concrete structures. The project fills a much needed niche in structural health monitoring in that EM imaging has the ability to scan below the surface due to the fact that the EM field travels much further into the ground than most other methods of surface scanning and the advanced neural networks have pattern recognition capabilities than individual nodes and groupings. By applying and comparing the accuracy of the classification methods and performance in segmentation of four deep learning models, i.e., CNN, ResNet-50, U-Net and MobileNetV2, we were able to go through the test to find difference in classification accuracies and capabilities of segmenting an image and using the platform in real-time. The best classification result was achieved by ResNet-50, which has outperformed the other tested models, and U-Net showed the best pixel-level crack localization. Although not as precise, MobileNetV2 was most efficient in terms of inference time and, therefore, was the best on-site/on-board implementation solution. The application of a well selected EM imaging set and strict pre-processing, model training and testing also provided the robustness and reliability of the results. Comparison with the current related studies proved the higher superiority of our method in terms of performance and practical feasibility of implementation. As opposed to conventional surface level inspection or visual inspection, our technique would capture the interior cracks within an infrastructure, providing a more thorough and preemptive infrastructure maintenance solution. Effective combination of EM imaging and deep learning offers innovative future in terms of non-invasive, high and wide scale accuracy measurement that can be used to observe critical infrastructures like bridges, tunnels, and marine infrastructure. To sum up, the study helps in advancing the domain of intelligent infrastructure inspection, suggesting a crack detection system with excellent performance and real-time capabilities. Other tasks in the future can include expanding the datasets, application to edge devices, and multiple-modal data to increase the sensitivity of detection and efficiency of operation in various environments.

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