

DEEP LEARNING-BASED CONCRETE AGGREGATE SEGMENTATION AND ANALYSIS FOR FORENSIC APPLICATIONS

Mati Ullah¹, Vagelis Plevris¹ and Afaq Ahmad²

¹Department of Civil and Environmental Engineering, College of Engineering,
Qatar University, Doha, Qatar
e-mail: {mu2401592, vplevris}@qu.edu.qa

² Department of Built Environment, Oslo Metropolitan University (OsloMet), Oslo, Norway
e-mail: afaq.ahmad@oslomet.no

Abstract. *Segmenting aggregates in sedimentation images is crucial for assessing particle distribution and stability characteristics. This study presents a deep learning-based approach for concrete aggregate segmentation to overcome the challenges of traditional evaluation methods. A comprehensive dataset of concrete images with varying mix designs and W/C ratios was curated. The dataset includes images from both the surfaces of cut concrete cylinders and broken concrete cylinders subjected to mechanical testing. The DeepLabV3+ architecture, integrated with multiple DCNN backbones, is employed to accurately extract aggregate regions. EfficientNet-B5 achieved the highest segmentation accuracy with mIoU and F1 scores of 0.92 and 0.96, respectively. The estimated aggregate proportions from segmented images closely aligned with theoretical mix design values. The ability of the proposed method to analyze aggregates from concrete fragments enhances its applicability in forensic investigations, enabling rapid, non-destructive assessment without requiring specialized sample preparation.*

Keywords: Concrete aggregate, Semantic segmentation, Computer vision, Deep learning, Concrete forensic analysis.

1 INTRODUCTION

The properties of concrete are significantly influenced by the shape, size, proportion and spatial arrangement of coarse aggregates within the cement matrix. Petrographic analysis, as outlined in ASTM C856, is a widely recognized method for evaluating various characteristics of concrete, including composition and distribution of aggregates, W/C ratio, and air voids [1]. Traditionally, this analysis has been performed manually by experts who examine cross-sections of hardened concrete to assess aggregate distribution and overall stability [2]. Aggregate sizes are typically measured using mechanical sieving or manual calipers. However, these conventional approaches are susceptible to human error, subjectivity, and inefficiencies due to their labor-intensive nature. To address these limitations, researchers have explored imaging techniques such as scanning electron microscopy (SEM), optical microscopy, and various image processing (IP) methods for analyzing concrete microstructures and predicting mechanical performance [3, 4]. While these methods offer detailed insights, they require advanced equipment and specialized expertise, making them less accessible for routine analysis.

Although extensive research has been conducted on the segmentation of aggregates in asphalt mixtures, studies on aggregate segmentation in concrete are still in their early phases. The primary challenge stems from the similar color appearance of aggregates and cement paste. Traditional methods use phenolphthalein dye to enhance contrast, simplifying segmentation. However, few studies [5, 6] have applied deep learning (DL) for gray or colored aggregate segmentation, and those that have relied on high-resolution microscopy images. These images capture fine boundary details and intensity variations, aiding segmentation. Yet, the requirement for specialized equipment limits their practical use in routine concrete quality control. With advancements in imaging, affordable 4K and 8K sensors are now available and are being used to measure the mechanical performance of concrete [7], but their effectiveness in capturing aggregate details for concrete analysis remains unexplored. Moreover, previous research has primarily focused on aggregate segmentation in cut concrete sections, requiring precise sample preparation. In forensic analysis, after catastrophic events, such as earthquakes or structural failures, the assessment of aggregate proportions from images of concrete fragment surfaces needs to be explored.

This study introduces a novel approach by assuming concrete fragments for aggregate segmentation, enabling the estimation of aggregate proportions in forensic analysis without the need for specialized sample preparation. To achieve this, an image processing-inspired technique is developed for evaluating aggregate proportions in cut and broken concrete samples. A deep learning approach for segmenting concrete aggregates is designed, implemented, and validated using the DeepLabV3+ [8] semantic segmentation framework. Various encoder architectures, including InceptionResNetV2 [9], Xception [10], ResNet101 [11], and EfficientNetB-5 [12], are trained as backbone models in DeepLabV3+. A self-compiled dataset, specifically curated for concrete aggregate segmentation, is used to train these models. To facilitate practical field application, image acquisition is carried out using a DSLR camera. Following segmentation, the extracted proportion of coarse aggregate particles is quantified.

2 LITERATURE REVIEW

Image processing techniques have been widely used in various studies to segment concrete aggregates in images, enabling the analysis of their distribution. In the study by [13], OTSU thresholding [14] was utilized to access the characteristics and distribution of coarse aggregate after segmentation. To enhance aggregate recognition in microscopic and low-contrast SEM

images, [15] employed K-means clustering along with the level set method (LSM), where LSM demonstrated superior performance in aggregate identification. Meanwhile, the real-time composition of recycled aggregates was evaluated in [16] using the watershed algorithm to separate aggregate particles and the background. In [17], a segmentation technique based on standard deviation was implemented to process X-ray computed tomography (XRCT images) and distinguish aggregates from cement paste. Similarly, [18] applied a comparable method using borehole camera technology to determine the characteristics of coarse aggregates. Color-based thresholding was used in [19] for coarse aggregate segmentation to analyze the distribution of aggregate sizes in color-treated hardened concrete samples. In [20], contrast enhancement and morphological processing were applied to CT-scanned slice images to extract coarse aggregates, facilitating the reconstruction of a mesoscale concrete model.

These studies primarily relied on traditional IP approaches [21], including K-means clustering, thresholding, edge detection, and morphological operations for segmentation and analysis of aggregates. However, these conventional methods present several challenges. Edge detection is sensitive to noise and grayscale discontinuities, leading to weak anti-interference properties and incomplete boundary extraction. Thresholding and K-means clustering depend on predefined threshold values which results in inconsistent segmentation outcomes. Morphological operations like dilation and erosion can cause shape distortions. Moreover, factors such as heterogeneous backgrounds, shadows, and image noise further hinder the accuracy of these segmentation techniques.

With advancements in computational power, DL-based techniques have significantly improved IP tasks, particularly in segmentation [22–24]. In the study by [25], DL was successfully applied in petrographic analysis of concrete, where a deep convolutional neural network (DCNN) was trained on high-resolution scans of various concrete mixtures to segment paste, aggregates, and voids. A study in [5] introduced a segmentation method for concrete aggregates, utilizing an encoder-decoder framework with a modified ResNeXt50 network for feature extraction. Similarly, [26] employed a U-Net model to segment SEM images, facilitating the evaluation of concrete microstructures. Instance-based segmentation for petrographic concrete slice analysis was utilized in [6], where Mask R-CNN model was trained to detect aggregates and air voids in microscopic images. Aggregate segmentation in stockpile images was achieved through an object detection framework, as demonstrated in [27]. Moreover, a semi-supervised segmentation technique incorporating prior knowledge via class distribution and auto-encoder constraints was proposed in [28], enhancing segmentation accuracy. Further advancements include the cascaded DL model developed in [29], which utilized stereo vision for automatically identifying and analyzing coarse aggregate particles, enabling accurate classification and size measurement. In [30] a CNN-based DeepLabV3+ model with various backbones (e.g., MobileNet, Xception, EfficientNetV2-S) was used for segmentation of coarse aggregates. Among these, the EfficientNetV2-S variant achieved the best performance with the highest mIoU value. Moreover, [31] implemented a DCNN-based approach to segment stacked coarse aggregate images, effectively differentiating aggregates based on material composition, size, and mixing proportions.

3 OVERVIEW OF THE METHODOLOGY

The methodology begins with curating the image dataset of concrete specimens, followed by the development of a semantic segmentation-based DCNN model to extract aggregates from the images. After segmentation, IP techniques are applied to determine aggregate proportions. This section outlines the details of the curated image dataset and the developed architectures of

DCNN segmentation models.

3.1 Curation of Dataset

Two sets of concrete samples were prepared using five mix ratios (1:4:8, 1:3:6, 1:2:4, 1:1.5:3, and 1:1:2) with gray aggregates. The reason for using gray aggregates, resembling cement paste is to aid generalization in segmentation. Further, aggregates with gray color are widely used in South Asia due to their availability and compatibility. Figure 1 illustrates the overall setup of dataset curation. Each mix was prepared with three different W/C ratios (0.6, 0.5, and 0.4), following ACI 318 [32] and ASTM C 94 [33], resulting in 15 unique mix designs. Table 1 presents an overview of the mix designs for concrete cylinders casting. One set of cylinders with a height of 300 mm and diameter of 152 mm were sliced into three sections at $1/3^{rd}$ and $2/3^{rd}$ heights using a stone saw, resulting in the creation of six faces. The outer faces of the first and third slices contained minimal aggregate and were excluded, leaving four usable faces for imaging. The second set of cylinders were subjected to mechanical failure in order to obtain broken concrete fragments.

Images of the cut concrete and concrete fragment specimens were captured in a controlled setup using a Canon EOS 4000D (18 MP, ISO 1000) camera. Black sheets blocked external light, while two 30 W LED bulbs provided uniform 2000 lux illumination. The camera, fixed at 550 mm from the sample, captured 60 high-resolution images (5184×3456 pixels) for cut specimens and fragments, respectively.

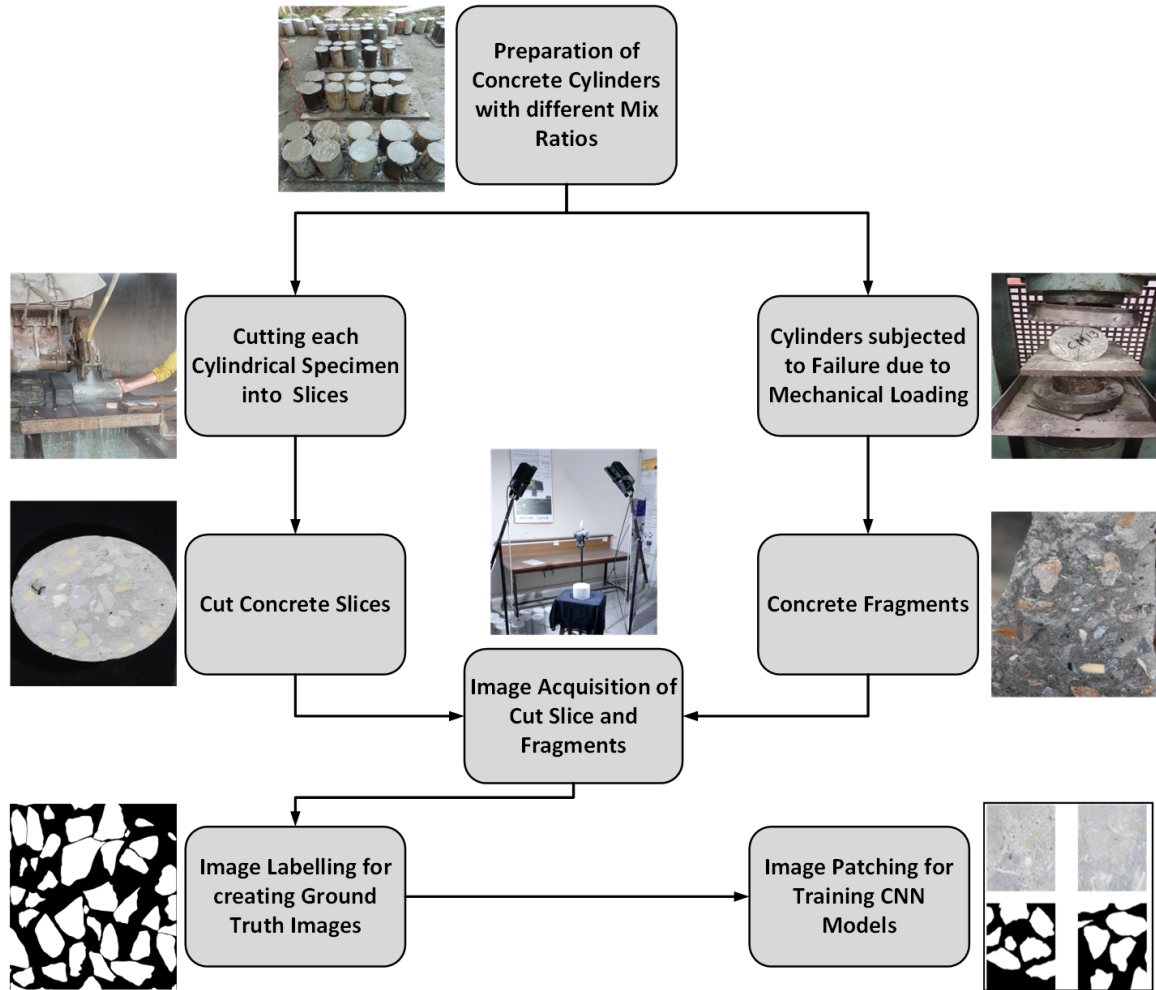


Figure 1: Curation of dataset, from cylinder casting to image labeling.

The background was removed by cropping the central portion of each image to a size of 2048×2048 pixels. Aggregates and background were manually labeled in MATLAB Image Labeler, using a graphics tablet. Each 2048×2048 image was segmented into 16 patches (512×512 pixels), yielding 1,920 images. The sample concrete and labeled aggregates images can be observed in Figure 1, where white pixels denote aggregates.

S.No.	Mix Ratios	Proportions in kg/m ³			
		Cement	Fine Aggregate	Coarse Aggregate	Water Content
1	1:4:8	177.09	746.01	1544.04	70.84
2	1:4:8	177.09	746.01	1544.04	88.55
3	1:4:8	177.09	746.01	1544.04	106.25
4	1:3:6	230.22	727.36	1505.44	92.09
5	1:3:6	230.22	727.36	1505.44	115.11
6	1:3:6	230.22	727.36	1505.44	138.13
7	1:2:4	328.89	692.72	1433.75	131.56
8	1:2:4	328.89	692.72	1433.75	164.45
9	1:2:4	328.89	692.72	1433.75	197.33
10	1:1.5:3	418.59	661.23	1368.58	167.44
11	1:1.5:3	418.59	661.23	1368.58	209.30
12	1:1.5:3	418.59	661.23	1368.58	251.15
13	1:1:2	575.56	606.13	1254.53	230.22
14	1:1:2	575.56	606.13	1254.53	287.78
15	1:1:2	575.56	606.13	1254.53	345.34

Table 1: Overview of mix designs for sample casting.

3.2 Segmentation Architectures

Advancements in deep convolutional neural networks (DCNNs) have significantly improved image segmentation tasks. Modern segmentation models often employ encoder-decoder architectures, as seen in fully convolutional networks (FCN) [34], U-Net [35], SegNet [36], and DeepLab [8]. The encoder extracts image features, while the decoder generates segmentation masks. Selecting an appropriate architecture is crucial for accurate concrete aggregate segmentation. This study implements a customized DeepLabV3+ architecture to address the task. DeepLabV3+ consists of three primary components: an encoder, an atrous spatial pyramid pooling (ASPP) module, and a decoder. The architecture of the DeepLabV3+ model is shown in Figure 2. The DCNN-based encoder extracts hierarchical features from input images. It progressively reduces spatial resolution while capturing high-level features. To enhance segmentation accuracy, additional convolution techniques such as dilated convolutions and depthwise separable convolutions improve computational efficiency.

The ASPP module aggregates multi-scale features by applying parallel atrous convolutions with different dilation rates. This technique expands the receptive field without increasing computational complexity, allowing the model to accurately segment objects of varying sizes. A global average pooling operation further enhances contextual information.

The decoder refines the segmentation mask by combining low-level spatial details with high-level semantic features. The encoder output is upsampled and merged with early feature maps via skip connections, preserving spatial accuracy. Bilinear interpolation is applied during up-sampling, reducing computational cost without performance loss. A final convolution operation generates the mask image, distinguishing regions of aggregate and non-aggregate.

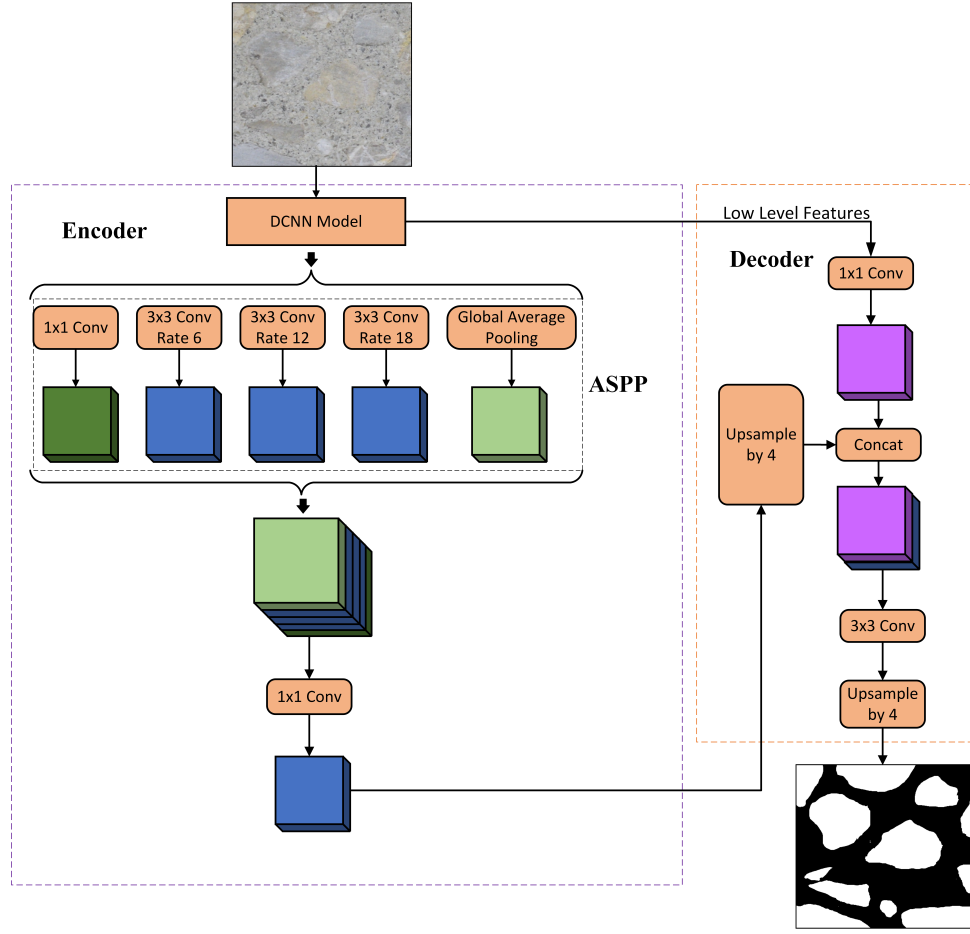


Figure 2: Architecture of DeepLabV3+.

4 EXPERIMENTS AND RESULTS

4.1 Model Training

To ensure robust model evaluation and avoid data leakage, the dataset of concrete images and its corresponding ground truth images was partitioned randomly into three non-overlapping subsets. 50% of the images were used for training, while 25% were used for validation and the remaining 25% for testing. The segmentation models were built using PyTorch and trained on NVIDIA RTX 3060 GPU. Optimization leveraged the Adam algorithm with a CosineAnnealingLR learning rate scheduler, initialized at 2×10^{-4} . Since our dataset was distinct, the model backbones, initially pre-trained using the PASCAL VOC dataset [37], were fully fine-tuned over 20 epochs using the Dice loss function for optimization and a batch size of 32. Training iterations involved epoch-wise data shuffling, with checkpointing based on validation accuracy and loss metrics.

Common data augmentations were employed to enhance the model's robustness. These operations included horizontal and vertical flips with a 40% chance, random translations within ± 20 pixels, the addition of Gaussian noise (mean = 0, standard deviation = 0.01), and brightness adjustments. Such modifications contributed to improved generalization by simulating real-world variations.

4.2 Segmentation Performance Evaluation

Performance was evaluated using Intersection over Union (IoU), precision, recall, and F1-score:

$$IoU = \frac{TP}{TP + FN + FP} \quad (1)$$

$$Precision (P) = \frac{TP}{TP + FP} \quad (2)$$

$$Recall (R) = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - Score = 2 \times \left(\frac{P \times R}{P + R} \right) \quad (4)$$

where TP denotes correctly segmented aggregate pixels, FP are misclassified non-aggregate pixels, and FN are missed pixels of aggregates.

4.3 Segmentation Results

The performance of DeepLabV3+ segmentation is strongly influenced by the selected DCNN encoder. We trained the model using four different encoders, ResNet101 [11], InceptionResNetV2 [9], Xception [10], and EfficientNet-B5[12]. These encoders differ in complexity and layer structure as shown in Table 2. While deeper networks extract richer features, they may also suffer from overfitting. Thus, we evaluated multiple backbones to determine the optimal architecture for segmentation of aggregates in concrete.

DCNN Model	Layers	Trainable Parameters	FLOPs (B)	Inference Time (ms)
InceptionResNetV2	572	59.44 B	55.86 M	41.9
Xception	126	8.07 B	22.87 M	4.8
ResNet101	101	7.80 B	44.6 M	3.9
EfficientNet-B5	342	8.8 B	22 M	10.3

Table 2: Specifications of various DCNN models.

Table 3 shows the performance of DeepLabV3+ with different backbones, evaluated using mIoU, precision, recall, and F1-score. EfficientNet-B5 achieved the highest mIoU of 0.92 and F1-score of 0.96, demonstrating superior segmentation performance. The InceptionResNetV2 achieved the lowest values for the performance metrics. In Figure 3, ground truth and output mask images generated by InceptionResNetV2 and EfficientNet-B5 are presented. False negatives appear in green color, while false positives are depicted in pink color. The InceptionResNetV2 struggled with segmentation as evident in higher false positives. In contrast, EfficientNet-B5, developed using Neural Architecture Search (NAS) [38], delivered optimal computational efficiency alongside segmentation precision. NAS enables the automatic discovery of optimal network architectures, allowing EfficientNet models to balance accuracy and computational cost more effectively than manually designed networks.

Backbone DCNN	mIoU	Precision	Recall	F1-Score
InceptionResnetV2	0.83	0.93	0.89	0.95
ResNet101	0.90	0.94	0.93	0.95
Xception	0.88	0.93	0.91	0.96
EfficientNet-B5	0.92	0.95	0.94	0.96

Table 3: Performance metrics of aggregate segmentation with different DCNN encoders.

4.4 Aggregate Proportion

The ratio of coarse aggregates in concrete is crucial for concrete's rheology, strength, stability, and durability. The mask output images generated by the trained DeepLabV3+ architecture are used for analysis of aggregate proportion in concrete. Cavalieri's principle [39] indicates that the proportion of area of any object observed in 2D images approximates the volume percentage in 3D. Previous studies validate the use of 2D imaging for capturing 3D aggregate characteristics [13, 40, 41]. Thus, our analysis assumes that 2D coarse aggregate properties represent their 3D counterparts.

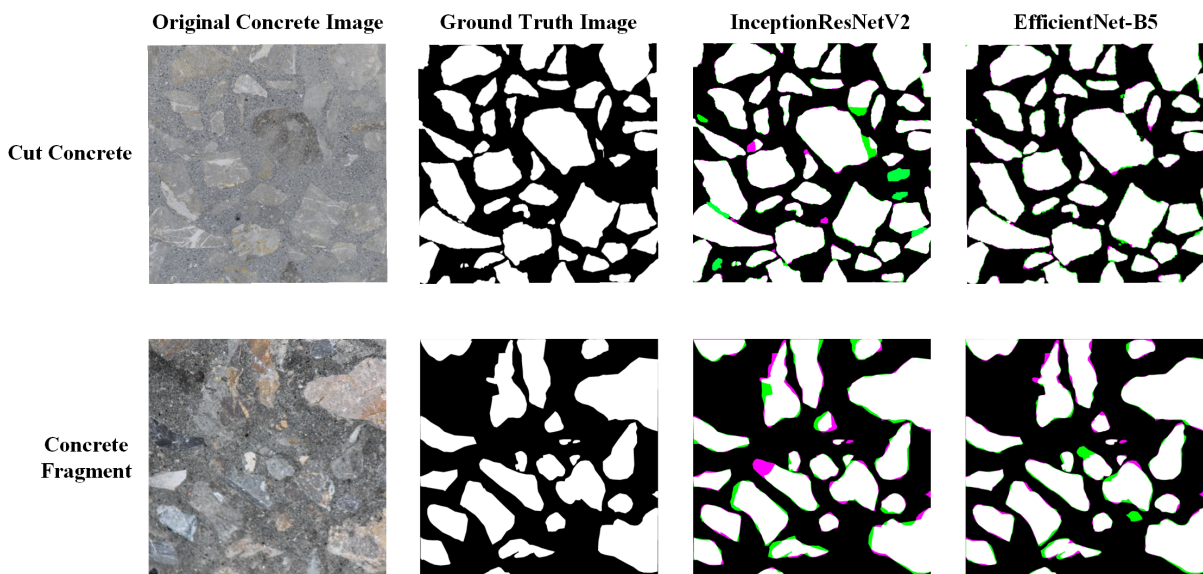


Figure 3: Output Mask generated by DCNN models.

Aggregate area percentage was quantified through pixel-wise analysis of the segmented binary masks, where foreground pixels (representing aggregates) were counted and normalized against the total image pixels. This computational approach aligns with stereological principles, translating planar measurements into volumetric approximations. To validate the accuracy of the DeepLabV3+ segmentation pipeline, the derived aggregate area percentages were systematically compared with theoretical values calculated from concrete mix design ratios, which define the expected volumetric proportions of constituents. The results in Table 4 show that the aggregate proportion predicted by the IP-based method for cut concrete samples closely aligns with the theoretical mix design values. However, in fragmented concrete samples, the estimated aggregate proportion is lower, especially in low-strength concrete. This deviation occurs due to the dislodgement of some aggregates, leading to a reduced count in the segmented images. Additionally, in low-strength concrete, failure primarily occurs in the cement paste rather than

the aggregates, meaning the aggregates remain intact and are not broken. Many of these intact aggregates remain surrounded by cement paste, making them difficult to distinguish and label, which resulted in underestimation of aggregate proportion. In high-strength concrete mix ratios, the results are relatively more accurate, as the stronger cement matrix ensures better cohesion, reducing aggregate displacement and allowing the broken surface to reveal aggregate information for a more precise estimation of aggregate proportion.

Mix Ratio	Aggregate Proportion at Mixing Time	IP-based Aggregate Proportion	
		Cut Concrete	Fragments Concrete
1:4:8	0.615	0.593	0.475
1:3:6	0.600	0.587	0.541
1:2:4	0.571	0.552	0.518
1:1.5:3	0.545	0.538	0.506
1:1:2	0.500	0.512	0.487

Table 4: Comparison of proportion of coarse aggregates.

5 CONCLUSION

This study proposed a deep learning-based methodology for the segmentation and analysis of coarse aggregates in concrete, tailored for both laboratory-prepared specimens and post-failure fragment samples. A curated dataset encompassing varying mix designs and different w/c ratios enabled robust training and testing of the DeepLabV3+ segmentation model. The EfficientNet-B5 backbone outperformed other architectures, achieving high mIoU and F1-scores. The model also performed well on fragment concrete surfaces with cracks, spalling, and shadows, demonstrating its applicability in forensic investigations. The aggregate proportions of cut concrete specimens, estimated from segmented images, closely aligned with theoretical proportions derived from the actual mix ratios, showing only minor discrepancies. This consistency confirms that 2D measurements from digital images reasonably approximate volumetric ratios in concrete, in most cases. However, in low-strength concrete fragments, the aggregate proportion values deviated due to the dislodgement of some aggregates from the surface, leading to depressions and uncounted aggregates in the image segmentation process.

Future research should expand the dataset, considering variations in aggregate colors, surface finishes, and environmental lighting conditions, to enhance model generalization. Furthermore, statistical validation, particularly through an Analysis of Variance (ANOVA) test, is recommended to assess the consistency and statistical significance of the aggregate proportion measurements.

The proposed method's ability to estimate aggregate proportions from fractured concrete surfaces eliminates the need for specialized sample preparation, making it highly valuable for post-earthquake assessments, forensic investigations, and structural failure analysis. Overall, the findings highlight the potential of deep learning-based image analysis as a practical tool for rapid, non-destructive evaluation of concrete structures.

Acknowledgment

The authors gratefully acknowledge the support received through the Graduate Assistantship (GA) program at Qatar University.

References

- [1] Standard Practice for Petrographic Examination of Hardened Concrete, ASTM C–856, American Society for Testing and Materials (ASTM) (2020).
- [2] M. A. Esfahani, M. Kalani, Petrographic analysis method for evaluation and achieving durable hot mix asphalt, *Construction and Building Materials* 234 (2020) 117408. <https://doi.org/10.1016/j.conbuildmat.2019.117408>.
- [3] M. Waris, J. Mir, V. Plevris, A. Ahmad, Predicting compressive strength of crm samples using image processing and ann, in: *IOP conference series: materials science and engineering*, Vol. 899, IOP Publishing, 2020, p. 012014. <https://doi.org/10.1088/1757-899X/899/1/012014>.
- [4] J. Yang, J. Moon, Experimental study on tracing the initial water-to-cement ratio of hardened concrete using petrography analysis, *Construction and Building Materials* 403 (2023) 133199. <https://doi.org/10.1016/j.conbuildmat.2023.133199>.
- [5] W. Wang, C. Su, H. Zhang, Automatic segmentation of concrete aggregate using convolutional neural network, *Automation in Construction* 134 (2022) 104106. <https://doi.org/10.1016/j.autcon.2021.104106>.
- [6] B. Hilloulin, I. Bekrine, E. Schmitt, A. Loukili, Modular deep learning segmentation algorithm for concrete microscopic images, *Construction and Building Materials* 349 (2022) 128736. <https://doi.org/10.1016/j.conbuildmat.2022.128736>.
- [7] M. I. Waris, V. Plevris, J. Mir, N. Chairman, A. Ahmad, An alternative approach for measuring the mechanical properties of hybrid concrete through image processing and machine learning, *Construction and Building Materials* 328 (2022) 126899. <https://doi.org/10.1016/j.conbuildmat.2022.126899>.
- [8] L.-C. Chen, Y. Zhu, G. Papandreou, F. Schroff, H. Adam, Encoder-decoder with atrous separable convolution for semantic image segmentation, in: *Proceedings of the European Conference on Computer Vision (ECCV)*, 2018, pp. 801–818. https://doi.org/10.1007/978-3-030-01234-2_49.
- [9] C. Szegedy, S. Ioffe, V. Vanhoucke, A. Alemi, Inception-V4, Inception-Resnet and the impact of residual connections on learning, in: *Proceedings of the Association for the Advancement of Artificial Intelligence (AAAI) Conference on Artificial Intelligence*, Vol. 31, 2017, pp. 4278–4284. <https://doi.org/10.1609/aaai.v31i1.11231>.
- [10] F. Chollet, Xception: Deep learning with depthwise separable convolutions, in: *Proceedings of the Institute of Electrical and Electronics Engineers (IEEE) Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 1251–1258. <https://doi.org/10.1109/cvpr.2017.195>.
- [11] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in: *Proceedings of the Institute of Electrical and Electronics Engineers (IEEE) Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778. <https://doi.org/10.48550/arXiv.1512.03385>.

- [12] M. Tan, Efficientnet: Rethinking model scaling for convolutional neural networks, arXiv preprint arXiv:1905.11946 (2019). <https://doi.org/10.48550/arXiv.1905.11946>.
- [13] J. Han, K. Wang, X. Wang, P. J. Monteiro, 2D image analysis method for evaluating coarse aggregate characteristic and distribution in concrete, *Construction and Building Materials* 127 (2016) pp. 30–42. <https://doi.org/10.1016/j.conbuildmat.2016.09.120>.
- [14] X. Xu, S. Xu, L. Jin, E. Song, Characteristic analysis of Otsu threshold and its applications, *Pattern Recognition Letters* 32 (2011) pp. 956–961. <https://doi.org/10.1016/j.patrec.2011.01.021>.
- [15] L. Chen, W. Shan, P. Liu, Identification of concrete aggregates using K-means clustering and level set method, *Structures* 34 (2021) 2069–2076. <https://doi.org/10.1016/j.istruc.2021.08.048>.
- [16] J. D. L. H. Hoong, J. Lux, P.-Y. Mahieux, P. Turcry, A. Ait-Mokhtar, Determination of the composition of recycled aggregates using a deep learning-based image analysis, *Automation in Construction* 116 (2020) 103204. <https://doi.org/10.1016/j.autcon.2020.103204>.
- [17] M. M. Thakur, S. Enright, R. C. Hurley, Phase segmentation in X-Ray CT images of concrete with implications for mesoscale modeling, *Construction and Building Materials* 403 (2023) 133033. <https://doi.org/10.2139/ssrn.4435898>.
- [18] C. Wang, Z. Han, Y. Wang, C. Wang, S. Chen, A novel method for measuring and analyzing the characteristics of coarse aggregates in concrete, *Journal of Building Engineering* 78 (2023) 107730. <https://doi.org/10.1016/j.jobbe.2023.107730>.
- [19] M. Pourebrahimi, V. Shahhosseini, A. A. Ramezaniapour, Innovative sieve simulation and microstructure image analysis techniques for estimation of aggregate size distribution in hardened concrete, *Construction and Building Materials* 384 (2023) 131456. <https://doi.org/10.1016/j.conbuildmat.2023.131456>.
- [20] Y. Liu, J. Zhang, T. Zhao, Z. Wang, Z. Wang, Reconstruction of the meso-scale concrete model using a deep convolutional generative adversarial network, *Construction and Building Materials* 370 (2023) 130704. <https://doi.org/10.1016/j.conbuildmat.2023.130704>.
- [21] E. R. Dougherty, *Digital image processing methods*, CRC Press, 2020. <https://doi.org/10.1201/9781003067054>.
- [22] T. Savino, Pierclaudio, Francesco, Civil infrastructure defect assessment using pixel-wise segmentation based on deep learning, *Journal of Civil Structural Health Monitoring* 13 (1) (2023) pp. 35–48. <https://doi.org/10.1007/s13349-022-00618-9>.
- [23] W. Qayyum, R. Ehtisham, A. Bahrami, J. Mir, Q. U. Z. Khan, A. Ahmad, Y. Onuralp, Predicting characteristics of cracks in concrete structure using convolutional neural network and image processing, *Frontiers in Materials* 10 (2023). <https://doi.org/10.3389/fmats.2023.1210543>.
- [24] M. M. Woldeamanuel, T. Kim, S. Cho, H.-K. Kim, Estimation of concrete strength using thermography integrated with deep-learning-based image segmentation: Case studies and economic analysis, *Expert Systems with Applications* 213 (2023) 119249. <https://doi.org/10.1016/j.eswa.2022.119249>.

- [25] Y. Song, Z. Huang, C. Shen, H. Shi, D. A. Lange, Deep learning-based automated image segmentation for concrete petrographic analysis, *Cement and Concrete Research* 135 (2020) 106118. <https://doi.org/10.1016/j.cemconres.2020.106118>.
- [26] S. S. Bangaru, C. Wang, X. Zhou, M. Hassan, Scanning electron microscopy image segmentation for microstructure analysis of concrete using U-Net convolutional neural network, *Automation in Construction* 144 (2022) 104602. <https://doi.org/10.1016/j.autcon.2022.104602>.
- [27] H. Huang, J. Luo, E. Tutumluer, J. M. Hart, A. J. Stolba, Automated segmentation and morphological analyses of stockpile aggregate images using deep convolutional neural networks, *Transportation Research Record* 2674 (10) (2020) pp. 285–298. <https://doi.org/10.1177/0361198120943887>.
- [28] M. Coenen, T. Schack, D. Beyer, C. Heipke, M. Haist, Semi-supervised segmentation of concrete aggregate using consensus regularisation and prior guidance, *International Society for Photogrammetry and Remote Sensing (ISPRS) Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 2 (2021) pp. 83–91. <https://doi.org/10.5194/isprs-annals-v-2-2021-83-2021>.
- [29] N. M. Tuan, Y. Kim, J.-Y. Lee, S. Chin, Automatic stereo vision-based inspection system for particle shape analysis of coarse aggregates, *Journal of Computing in Civil Engineering* 36 (2) (2022) 04021034. [https://doi.org/10.1061/\(asce\)cp.1943-5487.0001005](https://doi.org/10.1061/(asce)cp.1943-5487.0001005).
- [30] M. Ullah, J. Mir, S. S. Husain, M. L. U. R. Shahid, A. Ahmad, Concrete forensic analysis using deep learning-based coarse aggregate segmentation, *Automation in Construction* 162 (2024) 105372. <https://doi.org/10.1016/j.autcon.2024.105372>.
- [31] X. Hu, H. Fang, J. Yang, L. Fan, W. Lin, J. Li, Online measurement and segmentation algorithm of coarse aggregate based on deep learning and experimental comparison, *Construction and Building Materials* 327 (2022) 127033. <https://doi.org/10.1016/j.conbuildmat.2022.127033>.
- [32] American Concrete Institute, Building code requirements for structural concrete (ACI 318-08) and commentary, American Concrete Institute, American Concrete Institute, 2008.
- [33] D. G. Daniel, C. L. Lobo, User's Guide to ASTM Specification C 94 on ready-mixed Concrete, American Society for Testing and Materials (ASTM), American Society for Testing and Materials (ASTM), 2005.
- [34] J. Long, E. Shelhamer, T. Darrell, Fully convolutional networks for semantic segmentation, in: *Proceedings of the Institute of Electrical and Electronics Engineers (IEEE) Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015, pp. 3431–3440. <https://doi.org/10.1109/cvpr.2015.7298965>.
- [35] N. Siddique, S. Paheding, C. P. Elkin, V. Devabhaktuni, U-Net and its variants for medical image segmentation: A review of theory and applications, *Institute of Electrical and Electronics Engineers (IEEE) Access* 9 (2021) pp. 82031–82057. <https://doi.org/10.1109/access.2021.3086020>.

- [36] V. Badrinarayanan, A. Kendall, R. Cipolla, Segnet: A deep convolutional encoder-decoder architecture for image segmentation, *Institute of Electrical and Electronics Engineers (IEEE) Transactions on Pattern Analysis and Machine Intelligence* 39 (12) (2017) pp. 2481–2495. <https://doi.org/10.1109/tpami.2016.2644615>.
- [37] M. Everingham, L. Van Gool, C. K. Williams, J. Winn, A. Zisserman, The pascal visual object classes (VOC) challenge, *International Journal of Computer Vision* 88 (2010) pp. 303–338. <https://doi.org/10.1007/s11263-009-0275-4>.
- [38] P. Ren, Y. Xiao, X. Chang, P.-Y. Huang, Z. Li, X. Chen, X. Wang, A comprehensive survey of neural architecture search: Challenges and solutions, *ACM Computing Surveys (CSUR)* 54 (4) (2021) 1–34. <https://doi.org/10.1145/3447582>.
- [39] A. Baddeley, E. B. V. Jensen, *Stereology for statisticians*, CRC Press, 2004, ISBN 1135438366. <https://doi.org/10.1201/9780203496817>.
- [40] M. B. Haha, E. Gallucci, A. Guidoum, K. L. Scrivener, Relation of expansion due to alkali silica reaction to the degree of reaction measured by SEM image analysis, *Cement and Concrete Research* 37 (8) (2007) pp. 1206–1214. <https://doi.org/10.1016/j.cemconres.2007.04.016>.
- [41] E. Masad, B. Muhunthan, N. Shashidhar, T. Harman, Internal structure characterization of asphalt concrete using image analysis, *Journal of Computing in Civil Engineering* 13 (2) (1999) pp. 88–95. [https://doi.org/10.1061/\(asce\)0887-3801\(1999\)13:2\(88\)](https://doi.org/10.1061/(asce)0887-3801(1999)13:2(88)).