



A Novel Image-Based Forensic Framework for Concrete in Historical and Modern Structures

Afaq Ahmad¹ , Mati Ullah² , Vagelis Plevris² , Junaid Mir³ ,
and Syed Sameed Husain⁴ 

¹ Department of Built Environment, Oslo Metropolitan University, Oslo, Norway
Afaq.ahmad@oslomet.no

² Department of Civil and Environmental Engineering, Qatar University, Doha, Qatar

³ Department of Electrical Engineering, University of Engineering and Technology Taxila,
Taxila, Pakistan

⁴ Centre for Vision, Speech and Signal Processing, University of Surrey, Guildford, UK

Abstract. This study introduces an innovative, field-oriented framework for Forensic Concrete Analysis (FCA) applicable to both historical and modern structures. Our approach accurately segments gray-toned coarse aggregates using advanced encoder-decoder models, while relying solely on standard camera images without color enhancements or microscopy. Specifically, we employ a Vision Transformer (SwinTV2 + SegFormer) and a convolutional Neural Network (CNN) (EfficientNetV2 + DeepLabV3+) to achieve high-precision segmentation. This enables detailed quantification of aggregate properties, such as area, size, and spatial distribution through Image Processing (IP) techniques, allowing analysis of concrete segregation influenced by varying water-cement ratios and Supplementary Cementitious Materials (SCMs). A strategy for evaluating structural health is proposed using aggregate proportions as indicators of mix consistency to enhance the FCA. A comparative study of three mix ratios (1:3:6, 1:2:4, and 1:1.5:3) assesses aggregate distribution using area aggregate ratio (AAR) from 2D image data. Results show a strong correlation between mean AAR the theoretical mix ratio values. The method provides a Nondestructive alternative to traditional techniques like ASTM C856, offering particular advantages for preserving historical structures. This robust, image-based framework supports effective structural health monitoring and maintenance planning.

Keywords: Concrete Forensic Analysis · Vision Transformer Segmentation · Aggregate Distribution Quantification · Structural Health Monitoring (SHM) · Nondestructive Testing

1 Introduction

Concrete remains a cornerstone material in civil infrastructure, valued for its strength, durability, reflectivity, adaptability, and widespread availability. It is composed of aggregates, cement, and water, with the cement paste acting as the binding medium and aggregates of various types, sizes, and shapes embedded within the matrix. It consists of a

mixture of aggregates, cement, and water. The cement paste is the binding agent, formed by combining hydraulic cement and water. At the same time, aggregates of varying types (such as lightweight or heavy weight), shapes (angular, round or flat), and sizes (typically between 0.1 mm and 32 mm) are embedded within this matrix [1].

Cement, the most costly concrete component, contributes significantly to rising CO₂ emissions as global demand and production increase. To address this environmental concern, supplementary cementitious materials (SCMs) like silica fume (SF) and fly ash (FA) are increasingly used as cement partial replacements [2]. The aggregate particles' size, shape, distribution, and proportion play a vital role in determining the mechanical behavior and overall durability of concrete. These characteristics affect how aggregates bond with the cement matrix, influencing the mixture's strength, workability, and resistance to cracking or segregation [3]. Thus, mixing and proportioning materials during production play a critical role in determining the influence on the structural integrity and long-term durability [4, 5]. Traditionally, concrete properties such as W/C ratio, aggregate distribution, porosity, and air voids are evaluated using methods like petrographic analysis (ASTM C856) [6, 7]. Aggregate distribution helps assess concrete stability and is typically analyzed visually in hardened sections [8]. Manual techniques like calipers or sieving are still used but suffer from human error and inefficiency.

In recent decades, digital image processing has become a key tool in the health monitoring of materials and structures, offering automated solutions for advanced concrete analysis [9]. Researchers have used image-based techniques to study concrete aggregate distribution, shape, and stability. For instance, one study assessed self-consolidating concrete by analyzing aggregate area, size, and distribution using grayscale thresholding [10]. Others have examined pore structure and mechanical properties using micro-CT and tomography, especially in concrete modified with nano-silica (NS) and rice husk ash [11, 12]. Segmentation techniques like OTSU thresholding [13, 14], level set methods (LSM) and K-means clustering [15] have been applied to distinguish aggregates from cement paste. While OTSU separates foreground and background based on grayscale intensity, LSM has proven more effective for low-contrast SEM images. Other approaches, such as watershed segmentation and edge detection, have evaluated asphalt mixtures and recycled aggregates [16–18]. However, traditional methods face limitations, including noise sensitivity, discontinuous edge detection, and shape distortion from morphological operations [19, 20].

In recent years, deep learning has demonstrated unprecedented performance in image segmentation tasks, enabling automated, fast, and accurate identification of concrete phases [21, 22]. Malik et al. [23] demonstrated that even a lightweight DeepLabV3+ model with a MobileNet backbone could achieve high segmentation accuracy on grayscale concrete core images, outperforming classical methods like Otsu thresholding and K-means clustering. Hilloulin et al. [24] introduced a modular CNN-based segmentation framework using two specialized networks one for voids and one for aggregates on high-resolution optical microscopy images, enabling detailed quantification of air void spacing and Protected Paste Volume (PPV), which showed strong correlation with freeze–thaw durability. Similarly, Song et al. [21] developed a CNN model to segment air voids in petrographic images without the need for dye or epoxy staining, achieving expert-level accuracy and rapid processing, thus facilitating routine quality control of

concrete's air void system. Chen et al. [22] focused on multi-phase segmentation of pervious concrete in CT scan images using three advanced CNNs (Res-UNet, ED-SegNet, G-ENet), where Res-UNet achieved ~94% accuracy, enabling simultaneous analysis of pores, aggregates, and cement paste for mesostructural modeling. To reduce annotation overhead, Shi et al. [25] proposed a weakly supervised deep learning method that segmented aggregates using only image-level labels, accurately identifying segregation in large-scale concrete applications, thus making deep learning more scalable for real-world use. Wang et al. [26] introduced a highly precise model (TA-DCMamUNet) by combining triple-attention mechanisms and a dual-channel Mamba U-Net structure, which surpassed baseline models like DeepLabV3+ and Mask R-CNN with an IoU of 88.4%, while maintaining efficient memory usage and fast inference.

Despite advances in deep learning for concrete analysis, most existing methods rely on color-enhanced or microscopic images, limiting their use in field conditions and with gray-toned aggregates, ignoring challenges in real-world forensic evaluations. This study bridges that gap by introducing a novel dual-model framework using standard RGB images for accurate segmentation of gray coarse aggregates. Leveraging EfficientNetV2 + DeepLabV3+ and SwinTV2 + SegFormer, it enables Nondestructive assessment and 2D-to-3D inference. The method provides a scalable, interpretable solution for analyzing historical and modern concrete, offering a robust tool for detecting mix inconsistencies.

2 Materials and Methods

The methodology begins with curating an image dataset, followed by developing a Deep Convolutional Neural Network (DCNN)-based semantic segmentation architecture to isolate aggregates from concrete images. Subsequently, forensic analysis is conducted on the segmented aggregates to evaluate their properties and assess concrete stability.

A significant challenge in deep learning (DL) applications is obtaining sufficient and relevant training data. While an existing dataset containing 1,144 colored aggregate images (448×448 resolution) is available, it is unsuitable for analyzing gray aggregates. Thus, a custom dataset was created. Figure 1 illustrates the dataset development workflow, beginning with sample preparation and proceeding through image acquisition. Three distinct concrete mix designs were prepared with cement-sand-aggregate ratios of 1:3:6, 1:2:4, and 1:1.5:3. The water-cement (W/C) ratios (0.4, 0.5, 0.6) were selected in compliance with ACI 318 and ASTM C 94 standards, resulting in nine mix variations. To enhance dataset generality, supplementary cementitious materials (SCMs), silica fume (SF), and fly ash (FA), were incorporated at replacement levels of 0%, 15%, and 25%. SCMs influence cement paste color and improve fluidity, affecting aggregate distribution.

Gray granite and limestone aggregates were chosen due to their widespread use in South Asian construction, while other aggregate types (e.g., basalt) were excluded to avoid color-based segmentation bias. The aggregates exhibited uniform gradation, with sizes up to 24.8 mm and aspect ratios between 1.2 and 1.8. Two size fractions (25.4 mm and 12.7 mm) were evenly blended for homogeneity. 48 cylindrical samples (150 mm diameter, 300 mm height) were cast and cured for 14 and 28 days. Each cylinder was sliced into three sections, with imaging focused on the four interior faces to avoid fine-material accumulation at the top and bottom as shown in the Fig. 2.

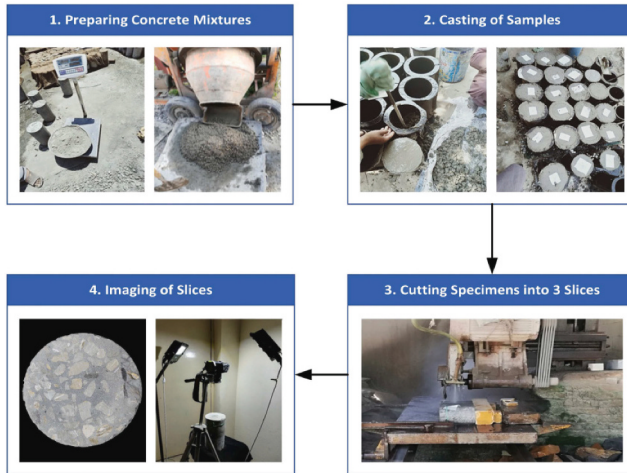


Fig. 1. Workflow of specimen preparation and imaging: mixing, casting, slicing, and image acquisition.

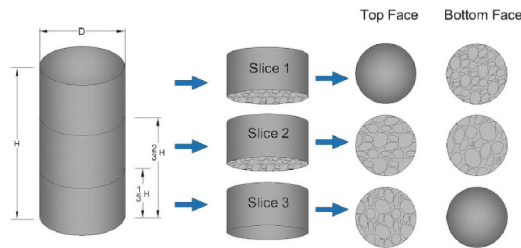


Fig. 2. Cutting mechanism for the capturing images

The imaging setup ensured consistency: a controlled $2.00 \text{ m} \times 2.50 \text{ m}$ room with 2000 lx LED illumination minimized shadows and noise. A 24-megapixel Nikon DSLR captured 192 high-resolution (6000×4000) images, later cropped into 512×512 sub-images. After removing redundant backgrounds and non-informative regions, the final dataset comprised 9,572 images, with 41.4% of pixels labeled as aggregates. The original cylindrical images and their corresponding ground truth segmentations are shown in Fig. 3, illustrating the full concrete cross-section. To enhance detail and improve segmentation accuracy, image patches were extracted from the full slices, as depicted in Fig. 4, where original patch images are aligned with their manually labeled ground truth masks.

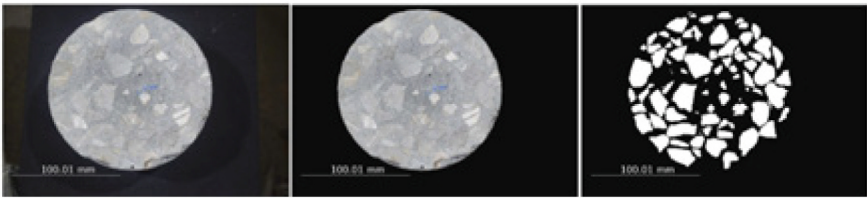


Fig. 3. Original Images with Ground Truth Images of full cylinder

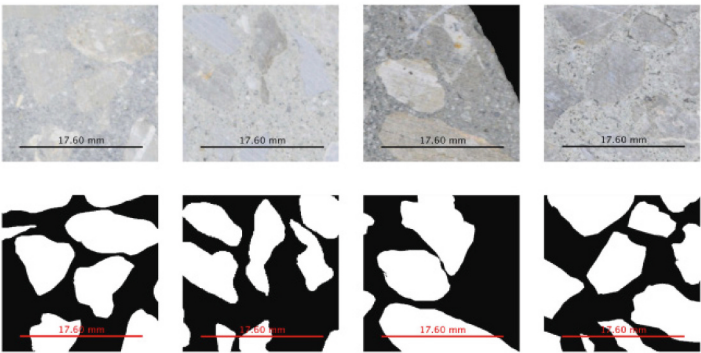


Fig. 4. Original Images with Ground Truth Images of patching

3 Aggregate Segmentation and Analysis

DCNNs have revolutionized computer vision tasks, including semantic segmentation. Popular architectures like U-Net [27], SegNet [28], and DeepLab [29] employ encoder-decoder frameworks, where the encoder extracts features and the decoder generates segmentation masks. This study adapts DeepLabV3+ [29] and SegFormer [30] for aggregate segmentation.

The trained DeepLabV3+ model generates binary mask images that isolate aggregates from concrete slices. These masks are then processed using image analysis techniques to quantify key aggregate properties. However, since the analysis is performed on 2D images, it is essential to establish their relationship with real-world 3D aggregate characteristics.

To ensure accurate measurements, we first calibrate pixel dimensions using the known diameter of the concrete cylinder (152.4 mm). The Moore-Neighbor tracing algorithm detects the cylinder's boundary as illustrated by the green outline and the diameter (measured in pixels) by the red line in Fig. 5a. The unit pixel area (mm/pixel) is then calculated by dividing the actual diameter (152.4 mm) by the pixel length of the diameter. This calibration allows precise conversion of pixel-based measurements to real-world dimensions.

The proportion of coarse aggregates in mortar significantly influences concrete's rheology, strength, durability, and cost. The binary mask is processed to count all white pixels which represent the aggregates. The total aggregate area is obtained by multiplying

the pixel count by the unit pixel area. Subsequently, the size of the aggregates is evaluated based on the creation of bounding boxes or rectangles in an orientation so that it has the least area. Then the feret diameter (maximum distance between boundary points) is computed for each aggregate as shown in Fig. 5b. A minimum-area bounding rectangle is drawn around the particle, with its length and width recorded as the aggregate's dimensions. This method provides precise size distribution data, crucial for assessing aggregate gradation and its impact on concrete performance.

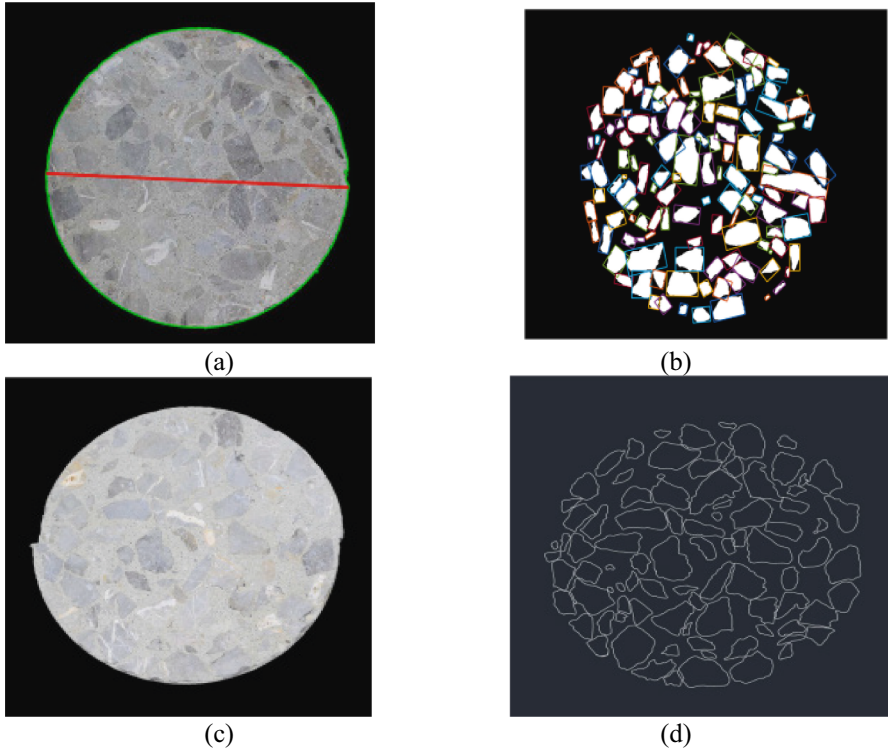


Fig. 5. Calculation of the Area of the aggregates by different methods

4 Experiments and Results

The study implemented a rigorous methodology for training and evaluating deep learning models for concrete aggregate segmentation. The dataset was carefully partitioned into training (50%), validation (25%), and test sets (25%) to ensure unbiased evaluation, with strict separation maintained to prevent data leakage. Model development utilized the PyTorch framework, with training conducted on eight NVIDIA RTX 3060 GPUs. The Adam optimizer was employed with an initial learning rate of 2×10^{-4} , using Cosine Annealing LR scheduling and Dice loss minimization over 20 epochs (batch size = 32). While models were pretrained on PASCAL VOC, all weights were fine-tuned on our specialized concrete dataset. To enhance model robustness, comprehensive data

augmentation was applied including random flips (40% probability), translations (± 20 pixels), Gaussian noise ($\sigma = 0.01$), and illumination variations. Performance was quantitatively assessed using standard metrics: IoU (measuring overlap between predictions and ground truth), precision (correct aggregate identifications), recall (completeness of detection), and their harmonic mean (F1-score). The DeepLabV3+ architecture was evaluated with five different backbones, with EfficientNetV2-S emerging as the top performer ($mIoU = 0.93$). For transformer-based approaches, a modified SegFormer incorporating SwinTV2 achieved superior results ($mIoU = 0.947$), benefiting from its hierarchical feature learning capabilities. Qualitative analysis of segmentation outputs visualized false positives and false negatives clearly demonstrating the strengths of the top-performing models in handling challenging aggregate boundaries while revealing limitations of more complex architectures like InceptionResNetV2. The systematic evaluation demonstrated that proper backbone selection and architectural modifications significantly impact segmentation accuracy for this specialized computer vision task in construction materials analysis.

The study employed a comprehensive approach to analyzing concrete aggregate properties using 2D image segmentation and computational techniques. Building on Cavalieri's principle [31], which establishes that 2D cross-sectional area percentages correspond to 3D volume distributions, we developed methods to quantify critical aggregate characteristics from segmented images. Our analysis began with spatial calibration, where we determined pixel-to-millimeter conversion by measuring the known 152.4 mm cylinder diameter in images using Moore-Neighbor boundary tracing. This calibration enabled accurate physical measurements of aggregate features.

Figure 6 represents a comparison of the Average Area Ratio (AAR) values for three concrete mix designs computed from the proposed method, with theoretical mix ratios assumed at the time of mixing. The box plots display the distribution, median, and variability of AAR for each mix. The proposed method yields AAR values that closely align with the theoretical aggregate proportions, demonstrating its accuracy and reliability in FCA. Hence, the proposed methods can be used to determine the aggregate proportion in real-time monitoring of concrete structures.

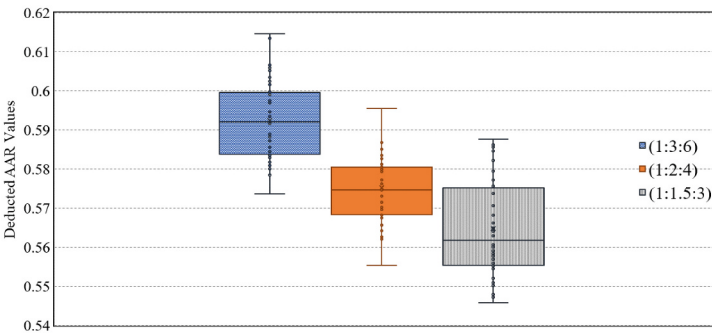


Fig. 6. Comparison of Estimated AAR values for three mix ratios with the theoretical mix ratio values

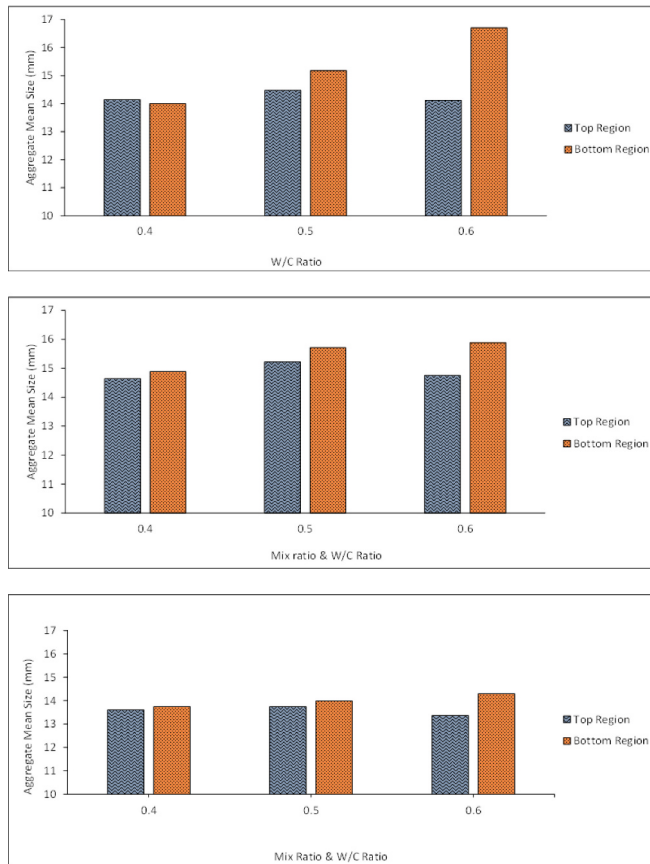


Fig. 7. Comparison of mean sizes of aggregate between top and bottom regions of concrete cylinders; (Top) 0% SCM, (Middle) 15% SCM, (Bottom) 25% SCM

Figure 7 illustrates the variation in mean aggregate sizes between the top and bottom regions of concrete cylinders for different W/C ratios and SCM contents. It can be observed that the size disparity is more prominent at higher W/C ratios and lower SCM percentages, indicating increased segregation. Conversely, increasing the SCM content reduces this difference, suggesting improved homogeneity in the concrete mix. The segregation effects demonstrated that higher water-cement ratios (0.4–0.6) led to increased size differentials between top and bottom cylinder sections, indicating better particle settling. However, SCM at 15–25% replacement levels effectively mitigated this segregation by improving mix cohesion and reducing bleeding. The fine SCM particles filled voids between cement grains, creating a denser matrix that resisted aggregate settling.

Figure 8 represents the distribution of distances between coarse aggregates for different W/C ratios and SCM contents. Spatial distribution analysis using nearest-neighbor techniques revealed that most aggregates maintained a spacing of 10–20 mm, with clustering tendencies observed in SCM-free mixes. The 15% SCM specimens showed the

most uniform distributions, while both 0% and 25% SCM mixes exhibited tighter particle groupings. This nonlinear response suggests an optimal SCM dosage for achieving ideal aggregate dispersion, as excessive SCM content may increase mix viscosity and lead to increased particle interactions.

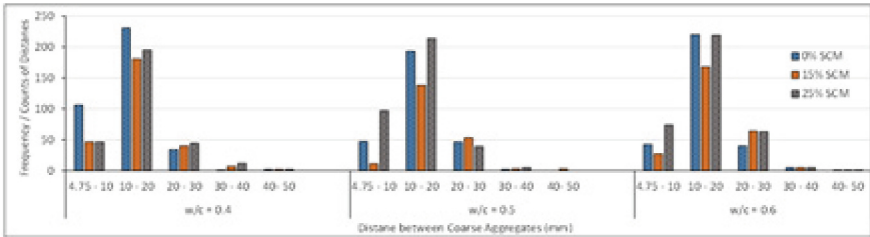


Fig. 8. Center-to-center spacing distribution between coarse aggregate particles.

These quantitative methods provide concrete technologists with powerful tools for evaluating mix designs. The 2D-to-3D correlations established through Cavalieri's principle and our automated measurement techniques provide a practical framework for assessing aggregate distribution, segregation resistance, and spatial arrangement—all critical factors influencing concrete's mechanical performance and durability. The demonstrated effects of water-cement ratio and SCM content provide actionable insights for mix optimization in laboratory and field applications.

5 Conclusions

This work proposes an innovative forensic analysis framework for the evaluation of concrete using standard photographs captured under normal field conditions. By segmenting gray-toned coarse aggregates without the need for specialized imaging or color treatments, the approach offers a Nondestructive, accessible, and efficient method for assessing concrete quality and composition. A segmentation model utilizing a vision transformer architecture was developed, combining a SwinTransformerV2 encoder with a SegFormer decoder, achieving exceptional performance with mIoU of 94.7%, F1 score of 96% and precision and recall of 96%. Transformer-based architectures, particularly the combination of SwinTV2 and SegFormer, achieved better performance compared to the DCNN-based EfficientNetV2 integrated with DeepLabV3+.

Image processing techniques effectively determine the proportion, distribution, and characteristics of coarse aggregates in sedimentation images. The results indicated that incorporating SCM into concrete promotes a more uniform aggregate distribution, reducing size variations between upper and lower layers and mitigating segregation. Statistical analysis confirmed that this forensic method provides a quantitative and interpretable approach to evaluating concrete composition across various mix designs. Calculated AAR from slice images provided insights into aggregate proportions, supporting SHM applications.

The study focused solely on coarse aggregate segmentation, as fine aggregate segmentation in prior research relied on microscopy. However, future work will explore

fine aggregate segmentation in standard images using colored cement paste (e.g., with calcined clay). Additionally, since factors such as temperature, humidity, and curing duration may affect the grayscale properties of cement paste, further validation will assess the method's robustness across diverse curing conditions and mix designs with varying materials. Furthermore, future research will investigate the robustness of the proposed method across diverse environmental conditions, including variations in temperature, humidity, curing durations, and mix constituents, to ensure broad applicability across different construction scenarios.

Acknowledgments. The authors are thankful to Oslomet University for investigating this research.

Funding. This is part of the Project “Forensic Analysis of Concrete Through Image Processing” (FACIP), funded by the EU under Grant Agreement ID: 101153307, <https://cordis.europa.eu/project/id/101153307>.

References

1. Lyu, K., She, W., Chang, H., Gu, Y.: Effect of fine aggregate size on the overlapping of interfacial transition zone (ITZ) in mortars. *Constr. Build. Mater.* **248**, 118559 (2020)
2. Vivek, S., Dhinakaran, G.: Durability characteristics of binary blend high strength SCC. *Constr. Build. Mater.* **146**, 1–8 (2017)
3. El Ouni, M.H., Raza, A., Elhadi, K.M., Azab, M., Arshad, M.: Parametric investigation of GFRP-RCC jute fibre-reinforced recycled aggregate concrete elements. In: *Proceedings of the Structures*, pp. 1043–1061. Elsevier (2022)
4. Shao, R., Wu, C., Li, J.: A comprehensive review on dry concrete: application, raw material, preparation, mechanical, smart and durability performance. *J. Build. Eng.* **55**, 104676 (2022)
5. Hayat, K., et al.: Statistical subspace-based damage detection and jerk energy acceleration for robust structural health monitoring. *Buildings* **13**(7), 1625 (2023)
6. ASTM, C., 856. Standard practice for petrographic examination of hardened concrete. ASTM, West Conshohocken (1998)
7. Walker, H.N., Lane, D.S., Stutzman, P.E.: Petrographic methods of examining hardened concrete: a petrographic manual (2006)
8. Esfahani, M.A., Kalani, M.: Petrographic analysis method for evaluation and achieving durable hot mix asphalt. *Constr. Build. Mater.* **234**, 117408 (2020)
9. Koch, C., Georgieva, K., Kasireddy, V., Akinci, B., Fieguth, P.: A review on computer vision based defect detection and condition assessment of concrete and asphalt civil infrastructure. *Adv. Eng. Inform.* **29**(2), 196–210 (2015)
10. Ozyildirim, H.C., Moruza, G.M.: Recent virginia department of transportation applications with self-consolidating concrete. *Transp. Res. Rec.* **2508**(1), 79–83 (2015)
11. Avudaiappan, S., et al.: Experimental investigation and image processing to predict the properties of concrete with the addition of nano silica and rice husk ash. *Crystals* **11**(10), 1230 (2021)
12. Sikora, P., Rucinska, T., Stephan, D., Chung, S.-Y., Abd Elrahman, M.: Evaluating the effects of nanosilica on the material properties of lightweight and ultra-lightweight concrete using image-based approaches. *Constr. Build. Mater.* **264**, 120241 (2020)

13. Arunachalam, K.P., Henderson, J.H.: Experimental study on mechanical strength of vibro-compacted interlocking concrete blocks using image processing and microstructural analysis. *Iran. J. Sci. Technol. Trans. Civ. Eng.* **47**(6), 3571–3589 (2023)
14. Han, J., Wang, K., Wang, X., Monteiro, P.J.: 2D image analysis method for evaluating coarse aggregate characteristic and distribution in concrete. *Constr. Build. Mater.* **127**, 30–42 (2016)
15. Xu, X., Xu, S., Jin, L., Song, E.: Characteristic analysis of Otsu threshold and its applications. *Pattern Recogn. Lett.* **32**(7), 956–961 (2011)
16. Zhang, K., Zhang, Z., Luo, Y., Huang, S.: Accurate detection and evaluation method for aggregate distribution uniformity of asphalt pavement. *Constr. Build. Mater.* **152**, 715–730 (2017)
17. Chen, L., Shan, W., Liu, P.: Identification of concrete aggregates using K-means clustering and level set method. In: *Proceedings of the Structures*, pp. 2069–2076. Elsevier (2021)
18. Xing, C., Xu, H., Tan, Y., Liu, X., Ye, Q.: Mesostructured property of aggregate disruption in asphalt mixture based on digital image processing method. *Constr. Build. Mater.* **200**, 781–789 (2019)
19. Shi, L., Wang, D., Jin, C., Li, B., Liang, H.: Measurement of coarse aggregates movement characteristics within asphalt mixture using digital image processing methods. *Measurement* **163**, 107948 (2020)
20. Tang, F., Han, C., Ma, T., Chen, T., Jia, Y.: Quantitative analysis and visual presentation of segregation in asphalt mixture based on image processing and BIM. *Autom. Constr.* **121**, 103461 (2021)
21. Song, Y., Huang, Z., Shen, C., Shi, H., Lange, D.A.: Deep learning-based automated image segmentation for concrete petrographic analysis. *Cem. Concr. Res.* **135**, 106118 (2020)
22. Chen, D., et al.: Deep learning-based segmentation model for permeable concrete meso-structures. *Comput.-Aided Civ. Infrastruct. Eng.* **39**(23), 3626–3645 (2024)
23. Malik, M., Mir, J., Ahmad, A.: Concrete aggregate segmentation for structural health monitoring (2023)
24. Hilloulin, B., Bekrine, I., Schmitt, E., Loukili, A.: Modular deep learning segmentation algorithm for concrete microscopic images. *Constr. Build. Mater.* **349**, 128736 (2022)
25. Shi, M., Hua, T., Yang, Z.J., Tan, C., Wen, Y.: Weakly supervised deep learning-based concrete aggregates automatic segmentation for assessing separation degree. *J. Build. Eng.* **82**, 108342 (2024)
26. Wang, D., et al.: Evaluation of aggregate distribution uniformity using vision mamba-based dual networks for concrete aggregate segmentation. *Expert Syst. Appl.* **266**, 126076 (2025)
27. Ronneberger, O., Fischer, P., Brox, T.: U-net: convolutional networks for biomedical image segmentation. In: *Proceedings of the Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, 5–9 October 2015, Proceedings, Part III* 18, pp. 234–241. Springer (2015)
28. Badrinarayanan, V., Kendall, A., Cipolla, R.: SegNet: a deep convolutional encoder-decoder architecture for image segmentation. *IEEE Trans. Pattern Anal. Mach. Intell.* **39**(12), 2481–2495 (2017)
29. Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., Yuille, A.L.: Deeplab: semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. *IEEE Trans. Pattern Anal. Mach. Intell.* **40**(4), 834–848 (2017)
30. Xie, E., et al.: SegFormer: simple and efficient design for semantic segmentation with transformers. *Adv. Neural. Inf. Process. Syst.* **34**, 12077–12090 (2021)
31. Michel, R.P., Cruz-Orive, L.M.: Application of the Cavalieri principle and vertical sections method to lung: estimation of volume and pleural surface area. *J. Microsc.* **150**(2), 117–136 (1988)