Research Article

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Deep learning-based image analysis for confirming segregation in fresh self-consolidating concrete

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Abstract: Segregation in self-consolidating concrete (SCC) can significantly impact the quality and structural integrity of concrete applications. Traditional methods for assessing segregation, such as the visual stability index and column segregation tests, often involve manual intervention, introducing subjectivity and delaying the assessment process. This study proposes a novel image-based approach using deep learning, specifically the YOLOv8 segmentation model, to quantify and assess segregation in fresh SCC mixes. Utilizing high-resolution images from slump flow tests, the model identifies critical indicators of segregation, including the mortar halo and aggregate pile. These features are evaluated with two newly introduced quantitative metrics: the mortar halo index (I_{mh}) and the aggregate pile index (I_{ap}). Experimental validation demonstrates high model precision (96.4%) and recall (85.6%), establishing it as a robust tool for on-site quality control. Furthermore, the study examines the relationship between segregation levels and compressive strength, revealing a strong correlation between increased segregation and reduced strength. The proposed feedback-based optimization strategy for mix proportions enables real-time adjustments to mitigate segregation risks. This approach enhances the objectivity and efficiency of segregation assessments, facilitating improved mix design and overall concrete performance on construction sites.

Keywords: self-consolidating concrete, segregation, deep learning segmentation, image-based analysis, compressive strength

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1 Introduction

Self-consolidating concrete (SCC) is a significant advancement in concrete technology, designed to flow under its own weight and fill formwork without the need for mechanical vibration [1]. Introduced in Japan in the late 1980s, SCC has transformed the construction industry by addressing critical challenges related to concrete placement and compaction [2,3]. Its highly fluid properties allow for superior consolidation even in densely reinforced sections without segregation [4]. This characteristic ensures uniform strength and durability throughout the structure while significantly reducing the labor and time associated with conventional concrete methods [5]. Moreover, SCC offers practical advantages such as reducing noise pollution from mechanical vibrations and enhancing workplace safety by minimizing tripping hazards [6]. In addition, SCC allows for increased flexibility in detailing reinforcing bars, thereby improving the overall efficiency and safety of construction projects [7].

Despite its numerous advantages, the application of SCC presents challenges, particularly issues related to segregation. Maintaining a uniform distribution of components is key to the stability of SCC, which resists segregation to ensure a consistent mixture [8]. Segregation occurs when aggregates settle due to insufficient buoyant and restoring forces, leading to water bleeding, uneven material distribution, and reduced concrete quality [4,9]. The loss of stability in SCC can cause various issues such as pipe blockages during pumping, obstructions around reinforcement, the formation of voids, and honeycomb defects [10]. An optimal balance between workability and stability can be achieved through precise control over mix proportions and the selection of appropriate materials [11]. Several methods have been proposed to assess SCC stability and quantify segregation, including column segregation [12], segregation probe [13,14], flow trough [15], and sieve stability tests [16]. However, these tests are often costly, resource-intensive, and time-consuming, involving iterative procedures by operators [17].

To overcome these limitations, researchers have developed automated methods to monitor and enhance stability, providing more precise and reliable assessments of segregation. For example, an innovative approach was introduced employing image processing technology to analyze images of cut-hardened concrete specimens [18]. In this process, images were converted into binary representations, and algorithms were applied to identify aggregate particles, measure their radii, and assess the mortar layer necessary for evaluating stability. The hardened visual stability index, a quantitative metric, was used to provide a more precise and efficient assessment of SCC stability compared to traditional visual methods. Despite the advantages of this automated approach, it remains constrained by the need to create and harden cylinder specimens, resulting in delays in stability assessment and limiting its ability to evaluate segregation risks in the fresh state.

With the development of artificial intelligence techniques, machine learning and deep learning algorithms have been adopted to predict the rheology, workability, and mechanical properties of SCC [19]. For instance, a comprehensive dataset of several SCC mixtures with thirteen parameters related to their compositions was assembled, and a random forest algorithm was employed to forecast the rheological properties of SCC, which were subsequently used to estimate various SCC characteristics, including the segregation rate. The results demonstrated a high level of accuracy in predicting both the rheological and mechanical properties of SCC. However, the practical applicability of this model was limited by the restricted number of input parameters and potential biases inherent in the published data used for model training. In addition, 3D point cloud analysis has been utilized for assessing aggregate segregation in fresh SCC [20]. This approach involved scanning the surface of the slump flow to capture 3D point cloud data, encompassing spatial and RGB color information. Post-processing techniques were employed to segment the point cloud data of SCC, enabling detailed analysis of the diameter, height, and curvature of the slump flow. Aggregate segregation was quantified by calculating the volume of segregation suspicious region at the core of the slump flow. The depth-data-based methodology was validated through comparisons with standardized qualitative tests and digital image analysis of hardened SCC specimens, demonstrating significant reliability and effectiveness. Nevertheless, this methodology primarily focused on SCC containing coarse aggregates up to 25 mm in size and did not account for bleeding phenomena, potentially affecting the comprehensive representation of segregation patterns.

To address these limitations, a novel image-based method for quality control of fresh concrete was introduced [21]. This approach involved capturing digital images of fresh concrete following the standard slump flow test and employing a segmentation model for semi-supervised learning to extract relevant information [22]. Correlations between image-derived parameters and conventional concrete properties were successfully established, demonstrating the potential of digital techniques for improving quality control in SCC production. However, the practical implementation and interpretation of the results may be challenged by the complexity of the convolutional neural network model used. These previous studies have made substantial contributions to the development of automated methods for addressing segregation issues in concrete, offering valuable insights into innovative approaches for assessing segregation and enhancing concrete quality control. Despite these advancements, there remains a substantial gap in practical and objective methods for monitoring segregation during SCC-related construction activities. Proposed methodologies often face challenges with onsite implementation, limiting their applicability in real-world scenarios. Additionally, the absence of a feedback-based approach to optimize SCC mixes in response to segregation issues further exacerbates this problem. Developing a practical solution that reduces subjectivity in stability assessment and facilitates mix design optimization is essential for improving construction efficiency and reliability, thereby ensuring the integrity and longevity of SCC structures.

This study aims to reduce subjectivity in the segregation assessment of fresh SCC by developing an approach that minimizes individual interpretations through numerical indexes, thus enhancing reliability and consistency. To achieve this, the YOLOv8 segmentation model was adopted to quantify and assess segregation in fresh SCC mixes. Utilizing high-resolution images from slump flow tests, the model identifies critical indicators of segregation, including the mortar halo and aggregate pile. The proposed approach seeks to be practically applicable in construction site settings, considering cost, time, and resource requirements, thereby bridging the gap between theoretical advancements and practical construction practices. In addition, the study introduces a feedback-based methodology for optimizing SCC mixes, enabling adjustments based on segregation assessment results, ultimately improving the quality and durability of SCC structures. Through these efforts, the study confirms an image-based approach for more objective segregation assessment and proposes mix optimization strategies tailored to observed segregation levels, facilitating continuous improvement in concrete quality and structural integrity.

2 Materials and methods

2.1 Dataset preparation

To develop an accurate image segmentation model, two distinct datasets were carefully prepared. The first dataset consisted of 107 slump flow images collected from various sources, including publications, books, and websites. Despite certain limitations, such as imbalanced representation and inconsistent image quality, this dataset enabled the model to refine its performance by adjusting its weights, thereby reducing the need for additional data collection. The second dataset was generated through experimental work involving slump flow tests on SCC mixtures. The mixtures, summarized in Table 1, were formulated using the mix designs outlined in [20,23–25], which specify the compositions required to achieve different levels of segregation. A total of 89 high-resolution images were captured under controlled conditions, depicting SCC mixtures with varying degrees of segregation. The images were taken from a height of 150 cm above the concrete flow to ensure full coverage and avoid distortion, providing an accurate representation of the concrete's behavior while maintaining consistency and standardization in the image acquisition process.

The images were manually labeled into three categories – concrete flow, mortar halo, and aggregate pile – using the Roboflow software [26]. Preprocessing included resizing the images to 640 × 640 pixels and applying data augmentation techniques such as flipping, rotating, and adjusting brightness to enhance the diversity of the dataset and ensure image quality [27,28]. Transfer learning was employed with a pre-trained YOLOv8 model to improve segmentation accuracy, enabling the model to perform effectively even with a relatively small dataset [29].

2.2 Segmentation of segregation features in slump flow images

The initial phase of the methodology involved segmenting segregation features in slump flow images of SCC. The visual stability index (VSI) was used to identify visible properties indicative of segregation, a crucial factor in evaluating the stability of SCC mixtures. VSI, widely utilized in both laboratory and construction settings, assigns values ranging from 0 to 3 based on SCC's resistance to segregation. Lower VSI values indicate better stability, with SCC mixtures rated 0 or 1 considered acceptable for use, while those rated 2 or 3 require modification of the mixture [30]. Based on the VSI, segregation in SCC is typically characterized by two primary visual features: the pile of aggregate at the center of the concrete flow and the mortar halo at the outer edge. These features are critical for assessing the stability and quality of the concrete mixture. Consequently, the segmentation of these features was a key focus of this study.

To achieve this, computer vision techniques were employed to effectively analyze visual data and extract meaningful information [31]. The You Only Look Once (YOLO) model, first introduced in 2016, revolutionized object detection by enabling real-time processing with a single network pass, eliminating the need for sliding window or two-stage detection approaches [32]. YOLOv8, released by Ultralytics in 2023, was employed in this study for instance segmentation due to its superior speed and accuracy [33]. The model leverages a convolutional

Table 1: Mix proportions of the samples

Mix	Water (kg/m^3)	Cement (kg/m^3)	Fly ash (kg/m^3)	Coarse aggregate (kg/m^3)	Sand (kg/m^3)	SP* (kg/m^3)	*w/b*	Sand/TA**
SCC1	180	450	—	845	845	5.4	0.40	0.50
SCC2	180	450	—	845	940	5.4	0.40	0.53
SCC3	180	450	—	845	1,020	5.4	0.40	0.55
SCC4	190	450	—	845	1,020	5.4	0.42	0.55
SCC5	200	450	—	845	1,020	5.4	0.44	0.55
SCC6	190	360	90	870	935	5.4	0.42	0.52
SCC7	190	360	90	870	1,050	5.4	0.42	0.55
SCC8	210	360	90	870	1,050	5.4	0.47	0.55
SCC9	220	360	90	870	1,050	5.4	0.49	0.55
SCC10	220	360	90	870	1,050	6.2	0.49	0.55
SCC11	220	405	90	870	1,050	6.2	0.44	0.55
SCC12	220	405	90	870	1,090	6.2	0.44	0.56
SCC13	235	405	90	870	1,090	6.2	0.47	0.56

*SP: superplasticizer, **Sand/TA: sand–to-total aggregate ratio.

architecture with key components such as the C2f module and Spatial Pyramid Pooling Fusion, which enhance gradient flow, feature extraction, and overall detection accuracy [34]. Specifically, we utilized YOLOv8s-seg, an instance segmentation variant of YOLOv8, to precisely detect segregation features in slump flow images. Model training and inference were conducted using Google Colab Pro, leveraging high-performance cloud computing resources. The training process utilized an NVIDIA Tesla T4 GPU to accelerate deep learning computations. The model's input consists of images paired with corresponding segmentation labels stored in YOLO format, where each labeled instance includes a class ID (e.g., slump flow, mortar halo, or aggregate pile) and a segmentation mask represented by polygon coordinates defining the object boundary. The output comprises bounding boxes and segmentation masks highlighting detected objects within the image, class labels identifying each region, and confidence scores indicating prediction reliability. The segmentation model's performance was evaluated using precision (P), recall (R), mean Average Precision at a 50% overlap threshold (mAP50), and mean Average Precision across overlap thresholds from 50 to 95% (mAP50-95). These metrics provided a robust assessment of the model's ability to accurately classify and identify relevant instances of segregation [35]. The results confirmed the model's efficacy in detecting and segmenting segregation features with high accuracy.

2.3 Quantitative metrics for segregation evaluation

To reduce subjectivity in segregation assessment, this study introduced quantitative metrics for evaluating the severity of segregation in SCC. Two key parameters were proposed: the mortar index, I_{mh}, and the aggregate pile index, I_{ap}, which quantify the relative sizes of the mortar halo and aggregate pile, respectively. These metrics provide a reliable and reproducible means to assess segregation risk, enabling construction site workers to implement corrective actions as needed. The metrics are calculated using the following formulas:

$$I_{mh} = \frac{A_{mh}}{A_{cf} + A_{ap}}, \tag{1}$$

$$I_{ap} = \frac{A_{ap}}{A_{cf} + A_{ap}}, \tag{2}$$

where A_{mh} is the area of the mortar halo, A_{cf} is the area of the concrete flow, and A_{ap} is the area of the aggregate pile. These areas were determined by analyzing binary masks generated by the YOLOv8-seg model, ensuring precise quantification without duplication. It should be noted that the aggregate pile index (I_{ap}) is based on the footprint area of the aggregate pile rather than its height. While this approach effectively quantifies horizontal segregation patterns, it does not account for cases where severe segregation leads to vertical accumulation of aggregates. Since vertical distribution plays a crucial role in segregation severity, incorporating 3D imaging techniques in future studies could provide a more comprehensive assessment by capturing height variations in aggregate piles. Previous studies have demonstrated the potential of 3D imaging techniques in assessing fresh concrete properties, which could offer valuable insights into the vertical distribution of aggregates [36].

To establish segregation levels, the indexes were calculated using images from published literature representing various segregation levels based on the VSI [30,31]. Percentiles, such as the 5th, 15th, and 40th, were systematically used to define thresholds through statistical analysis of the index data. While some degree of subjectivity may persist in interpreting the results, the primary goal was to provide general recommendations rather than rigid classifications. The proposed thresholds guide the assessment of segregation severity and inform intervention strategies. Table 2 summarizes these thresholds, offering a reference for categorizing segregation severity and implementing appropriate corrective measures.

To analyze the relationship between segregation levels and concrete compressive strength, cubic samples measuring 50 × 50 × 50 mm^3 were prepared using various SCC mixtures. As shown in Table 1, the mixtures included cement-only binders as well as cement-fly ash binders to evaluate the influence of different binder compositions on compressive strength development. Each mixture produced three samples, resulting in a total of 39 specimens. After casting, the samples were demolded 24 h later and cured in water for 28 days. Compressive strength tests were conducted following the curing period. Compressive strength testing was conducted using a universal testing machine. Theoretical strength values were calculated

Table 2: Ranges of quantitative metrics for segregation evaluation

Segregation level	Mortar halo index (I_{mh})	Aggregate pile index (I_{ap})
No/Low	<0.030	<0.040
Slight	0.030–0.090	0.040–0.052
Moderate	0.090–0.120	0.052–0.072
Severe	>0.120	>0.072

based on an adjusted Abrams-type relation for 50 mm cubes, with a conversion factor applied to account for differences in specimen size [37,38]. Statistical analyses, including correlation coefficients and error assessment, were performed to evaluate the influence of segregation on the mechanical properties of the SCC mixes [39]. This methodology facilitated a detailed analysis of how segregation impacts compressive strength, providing insights into the relationship between concrete stability and its structural performance.

2.4 Feedback-based recommendations for mix proportions

Feedback-based recommendations for optimizing mix proportions were developed using the mortar halo and aggregate pile indices as key indicators. These recommendations, grounded in literature that examines the effects of factors such as cementitious material content, water-to-cement ratio, and admixture types on segregation behavior, are designed to address varying degrees of segregation [10,11,40,41]. The approach considers scenarios where both the aggregate pile and mortar halo features are present, as well as cases where only one feature is observed. This ensures targeted optimization strategies to effectively mitigate segregation issues in SCC production.

3 Results and discussion

3.1 Performance of image segmentation model

The performance of the image segmentation model was examined using two datasets: a pre-training dataset of 107 images and a produced dataset of 89 images. The YOLOv8 segmentation model pre-trained on the COCO dataset [42] was used, with data augmentation expanding the training set to 252 images. Fine-tuning was conducted by adjusting the batch size to 16, achieving the best balance between precision, recall, and mAP50.

The produced dataset was also augmented, increasing the training set to 219 images. The model, trained for 214 epochs with a batch size of 16, demonstrated excellent pixel-wise segmentation (Mask) performance, achieving a precision of 94.6%, recall of 85.6%, mAP50 of 90.4%, and mAP50-95 of 72.6%. Detailed class-wise performance metrics, including both bounding box detection (Box) and pixel-wise segmentation (Mask), are summarized in Table 3. For the "concrete flow" and "aggregate pile" classes, the model achieved perfect precision and recall of 100%, while for the "mortar halo" class, precision was 83.7%, and recall was 56.9%, reflecting the complexity of the feature. The model demonstrated rapid convergence, with a training time of 0.145 h and an inference time of 3.9 ms. These results illustrate the high accuracy and efficiency of the model, making it suitable for handling large datasets. Figure 1 presents the test set segmentation masks, highlighting the model has strong generalization capability.

3.2 Quantitative evaluation of segregation features

A quantitative assessment of segregation features is presented based on the segmentation results. The model computed the mortar halo and aggregate pile indices to characterize segregation levels. These indices provide quantitative measures to evaluate the degree of segregation. The analysis identified varying segregation levels across the material samples. In Figure 2, a significant mortar halo indicated moderate segregation, whereas Figure 3 highlighted both mortar halo and aggregate piles, indicating severe segregation. These findings aligned with the original images, validating the effectiveness of the model in identifying and classifying segregation features. Furthermore, the predicted indices were compared with true labels, revealing a low error rate. The model demonstrated a 13.15% error for the mortar halo index and a 6.12% error for the aggregate pile index, confirming its reliability in segregation characterization.

Table 3: Performance metrics of the pre-trained model on the produced dataset

Class	Box				Mask			
	P (%)	R (%)	mAP50 (%)	mAP50-95 (%)	P (%)	R (%)	mAP50 (%)	mAP50-95 (%)
All	94.6	85.6	90.5	78.0	94.6	85.6	90.4	72.6
Concrete flow	100	100	99.5	98.6	100	100	99.5	97.7
Mortar halo	83.7	56.9	72.5	48.8	83.7	56.9	72.2	35.0
Aggregate pile	100	100	99.5	86.5	100	100	99.5	85.1

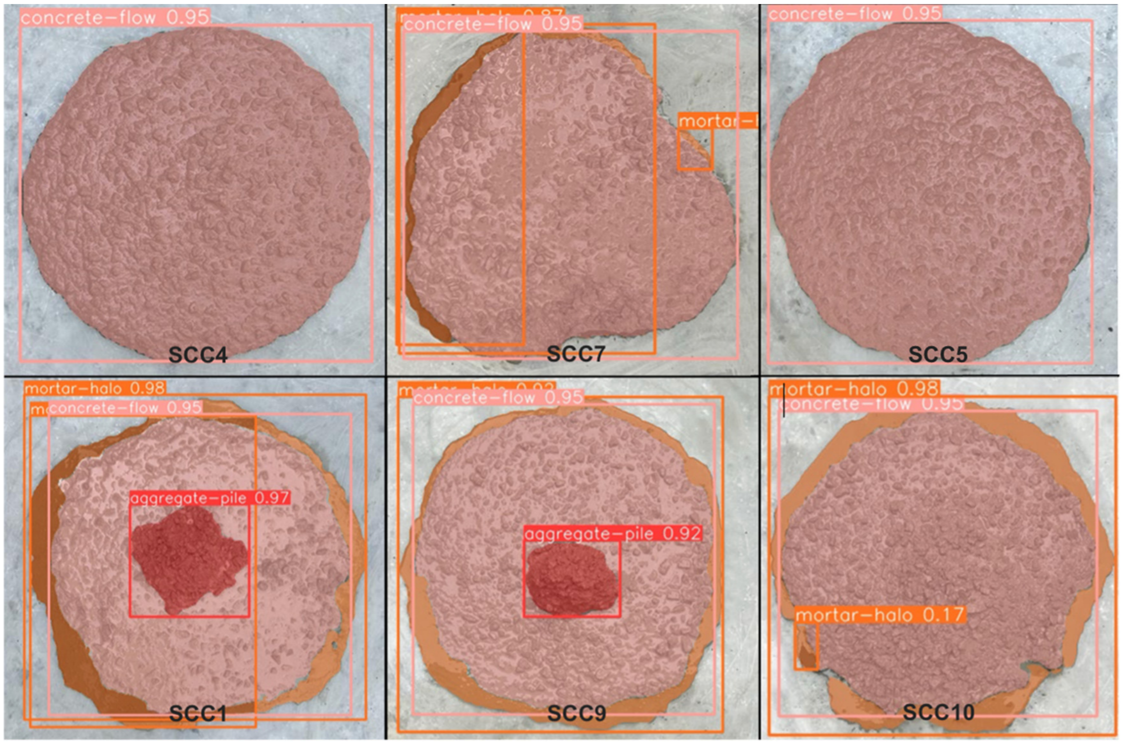

Figure 1: Segmented images from the test set.

3.3 Correlation of segregation level with compressive strength

To investigate the relationship between segregation level and concrete compressive strength, experimental results from 39 SCC samples were analyzed. The sample preparation, curing, and testing procedures were conducted as described in Section 2.3. Compressive strength values were compared to theoretical predictions to assess the impact of segregation on mechanical performance. The samples were demolded after 24 h and cured in water for 28 days until compressive strength testing. Experimental and theoretical values were analyzed to examine the influence of segregation on concrete strength. Theoretical

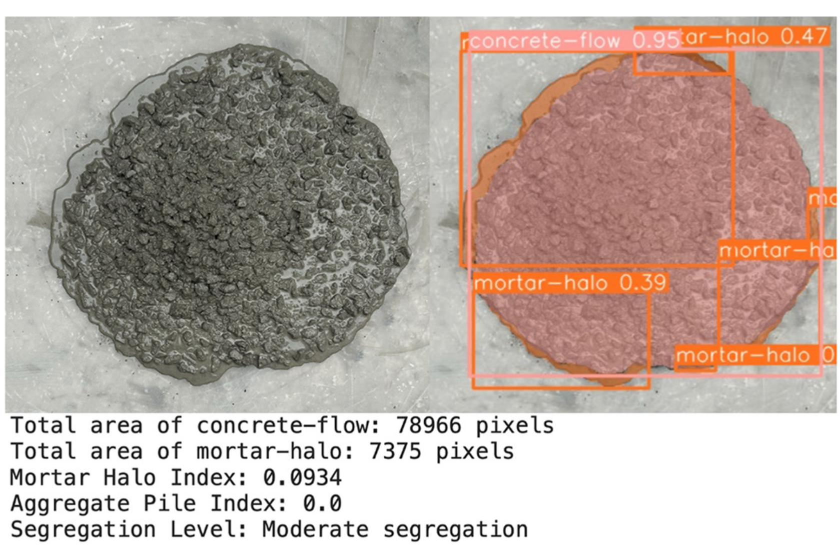

Figure 2: Results of quantitative evaluation of test image (moderate case of segregation, SCC7).

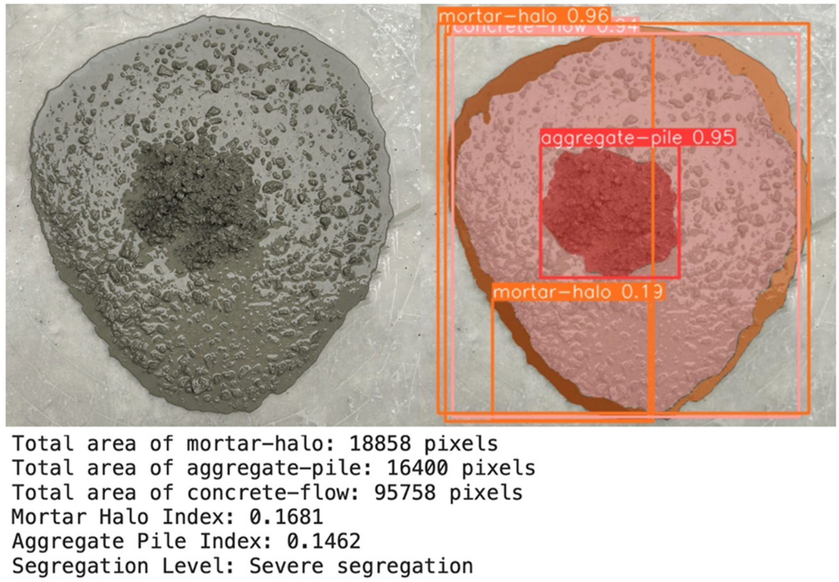

Figure 3: Results of quantitative evaluation of test image (severe case of segregation, SCC9).

compressive strength values were calculated using an Abrams-type relation adjusted for 50 × 50 × 50 mm^3 samples [37]. The formula applied is:

$$f_{c,\text{theoretical}} = \frac{195}{12.65^{\frac{w}{b}}}. \tag{3}$$

A conversion factor of 0.89 was applied to these values – since the formula was originally calculated for 100-mm cube specimens – to ensure consistency with the experimental results from the 50-mm cube samples [38].

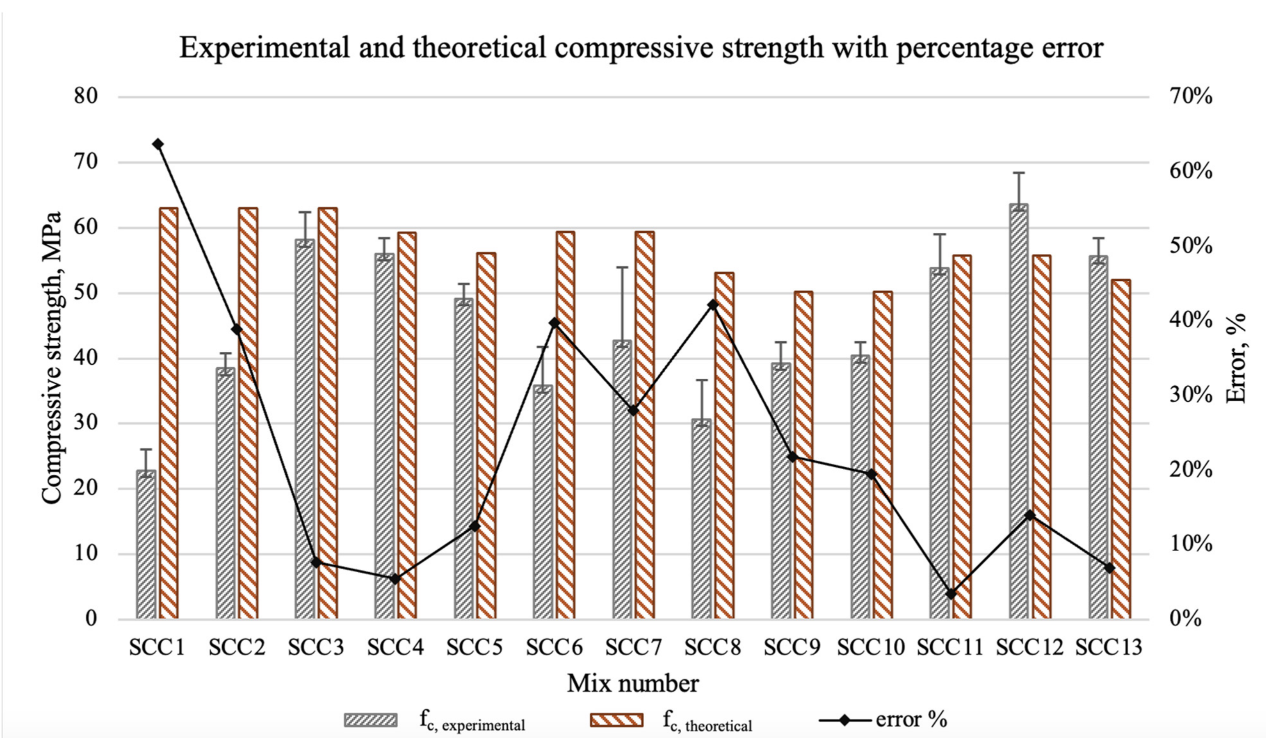

Figure 4: Comparison of experimental and theoretical compressive strength with error percentage.

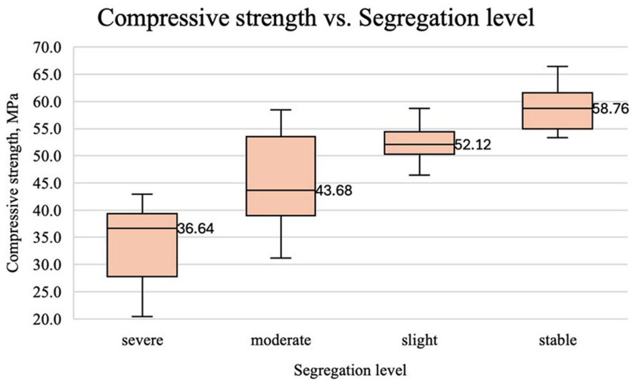

Figure 5: The relationship between segregation level and compressive strength.

Figure 4 presents a clustered column bar chart comparing the experimental compressive strength values with theoretical values for each concrete mix. The results indicate that severe segregation generally leads to lower compressive strength compared to mixes with moderate or slight segregation. This trend is reflected in the reduced average compressive strength for mixes exhibiting severe segregation. Conversely, mixes with stable properties achieve higher compressive strength, with those incorporating fly ash achieving the highest values. The obtained results also highlight percentage errors between experimental and theoretical values, showing that mixes with severe and moderate segregation have larger variance compared to stable and slightly segregated mixes.

The box plot presented in Figure 5 illustrates the relationship between segregation level and compressive strength in concrete samples. Each box represents the interquartile range (25th to 75th percentiles) of compressive strength values for a given segregation level, providing insights into data variability and central tendency. The whiskers extend to the minimum and maximum values, while the line inside each box represents the median compressive strength. A clear trend is observed that samples with higher segregation levels tend to exhibit lower compressive strength, reinforcing the detrimental effects of segregation on mechanical performance. This suggests that as segregation severity increases, the

Table 4: Correlation coefficients and *p*-values

Data	Pearson's correlation coefficient (*r*)	*p*-value
Mixes with cement binder	0.971	1.782×10^{-9}
Mixes with cement and fly ash binder	0.842	2.417×10^{-7}
All mixes	0.827	8.708×10^{-11}

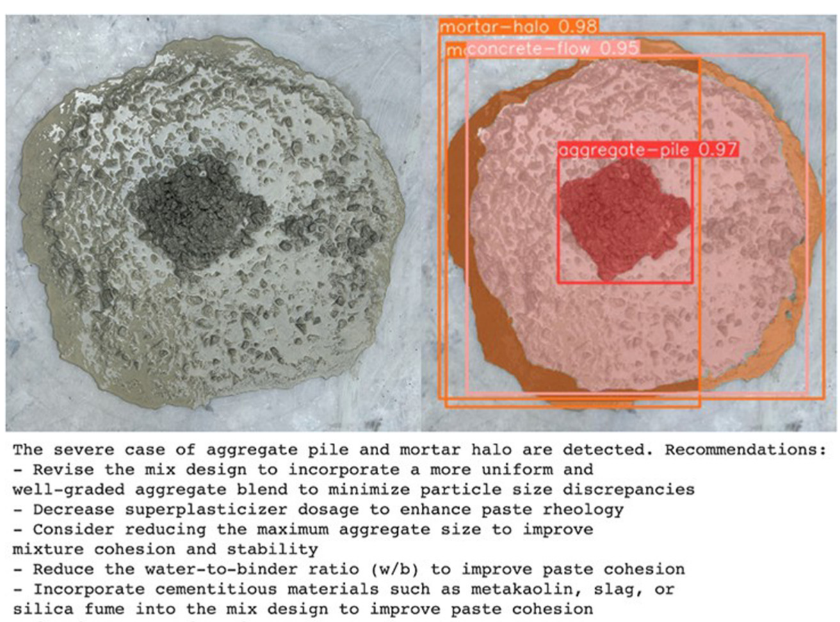

Figure 6: Mix optimization recommendations for SCC1 mix.

Figure 7: Mix optimization recommendations for SCC10 mix.

structural integrity of the material is compromised, resulting in reduced load-bearing capacity. In contrast, samples with slight and stable segregation demonstrate higher and more consistent compressive strength, indicating that a well-mixed and homogeneous composition enhances mechanical properties. In addition, the increased variability in compressive strength for samples with severe and moderate segregation, as indicated by the extended box sizes, suggests that higher segregation levels introduce inconsistencies in material distribution. This may lead to unpredictable structural performance. These findings emphasize not only the negative impact of segregation on strength but also the importance of mitigating segregation through optimized mix design and stringent quality control.

Pearson correlation coefficients and *p*-values were calculated to quantify the relationship between segregation and compressive strength. The Pearson correlation coefficient r measures the strength and direction of the linear relationship between segregation level and compressive strength, while the *p*-value evaluates the statistical significance of the correlation coefficient [39]. The results summarized in Table 4 demonstrate a strong positive correlation between segregation level and compressive strength, with high correlation coefficients and significant *p*-values for mixes with cement-only binders and those with cement–fly ash binders. This indicates a consistent relationship between segregation and compressive strength, highlighting the substantial impact of segregation on the mechanical properties of concrete.

Figure 8: Mix optimization recommendations for SCC7 mix.

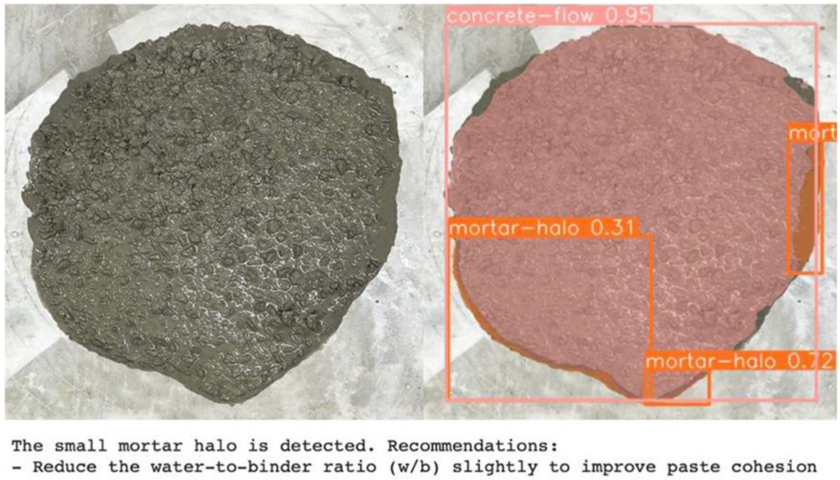

Figure 9: Mix optimization recommendations for SCC13 mix.

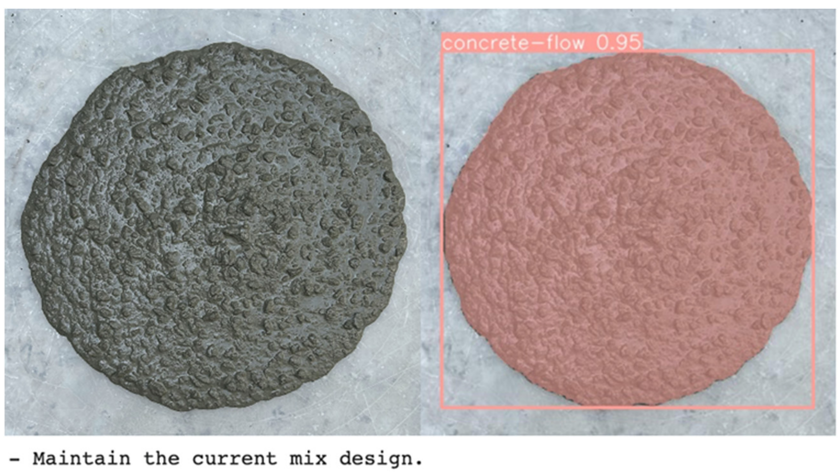

Figure 10: Mix optimization recommendations for SCC4 mix.

These findings underscore the importance of controlling segregation to maintain desirable strength characteristics in concrete mixes. The analysis provides valuable insights into the influence of segregation levels on concrete performance, reinforcing the need for precise control and monitoring during mix design and production.

3.4 Analysis of optimization recommendations

The analysis of optimization recommendations proposed by the image-based approach evaluates the feasibility of suggested improvements for concrete mix proportions based on observed segregation features. The recommendations focus on addressing specific segregation issues while adhering to established practices for optimizing concrete mix designs. Figure 6 presents the model's recommendations for mitigating severe segregation in the SCC1 mix, characterized by a fine aggregate-to-total aggregate ratio (FA/TA) of 0.5 and a water-to-binder ratio (w/b) of 0.4. The proposed adjustments include revising the mix design, enhancing the uniformity of the aggregate blend, and optimizing the superplasticizer dosage. These measures aim to improve mix stability and address observed segregation challenges effectively.

Figure 7 presents the model's recommendations for addressing severe segregation in the SCC10 mix (FA/TA = 0.55, high superplasticizer dosage, w/b = 0.49), where a prominent mortar halo indicates segregation. Suggested modifications include reducing the water-to-binder ratio and incorporating additional cementitious materials to enhance paste cohesion and minimize bleeding. These adjustments are aimed at improving mix stability by reducing water demand and addressing segregation at its source. Figure 8 highlights recommendations for mitigating moderate segregation observed in the SCC7 mix, specifically a visible mortar halo. For this mix (w/b = 0.42), the model suggests lowering the water-to-binder ratio further and incorporating a viscosity-modifying admixture to improve paste cohesion and reduce bleeding, enhancing overall stability. Figure 9 shows recommendations for slight segregation in the SCC13 mix (FA/TA = 0.56, w/b = 0.47, increased SP dosage). Here, the model advises a minor reduction in the water-to-binder ratio to bolster paste cohesion. This approach is deemed sufficient for addressing the observed segregation with minimal adjustments. Figure 10 presents the model's evaluation of the stable SCC4 mix, which indicates no changes are required. The current mix composition is identified as optimal, reflecting the model's capability to distinguish stable mixes from those requiring modifications.

The proposed recommendations specifically address the identified segregation issues, ranging from severe to slight, and align with best practices for optimizing concrete mix designs. Implementing these adjustments can enhance concrete quality and contribute to improved construction outcomes.

4 Conclusions

This study presents an image-based approach utilizing YOLOv8 segmentation to evaluate segregation in SCC. The proposed methodology enhances objectivity and accuracy in assessing concrete quality, addressing the critical need for reliable on-site evaluation tools. Key findings and contributions of this research include the following:

- Two comprehensive datasets were developed: one from publicly available sources and another from experimental work, comprising a total of 196 images. These datasets enabled precise labeling and effective model training, allowing for a detailed analysis of segregation features.
- The analysis revealed a strong positive correlation between segregation levels and compressive strength. Segregated samples generally exhibited lower compressive strength, emphasizing the importance of mitigating segregation to achieve desired strength properties in SCC.
- The YOLOv8 model demonstrated high precision (94.6%) and recall (85.6%) in identifying segregation features. Although the performance for detecting the mortar halo was slightly lower, the model showed robust capabilities for real-world concrete quality assessment. Recommendations generated by the model include adjusting the mix design, optimizing the water-to-binder ratio, and incorporating specific additives to minimize segregation and enhance concrete performance.

The incorporation of an image-based approach guided by the VSI represents a significant advancement by reducing subjectivity and enhancing reliability. Despite these advances, achieving absolute certainty in detecting segregation solely from slump flow tests remains challenging. Future research should aim to expand the model's applicability by integrating a wider variety of mix compositions, binder types, and aggregate sizes. Enhancing segmentation accuracy for features such as mortar halo can be achieved by increasing dataset diversity and improving image quality under varying lighting conditions. In addition, further research could explore the integration of 3D imaging techniques to capture height variations in aggregate piles, providing a more comprehensive assessment of segregation severity and enhancing the reliability of automated detection methods. Addressing these limitations will enhance the model's effectiveness for practical applications and advance the field of SCC quality evaluation.

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Author contributions: Azhar Akbotina: ideas, methodology, validation, data curation, supervision, writing – original draft, and review & editing. Sang-Yeop Chung: validation, formal analysis, data curation, writing – original draft, and review & editing. Pawel Sikora: investigation, validation, and writing – review & editing.

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Ethical statement: The conducted research is not related to either human or animal use.

Data availability statement: The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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