



Prediction of Concrete Strength Through Image Processing

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Abstract. Reliable and equipment-light prediction of concrete strength is essential for rapid quality assessment and structural health monitoring. This paper presents an end-to-end image-based pipeline that utilizes deep semantic segmentation to isolate coarse aggregates from concrete slice images. Then it regresses mechanical properties using a compact artificial neural network (ANN) with only aggregate-level descriptors. A DeepLabV3+ segmenter (ResNet101 backbone) produces high-quality masks with mIoU up to 0.90, from which six descriptors, i.e., aggregate proportion, size, roundness (elongation), aspect ratio, Feret-based dimensions, and nearest-neighbor spacing, are extracted automatically. These features, computed across compacted and non-compacted cylinders spanning common mix ratios and water–cement levels, feed a lightweight ANN model (AggNet) to predict compressive strength (f_c) and tensile strength (f_t). On the held-out test set, AggNet achieves an R^2 value of 0.783, an MAPE of 0.362, and an RMSE of 0.113, demonstrating that aggregate morphology carries an actionable signal for strength estimation without destructive testing or mortar texture cues. The results highlight aggregate skeleton characteristics as practical surrogates for mixture quality and consolidation effects, suggesting a complementary role to conventional NDT for fast, low-cost strength evaluation in the field.

Keywords: Image processing · Aggregate segmentation · Concrete strength · Structural health monitoring

1 Introduction

Concrete remains the backbone of modern infrastructure due to its widespread availability, versatility, and desirable engineering properties, including strength, durability, and adaptability [1]. The reliable prediction of its mechanical performance, particularly compressive strength (f_c) and tensile strength (f_t), is central to the design and maintenance of sustainable and resilient structures [2, 3]. Traditional testing approaches, both destructive and nondestructive, have been extensively used for this purpose. Destructive testing, such as compression and split-cylinder tests, provides accurate measurements but requires sampling, which is time-consuming, costly, and often leads to permanent

structural damage. In contrast, nondestructive techniques such as ultrasonic pulse velocity (UPV) [4], rebound hammer (RH) [5], and combined SonReb methods [6] offer practical alternatives. Yet, they are heavily dependent on specialized equipment, calibration procedures, and experienced operators [7]. This makes them less suitable for routine or large-scale assessment, especially in aging infrastructure.

With the rapid development of computer vision and machine learning, image-based approaches have emerged as powerful tools to complement or replace conventional testing methods in civil engineering [8, 9]. Structural health monitoring (SHM) increasingly incorporates digital imaging and pattern recognition to evaluate material conditions [10]. High-resolution microscopy and scanning electron microscopy (SEM) enable the visualization of the internal structure of concrete, while classical image analysis techniques, such as edge detection, morphological filtering, and texture-based analysis, facilitate the quantification of features directly linked to material performance [11–13]. When integrated with artificial neural networks (ANNs), these image-derived descriptors can be mapped to mechanical properties with high predictive accuracy.

Several studies have reported on the successful application of ANNs to predict the strength of concrete using image-based features. Dogan et al. [14] demonstrated that aggregate- and texture-based ANN models outperformed conventional regression in estimating compressive strength and elasticity. Waris et al. [15] showed that statistical measures extracted from images, such as skewness and entropy, when combined with ANN and ANFIS models, yielded R^2 values exceeding 0.97. Similarly, Li et al. [16] highlighted that digital image analysis can effectively capture crack propagation and strength development under load, while Gucluer et al. [17] confirmed that aggregate shape and aspect ratio have a direct impact on compressive strength. These findings underscore the significance of aggregate morphology in influencing concrete behavior.

Recent advances in deep learning, particularly convolutional neural networks (CNNs), have further strengthened the role of image-based modeling in concrete research. CNNs are capable of learning complex visual patterns from raw images, which has led to significant progress in concrete strength prediction [18–20]. Nonetheless, many CNN-based regression approaches treat images as holistic inputs, thereby overlooking detailed aggregate-level features such as size distribution, roundness, and spatial arrangement. Hybrid CNN–SVR approaches [21, 22] have attempted to address this by incorporating manually measured aggregate parameters; however, such procedures are labor-intensive and lack scalability.

Motivated by these limitations, this work focuses exclusively on the role of coarse aggregate morphology in predicting strength. A dedicated ANN framework, termed AggNet, is proposed, which uses only aggregate-level features derived from deep-learning-based segmentation. Through image processing, six key aggregate descriptors, proportion, size, roundness, aspect ratio, Feret dimensions, and nearest-neighbor distances are automatically extracted and provided as inputs to the network. By focusing solely on aggregates, AggNet highlights their independent contribution to concrete mechanical performance, eliminating the need for manual measurements.

2 Materials and Methods

The adopted methodology involved preparing cylindrical concrete specimens with a range of mix proportions and water–cement (W/C) ratios. The specimens were grouped into three categories: compacted, non-compacted, and very-high W/C. To establish reference mechanical properties, destructive (DT) and non-destructive (NDT) tests were carried out. Afterwards, the cylinders were cut into slices, and high-resolution photographs were taken under controlled conditions. These images were then annotated at the pixel level to produce ground-truth labels for aggregates, thereby generating a specialized dataset for subsequent analysis and ANN model development. A schematic overview is shown in Fig. 1.

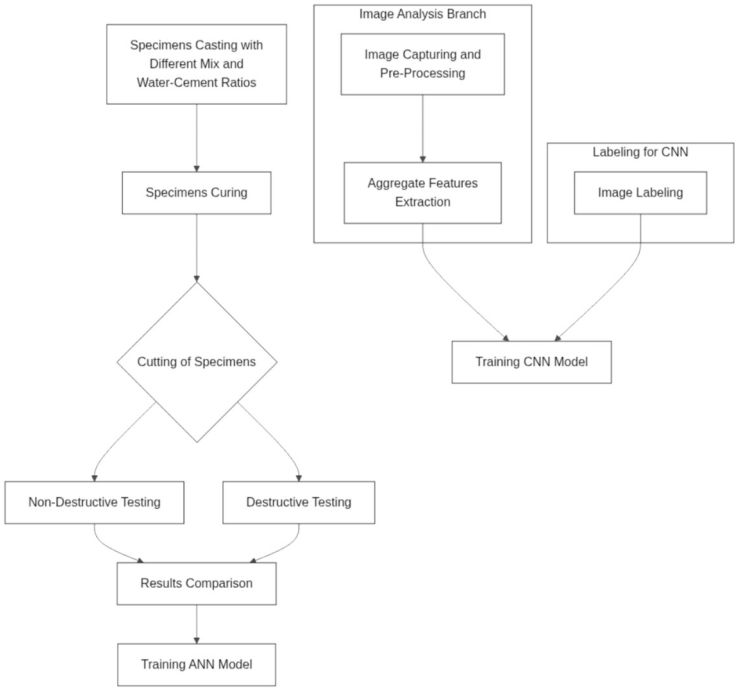


Fig. 1. Flowchart depicting stepwise procedure from dataset curation to ANN training

2.1 Cylinder Casting and Testing

Concrete mixes were prepared using five design ratios (1:4:8, 1:3:6, 1:2:4, 1:1.5:3, and 1:1:2). The coarse aggregate consisted primarily of gray granite and limestone, complemented by colored aggregates (basalt, siliceous, and calcined). Approximately 70% of the total aggregate was gray, a choice reflecting both its practical prevalence in South Asia and its relevance for testing segmentation models under challenging conditions, given its close resemblance to cement paste. In contrast, colored aggregates offered

clear contrast boundaries, making segmentation comparatively straightforward. Each mix was prepared with three water-to-cement (W/C) ratios (0.4, 0.5, and 0.6), following the guidelines in ACI 318 [23] and ASTM C94 [24].

To examine the effects of workmanship and extreme mixture conditions, non-compacted cylinders were prepared at the same five mix ratios and three w/c levels. Table 1 summarizes the conditions and the corresponding destructive test results. Across all conditions, 180 cylinders were cast and cured for 28 days; for each condition, two cylinders were assigned to imaging, two to compressive testing, and two to split-tensile testing.

Table 1. Material and mix ratio

S. No.	Mix design notation	Mix ratios	W/C	Compressive strength (MPa)
1	CM1	01:04:08	0.4	3.43
2	CM2	01:04:08	0.5	4.06
3	CM3	01:04:08	0.6	5.16
4	CM4	01:03:06	0.4	5.84
5	CM5	01:03:06	0.5	7.4
6	CM6	01:03:06	0.6	8.78
7	CM7	01:02:04	0.4	14.53
8	CM8	01:02:04	0.5	11.66
9	CM9	01:02:04	0.6	10.17
10	CM10	01:05.5	0.4	18.07
11	CM11	01:05.5	0.5	16.76
12	CM12	01:05.5	0.6	14.37
13	CM13	01:01:02	0.4	21.03
14	CM14	01:01:02	0.5	14.78
15	CM15	01:01:02	0.6	13.74

Mechanical strengths were obtained using a compression testing machine (CTM). Both uniaxial compression and split-cylinder tests were carried out in accordance with ASTM C39 [25] and ASTM C496 [26]. The resulting compressive and tensile strengths were used as ground-truth values for training the ANN model. Furthermore, NDT was performed on imaging specimens. Surfaces were first smoothed before applying the rebound hammer (RH) test (ASTM C805 [27]) to estimate compressive strength from R-values. Ultrasonic pulse velocity (UPV) tests were conducted in accordance with ASTM C597 [28]. Ultrasonic waves at 250 kHz were passed through each slice, and travel times were recorded to compute velocity.

2.2 Concrete Image Dataset

Since existing aggregate segmentation datasets [29] contain only colored aggregates and are limited in size, a new dataset was developed in this study. Cylinders ($H = 300$ mm, $D = 152$ mm) were cut into three slices at approximately one-third and two-thirds of their height using a stone saw as shown in Fig. 2. Due to the accumulation of fines, the top surface of the first slice and the bottom surface of the third provided little aggregate information and were excluded, leaving four usable faces for imaging. Images were captured in a controlled indoor setup. External light was blocked, and two 30W LED lamps supplied uniform illumination (approximately 2000 lx). A Canon EOS 4000D digital camera (18 MP, ISO 1000) mounted at 550 mm from the sample face was used to capture 280 raw images at a resolution of 5184×3456 .



Fig. 2. Experimental workflow: (a) casting, (b) curing and cutting, (c) Testing, and (d) imaging of specimens.

Each raw image contained both the specimen face and the background. A preprocessing routine (including grayscale conversion, binarization, hole filling, morphological closing, connected components, and mask extraction) was used to remove the background. Using MATLAB Image Labeler, aggregates were manually traced with a graphics tablet, ensuring acceptable boundary accuracy. Structural engineering experts verified the annotated masks before being finalized. Each full-resolution image was then partitioned into 74 tiles of 512×512 pixels, yielding 17,760 patches. After excluding redundant patches containing only background, the dataset comprised 10,154 images. Figure 3 represents examples of preprocessing stages and the resulting labeled patches. Overall, 42.8% of the labeled pixels represented aggregates, while 57.2% corresponded to mortar and other phases.

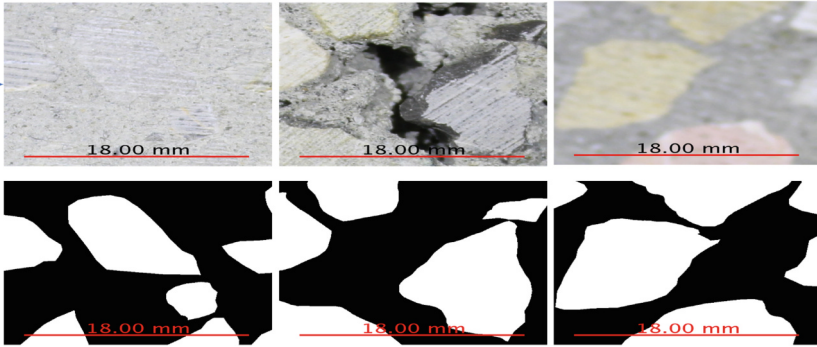


Fig. 3. Examples of 512×512 dataset patches (top) and their corresponding ground-truth masks (bottom). White pixels indicate aggregates.

3 Segmentation and Analysis of Aggregate

Accurate aggregate segmentation is fundamental to characterizing the morphology of coarse aggregates. By delineating aggregate pixels from the surrounding matrix, we can compute distribution, size, and shape descriptors that are later used to interpret and ultimately predict mechanical behavior. Applying state-of-the-art semantic segmentation to concrete slice images enables a clean separation of material phases, improving measurement fidelity and supporting data-driven mix optimization.

3.1 Segmentation Architectures

Advances in deep learning and large-scale training corpora have established deep convolutional neural networks (DCNNs) as a leading solution for semantic segmentation, where an image is partitioned into label-consistent regions for downstream analysis. Canonical encoder–decoder designs, such as Fully Convolutional Networks [30], U-Net [31], SegNet [32], and the DeepLab family [33, 34], compress spatial detail to extract robust features and then decode them into dense masks; the architectural choice strongly influences boundary precision and class consistency. In this work, we adopt DeepLabV3+ [35] for aggregate segmentation. Compared with DeepLabV3 [34, 35], the “plus” variant enhances fine-detail recovery by coupling Atrous Spatial Pyramid Pooling (ASPP) with a lightweight decoder. The DeepLabV3+ is composed of three components: an encoder with a backbone DCNN, an ASPP block for multi-scale context aggregation, and a decoder to refine object boundaries.

The encoder transforms the input image into a hierarchy of feature maps with progressively richer semantics. Each convolutional layer produces activations that are passed through non-linearities (e.g., ReLU or leaky ReLU) and normalization layers (e.g., batch normalization) to stabilize the training process. Pooling operations reduce spatial resolution while retaining salient information. Modern encoders may also employ dilated convolutions to enlarge the receptive field without increasing the number of parameters, or depth-wise separable convolutions to reduce computational cost. The outcome is a compact, semantically rich representation suitable for decoding.

To accommodate the wide range of object scales in concrete microstructure, the ASPP module runs multiple parallel atrous (dilated) convolutions at different dilation rates, effectively scanning the scene with receptive fields of varied sizes. This captures both local texture and broader context. A global-average-pooling branch supplies an image-level prior; all branches are concatenated and fused via a 1×1 convolution to yield the ASPP output.

Finally, the DeepLabV3+ decoder sharpens boundaries and restores detail with minimal overhead. The ASPP output is unsampled (factor 4 via bilinear interpolation) and merged with a low-level encoder feature map that a 1×1 convolution has filtered to limit the channel count. A subsequent 3×3 convolution and a final up sampling step produce the dense segmentation map, balancing high-level semantics with low-level spatial cues.

3.2 Training Protocol

To ensure fair evaluation, the dataset was randomly divided into training (60%), validation (20%), and test (20%) splits, independent of mix design and W/C ratio. Models were implemented in MATLAB’s Deep Learning Toolbox and trained on a Windows workstation (Intel Core i7-10700 @ 2.90 GHz, 32 GB DDR4, NVIDIA GeForce RTX 3060).

Weights were initialized using He/Kaiming initialization [36]. Optimization used stochastic gradient descent with momentum (SGDM) [37] with initial learning rate $1 \times 10^{(-3)}$, momentum 0.9, L2 regularization 0.005, step decay every 10 epochs (factor 0.3), for 25 epochs, and mini-batch size 8. Pretrained backbones on PASCAL VOC [38] were fine-tuned to our domain using a composite loss of cross-entropy and Lovász–Softmax, which emphasizes IoU optimization, as described in Table 2. After each epoch, the data order was reshuffled, and checkpoints were saved; loss and accuracy were monitored throughout.

To improve generalization and reduce overfitting, we applied data augmentation: horizontal/vertical flips (probability 0.35 each), random translations in $[-30, 30]$ pixels, illumination jitter, and additive Gaussian noise (mean 0, standard deviation 0.01). These perturbations encourage invariance to view, alignment, and lighting.

Table 2. Performance metrics of different backbone DCNNs for aggregate segmentation.

Backbone DCNN	Performance metrics			
	mIoU	F1-score	Precision	Recall
2–5				
InceptionResnetV2	0.83	0.93	0.89	0.95
Xception	0.88	0.93	0.91	0.96
ResNet101	0.90	0.94	0.93	0.95

4 Aggregate Segmentation Results

Backbone selection has a significant impact on the quality of the mask produced by DeepLabV3+. To examine this sensitivity, we coupled the DeepLabV3+ head with three encoders: InceptionResNetV2 [39], Xception [40], and ResNet101 [41–46]. These networks span a range of depths, connectivity patterns, and computational costs. While bottomless models can encode rich semantics, increased depth alone is not a guarantee of better masks, as it may lead to potential overfitting and optimization challenges. We therefore benchmarked all four variants on the same data to determine the most suitable encoder for aggregate segmentation. As reported in Table 1, ResNet101 yields the top mean IoU (0.90) and the strongest F1-score, indicating a favorable balance between precision and recall. These values demonstrate smooth convergence and do not suggest either underfitting or overfitting for this configuration.

4.1 Aggregate Proportion

Real-world scaling from images typically requires a fixed camera distance; to avoid this constraint, we recover the pixel size from the known cylinder diameter (152.4 mm). The circular boundary is traced using the Moore–Neighbor method with 8-connectivity [47, 48], which is resilient to noise and minor artifacts. With the image-space diameter measured as shown in Fig. 4a, we convert pixel counts to area (mm^2). Aggregate area is computed by counting white pixels and multiplying by the unit pixel area.

4.2 Aggregate Characteristics

Aggregate geometry (size, shape, orientation) is quantified via the Feret rectangle method [49]. The Feret diameter, which represents the maximum boundary-to-boundary distance, is computed by scanning boundary point pairs. A minimum-area oriented rectangle is then fitted with its long side aligned to this diameter, as depicted in Fig. 4b. We use the rectangle’s length as the aggregate size and define roundness as the long-to-short side ratio (1 for a square, and larger values indicate elongation).

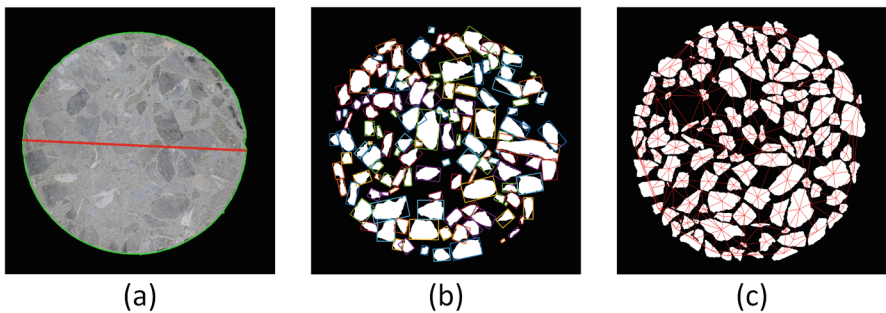


Fig. 4. (a); Boundary (green) and diameter (red) used to compute unit pixel size for metric measurements, (b); Feret-based oriented rectangles used to extract size and elongation measures from each aggregate, (c); Nearest-neighbor network among aggregate centroids for spacing analysis.

4.3 Distance Between Aggregates

Packing density and potential crack paths are reflected in inter-aggregate spacing. We compute nearest-neighbor distances (NND) between aggregate centroids as shown in Fig. 4c by evaluating pairwise Euclidean distances and retaining the minimum per aggregate.

5 Results ANN Modelling and Training

Image-derived features were used to train a single artificial neural network, focused on aggregate morphology, hereafter referred to as AggNet. Laboratory measurements of compressive strength (f_c) and tensile strength (f_t) served as target outputs. To harmonize scales, all inputs and outputs were normalized.

AggNet consists of an input layer, two hidden layers, and a two-node output layer for (f_c , f_t) as shown in Fig. 5. The two-hidden-layer design was selected after iterative trials to strike a balance between expressiveness and generalization. The input layer dimension equals the number of aggregate descriptors obtained from the segmentation pipeline, and the hidden layers use matching widths to limit computational cost.

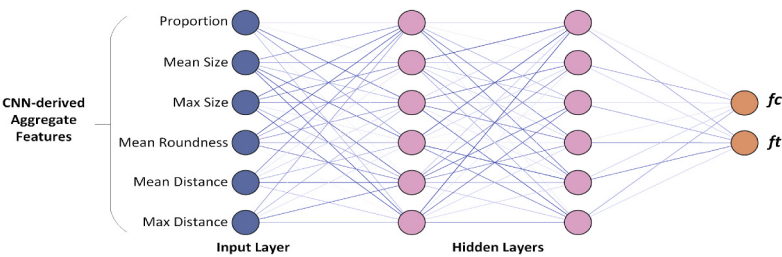


Fig. 5. AggNet architecture (6-6-6-2): ANN using only aggregate-derived features.

Learning employed the Levenberg–Marquardt backpropagation (LM-BP) algorithm [50–53]. A logarithmic schedule was used to modulate the effective learning rate (lr) and stabilize updates. Hyperparameters were set to $lr = 0.9$, momentum coefficient $mc = 0.2$, and a maximum of 10,000 iterations. Hidden-layer activations were tanh and log-sigmoid. The objective was to minimize the mean absolute error. The aggregate features extracted from 240 images (60 samples) were randomly partitioned into 70% training, 15% validation, and 15% testing.

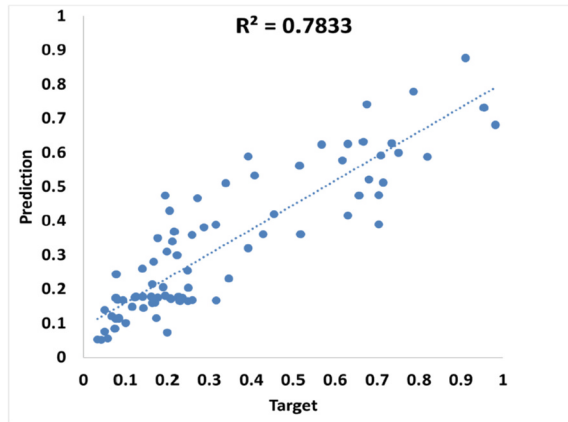


Fig. 6. Predicted versus target strengths for AggNet on the test set.

Figure 6 shows predicted versus target values for AggNet on the held-out test set. Using aggregate proportion, size, elongation (roundness), and spacing descriptors as inputs, AggNet provides consistent estimates of both (f_c and f_t). The Proposed model achieved representative performance of $R^2 = 0.783$, $MAPE = 0.362$, and $RMSE = 0.113$. These values reflect the predictive signal carried by coarse-aggregate morphology alone, where no mortar statistics or global intensity features were included.

6 Conclusion

This study introduced an aggregate-only predictive workflow that couples deep segmentation with classical image analysis and a compact ANN to estimate (f_c and f_t). From concrete slice images, DeepLabV3+ with the encoder ResNet101 achieved a mean IoU value of 0.90, along with F1-score, precision, and recall values of 0.94, 0.93, and 0.95, respectively, providing reliable inputs for downstream feature extraction. Six automatically derived aggregate descriptors were used as inputs in the proposed AggNet model, which achieved representative test-set performance ($R^2 = 0.783$, $MAPE = 0.362$, $RMSE = 0.113$). This work demonstrated that coarse-aggregate morphology can provide a strong, non-destructive proxy for estimating concrete strength from single cross-section images, by coupling a DeepLabV3+ segmenter with classical geometry and spacing-based descriptors and learning a compact regressor.

Future work will enrich the dataset with broader mixture types and explore additional aggregate descriptors, such as orientation distributions and multi-scale texture, to further enhance aggregate-only predictions. Integration with selective mortar statistics or hybrid encoders can be considered in extended studies.

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