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# Modular Deep Learning Segmentation Algorithm for Concrete Microscopic Images

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## 28 **1. Introduction**

29 Concrete formulations can be adapted to withstand particular exposure conditions, and  
30 formulation guidelines are most of the time given in the standards. Nonetheless, due to its  
31 heterogeneous nature, concrete is a complex material. While its macroscopic properties have  
32 been studied for a long time, its microscopic properties, governing the macroscopic ones, are  
33 historically less studied. One of the critical properties of concrete related to its durability,  
34 especially to freeze-thaw and permeability properties, is its air-void structure [1]. Air  
35 entraining agents can be employed to control the pore size distribution and the air content of  
36 concrete to increase its durability [2–5]. The number of pores and pore size distribution also  
37 impacts the mechanical properties of concrete. Pores are usually classified depending on their  
38 diameter: gel pores ( $\leq 10$  nm), transition pores (10nm-100nm), capillary pores (100nm-  
39 1000nm), and air voids ( $\geq 1000$ nm). The latter two are mainly due to the evaporation of free  
40 water during concrete life and created during the mixing process, respectively.

41 Various techniques can be used for pore structure analysis, such as mercury intrusion  
42 porosimetry, gas absorption, nuclear magnetic resonance, and electron microscopy. However,  
43 due to sample size limitations, they are hardly applicable from an industrial point of view to  
44 get the overall properties of decimeters-large concrete samples. Therefore, generally manual  
45 or time-consuming techniques are defined in the standards such as fresh state air-void content  
46 [6] and petrographic analysis based on microscopic images. The ASTM [7] and Eurocode [8]  
47 methods consist in sectioning a concrete block, the section is then polished and air voids are  
48 detected and counted visually using the help of a microscope [9]. Additional parameters like  
49 the protected paste volume can be calculated [10,11]. Several methods have been proposed to  
50 enhance the contrast between the air voids of the concrete matrix and the aggregates that is a  
51 critical issue. For example, manual color treatment (using black ink to color the surface and a  
52 white powder to fill air-voids, or a phenolphthalein-based color treatment to increase the

53 contrast between the paste and the aggregates ) has been proved to be efficient but can be both  
54 time-consuming and skill-dependent [12–14]. Indeed, the colorant that is added to distinguish  
55 the paste and the aggregates can be trapped in some aggregate or sand particles because of  
56 their porosity or polishing defects, while the clear powder used to detect the air voids can be  
57 easily trapped in the cement paste because of bad polishing. Then, it has been shown that the  
58 image analysis process can be accelerated using automatic methods like the RapidAir 457  
59 testing instrument [12,15]. These methods have been well documented but mostly rely on the  
60 manual or semi-automatic distinction between air voids and the remaining concrete matrix by  
61 coloration, which depends on the operator and is a critical error-prone step. This critical  
62 coloration procedure might significantly impact on the later analysis, such as automated  
63 segmentation, and leads to the loss of a massive amount of image information, as in the case  
64 of the black and white coloration procedure, which mainly requires the use of a grey-scale  
65 version of the images. For these reasons, completely automated techniques, without any  
66 coloration step, could help improve the concrete air void analysis making it faster and more  
67 reliable.

68 As for criterion settlement regarding air-void system quality in terms of frost-resistance,  
69 Powers' spacing factor  $\bar{L}$  [3], which corresponds approximatively to the maximal distance of  
70 any point in cement paste to the edge of the nearest void, remains the most used in the  
71 normative context. It is commonly considered that concrete with a  $\bar{L} \leq 200 \mu\text{m}$  is freeze/thaw  
72 immune. However, several other parameters have been proposed and studied, such as the  
73 content of micropores  $A_{300}$  and the protected paste volume (PPV) calculated following  
74 different approaches [11,16]. In [11], the presence of aggregates was partially taken into  
75 account in calculating PPV by subtracting the area of aggregates on protected paste calculated  
76 images. A comparison with the spacing factor of frost-resistant concretes was conducted, and  
77 the results suggested a better correlation between the frost resistance and the PPV than

78 between the frost resistance and the spacing factor. The authors highlighted the need for  
79 further studies and the time-consuming and challenging segmentation procedure because of  
80 the manual preparation and microscopic examination.

81 Machine Learning (ML) based techniques have been applied to various Civil Engineering  
82 problems such as concrete properties predictions like strength [17], creep [18] and shrinkage  
83 [19]. Image-related problems have also been addressed for some years, from edge detection  
84 [20] to visual crack detection and monitoring [21,22] to component detection and  
85 classification [23,24] or industrial applications like helmet use detection for construction  
86 safety [25]. ML-based techniques have also been used to supplement image information by  
87 other measurements such as chemical analysis [26] indentation measurements [27,28].  
88 Therefore, advanced image analysis techniques could help solve the issues related to air voids  
89 structure analysis and phase segmentation in concrete. In computer vision, deep learning  
90 image analysis has become popular for image analysis-related problems. Convolutional neural  
91 networks (CNN) have achieved unprecedented accuracy and efficiency in pattern recognition  
92 and semantic segmentation. Using training images, then comparing the model's error using  
93 validation images, and finally testing the model performance on a test set of images, complex  
94 CNN architectures made of successive convolutional and pooling layers have been built. For  
95 example, the Resnet architecture [29], introduced some years ago, has considerably improved  
96 CNN results in international competitions.

97 Recently, semantic segmentation CNN models have successfully addressed air voids detection  
98 problems in concrete materials petrographic analysis [30] [31]. These latter models exhibited  
99 good accuracy, but several major difficulties remain and need to be overcome before an  
100 eventual large-scale use. First, the semantic segmentation models inherently lack accuracy in  
101 distinguishing close instances, e.g., air voids in this problem, which is a major drawback  
102 because of the importance of the size distribution and location of air voids regarding

103 concrete's durability [32]. This shortcoming can be addressed using other cutting-edge CNN  
104 models like deep learning instance segmentation models such as the Mask R-CNN or the  
105 PANet model [33]. These models, based on backbones like Resnet can lead to better accuracy  
106 with a limited amount of resources because they create masks of the detected instances  
107 besides bounding boxes. Mask R-CNN [34] model has been successfully applied recently in  
108 Civil Engineering for crack inspection [35–37] after similar work done using semantic  
109 segmentation using Unet [38,39], 3D micro-tomography image analysis [40]. Various studies  
110 published up-to-date make Mask R-CNN a good candidate for industrial usage as it might  
111 show a better precision than other models such as PANet [41]. Recently, Mask R-CNN  
112 proved to be a very effective algorithm for macro-pore detection [42].

113 The present manuscript addresses the challenge of fast and accurate phase segmentation of  
114 concrete with the minimum amount of sample preparation and human bias-prone preparation  
115 and interpretation. The main objective is to demonstrate the potential of the instance  
116 segmentation technique as opposed to classic pixel-based techniques for air voids and  
117 aggregate detection in concrete prior to a potential industrial deployment of a modular model  
118 for cementitious materials with various microstructures: from normal strength, eventually  
119 with lightweight aggregates, concrete to ultra-high performance concrete, with different types  
120 of aggregates and eventually mineral substitutions (calcined clay, slag) to considerably  
121 change the concrete aspect and properties [43,44]. To this end, an extended dataset of  
122 concrete, mortar, and cement paste microscopic images is built to train two complementary  
123 instance segmentation models based on Mask R-CNN architecture to quickly and accurately  
124 detect air voids and aggregates, respectively. The accuracy of the trained model is quantified  
125 and validated on test images, and its versatility is demonstrated. Then, an inference strategy  
126 on large-scale concrete images is defined to study the aggregates and air void structure on  
127 real petrographic concrete slices. The model performance is discussed to highlight its benefits

128 and possible improvements. Finally, the Protected Paste Volume is calculated using the large-  
129 scale segmented images using a novel multi-threaded open source algorithm, and the relation  
130 with scaling-resistance is established.

131

## 132 **2. Materials and methods**

### 133 *2.1 Mix designs, samples preparation, and experimental tests*

#### 134 2.1.1 Concrete, mortar & cement paste specimens dedicated to model training

135 During the training stage, 30 concrete, mortar and cement paste specimens of 12 various  
136 compositions (8 concrete, 2 mortar, and 2 cement pastes formulations) were studied. In order  
137 to cover a wide variety of air void structures, some concrete formulations included AEA,  
138 generating an important number of air voids, while others, like self-compacting concretes  
139 (SCCs) contained a limited amount of air voids. All the concrete formulations were similar to  
140 formulations used on site, some of them to design frost-resistant concrete (XF2 or XF3  
141 according to Eurocodes) or normal to high-strength concretes with or without commonly used  
142 supplementary cementitious materials (SCM) like slag or calcined clay, giving different  
143 colors to the cement paste. Special attention was paid to the variety of the aggregates  
144 (siliceous, calcareous, granite, basalt) and their size distribution. Figure 1 illustrates the  
145 variety of the samples studied and Table 1, resp. Table 2, gives the composition of one  
146 concrete, resp. one mortar. The other formulations are not given due to confidentiality  
147 restrictions. After at least 7 days of curing, the samples were sawn in order to obtain slices:  
148  $4 \times 4 \times 1 \text{ cm}^3$  slices for cement pastes and mortars and  $10 \times 10 \times 2 \text{ cm}^3$  ones for concrete  
149 specimens. The slices were then polished with SiC paper down to SiC 4000 before image  
150 acquisition described in paragraph 2.1.3.

151

152 **Table 1.** Example of one concrete formulation ( $\text{kg}/\text{m}^3$ )

Cement	Sand 0/4	Gravel 4/10	Gravel 10/20	Water	Superplasticizer
385	850	289	640	169	1.925

153

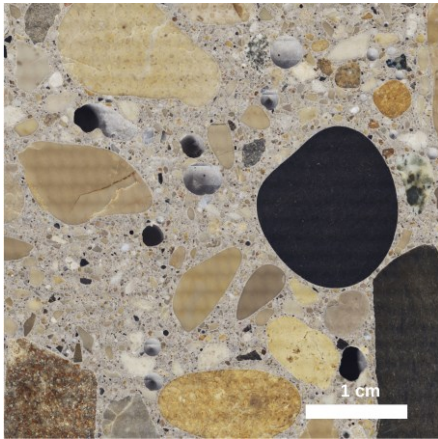
154 **Table 2.** Example of one mortar composition

Cement (kg/m <sup>3</sup> )	Calcareous Sand 0/4 (kg/m <sup>3</sup> )	Water (kg/m <sup>3</sup> )	W/C	Paste volume (%)
566	1344	270	0.43	45

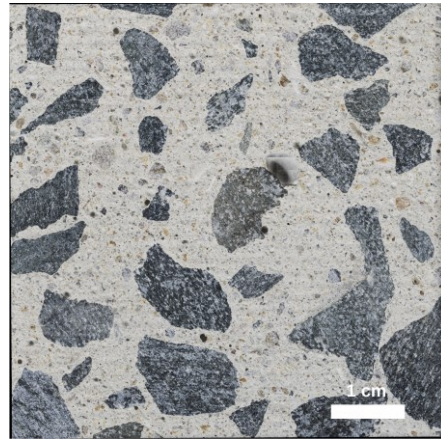
155

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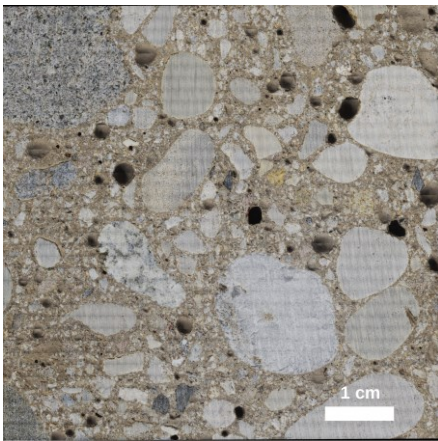
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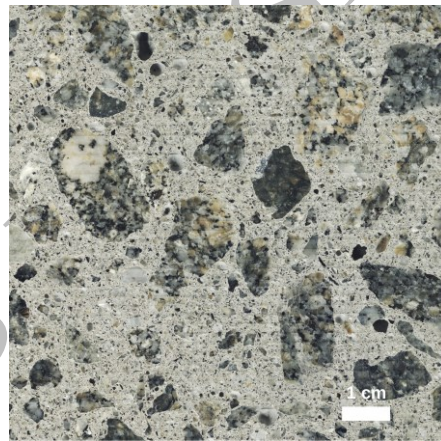
b)



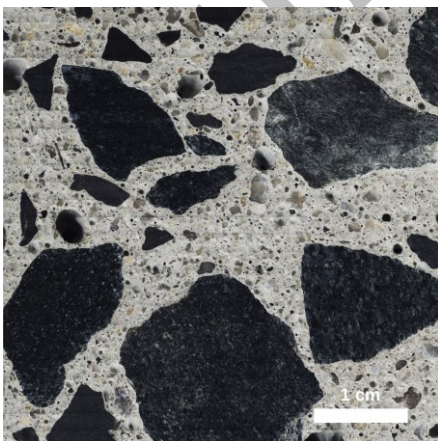
c)



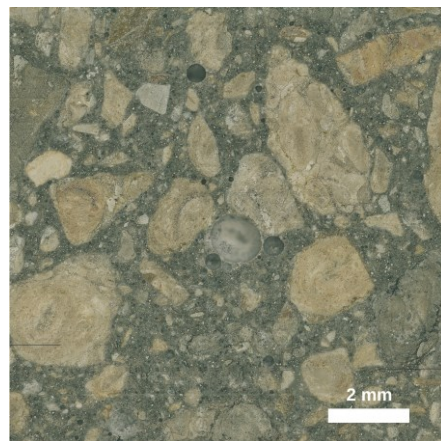
d)



e)

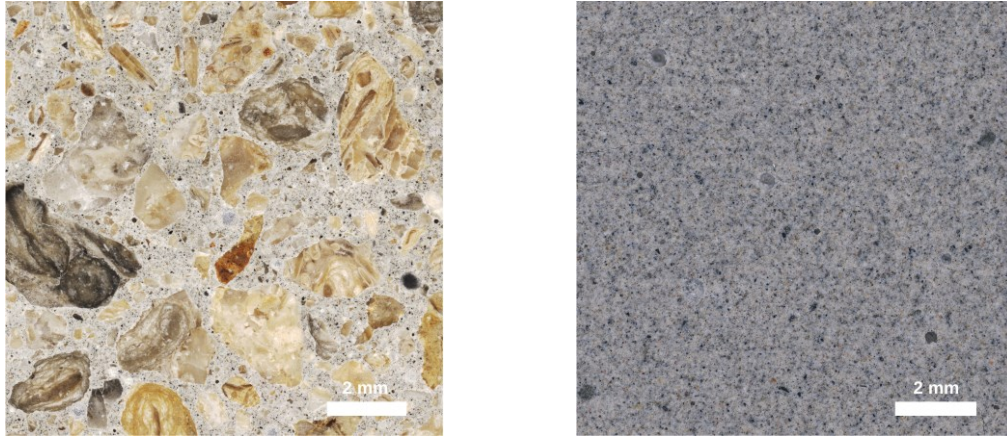


f)



g)

h)



156 **Fig 1:** Overview of some samples photographs used in the deep learning instance  
157 segmentation model: a) – e) concrete samples, f) and g) mortar samples (mortars 1 and 2), h)  
158 cement paste sample (cement paste 1).

159

#### 160 2.1.2 Specimens and experiments for model testing and validation

161 In order to test, validate the model and calculate the protected paste volume, concretes of 15  
162 different formulations were prepared. The compositions are reported in Table 3). AEA was  
163 added to the mix and with various contents. Air content and slump were measured after  
164 mixing according to NF EN 12350-7 and NF EN 12350-2 standards, respectively. Concrete  
165 samples were cast in  $15 \times 15 \times 15 \text{ cm}^3$  molds, covered with plastic foil and cured for 1 day in  
166  $20^\circ\text{C}$  and 50% relative humidity room. After 24h, the cubes were unmolded and cured in  
167 water 7 days; then some of the cubes were subjected to standard spacing factors  
168 measurements (ASTM C457 / C457M-16) and freeze-thaw tests according XP P18-420  
169 standard, others were further cured in water until testing time. Two slices were cut from the  
170 same cubic sample to measure the standard spacing factor and the air content in the solid  
171 section. Besides, scaling was measured during 56 freeze-thaw cycles on four  $15 \times 15 \times 7 \text{ cm}^3$   
172 prisms for C1 to C4, C8, C9, C10 and C12 concretes. The measured properties are  
173 summarized in Table 4.

174

175 **Table 3.** Concrete compositions (kg / m<sup>3</sup>) (add 1 and add 2 refer to admixtures, by default in  
 176 kg / m<sup>3</sup>, sometimes only in percentage relative to cement mass (%), C5a to C5d differ by the  
 177 cement provider only, C6 and C7 include CEM II/A-LL 42.5N instead of CEM I 52.5 N for  
 178 other concretes)

Name	Cement	Sand 0/4	Sand 0/1	Gravel 4/10	Gravel 10/20	Water	Add 1	Add 2	AEA	W/C
C1	385	795	-	244	701	171	3.08	0.963	0.193	0.42
C2	385	795	-	245	701	181	3.08	0.963	0.231	0.42
C3	350	880	-	918	-	162	2.275	0.350	0.420	0.44
C4	385	795	-	244	701	171	3.08	0.963	0.501	0.42
C5a-d	385	850	-	289	640	169	1.925	-	0.270	0.45
C6	320	537	249	310	641	172	4.160	0.640	0.128	0.50
C7	320	537	249	310	641	172	4.160	0.640	0.128	0.50
C8	385	750	-	300	760	155	0.35%	0.2%	0.13%	0.40
C9	385	768	-	421	610	165	1.06%	-	1.54%	0.43
C10	420	770	-	420*	530	170	3.4	1.58	0.75	0.40
C12	385	811	-	355	613	162	0.45%	0.1%	0.05%	0.42

179 \* Gravel 4/16

180

181 **Table 4.** Slump and freeze-thaw related properties of concretes (spacing factor and air content  
 182 in the solid sections are the mean values of two measurements, scaling is the mean value of  
 183 four measurements)

Name	Slump (cm)	Air content (%)	Spacing factor ( $\mu$ m)	Scaling (g/m <sup>2</sup> )
C1	16.0	3.6	411	2192

C2	15.0	4.0	382	3784
C3	3.0	4.5	302	3454
C4	11.0	4.5	310	561
C5a	20.7	11.6	132	-
C5b	13.5	9.8	142	-
C5c	9	9.2	154	-
C5d	10	9.14	155	-
C6	14.0	6.7	177	-
C7	17.0	5.2	258	-
C8	16.0	6.13	173	717
C9	0.35	7.93	115	542
C10	21.0	8.13	138	59
C11	18.0	5.3	259	-
C12	12.0	4.27	222	1570

184

### 185 2.1.3 Image acquisition of samples surface

186 2D maps of the sections surfaces were obtained using a Hirox RH-2000 3D microscope by  
187 merging hundreds of images evenly spaced along the section. The size of the equivalent field  
188 of vision was around 8-10 x 8-10 cm<sup>2</sup> for concrete samples and 3.5 x 3.5 cm<sup>2</sup> for cement paste  
189 and mortar samples. Magnification of x 50 was chosen according to the standard suggestion  
190 leading to final horizontal resolutions of the 2D projected image of 3.13 μm / pix. High-  
191 definition images of around 30000 x 30000 pix were finally obtained for concrete samples.  
192 Various parts of these images of samples described in paragraph 2.1.1, referenced as ‘raw  
193 images’ in the article, were selected to train and test the deep neural network algorithm, while  
194 images from samples described in paragraph 2.1.2 were used to test the model and compare

195 its results with manual spacing factor measurements and freeze-thaw resistance of the various  
196 concrete formulations.

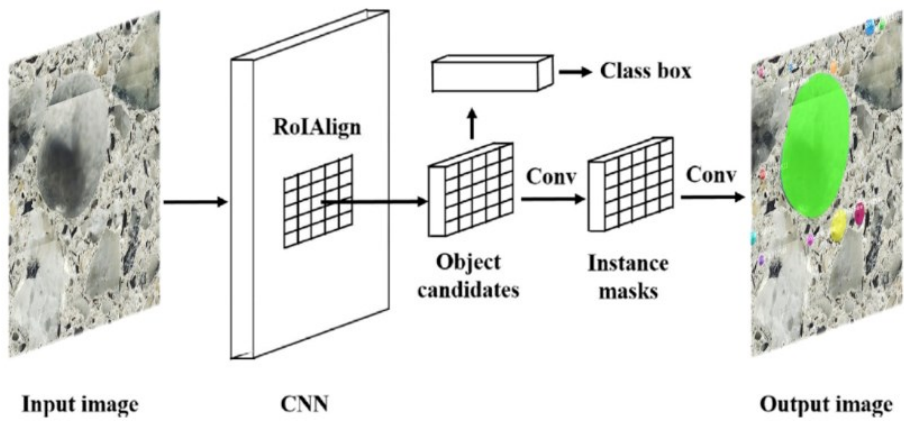
197

## 198 *2.2 CNN model*

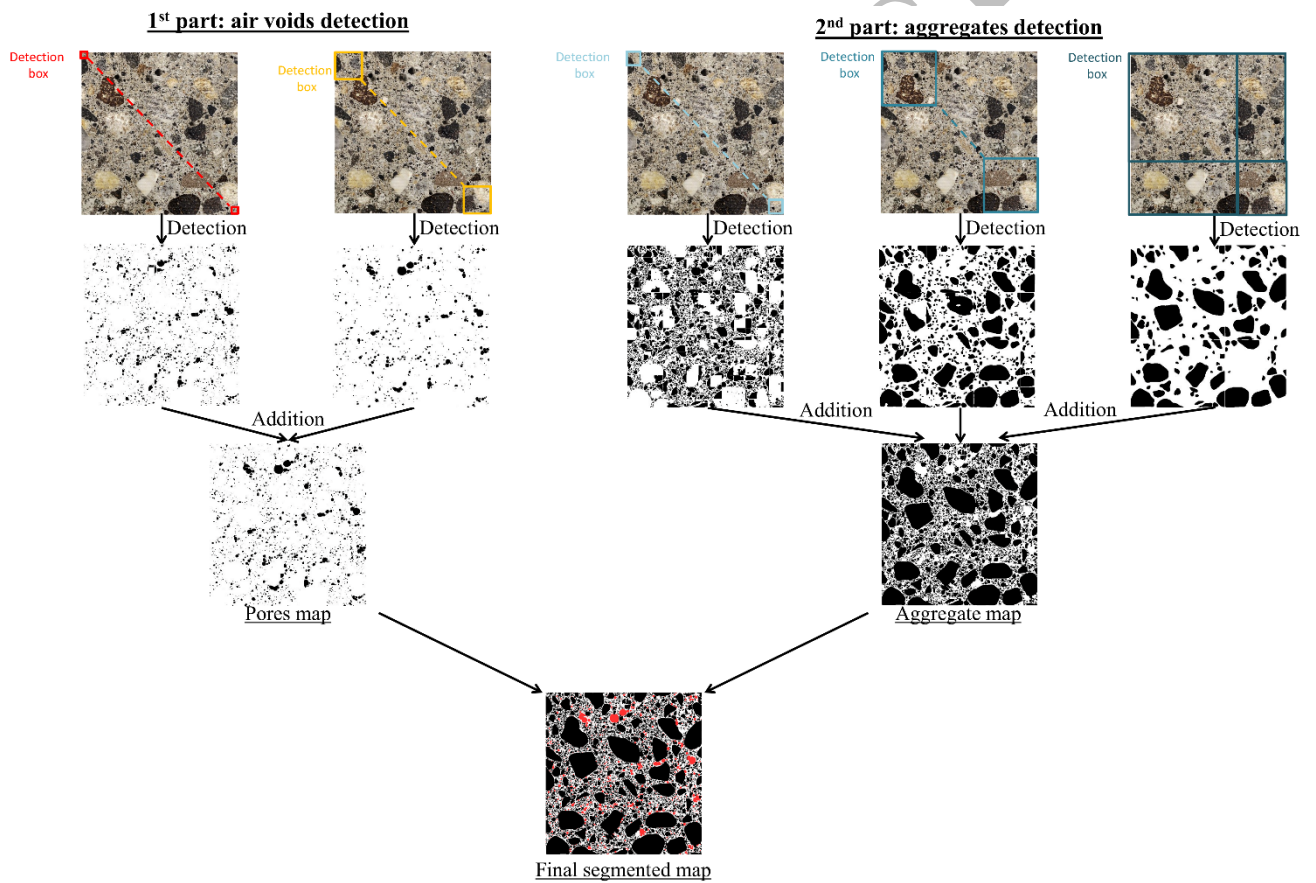
### 199 2.2.1 CNN model architecture

200 A deep learning instance segmentation model was used in order to detect circular-shape voids  
201 and polygonal-shape aggregates at a multi-pixel level. Mask R-CNN was used due to its  
202 accuracy, relatively good detection speed, and the limited number of training images needed  
203 [45]. As illustrated in Fig. 2 Mask R-CNN model is a multi-layered convolution neural  
204 network based on Tensorflow 1.14, which uses the convolution kernels to extract features and  
205 generate masks. The image is finally restored to its original size with the associated mask  
206 using upsampling strategies. Resnet-101 backbone architecture was selected due to its  
207 sensitivity.

208 Two separate Mask R-CNN, detecting air voids and aggregates respectively, were combined.  
209 Even though detection by a single model would be faster, the combination of two models  
210 enhances the model's modularity, and several other single models would be added to either  
211 the pore detection or the aggregate detection algorithm in the future. After training, which will  
212 be developed in the next section, detection could then be performed on the same concrete  
213 image with several resolutions from the original resolution to a 16 x smaller resolution, as  
214 illustrated in Fig. 3. Several detection results could be obtained using these two models and  
215 several input image resolutions: smaller instances (voids or aggregates) were detected using  
216 the high definition images, while larger instances were detected using lower resolution  
217 images. After detection, binary images of the detected instances were generated and merged  
218 in order to obtain a high resolution map of the air voids and a high-resolution map of the  
219 aggregates. The code is open-sourced at [46].



220 **Input image** **CNN** **Output image**  
 221 **Fig. 2.** Mask R-CNN architecture  
 222



223  
 224 **Fig. 3.** Combination of deep learning air voids detection algorithm and deep learning  
 225 aggregate detection algorithm for modular deep learning instance-based concrete  
 226 segmentation.

## 227 2.2.2 CNN model training

228 Subparts with sizes of 608 x 608 pix of the raw images with a resolution divided by 2, 8 or 16  
229 were used to train the aggregate-detection algorithm, while 608 x 608 pix subparts of the raw  
230 images with the original resolution and a resolution divided by 4 were used to train the air  
231 voids detection algorithm. Two sample datasets, containing 1470 images and 554 images,  
232 were built for the air voids detection and the aggregate detection algorithm respectively. The  
233 training dataset composition of the air voids detection model is described in Table 5. These  
234 datasets were divided into training, validation and test sets given the following proportions:  
235 78%, 13%, 9% for the air voids detection algorithm and 56% 22% and 22% for the aggregate  
236 detection algorithm. All the images were annotated using VGG Image Annotation software  
237 [47] at an approximate pace of 50 - 100 instances per hour (total annotating time around 30  
238 hours) by an experienced operator. Polygonal shapes were used to manually annotate the  
239 images used to train the model for aggregate detection. These annotations were divided into  
240 'sand' and 'aggregate' based on the visual size of the elements, as illustrated in Fig. 4. Similar  
241 circular annotations were done to prepare training images for the air voids detection  
242 algorithm. These circular annotations can help the model detect air voids with similar shapes.  
243 Aggregates were annotated using polygonal shapes to help the algorithm find the air void and  
244 aggregate cutting surface. In some cases, small sand particles with a diameter smaller than 30  
245  $\mu\text{m}$  have not been annotated as the model could hardly detect them due to resolution  
246 limitations.

247

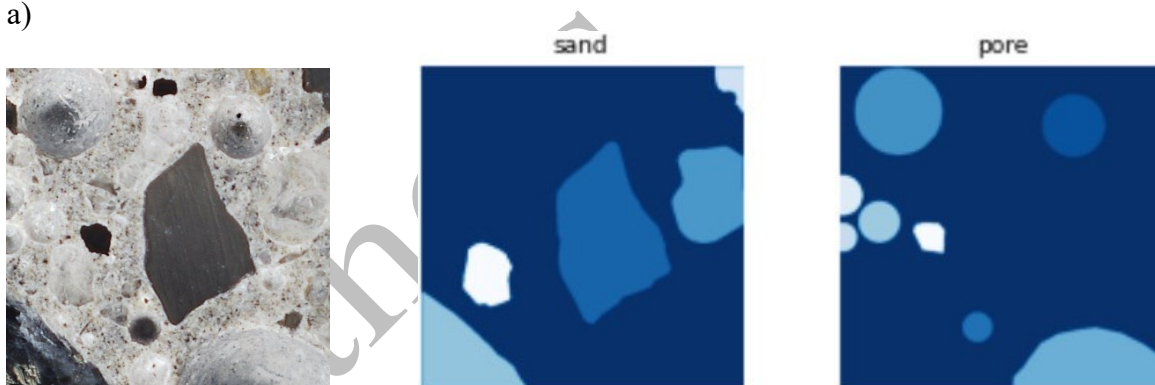
248 **Table 5.** Image dataset main characteristics

<b>Specimen type</b>	<b>Number of images</b>	<b>Magnifications</b>	<b>Resolutions (<math>\mu\text{m}/\text{pix}</math>)</b>
Cement paste 1	32	$\times 50, \times 25, \times 12.5$	3.13, 6.27, 12.54

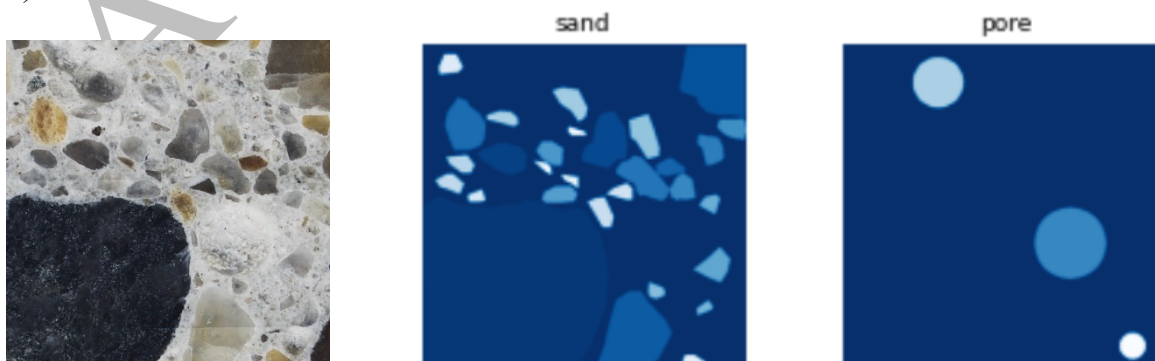
Cement paste 2	19	$\times 50, \times 25, \times 12.5$	3.13, 6.27, 12.54
Mortar 1	210	$\times 50, \times 12.5$	3.13, 6.27
Mortar 2	188	$\times 50, \times 12.5$	3.13, 6.27
Concrete 1	59	$\times 50$	3.13
Concrete 2	52	$\times 50$	3.13
Concrete 3	129	$\times 50, \times 12.5$	3.13, 6.27
Concrete 4	350	$\times 50, \times 25, \times 12.5$	3.13, 6.27, 12.54
Concrete 5	121	$\times 50, \times 25, \times 12.5$	3.13, 6.27, 12.54
Concrete 6	125	$\times 50, \times 25$	3.13, 6.27
Concrete 7	105	$\times 50$	3.13
Concrete 8	80	$\times 50$	3.13

249

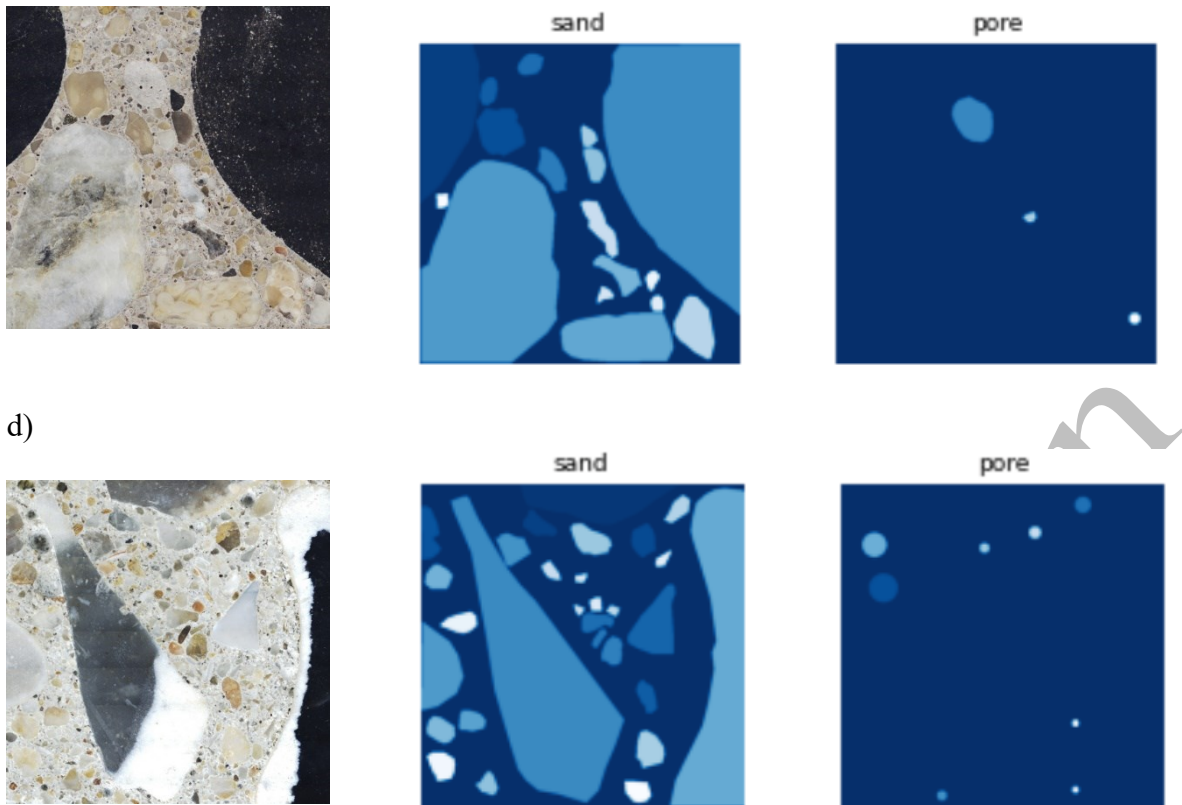
a)



b)



c)



250 **Fig. 4.** Training images for the aggregates detection model (sand and aggregates in light blue  
 251 shades or white and unannotated portions in dark blue)

252

253 Data augmentation has been used to generate more training images artificially. Three  
 254 techniques were used in a random order using the ImgAug package [48]: horizontal flip,  
 255 vertical flip, and multiplication to generate brighter or darker images.

256 Both models were trained using commercial GPU (Nvidia RTX 2080 Ti, 11 Go GDDR6) as  
 257 follows: initial weights from COCO dataset were used then, first, during stage 1 of training,  
 258 the head layers were trained during 125 epochs (250 steps/epoch) to build a good model  
 259 adapted to air voids detection quickly (but not optimized regarding low-level features), then,  
 260 during the stage 2 of training, all the layers except the first four were trained during 125 more  
 261 epochs to tune almost all the weights of the Resnet-101 model, and finally, during the last  
 262 stage, all the layers were trained during ten extras steps. The best model regarding the mean  
 263 average precision (mAP) calculated on the test set was selected among the ten last ones.

264 Training parameters were adjusted to allow a fast convergence. These parameters are given in  
 265 Table 6.

266 **Table 6.** Training parameters of the Mask R-CNN model for aggregate and air voids detection

<b>General parameters</b>	<b>Aggregates</b>	<b>Air voids</b>
Batch size	4	4
Image dimension	512 x 512	512 x 512
Image resize mode	Crop	Crop
Min confidence detection	0.7	0.7
Validation steps	50	50
Learning momentum	0.9	0.9
Weight decay	0.0001	0.0001
<b>Training stage 1</b>		
Epochs	150	125
Steps per epoch	250	250
Learning rate	0.001	0.001
<b>Training stage 2</b>		
Epochs	125	500
Steps per epoch	250	250
Learning rate	0.0005	0.0005
<b>Training stage 3</b>		
Epochs	10	10
Steps per epoch	250	250
Learning rate	0.0001	0.0005

267

### 268 2.2.3 CNN model validation

269 Model results on the test images were first manually checked to assess the detection quality of  
270 hardly visible instances (small or irregular air voids, aggregates with a color similar to the  
271 surrounding cement paste, or granite aggregates with very irregular color patterns). Then,  
272 after training, mean average precisions (mAP) for IoU values between 0.5 and 0.95 (mAP  
273 @0.5-0.95) of the air voids detection algorithm and the aggregates detection algorithm were  
274 computed on test images. The general definition for the Average Precision (AP) is the area  
275 under the precision-recall curve for a given image. mAP is defined as follows:

$$mAP = \frac{\sum_{q=1}^Q AveP(q)}{Q} \quad (1)$$

276 where  $Q$  is the number of queries in the set and  $AveP(q)$  is the average precision (AP) for a  
277 given query,  $q$ .

278 All the precision - recall curves can be generated for the test images but a more visual idea of  
279 the quality of the prediction can be obtained by plotting the predictions vs. the ground truth  
280 definition. mAP indicator has the advantage of being discriminative enough to classify  
281 modern models precisely. The intersection over union (IoU) parameter has also been  
282 calculated for some of the final models.

### 283 2.3 Protected Paste Volume (PPV) and distance-to-air-void calculation using segmented 284 images

#### 285 2.3.1 Distance-to-air-void calculation considering aggregates effect

286 Several algorithms were implemented in Julia language using a multi-threaded approach to  
287 analyze the high-definition pores and aggregates segmented images [49]. First, the distance  
288 between any point in the cement paste to the nearest void was calculated considering the  
289 aggregate presence. The median distance-to-air-void in the entire image was then saved in

290 order to be compared to experimentally measured spacing factor values. The algorithm can be  
291 summarized as follows:

292 -locate all the pixels at the periphery of the pore,

293 - compute the distance of their neighbors if they are not aggregates and select the minimum  
294 distance for each of these pixels,

295 - repeat the procedure using these pixels as inputs and stop when 99.5% of the distances have  
296 been found.

297 Several input segmented image resolution were used to find to the best compromise between  
298 precision of the calculated distances and computational time. The best results were obtained  
299 using segmented images with a resolution of  $24 \mu\text{m} / \text{pix}$  and a size around  $3500 \times 3500 \text{ pix}$   
300 (raw images with a height and a width divided by 8). The distance-to-air-void calculation can  
301 be performed in approximately 100-150s using such parameters and a 10-cores commercial  
302 desktop computer.

### 303 2.3.2 Protected Paste Volume (PPV) calculation

304 The protected paste volume defined in [11] was calculated based on the segmented concrete  
305 images by the deep learning model. PPV represents the proportion of points in the paste for  
306 which the straight line distance to an air void is smaller than  $200 \mu\text{m}$ . PPV was calculated  
307 using Julia and PPV values were saved to be compared to experimental spacing factors. High  
308 definition maps of the protected paste areas were finally generated for all the concrete  
309 samples. The number of air voids in the high definition images has been numerically  
310 calculated to complement PPV calculation by using ImageJ software.

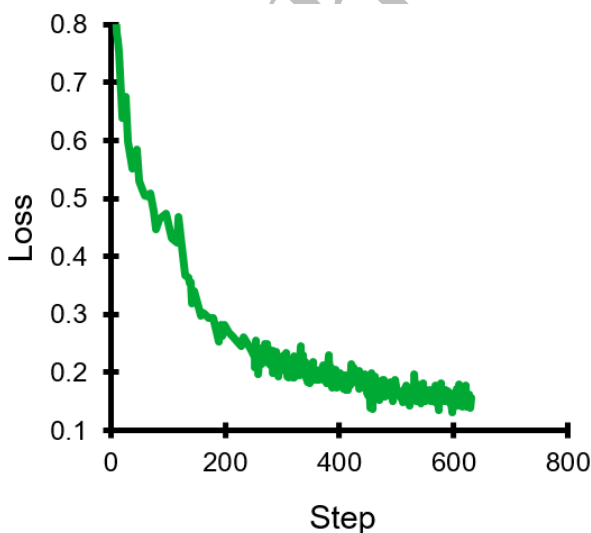
### 311 3. Results and discussion

#### 312 3.1 CNN model training results

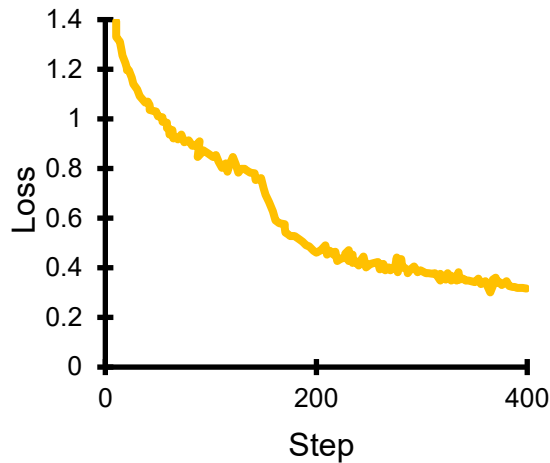
313 The loss curves recorded during training are displayed in Fig. 5. A two-step decrease can be  
314 observed for both models as expected due to the first two stages during training. The loss  
315 reduction rate becomes relatively small after 300 to 400 steps (75k to 100k epochs), as the  
316 subsequent improvement could mainly be attributed to model overfitting (slow decrease of  
317 mAP calculated on the test set with increasing training). Indeed, a maximum mean average  
318 precision (mAP) (calculated on test images) of 0.5829 has been obtained after 154 steps (38.5  
319 k epochs) for the aggregate detection model, while a maximum mAP of 0.677 has been  
320 obtained after 275 steps (68.75k epochs) for the air voids detection model. These results  
321 confirm that the Mask R-CNN model is slightly slower to train than other models[31], but the  
322 obtained mAP values are on par with precisions of around 0.65 obtained on very large  
323 datasets in image recognition reference studies [34], highlighting the potential of the model.

324

a)



b)



325 **Fig. 5.** Loss curves obtained during training: loss value vs step number (each step corresponds  
 326 to 250 epochs) for a) the air voids detection model, and b) the aggregates detection model.

327

### 328 3.2 CNN model accuracy on test images

#### 329 3.2.1 Results of the air voids detection model

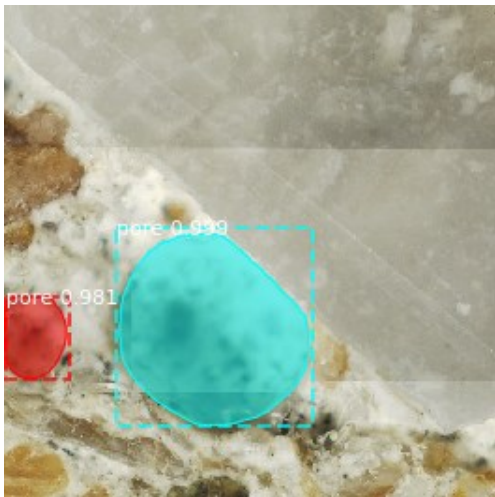
330 Results of the model can be analyzed using the predictions on the test images in order to  
 331 identify the most common shortcomings of the algorithm and its advantages compared to  
 332 previously reported performances on similar algorithms.

333 Fig 6 illustrates the testing performance of the air voids detection model on 608 x 608 pix  
 334 images of different mortar and concrete samples with various types of aggregates with x 50  
 335 magnification or an equivalent x 12.5 magnification (obtained dividing the size of x 50 by 4).

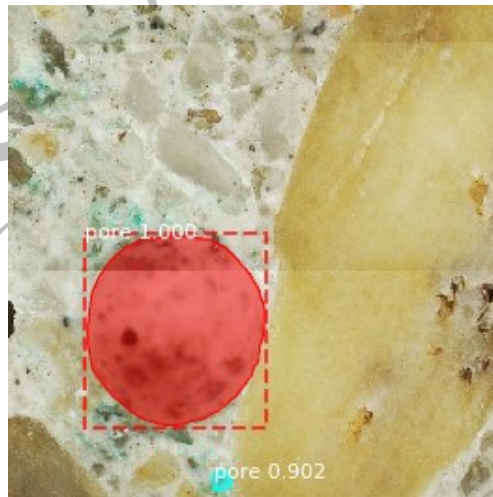
336 The Mask R-CNN model performs well even in challenging situations and is able to detect the  
 337 vast majority of the air voids with high confidence levels indicated by scores close to the  
 338 masks in Fig. 6. As illustrated in Fig. 6.a) and 6. b) the model can detect non-circular air voids  
 339 close to grey-color aggregates while a majority of the identified air voids used for training  
 340 were declared of circular shape. Various air voids sizes can also be detected in the same  
 341 image as illustrated by Fig. 6 c) due to an appropriate number of regions of interest (ROI)

342 used during training. The model is also robust regarding air voids detection in aggregates, as  
343 illustrated in Fig. 6 d) though this problem is relatively common in segmentation models  
344 previously described in the literature. Finally, because of the variety of the images in the  
345 training set, the model prediction capacity is relatively good in the case of poorly prepared  
346 images with relatively rough surfaces and illumination issues as illustrated by Fig. 6 g) and h).  
347 Last but not least, because the model is an instance-based model, it is able to distinguish very  
348 close air voids sharing some borders as exemplified by red and green air voids in Fig. 6 h).  
349 This capacity may potentially lead to a better estimation of the air voids size distribution in  
350 samples.

a)

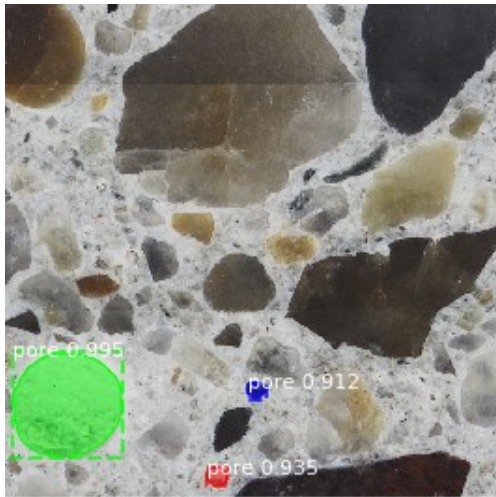


b)

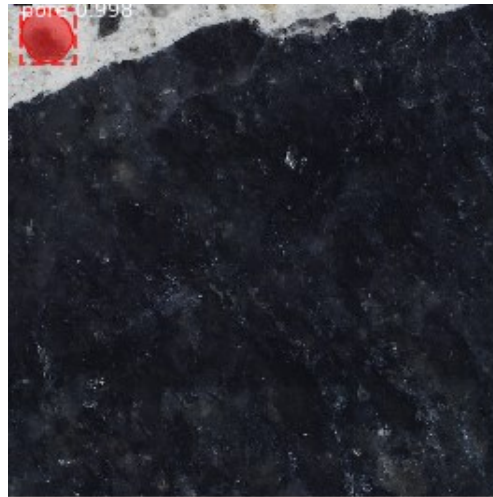


c)

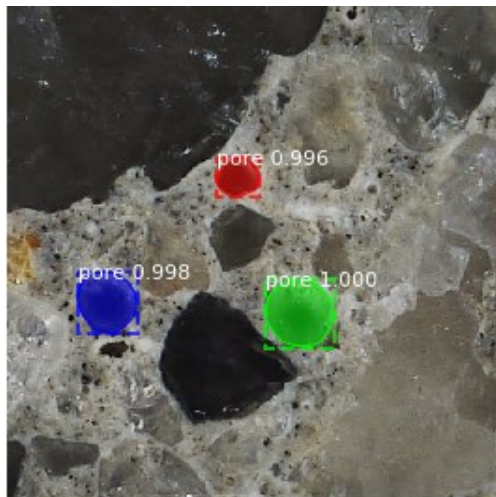
d)



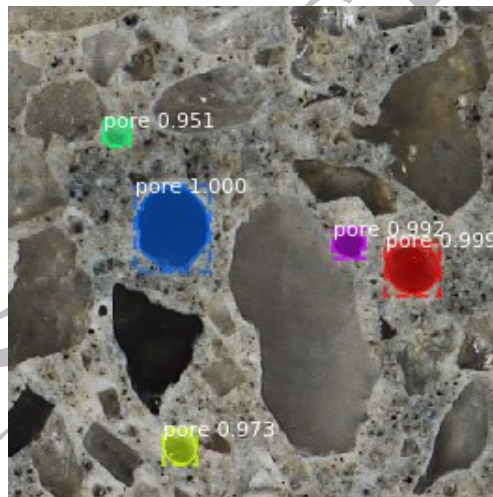
e)



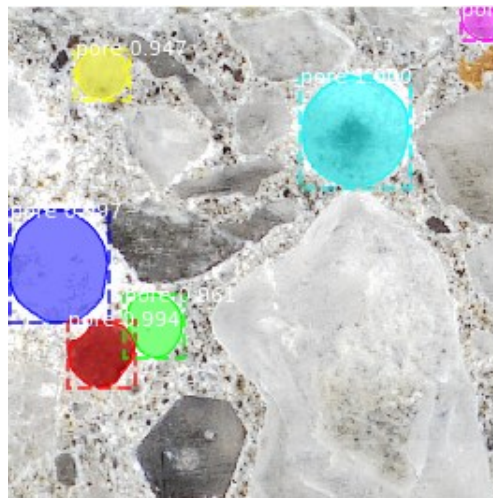
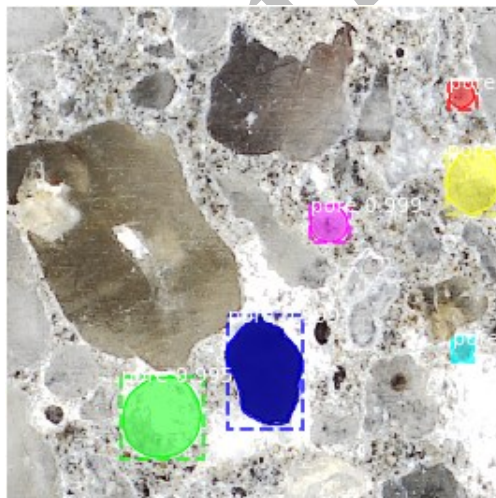
f)



g)



h)



351 **Fig. 6.** Inference results of the instance segmentation model on various test images

352

353 The accuracy of the model can be measured using the mean average precision indicator on the  
 354 test set. The general definition for the Average Precision (AP) is the area under the precision-  
 355 recall curve for a given image. All the precision - recall curves can be generated for the test  
 356 images, but a more visual idea of the quality of the prediction can be obtained by plotting the  
 357 predictions vs the ground truth definition as illustrated in Fig. 7 As it can be seen, the  
 358 predictions closely match the ground truth manual definition of the air voids leading to a good  
 359 precision even at relatively high IoU values. Computing the various precisions of the  
 360 prediction for IoU values between 0.5 and 0.95, an average prediction value AP @0.50-0.95  
 361 can be calculated for each image as illustrated in Table 7.

362

363 **Table 7.** Average precision for different IoU values for one typical test image.

Average precision at given IoU	Value
AP @0.50:	1.000
AP @0.55:	1.000
AP @0.60:	1.000
AP @0.65:	1.000
AP @0.70:	1.000
AP @0.75:	1.000
AP @0.80:	1.000
AP @0.85:	1.000
AP @0.90:	0.500
AP @0.95:	0.500
AP @0.50-0.95:	0.900

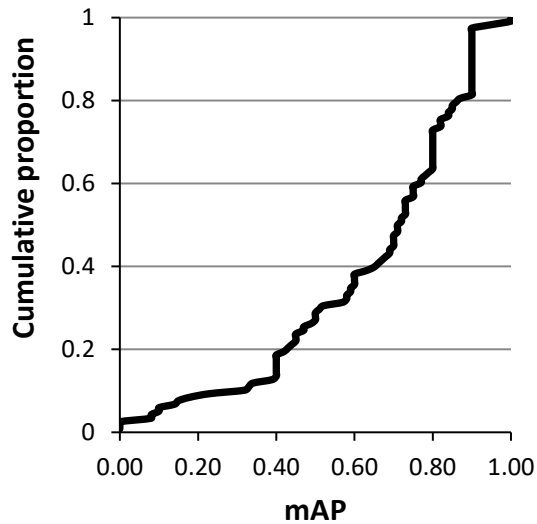
364

365 The final mean average precision of the model can then be calculated using the average  
366 precision of all the images. The cumulative distribution of the mAP values on the test set after  
367 230 steps (eg 57.5 k epochs) is reported in Fig. 7 a. The model exhibits mAP value higher  
368 than 0.5 for 70% of the test images and only 13.5% of the images are associated with a mAP  
369 smaller than 0.4. After 230 training steps, a mAP value of 0.6452 is obtained over the entire  
370 test set which is on par with mAP values reported for other datasets [27].

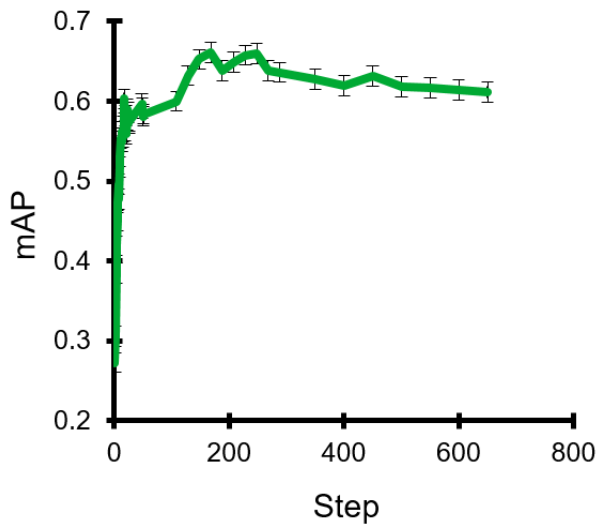
371 The mean average precision obtained on the test set can be calculated depending on the  
372 duration of the training stage. As illustrated in Fig. 7 b), mAP quickly increased as the top  
373 layers of the model were trained during the first stage of training. Then, during the second  
374 stage of training (starting after 125 steps), the precision of the model initially increased until  
375 275 training steps and a maximum mAP of 0.677 has been obtained with one model while  
376 several models exhibited mAP above 0.65 with a training duration between 230 and 2100  
377 steps. However, with more training steps (above 300 steps), even though the loss curve  
378 decreased, mAP started decreasing slightly and dropped to values close to 0.61 after 630  
379 training steps because of the model overfitting. Therefore, the later results about the model  
380 application will be based on the best model, considering mAP on the test set, obtained after  
381 244 training steps in stage 1 and 2 and 2 training steps of all the model layers in step 3 (see  
382 Table 6).

383

a)



b)



384 **Fig. 7.** Calculated mean average precisions of the model: a) typical cumulative distribution of  
 385 the mean average precision (mAP@0.5-0.95) over the test set after 230 training steps; b) mAP  
 386 on the test set depending on the training duration (1 step = 250 epochs).

387

### 388 3.2.2 Results of the aggregate detection model

389 Additionally, several predictions of the aggregate model have been displayed alongside  
 390 original 'ground truth' manual annotations in Fig. 8 for eight test images with various mAP.

391 First, it can be observed that the model correctly find the various types of aggregates in the

392 test images even for relatively small mAP of around 0.3 (Fig. 8 a and b), proving its  
393 versatility in detecting aggregates in a wide range of cementitious materials. The aggregate  
394 model could also detect some air voids with a relatively good precision even if the air voids  
395 specific model is more precise. Based on the analysis of the precision of the model on all the  
396 test images, it has been observed that the model exhibited very good results when the contrast  
397 between the aggregates, air voids and cement paste was high, for example in the case of light  
398 grey paste and dark aggregates.

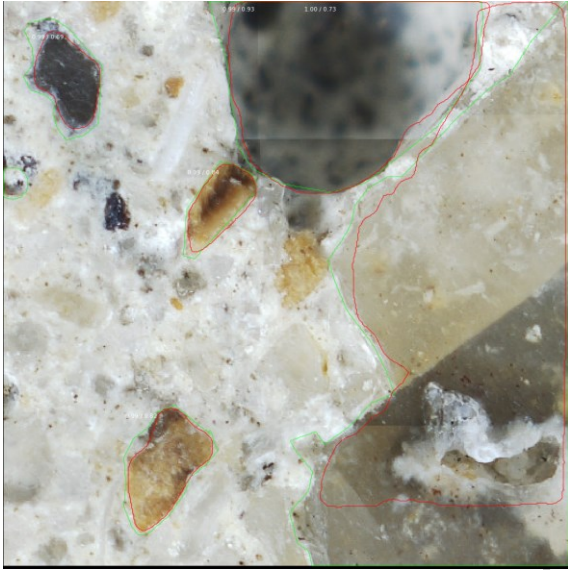
399 Fig 8 a) and b) illustrate the major shortcomings of the aggregate model during detection that  
400 occur for less than 8% of test images. As illustrated in Fig. 8 a), aggregates located at the  
401 border of images or cut by the image border were likely not entirely detected, and, as shown  
402 in Fig. 8 b), small bright aggregates or sand particles inside bright cement paste could not be  
403 detected at all in images with medium magnification. The first shortcoming was effectively  
404 reduced in high-definition concrete images by selecting several image magnifications (see  
405 paragraph 2.2.1) while the second shortcoming could be eliminated using higher  
406 magnification images.

407 Median precision results are illustrated in Fig. 8 c) and d). These figures show that the  
408 aggregate model can detect the annotated aggregates very precisely from bright to dark  
409 aggregates, eventually with some local defects (here indentation imprints). In the mortar  
410 image, only a very limited amount of aggregates has not been found by the algorithm while,  
411 interestingly, the model correctly detected some aggregates in the normal strength concrete  
412 image even though they have not been manually annotated.

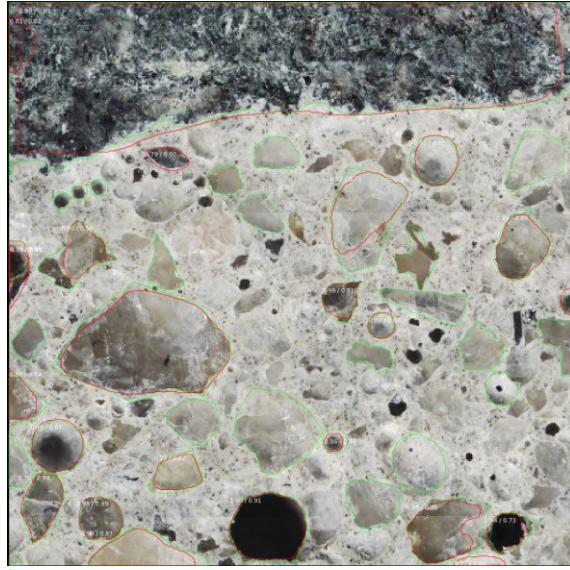
413 The aggregate model exhibited relatively good mAP of around 0.45 to 0.5 on ultra-high  
414 strength slag-based concrete and lightweight aggregate concrete as illustrated in Fig. 8 e) and  
415 f) respectively. Most of the basalt aggregates were detected in the ultra-high performance  
416 concrete image while some small quartz particles were not detected. Concerning the

417 lightweight aggregate image, the instance-segmentation model correctly captured the  
418 aggregates, both their shape and size, without being influenced by the inner porosity leading  
419 to segmented images with a clear distinction between aggregates, air voids and cement paste  
420 as opposed to pixel-based models [31].

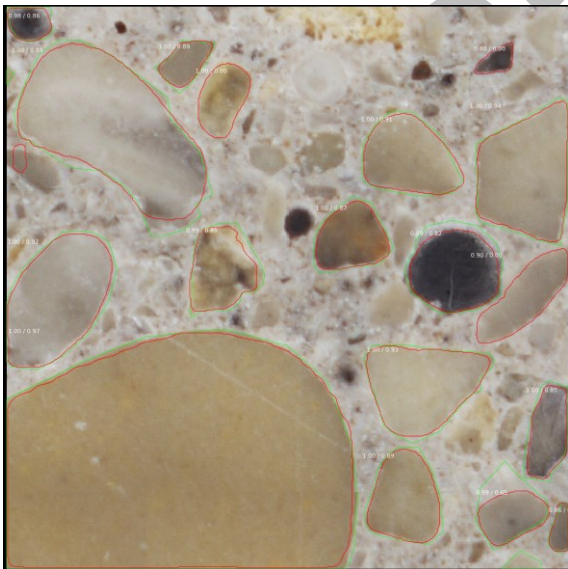
a)



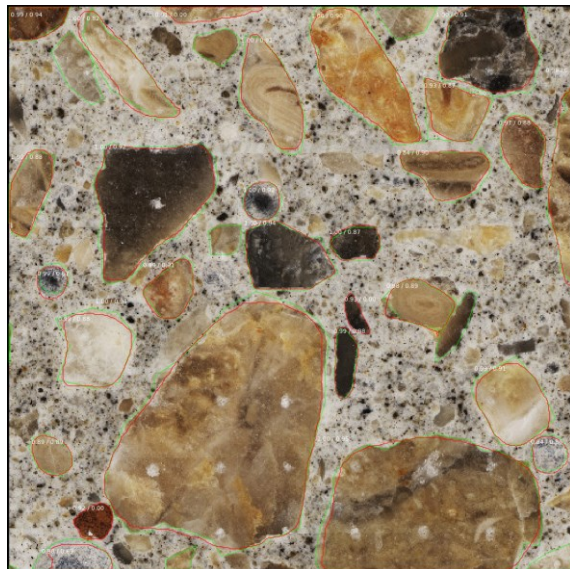
b)



c)



d)

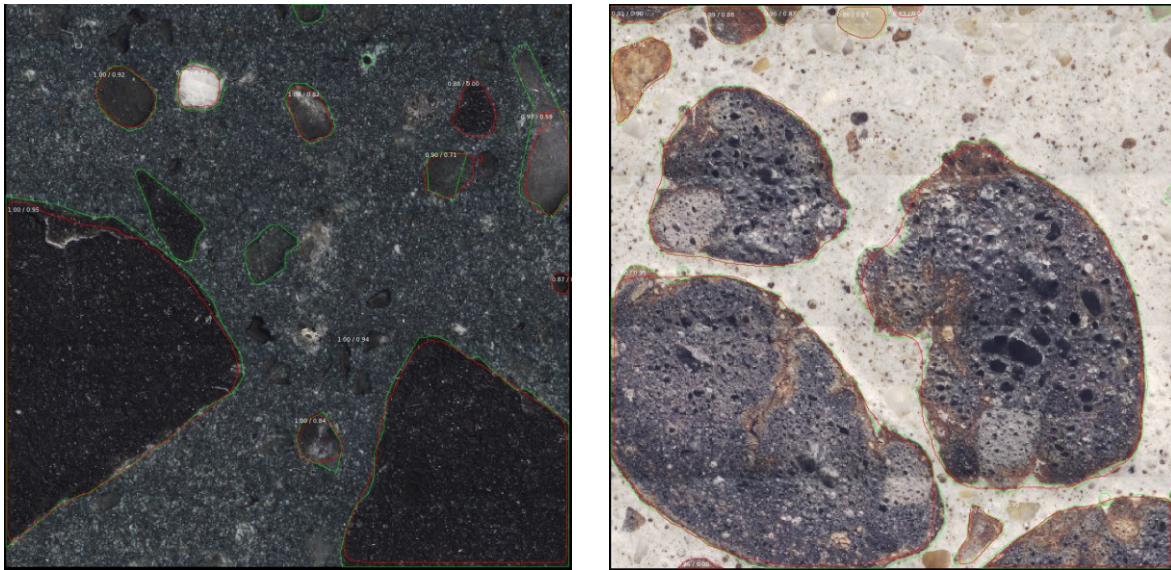


e)



f)





421 **Fig 8.** Typical predictions on test images with various mean average precisions (mAP): a)  
 422 prediction on a  $\times 50$  normal strength concrete image with mAP 0.313; b) prediction on a  $\times 12.5$   
 423 normal strength concrete image with mAP 0.292; c) prediction on a  $\times 50$  normal strength  
 424 concrete image with mAP 0.589; d) prediction on a  $\times 50$  high strength mortar image with mAP  
 425 0.571 (partly covered with indentation imprints on the bottom part); e) prediction on a  $\times 12.5$   
 426 ultra-high strength slag-blended concrete image with mAP 0.447; f) prediction on a  $\times 12.5$   
 427 lightweight aggregate concrete image with mAP 0.49 (red contours: predictions, green  
 428 contours: annotations)

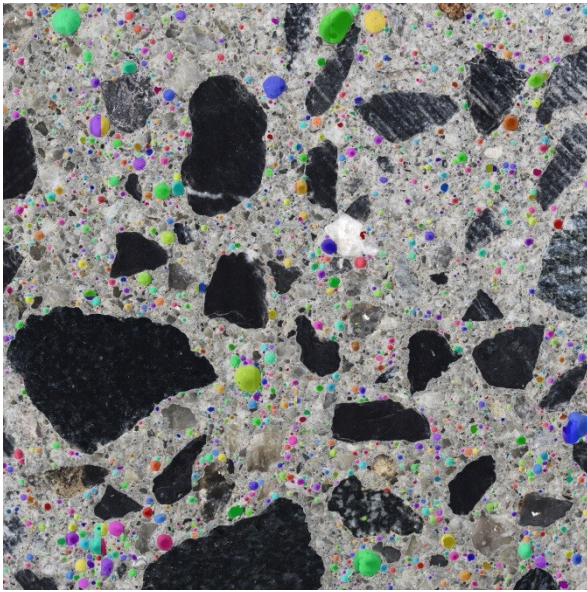
429

### 430 3.3 Application of the air voids detection model on concrete petrographic slices

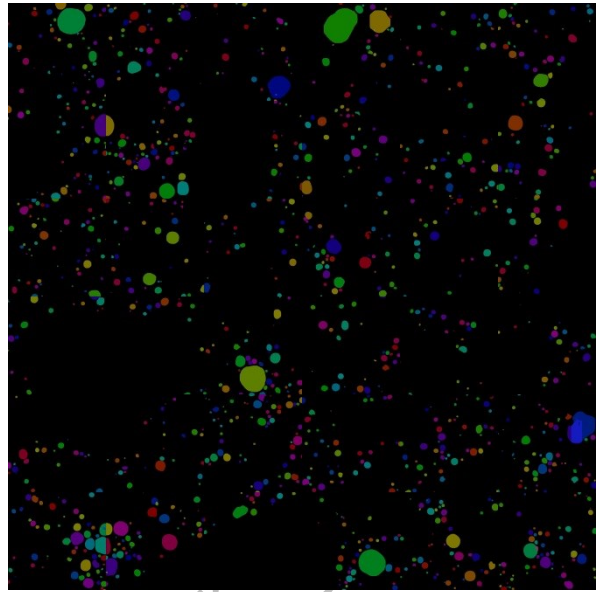
431 Using the air voids model alone and the aforementioned strategy, the model can be applied on  
 432 a wide variety of large-scale concrete petrographic slices. Fig. 9 exposes the results obtained  
 433 on an unknown concrete slice from an industrial partner with a size of approximately  
 434 60 mm x 60 mm. Fig. 9 a) and b) detail the prediction results obtained in the high resolution  
 435 reconstructed  $\times 50$  magnification image. As it can be seen, the model localizes various air  
 436 voids of several sizes and does not predict the presence of air voids on the aggregates (even in  
 437 the case of multicolored or white aggregates in the central part of the image, nor gray and

438 brown sand particles). However, due to the split of the images in several parts, some large air  
439 voids overlapping between several images may not be accurately detected. For this reason, the  
440 model is run on a reduced-size image as illustrated in Fig. 9 c) and d) in order to associate one  
441 instance to the largest air void. The model detects these air voids with a good accuracy but,  
442 due to the image size reduction, the model applied on a reduced-size image cannot detect the  
443 small air voids. Thus, the predicted air void content drops from 7.48 % for the full-size image  
444 to 3.94 % for the reduced-size image. However, thanks to the implemented strategy  
445 associating the detection on full-size and reduced-size image, the detection of air voids with  
446 various sizes with minimal diameters of around some pixels is possible (around 10-20  $\mu\text{m}$ )  
447 and a final air void content of 7.76 % is predicted which is on par with the industrially-  
448 measured air content. Further analysis can be performed, and the algorithm's superior  
449 performance compared to manual contrast enhancement methods has been highlighted in  
450 another study [50].

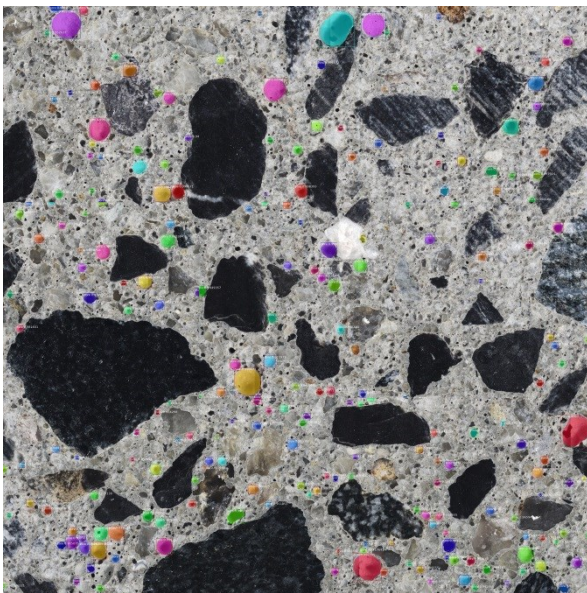
a)



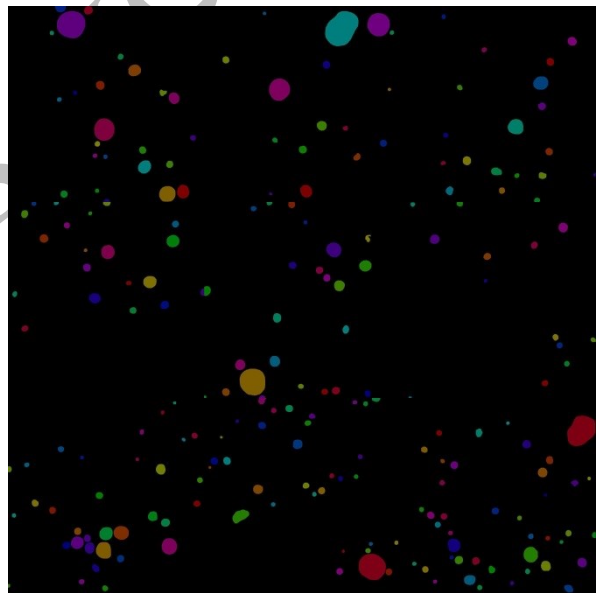
b)



c)



d)



451 **Fig. 9.** Inference result on a high-definition concrete slice image: a) full-size raw image and  
452 detected air voids instances, b) mask of the detected instances in the full-size image, c)  
453 reduced-size raw image and detected air voids instances, b) mask of the detected instances in  
454 the reduced-size image  
455

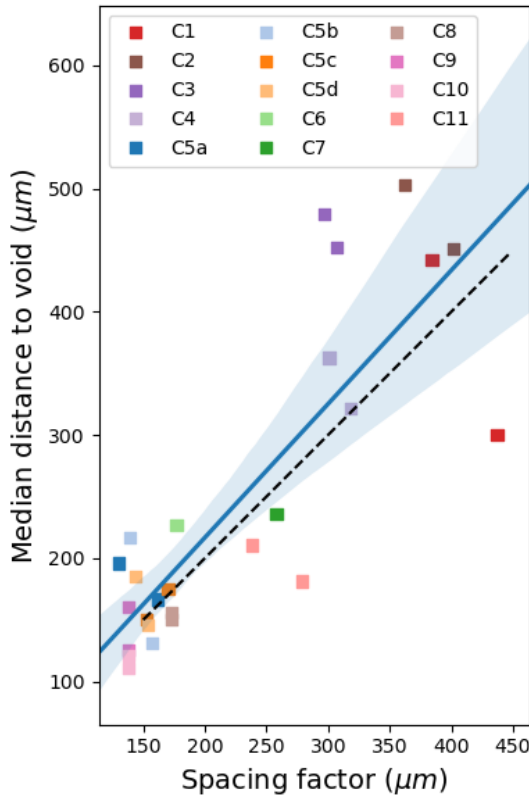
456 3.4 Application of the modular deep learning model: interest of Protected Paste Volume  
457 (PPV) and distance-to-air-void calculation to assess freeze-thaw resistance

458 3.4.1 Modular deep learning algorithm performance and automated distance-to-air-void  
459 calculation

460 Combining the air voids and aggregate detection algorithms, the modular CNN model enables  
461 fast and accurate calculation of the distance of any point in the cement paste to the closest air  
462 void. The overall algorithm performance has been evaluated on concrete high-definition  
463 images. A mean mAP value of 0.66 was obtained, and the IoU calculated on several concrete  
464 images ranged from 0.855 to 0.910, highlighting outstanding results on par with pixel-based  
465 segmentation techniques.

466 The median distance-to-air-void has been extracted from the cumulative curves as illustrated  
467 in Fig. 10. As expected based on Power's theory, a positive correlation has been found as the  
468 median distance-to-air-void gradually increases for L factor ranging from around 130  $\mu\text{m}$  to  
469 more than 430  $\mu\text{m}$ . The best-fitting linear regression is found close to the identity line,  
470 demonstrating the model capacity for distance-to-air-void calculation. Interestingly, the  
471 median distance-to-air-void is found to be slightly larger than the experimentally measured L  
472 factor. This could be explained by the fact that some very small air bubbles might not have  
473 been detected as some samples with L factors smaller than 200  $\mu\text{m}$  have slightly higher  
474 median distance-to-air-void, but this finding could more probably be attributed to samples  
475 with larger spacing factors (top right of the figure) as the algorithm takes into account the  
476 presence of aggregates which increase the larger distances to air voids as water should turn  
477 around the aggregate before reaching an air void. Finally, although a relatively large number  
478 of samples has been observed, it is worth noting that the 95 % confidence interval is rather  
479 extended and no clear distinction can be made between samples with spacing factors smaller  
480 than 300  $\mu\text{m}$  while some of them might be frost resistant while others no. Last but not least,

481 although providing novel information and filling the gap between experimental and analytical  
 482 models, cumulative distribution functions calculation is computationally expensive as all the  
 483 distances to air voids might be calculated first. Therefore, other indicators should be found to  
 484 better characterize concrete samples air void structure.



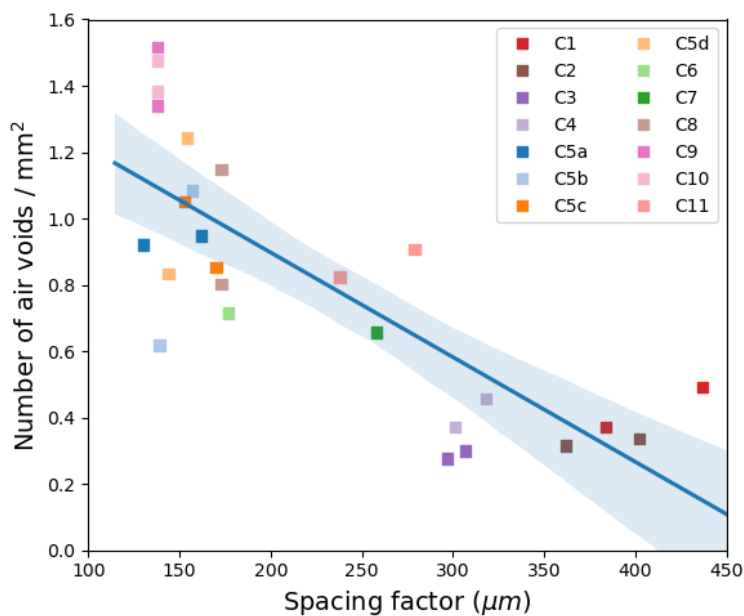
485  
 486 **Fig. 10.** Distance-to-air-void vs measured spacing ratio (dashed line represents identity line,  
 487 blue line linear regression and light blue zone 95 % confidence interval)

488  
 489 3.4.2 Automated Protected Paste Volume (PPV) calculation and correlation with spacing  
 490 factor

491 The number of air voids per unit area, which is an easily computable parameter, has been  
 492 compared with experimentally spacing factor for each concrete sample. As illustrated in  
 493 Fig. 11, the number of air voids per unit area detected by the deep learning model ranged from  
 494 around 0.3 air void per square millimeter to more than 1.2 air void per square millimeter on

495 average which illustrate the large variability of this parameter. The number of air voids per  
 496 unit area exhibits an inverse correlation with the spacing factor. The correlation can be  
 497 approximated by a linear regression confirming the capacity of the model to detect air voids  
 498 and their critical role in the spacing factor determination. A relatively thin confidence interval  
 499 has been found but the hardly physically interpretable values of the number of air voids per  
 500 unit area limit the usage of this indicator.

501



502

503 **Fig. 11.** Evolution of air voids content regarding experimentally measured spacing factor

504

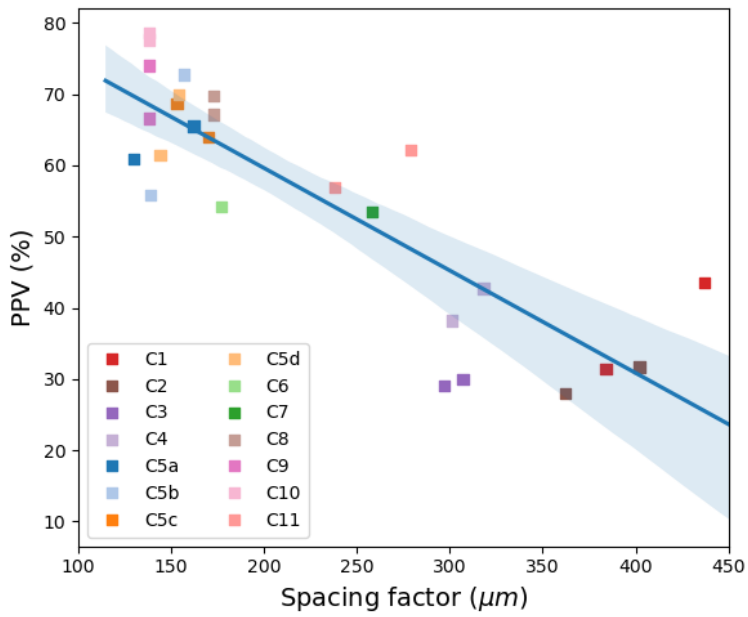
505 For this reason, the calculation of the PPV has been performed based on the high definition  
 506 segmented maps provided by the deep learning model. In Fig. 12-a), PPV has been  
 507 represented regarding experimentally measured spacing factor. The calculated PPV is in good  
 508 agreement with the values reported in the literature based on the measure of air voids in  
 509 concrete samples prepared manually following a time-consuming procedure from the authors'  
 510 opinion[11]: PPV values calculated based on the high definition images segmented using the  
 511 deep learning algorithm ranged from 28% to 73%. The model is therefore able to considerably

512 accelerate the 2D calculation of PPV and the total computational time on a desktop computer  
513 has been measured to be around 5 to 10 minutes (including the deep learning segmentation  
514 and the multi-threaded PPV calculation). Therefore PPV can be calculated almost exclusively  
515 numerically (excepting for the polishing step of the sample) and then provide a quantitative  
516 and discriminative criteria between various concrete samples.

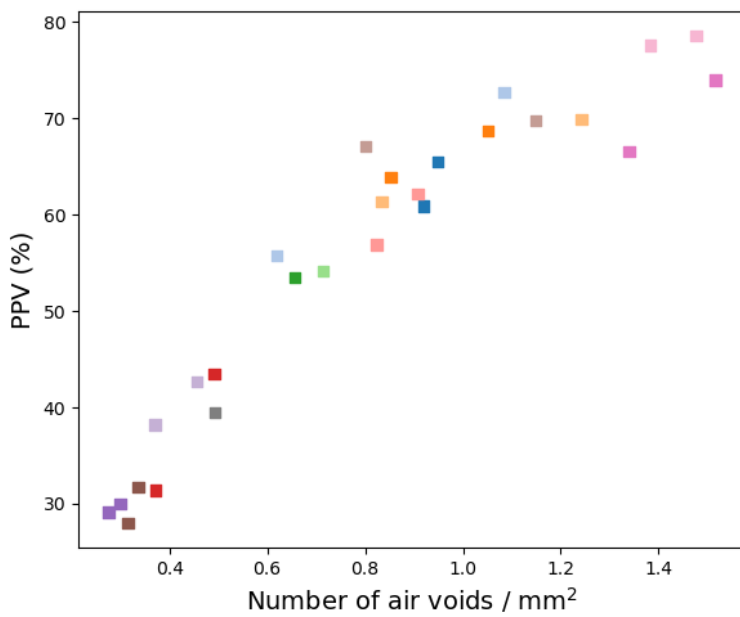
517 Numerically calculated PPV evolution regarding spacing factor has been approximated using  
518 a linear regression. Samples with spacing factors smaller than around 200  $\mu\text{m}$  have been  
519 found to exhibit PPV higher than 54 % which is close to the 80% limit supposed to be freeze-  
520 thaw protective [32]. On the contrary, for samples exhibiting experimental spacing factors  
521 higher than 300  $\mu\text{m}$ , calculated PPV has been found to be smaller than 43 % with some values  
522 around 30 % or less. The freeze-thaw resistance of such samples would then be relatively  
523 poor. Interestingly, a critical spacing factors range can be evidenced around 200  $\mu\text{m}$  to  
524 300  $\mu\text{m}$  as the PPV abruptly drops between samples with spacing factors close to 270  $\mu\text{m}$  and  
525 PPV higher than 54% and samples with spacing factors close to 290  $\mu\text{m}$  with PPV smaller  
526 than 30 - 40%. Therefore, a critical attention must be paid to concrete samples with spacing  
527 factors around 200  $\mu\text{m}$  to 300  $\mu\text{m}$  and PPV calculation would help assessing their potential  
528 freeze-thaw resistance.

529 A positive correlation has been evidenced between PPV and the number of air voids per unit  
530 area as illustrated in Fig. 12-b). A linear trend can be observed for PPV smaller than 65-70%,  
531 then PPV might potentially ceil as no difference could be clearly established between samples  
532 with a high number of air void. Indeed a sample with more than 1.2 void /  $\text{mm}^2$  has been  
533 found to exhibit a PPV of around 70% close to samples with a smaller number of air voids of  
534 around 1.1 void /  $\text{mm}^2$ . This observation confirms that overlapping air void do not increase  
535 PPV and might not lead to a better freeze-thaw resistance (while decreasing the mechanical  
536 properties).

a)



b)



537

538 **Fig. 12.** PPV calculation of the concrete samples: a) regarding the experimental L factor, b)

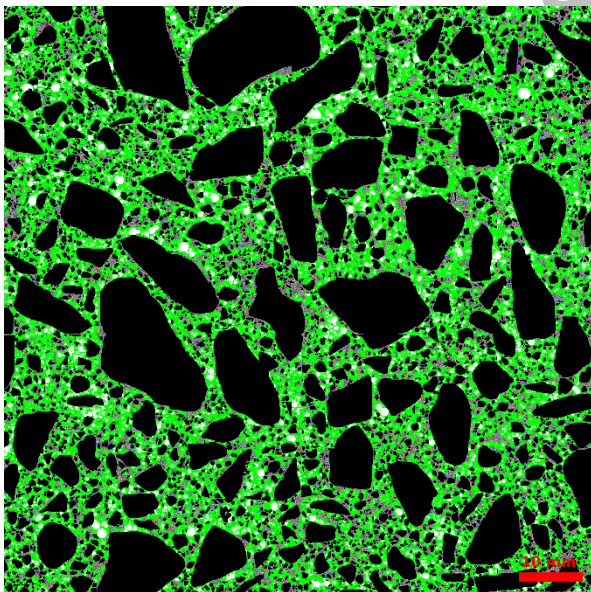
539 regarding the number of air void per unit area.

540

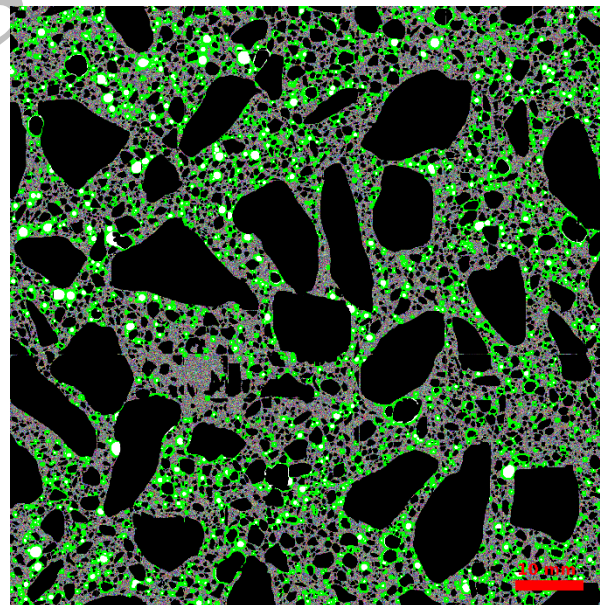
541 In order to visualize protected paste regions and locate unprotected areas, high definition  
542 maps have been generated as illustrated in Fig. 13. A clear distinction can be observed  
543 between concrete samples exhibiting high and low PPV values. The extent of the green  
544 'protected' paste considerably varies. In samples with high PPV values as illustrated in Fig 13  
545 a), only a small portion of the cement paste cannot be considered as protected. Based on the  
546 visual observation of the generated maps, some of the unprotected zones have been located  
547 around the large aggregates confirming the importance of sand-to-aggregate ratio adjustment.  
548 Conversely, in samples with low PPV values, larger unprotected area have been found far  
549 from the large aggregates in large cement paste portions. In this case a lack of air voids in the  
550 paste, relatively far from any potentially influencing particle, might be mostly responsible of  
551 low PPV values.

552

a)



b)



553 **Fig. 13.** Protected Paste Volume maps : a) concrete with a high PPV ratio, b) concrete with a  
554 low PPV ratio (green zone denotes the protected paste)

555

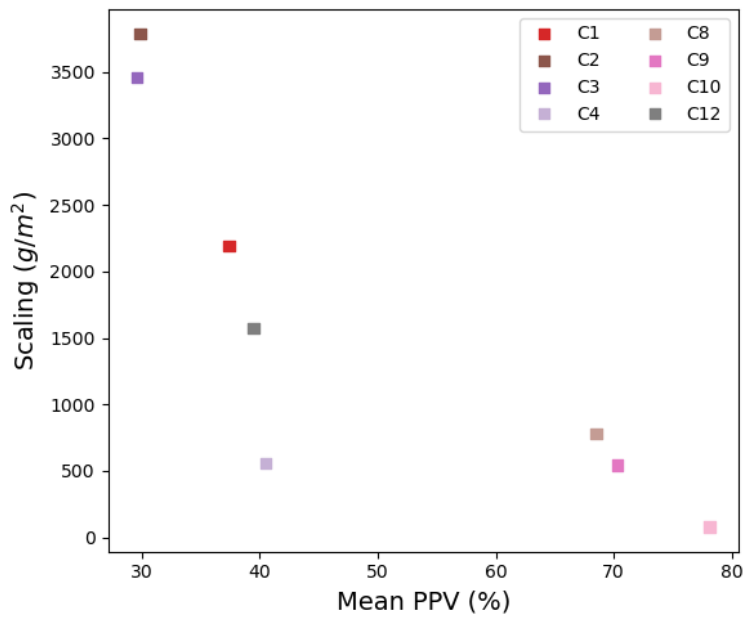
556 3.4.3 Comparison of experimental scaling values to numerical PPV and experimental spacing  
557 factor

558 Fig. 14 represents measured scaling values of C1 to C4 concretes relatively to the numerically  
559 calculated mean PPV value or to the experimentally measured mean spacing factor, both  
560 calculated using two slices per concrete. It can be observed that the scaling resistance almost  
561 linearly decreased as regards to the numerically calculated mean PPV values starting from  
562 scaling values close to 3500 g/m<sup>2</sup> at low PPV around 30 % (C2 and C3) to 581 g/m<sup>2</sup> at  
563 intermediate PPV around 40 % for C4 concrete. Interestingly, C1 concrete which included the  
564 smallest amount of AEA did not generate more scaling than C2 and C3 concretes. This result  
565 could have be anticipated calculating PPV value based on the microscopic images as an  
566 almost linear trend has been found between numerically-calculated PPV and experimental  
567 scaling values.

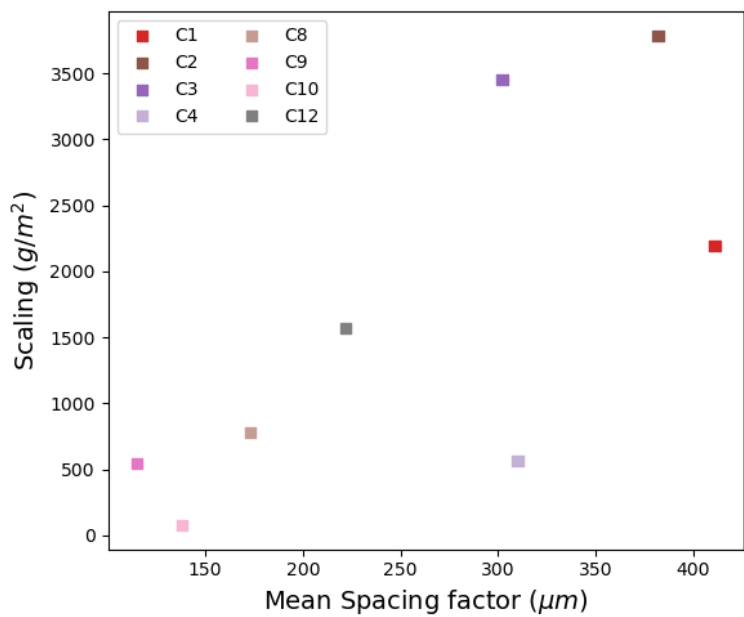
568 Conversely, as illustrated in Fig. 14 b, scaling values are not correlated with spacing factor for  
569 C1 to C4 concrete. C1 concrete exhibited the highest spacing factor while it did not lead to the  
570 highest scaling. Based on the generated PPV image, this could be due to an effective  
571 repartition of the air voids in the concrete volume even though a limited amount of AEA has  
572 been used. Moreover, C3 and C4 spacing factors were similar (around 310 μm) while their  
573 scaling behavior was found very different. Their scaling resistance cannot be explained by the  
574 experimentally spacing factor alone, while 2D-based numerically calculated PPV was found  
575 sensitive to the different air void distribution which is probably influenced by the difference  
576 in the maximum aggregate size in this case.

577

a)



b)



578

579 **Fig. 14.** Measured scaling values concretes relatively to: a) numerically calculated mean PPV  
 580 value using the deep learning algorithm, b) the experimentally measured mean spacing factor.

581

## 582 4. Conclusions

583 The main objective of this work was to demonstrate the potential of modular deep learning for  
584 civil engineering applications. To this end, a modular deep learning-based instance  
585 segmentation algorithm of concrete microscopic images has been developed. The algorithm is  
586 based on two CNN models dedicated to air voids and aggregate detection. Secondly, these  
587 two CNN models have been combined to perform the segmentation of high-definition  
588 concrete microscopic images. Then, the model has then been applied to freeze-thaw-related  
589 air void system characterization, namely Protected Paste Volume (PPV) and distance-to-air-  
590 void calculation. The results can be summarized as follows:

- 591 - The modular CNN model composed of two complementary Mask R-CNN  
592 architectures can be trained using distinct image sets of various magnifications.
- 593 - The model can effectively detect air voids and aggregates considering their usual  
594 shape and generate segmented images containing separated instances. Due to the  
595 region-based algorithm, segmented images correctly represent the various instances  
596 sizes and shapes because of the mask usage (conversely to pixel-level based  
597 segmentation algorithms).
- 598 - The large-scale predictions of the air voids model are in good agreement with the fresh  
599 state air void content and the ASTM 457-measured air void content due to the capacity  
600 of the model to detect both small air voids and large air voids.
- 601 - The high definition-segmented images with aggregates and air-void instances can be  
602 used to quantify 2D parameters concerning freeze-thaw resistance of concrete such as  
603 Protected Paste Volume (PPV) and distance-to-air-void. While using a modern  
604 programming language and a multi-threaded approach, these parameters can be  
605 effectively calculated on commercial computers in some minutes.

- 606 - Algorithm speed and precision facilitate the analysis of concrete sections. Based on  
607 the analysis of 20 sections, it has been shown that very good correlations can be found  
608 between the calculated 2D parameters and experimentally measured spacing factors.
- 609 - Based on the PPV calculated values, a critical spacing factor range has been evidenced  
610 around 200  $\mu\text{m}$  to 300  $\mu\text{m}$ . PPV can sharply decrease in this spacing factor range to  
611 around 80%, allegedly freeze-thaw protective, to around 40%, characterizing non-  
612 resistant concretes.
- 613 - Numerically calculated PPV using the modular deep learning algorithm is correlated  
614 with experimental freeze-thaw scaling resistance of moderately resistant and non-  
615 resistant concrete.

616 Future research directions towards improving the algorithm capabilities include the very  
617 small air voids detection and the delimitation of the small aggregates and air voids  
618 boundaries. Overall, this study might open up novel research paths regarding the potential  
619 modularity enhancement of deep learning models. Moreover, the precision of such  
620 models, which allowed a precise quantification of freeze-thaw parameters in this study,  
621 might help accelerate research towards novel findings.

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## 625 **References**

- 626 [1] J.Elsena, N.Lensa, J.Vynckea, T.Aarreb, D.Quenardc, V.Smolej, Quality assurance and  
627 quality control of air entrained concrete, Cement and Concrete Research. 24 (1994) 1267–  
628 1276.
- 629 [2] T.C. Powers, A working hypothesis for further studies of frost resistance of concrete, in:  
630 Proceedings of the American Concrete Institute, 1945: pp. 245–272.

- 631 [3] T.C. Powers, Willis, T. F., The air requirement of frost resistant concrete., in: Proceedings  
632 of the Highway Research Board, 1950: pp. 184–211.
- 633 [4] M. Pigeon, P. Plante, Study of cement paste microstructure around air voids: Influence  
634 and distribution of soluble alkalis, *Cement and Concrete Research*. 20 (1990) 803–814.  
635 [https://doi.org/10.1016/0008-8846\(90\)90014-O](https://doi.org/10.1016/0008-8846(90)90014-O).
- 636 [5] K.A. Snyder, Numerical test of air void spacing equations, *Advanced Cement Based  
637 Materials*. 8 (1998) 28–44. [https://doi.org/10.1016/S1065-7355\(98\)00007-8](https://doi.org/10.1016/S1065-7355(98)00007-8).
- 638 [6] D.D. Magura, Air void analyzer evaluation, Federal Highway Administration, 1996.  
639 <https://rosap.ntl.bts.gov/view/dot/42581> (accessed July 30, 2021).
- 640 [7] ASTM C457 / C457M-16, Standard Test Method for Microscopical Determination of  
641 Parameters of the Air-Void System in Hardened Concrete, ASTM International, West  
642 Conshohocken, PA. (2016). <https://doi.org/10/ghdg8z> (accessed July 30, 2021).
- 643 [8] EN 480-11, Admixtures for concrete, mortar and grout. test methods. Determination of air  
644 void characteristics in hardened concrete, European Committee for Standardization.  
645 (2005).  
646 [https://www.cstc.be/homepage/index.cfm?cat=services&sub=standards\\_regulations&pag](https://www.cstc.be/homepage/index.cfm?cat=services&sub=standards_regulations&pag)  
647 [=list&art=search&id=CSTC96276](https://www.cstc.be/homepage/index.cfm?cat=services&sub=standards_regulations&pag) (accessed July 30, 2021).
- 648 [9] J. Elsen, Automated air void analysis on hardened concrete Results of a European  
649 intercomparison testing program, *Cement and Concrete Research*. (2001) 5.
- 650 [10] A.-S. Dequiedt, M. Coster, L. Chermant, J.-L. Chermant, Distances between air-voids  
651 in concrete by automatic methods, *Cement and Concrete Composites*. 23 (2001) 247–254.  
652 [https://doi.org/10.1016/S0958-9465\(00\)00055-X](https://doi.org/10.1016/S0958-9465(00)00055-X).
- 653 [11] J. Wawrzeńczyk, W. Kozak, Protected Paste Volume (PPV) as a parameter linking the  
654 air-pore structure in concrete with the frost resistance results, *Construction and Building  
655 Materials*. 112 (2016) 360–365. <https://doi.org/10.1016/j.conbuildmat.2016.02.196>.
- 656 [12] U.H. Jakobsen, C. Pade, N. Thaulow, D. Brown, S. Sahu, O. Magnusson, S. De Buck,  
657 G. De Schutter, Automated air void analysis of hardened concrete — a Round Robin  
658 study, *Cement and Concrete Research*. 36 (2006) 1444–1452.  
659 <https://doi.org/10.1016/j.cemconres.2006.03.005>.
- 660 [13] K. Peterson, J. Carlson, L. Sutter, T. Van Dam, Methods for threshold optimization for  
661 images collected from contrast enhanced concrete surfaces for air-void system  
662 characterization, *Materials Characterization*. 60 (2009) 710–715.  
663 <https://doi.org/10/c49mwc>.
- 664 [14] Y. Song, R.M. Damiani, C. Shen, D.I. Castaneda, D.A. Lange, A 3D petrographic  
665 analysis for concrete freeze-thaw protection, *Cement and Concrete Research*. 128 (2020)  
666 105952. <https://doi.org/10.1016/j.cemconres.2019.105952>.
- 667 [15] T. Fantous, A. Yahia, Air-void characteristics in highly flowable cement-based  
668 materials, *Construction and Building Materials*. 235 (2020) 117454.  
669 <https://doi.org/10.1016/j.conbuildmat.2019.117454>.
- 670 [16] R.E. Philleo, A Method for Analyzing Void Distribution in Air-Entrained Concrete,  
671 *CCA*. 5 (1983) 128–130. <https://doi.org/10.1520/CCA10263J>.
- 672 [17] I.-C. Yeh, Modeling of strength of high-performance concrete using artificial neural  
673 networks, *Cement and Concrete Research*. 28 (1998) 1797–1808.  
674 [https://doi.org/10.1016/S0008-8846\(98\)00165-3](https://doi.org/10.1016/S0008-8846(98)00165-3).
- 675 [18] M. Liang, Z. Chang, Z. Wan, Y. Gan, E. Schlangen, B. Šavija, Interpretable  
676 Ensemble-Machine-Learning models for predicting creep behavior of concrete, *Cement  
677 and Concrete Composites*. (2021) 104295.  
678 <https://doi.org/10.1016/j.cemconcomp.2021.104295>.
- 679 [19] B. Hilloulin, V.Q. Tran, Using machine learning techniques for predicting autogenous  
680 shrinkage of concrete incorporating superabsorbent polymers and supplementary

- 681 cementitious materials, *Journal of Building Engineering*. 49 (2022) 104086.  
682 <https://doi.org/10.1016/j.jobe.2022.104086>.
- 683 [20] F. Fueten, J. Mason, An artificial neural net assisted approach to editing edges in  
684 petrographic images collected with the rotating polarizer stage, *Computers &  
685 Geosciences*. 33 (2007) 1176–1188. <https://doi.org/10/cr46mh>.
- 686 [21] Y.J. Cha, W. Choi, O. Büyüköztürk, Deep Learning-Based Crack Damage Detection  
687 Using Convolutional Neural Networks, *Computer-Aided Civil and Infrastructure  
688 Engineering*. 32 (2017) 361–378. <https://doi.org/10.1111/mice.12263>.
- 689 [22] S. Dorafshan, R.J. Thomas, M. Maguire, Comparison of deep convolutional neural  
690 networks and edge detectors for image-based crack detection in concrete, *Construction  
691 and Building Materials*. 186 (2018) 1031–1045.  
692 <https://doi.org/10.1016/j.conbuildmat.2018.08.011>.
- 693 [23] F. Guo, Y. Qian, Y. Wu, Z. Leng, H. Yu, Automatic railroad track components  
694 inspection using real-time instance segmentation, *Computer-Aided Civil and  
695 Infrastructure Engineering*. (2020) mice.12625. <https://doi.org/10/ghdj6k>.
- 696 [24] J.D. Lau Hiu Hoong, J. Lux, P.-Y. Mahieux, P. Turcry, A. Ait-Mokhtar,  
697 Determination of the composition of recycled aggregates using a deep learning-based  
698 image analysis, *Automation in Construction*. 116 (2020) 103204.  
699 <https://doi.org/10/ghdg8g>.
- 700 [25] A.H. Rubaiyat, T.T. Toma, M. Kalantari-Khandani, S.A. Rahman, L. Chen, Y. Ye,  
701 C.S. Pan, Automatic detection of helmet uses for construction safety, in: 2016  
702 IEEE/WIC/ACM International Conference on Web Intelligence Workshops (WIW),  
703 IEEE, 2016: pp. 135–142. <https://doi.org/10/gg7wh6>.
- 704 [26] W. Wilson, L. Sorelli, A. Tagnit-Hamou, Automated coupling of NanoIndentation and  
705 Quantitative Energy-Dispersive Spectroscopy (NI-QEDS): A comprehensive method to  
706 disclose the micro-chemo-mechanical properties of cement pastes, *Cement and Concrete  
707 Research*. 103 (2018) 49–65. <https://doi.org/10.1016/j.cemconres.2017.08.016>.
- 708 [27] B. Hilloulin, M. Robira, A. Loukili, Coupling statistical indentation and microscopy to  
709 evaluate micromechanical properties of materials: Application to viscoelastic behavior of  
710 irradiated mortars, *Cement and Concrete Composites*. 94 (2018) 153–165.  
711 <https://doi.org/10.1016/j.cemconcomp.2018.09.008>.
- 712 [28] B. Hilloulin, M. Lagrange, M. Duvillard, G. Garioud,  $\epsilon$ -greedy automated indentation  
713 of cementitious materials for phase mechanical properties determination, *Cement and  
714 Concrete Composites*. (2022) 104465.  
715 <https://doi.org/10.1016/j.cemconcomp.2022.104465>.
- 716 [29] K. He, X. Zhang, S. Ren, J. Sun, Deep Residual Learning for Image Recognition, in:  
717 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, Las  
718 Vegas, NV, USA, 2016: pp. 770–778. <https://doi.org/10/gdcfkn>.
- 719 [30] S. Zhou, W. Sheng, Z. Wang, W. Yao, H. Huang, Y. Wei, R. Li, Quick image analysis  
720 of concrete pore structure based on deep learning, *Construction and Building Materials*.  
721 208 (2019) 144–157. <https://doi.org/10.1016/j.conbuildmat.2019.03.006>.
- 722 [31] Y. Song, Z. Huang, C. Shen, H. Shi, D.A. Lange, Deep learning-based automated  
723 image segmentation for concrete petrographic analysis, *Cement and Concrete Research*.  
724 135 (2020) 106118. <https://doi.org/10.1016/j.cemconres.2020.106118>.
- 725 [32] A. Molendowska, J. Wawrze, Development of the Measuring Techniques for  
726 Estimating the Air Void System Parameters in Concrete Using 2D Analysis Method,  
727 *Materials*. 13 (2020) 428. <https://doi.org/10.3390/ma13020428>.
- 728 [33] S. Liu, L. Qi, H. Qin, J. Shi, J. Jia, Path Aggregation Network for Instance  
729 Segmentation, in: 2018 IEEE/CVF Conference on Computer Vision and Pattern

730 Recognition, IEEE, Salt Lake City, UT, 2018: pp. 8759–8768.  
731 <https://doi.org/10.1109/CVPR.2018.00913>.

732 [34] K. He, G. Gkioxari, P. Dollár, R.B. Girshick, Mask R-CNN, in: 2017 IEEE  
733 International Conference on Computer Vision (ICCV), Venice (Italy), 2017: pp. 2980–  
734 2988. <https://doi.org/10/gfghjd>.

735 [35] B. Kim, S. Cho, Image-based concrete crack assessment using mask and region-based  
736 convolutional neural network, *Struct Control Health Monit.* (2019) e2381.  
737 <https://doi.org/10.1002/stc.2381>.

738 [36] N. Patel, S. Shinde, F. Poly, Automated Damage Detection in Operational Vehicles  
739 Using Mask R-CNN, in: H. Vasudevan, A. Michalas, N. Shekokar, M. Narvekar (Eds.),  
740 *Advanced Computing Technologies and Applications*, Springer Singapore, Singapore,  
741 2020: pp. 563–571.

742 [37] P. Guo, W. Meng, Y. Bao, Automatic identification and quantification of dense  
743 microcracks in high-performance fiber-reinforced cementitious composites through deep  
744 learning-based computer vision, *Cement and Concrete Research.* 148 (2021) 106532.  
745 <https://doi.org/10.1016/j.cemconres.2021.106532>.

746 [38] C.V. Dung, L.D. Anh, Autonomous concrete crack detection using deep fully  
747 convolutional neural network, *Automation in Construction.* 99 (2019) 52–58.  
748 <https://doi.org/10.1016/j.autcon.2018.11.028>.

749 [39] Z. Liu, Y. Cao, Y. Wang, W. Wang, Computer vision-based concrete crack detection  
750 using U-net fully convolutional networks, *Automation in Construction.* 104 (2019) 129–  
751 139. <https://doi.org/10.1016/j.autcon.2019.04.005>.

752 [40] W. Tian, X. Cheng, Q. Liu, C. Yu, F. Gao, Y. Chi, Meso-structure segmentation of  
753 concrete CT image based on mask and regional convolution neural network, *Materials &*  
754 *Design.* 208 (2021) 109919. <https://doi.org/10.1016/j.matdes.2021.109919>.

755 [41] S. Zhao, M. Shadabfar, D. Zhang, J. Chen, H. Huang, Deep learning-based  
756 classification and instance segmentation of leakage-area and scaling images of shield  
757 tunnel linings, *Struct Control Health Monit.* 28 (2021). <https://doi.org/10.1002/stc.2732>.

758 [42] H. Zhang, R. Zhang, D. Sun, F. Yu, Z. Gao, S. Sun, Z. Zheng, Analyzing the pore  
759 structure of pervious concrete based on the deep learning framework of Mask R-CNN,  
760 *Construction and Building Materials.* 318 (2022) 125987.  
761 <https://doi.org/10.1016/j.conbuildmat.2021.125987>.

762 [43] R.-S. Lin, Y. Han, X.-Y. Wang, Macro–meso–micro experimental studies of calcined  
763 clay limestone cement (LC3) paste subjected to elevated temperature, *Cement and*  
764 *Concrete Composites.* 116 (2021) 103871.  
765 <https://doi.org/10.1016/j.cemconcomp.2020.103871>.

766 [44] C. Youssef Namnoum, B. Hilloulin, F. Grondin, A. Loukili, Determination of the  
767 origin of the strength regain after self-healing of binary and ternary cementitious materials  
768 including slag and metakaolin, *Journal of Building Engineering.* 41 (2021) 102739.  
769 <https://doi.org/10.1016/j.jobe.2021.102739>.

770 [45] W. Abdulla, Mask R-CNN for object detection and instance segmentation on Keras  
771 and TensorFlow, GitHub Repository. (2017). [https://github.com/matterport/Mask\\_RCNN](https://github.com/matterport/Mask_RCNN)  
772 (accessed July 30, 2021).

773 [46] B. Hilloulin, Concrete Deep Segmentation, (2021). [https://git.gem.ec-](https://git.gem.ec-nantes.fr/bhilloul/concrete-deep-segmentation)  
774 [nantes.fr/bhilloul/concrete-deep-segmentation](https://git.gem.ec-nantes.fr/bhilloul/concrete-deep-segmentation) (accessed March 10, 2022).

775 [47] A. Dutta, A. Zisserman, The VIA Annotation Software for Images, Audio and Video,  
776 in: *Proceedings of the 27th ACM International Conference on Multimedia*, Association  
777 for Computing Machinery, New York, NY, USA, 2019: pp. 2276–2279.  
778 <https://doi.org/10/ggk524>.

- 779 [48] A.B. Jung, K. Wada, J. Crall, S. Tanaka, J. Graving, C. Reinders, S. Yadav, J.  
780 Banerjee, G. Vecsei, A. Kraft, Z. Rui, J. Borovec, C. Vallentin, S. Zhydenko, K. Pfeiffer,  
781 B. Cook, I. Fernández, F.-M. De Rainville, C.-H. Weng, A. Ayala-Acevedo, R. Meudec,  
782 M. Laporte, others, *ImgAug*, (2021). <https://github.com/aleju/imgaug> (accessed July 30,  
783 2021).
- 784 [49] J. Bezanson, A. Edelman, S. Karpinski, V.B. Shah, *Julia: A Fresh Approach to*  
785 *Numerical Computing*, *SIAM Rev.* 59 (2017) 65–98. <https://doi.org/10.1137/141000671>.
- 786 [50] B. Hilloulin, I. Bekrine, E. Schmitt, A. Loukili, Open-source deep learning-based air-  
787 voids detection algorithm for concrete microscopic images, *Journal of Microscopy*.  
788 (2022) jmi.13098. <https://doi.org/10.1111/jmi.13098>.
- 789  
790

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