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Modular Deep Learning Segmentation Algorithm for Concrete Microscopic Images

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Abstract

Segmentation procedures of concrete microscopic images and standard test methods devoted to the spacing factor calculation for the freeze-thaw resistance assessment of concrete are time-consuming and skill-dependent. Moreover, manual color treatment and careful image examination are often needed. Within the past few years, Convolutional neural networks (CNN) have proved unprecedented performances in image segmentation and object detection tasks, though they often showed limited reusability and modularity. This study introduces an open-source modular deep learning segmentation algorithm of concrete microscopic images. The algorithm is based on two CNN models dedicated to air voids and aggregates detection. The algorithm performances have been calculated using various concrete, mortar, and cement paste samples. The Protected Paste Volume (PPV) and distance-to-air-void have been computed and agreed well with the experimental spacing factor. Moreover, a better correlation between PPV and scaling was found than between experimentally measured spacing factors and scaling, highlighting a critical spacing factor interval from 200 μm to 300 μm .

Keywords: Deep Learning; Air-void analysis; Freezing and Thawing; Image Analysis; Microstructure.

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 (≤ 10 nm), transition pores (10nm-100nm), capillary pores (100nm-
39 1000nm), and air voids (≥ 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 (kg/m^3)

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

153

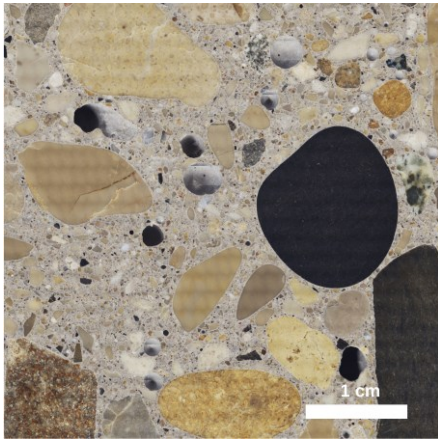
154 **Table 2.** Example of one mortar composition

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

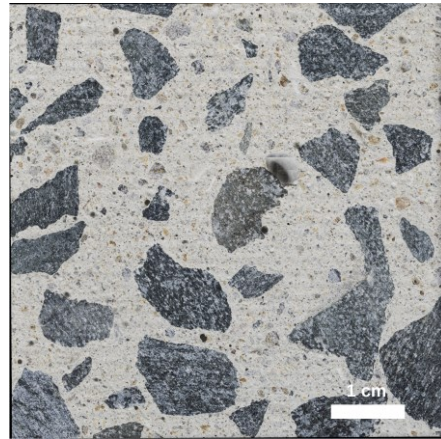
155

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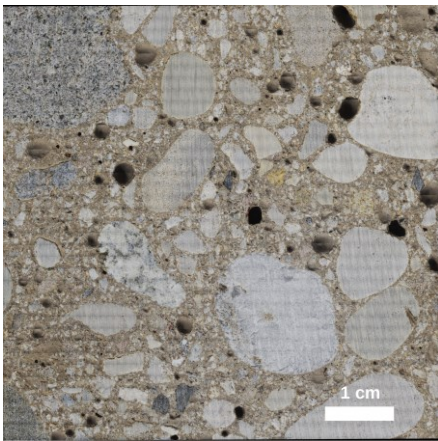
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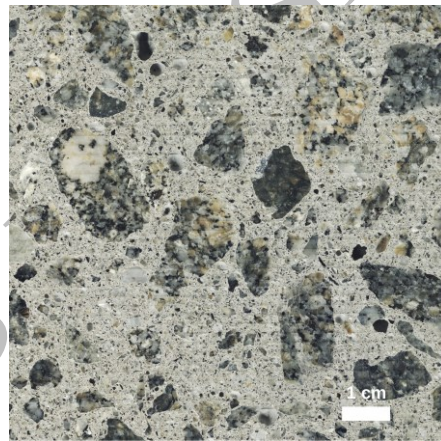
b)



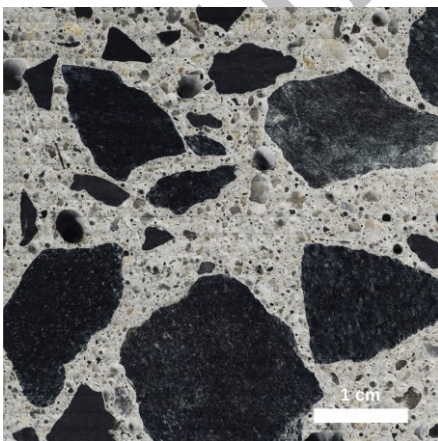
c)



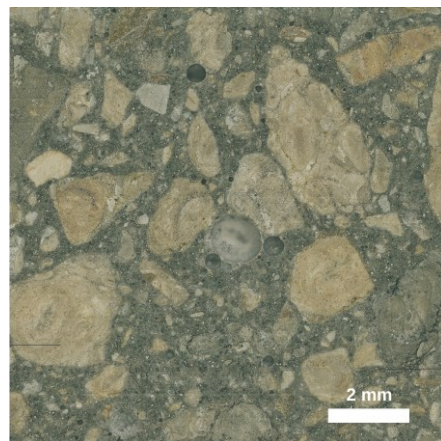
d)



e)

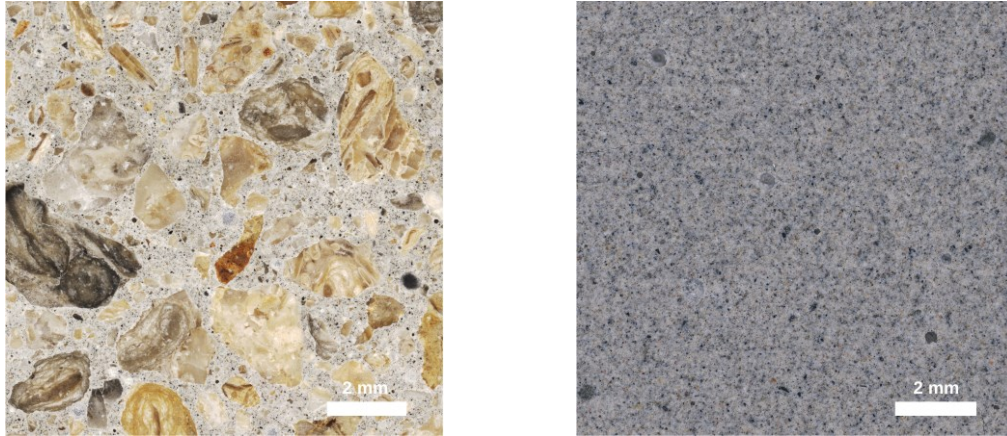


f)



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°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 / m³) (add 1 and add 2 refer to admixtures, by default in
 176 kg / m³, 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 (μ m)	Scaling (g/m ²)
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 cm² for concrete samples and 3.5 x 3.5 cm² 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.

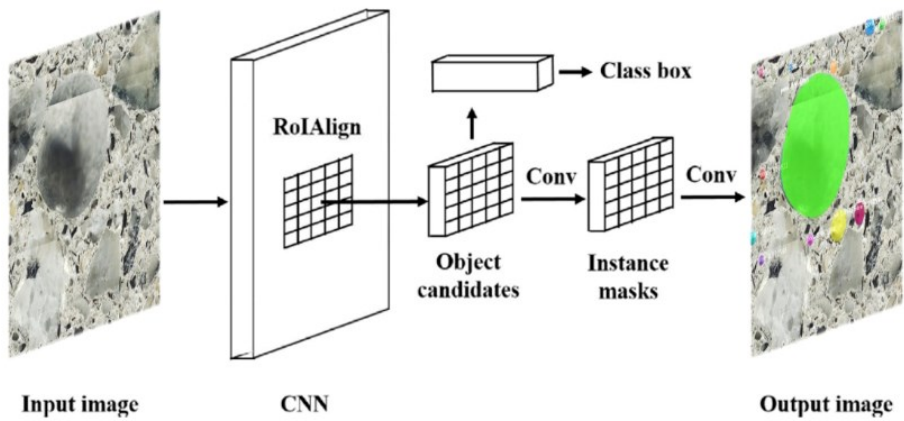
197

198 *2.2 CNN model*

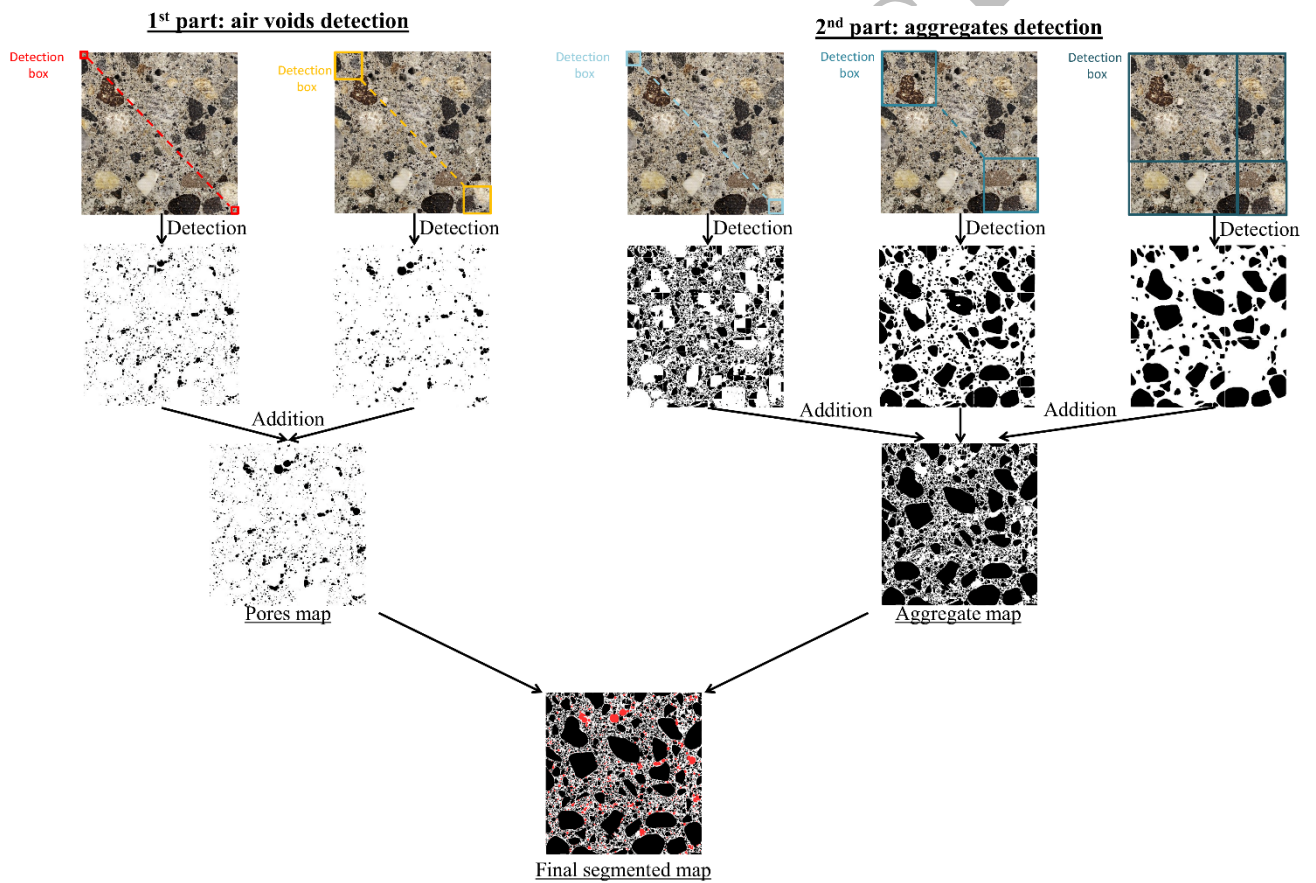
199 2.2.1 CNN model architecture

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 μm have not been annotated as the model could hardly detect them due to resolution
246 limitations.

247

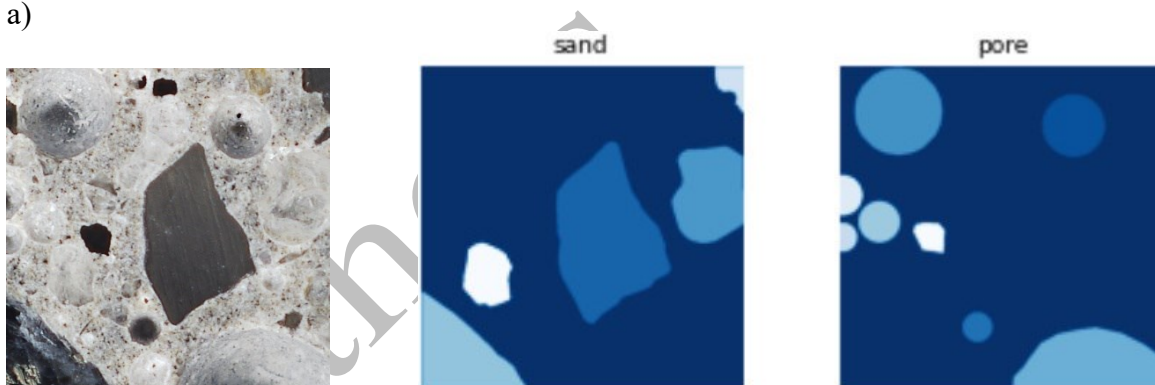
248 **Table 5.** Image dataset main characteristics

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

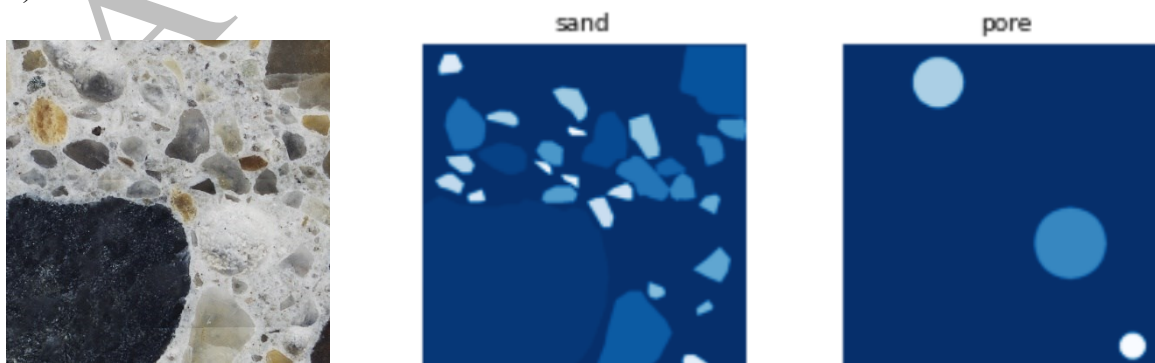
Cement paste 2	19	$\times 50, \times 25, \times 12.5$	3.13, 6.27, 12.54
Mortar 1	210	$\times 50, \times 12.5$	3.13, 6.27
Mortar 2	188	$\times 50, \times 12.5$	3.13, 6.27
Concrete 1	59	$\times 50$	3.13
Concrete 2	52	$\times 50$	3.13
Concrete 3	129	$\times 50, \times 12.5$	3.13, 6.27
Concrete 4	350	$\times 50, \times 25, \times 12.5$	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

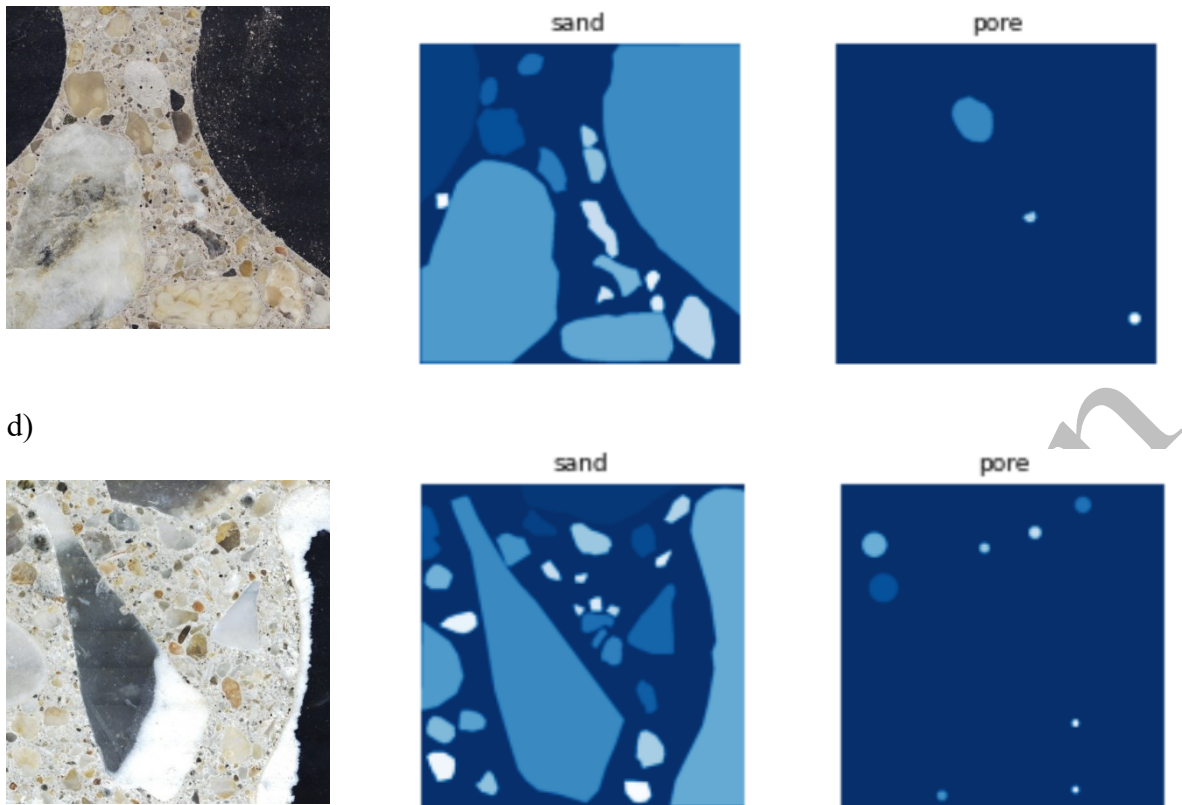
a)



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

General parameters	Aggregates	Air voids
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
Training stage 1		
Epochs	150	125
Steps per epoch	250	250
Learning rate	0.001	0.001
Training stage 2		
Epochs	125	500
Steps per epoch	250	250
Learning rate	0.0005	0.0005
Training stage 3		
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.

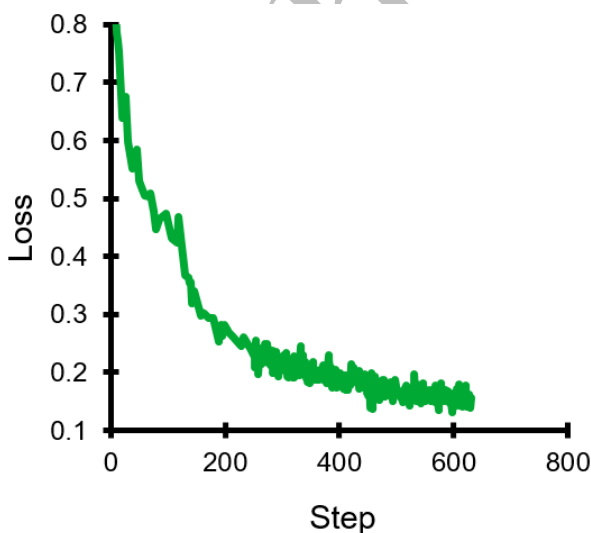
311 3. Results and discussion

312 3.1 CNN model training results

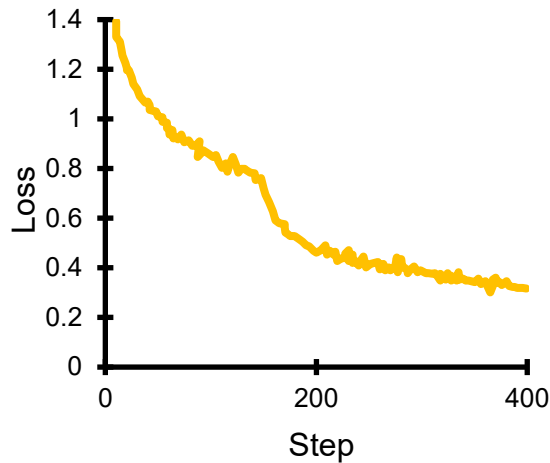
313 The loss curves recorded during training are displayed in Fig. 5. A two-step decrease can be
314 observed for both models as expected due to the first two stages during training. The loss
315 reduction rate becomes relatively small after 300 to 400 steps (75k to 100k epochs), as the
316 subsequent 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

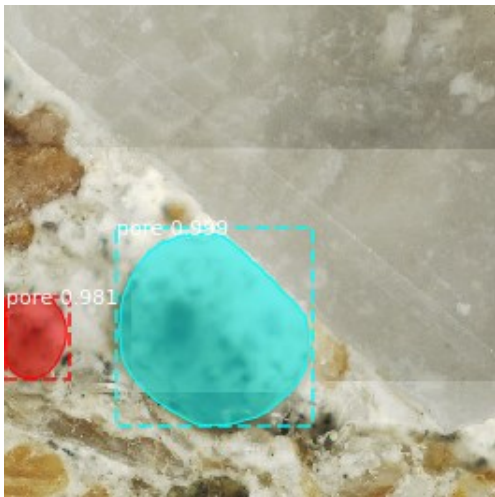
330 Results of the model can be analyzed using the predictions on the test images in order to
 331 identify the most common shortcomings of the algorithm and its advantages compared to
 332 previously reported performances on similar algorithms.

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).

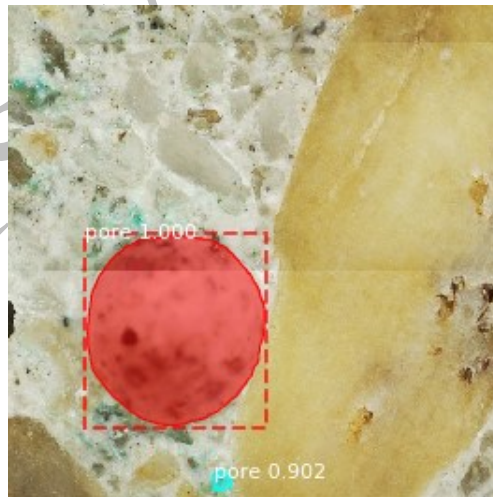
336 The Mask R-CNN model performs well even in challenging situations and is able to detect the
 337 vast majority of the air voids with high confidence levels indicated by scores close to the
 338 masks in Fig. 6. As illustrated in Fig. 6.a) and 6. b) the model can detect non-circular air voids
 339 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)

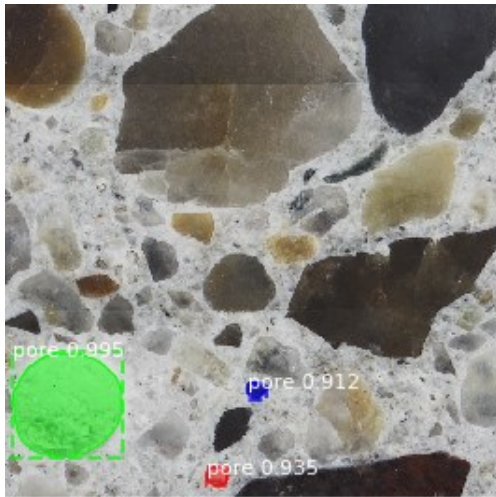


b)

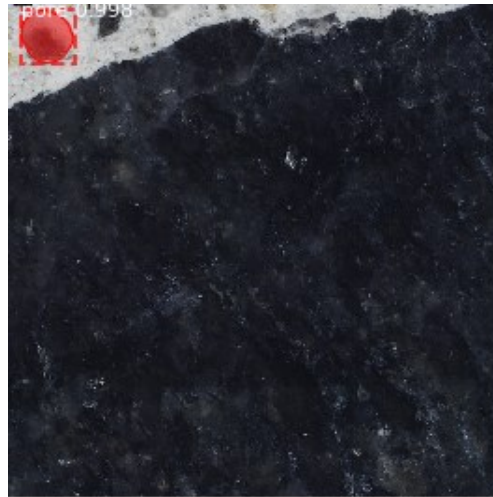


c)

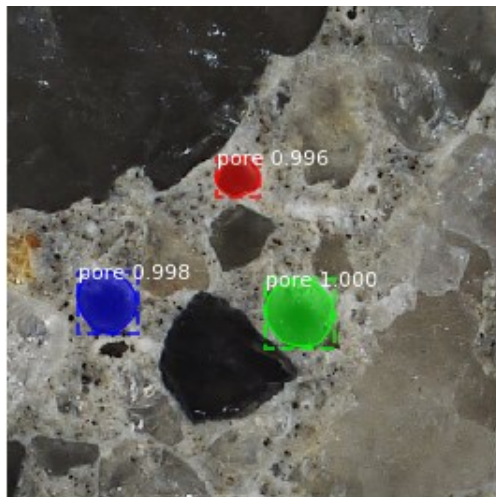
d)



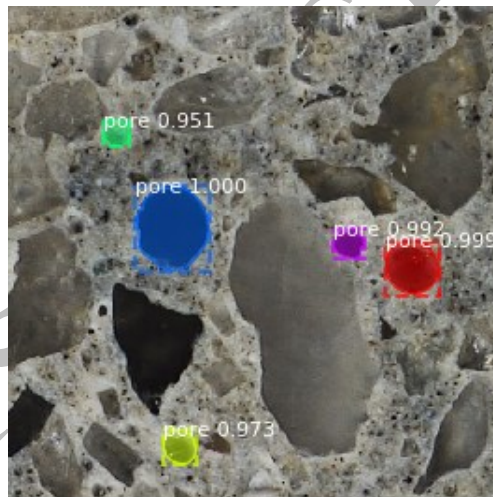
e)



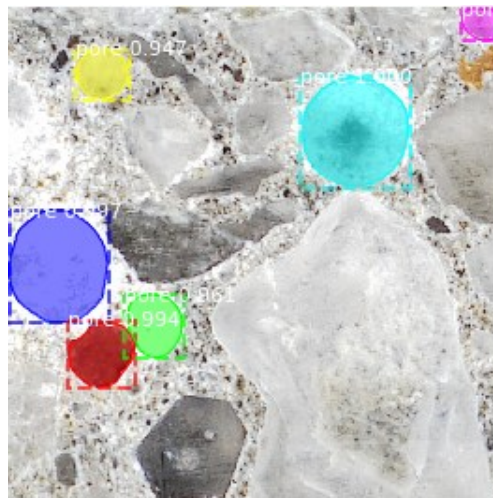
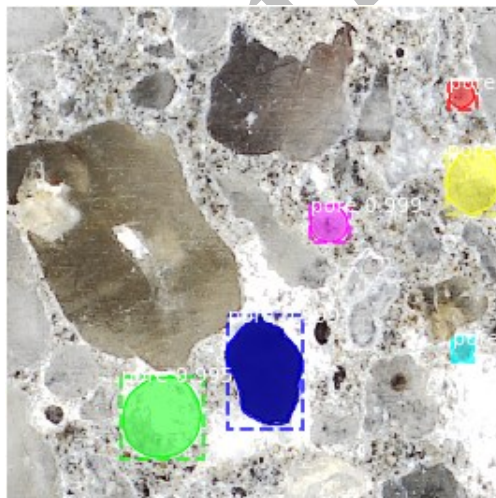
f)



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

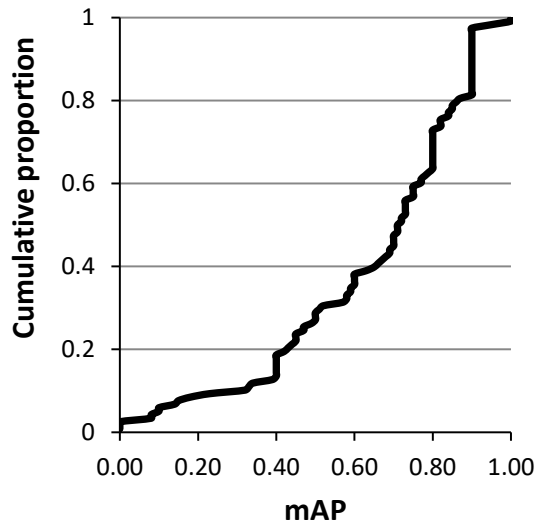
364

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].

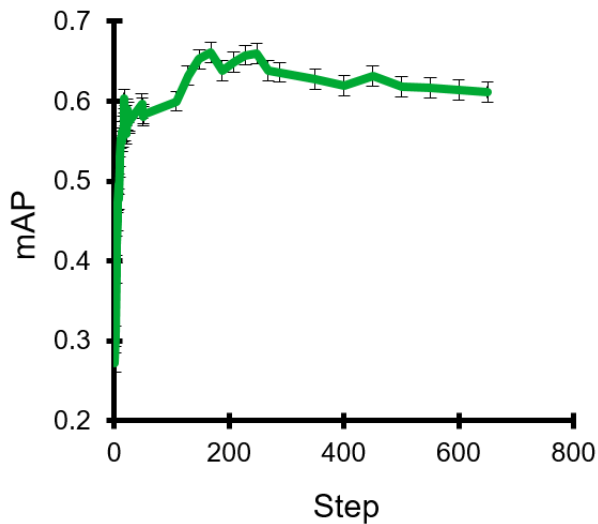
371 The mean average precision obtained on the test set can be calculated depending on the
372 duration of the training stage. As illustrated in Fig. 7 b), mAP quickly increased as the top
373 layers of the model were trained during the first stage of training. Then, during the second
374 stage of training (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.

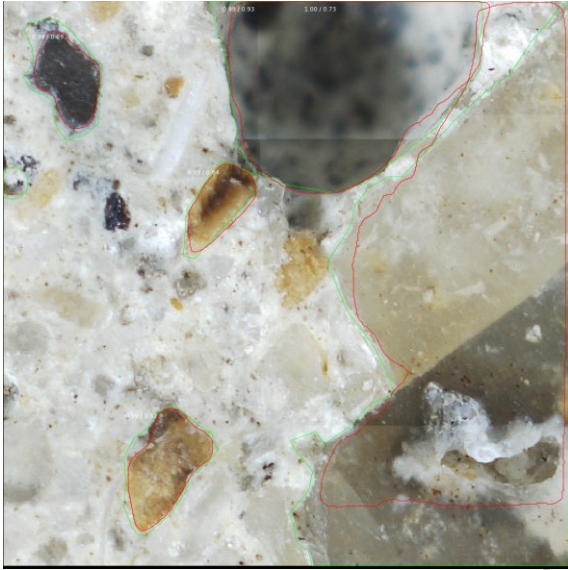
399 Fig 8 a) and b) illustrate the major shortcomings of the aggregate model during detection that
400 occur for less than 8% of test images. As illustrated in Fig. 8 a), aggregates located at the
401 border of images or cut by the image border were likely not entirely detected, and, as shown
402 in 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.

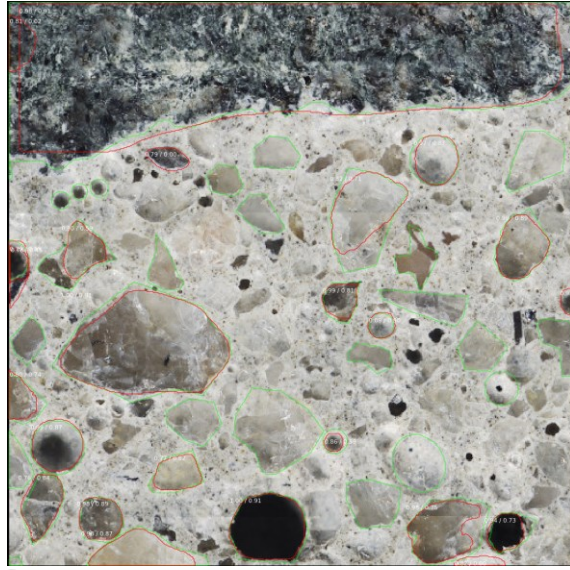
413 The aggregate model exhibited relatively good mAP of around 0.45 to 0.5 on ultra-high
414 strength slag-based concrete and lightweight aggregate concrete as illustrated in Fig. 8 e) and
415 f) respectively. Most of the basalt aggregates were detected in the ultra-high performance
416 concrete image 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].

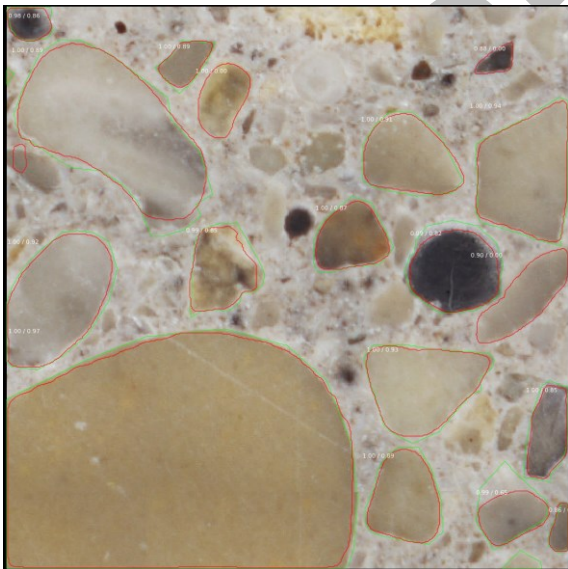
a)



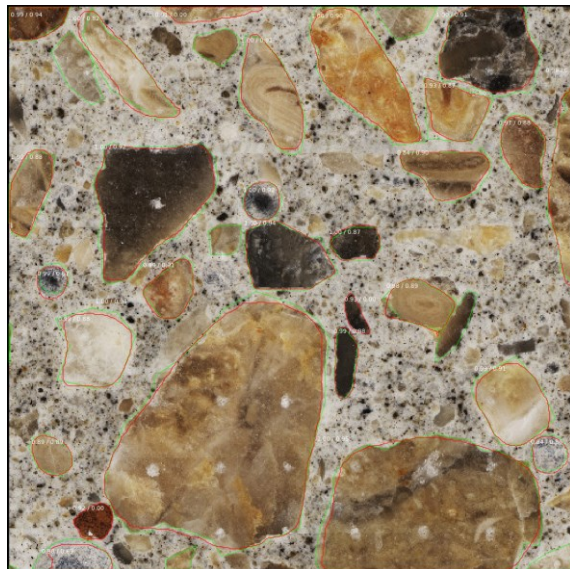
b)



c)



d)

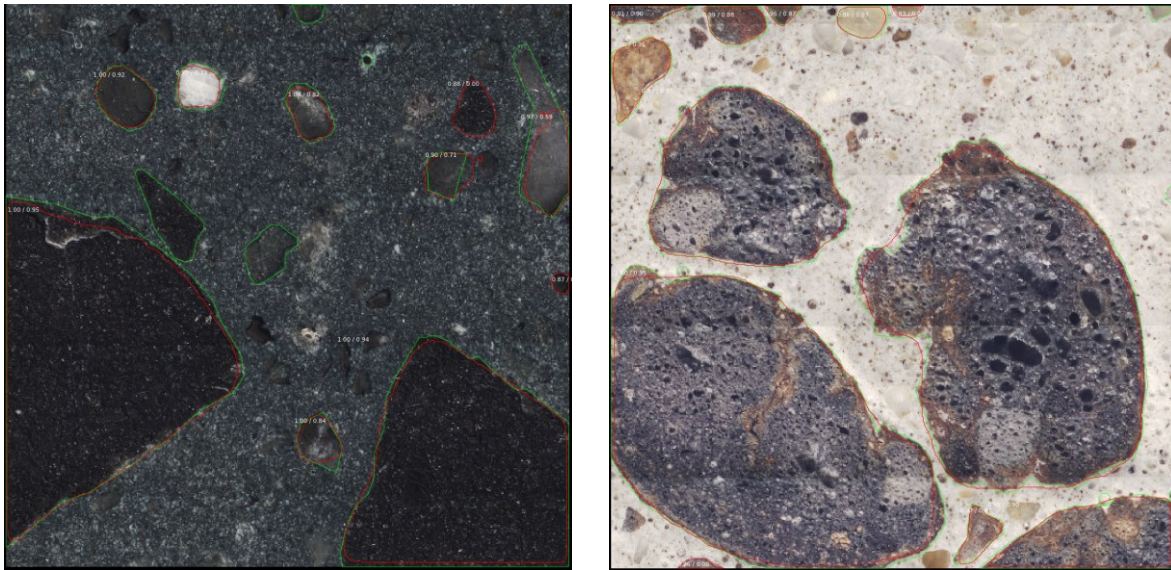


e)



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)

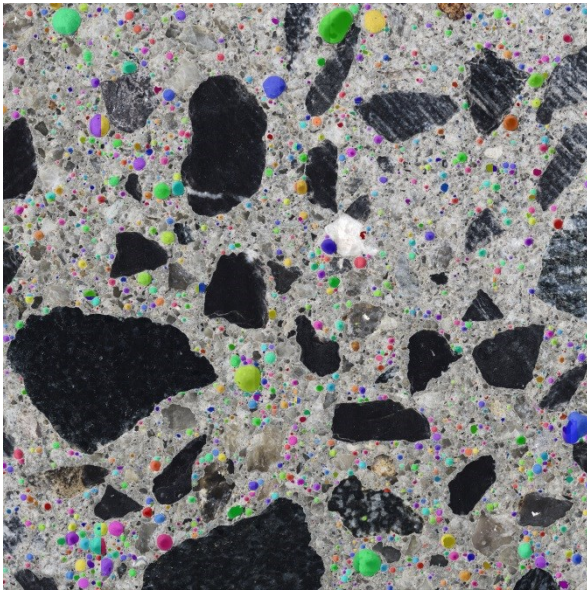
429

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

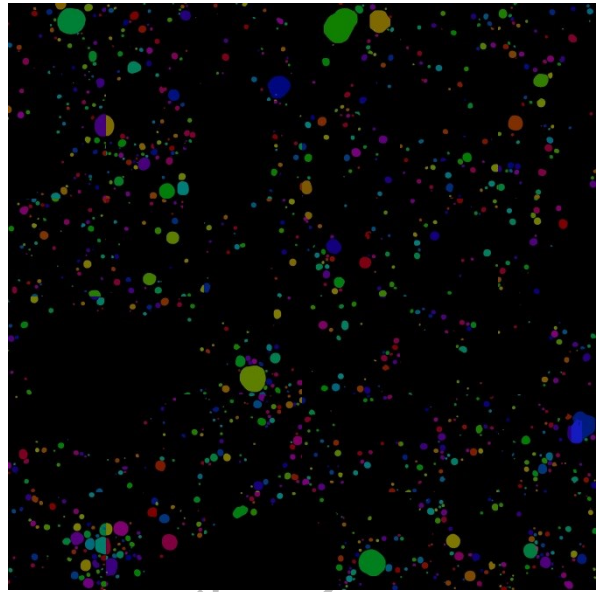
431 Using the air voids model alone and the aforementioned strategy, the model can be applied on
 432 a wide variety of large-scale concrete petrographic slices. Fig. 9 exposes the results obtained
 433 on an unknown concrete slice from an industrial partner with a size of approximately
 434 60 mm x 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 μm)
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].

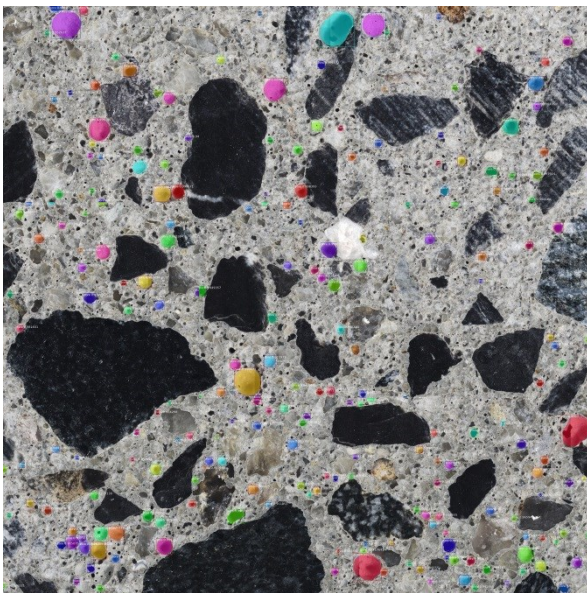
a)



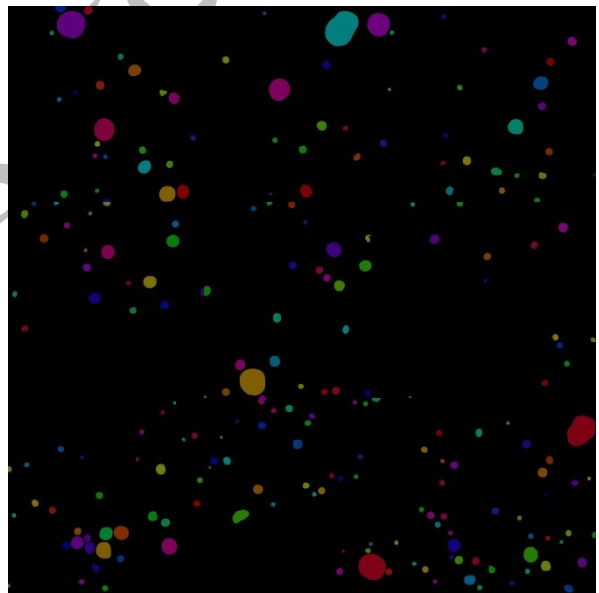
b)



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

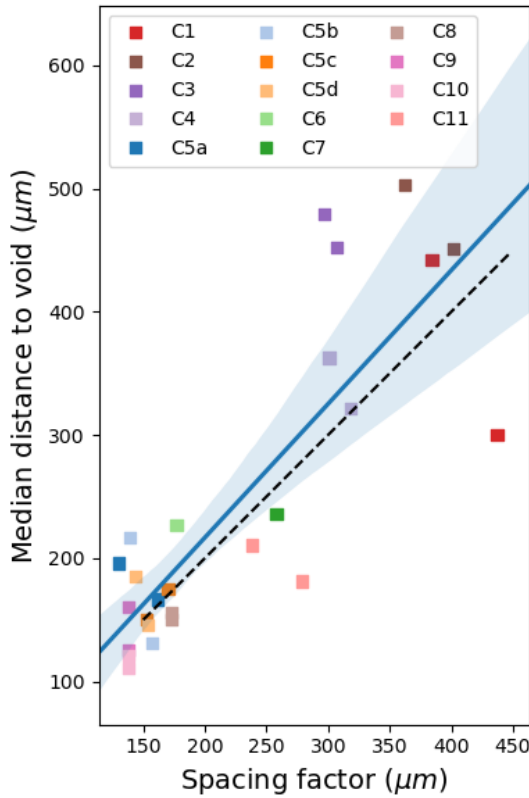
456 3.4 Application of the modular deep learning model: interest of Protected Paste Volume
457 (PPV) and distance-to-air-void calculation to assess freeze-thaw resistance

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 μm to
469 more than 430 μm . 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 μm 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 μm 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.



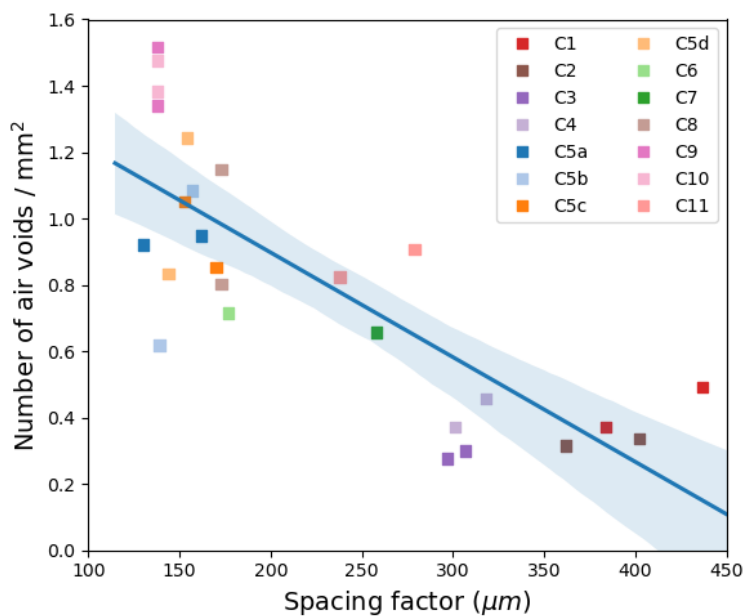
485
 486 **Fig. 10.** Distance-to-air-void vs measured spacing ratio (dashed line represents identity line,
 487 blue line linear regression and light blue zone 95 % confidence interval)

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

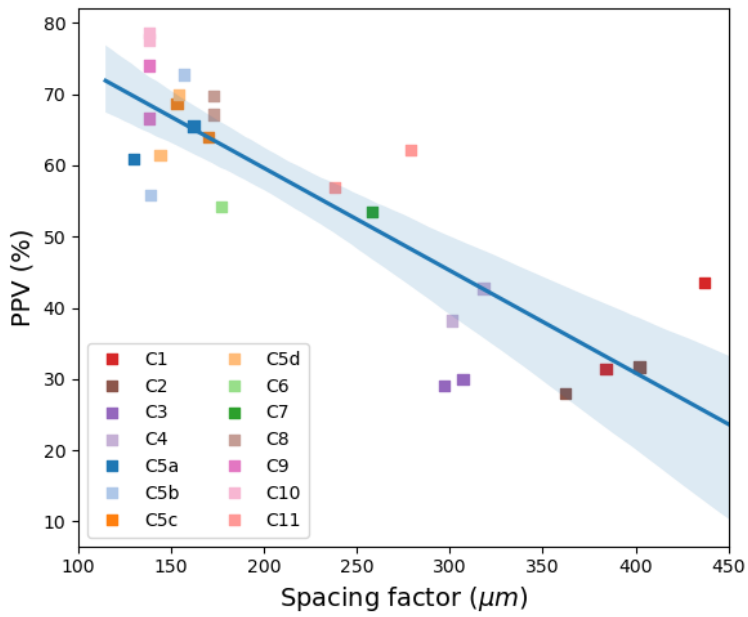
505 For this reason, the calculation of the PPV has been performed based on the high definition
 506 segmented maps provided by the deep learning model. In Fig. 12-a), PPV has been
 507 represented regarding experimentally measured spacing factor. The calculated PPV is in good
 508 agreement with the 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.

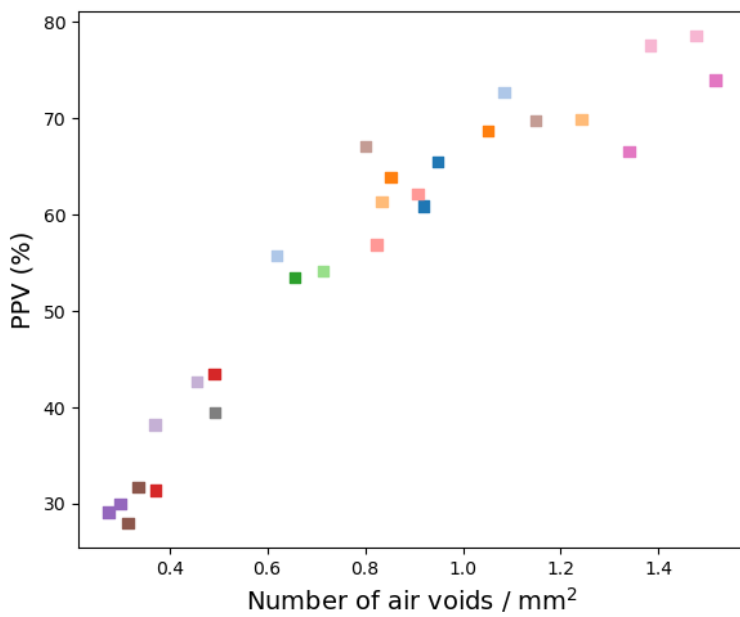
517 Numerically calculated PPV evolution regarding spacing factor has been approximated using
518 a linear regression. Samples with spacing factors smaller than around 200 μm have been
519 found to exhibit PPV higher than 54 % which is close to the 80% limit supposed to be freeze-
520 thaw protective [32]. On the contrary, for samples exhibiting experimental spacing factors
521 higher than 300 μm , 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 μm to
524 300 μm as the PPV abruptly drops between samples with spacing factors close to 270 μm and
525 PPV higher than 54% and samples with spacing factors close to 290 μm with PPV smaller
526 than 30 - 40%. Therefore, a critical attention must be paid to concrete samples with spacing
527 factors around 200 μm to 300 μm 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 / 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 / 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)

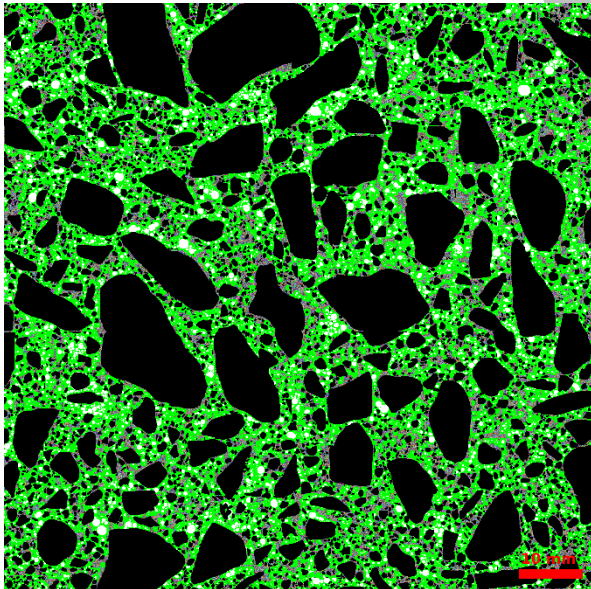
539 regarding the number of air void per unit area.

540

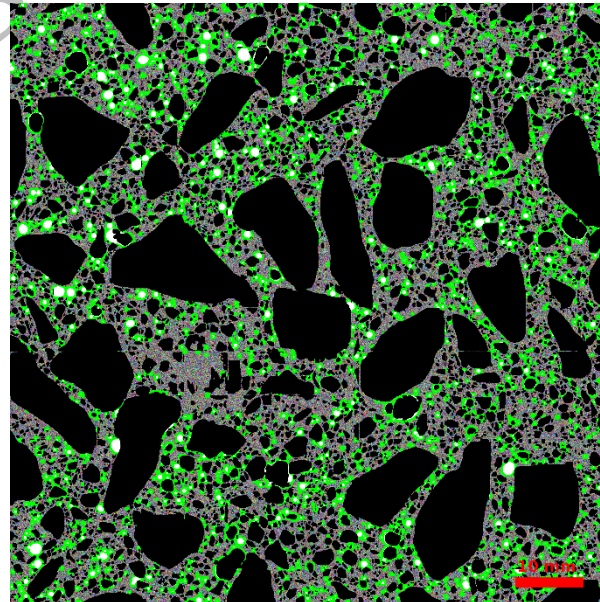
541 In order to visualize protected paste regions and locate unprotected areas, high definition
542 maps have been generated as illustrated in Fig. 13. A clear distinction can be observed
543 between concrete samples exhibiting high and low PPV values. The extent of the green
544 'protected' paste considerably 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

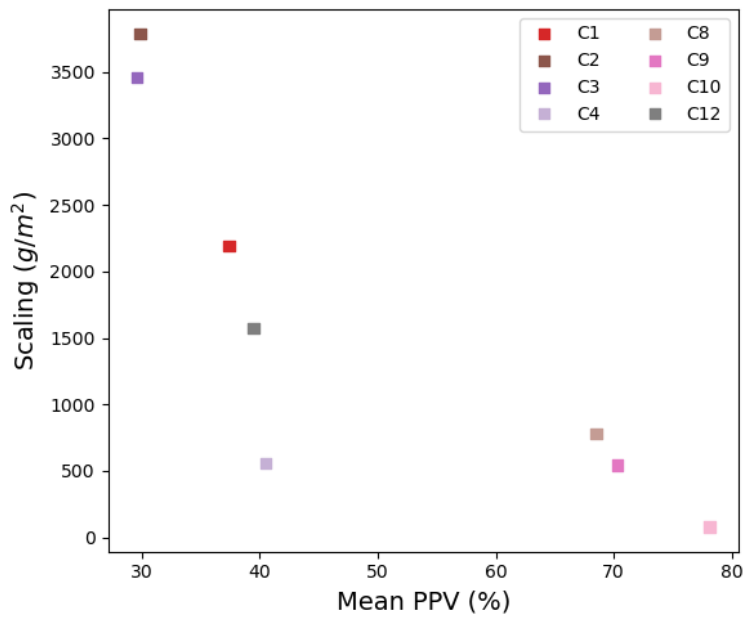
556 3.4.3 Comparison of experimental scaling values to numerical PPV and experimental spacing
557 factor

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/m² at low PPV around 30 % (C2 and C3) to 581 g/m² 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 been 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.

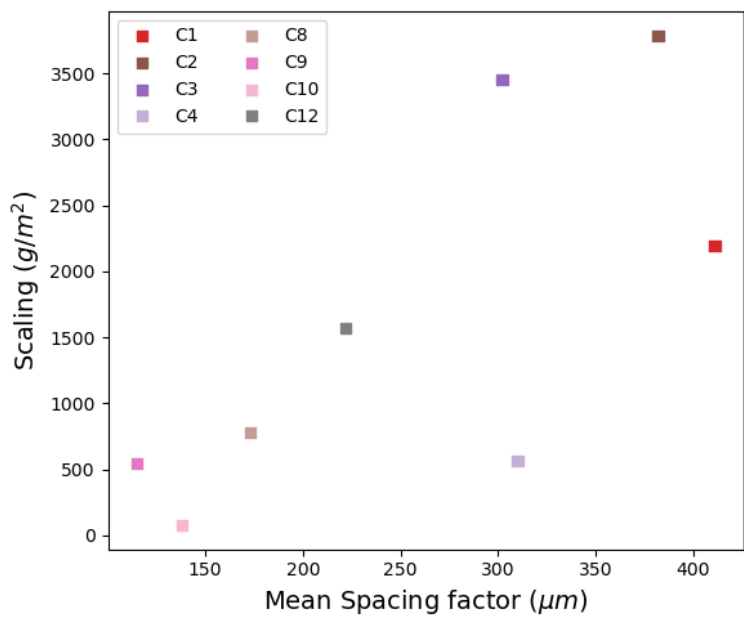
568 Conversely, as illustrated in Fig. 14 b, scaling values are not correlated with spacing factor for
569 C1 to C4 concrete. C1 concrete exhibited the highest spacing factor while it did not lead to the
570 highest scaling. Based on the generated PPV image, this could be due to an effective
571 repartition 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 μm to 300 μm . 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**

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