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## Deep learning approaches to study floods through river cameras

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The monitoring of river water-levels is essential to study floods and mitigate their risks. However, it is difficult to obtain accurate measurements of river water-levels: indeed, the river gauges commonly used to measure these levels can be overwhelmed during flood events, and their number is declining globally [1,2]. This means that the monitoring and study of floods relying on gauge station measurements can only be based on sparse and possibly inaccurate river water-level data distributed unevenly along the rivers, sometimes several kilometres away from the location of interest.

We investigate if deep learning can be used to monitor river water-levels in a more flexible and efficient way. More specifically, we apply two deep learning approaches on river cameras, which are CCTV cameras commonly used to monitor the surroundings of rivers and could be easily installed at new locations. The first approach [3,4] relies on transfer learning to train water segmentation networks able to find the water pixels within the camera images and use the number of water pixels within (regions of) the images to monitor the relative evolution of the river water-level. The second approach is based on the creation of a large dataset of 32,715 images annotated with distant gauge water-level data in order to accurately train networks able to produce river water-level indexes independent from the field of view of the cameras.

We show that both approaches can be used as sources of river water-level data. The first approach is able to produce river water-level indexes highly correlated with ground truth river water-levels (Pearson correlation coefficient >0.94). While the second approach is less accurate (Pearson correlation coefficients between 0.8 and 0.94), it is able to produce calibrated indexes independent from the field of view of the camera.

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