AI for flood risk warning and communication: a network of rain gauge cameras on a 5G telecommunication network

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Outline

1. Lab Presentation

2. AI for flood risk mapping

3. AI for supporting flood early warning system

4. AI rain gauge cameras on a 5G telecommunication network

UNIVERSITA' DEGLI STUDI DELLA BASILICATA

Location

School of engineering of the University of Basilicata

The School of engineering of the of the Basilicata University has a group of researchers that cover a wide range of research activities in the field of Hydraulic Constructions, Hydraulics, Hydrology and Water Resource Management.

Staff:
Prof. A. Sole, Prof. S. Manfreda, Dr. R. Albano, Dr. D. Mirauda, Dr. B. Onorati, V. Scuccimarra, Eng. L. Mancusi, Dr. A. Cantisani, Dr. Silvano dal Sasso, Dr. Nicla Notarangelo and Eng. Arianna Mazzariello

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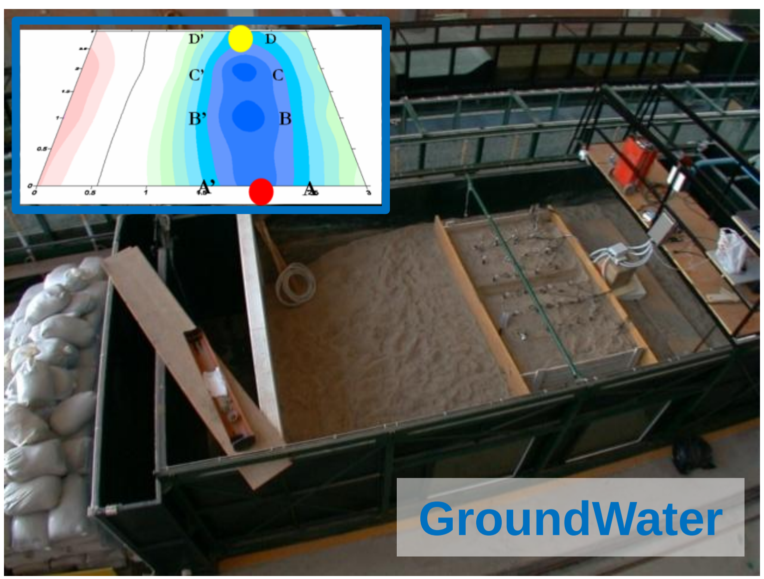
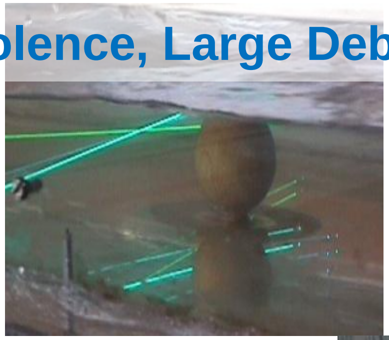
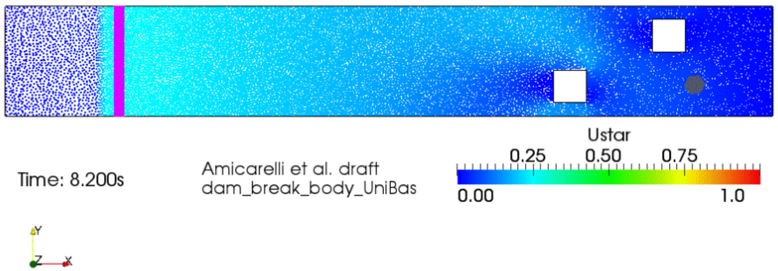
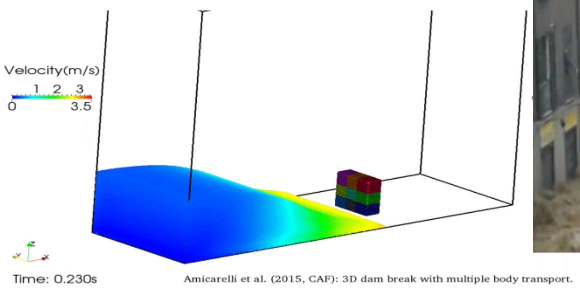
Laboratory of Hydraulic Construction and Hydraulic



FLUME – Turbolence, Large Debris transport



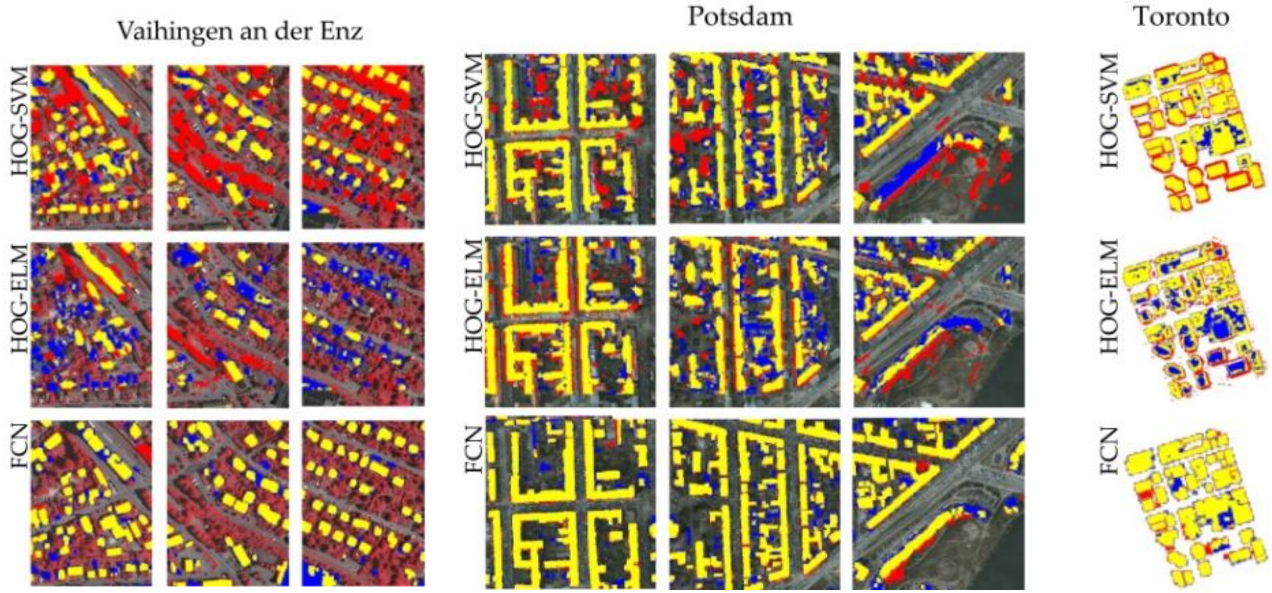




In situ - River Monitoring

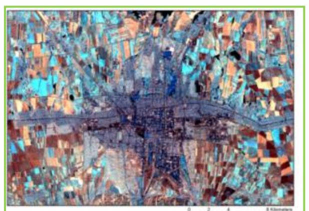
Flood Risk Mapping

[AI for buildings detection and land-use classification]



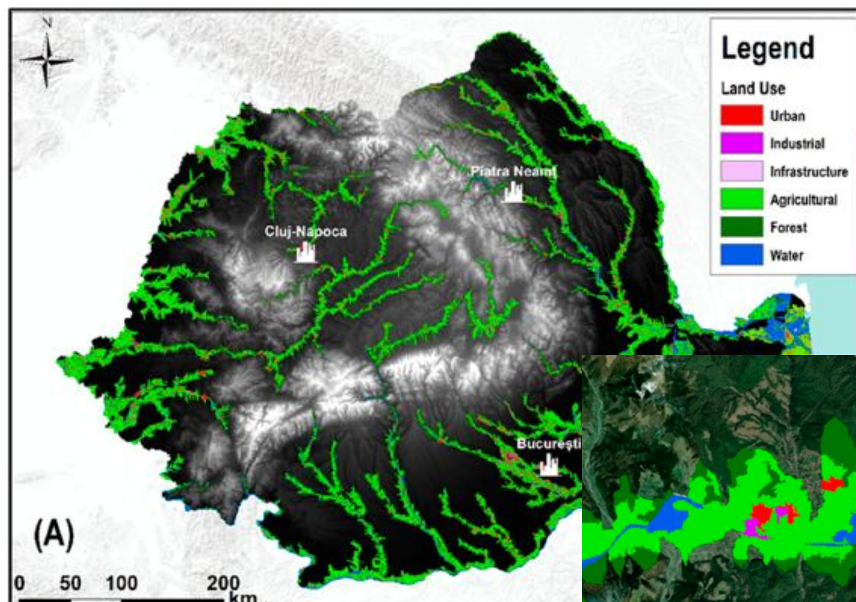
Contingency maps obtained from a pixel-to-pixel comparison between the masks outputted by the models and the ground truth by urban area: true positives are shown in yellow, false positives in red, and false negatives (missed building pixels) in blue.

1. Pre-processing

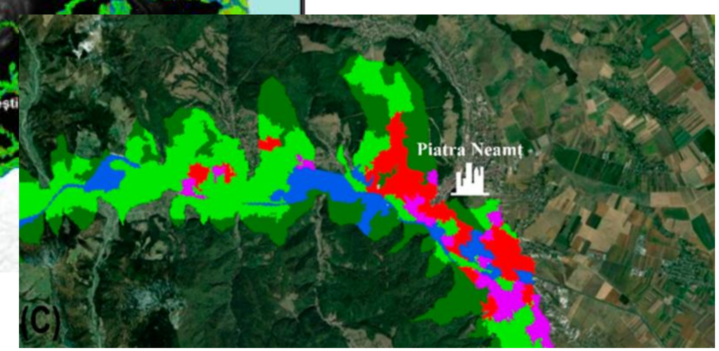


2. Segmentation

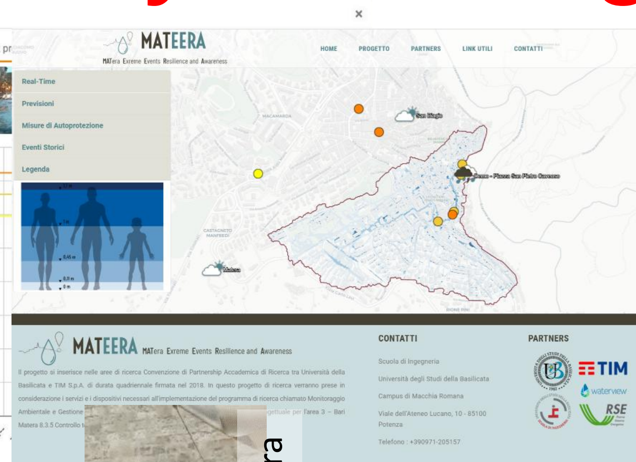
3. Feature Description

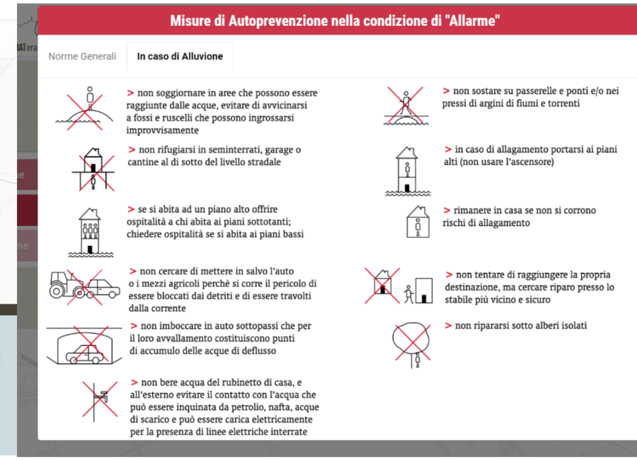


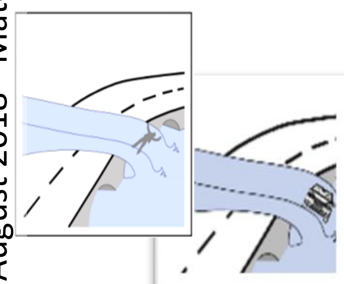
4. Classification



Flood Early Warning System







pluviometric forcing

Risk and Event Scenarios

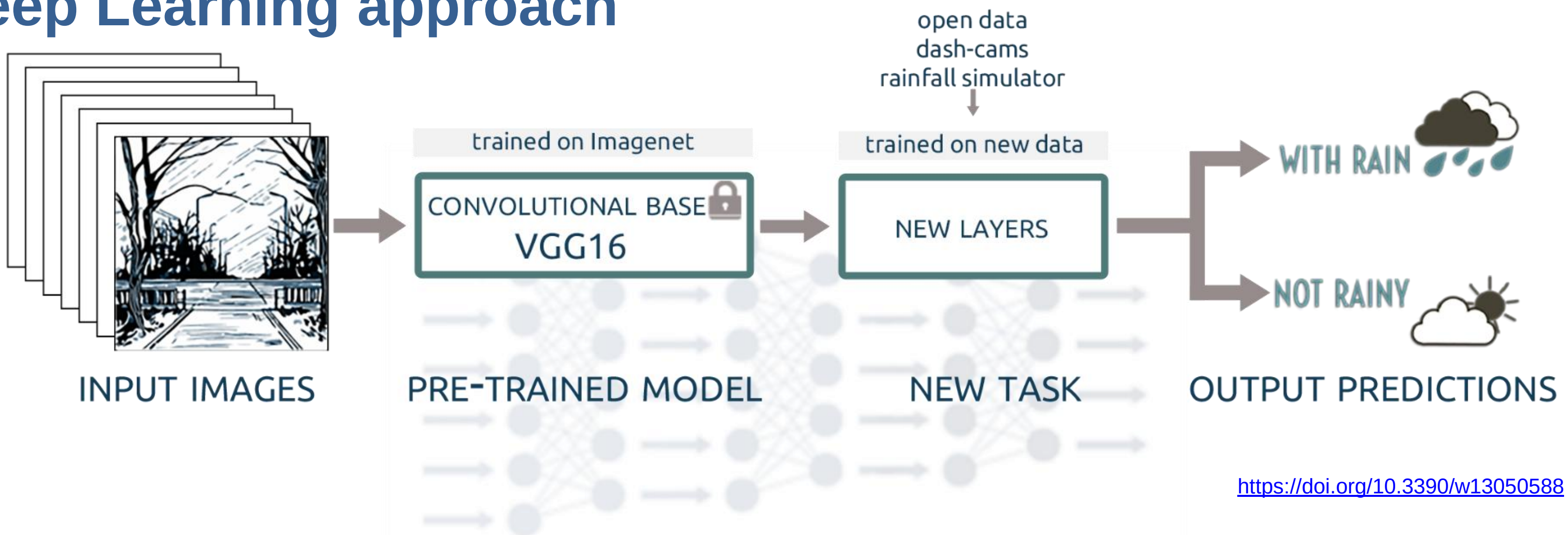
Early Warning

AI for near real time camera rain gauges

Historical data - GIS layers
Hydrodynamic models on an urban scale

Levels of criticality -
Levels of alert
Indications – Warnings

Camera-based rain detectors
A Deep Learning approach



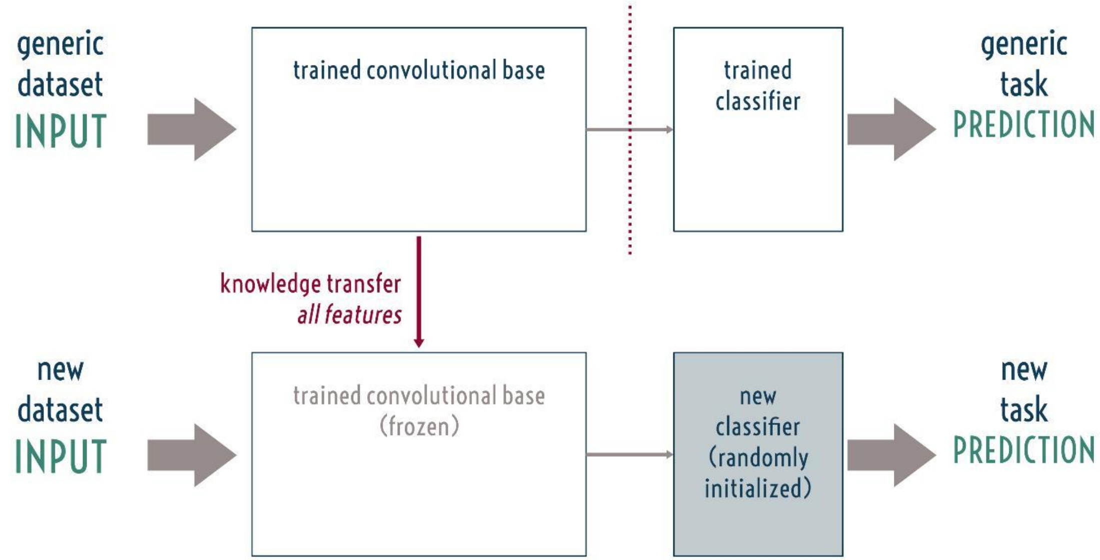
https://doi.org/10.3390/w13050588

Easily available photographing devices serve as AI-based rain detectors for monitoring the onset and end of rain-related events.
Software_ **R with Keras and Tensorflow** (Chollet & Allaire, 2018)
Classes_ **With Rain (WR)** and **No Rain (NR)**

Dataset criteria

- Outdoor images
- Presence of natural rain (not digitally synthetized)
- Rainfall visibility
- Heterogeneous sceneries

Transfer Learning with Feature extraction Model Architecture

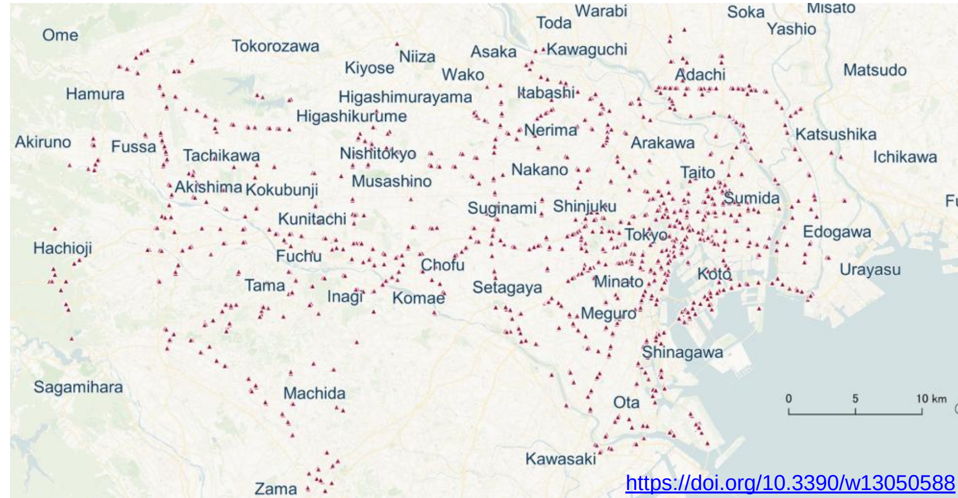


Layer (type)	Output Shape	Param #
vgg16 (Model)	(None, 6, 6, 512)	14714688
flatten (Flatten)	(None, 18432)	0
dense (Dense)	(None, 256)	4718848
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 1)	257

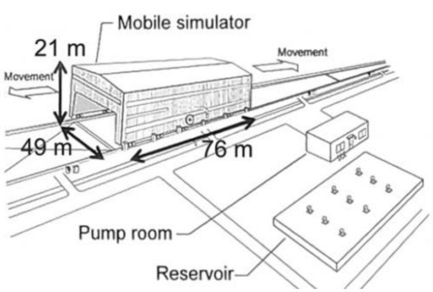
Total params: 19,433,793 – trainable: 4,719,105

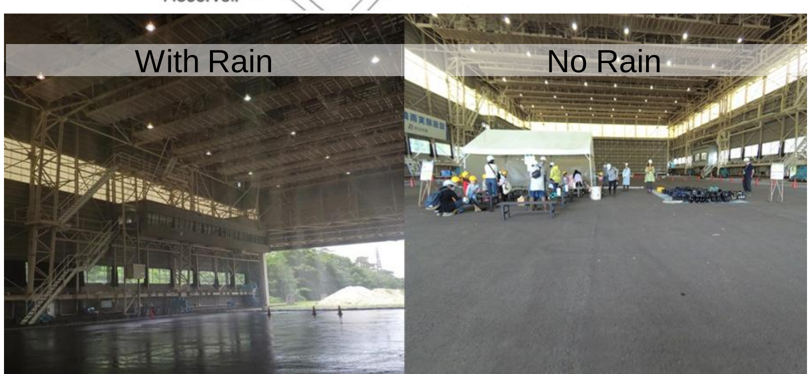
Dataset

Image2Weather (Chu et al., 2017)



Dashcams moving around Tokyo metropolitan area (©NIED) and XRAIN radar (©NIED, Hirano et al. 2014; Hirano and Maki 2018).





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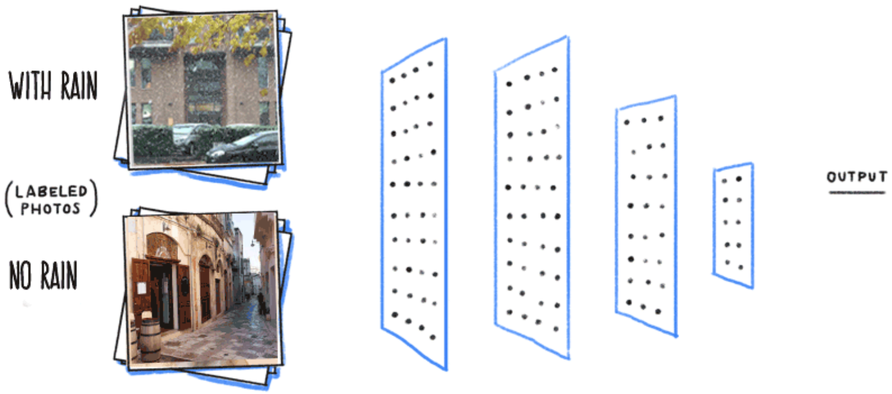
防災科研
NIED

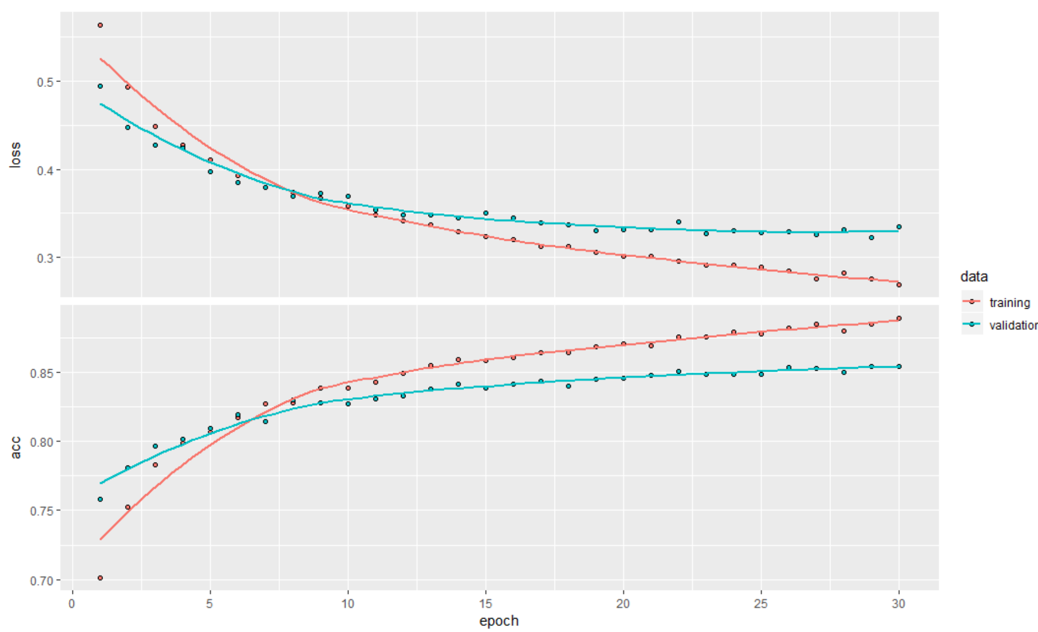
Experiments in Large-scale Rainfall Simulator of the NIED located in Tsukuba, devices: Canon XC10, Sony DSC-RX10M3, Olympus TG-2, XiaoYI YDXJ 2, XiaoMi MI8. 15 minutes intervals with constant produced intensity (20 mm/h - 150 mm/h)

Training and validation



Data Augmentation
Dropout
Metric: accuracy
Loss: binary cross entropy
RMSprop Optimizer
Dropout
Learning rate: lr = $1x10^{-5}$

Training: accuracy **88.95%**
loss **0.27**
Validation: accuracy **85.47%**
loss **0.33**

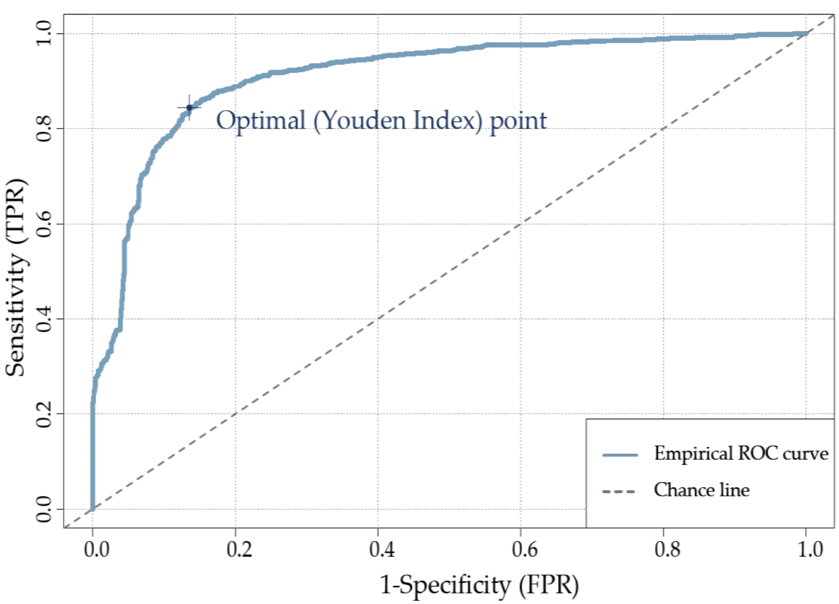


$$Binary\ Cross\ Entropy = -\sum_{i=1}^{C'=2} t_i \log(f(s_i))$$

Where t_i = groundtruth
s_i = score for the C_i class
$f(s_i) = \frac{1}{1+e^{-s_i}}$ = sigmoid activation function.

Use Case

The model was implemented in a real world setting with a Reolink surveillance camera installed by TIM using 5G connectivity. The camera frames piazza Vittorio Veneto - the main square in UNESCO World Heritage Site of Matera (Italy). Being a touristic point, the scene is often populated by moving pedestrians, bicycles, police cars, and service vehicles.



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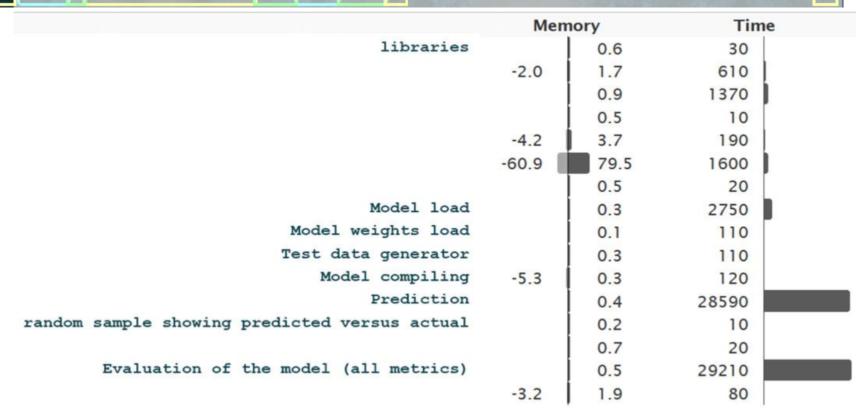
Metric	Value test set	Value TIM set	Reference Values*
Overall accuracy	85.28%	85.13%	worst=0% best=100%
Cross Entropy Loss	0.3400635	0.3960878	perfect ≈ 0
Sensitivity - Recall	90.44%	83.14%	worst=0% best=100%
Specificity	80.13 %	87.12%	worst=0% best=100%
Precision	81.98%	86.58%	worst=0% best=100%
F_1	0.8600	0.8482	worst=0 best=1
Matthews correlation coefficient MCC	0.7094	0.7031	worst=-1 best=+1

*Goodfellow et al. 2016; Zheng 2015; Murphy 2012; Chicco and Jurman 2020.

Use Case

A frame in rainy condition (26th March 2020) and its corresponding Gradient-weighted Class Activation Mapping (**Grad-CAM**) (Selvaraju et al. 2016), a heatmap visualizing the input regions considered more “rainy-like” by the CNN.




```
Interval 10 ms - total   64830 ms  (100 img)
                        122600 ms  (200 img)
                        166850 ms  (400 img)
                        275260 ms  (700 img)
                        461180 ms  (1100 img)
                        513740 ms  (1600 img)
```

Algorithm profiling with R Profvis library (Chang and Luraschi 2018)

Results compared to literature

Method	Model and Features used	Image source	Classes	Overall Accuracy	Sensitivity (Rain)
Yan *et al.* (2009)	Real AdaBoost with histogram of gradient amplitude, HSV color histogram, road information	In-vehicle vision system	Sunny, Cloudy, Rainy	**91.92%**	90.41%
		Crawled outdoor scenes, (reported in Zhang et al. 2016)		18.89%	-
Zhang *et al.* (2016)	Multiple kernel learning with engineered features (sky, shadow, rain streak, snowflake, dark channel, contrast, saturation)	Crawled outdoor scenes	Sunny, Rainy, Snowy, Haze	71.39%	67%
Chu *et al.* (2017)	Random Forest with time, RGB color histogram, Gabor wavelet, intensity histogram, local binary pattern, cloud, haze, and contrast features	Crawled outdoor scenes	Sunny, Cloudy, Snowy, Rainy, Foggy.	76.8%	68%
Proposed method	CNN with pre-learned filters	Dash-cams, consumer cameras, outdoor scenes (Chu et al. 2017), smartphone	With Rain, No Rain.	85.28%	**90.44%**
		Surveillance camera		85.13%	83.14%

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Work in progress…

The proposed methodology was applied to a second scenario: a multi-class classification describing a range of quasi-instantaneous rainfall intensity. **The cameras act as rain estimators**.
The multi-class model reached test average accuracy and macro-averaged F1 score values of 77.71% and 0.73 for a 6-way classifier, and 78.05% and 0.81 for a 5-class. The best performances were obtained in heavy rainfall and no-rain conditions, whereas the mispredictions are related to less severe precipitation.

Future steps

Further experiments

- Increase in spatial density of rain observations
- Opportunistic sensing (Dickinson et al. 2010)

Mobile app development

- Crowdsourced data
- Users as volunteer sensors (Goodchild 2007)

Public Initiatives

- Outreach

Incremental Learning

- Model improvement during use
- Robustness to rainfall intensity and artifacts
- Use case scenarios: site-specific rainfall thresholds, snow, etc.

Smartness

- Communication
- Participation
- Public awareness,
- Emergency response
- Smart city

Thank you for your attention

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