Royal Netherlands
Meteorological Institute
Ministry of Infrastructure
and Water Management

FOG DETECTION FROM CAMERA IMAGES

EXPERIENCES AT KNMI

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Agenda

- Focus after last time
- Brief recap of the approach
- Model performance
- Fog detection APP (with DEMO)
- Future work ideas

Fog as hazard

- Substantial impact on air, marine, and road traffic
- Appears and dissipates suddenly
- Large spatial differences (local phenomenon)
- Hard to accurately forecast

KNMI Goal

Short term

- Increase fog observations without placing new visibility sensors
- Use cameras to identify fog conditions and issue warnings

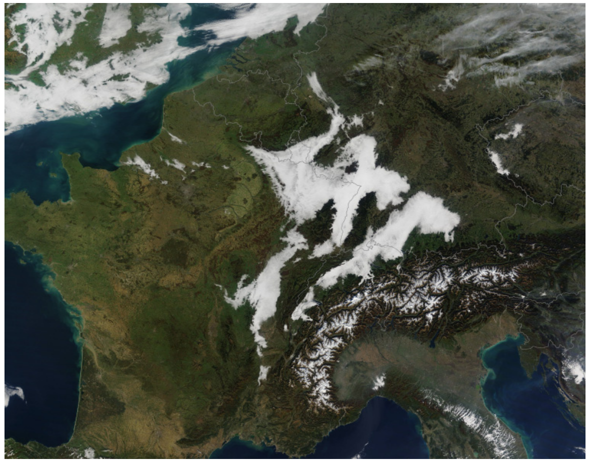
Long term

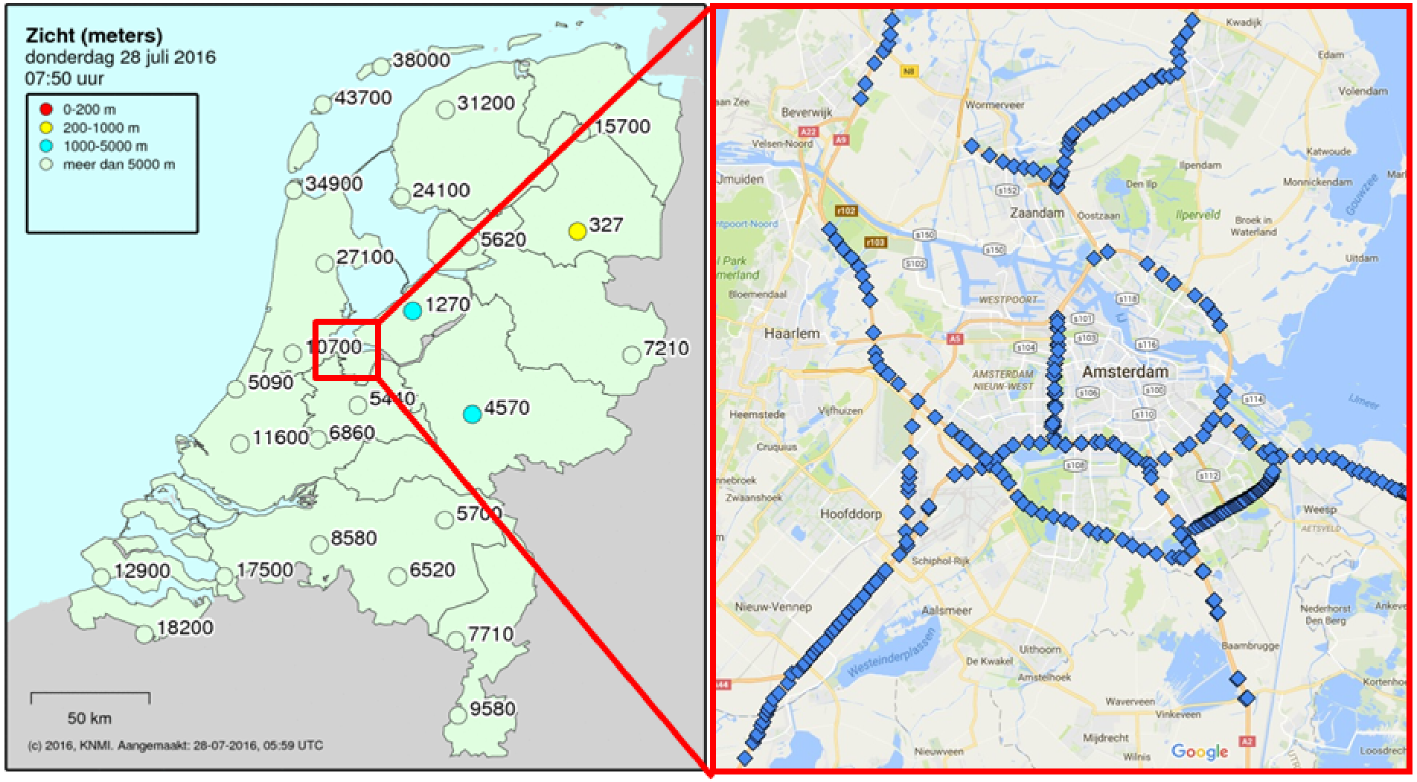
- Feed detected fog from camera observations to weather rooms and traffic control centers
- Assimilate detected fog into weather model to improve fog predictions

Limitations

- Daylight fog identification from static and moving cameras using image analysis

Satellite vs. visibility sensors vs. traffic cameras

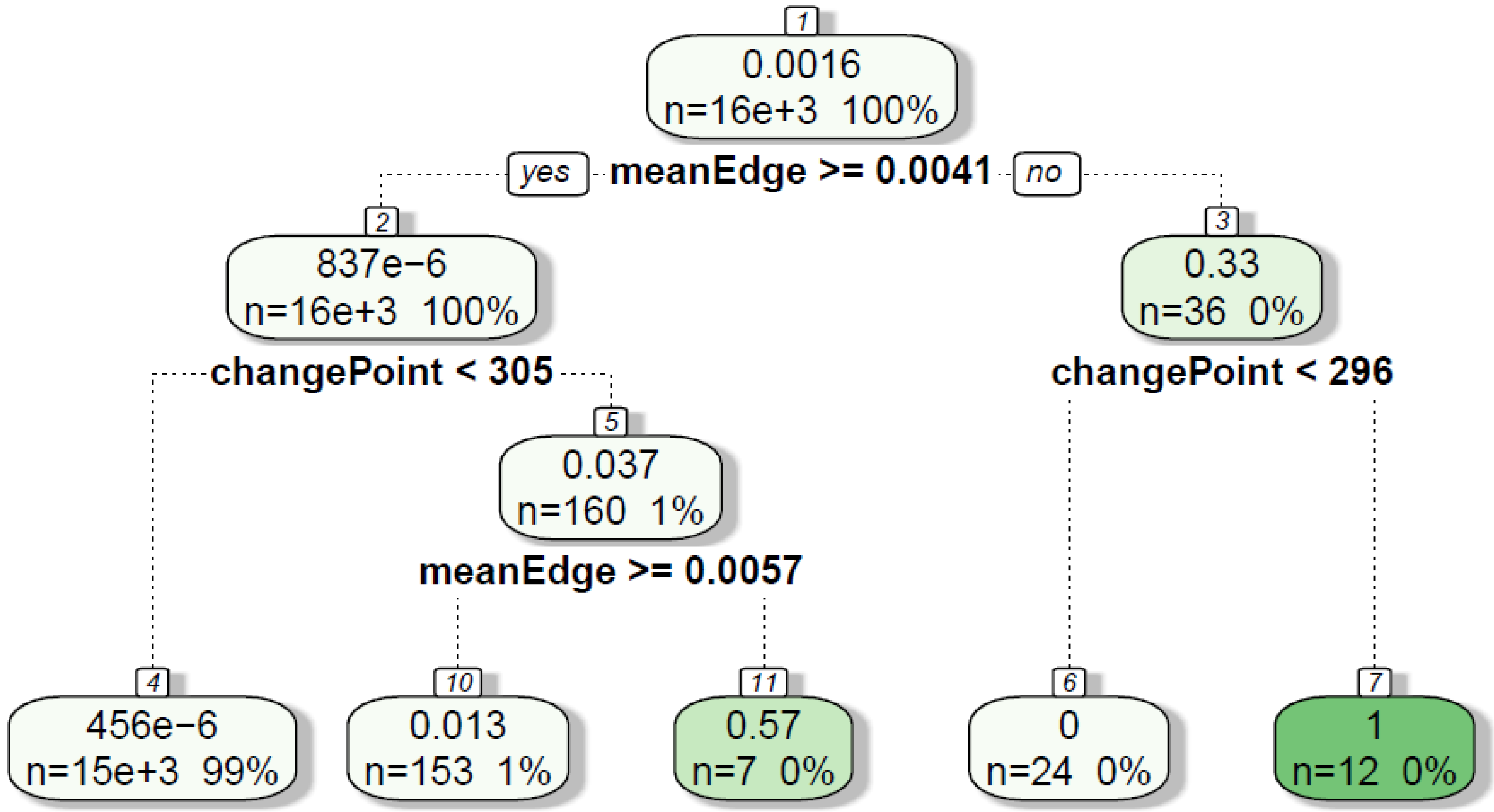




First Steps:
decision trees and random forest on KNMI test field pictures (7/2016)

- *Features:*
- **Mean Edges**: for finding the boundaries of objects within images. It works by detecting discontinuities in the image (e.g., foreground and background elements).
- **Mean Brightness**: perception of a source of radiating/reflecting light.
- **Mean Saturation**: is a measure of the purity of the color. The purest (most saturated) color is achieved by using just one wavelength, less pure come from a combination at different wavelengths.
- **Mean HUE**: perception of a source of being similar to one of the perceived colors: red, yellow, green, and blue, or to a combination of two of them.
- **Fractal Dimension**: self similarity in filling space.
- **Transmission smoothness**: transmission of the darkchannel of the image (smoothed indicator).
- **Transmission changepoint**: horizontal point where the transmission of the dark channel is subject to change.

Example decision tree for De Bilt



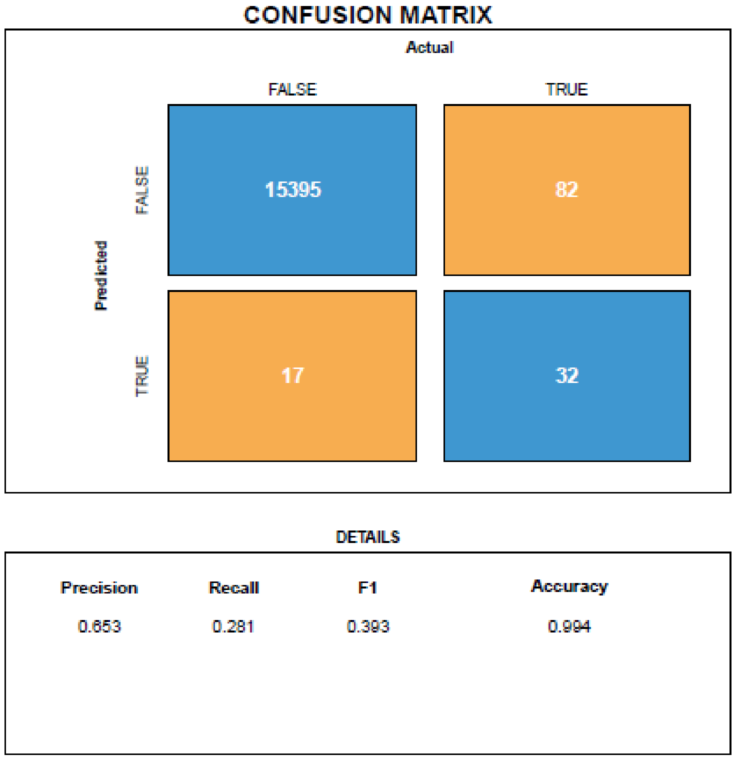
Static sceneries

De Bilt test field

Cabauw station

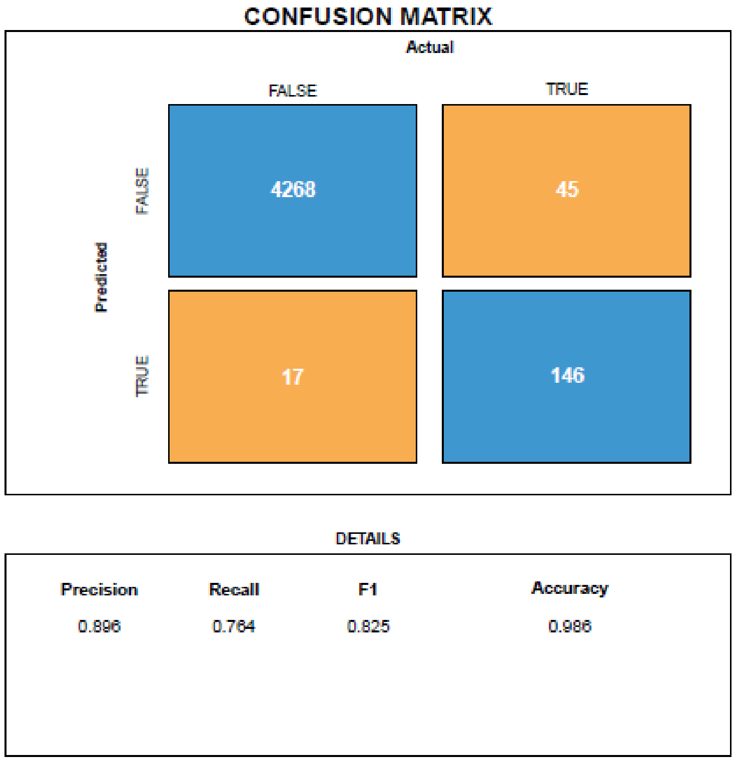
Results for static cameras

De Bilt test field



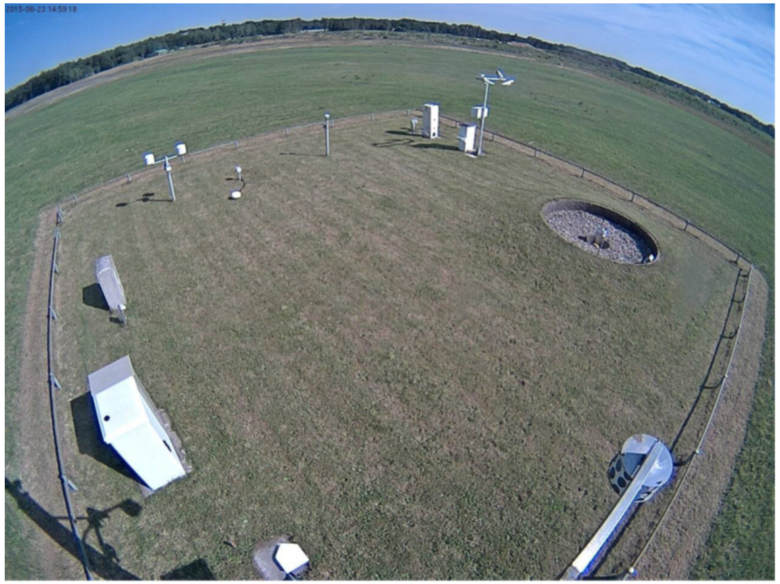
Train set (year 2016): 23174
Test set (6-12/2015): 15526

Cabauw station



Train set (year 2017): 18266
Test set (10-12/2016): 4476

Tests with Twente station



- fish-eye lens
- only a few edges in the range of 50–250m
- fully unprotected camera

Weather (un)protection

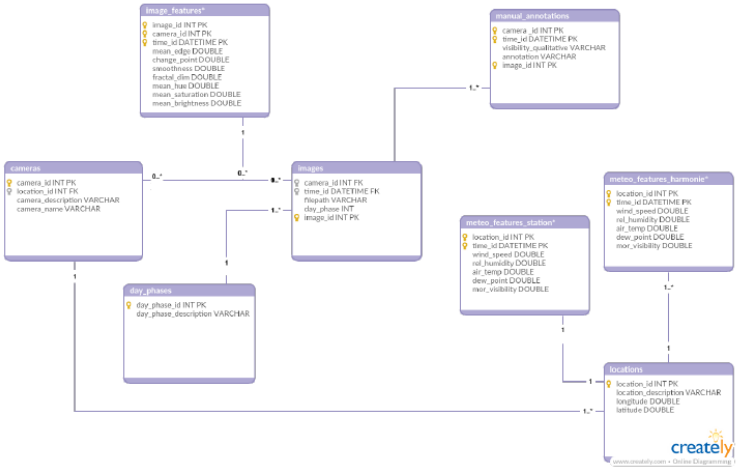
Ice on the camera enclosure

Water drops on the camera enclosure

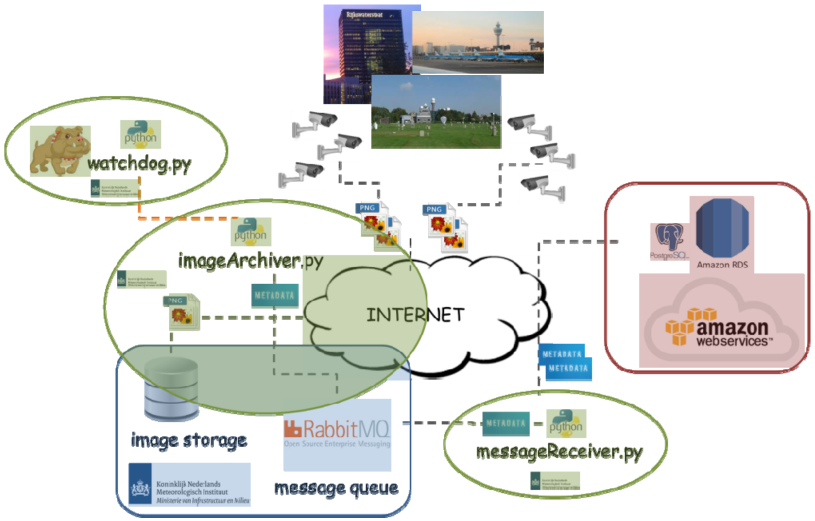
New phase with road department (since 01/2017)

- KNMI-RWS collaboration: partner to address a high-impact societal issue
- RWS (road dept):
  - test new/innovative solution for mobility problems
  - more automatic warnings
  - more coverage than manual operators
- KNMI:
  - have more data
  - test/improve ML models
  - deal with static and moving cameras of RWS domain
  - re-size the approach to deal with more data feeds

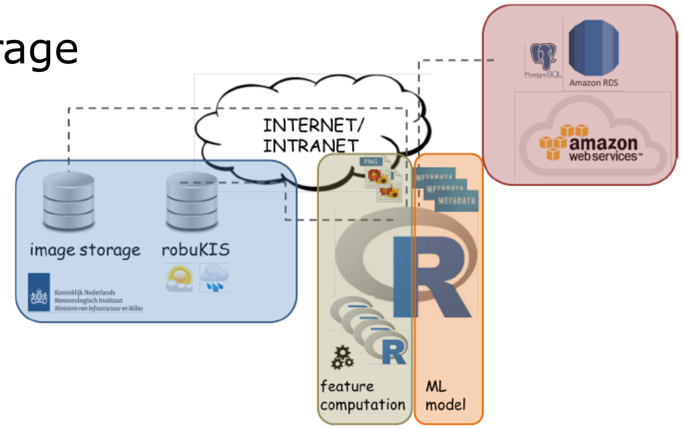
While waiting privacy clearance (6+ months)



DB for images metadata storage



Architecture for archiving images



Fetching relevant observations automatically

The dataset (finally)

- 7 cameras at KNMI Automatic Weather Stations
- 160 cameras along Dutch highways (since June 2017) + 160 new cameras (since October 2018)
- ~14 million images archived (and counting)
- Image sampling every 10 minutes
- Upon collection day phase is associated (day, night, dawn, dusk)
- Limited camera metadata (only lat/long position)

Change in approach: Why Neural Network (09/2017)

- Used proficiently in image processing and image classification
- More general method of fog detection than our previous attempt with decision trees and image features
- Sceneries are too different also for the same camera (e.g., zoom, pan, tilt)

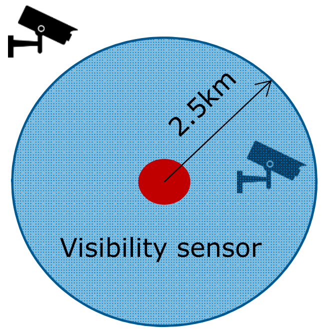
Same camera, same day, few hours apart

Labeling the data

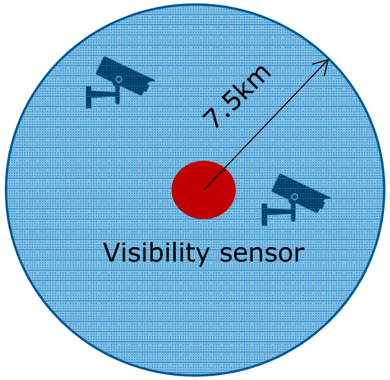
- Visibility via meteorological optical range (MOR)
- From visibility to categorical indicator:
  - MOR<=250m → FOG
  - MOR>250m → NO FOG
- Only few cameras with co-located visibility sensors
- Trade-off:
  - automatic labeling vs. manual labeling
  - enough data and enough GOOD data

Labeling for a case study (9/2018)

- Two cases are considered for a work for CIMO-TECO WMO 2018 conference:



Case A

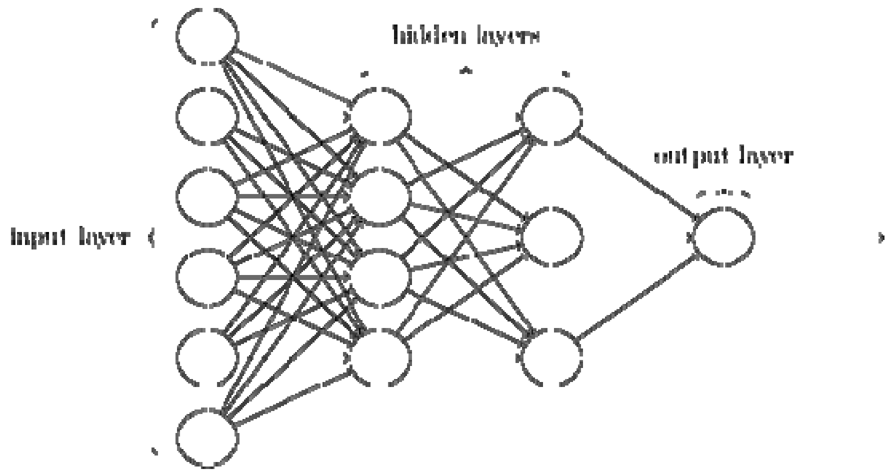


Case B

- Case A: 16 cameras along the highways in range of 4 MOR sensors
- Case B: 82 cameras along the highways in range of 7 MOR sensors

Neural network

- Brain inspired
- Each node (neuron) operates on the inputs and if a threshold is passed it “fires”
- Goal: learn about the phenomenon under investigation without explicitly providing specific rules
- A node sums up the (weighted) inputs and applies a rectifier



Neural network

- Learning phase: find the right weights that are best suited in approximating the desired output

- Weights start from an initial random guess and they are updated iteratively in order to minimize a loss function using some form of gradient descent

- By exposing to many (tens of thousands to millions) examples, the network will learn to approximate the output from the inputs provided

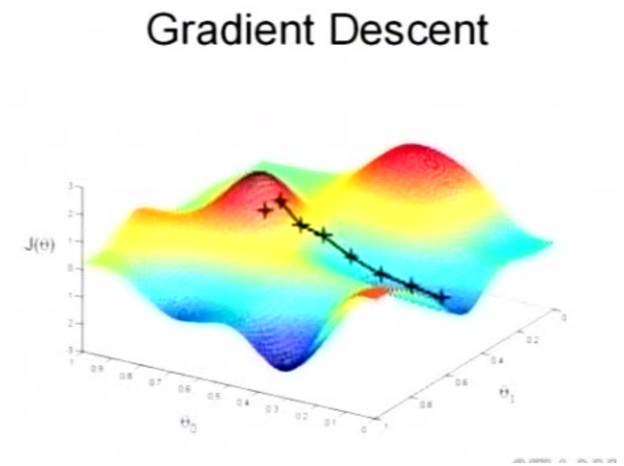


Image pre-processing

Reshape to 28x28 px
Image blurring
to
Harmonize images
Reduce computation
Counter overfitting

From image to features

- RGB channels extracted
- RGB pixel intensity
- Pixels intensity are the features (i.e., predictors)
- The input of the image to the neural network is constituted by a vector of 28x28x3=2352 variables

Full data transformation and feature extraction

Model fitting

- Dataset split

  - Training (60%) – Case A ~350k images – Case B ~1.2M images
  - Validation (20%)
  - Test (20%)
- Deep neural network fitting via R and H2O library
- Hyperparameters optimization via random grid search

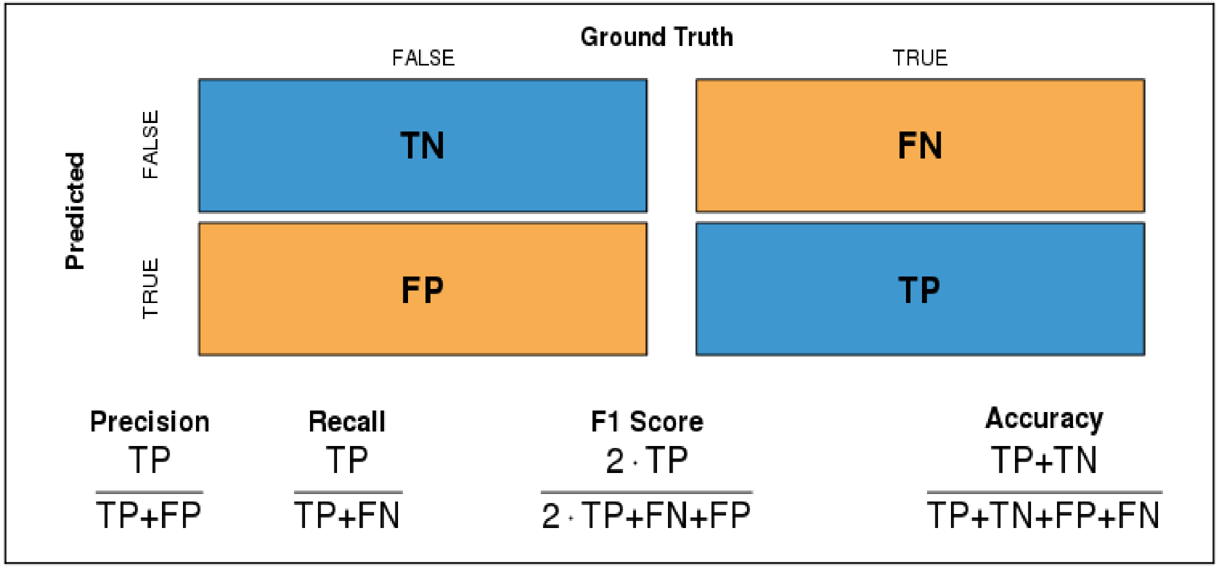
Model fitting

Case	Number of layers	Number of nodes in hidden layers	Activation function in hidden layers	F1 score training subset*
2.5km data set	7 (Input, 5 hidden layers, output)	75, 75, 50, 50, 10	Rectifier	0.986
7.5km data set	7 (Input, 5 hidden layers, output)	50, 50, 50, 25, 10	Rectifier	0.981

*F1 score computed on a balanced subset from the training set of 10000 images per class.

Results

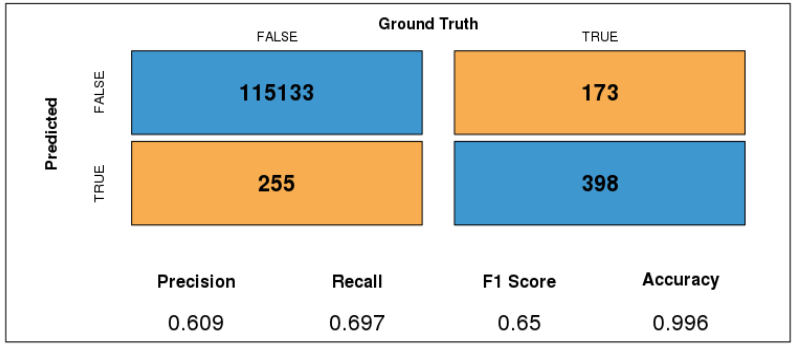
How to interpret



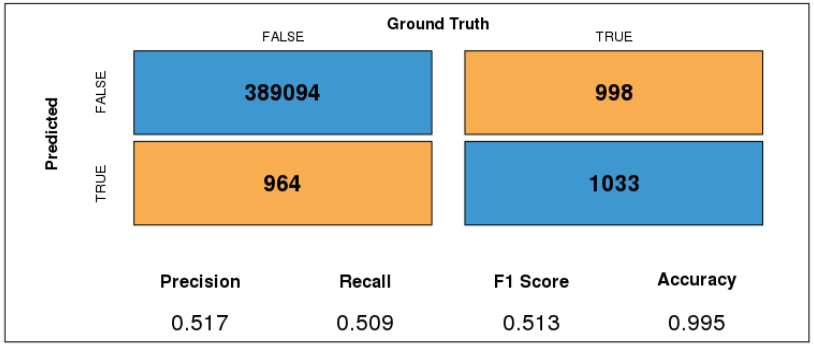
TRUE=foggy

Results

Case A

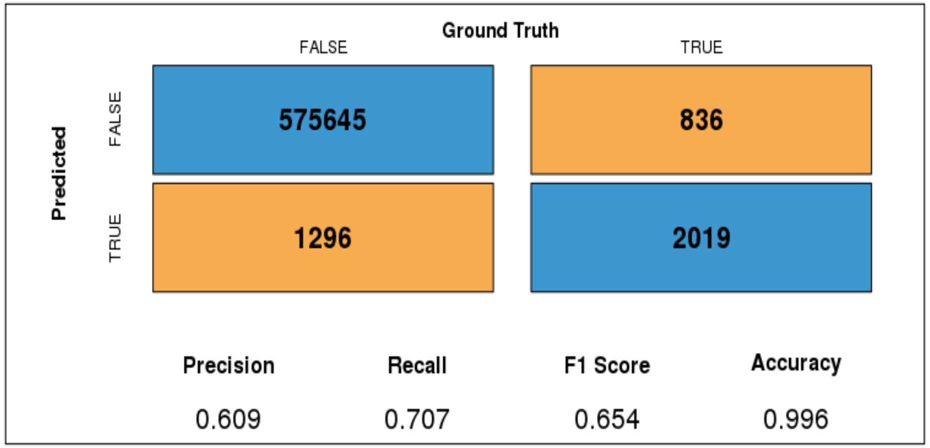


Case B



Results

- **All data of case A**



False Positives and False Negatives

False Positives (model says FOG, label is NO FOG)

Strange scenery

Lens not protected

Just wrong

I'm (not) loving it ;-)

False Negatives (models says NO FOG, label is FOG)

Indeed no fog

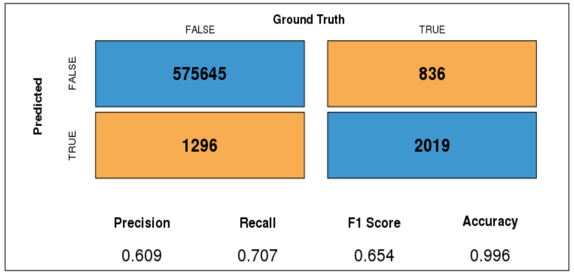
Strange scenery

Just wrong

Not sure...

Analysis of results

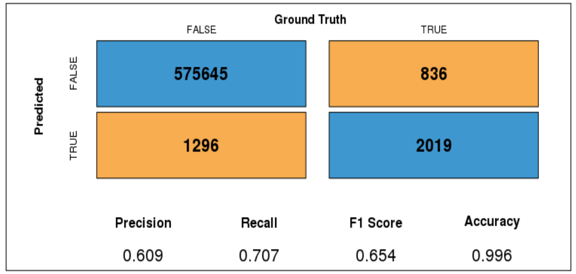
- 1296 FP cases (model predicts dense fog and the sensor reports no dense fog)
- 707 (55%) the sensor reports fog (MOR<1000m)
- 235 cases (18%) not even report haze (MOR<5000m)
- FP occur mainly isolated in time (603 cases) and space (914 cases)



Examples FP cases

Analysis of results

- 836 FN cases (model predicts no dense fog and the sensor reports dense fog)
- FN isolated in time (270 cases)
- FN occurs less often spatially isolated (305 cases)



Examples FN cases

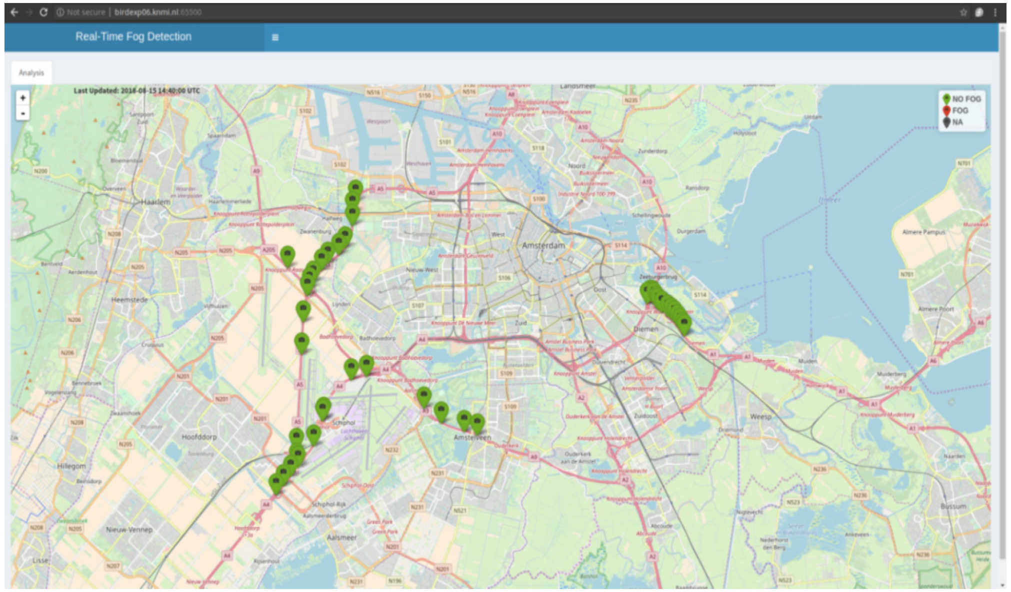
Possibilities of post processing

- Based on consistency in space and time

Post processing	Precision	Recall	F1 score	Accuracy	% omitted	Precision*	% fog
none	60.9%	70.7%	65.4%	0.9963	0.00%		
change	70.2%	74.7%	72.4%	0.9975	0.26%	22.5%	11.7%
change F --> T	70.2%	69.3%	69.7%	0.9972	0.11%	21.5%	4.8%
change T --> F	60.9%	76.0%	67.6%	0.9967	0.15%	23.3%	6.9%
difference with nearest	74.8%	77.6%	76.2%	0.9982	0.37%	31.2%	23.7%
change OR nearest	79.7%	80.6%	80.2%	0.9986	0.54%	28.4%	31.0%
change AND nearest	67.4%	72.7%	69.9%	0.9971	0.09%	23.4%	4.3%

GUI implementation (8/2018)

- Web application using R shiny
- Goal: MVP (quick and dirty)
- But: standardized data exchange format (GeoJSON)
- MVP available for test at KNMI weather room



Work ideas for 2019

- Fog in dawn/dusk conditions
- Model for multiple visibility classes
- Feedback from weather room experience
- Upscaling number of cameras and stress test
- **CNN work with Ernir**


Thank
You
Vinaka
köszönöm
Kiitos
Maake
Asante
Shukria
Dhanyavadagalu
감사합니다
Dankscheen
спасибо
Kam Sah Hammida
اركش
Manana
Dankon
Diolch i Chi
Terima Kasih
Matondo
Dank Je
Mauruuru
Biyan
Taiku
Tack
Blagodaram
Ngiyabonga
Dziekuje
Chokrane
Grazie
Juspaxar
Arigato
Mochchakkeram
Gracias
Khap
Paldies
Tingki
நன்றி
Bedankt
D'akujem
धन्यवाद
cảm ơn bạn
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Ua Tsaug Rau Koj
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Kia Ora
Obrigado
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Nirringrazzjak
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Djiere Dieuf
Misaotra
Danke
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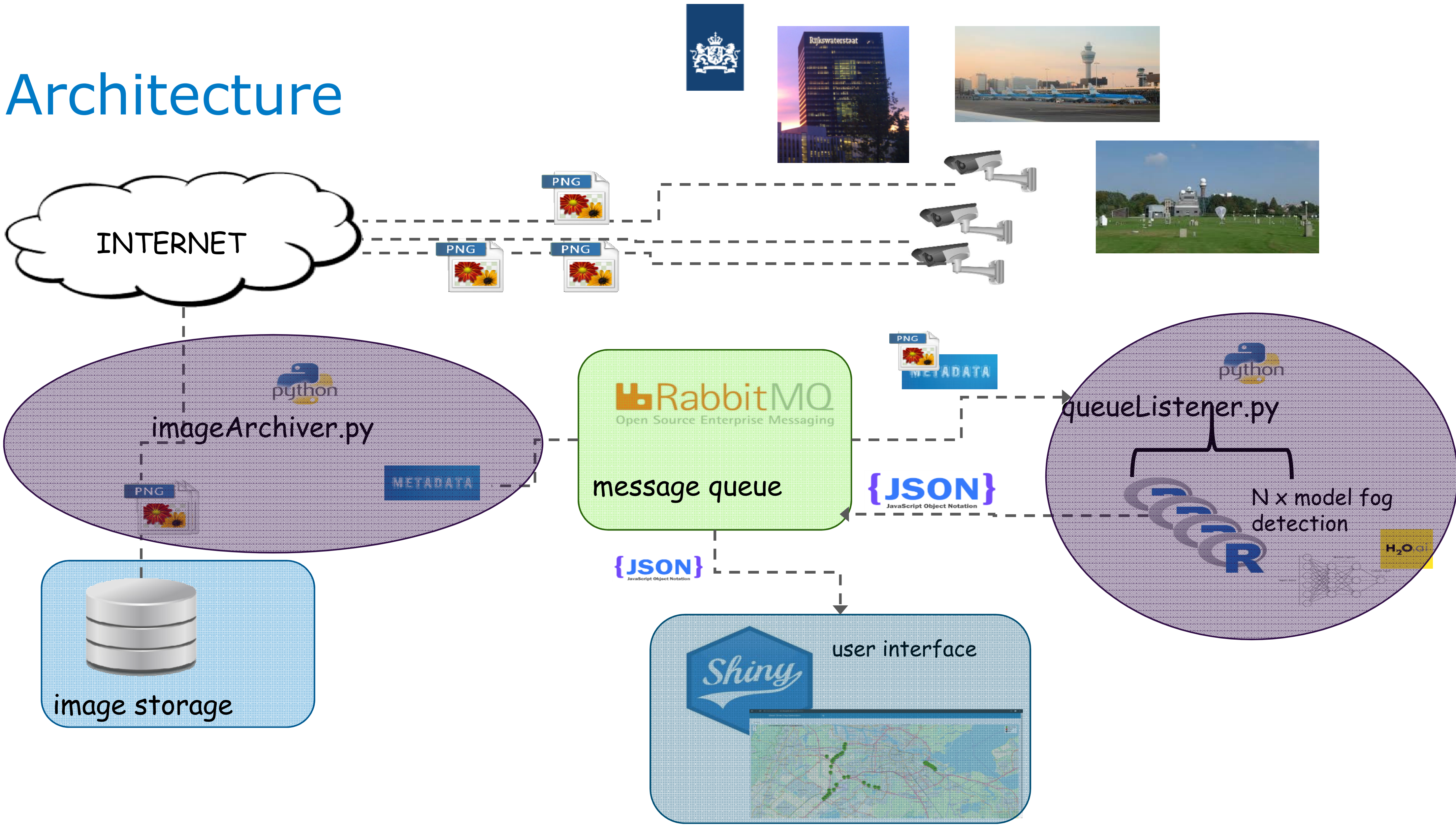
Eskerrik Asko
Salamat
ขอบคุณ
Najis

Architecture



Architecture