Multi-modal machine learning and deep learning for earth observations and climate change mitigation in sub-Arctic and Arctic regions

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Insight SFI Research Centre for Data Analytics Visiting Researchers Programme Seminar

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Outline

- Research group introduction
- AI for earth observations and climate change mitigation
- Short highlights of on-going activities in AoF project
  - Snow water equivalent forecasting
  - Surrogate models and their application to geophysical soil simulations
  - Satellite remote sensing: image enhancement and segmentation
- Multi-source road quality forecasting
- Future plans

Research Group and Activities

Biomimetics and Intelligent Systems Group

- Research unit in Faculty of ITEE of 40+ researcher studying different aspects of intelligent systems, led by Prof. Juha Röning
- Data Analysis and Inference Group (DataAI)
  - Statistical signal processing, machine learning, data mining, applied AI, XAI
- Robotics Group
  - Mobile robotics, control and sensing systems, perception and machine intelligence
- Oulu University Secure Programming Group (OUSPG)
  - Software security, vulnerabilities, cybersecurity
- Bio-ICT
  - Integrating technology with biology/biomedicine, bioinformatics, biosensors

DataAI Group

- Senior Researchers
  Dr. Jaakko Suutala, Asst. Prof.
  Dr. Pekka Siirtola, Adj. Prof.
  Dr. Satu Tamminen, Uni. Lecturer
- Post-docs
  Dr. Lauri Tuovinen
  Dr. Henna Tiensuu





- Doctoral Candidates: Gunjan Chandra, Anusha Ihalapathirana, Miika Malin
- Research Assistants: Joonas Tuutijärvi, Samuli Paloniemi, Justin Seby, Nirzor Talukder

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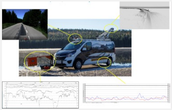
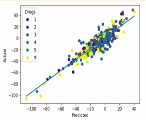
Research Themes

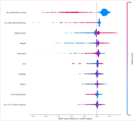
DataAI

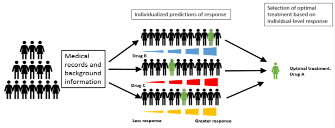
ML SUPPORTED SUSTAINABILITY



HEALTH AND WELLBEING MODELING

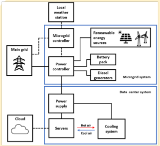


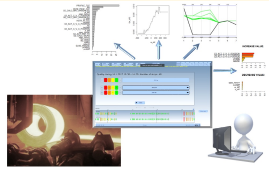




ROBUST, EXPLAINABLE, AND ETHICAL AI & DECISION SUPPORT

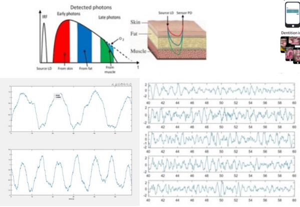
INDUSTRIAL DATA MINING



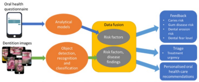


Some Recent Research Activities

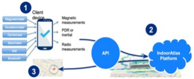
BioLiDAR: time-contrastive learning and ICA for novel heart rate detection (from time-resolved diffuse optics)

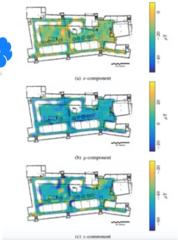


Medical and dental imaging, personalised medicine

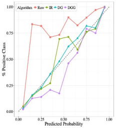


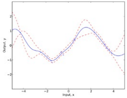
Gaussian processes, sensor fusion, magnetic indoor mapping and localization

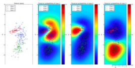


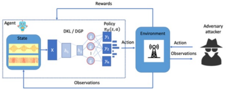


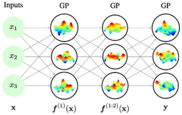
Data-efficient and adversarial robust ML/RL, uncertainty quantification



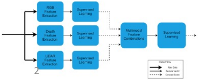


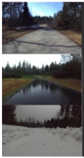


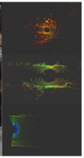




Deep multimodal fusion for mobile robotics



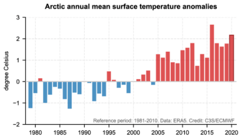


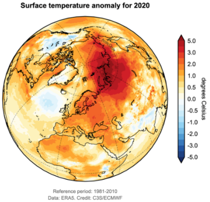


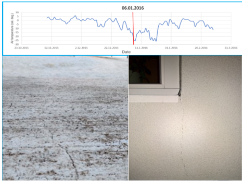
Data-driven Climate Change Adaptation and Mitigation

Climate Change Mitigation

- Extreme and unusual weather conditions are increasing (including sub-Arctic and Arctic regions)
    - Climate change can affect the urban infrastructure: buildings, roads etc.
    - Causing frost quakes, changes in ground frost, snow characteristics, groundwater levels, etc.







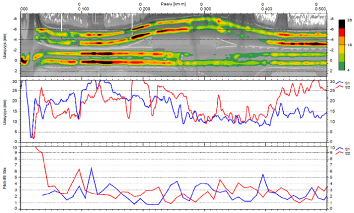
Images: CC0 Public Domain, Dr. Jarkko Okkonen (GFS)

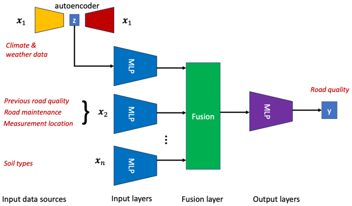
Climate Change Mitigation (cont'd)

- Detecting and predicting long-term and sudden changes, and possible future hazards and damages in proactive manner
  - Resilience and adaptation for a changing climate
- Multi-disciplinary approach combining expertise of geophysics, computer science, and AI to tackle climate change adaption and mitigation
  - Academy of Finland funded Green Deal project 2022-2024
  - Participants: University of Oulu (BISG, OMS) and Geological Survey of Finland
- Our group is interested in applying data-driven approaches to earth observation data to build predictive models and tools

AI and ML for Earth Observations

- Spatio-temporal modelling and forecasting
  - Multi-modal deep learning and probabilistic modelling
  - Combining spatial data and time-series in multi-modal neural network architectures

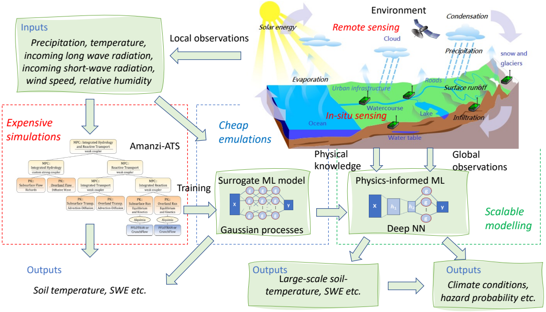




Left image: Roadscanners Ltd.

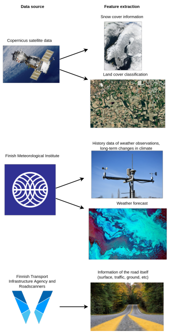
AI and ML for Earth Observations (cont'd)

- Physics-aware machine learning
  - Speed-up physical and geophysical simulations by statistical surrogate models and Bayesian optimization (e.g., Gaussian processes)
  - Physics-informed ML/DL to combine traditional and data-driven approaches to increase the performance and explainability of the models (e.g., in the case of limited data)



Multi-modal and Multi-source approaches

- Multi-source data-driven approaches for modelling and forecasting
  - Machine learning framework for combining multi-modal data
  - Analysis of seasonal weather, geological data, and remote sensing data, and their effects to unusual phenomena, hazards etc.
  - Practical forecasting models from sparse time-series measurements, images, and simulations



Images: Copernicus, Creative Commons

Highlights of Project Activities

Snow Water Equivalent Forecasting

Snow Water Equivalent Forecasting with Recurrent Neural Networks

- Snow water equivalent (SWE) = the amount of water in the snowpack
- Affected by the weather conditions throughout the winter
- Difficult information to collect
  - Measured from 2 to 4 km long snow course
  - Depth is measured from 80 points, and the snow is weighted at 8 points to get the snow density
  - Combined with snow cover information to get the average estimate for SWE (on snow course)

Images: Creative Commons, Hannula et al. (2016)

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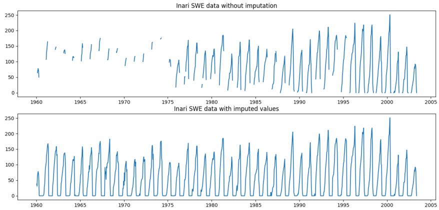
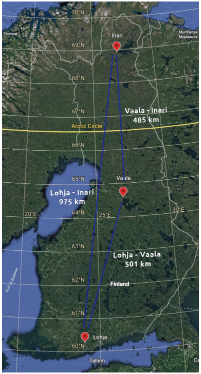
Snow Water Equivalent Forecasting with Recurrent Neural Networks (cont'd)

- Traditionally, modelling and forecasting is done using physical snow model
- We are interested if the SWE forecast could be enhanced and improved with recurrent neural networks
- Applications: flood predictions and modelling hydrological systems, seasonal changes etc.

Snow Water Equivalent Forecasting with Recurrent Neural Networks (cont'd)

- 3 test sites
- Long-term dataset 1960-2021
- Inputs: daily temperature, precipitation, and bi-weekly history SWE values of 180 days
- Output: Next SWE value

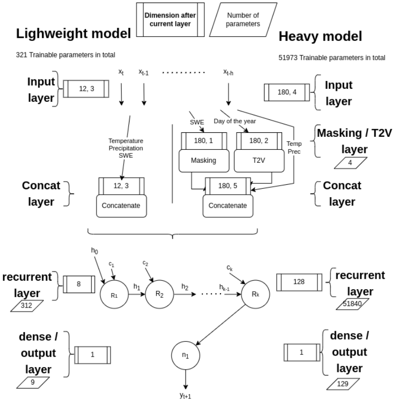




Right image: Google maps

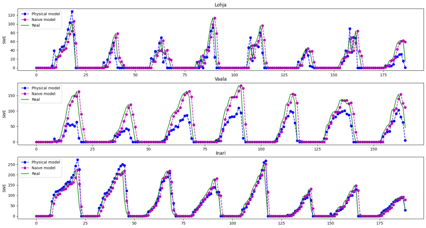
Snow Water Equivalent Forecasting with Recurrent Neural Networks (cont'd)

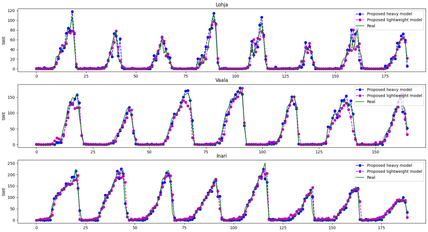
- Gated Recurrent Unit (GRU) -based neural network models



Snow Water Equivalent Forecasting with Recurrent Neural Networks (cont'd)

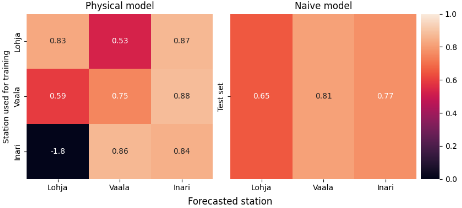
- Forecasting results of physical snow model, naive baseline, and GRU-based models

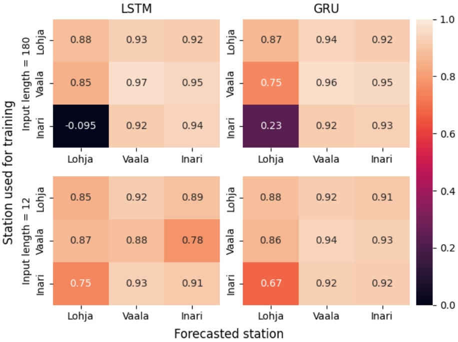




Snow Water Equivalent Forecasting with Recurrent Neural Networks (cont'd)

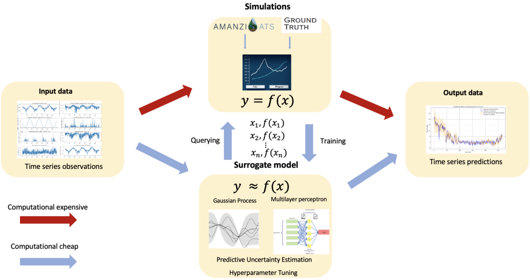
- Numerical comparison (NSE) of physical snow model, naive baseline, and LSTM/GRU-based models





Machine Learning -based Surrogate Modelling

ML-based Surrogate Models for Hydrogeological Simulation



- Emulators to speed-up computation of expensive (black-box) simulations
- Approximating the solution with subset of simulated points or online active learning
- Interpolating and extrapolating (with uncertainty quantification) outside simulated location
  - Enabling large-scale spatio-temporal modelling and prediction

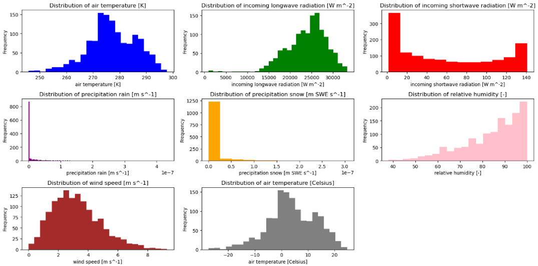
ML-based Surrogate Models for Hydrogeological Simulation (cont'd)

- New effective tools to analyse hydrological and mechanical properties of soil/ground to understand our environment from easy to get indirect measurement
- 4 years of data (2011-2015) recorded in northern Finland (Oulu area) with ground truth observations of soil temperature and water content (down to depth of 2 meters)

Image: Dr. Kari Moisio (OMS)

ML-based Surrogate Models for Hydrogeological Simulation (cont'd)

- Inputs: daily air temp., precipitation (rain/snow), wind speed, long- and shortwave radiation, relative humidity
- Outputs: soil temperature and water content (+ simulated ice content)



ML-based Surrogate Models for Hydrogeological Simulation (cont'd)

- Preliminary result utilizing Gaussian process regression (GPR), Multi-layer Perceptron (MLP)
- Prediction accuracy

Metric	Method		
	GPR	MLP	Simulator
$R^2 \uparrow$	0.82	0.89	0.96
RMSE $\downarrow$	1.93	1.59	0.89
MSE $\downarrow$	3.72	2.51	0.79

Table: Soil temperature prediction accuracy.

ML-based Surrogate Models for Hydrogeological Simulation (cont'd)

- Computation times (in seconds)
- ML models trained with standard and simulator with high-end laptop, respectively

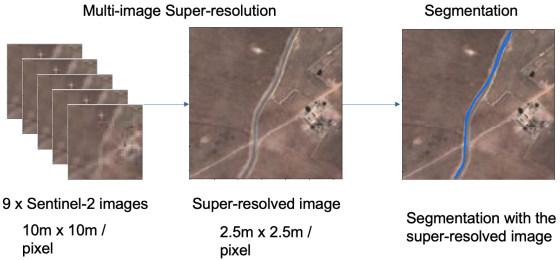
Comp. times	**Method**		
	GPR	MLP	Simulator
Training	14.0	79.0	-
Inference	0.2	1.8	-
Total	**14.2**	**80.8**	**320.0**

Table: Soil temperature computation times.

Satellite Remote Sensing for Monitoring Earth Surface and Environment

Remote Sensing for Land and Road Segmentation

- Remote sensing for large-scale monitoring of Earth surface and environment
- Multi-image super-resolution prediction from low-resolution satellite images
- Semantic segmentation from super-resolved image
  - Input: Sentinel-2 low-resolution optical images
  - Output: Segmentation map



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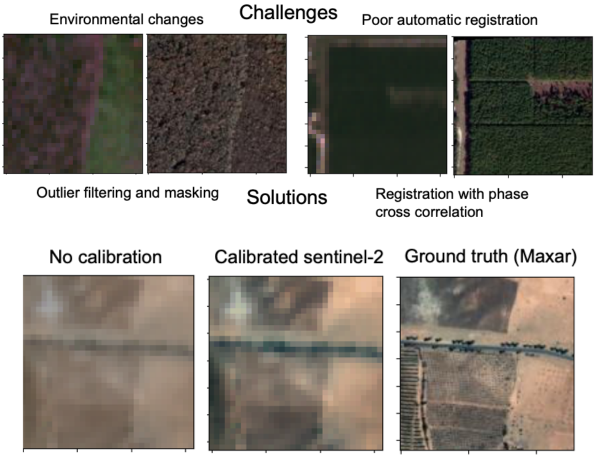
Remote Sensing for Land and Road Segmentation (cont'd)

- Image super-resolution: enhancement of low-resolution satellite images
  - Input: Sentinel 2 low-resolution (LR) optical images
  - Output: Super-resolution image
- Training data from Maxar high-resolution (HR) and low-resolution (LR) Sentinel-2 samples
- ca. 12 000 32x32 LR image sets (9 images) + HR-image (1 image)

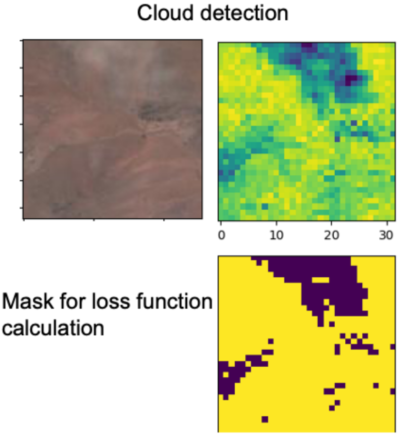
Remote Sensing for Land and Road Segmentation (cont'd)

- First research challenges: outlier detection, image registration, and image calibration (with histogram matching)



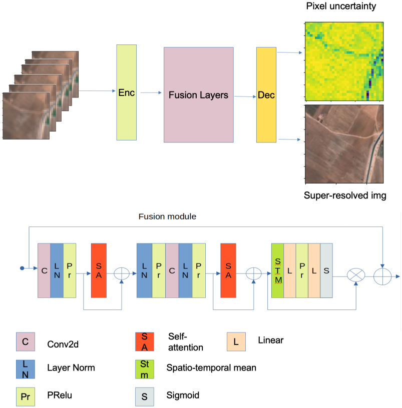
Remote Sensing for Land and Road Segmentation (cont'd)

- Cloud detection (with LR and downsampled HR differencing) and utilization of mask in DNN training



Remote Sensing for Land and Road Segmentation (cont'd)

- Permutation invariance and uncertainty network (PIUnet)



Valsesia et al. (2022). Permutation Invariance and Uncertainty in Multitemporal Image Super-Resolution. IEEE Trans. on Geoscience and remote sensing.

Remote Sensing for Land and Road Segmentation (cont'd)

- Next research steps
  - Training and evaluating the super-resolution model on the large-scale dataset
  - Accurate segmentation of small and narrow objects such as roads from super-resolved images
- Applications: monitoring roads and seasonal road conditions, snow melting, floods, etc.

Road Quality Forecasting

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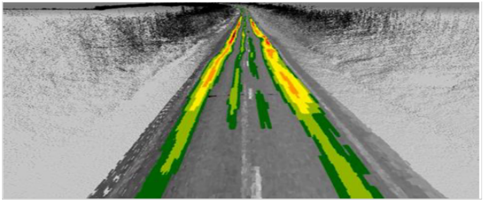
Multi-source Deep Learning for Long-term Road Conditions forecasting

- Preliminary research on data-driven road quality/damage forecasting and proactive maintenance
- Analysis of seasonal weather, climate, and geological data, and their effects to road quality and damages



Images: Roadscanners Ltd., CC0 Public Domain

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Study Sites

- Asphalt roads in northern Finland (sub-Arctic, near Arctic region)
- In this study, three different sites where we have:
  - Road surface quality data, 2015-2022
  - Long-term weather and road surface/ground data from road weather stations, 2010-2022
  - Additional data: meas. locations, past road maintenance info, surrounding soil types etc.

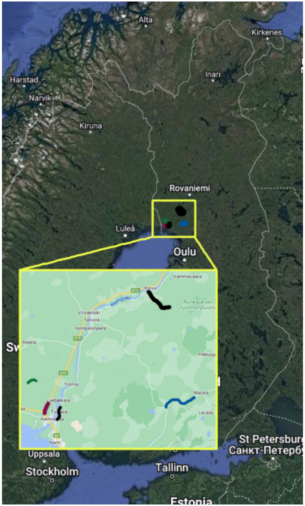
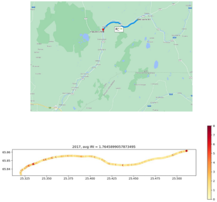
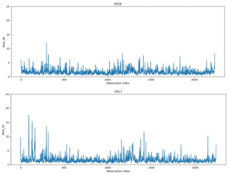


Image: Google maps

Measurements

- Annual road condition and quality data
  - Road surface: International Roughness Index (IRI) (Roadscanners Ltd., IMU-based system)
  - Past maintenance information (open data)
- Static ground data: soil types (open data)
- Daily and sub-hourly observations from the closest road weather stations (open data)
  - Ground temperature
  - Precipitation





Left image: Roadscanners Ltd.

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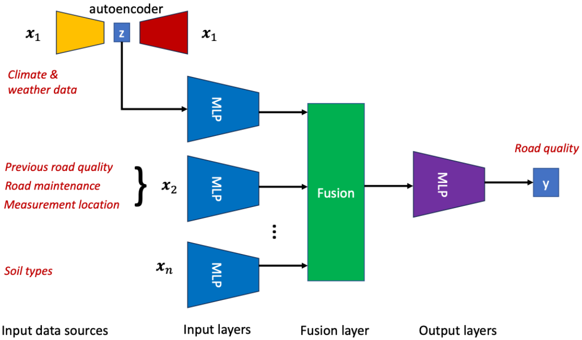
Dataset Preparation

- Pitch IRI measurements in 100 meter segments (10 meter interval)
  - Input: current year 10 IRI values from each segment
  - Output: next year 10 IRI values from each segment
- 2D Location of each IRI segment
- Past maintenance: days since last repair for each segment, 3+3 repair types from last two maintenance
- Daily road weather / climate data
  - 12 hand-coded features: ground temperature (mean & std) and precipitation (sum & std) for 3 seasons (autumn, winter spring)
  - 64 length latent feature vector: autoencoding of seasonal ground and precipitation observations
- 12 soil types: generic type (such as coarse soil, fine soil, clay etc.) in the road segment

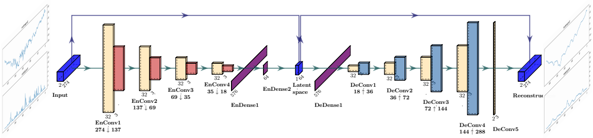
Road Quality Forecasting: Framework

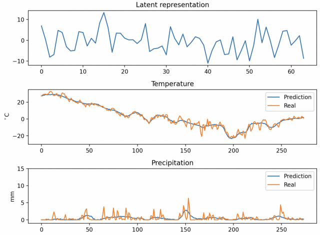
- Deep learning framework for forecasting road quality
  - Autoencoder and feed-forward backbone (input layers), fusion embedding (fusion layer), and regression feed-forward head (output layers)

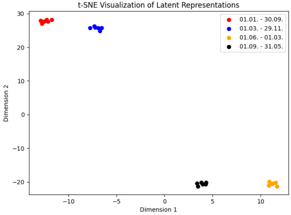


Road Quality Forecasting: Autoencoder

- Stacked convolutional autoencoder for feature extraction
- Latent low-dimensional representation of seasonal weather: daily ground temperature and precipitation

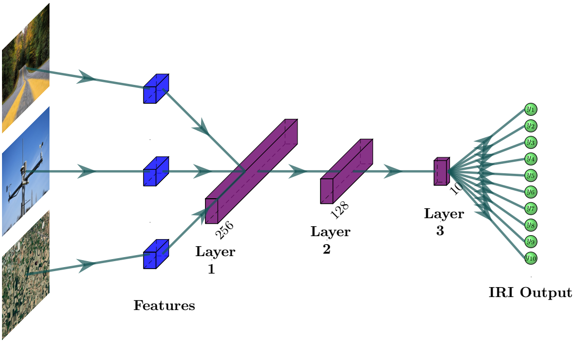






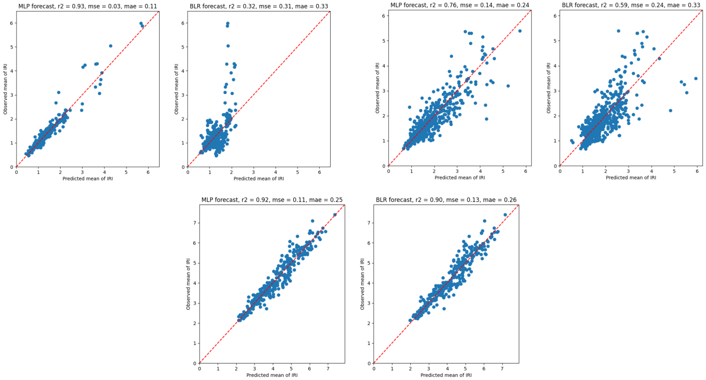
Road Quality Forecasting: MLP

- Feed-forward deep neural networks
  - Multi-layer perceptron (MLP) with multi-source inputs
  - Concatenated fusion, dense ReLU layers



Road Quality Forecasting: Results

- Deep learning approach: MLP + Conv. autoencoder (Early stopping, Adam optimizer with learning rate 1e-4)
- Baseline: Bayesian linear regression (BLR) model (Gaussian priors, HMC sampling with 4 chains and 8000 samples)



Road Quality Forecasting: Results (cont'd)

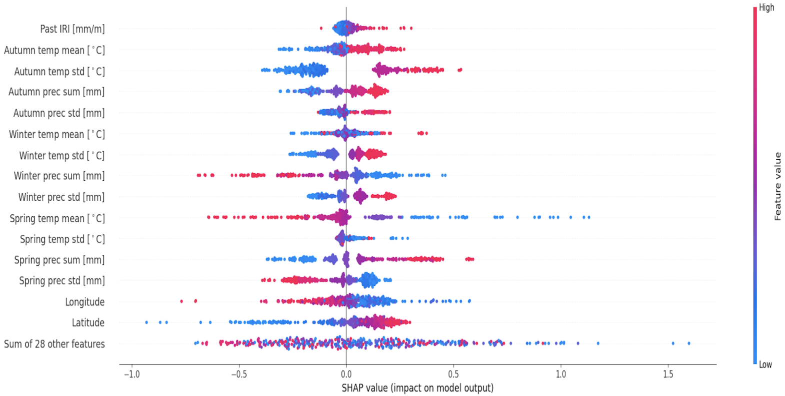
- Comparison of baseline (BLR), MLP, and MLP with convolutional autoencoder

Road	**Baseline (BLR)**			**MLP**			**MLP+Conv-AE**		
	$R^2 \uparrow$	MSE $\downarrow$	MAE $\downarrow$	$R^2 \uparrow$	MSE $\downarrow$	MAE $\downarrow$	$R^2 \uparrow$	MSE $\downarrow$	MAE $\downarrow$
428	0.32	0.31	0.33	0.91	0.04	0.12	**0.93**	**0.03**	**0.11**
924	0.59	0.24	0.33	**0.76**	**0.14**	**0.24**	**0.76**	**0.14**	**0.24**
19541	0.90	0.13	0.26	0.91	0.12	0.26	**0.92**	**0.11**	**0.25**
Avg.	0.60	0.23	0.31	0.86	0.10	0.21	**0.87**	**0.09**	**0.20**

Table: IRI prediction performance.

Road Quality Forecasting: Explainability

- Explainability of MLP predictions (Road 428)
- Shapley Additive Explanations (SHAP)



Road Quality Forecasting: Data Sources

- Influence to prediction performance by adding data sources (Road 428)

Metric	Fusion of data sources				
	IRI	+Weather	+Maint.	+Soil type	+Loc.
$R^2 \uparrow$	0.15	0.41	0.51	0.79	0.93
MSE $\downarrow$	0.39	0.28	0.23	0.10	0.03
MAE $\downarrow$	0.28	0.24	0.23	0.16	0.11

Table: IRI prediction performance with fusion of data sources.

Next Steps and Future Plans

Future Plans

- Road quality forecasting (in AoF project)
  - Extending ML models with different sources: road structural course (e.g., using ground penetrating radar), amount of daily traffic, snow water content and soil moisture, remote sensing etc.
  - Country (and other (sub-)Arctic regions) level long-term spatio-temporal forecasting
  - Studying of more advanced fusion strategies in framework
  - Adding more explainability and physics-aware properties to AI/ML framework

Future Plans (cont'd)

- Large-scale monitoring and forecasting applications by combining and extending the models and tools developed for particular small-scale problems to be able to
  - Combine the best properties from different limited yet complementary data sources and modelling approaches
  - Understand better effects of unusual weather and climate change to environment and infrastructure
  - Build practical forecasting and (multi-hazard) warning systems to increase the resiliency in proactive manner (e.g., frost quakes and road damages in sub-Arctic)

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