PREDICTION OF DAILY MAXIMUM OZONE THRESHOLD EXCEEDANCES BY ARTIFICIAL INTELLIGENCE TECHNIQUES IN GERMANY

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Overview

Motivation
- Social Impact

Introduction2.pdf

Motivation
- Regulation and Standard

`Regulations.png`

Normativity of O_3 in United State, European Union, Mainland China, and Hong Kong

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Research Questions and Objectives

- Predict the exceedances of the maximum 8h ozone concentrations in Germany

Research Questions:

- Can ***machine learning*** enhance the prediction accuracy for the air quality warning system ?
- How do different machine learning methods perform in the ***classification task*** of predicting threshold exceedances?
- ***How far in the future*** can make ozone prediction by machine learning/deep learning?

BW_locations.jpg

Map of the study region Baden-Württemberg in Germany (Source:onTheWorldMap.com)

Ground-level ozone

- Factors controlling ozone level

OzoneFormation4.pdf

Schematic diagram for ozone formation (Fowler et al., 2008)

Ground-level ozone
- Key variables

Table: Pollution variables as inputs for modelling

Variable	Description	Unit
o3_dma8eu	Daily maximum 8-hour average ozone	ppb
no_dma8eu	Daily maximum 8-hour nitrogen monoxide	ppb
no2_dma8eu	Daily maximum 8-hour nitrogen dioxide	ppb

Table: Meteorological variables as inputs for modelling

Variable	Description	Unit
pblheight_max	Maximum height of planetary boundary layer	m
relhum_max	Daily maximum relative humidity	%
temp_max	Daily maximum temperature	$^\circ$C
u_mean	Daily mean u-component (zonal) of wind	m/s
v_mean	Daily mean v-component (meridional) of wind	m/s
cloudcover_mean	Daily mean total cloud cover	%

pollu_corr.png

Moving average values of O_3, no_dma8eu and no2_dma8eu from 2012 to 2014 at Station DEBW010

meteo_corr.png

Moving average values of O_3, cloudcover_mean, pblheight_max, relhum_max, and temp_max from 2012 to 2014 at Station DEBW010

Data selection and preparation

- Tropospheric Ozone Assessment Report (TOAR) Database for variable selection

25 variables, more than ***10,000 measurement sites*** from over ***30 different sources*** around the world

TOAR2.png

TOAR1.png

Data selection and preparation
- Dataset structure for machine learning and Convolutional Neural Network

DataStructure1.pdf

Data selection and preparation

- Dataset structure for machine learning and Convolutional Neural Network

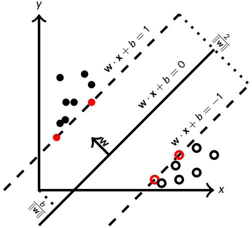
DataStructure2.pdf

Machine learning mechanism

- Random Forest, Support Vector Machine, and Convolutional Neural Network

RF.png

Random Forest



Support Vector Machine

DL.png

1D CNN

Imbalanced data solution
- Imbalanced data issue

imbalanceDataIssue.png

ImbalancAccuracy.png

		Observed	
		Minority	Majority
Predicted	Minority	TP	FP
	Majority	FN	TN

ExceedanceRate2.pdf

Exceedance frequency ($\frac{No.of\ Exceedances}{No.of\ samples}$) for all the monitoring stations in BW state

Imbalanced data solution

- Imbalanced data solution: Modifying class distribution

oversampling.png

DEBW048X_train_pca2.pdf

Scatter plot of raw data in 2 Dimensions

SMOTE.png

DEBW048X_res_pca2.pdf

Scatter plot of SMOTE data in 2 Dimensions

Synthetic Minority Over-sampling Technique(SMOTE)

Evaluation metrics
- Classification evaluation metrics

Generic evaluation metric

		Observed: Positive	Observed: Negative	Total
Predicted	Positive	a	b	$a+b$
	Negative	c	d	$c+d$
	Total	$a+c$	$b+d$	N

- Accuracy = $\dfrac{a+d}{a+b+c+d}$
- Precision = $\dfrac{a}{a+b}$
- Recall = $\dfrac{a}{a+c}$

Evaluation metric for imbalanced data

- F1 - Score = $\dfrac{2 \cdot Recall \cdot Precison}{Recall + Precison}$
- G-means = $\dfrac{a \cdot d}{(d+c) \cdot (a+c)}$

y_i are the prediction values, and $\hat{y}_i$ are the observed values.

Skill score

Use the skill score for comparing the target model *t* and reference model *ref* based on measurement *m*.

- $skill_m = (m - m_{ref})/m_{ref}$

Orig VS. SMOTE

- Does the SMOTE improve the model performance?

SVM_RF_DL_SMOTE_V4.png

Skill scores ($skill_{SMOTE} = (m_{SMOTE} - m_{orig})/m_{orig}$) corresponding to different evaluation metrics for comparing on raw data and SMOTE data from all the monitoring stations

ML VS. CNN
- Does CNN improves the prediction accuracy?

SVM_RF_DL_SMOTE_AbsValues3.png

Evaluation metrics for SVM, RF, and CNN models on SMOTE dataset for all the monitoring stations

Prediction accuracy on 4 leading days

- Forecasting 4 leading days

SMOTE_CNN_DAYS1_4.png

Evaluation metrics of CNN model on SMOTE to predict 4 days ahead for all the monitoring stations

Deep learning improvement
- Deep Learning diagnosis

orig_ref_acc.png

Accuracy-M1

orig_ref_loss.png

Loss-M1

orig_regulization1_acc.png

Accuracy-M1-Reg1-l-0.1

orig_regulization1_l

Loss-M1-Reg1-l-0.1

orig_regulization2_acc.png

Accuracy-M1-Reg1-l-10

orig_regulization2_loss.png

Loss-M1-Reg1-l-10

The reference 1D CNN was diagnosis as:

- Over-fitting
- Local minimal

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Conclusions and Future studies
- Preliminary conclusions and Future studies

- **Preliminary conclusions:**
  - SMOTE can improve the classification performance for model SVM and RF.
  - With current set-up CNN is not better than traditional ML techniques; RF wins.
  - The prediction accuracy decrease significantly from 1 leading day to 2 day prediction.

- **Future studies:**
  - Deep learning structure
    - Cost-sensitive CNN for imbalanced data
    - Universal network for all the stations
    - LSTM
  - Data Level
    - Size of variables (Feature engineering, spatial factors etc.)
    - Heterogeneous data sources

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IntelliAQ_logo_stacked_transparent.png

http://www.IntelliAQ.eu

erc_logo.png

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Thank You!

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References I

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