Camera-based Water Stage and Discharge Prediction with ML

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Introduction

Find a way to predict the state of water (stage and discharge) at any time in the future using ML, sensor data and photographs of water bodies.

Steps taken

- Understand research paper
- Analyze dataset
- Select features
- Clean data
- Create models
- Separate data by seasons
- Use images to create different models

	CaptureTime	Stage
0	2012-06-09	2.99
1	2012-06-09	2.99
2	2012-06-09	2.96
3	2012-06-09	2.94
4	2012-06-09	2.94

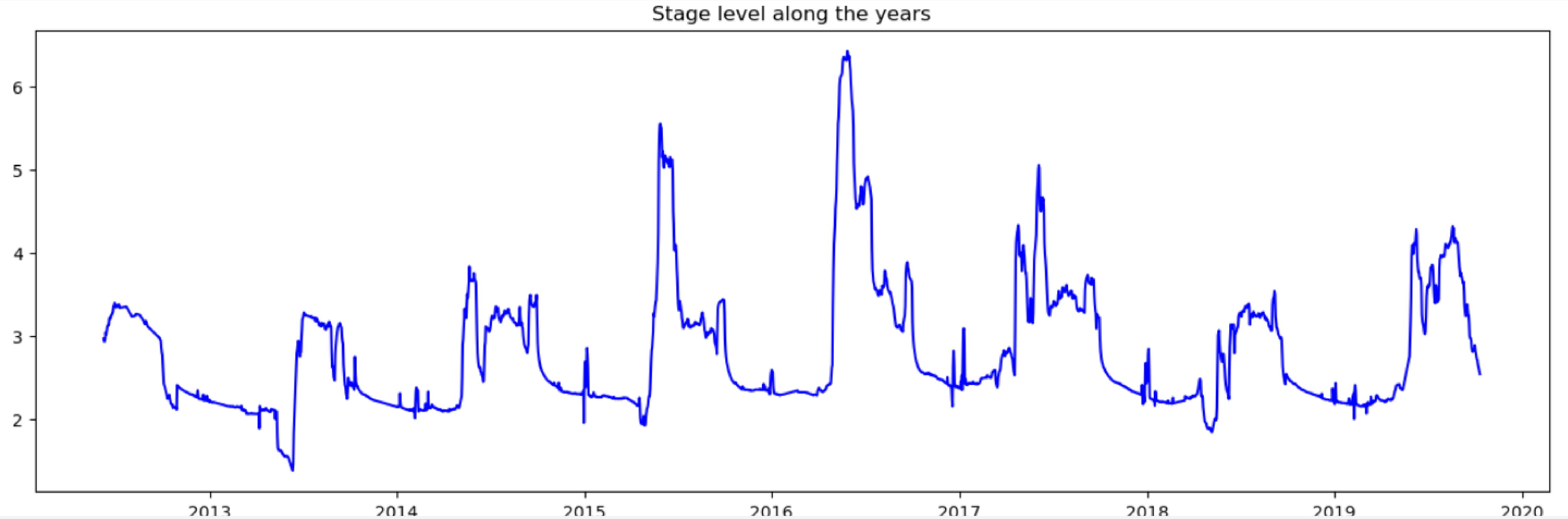
2012-06-09	2.965455
2012-06-10	2.931176
2012-06-11	2.931875
2012-06-12	2.965625
2012-06-13	3.042500

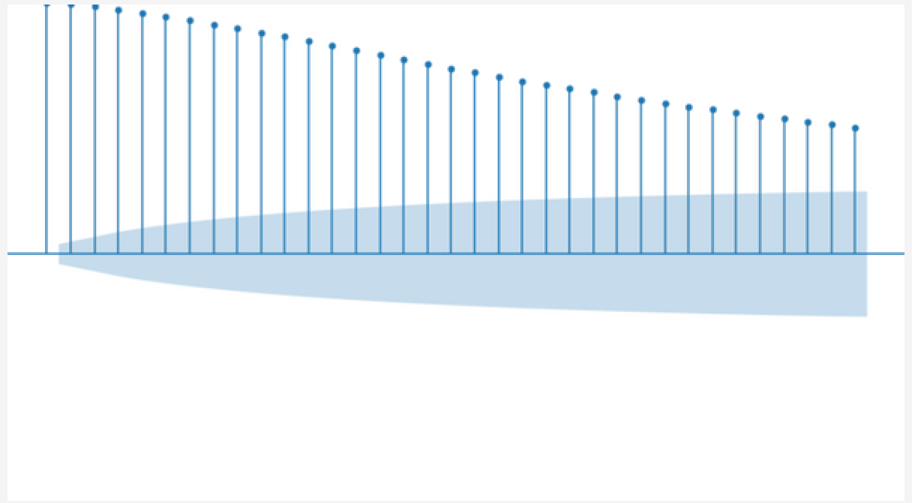
Time series analysis

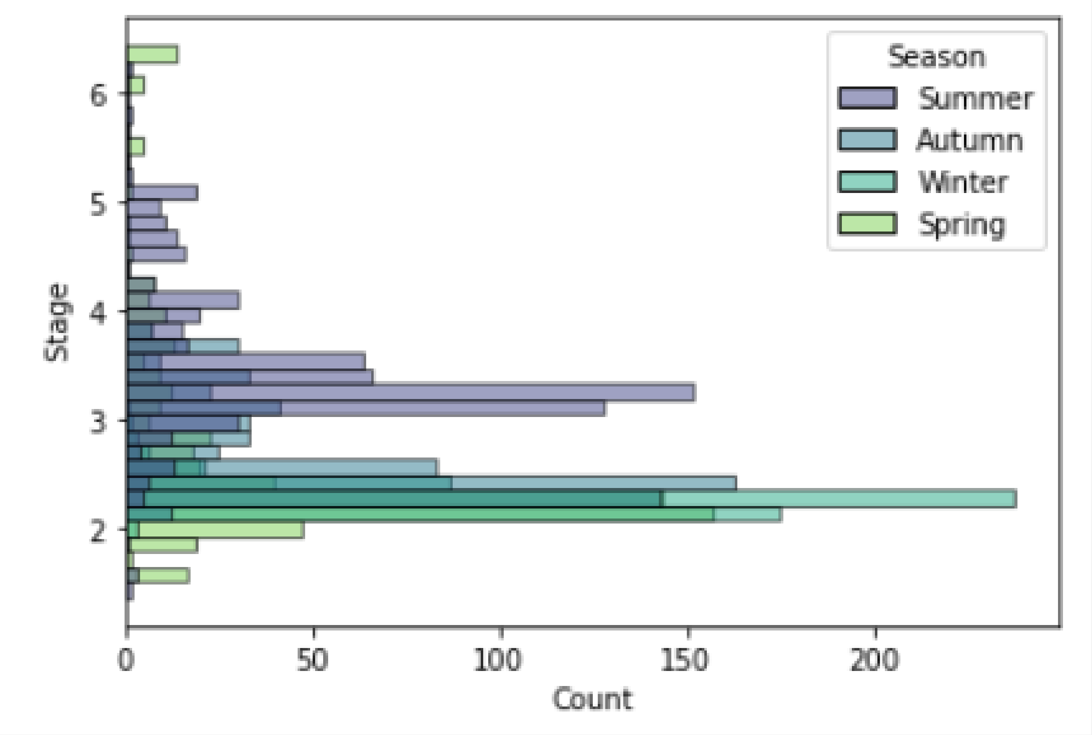
For our time series analysis we take into account only the *CaptureTime* and the *Stage*.

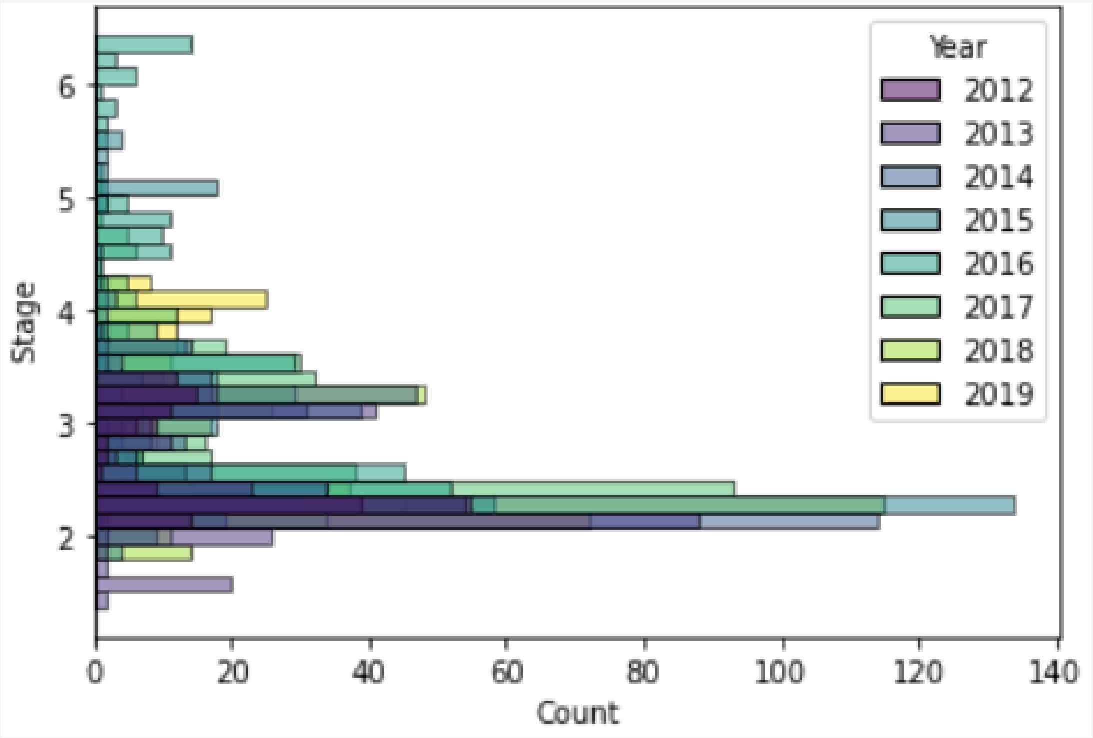
Because there were some records with the same date, we grouped the dates and obtained the mean from each date.

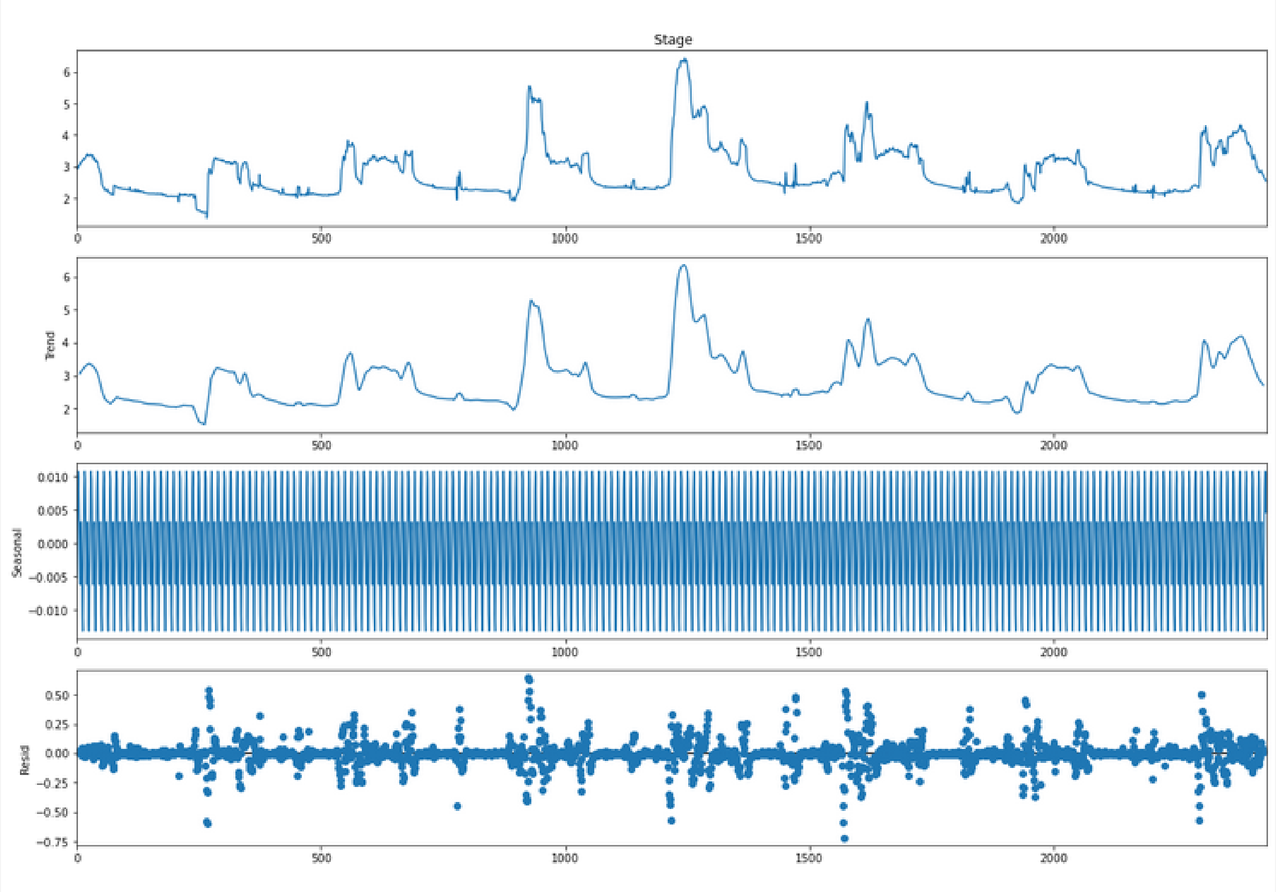
EDA


Stage level along the years
2
3
4
5
6
2013
2014
2015
2016
2017
2018
2019
2020

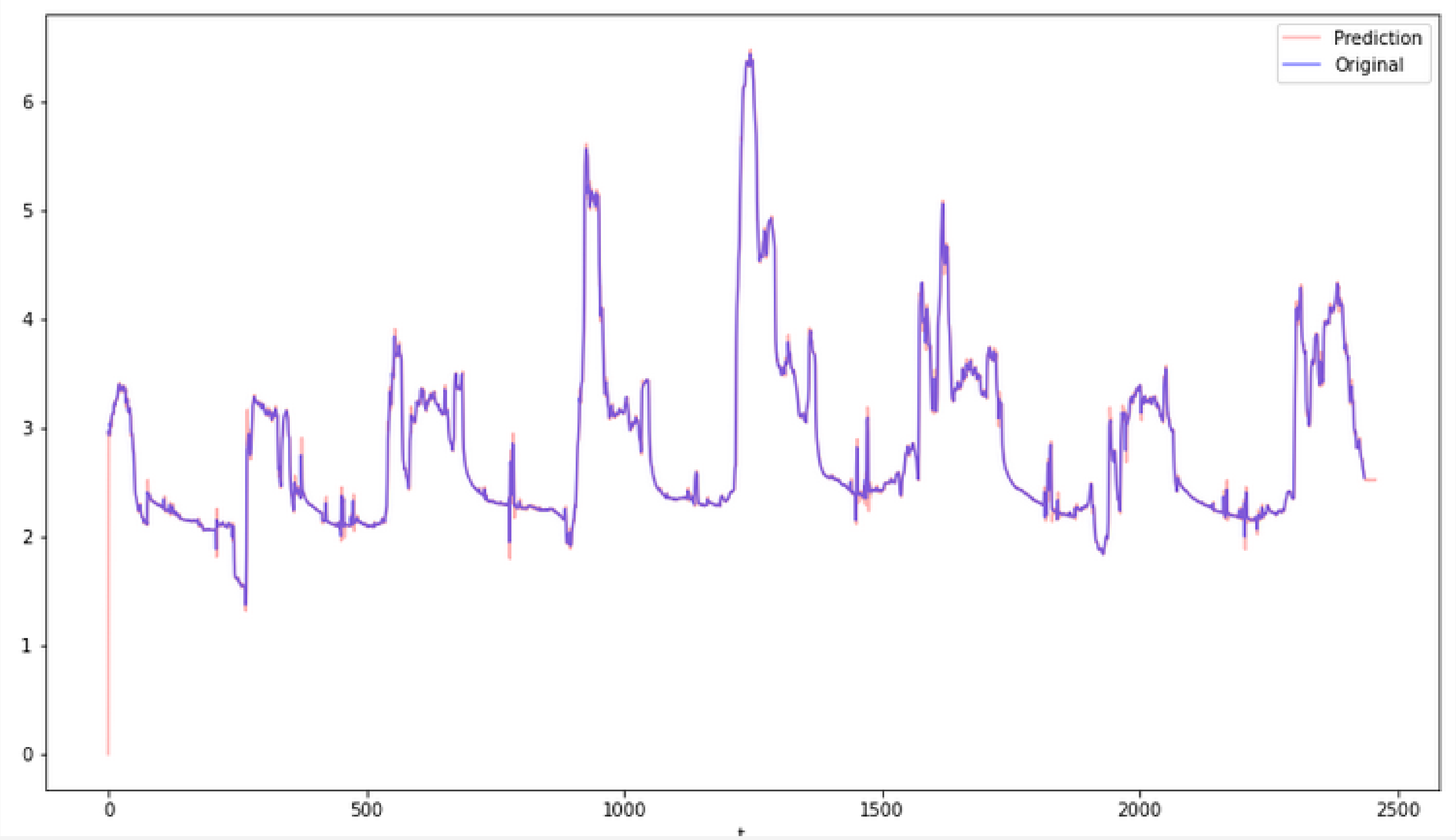


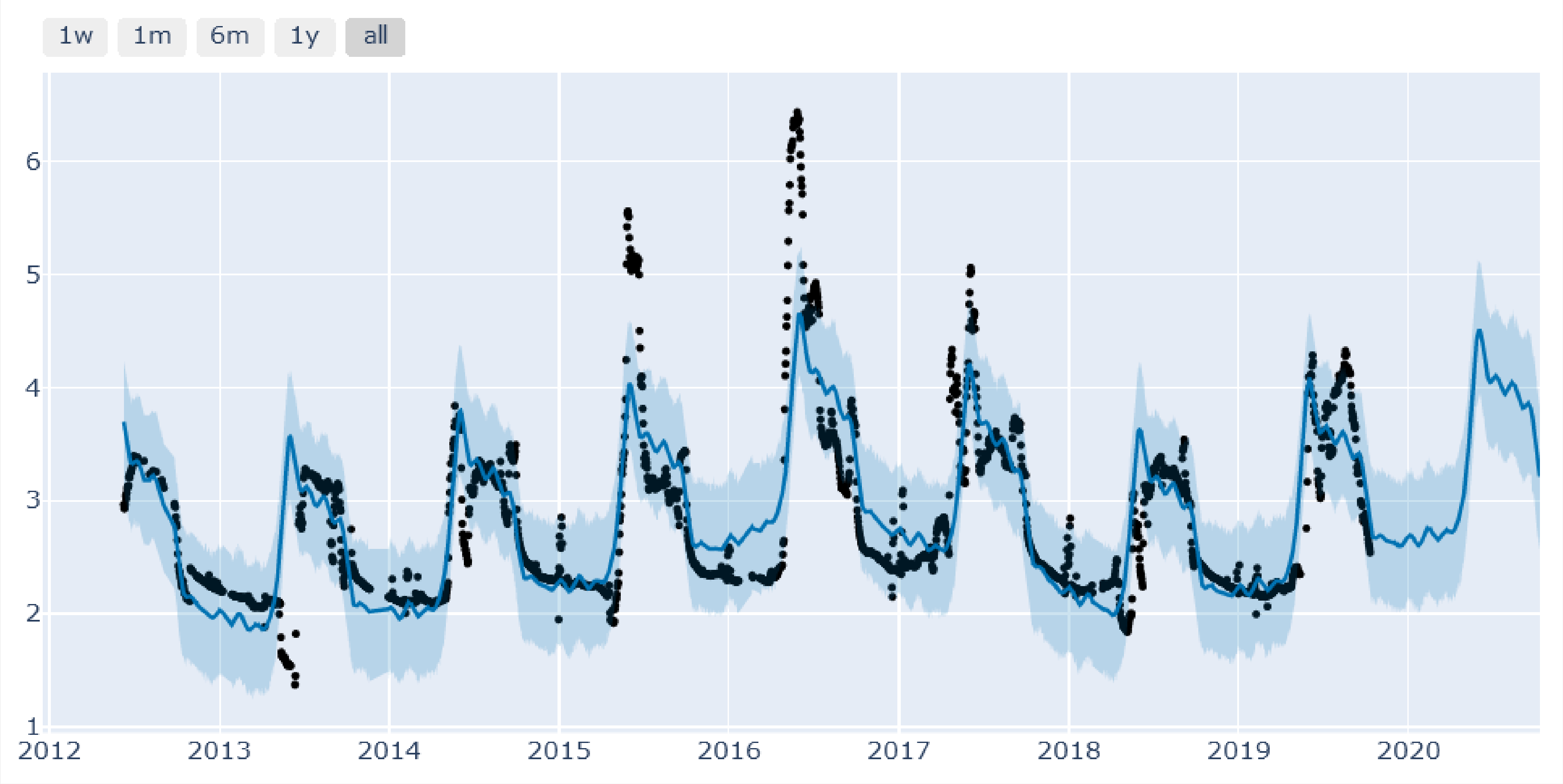

Season
Summer
Autumn
Winter
Spring
Stage
2
3
4
5
6
0
50
100
150
200
Count


Year
2012
2013
2014
2015
2016
2017
2018
2019
Stage
2
3
4
5
6
0
20
40
60
80
100
120
140
Count


Stage
Trend
Seasonal
Resid
0
500
1000
1500
2000

ARIMA and Prophet models





Predicting water stage level with regression models

Linear Regression model

With the dataframe provided, we built a a linear regression model in order to predict the water stage. We are still trying to determine what is causing the models overfitting. The next thing to do is to use some time series analysis in the variables if we can detect which variables have tendency.

First approach

OLS Regression Results

Dep. Variable:	Stage	R-squared:	0.663
Model:	OLS	Adj. R-squared:	0.663
Method:	Least Squares	F-statistic:	1286.
Date:	Mon, 28 Nov 2022	Prob (F-statistic):	0.00
Time:	14:14:27	Log-Likelihood:	-19302.
No. Observations:	29441	AIC:	3.870e+04
Df Residuals:	29395	BIC:	3.908e+04
Df Model:	45		
Covariance Type:	nonrobust		

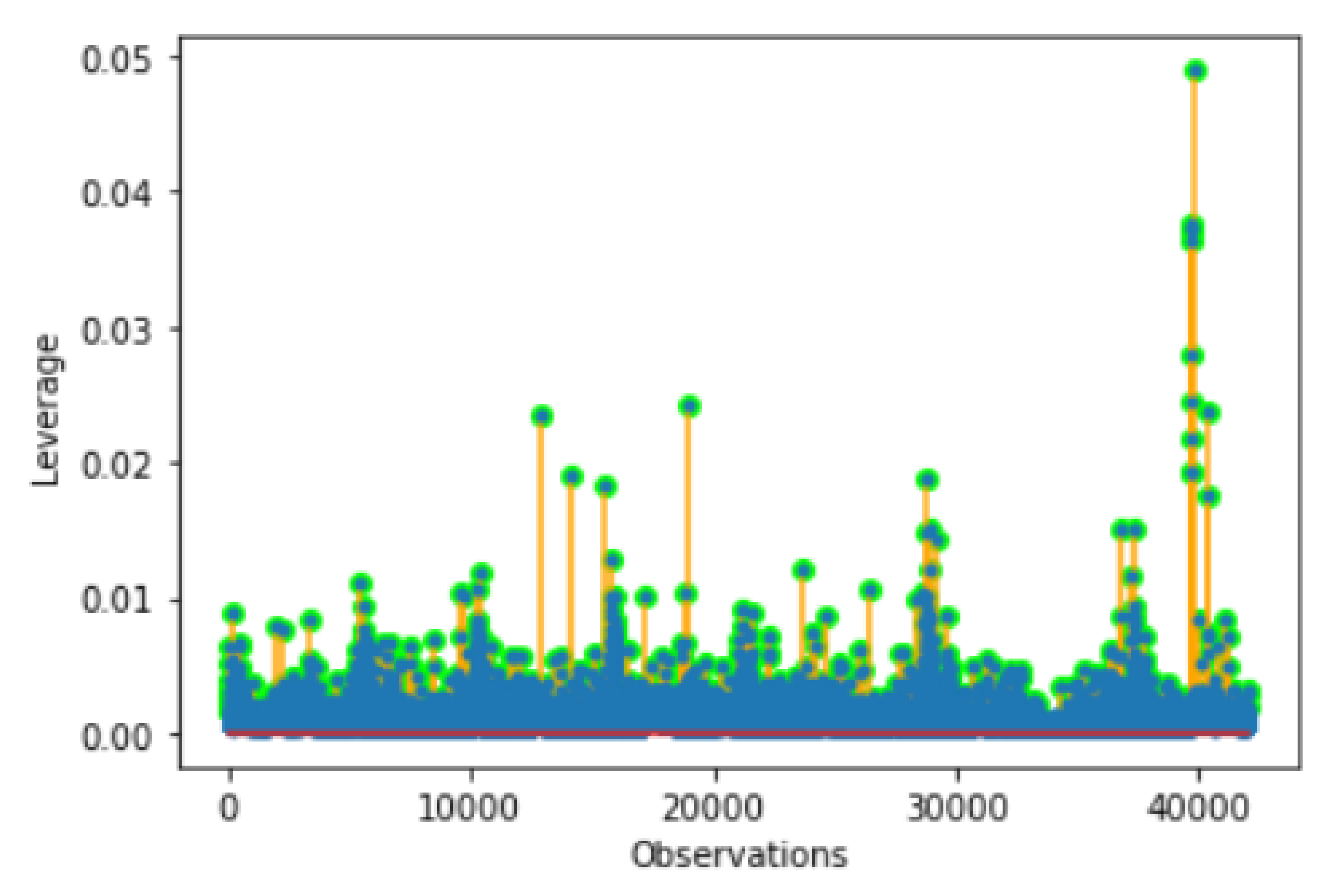
Second approach

OLS Regression Results

Dep. Variable:	Stage	R-squared:	0.672
Model:	OLS	Adj. R-squared:	0.671
Method:	Least Squares	F-statistic:	1368.
Date:	Thu, 01 Dec 2022	Prob (F-statistic):	0.00
Time:	14:05:49	Log-Likelihood:	-20730.
No. Observations:	28811	AIC:	4.155e+04
Df Residuals:	28767	BIC:	4.191e+04
Df Model:	43		
Covariance Type:	nonrobust		

Outlier removal

Once the variables with p-value higher than 0.05 were deleted, we proceeded to the outlier removal.



We used three different ways to detect and eliminate outliers:

- Studentized residuals
- Leveraging
- Cook distance

All three at the same time.

Final model first approach

```
Decision Tree Regressor scores
r2 score: 0.8252936823154983
Mean squared error (MSE): 0.07423337253189911
Root mean squared error (RMSE): 0.07423337253189911
Mean absolute error (MAE): 0.1578338527243486
------------------------------
Random Forest Regressor scores
r2 score: 0.9118831584291581
Mean squared error (MSE): 0.03744117793424774
Root mean squared error (RMSE): 0.03744117793424774
Mean absolute error (MAE): 0.1089957098760697
------------------------------
Support Vector Regressor scores
r2 score: 0.3048800757597723
Mean squared error (MSE): 0.2953590744420336
Root mean squared error (RMSE): 0.2953590744420336
Mean absolute error (MAE): 0.3969163167570166
------------------------------
MLP Regressor scores
r2 score: -1091.1091901902423
Mean squared error (MSE): 464.04130906878333
Root mean squared error (RMSE): 464.04130906878333
Mean absolute error (MAE): 19.270464385486186
```

OLS score
r2 score: 0.801
MSE: 0.084
RMSE: 0.290
MAE: 0.217

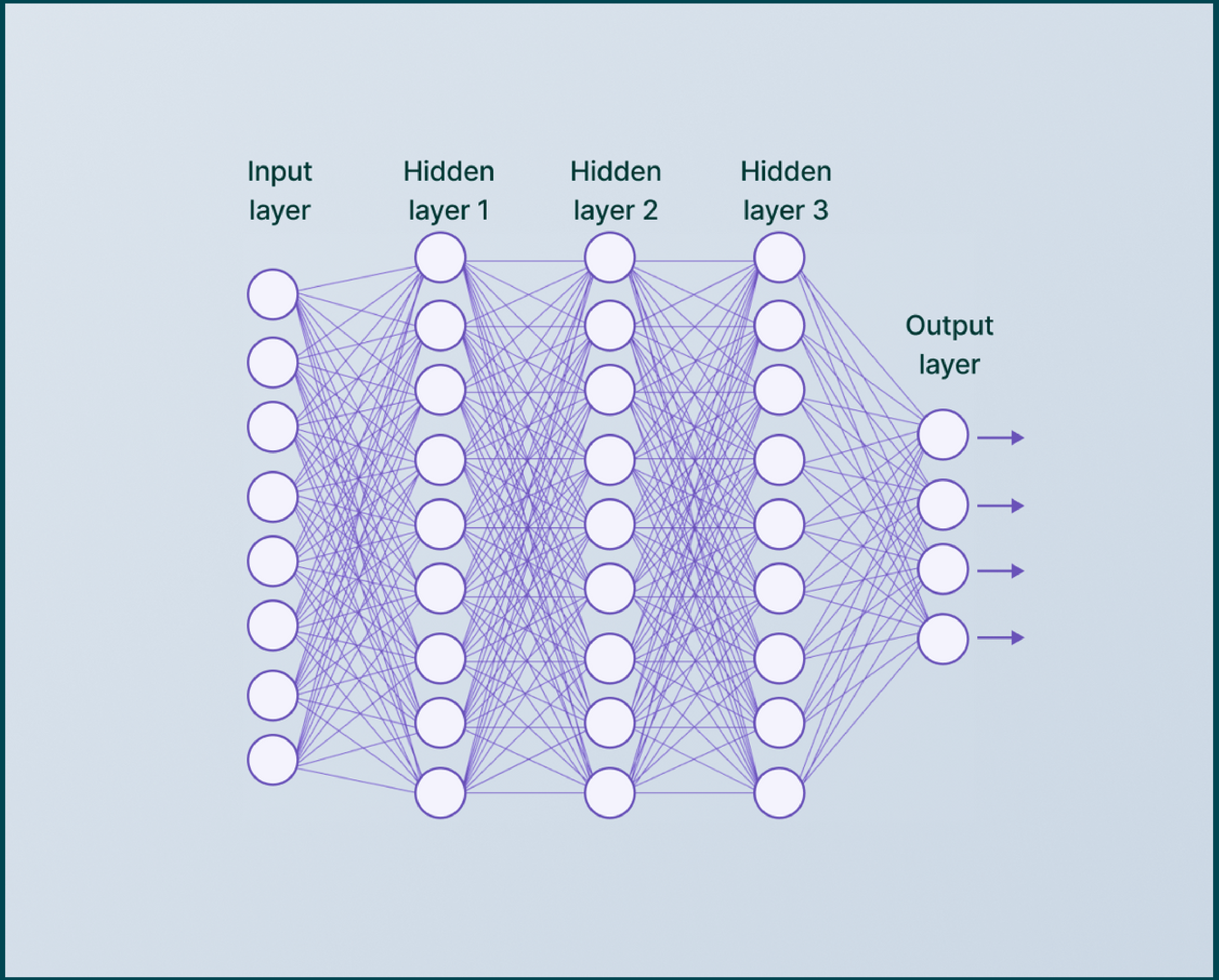
Final model second approach

```
Decision Tree Regressor scores
r2 score: 0.3438572335928919
Mean squared error (MSE): 0.2531083464969347
Root mean squared error (RMSE): 0.2531083464969347
Mean absolute error (MAE): 0.34076107139304734
------------------------------
Random Forest Regressor scores
r2 score: 0.5519599760739231
Mean squared error (MSE): 0.1728323094093502
Root mean squared error (RMSE): 0.1728323094093502
Mean absolute error (MAE): 0.29036569295015197
------------------------------
Support Vector Regressor scores
r2 score: 0.05946129616394302
Mean squared error (MSE): 0.36281463171174855
Root mean squared error (RMSE): 0.36281463171174855
Mean absolute error (MAE): 0.45964094953648577
------------------------------
MLP Regressor scores
r2 score: -1637.8183113941418
Mean squared error (MSE): 632.177346520528
Root mean squared error (RMSE): 632.177346520528
Mean absolute error (MAE): 16.035323478837054
```

OLS score
r2 score: 0.801
MSE: 0.206
RMSE: 0.454
MAE: 0.340

Images

CNN


Input layer
Hidden layer 1
Hidden layer 2
Hidden layer 3
Output layer




Original images

Train	Test	Validation
25,235	12,618	4,206

MSE	RMSE	MAE
0.123	0.35	0.22

Cropping (river edges)

Train	Test	Validation
25,235	12,618	4,206

MSE	RMSE	MAE
0.207	0.45	0.313

Cropping (white water)

Train	Test	Validation
25,235	12,618	4,206

MSE	RMSE	MAE
0.158	0.398	0.253

Split data by year

Spring

Summer

Fall

Winter

Data by year

Train	Test	Validation
21,421	15,242	5,396

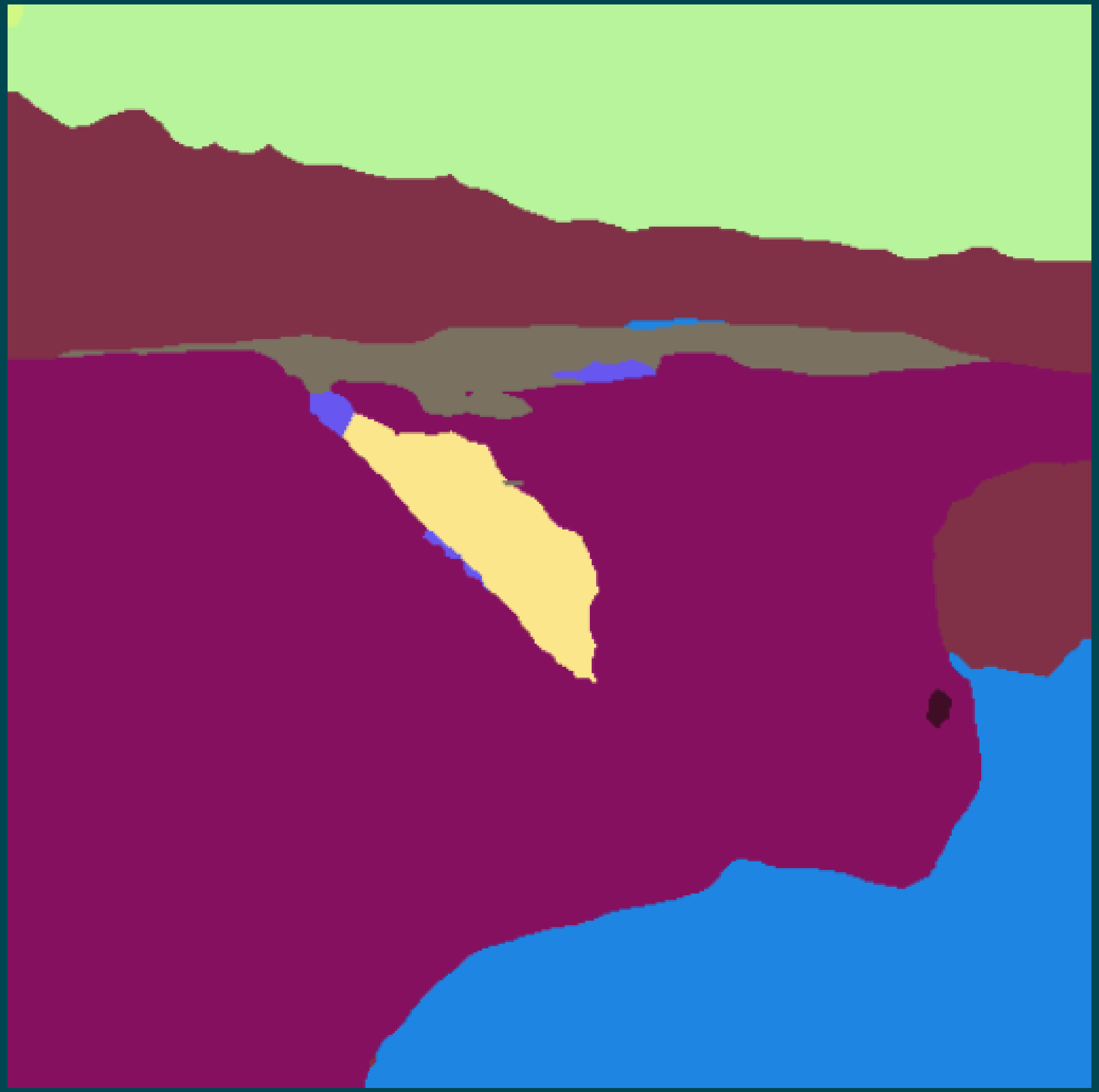
Train: 2012, 2013, 2014, 2015, 2016

Test: 2017, 2018

Validation: 2019

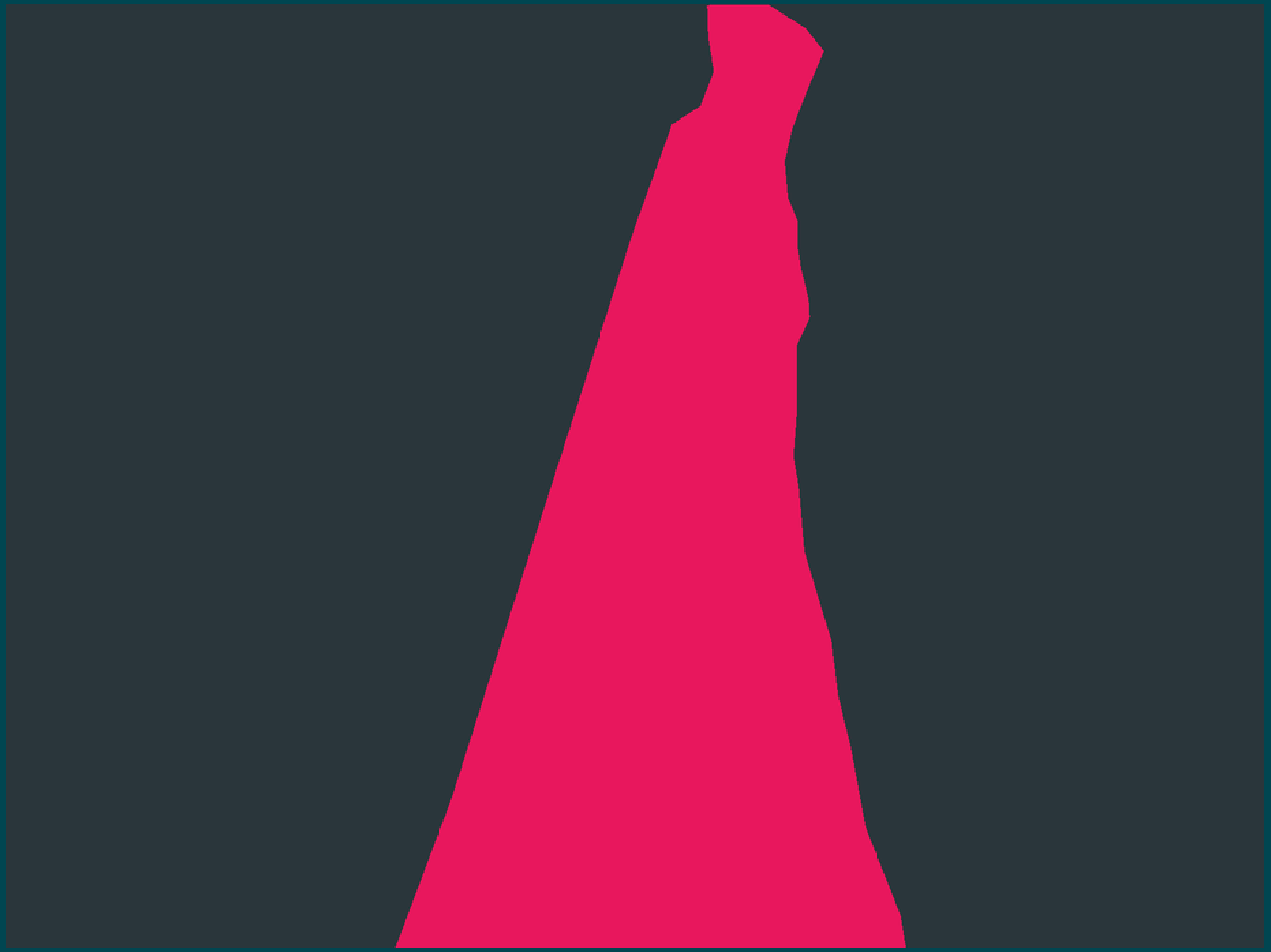
MSE	RMSE	MAE
0.27	0.52	0.34

Segmentation







Original article | Published: 09 May 2022

A two-stage image process for water level recognition via dual-attention CornerNet and CTransformer

Run Qiu, Zhaohui Cai, Zhuoqing Chang, Shubo Liu & Guoqing Tu

The Visual Computer (2022) | Cite this article

203 Accesses | 1 Altmetric | Metrics

Abstract

Image processing-based water level detectors have promising practical application value in intelligent agriculture and early water logging alerts. However, water level recognition based on image processing faces illumination, shooting angle, and sediment contamination challenges. In addition, due to the influence of water surface reflection, it is not easy to extract the water level ruler (WLR) on the water surface accurately. This paper proposes a novel dual-attention CornerNet for WLR image extraction and CTransformer for WLR sequence recognition. First, a dual-attention mechanism to obtain the global information is introduced to better predict semantic segmentation feature maps and corner information. Then, asymmetric convolution Resnet-50 is used to extract multi-local information to effectively recognize inconsistent character sizes caused by different shooting angles of WLRs. Recently, the design of vision backbone using self-attention becomes an exciting topic. In this work, an improved CTransformer is designed to retain sufficient global context information and extract more differentiated features for sequence recognition via multi-head self-attention. Evaluation using our in-house dataset shows that the proposed framework achieves an F-score of 91.37 in the detection stage and the accuracy of human estimation error within 0.3 cm in the recognition stage is 95.37%, respectively. The proposed method is also evaluated on several benchmarks. Experiment results demonstrate that the method in this paper is superior to the existing methods.

Article

Research on Water-Level Recognition Method Based on Image Processing and Convolutional Neural Networks

Gang Dou [1,2], Rensheng Chen [1,3,*], Chuntan Han [1,2], Zhangwen Liu [1] and Junfeng Liu [1]

Abstract: Water level dynamics in catchment-scale rivers is an important factor for surface water studies. Manual measurement is highly accurate but inefficient. Using automatic water level sensors has disadvantages such as high cost and difficult maintenance. In this study, a water level recognition method based on digital image processing technology and CNN is proposed. For achieving batch segmentation of source images, the coordinates of the water ruler region in the source image and characters' region and the scale lines' region on the ruler are obtained by using image processing algorithms such as grayscale processing, edge detection, and the tilt correction method based on Hough-transform and morphological operations. The CNN is then used to identify the value of digital characters. Finally, the water level value is calculated according to the mathematical relationship between the number of scale lines detected by pixel traversal in the binarized image and the value of digital characters. This method is used to identify the water levels of the water ruler images collected in the Hulu watershed of the Qilian Mountains in Northwest China. The results show that the accuracy compared with the actual measured water level reached 94.6% and improved nearly 24% compared to the template matching algorithm. With high accuracy, low cost, and easy deployment and maintenance, this method can be applied to water level monitoring in mountainous rivers, providing an effective tool for watershed hydrology research and water resources management.

Qiu, R., Cai, Z., Chang, Z. et al. A two-stage image process for water level recognition via dual-attention CornerNet and CTransformer. Vis Comput (2022). https://doi.org/10.1007/s00371-022-02501-6

Dou, G.; Chen, R.; Han, C.; Liu, Z.; Liu, J. Research on Water-Level Recognition Method Based on Image Processing and Convolutional Neural Networks. Water 2022, 14, 1890. https://doi.org/10.3390/w14121890

Contributions

Rodrigo Morales Aguayo

Separated data into different categories to create multiple linear regression models with adjustments to the variables.
Documented changes made.

Andrés Olvera Rodríguez

Researched various ML models to improve the linear regression models with new additions, and documented new changes.

Carlos Estrada Ceballos

Created CNN with images divided into years and seasons, including segmentation and image preprocessing.
Documented changes made.

Jessica Nicole Copado Leal

Added features to the models by researaching other strategies to work with the variables to obtain various results. Documented changes made.

Thank you!