Camera-based Water Stage and Discharge Prediction with ML

Rodrigo Morales Aguayo A01632834
Jessica Nicole Copado Leal A01637876
Andrés Olvera Rodríguez A01638129
Carlos Estrada Ceballos A01638214

Tecnológico de Monterrey

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

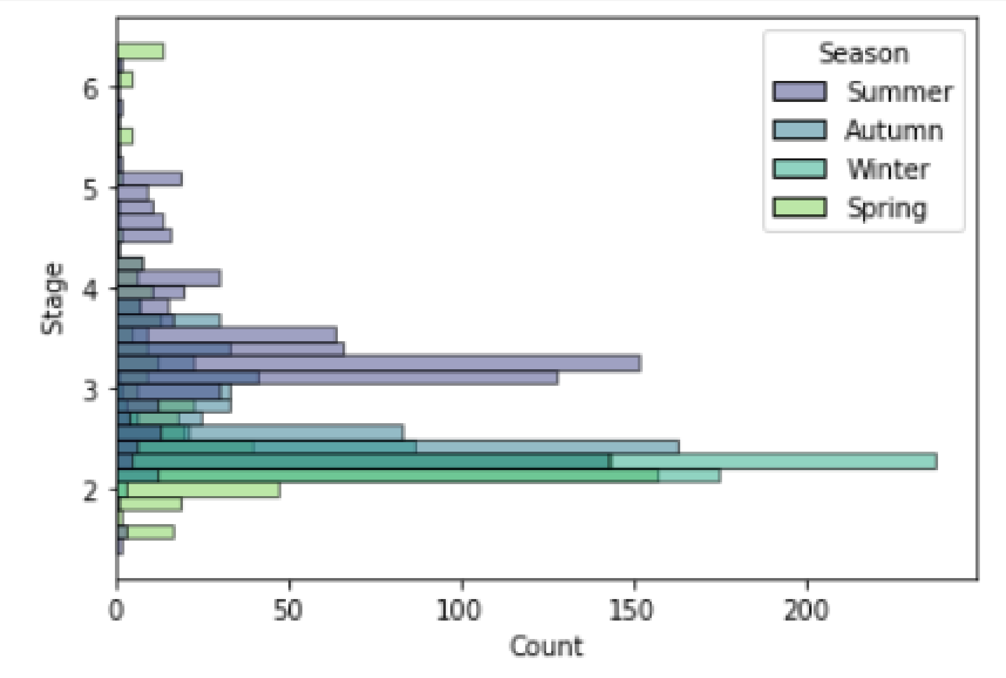
- Understand research paper
- Analyze dataset
- Select features
- Clean data
- Create models
- Separate data by seasons
- Use images to create different models

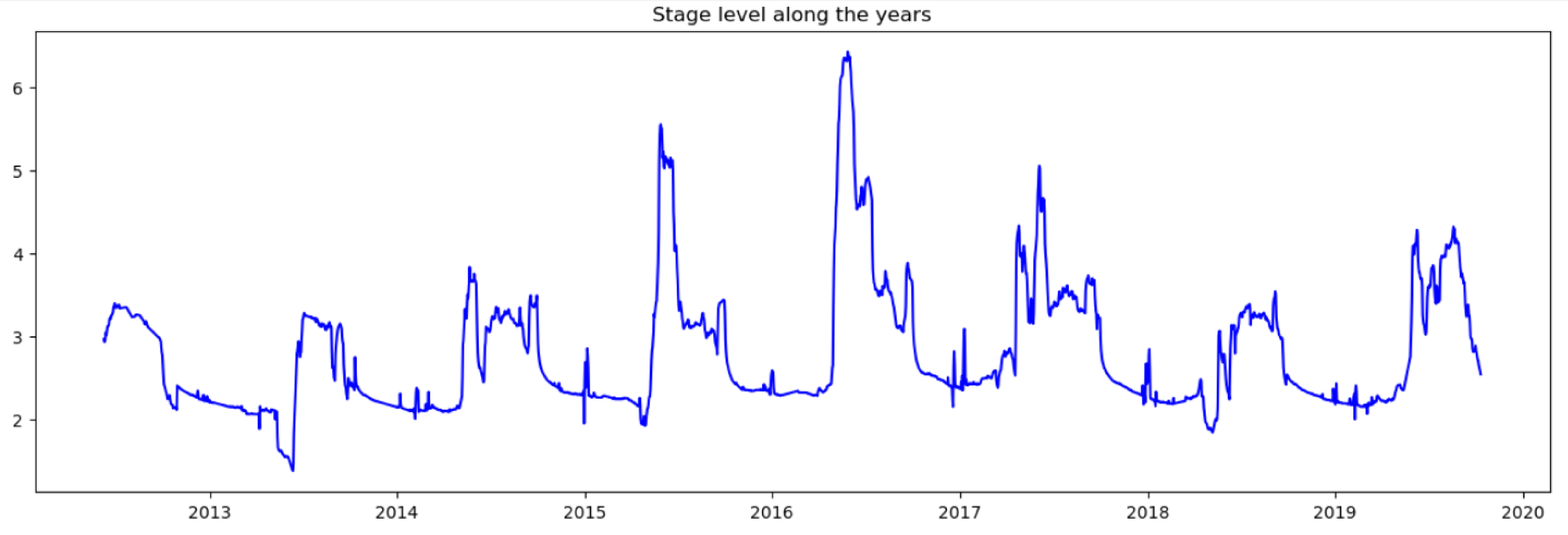
	CaptureTime	Stage
0	2012-06-09	2.99
1	2012-06-09	2.99
2	2012-06-09	2.96
3	2012-06-09	2.94
4	2012-06-09	2.94

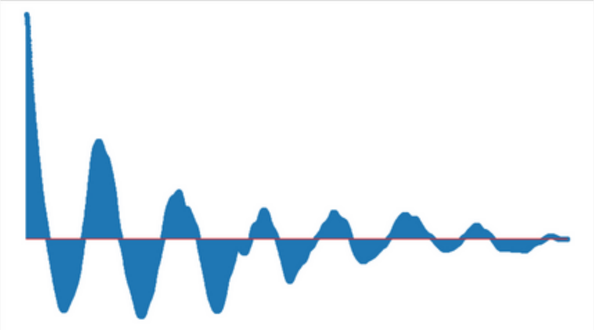
2012-06-09	2.965455
2012-06-10	2.931176
2012-06-11	2.931875
2012-06-12	2.965625
2012-06-13	3.042500

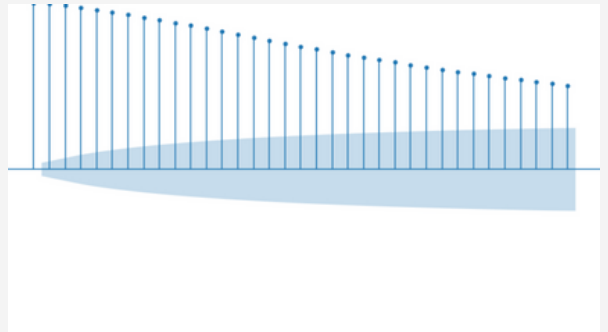
Time series analysis

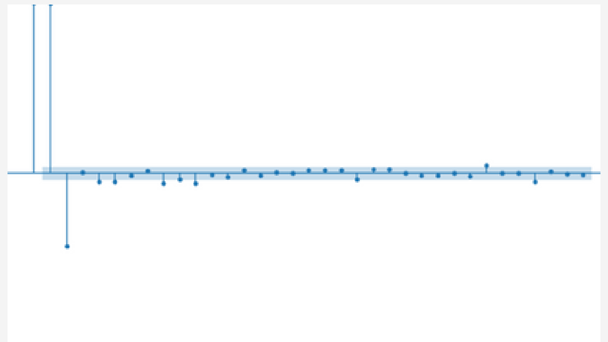
For our time series analysis we take into account only two variables, being the time of data capture and the stage level, which allows us to observe how our data behaves, as well as the difference in water level throughout the year.

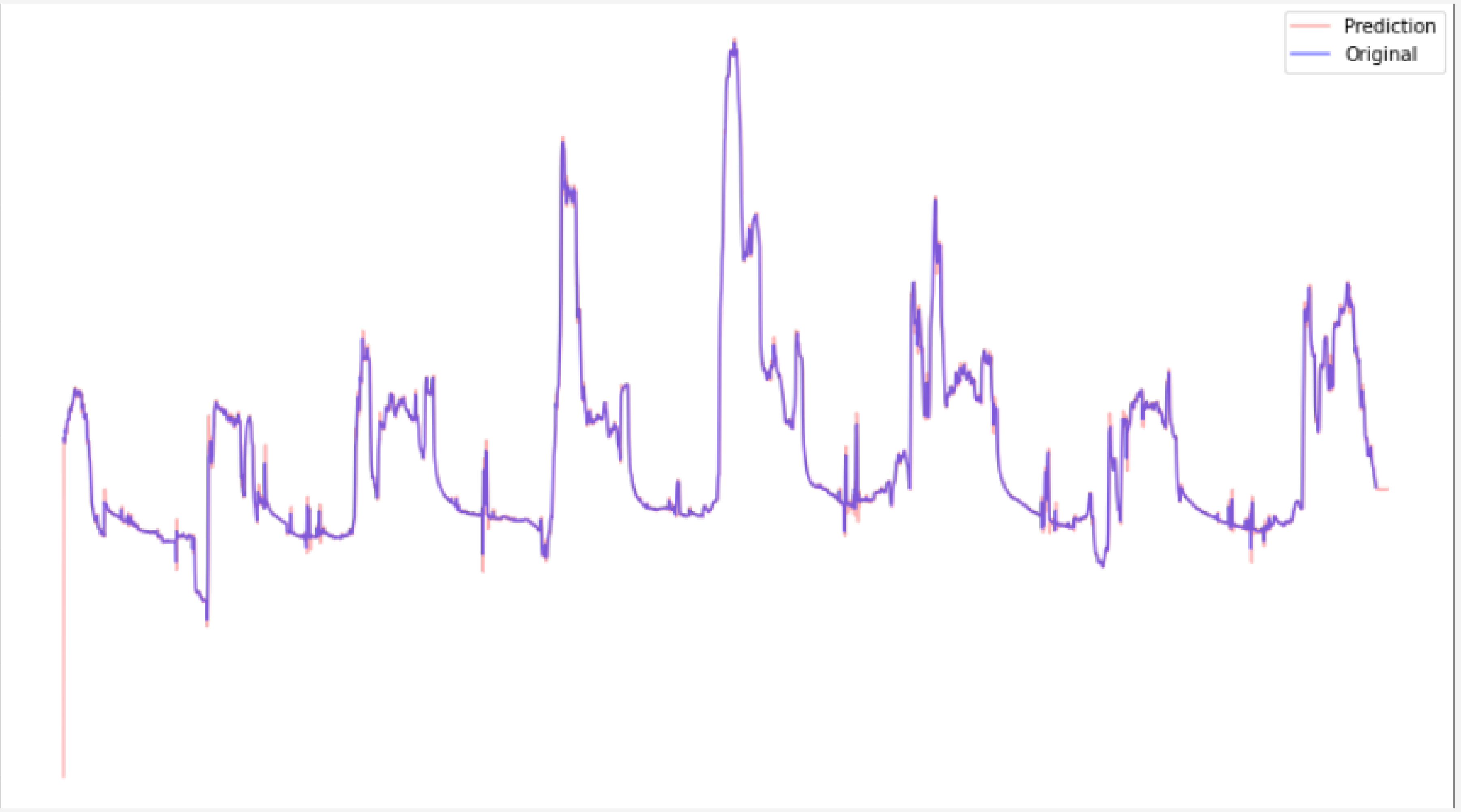

Season
Summer
Autumn
Winter
Spring
Stage
Count
0
50
100
150
200
2
3
4
5
6


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








Prediction
Original

Predicting water stage with Regression models

Linear Regression model

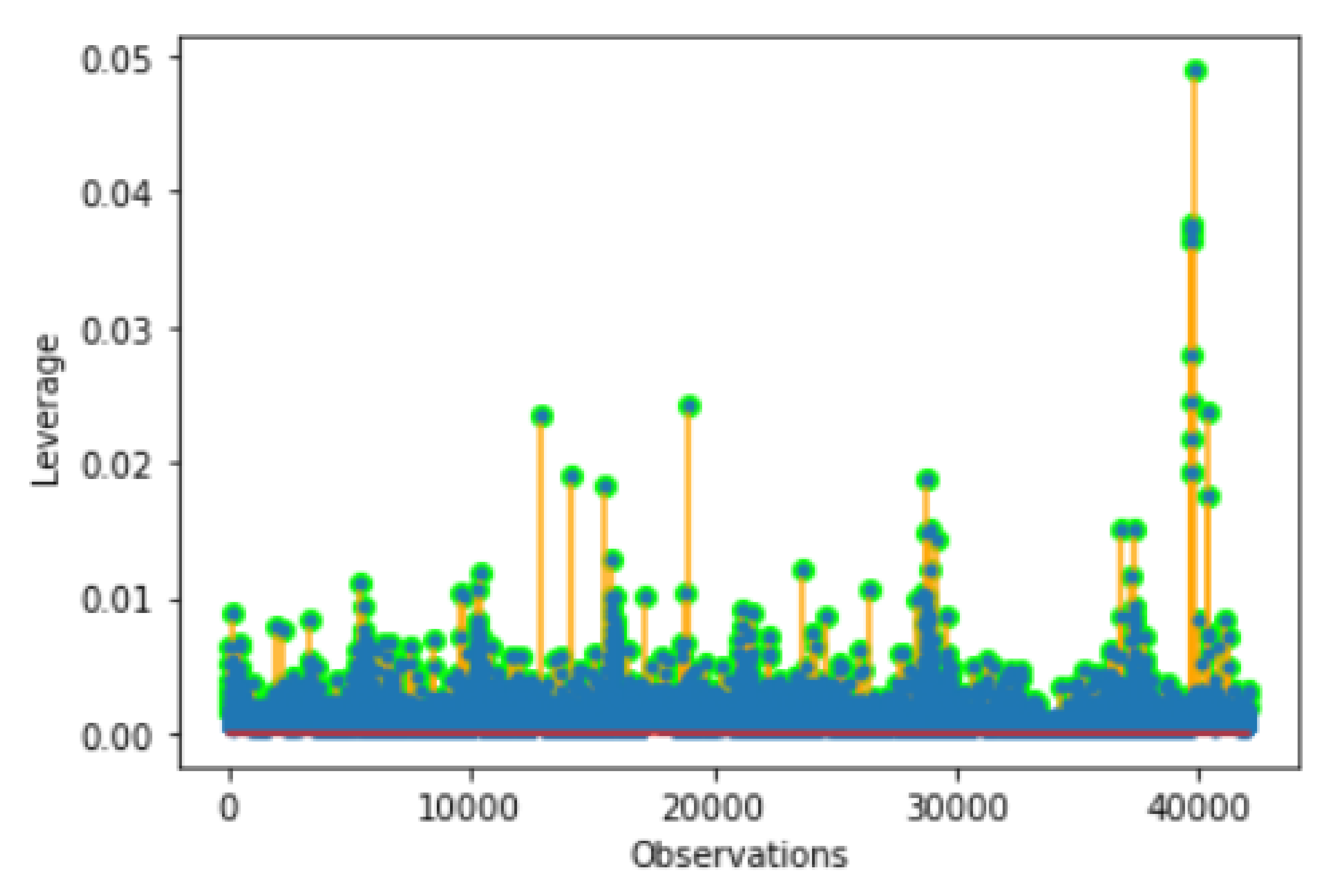
With the dataframe provided, we built a a linear regression model in order to predict the water stage. We are still trying to determine what is causing the models overfitting. The next thing to do is to use some time series analysis in the variables if we can detect which variables have tendency.

First model

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:                  Stage   R-squared:                       0.97
5
Model:                            OLS   Adj. R-squared:                  0.97
5
Method:                 Least Squares   F-statistic:                 3.395e+0
4
Date:                Mon, 14 Nov 2022   Prob (F-statistic):               0.0
0
Time:                        23:51:33   Log-Likelihood:                 2688
1.
No. Observations:               42059   AIC:                        -5.366e+0
4
Df Residuals:                   42010   BIC:                        -5.324e+0
4
Df Model:                          48
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

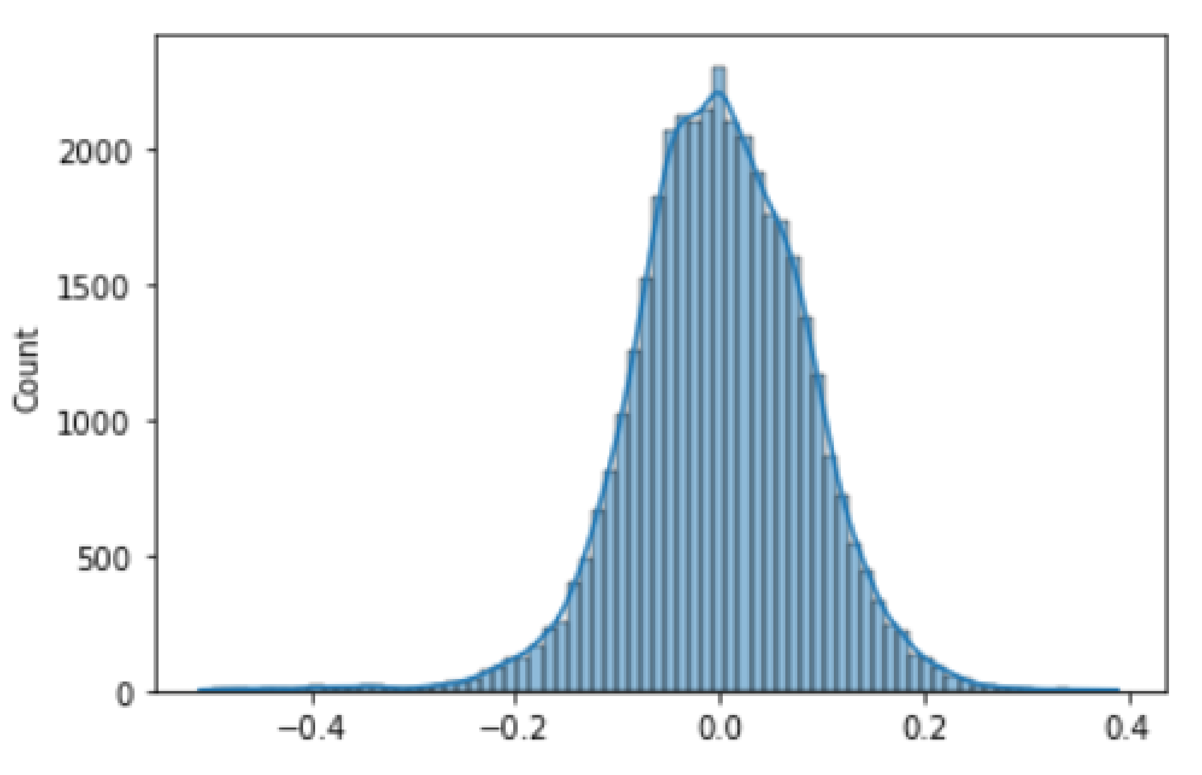
All three at the same time.

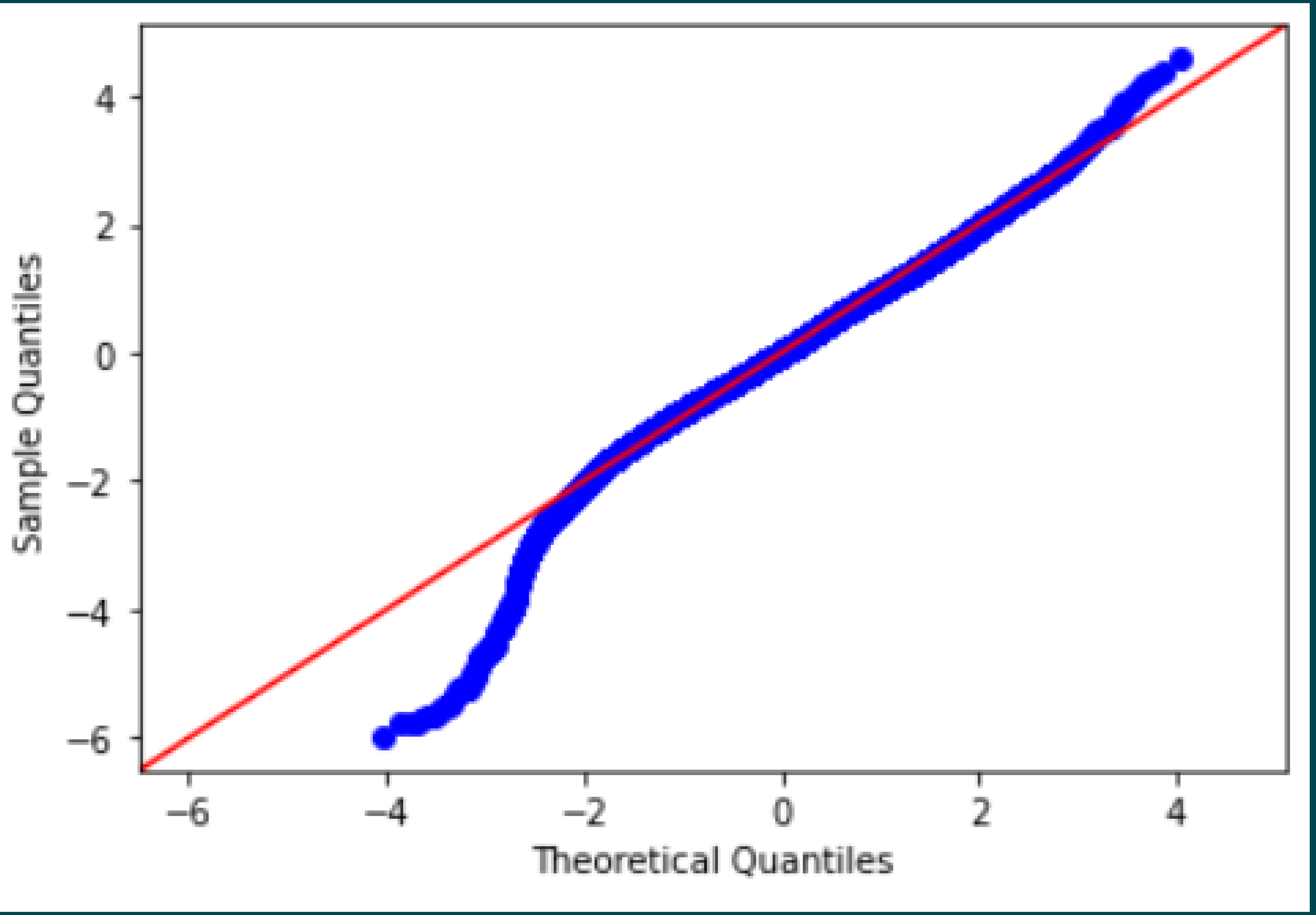
Final model

OLS Regression Results

Dep. Variable:	Stage	R-squared (uncentered):	0.999
Model:	OLS	Adj. R-squared (uncentered):	0.999
Method:	Least Squares	F-statistic:	5.894e+05
Date:	Mon, 14 Nov 2022	Prob (F-statistic):	0.00

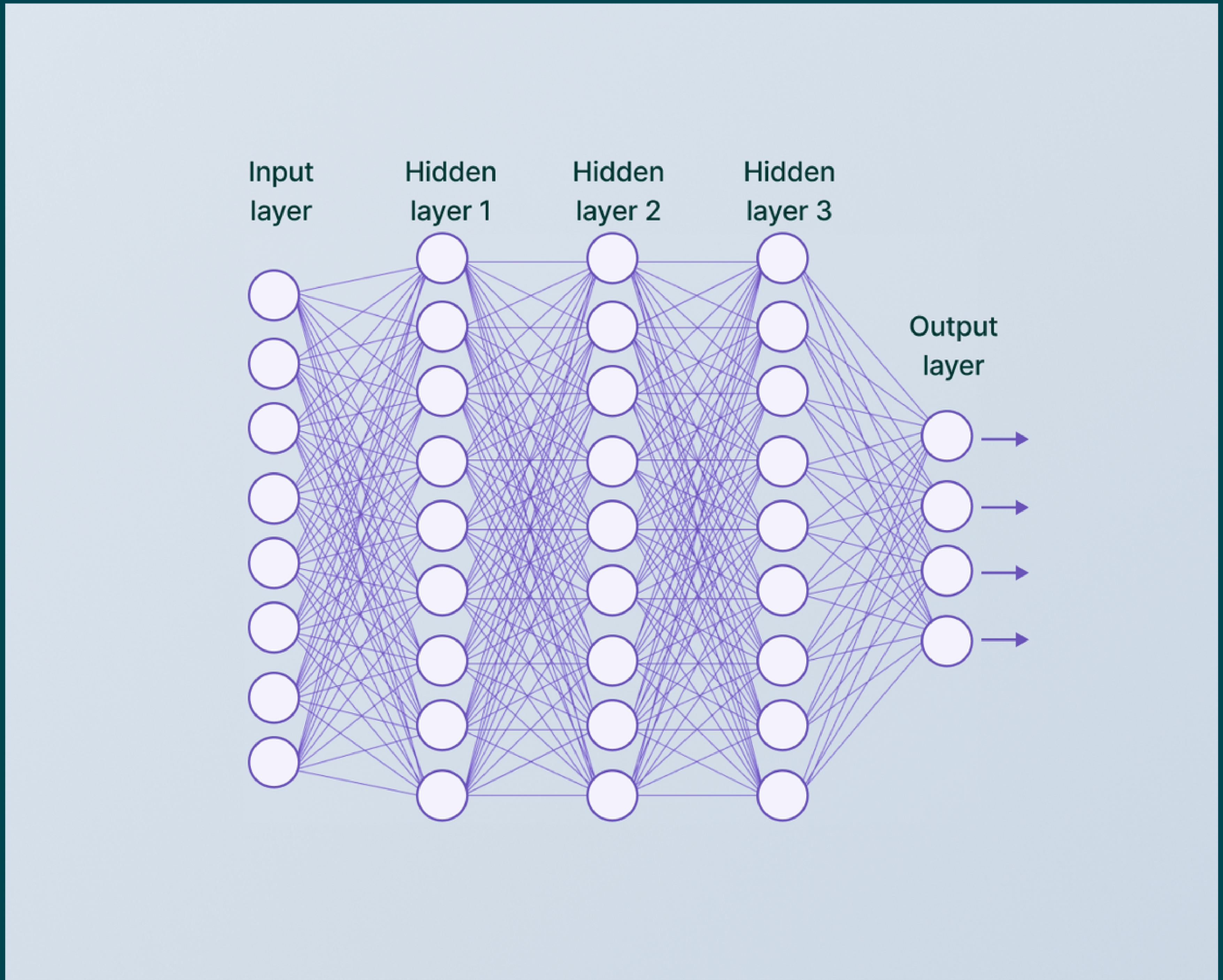
MSE: 0.007437074183154802
RSMSE: 0.08623847275523149
MAE: 0.0671800927704174
Error estandar: 0.086245088327837





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

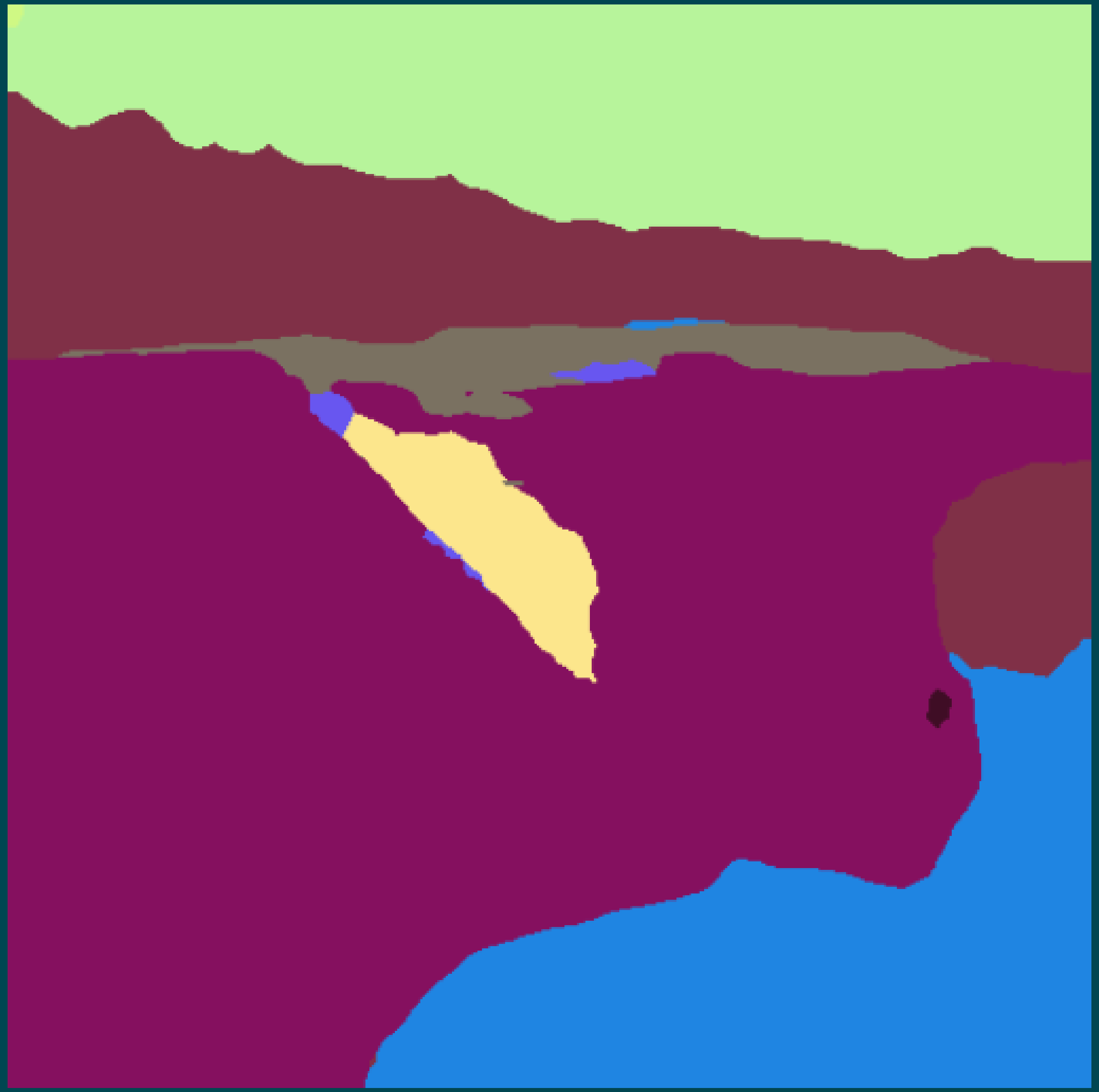
Train: 2012, 2013, 2014, 2015, 2016

Test: 2017, 2018

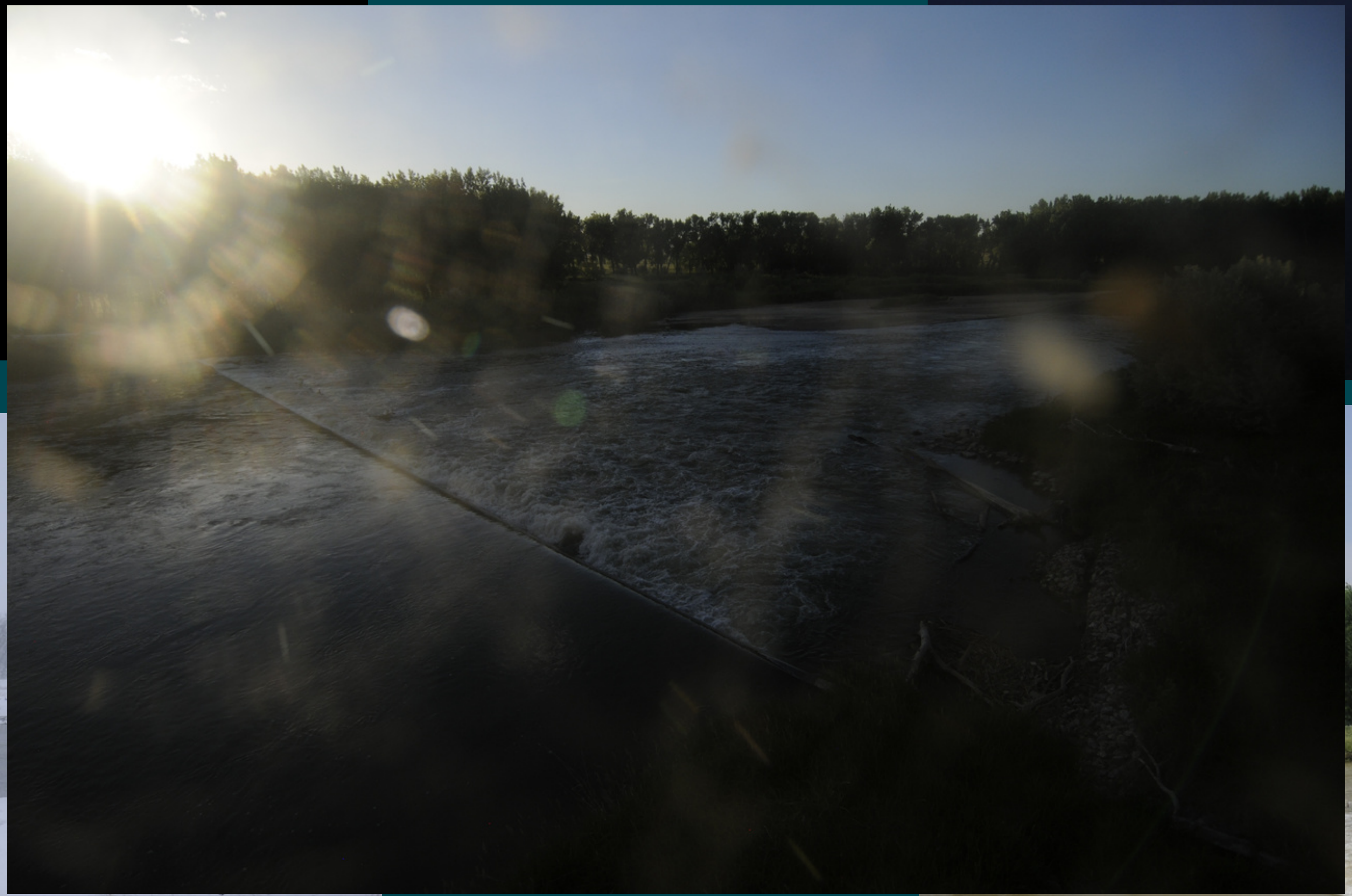
Validation: 2019

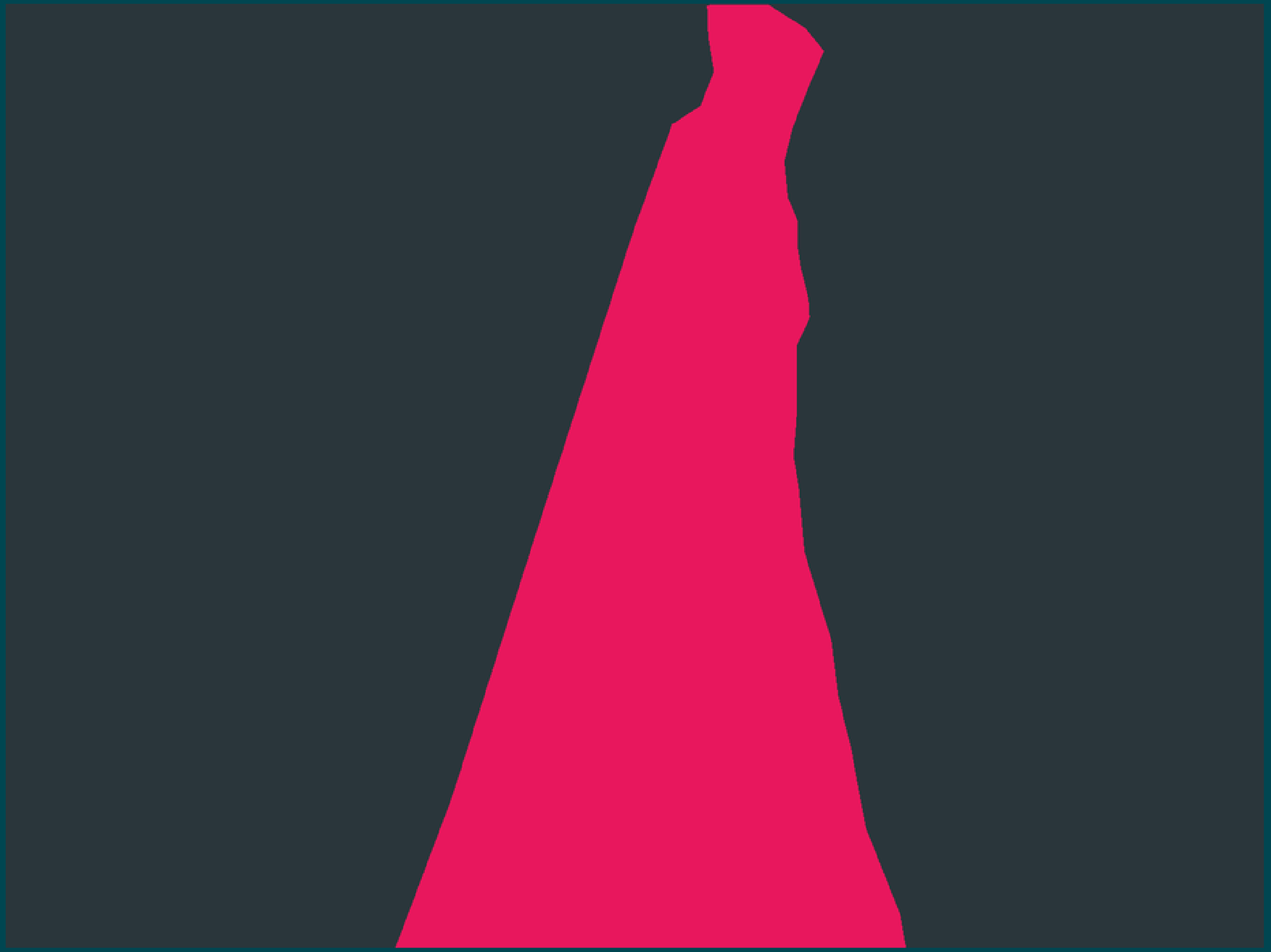
MSE	RMSE	MAE
0.27	0.52	0.34

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!