Stream Discharge and Stage Prediction with Machine Learning

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***Index Terms*—Machine Learning, CNN, Regression, Stream Discharge, Stream Stage.**

I. INTRODUCTION

A streamgage contains instruments that measure and record the amount of water flowing in the river or stream, or its discharge [1].

Having access to continuous data from streamgages is essential when calibrating and validating ground water and surface water models. Thus, encountering gaps in the data will increase uncertainty in the model predictions.

Cameras can help in this regard, since they provide redundancy with information unavailable from sensors. This imagery allows for hydrologic conditions to be visually verified (e.g., the presence of ice, obstructions, etc.).

In the instance of an actual gap in the data, having those images allows for a qualitative assessment to confirm that the chosen gap filling method accurately represents the actual state of the stream during that certain time period.

With this, the objective of the current work is to fill stream discharge and stage data gaps using machine learning models for a location with camera availability.

The literature seems to support the notion of using cameras as a plausible way of insuring a sort of 'backup' of the data will be available in case of any technical failure of the sensors at the streamgage. Eltner, A. et al. (2021) show in their research article *Using Deep Learning for Automatic Water Stage Measurements* [2] a similar use of deep learning tools as well as photogrammetric techniques to extract information from streamgage images to achieve more reliable water stage measurements. While the objective is most definitely not the same, the study sets a precedent for machine learning and image-based feature extraction applied to water monitoring.

II. DATA DESCRIPTION

Features were extracted from over 40,000 daylight images taken at one-hour intervals from 2012 to 2019. Dawn and dusk images that were too dark for feature extraction were removed.

The features were stored in a Comma Separated Value (CSV) file which contains the images' names as ' Filename' and, among many other features, the Stage and Discharge data from each image.

III. METHODOLOGY

A. *Data storage*

For a detailed explanation of the evolution and strategy for data management and storage, see *Appendix B. Data Storage*.

B. *Models generated with numeric data*

1) Data distribution: The numeric data available in the CSV file is separated into three different datasets: testing, training and validation data. These datasets were used when implementing the Multilayer Perceptron (MLP), Support Vector Regression (SVR) and Random Forest Regression (RFR) models for each of the dependent variables (stage and discharge).

2) Recreating the original models: The starting point of this work was to attempt to recreate the three models from the original research paper. Thus, the same ten features were used for the training stage: 'grayMean', 'graySigma', 'entropyMean', 'entropySigma', 'hMean', 'hSigma', 'sMean', 'sSigma', 'vMean', 'vSigma'.

3) Principal Component Analysis (PCA): PCA was used for feature selection and new iterations of the models were trained with these variables.

4) Preprocessing the data: All of the above methods were alternatively trained with re-scaled data, using each of the following scalers: Standard, Robust and MinMax. Strings and non-numeric values have been dropped, except for the date, which was processed to create a new column called 'year' of numeric datatype.

C. *Training Convolutional Neural Networks*

We opted to make use of the already trained architectures *EfficientNetB0* & *ResNet101* available in the *Keras Applications* module. We concluded that it'd be a better use of our time to focus on getting and comparing results rather than building an architecture from scratch, which, in the event of failure, we wouldn't really know if it failed due to errors in the implementation or if it just wasn't the right fit for the project. Thus, we preferred to work with preexisting models that have already been proven to work in order to speed up the process.

1) Data distribution: The images were separated into two datasets: training and testing data. The images of each dataset were selected by years (2015-17 for testing and the remaining years for training), this due to the seasonal behaviour exhibited by the data.

2) Preprocessing the data: The images provided were of really good quality and of really big size, so resizing them was necessary in the code to ensure that the CNNs could receive them.

3) EfficientNet: Convolutional Neural Networks (CNN) tend to have fixed resources; this is quite a limitation since, conventionally, a CNN's depth or width would be increased as much as possible within the resource budget in an attempt to achieve greater accuracy rates. These are tedious and costly processes that may not always yield the desired outcome. EfficientNet proposes a new and more efficient method of scaling that scales all dimensions (depth, width and resolution) uniformly [3].

4) ResNet: The deeper the neural network, the harder it is to train. Due to their depth, they are able to start converging and that causes a degradation problem of training accuracy. This degradation indicates that not all systems are equally easy to optimize. As a way to ease the fitting of networks, the ResNet framework reformulates the layers of the network as learning residual functions with reference to the layer inputs, instead of having to learn unreferenced functions [4].

5) Scope of the model: Both *ResNet101* and *EfficientNetB0* take an incredibly long time to train (6 and 8 hours, respectively), and according to Hafeez, U. U. & Gandhi, A. (2020) [5] execution times for CNN architectures are very costly and take up too many resources, even with the computational power of AWS. So it was decided to just train models to predict stream stage since the stage and discharge features are very highly correlated (making it possible to predict discharge with stage).

D. *Loss metrics*

The loss metrics (MAE, MSE, RMSE & SE) used to evaluate the models were selected from the original paper so that we would have a way to effectively compare the results of this study with those obtained previously by the University of Nebraska.

IV. RESULTS

A. *Regression models*

The regression models (MLP, RFR & SVR) trained with the numeric data extracted from the images as provided in the CSV file were overall more reliable predicting stage rather than discharge.

Tables I through VI showcase the results of each iteration of every regression model worked on in this study.

While most models were inaccurate predicting stream discharge, the Random Forest Regression using robust scaling surpassed them by a lot with an R^2 value of 0.831; error metrics, on the other hand, were pretty high all across the board and the RFR model got the lowest values of $MAE = 203.346$, $MSE = 232971.927$, $RMSE = 482.672$, $SE = 483.986$ (see *Table II*).

Table I
DISCHARGE MLP

	MAE	MSE	RMSE	$\hat{R2}$	SE
Normal*	821.795	1383311.929	1176.143	-0.001	1178.819
Normal (+ PCA)*	678.002	1093322.927	1045.621	0.209	1046.412
Standard*	365.059	475835.195	689.808	0.656	691.74
Standard (+ PCA)	940.685	2261749.889	1503.912	-0.637	1179.035
Robust*	362.85	459946.716	678.194	0.667	679.539
Robust (+ PCA)	939.757	2259791.988	1503.26	-0.636	1179.039
MinMax*	438.588	558835.307	747.553	0.595	746.6
MinMax (+ PCA)	940.688	2261749.761	1503.911	-0.637	1179.039

*Normal: Raw data - unprocessed.
*Standard: Standardly scaled data.
*Robust: Robustly scaled data.
*MinMax: MinMax Scaling applied to data.
*(+ PCA): PCA run on the specified data.

Table II
DISCHARGE RFR

	MAE	MSE	RMSE	$\hat{R2}$	SE
Normal*	203.481	233258.04	482.968	0.831	484.288
Normal (+ PCA)*	540.987	820620.085	905.881	0.406	908.206
Standard*	203.365	233030.754	482.733	0.831	484.048
Standard (+ PCA)	328.002	450925.772	671.51	0.674	673.313
Robust*	203.346	232971.927	482.672	0.831	483.986
Robust (+ PCA)	549.581	912066.012	955.021	0.34	957.622
MinMax*	203.43	233294.115	483.005	0.831	484.329
MinMax (+ PCA)	295.01	403544.252	635.251	0.708	637.103

*Normal: Raw data - unprocessed.
*Standard: Standardly scaled data.
*Robust: Robustly scaled data.
*MinMax: MinMax Scaling applied to data.
*(+ PCA): PCA run on the specified data.

Table III
DISCHARGE SVR

	MAE	MSE	RMSE	$\hat{R2}$	SE
Normal*	496.4	1069794.83	1034.309	0.226	995.413
Normal (+ PCA)*	631.762	1249238.979	1117.694	0.096	1071.32
Standard*	496.4	1069794.83	1034.309	0.226	995.413
Standard (+ PCA)	489.712	1047283.417	1023.369	0.242	990.208
Robust*	496.4	1069794.83	1034.309	0.226	995.413
Robust (+ PCA)	751.152	1515365.725	1231.002	-0.097	1125.931
MinMax*	496.4	1069794.83	1034.309	0.226	995.413
MinMax (+ PCA)	476.003	999011.14	999.505	0.277	969.637

*Normal: Raw data - unprocessed.
*Standard: Standardly scaled data.
*Robust: Robustly scaled data.
*MinMax: MinMax Scaling applied to data.
*(+ PCA): PCA run on the specified data.

For predicting stream stage specifically, the RFR using standard scaling yielded the best results out of all the regression models, with an R^2 value of 0.874, and overall error metrics measuring lower than 0.3 with $MAE = 0.14$, $MSE = 0.08$, $RMSE = 0.284$, $SE = 0.284$ (see *Table V*).

Table IV
STAGE MLP

	MAE	MSE	RMSE	$R\hat{2}$	SE
Normal*	0.638	0.639	0.799	-0.001	0.802
Normal (+ PCA)*	0.631	0.773	0.879	-0.212	0.877
Standard*	0.211	0.112	0.335	0.824	0.336
Standard (+ PCA)	0.296	0.227	0.476	0.644	0.478
Robust*	0.271	0.22	0.469	0.655	0.464
Robust (+ PCA)	0.633	0.635	0.797	0.004	0.8
MinMax*	0.237	0.142	0.377	0.777	0.376
MinMax (+ PCA)	0.265	0.196	0.443	0.692	0.445

*Normal: Raw data - unprocessed.
*Standard: Standardly scaled data.
*Robust: Robustly scaled data.
*MinMax: MinMax Scaling applied to data.
*(+ PCA): PCA run on the specified data.

Table V
STAGE RFR

	MAE	MSE	RMSE	$R\hat{2}$	SE
Normal*	0.14	0.08	0.283	0.874	0.284
Normal (+ PCA)*	0.408	0.36	0.6	0.435	0.602
Standard*	0.14	0.08	0.284	0.874	0.284
Standard (+ PCA)	0.234	0.169	0.411	0.735	0.412
Robust*	0.14	0.08	0.284	0.874	0.285
Robust (+ PCA)	0.418	0.407	0.638	0.361	0.64
MinMax*	0.14	0.08	0.283	0.874	0.284
MinMax (+ PCA)	0.21	0.141	0.375	0.779	0.376

*Normal: Raw data - unprocessed.
*Standard: Standardly scaled data.
*Robust: Robustly scaled data.
*MinMax: MinMax Scaling applied to data.
*(+ PCA): PCA run on the specified data.

Table VI
STAGE SVR

	MAE	MSE	RMSE	$R\hat{2}$	SE
Normal*	0.172	0.086	0.294	0.864	0.295
Normal (+ PCA)*	0.458	0.461	0.679	0.277	0.677
Standard*	0.172	0.086	0.294	0.864	0.295
Standard (+ PCA)	0.256	0.185	0.43	0.71	0.43
Robust*	0.172	0.086	0.294	0.864	0.295
Robust (+ PCA)	0.596	0.592	0.77	0.071	0.757
MinMax*	0.172	0.086	0.294	0.864	0.295
MinMax (+ PCA)	0.231	0.161	0.402	0.747	0.402

*Normal: Raw data - unprocessed.
*Standard: Standardly scaled data.
*Robust: Robustly scaled data.
*MinMax: MinMax Scaling applied to data.
*(+ PCA): PCA run on the specified data.

B. CNN models

The resulting values (see *Table VII*) might make it seem that *EffientNetB0* is the better model, but looking at the graph (*Figure 1*) reveals that *ResNet101*'s performance is much better (*EffientNetB0* has a lot of noise and is really just predicting an average of the samples).

Table VII
STAGE USING CNN

	MAE	MSE	RMSE
Resnet101	0.821	0.678	0.823
EfficientNetB0	0.338	0.184	0.4290

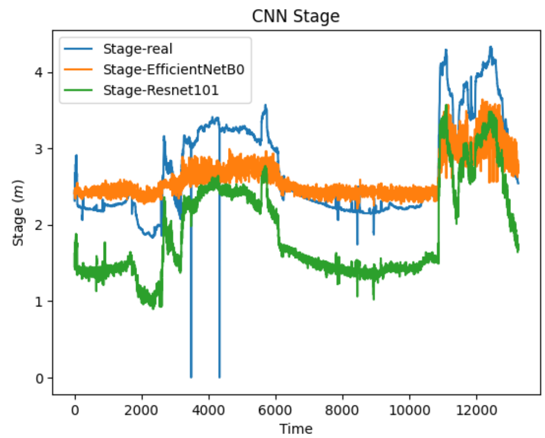

Figure 1. Comparison of models predicting stage

V. DISCUSSIONS AND CONCLUSIONS

In this project we proposed two different approaches: the first one using the variables from the CSV file with different scaling techniques and the second one using the 40,000+ images provided by the University of Nebraska to train preexisting CNN architectures. The best results we got were from the Random Forest Regression model using standard scaling (for predicting stage) with a MSE of 0.08 and a MAE of 0.14, which seem to be good results, however, these values are not strictly an indicator of how reliable the model is, as it could be predicting an average of the samples instead of following the seasonal pattern or trend as it should be.

We believe that better results can be obtained if we continue working on CNNs while tweaking several different aspects that were not explored in this project, for example, grouping the data by week of the year, or month, to better take into account the seasonality of the data.

VI. APPENDICES

A. Feature description

Header name	Description
Stage or Discharge	**Response variables**
grayMean	Grey scale mean of all the pixel intensities after conversion from RGB to grey
graySigma	Grey scale sigma of all the pixel intensities after conversion from RGB to grey
entropyMean	Shannon entropy mean of all the gray scale pixel intensities after conversion from RGB to grey
entropySigma	Shannon entropy sigma of all the gray scale pixel intensities after conversion from RGB to grey
hMean	Mean of all the pixel intensities in the hue channel after conversion from RGB to HSV
hSigma	Sigma of all the pixel intensities in the hue channel after conversion from RGB to HSV
sMean	Mean of all the pixel intensities in the saturation channel after conversion from RGB to HSV
sSigma	Sigma of all the pixel intensities in the saturation channel after conversion from RGB to HSV
vMean	Mean of all the pixel intensities in the value channel after conversion from RGB to HSV
vSigma	Sigma of all the pixel intensities in the value channel after conversion from RGB to HSV
grayMean 0	Gray scale mean of all the pixel intensities in the above weir ROI
graySigma 0	Gray scale sigma of all the pixel intensities in the above weir ROI
entropyMean 0	Shannon entropy mean of all the gray scale pixel intensities in the above weir ROI
entropySigma 0	Shannon entropy sigma of all the gray scale pixel intensities in the above weir ROI
hMean 0	Mean of all the pixel intensities in the hue channel in the above weir ROI
hSigma 0	Sigma of all the pixel intensities in the hue channel in the above weir ROI
sMean 0	Mean of all the pixel intensities in the saturation channel in the above weir ROI
sSigma 0	Sigma of all the pixel intensities in the saturation channel in the above weir ROI
vMean 0	Mean of all the pixel intensities in the value channel in the above weir ROI
vSigma 0	Sigma of all the pixel intensities in the value channel in the above weir ROI
grayMean 1	Gray scale mean of all the pixel intensities in the below weir ROI
graySigma 1	Gray scale sigma of all the pixel intensities in the below weir ROI
entropyMean 1	Shannon entropy mean of all the gray scale pixel intensities in the below weir ROI
entropySigma 1	Shannon entropy sigma of all the gray scale pixel intensities in the below weir ROI
hMean 1	Mean of all the pixel intensities in the hue channel in the below weir ROI
hSigma 1	Sigma of all the pixel intensities in the hue channel in the below weir ROI

Header name	Description
sMean 1	Mean of all the pixel intensities in the saturation channel in the below weir ROI
sSigma 1	Sigma of all the pixel intensities in the saturation channel in the below weir ROI
vMean 1	Mean of all the pixel intensities in the value channel in the below weir ROI
vSigma 1	Sigma of all the pixel intensities in the value channel in the below weir ROI
WeirAngle	Angle of the weir
WeirPt1X	Far end of weir calculation end point X pixel position
WeirPt1Y	Far end of weir calculation end point Y pixel position
WeirPt2X	Near end of weir calculation end point X pixel position
WeirPt2Y	Near end of weir calculation end point Y pixel position
WwRaw LineMin	Minimum pixel distance from weir line to whitewater raw down stream edge
WwRaw LineMax	Maximum pixel distance from weir line to whitewater raw down stream edge
WwRaw LineMean	Mean of pixel distances from weir line to whitewater raw down stream edge
WwRaw LineSigma	Sigma of pixel distances from weir line to whitewater raw down stream edge
WwCurve LineMin	Minimum pixel distance from weir line to whitewater curve fit down stream edge
WwCurve LineMax	Maximum pixel distance from weir line to whitewater curve fit down stream edge
WwCurve LineMean	Mean of pixel distances from weir line to whitewater curve fit down stream edge
WwCurve LineSigma	Sigma of pixel distances from weir line to whitewater curve fit down stream edge

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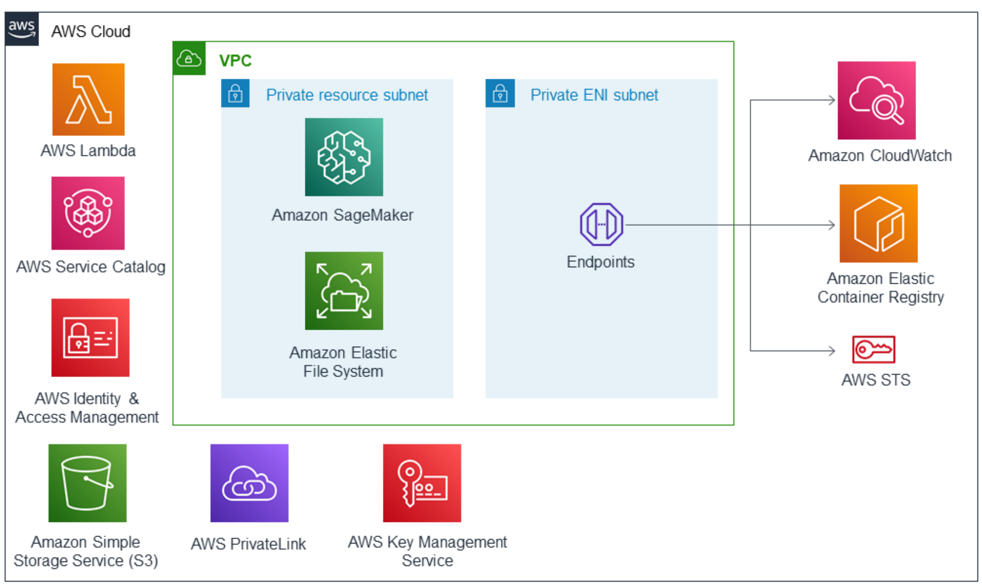
Evaluación - Módulo 4: Cloud

Hacer uso de servicios de Cloud se está volviendo cada vez más común, pues contar con servidores locales para el almacenamiento y procesamiento de nuestros datos no es sostenible y requiere demasiados recursos con los que muchas veces no contamos. Es más sencillo relegar esta tarea a un tercero que ya cuenta con la infraestructura necesaria para manejar tanta información.

Debe notarse que ese poder de procesamiento y almacenamiento no es gratuito. Aunque esto pueda parecer una limitación algo inconveniente, los precios de estos servicios han bajado y continuarán disminuyendo, mostrando la creciente migración a Cloud como una progresión natural.

A lo largo del reto, exploramos distintas herramientas comerciales en la nube esperando encontrar una que se acoplara bien al proyecto. Por conveniencia y disponibilidad, comenzamos trabajando con *Google Colab*. Al ver que la escala del proyecto sobrepasaba las limitaciones de la herramienta, optamos por investigar otros servicios de Cloud para facilitar el proceso de ejecución, almacenamiento y procesamiento de las imágenes y los modelos.



La primera propuesta que se tuvo fue para trabajar con el *CSV* que se nos proporcionó. Los servicios utilizados fueron *SageMaker* y *S3*. *SageMaker* se usó para el procesamiento de los datos, y correr los modelos de manera rápida y sin interrupciones. El *S3* es un servicio de almacenamiento seguro, pues gracias a sus políticas de *AWS Identity* y *Access Management*, cada usuario solo tiene permiso de ver lo necesario para hacer su trabajo; además el *S3* cuenta con control de versiones, lo que permite recuperar y restaurar los datos en caso de errores o para consultar resultados anteriores. Este servicio integral está protegido, pues solo se puede acceder a los datos estando dentro de la *VPC* o con una cuenta que tenga los permisos necesarios.

Esta opción es aplicable a nuestras necesidades sin gastar demasiados recursos, pero al implementar un modelo *CNN* usando las imágenes empezamos a consumir más recursos de los que teníamos; en 4 días gastamos 75 dólares solamente por tener las imágenes en el bucket de *S3*, entonces la opción dejó de ser viable.

Luego confirmamos que un servicio comercial de Cloud como *AWS* no era conveniente para nuestro proyecto, pues los costos por máquina que van de ~0.3 dólares a ~6 dólares por cada hora de uso (Hafeez, 2020) se disparan demasiado rápido considerando que nuestros modelos tardan alrededor de 6 horas en ejecutarse en su totalidad y que además sería necesario pasar por múltiples iteraciones de cada uno para llegar a un resultado aceptable.

Los recursos necesarios para un proyecto varían de acuerdo a qué se busca lograr, en cuánto tiempo debe hacerse y qué es realísticamente posible lograrse con los demás recursos materiales que se tienen disponibles. Entonces, para nosotros que ya contamos con equipos de cómputo con los cuales manejar el reto, no es realmente conveniente usar estas herramientas.

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