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Evaluating the Benefit of Using Artificial Intelligence to Predict the Values of Bridge Condition Index and Costs of Bridge Infrastructures Under the Impact of Climate Change in Ontario

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ABSTRACT: Efficient bridge management is crucial for governments, yet this task is increasingly challenging due to the accelerated deteriorations due to the climate change. In Ontario, the bridge infrastructure network is composed of 5,053 bridges with records from 2000 to 2020. Biannually, inspectors perform a bridge inspection and assign a grade to each structure that helps track, plan, and budget for their maintenance or replacement. In this study, two models were developed by using two machine learning and two statistical algorithms in R language with the focus on each region of the Ontario province in Canada. The models were made to predict the Bridge Condition Index (BCI) for bridges, the Investment Cost (IC) for infrastructure projects, and the associated data (e.g., bridge condition data, traffic volume, climate data), which were collected from the Ministry of Transportation (MTO) in Ontario and the Canadian Government. The BCI model uses a multivariable linear equation with R^2 = 0.85, Mean Absolute Error (MAE)=1.78, Root Mean Square Error (RMSE) = 3.82 and a Relative Error (RE)= 2.4% and the Cost model uses a GBM (Gradient Boosting Machine) model with R^2 = 0.99, MAE =3.27, RMSE = 4.22, and RE = 46.31%. These models can provide information about the bridge's maintenance and its investment strategies; however, they are not effective between the years of 2000 and 2022 because of the insignificant differences in temperature and precipitation changes across different Representative Concentration Pathways (RCP).

Key words – Bridge Management, Bridge Condition Index, Cost Prediction, Machine Learning, Climate Change, Ontario Bridges

1. INTRODUCTION

Climate change is one of the major factors that contributes in adjusting the approaches applied during the design, construction and management of infrastructure projects. Therefore, evaluating their health conditions and the cost of implementing the necessary rehabilitations and repairs pose common challenges for all municipalities especially for bridges, which are crucial components of the road's infrastructure network. Thus, municipalities must continuously evolve their approaches to ensure the longevity and safety of these critical infrastructures. Taghaddos and Mohamed, (2019) stated that the costs of maintenance and repair of bridges are significant in the provincial and municipal government's budgets. Predicting bridge conditions can help managers while allocating the needed annual costs in the budget. These challenges are exacerbated by the impacts of climate change as stated in the study done by Nasr et al., in 2020 where they pointed out that precipitation and temperature are the main parameters to be considered. In 2019, Taghaddos & Mohamed proposed a predictive model to evaluate bridges, which did not consider the climate parameters under different climate scenarios, nor accounted for other aspects that are specific to Ontario.

The *Ontario Structure Inspection Manual (OSIM, 2008*) recommended that inspections and evaluation of bridge structures must be performed every two years. One of the tools that may assist in managing highway structures is the Bridge Condition Index (BCI), as stated by He et al., (2024). That index helps monitor the extent and severity of the bridge's deterioration by assigning a grade to each structure. Another aspect to consider in this regard is the cost of investment in such infrastructure, as budgets allocated to this type of work are often sparse. Accordingly, governing bodies are forced to have to choose how funds are spent (MacDonald & Arjomandi, 2018).

In this study, the complex relationships between different variables of the Ontario Bridge dataset combined with the climate change parameters under different RCPs are analyzed with the help of Machine Learning Algorithms and Statistical methods. The aim is to understand the extent to which the variations in the precipitation and temperature affect the health of a bridge infrastructure in different regions and based on different materials, and how this will impact the cost of future investment in Ontario.

2. METHODOLOGY

2.1. General procedure

The procedure for aggregating, analysing and using the predictive models is presented in figure 1. The data comes from five sources: the bridge dataset; (*Bridge Conditions - Dataset - Ontario Data Catalogue*, 2021.), the traffic dataset; (*SydneyEnterprise: Portal*, 2022) , the climate dataset (Deng et al., 2018) and (Canada, 2018); and the financial dataset (Government of Canada, 2019).

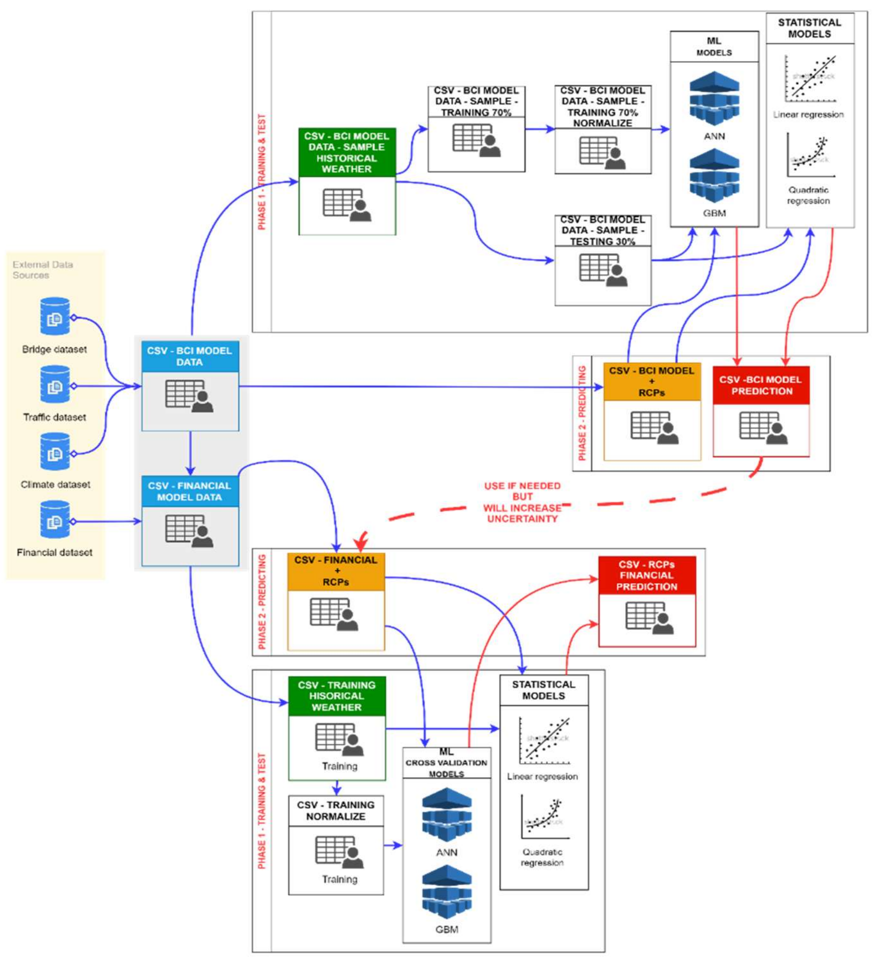

Figure 1: Flowchart diagram illustrating the analysis process

2.2. Ontario Data sets – characteristics

2.2.1 Bridges dataset

The bridge dataset contains records for 5,053 bridges with 44 fields of data. The information about the BCI is given in 21 fields ranging from the year 2000 to year 2020, and the rest of the data is mostly categorical data. From these fields, the following information is retrieved and used in the models:

- Variables for the BCI model include: Id, Year, Region, Year Built, Year of rehabilitation, Material, Length, Width, Service Under, and BCI.
- Variables for the Cost model include: Year, Year Built and the BCI.

2.2.2 Climate data set

Three datasets are used for establishing the climate data: the RCP data set; the Normal dataset from 1962 to 1980; and the historical weather data. The information used are recorded and their values are projected for Temperature and Precipitation.

2.2.3 Traffic data set

The information for this dataset provides the volume of traffic for each region in Ontario from 1988 to 2020. The field used is the truck AADT (Annual Average Daily Traffic).

2.2.4 Financial data set

The collected information comes from the data pertained to the investment cost for transportation assets in Ontario from 1981 to 2021. After filtering the collected data, the cost data from bridges' records is downloaded.

2.3 Ontario Data set – Aggregation

The different steps performed to integrate, summarize, group, and consolidate the data into an exploitable format are listed as follow:

2.3.1 Bridge dataset

This dataset was arranged in three parts:

1- Creating a dimensionless variable by using the equation [1]
   [1] Ratio_LW = Length / Width

2- Replacing the Year built with the Age of the bridge by using the equation [2]
   [2] Age = Year of analysis – Year built

3- Filling in the missing data, where the BCI values are recorded every two years or even more. Some values were missed either because the data was not recorded, or the bridge was recently built. Those missing data points were replaced by interpolating the values of two consecutive BCI values corresponding to an equal distribution of the deterioration or the improvement of the health of the bridge.

2.3.2 Climate datasets

To ensure consistency between the climate models and the historical data, the Normal value is calculated from year 1962 to year 1980. This value is then subtracted from the actual weather station information, which produces the values for the variation in the values from 2000 to 2020.

2.4 Models and data

2.4.1 BCI model

In the study performed by Taghaddos & Mohamed, (2019) on the Ontario dataset, a model was produced by selecting the most relevant variables, which were four. The step known as “Feature selection” is often an important step in the applications of machine learning methods, because Modern data sets are often described with far so many variables for building practical models (Kursa & Rudnicki, 2010). In 2023, Fang et al., presented a table listing comparable and relevant studies that have been performed on evaluating bridges’ conditions. In that table, the authors used ten variables from Lee et al., (2008) study; 8 variables from Creary & Fang, (2013) study, 5 variables from Huang et al., (2015) study; 9 variables from Shan et al., (2016) study; 12 variables from Ali et al., (2019) study; 7 variables from Lim & Chi, (2019) study; 14 variables from H. Liu & Zhang, (2020) study; 9 variables from Allah Bukhsh et al., (2020) study; 13 variables from Alogdianakis et al., (2022) study; 9 variables from Jaafaru & Agbelie, (2022) study; and 20 variables from Fang et al., (2023) study. None of those studies included climate parameters in their analysis. Therefore, this study considers 11 variables, as shown in the equation [3]:

$$[3]\ BCI_i = f(BCI_{i-1}, BCI_{i-2}, T_i, P_i, \text{Region}, \text{Age}, \text{YearRehabilitation}, \text{Material}, \text{RatioL}_W, \text{ServiceUnder}, T_{AADT})$$

Were,
BCI is the Bridge Condition Index for three consecutive years,
T_i is the variation in the temperature,
P_i is the variation in the precipitation,
Region is the regions in Ontario [Eastern, Western, Central, Northeastern, Northwestern],
Age is the age of the bridge,
YearRehabilitation is the year of the bridge’s last major rehabilitation,
Material is the bridge’s main material [Concrete, Steel],
RatioLw is the length to width ratio,
ServiceUnder is the bridge’s overpass (over land or over water),
T_{AADT} is the Truck Average Annual Daily Traffic.

A sample of randomly selected bridges was taken form the dataset for each region of Ontario. The sample was calculated with a confidence level of 95%. Table - 1 summarizes the data that had been analysed.

Table - 1 Variables used for the BCI model

Data	Inp1 temp	Inp2 pre	Inp3 reg	Inp4 age	Inp5 y_rehab	Inp6 mat	Inp7 ratioL_w	Inp8 s_u	Inp9 t_aadt	Inp10 Bci _i-2	Inp11 Bci _i-1	Out Bci
1	0.4	-3.3	5	66	2015	0	2.93	0	79630	55.4	55.4	61.55
2	-0.4	6.1	5	66	2015	0	2.93	0	80610	55.4	61.55	67.7
…	…	…	…	…	…	…	…	…	…	…	…	…
29130	-0.8	-17.3	1	25	0	1	30.12	1	998510	74.2	73.98	73.76
29131	0.7	-53.2	1	25	0	1	30.12	1	1001165	73.98	73.76	73.76

Note: Inp# means Input No #, Out means Output

2.4.2 Cost Model

In 2017, Barakchi et al. stated that bridge infrastructure costs are usually evaluated through three methods, which are 1) Parametric; 2) Artificial Neural Networks (ANN); and 3) Case-based Reasoning (CBR). In a study done by Juszczyk, (2020) the cost of bridges were evaluated with a Support Vector Machin (SVM) approach. Those methods are specifically used to evaluate the cost for bridges. A model for evaluating the cost of bridge network is presented in a study by Jaafaru & Agbelie, (2022), however the framework used

in that study is difficult to be implemented for Ontario because of the limited data found on the government website.
Because of these limitations, the following model is proposed to estimate the predictive costs for different climate scenarios in Ontario by using the equation [4].

$$[4]\ Cost_{i+1} = f\left(Year_i, T_{i+1}, P_{i+1}, \overline{Age_i}, T_{AADT_i}, \overline{BCI}_i, Cost_i, Cost_{i-1}, Cost_{i-2}, Cost_{i-3}\right)$$

Were,
$Year_i$ is the year under consideration,
T_{i+1} is the temperature for the next year,
P_{i+1} is the precipitation for the next year,
$\overline{Age_i}$ is the average age of the bridge infrastructure,
T_{AADTi} is the Truck Average Annual Daily Traffic,
$\overline{BCI_i}$ is the average bridge condition Index,
Cost is the cost of investment for the bridge infrastructure.

Table – 2 lists the cost model's dataset

Table 2: Dataset for Cost Model

Inp1 Year _i	Inp2 AvgT i+1	Inp3 AvgP i+1	Inp4 AADT _Ti	Inp5 A_Age_i	Inp6 AvgBCI_i	Inp7 Tcost _i-3	Inp8 Tcost _i-2	Inp9 Tcost _i-1	Inp10 Tcost _i	Out Tcost _i+1
0	0.141044	11.02985	5329150	28.47	76.39	9	2	4	53	40
1	1.245982	51.39144	5408900	29.04	75.25	2	4	53	40	35
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21	1.184581	-3.20582	6388740	39.32	77.19	36	130	98	39	491
22	0.151984	-39.7595	6242708	40.32	76.47	130	98	39	491	492

Note: Inp# means Input No #, Out means Output

2.5 Predictive modelling

In this study, each of the models are coded by using the "R" programing language (Team, 2014) where four algorithms were employed and afterward were tested to find the most efficient one.

2.5.1 Linear regression

In R, the function "lm", included in the base package, is used for a multivariable regression analysis. Regression is an analytical method that studies the change in a variable value corresponding to a change in the other (Faizi & Alvi, 2023). This type of analysis is performed two times, once for a linear model and another for a quadratic model.

2.5.2 Artificial Neural Network (ANN)

In "R", the install.packages("nnet") and library(nnet), should be included in the code to run the ANN algorithm. ANNs are modeled after the human brain's neural networks and consist of interconnected artificial neurons that can learn complex patterns from the used data (Z. Liu et al., 2025).

2.5.3 Gradient Boosting Method (GBM)

GBM is runed in "R" by using the install.packages("gbm") and library(gbm) or install.packages("Xgboost") and library(Xgboost). The main idea of boosting is to add new models to the ensemble sequentially. At each particular iteration, a new weak, base-learner model is trained with respect to the error of the whole ensemble learnt so far (Natekin & Knoll, 2013).

3. RESULTS

3.1 Comparing the models

3.1.1 Comparing the models – BCI model

The best model is selected by evaluating the performance of various models. For the BCI model, the data is split into training (70%) and testing (30%). Additionally, the training set is further split into a validation set, representing 20% of the training set. After splitting, all the data is normalized between 0.2 and 0.8 for the ANN and GBM models, respectively.

Tables 3 through 5 display the error values and R-squared between the predicted and the observed values. When averaging the values, the ANN model shows the lowest R-squared value, while the GBMGBM model shows the highest. The Linear Model (LM) model has the lowest Mean Absolute Error (MAE), and the ANN model has the highest. The Root Mean Square Error (RMSE) is lowest for the GBM model and highest for the ANN model.

Comparing the training set to the validation set, the GBM model exhibits the most significant variations for MAE, RMSE, R-squared, and Relative Error. These variations indicate overfitting. The ANN model has the second-highest variations. Between the models and the available data, the recommended model is the Linear Regression Model due to its low variation between the errors and R-squared values and the Artificial Neural Network, which shows slightly better performance

Table - 3 Training set errors and R-squared

Training Set Errors	Linear	Quadratic	ANN	GBM
Mean Absolute Error (MAE)	1.7814	1.7856	1.6415	1.4555
Mean Squared Error (MSE)	14.6598	14.4666	13.238	8.2724
Root Mean Squared Error (RMSE)	3.8288	3.8035	3.6384	2.8762
Sum of Absolute Errors (SAE)	29061	29131	26779	23745
Sum of Squared Errors (SSE)	239160	236008	215963	134955
R-squared	0.8561	0.8580	0.8701	0.9188
Relative Error	0.02491	0.02504	0.02324	0.02046

Table - 4 Validation set errors and R-squared

Validation Set Errors	Linear	Quadratic	ANN	GBM
Mean Absolute Error (MAE)	1.7487	1.7488	1.8358	1.8749
Mean Squared Error (MSE)	13.7828	13.2829	12.8917	11.8842
Root Mean Squared Error (RMSE)	3.7125	3.6446	3.5905	3.4473
Sum of Absolute Errors (SAE)	7131	7131	7486	7646
Sum of Squared Errors (SSE)	56206	54168	52572	48464
R-squared	0.8598	0.8649	0.8689	0.8791
Relative Error	0.02459	0.02473	0.02664	0.02742

Table - 5 Testing set errors and R-squared

Testing Set Errors	Linear	Quadratic	ANN	GBM
Mean Absolute Error (MAE)	1.7894	1.7872	2.915	2.6474
Mean Squared Error (MSE)	14.5016	14.2593	17.3282	15.7105
Root Mean Squared Error (RMSE)	3.8081	3.7761	4.1627	3.9636
Sum of Absolute Errors (SAE)	15637	15618	25474	23136
Sum of Squared Errors (SSE)	126729	124612	151431	137294
R-squared	0.8581	0.8605	0.8305	0.8463
Relative Error	0.0246	0.0246	0.0419	0.0386

3.1.2 Comparing the models – Cost model

Due to the limited amount of data point, K-fold cross validation was used for the cost model. The data was normalized between 0.2 and 0.8 for ANN and GBM.

Table - 6 Training set errors and R-squared

Training Set Errors	Linear	Quadratic	ANN Model	GBM
Mean Absolute Error (MAE)	44.9245	4.7716	54.0442	3.2713
Mean Squared Error (MSE)	3109.6824	36.9080	7782.1550	17.8837
Root Mean Squared Error (RMSE)	55.7645	6.0751	88.2165	4.2289
Sum of Absolute Errors (SAE)	1033	109	1243	75
Sum of Squared Errors (SSE)	71522	848.8843	178989	411
R-squared	0.8267	0.9979	0.5665	0.999
Relative Error	0.6572	0.06981	3.33	0.4631

The models that displayed the best performance are the Quadratic and the GBM because they have the lowest MAE, Relative Error, and the highest R-squared. The Quadratic method is recommended; however, the implementation will be complicated without using the R code.

3.2 Climate predictions

Predicting the variation in the values of the projected BCI and Cost under different RCP scenarios.

3.2.1 BCI model

The linear equation for estimating the BCI is given by the equation [5]:

$$[5]\ BCI_i = 11.5125 - 0.0728*T_i - 0.0014*P_i + 0.0019*Region - 0.025*Age – 2.597e\text{-}05*YearRehabilitation + 0.0316*Material + 5e\text{-}0.4*RatioL_w – 0.0271*ServiceUnder + 4e\text{-}08*T_{AADT} – 0.2683 * BCI_{i-2} + 1.1307*BCI_{i-1}$$

This equation can be limited to predicting values for up to 2 years (Taghaddos & Mohamed, 2019) because the evaluation of bridges is required to be performed every two years.

Figure 2 is a randomly selected example of the prediction that was done by using equation [5]. The BCI Predicted values under different Representative Concentration Pathways (RCP) scenarios do not vary significantly, which is an indication that the averages for all the anomalies (historical and simulation) between years 2000 to 2020 are close which is consistent with the climate predictions.

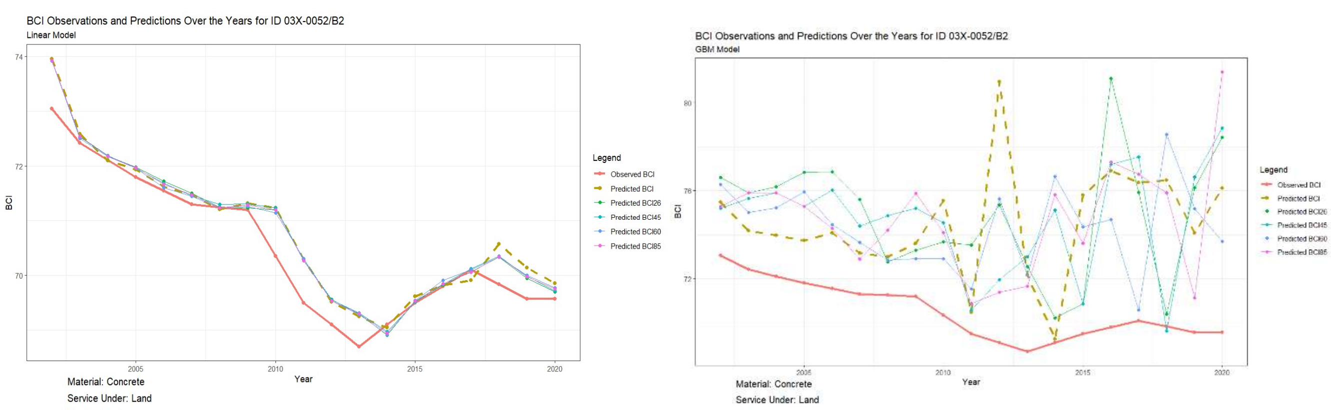

Figure - 2 Example of the evolution of BCI for a concrete bridge over land in Eastern Ontario. Best performing model – Linear model (right) and worst performing model – GBM (left)

3.2.2 Cost Model

The cost estimating model is using the quadratic model as shown in Figure – 3 and the GBM algorithms as seen in Figure – 4, which lets the cost model to perform well. The predictions are close to the observed values, with the GBM model having an advantage over the Quadratic model. Similar to the BCI model, the predictions for cost under different RCP does not indicate notable changes in the values.

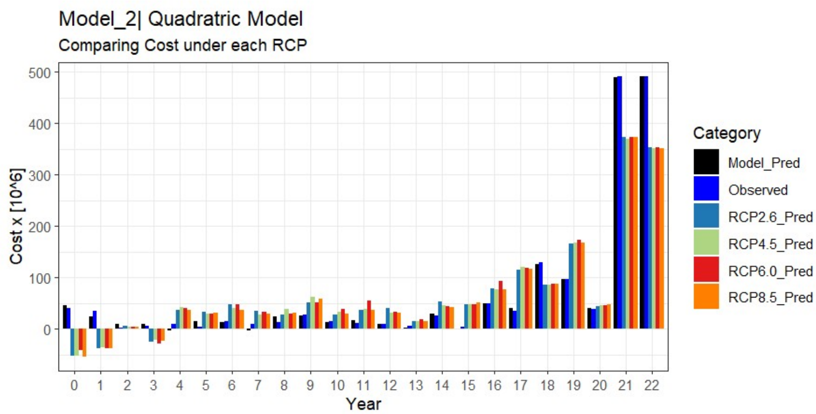

Figure - 3 Cost of infrastructure using the quadratic model

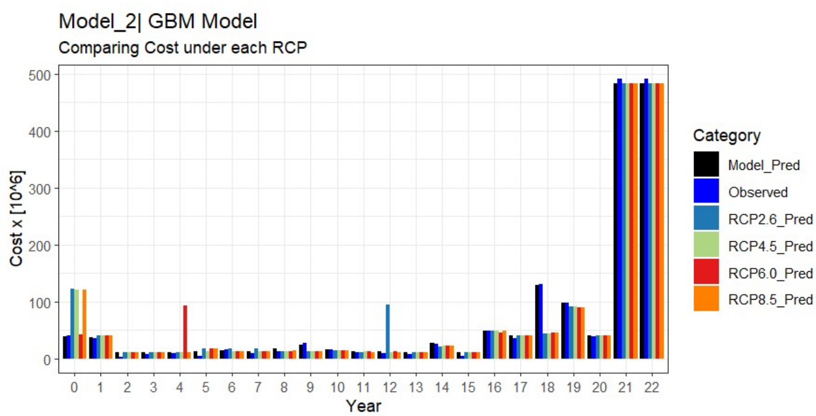

Figure - 4 Cost of infrastructure using GBM model

4. CONCLUSION

Developing a predictive model for infrastructure management would lead to a better planning, constructing, operating, and budgeting. Having these tools for the bridge network helps the municipal and federal government to better plan for future needs and target structures that require the most attention. In this study, the models were built with specific characteristics for Ontario by having the data categorized by region and by including climate parameters under different climate scenarios.

Two models were developed by using the "R" programming language. The first model can predict the Bridge Condition Index (BCI) and the second can evaluate the cost of future investments for Ontario. This is done by using historical data and predictive weather models for the temperature and precipitation and analyzing the data by using four algorithms: 1) multivariable linear regression; 2) multivariable quadratic regression; 3) ANN; and 4) GBM. The key findings are as following:

- The BCI model performs better by using the ANN that's has values of R^2 = 0.87; MAE =1.64; RMSE = 3.63; and RE = 2.3%. The ML model with R^2 = 0.85; MAE =1.78; RMSE = 3.82; and a RE = 2.4% has a slightly lower performance level but because we have an equation [5] is the recommended options.

- The Cost model performs better by using the GBM model R^2 = 0.99; MAE =3.27; RMSE = 4.22; and RE = 46.31%. The GBM can do forecast for different climate scenarios but not yet for regions. The data was not yet been classified per region.
- Integrating climate parameters under different climate scenarios and region for Ontario, helps forecast specific region needs.

- When looking at the climate scenarios during the years of 2000 to 2020, the variations are visibly small. However, climate change does impact infrastructure, but significant differences will probability be noticed when approaching the year 2050.

Because these approaches are based on updated data, predicting beyond two years increases the level of uncertainty. Caution is warranted when using the cost data, there is not a clear separation between the costs for rehabilitation and the ones for new construction, which means that a more accurate prediction could be achieved with a detailed bridge cost breakdown. While the goal of the cost model is to understand trends in its variations under different climate scenarios, the high-level of uncertainty during the examined period prevents the identification or reliable trends of those variations for future budget planning.

Additional improvement could be integrated in the datasets for a better understanding of the type of bridge deficiencies, which would improve the precision of the predictions for maintenance and rehabilitation, and the allocations of resources per region. The perspective is to integrate this predictive system into a user-friendly tool for stakeholders.

REFERENCES

Ali, G., Elsayegh, A., Assaad, R., El-adaway, I. H., & Abotaleb, I. S. (2019). *Artificial Neural Network Model for Bridge Deterioration and Assessment*.

Allah Bukhsh, Z., Stipanovic, I., Saeed, A., & Doree, A. G. (2020). Maintenance intervention predictions using entity-embedding neural networks. *Automation in Construction*, *116*, 103202. https://doi.org/10.1016/j.autcon.2020.103202

Alogdianakis, F., Dimitriou, L., & Charmpis, D. C. (2022). Data-driven recognition and modelling of deterioration patterns in the US National Bridge Inventory: A genetic algorithm-artificial neural network framework. *Advances in Engineering Software*, *171*, 103148. https://doi.org/10.1016/j.advengsoft.2022.103148

Barakchi, M., Torp, O., & Belay, A. M. (2017). Cost Estimation Methods for Transport Infrastructure: A Systematic Literature Review. *Procedia Engineering*, *196*, 270–277. https://doi.org/10.1016/j.proeng.2017.07.199

Bridge conditions—Dataset—Ontario Data Catalogue. (2021). https://data.ontario.ca/dataset/bridge-conditions

Canada, E. and C. C. (2018, September 26). *Scenarios and climate models*. https://www.canada.ca/en/environment-climate-change/services/climate-change/canadian-centre-climate-services/basics/scenario-models.html

Creary, P. A., & Fang, F. C. (2013). The Data Mining Approach for Analyzing Infrastructure Operating Conditions. *Procedia - Social and Behavioral Sciences*, *96*, 2835–2845. https://doi.org/10.1016/j.sbspro.2013.08.316

Deng, Z., Liu, J., Qiu, X., Zhou, X., & Zhu, H. (2018). Downscaling RCP8.5 daily temperatures and precipitation in Ontario using localized ensemble optimal interpolation (EnOI) and bias correction. *Climate Dynamics*, *51*(1–2), 411–431. https://doi.org/10.1007/s00382-017-3931-3

Faizi, N., & Alvi, Y. (Eds.). (2023). Biostatistics Manual for Health Research. In *Biostatistics Manual for Health Research* (p. iii). Academic Press. https://doi.org/10.1016/B978-0-443-18550-2.01001-X

Fang, J., Hu, J., Elzarka, H., Zhao, H., & Gao, C. (2023). An Improved Inspection Process and Machine-Learning-Assisted Bridge Condition Prediction Model. *Buildings*, *13*(10), 2459. https://doi.org/10.3390/buildings13102459

Government of Canada, S. C. (2019, April 17). *Infrastructure Economic Accounts, investment and net stock by asset, industry, and asset function*. https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3610060801

He, Z., Song, Y., Guan, H., & Yu, L. (2024). Predicting bridge condition index using an improved back-propagation neural network. *Alexandria Engineering Journal*, *106*, 328–336. https://doi.org/10.1016/j.aej.2024.07.029

Huang, Q., Ong, K.-L., & Alahakoon, D. (2015). *Improving Bridge Deterioration Modelling Using Rainfall Data from the Bureau of Meteorology*. *168*.

Jaafaru, H., & Agbelie, B. (2022). Bridge Maintenance Planning Framework Using Machine Learning, Multi-Criteria Decision Analysis and Evolutionary Optimization Models. *Automation in Construction*, *143*, 104585. https://doi.org/10.1016/j.autcon.2022.104585

Juszczyk, M. (2020). On the Search of Models for Early Cost Estimates of Bridges: An SVM-Based Approach. *Buildings*, *10*(1), Article 1. https://doi.org/10.3390/buildings10010002

Kursa, M. B., & Rudnicki, W. R. (2010). Feature Selection with the Boruta Package. *Journal of Statistical Software*, *36*, 1–13. https://doi.org/10.18637/jss.v036.i11

Lee, J., Sanmugarasa, K., Blumenstein, M., & Loo, Y.-C. (2008). Improving the reliability of a Bridge Management System (BMS) using an ANN-based Backward Prediction Model (BPM). *Automation in Construction*, *17*(6), 758–772. https://doi.org/10.1016/j.autcon.2008.02.008

Lim, S., & Chi, S. (2019). Xgboost application on bridge management systems for proactive damage estimation. *Advanced Engineering Informatics*, *41*, 100922. https://doi.org/10.1016/j.aei.2019.100922

Liu, H., & Zhang, Y. (2020). Bridge condition rating data modeling using deep learning algorithm. *Structure and Infrastructure Engineering*, *16*(10), 1447–1460. https://doi.org/10.1080/15732479.2020.1712610

Liu, Z., Gu, Z., & Liu, P. (Eds.). (2025). Transportation Big Data. In *Transportation Big Data* (p. iii). Elsevier. https://doi.org/10.1016/B978-0-443-33891-5.01001-2

MacDonald, A., & Arjomandi, K. (2018). MAINTENANCE PRIORITIZATION OF BRIDGE STRUCTURES. *CSCE*, 10.

Nasr, A., Kjellström, E., Björnsson, I., Honfi, D., Ivanov, O. L., & Johansson, J. (2020). Bridges in a changing climate: A study of the potential impacts of climate change on bridges and their possible adaptations. *Structure and Infrastructure Engineering*, *16*(4), 738–749. https://doi.org/10.1080/15732479.2019.1670215

Natekin, A., & Knoll, A. (2013). Gradient boosting machines, a tutorial. *Frontiers in Neurorobotics*, *7*. https://doi.org/10.3389/fnbot.2013.00021

Ontario Structure Inspection Manual (OSIM) 2008. (n.d.). Sydney PROD. Retrieved December 4, 2024, from https://www.library.mto.gov.on.ca/SydneyPLUS/Sydney/Portal/default.aspx?component=AAAAIY&record=2cc7e50c-3d41-4468-90f1-0788368ce945

Shan, Y., Contreras-Nieto, C., & Lewis, P. (2016). *Using Data Analytics to Characterize Steel Bridge Deterioration*. 1691–1699. https://doi.org/10.1061/9780784479827.169

Taghaddos, M., & Mohamed, Y. (2019, May 24). *Predicting Bridge Conditions in Ontario: A Case Study*. 36th International Symposium on Automation and Robotics in Construction, Banff, AB, Canada. https://doi.org/10.22260/ISARC2019/0023

Team, R. (2014). R: A language and environment for statistical computing. *MSOR Connections*. https://www.semanticscholar.org/paper/R%3A-A-language-and-environment-for-statistical-Team/659408b243cec55de8d0a3bc51b81173007aa89b