The application of Artificial Intelligence of Things to predict and classify potential hazards under the Sidi Rached bridge of Constantine*

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Abstract

The Sidi Rached bridge of Constantine is one of the most important landmarks and infrastructures of the city, it is used daily by the citizens as a mandatory passage; However, this can change soon if no actions are to be taken in the near future due to the critical conditions it is sat on; This bridge has been undergoing so many fixing works which were merely temporary solutions to the landslide occurring which is worsened by the soil erosion coming from natural factors(wind and water); In this paper, we address an Artificial Intelligence of Things (AIoT) based solution for remote monitoring and prediction of the coming hazards under the bridge foundation especially on the right bank. The method consists of using the a regression model for RUSLE and WEQ equation parameters calculation and future erosion estimation along with risk level classification with random forest model. For real life realization: The data that shall then be tested and classified is to be taken from the different sensors installed around the area.

Keywords

Bridge, Erosion, Artificial Intelligence of Things, Landslide.

1. Introduction

Bridges are very crucial infrastructures when it comes to transportation [1]. For the city of Constantine Algeria: One of the most important landmarks is the Bridge of Sidi Rached as it connects two side of the city above a huge gorge with the height of 102m [2]; This is considered to be a mandatory infrastructure for the citizens as they use it on a daily basis [3].Unfortunately though, it is not as safe as it should be. In reality, the right bank of the Sidi Rached bridge is menaced due to the instability of the slope. The hazards were noticed at the time of construction [4] then in 2008, the seriousness of the threat was confirmed after the landslide that occurred leaving real damage on the right bank piers , the bridge foundation is situated on limestone bedrock on the left bank and argillite formation that sits on limestone on the right bank [2] which is the most vulnerable part due to the soil components. It is important to note that the climate is one of the factors contributing in the failed stabilization [4]. This instability problem has been solved few times using different methods such as drainage pit [2] but those were temporary attempts of rescue [3] [4] As it presents an important national heritage that needs to be preserved, constant monitoring is necessary to take action in the right time[3] [5]

To help ourselves react in the right way and time, it is necessary to have good view on the source of the problem which is considered to be the soil erosion under the right bank;This phenomenon is a global issue which technically is the effect of having soil particles transported due to natural causes like wind and water; [6] [7] where water soil erosion is more common and severe [8] [9]

It is worth to mention that different type of soil have different levels of erosion susceptibility because of their distinct geological formations because they affect in a direct and indirect way the soil erodibility

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factor K [6] [10] that is why every area and part needs to be studied on its own using the accurate data for better estimation and effective prediction.

Still; wind erosion needs to be taken in consideration especially seeing the fact that is estimated to increase by the coming years due to the climate change, when the wind intensity is stronger than the force maintaining the soil particles it drives them away causing erosion. For this matter as well; the soil texture plays a role in the level of wind erodibility, vegetation especially trees have high effectiveness in protecting the land against wind erodibility [11][12] [13]

2. Related works:

As soil erosion represents a serious global issue so many researches and works addressed solutions to either predict, analyze or classify the coming hazards. When it comes to water erosion, a very common method is used which the Revised Universal Soil Loss Equation RUSLE; It consists of several factors related to the soil and its surroundings to estimate the amount of soil loss per year [14]

For instance; basing on the RUSLE, a work introduced new approaches like imagery, soil data and Artificial Intelligence to enhance the the soil erosion maps [15] Another work used ANN with several soil erodibility indices like Clay Ratio (CR)and modified clay ratio (MCR) to find the its probability. [16]

Also, in this study [17] the researchers used the GIS techniques and RUSLE equation to predict and estimate soil erosion risk. But to further dig into this formula; [18] focused on the calculating of cover factor basing on two subfactors, with phytoecological data along with the remote sensing GIS which helped mapping larger areas, this research found that the gravel-pebbles protection against erosion is even more effective than vegetation cover seeing the impact of the cover factor, [7] used an erosion mapping model to remotely detect the occurrence of erosion on a certain area by analyzing the vegetation cover through imagery; This method helps analyzing erosion phenomenon in a wide land in a short time. Others suggested the improvement of soil erosion prediction through analyzing the Land Use / Cover LULC change [9]

And although the RUSLE model seems to be linear, studies showed that it is hard to calculate the factors due to changing according to the regions and data [19] Hence why in this paper; we suggest the application of Artificial Intelligence because it finds its own parameters basing on constant data it keeps getting supposedly from the sensors installed around the area in question

3. Paper contribution:

AIoT as a technology has been used to solve multiple issues around the world in different aspects; When it comes to the Sidi Rached bridge risks, only temporary measures were given but no work has provided means to predict, estimate or classify any of the potential hazards facing it; Which is why hitherto we can say that this work is the first to exploit the benefits of AIoT to prevent upcoming safety menaces by predicting and classifying the erosion under the bridge foundation using the location specific features such as climate values and soil type; As well as being the first to use both water and wind erosion together to get the total loss and evaluate the coming risks in the following years according to the area's climatic change pattern.

We can summarize this paper's contributions as follows:

- Application of IoT systems to collect data from the actual site for more specific analysis
- Application of AI to analyze both the historical and actual data to predict any anomaly and upcoming hazard
- Exploiting both water and wind erosion formulas for better estimation of the erosion level under the Sidi Rached bridge

4. Proposed Solution:

seeing the common disregard of the wind erosion affect that can occur along with water erosion; we built in our solution in consideration of both phenomenons; Our solutions goes as follow:

- Application of the linear regression model for future counting and estimating of the soil erosion due to the water effects
- Application of the linear regression model for future counting and estimating of the soil erosion due to the wind effects
  These models would take in and train on data of the regular climate scenarios of the area around the right bank of the Sidi Rached bridge; learn the patterns and parameters and then estimate the annual soil erosion
- The decision tree takes climate features and erodibility predicted values to be able to correlate the climate and weather factors with coming erosion for both wind and water and then estimate the risk level and alert before it happens
- In realization of this work; different sensors mainly climate related (rainfall & wind) will give the data to the models which will help them estimate and learn the climate change patterns; this helps improving the accuracy and then give precise prediction of the coming hazards; the data does not need to be taken in real time in short periods and treated rapidly because the climate pattern has low progression speed.

4.1. Soil erosion due to water:

using the RUSLE formula we get the equation:

$$A = K * R * C * LS * P \tag{1}$$

where

- A = Estimated erosion or loss of material
- R = Rainfall erosivity factor
- K = Soil erodibility factor
- LS = Topographic factor
- C = Cover management factor
- P = Erosion control practices

We took in the values as follow according to the city of Constantine climate and estimation of area under the bridge conditions (slope, vegetation...etc.)
The data used is generated by programming given specific values and intervals
K= Ranges from [0.02 to 0.1] due to the different component and level of clay/ sand and other geological properties in that area
R= Ranges from [50 to 100] according to the city average precipitation
LS=12 Estimated using the LS formula for slope and steepness of 30° and 70m
C=0.5
P=0.25
Due to the small amount of natural vegetation and drainage system applied.

Seeing the fact that linear regression works with straight linear inputs and our tests included two variables (K and R) we opted for estimating the logarithmic value of A and then extract it reversely
In the figures below; we display the ability of the model to quickly learn the pattern of the factors after training with corresponding data

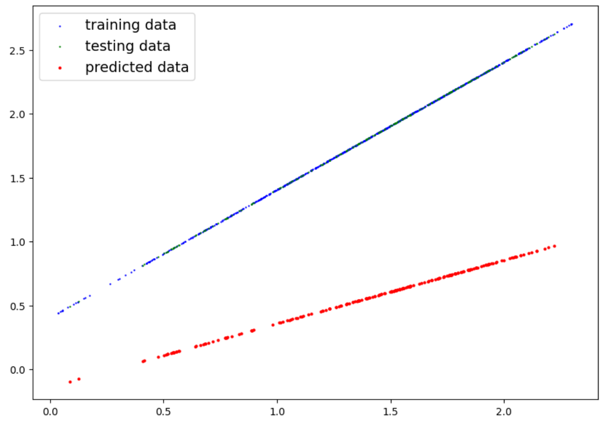

Figure 1: Water erosion prediction-before training

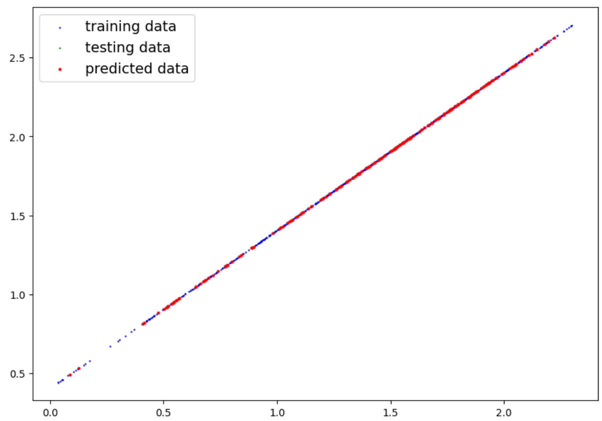

Figure 2: Water erosion prediction-after training

4.2. Soil erosion due to wind:

as performed with the RUSLE in the water erosion; we opted for the WEQ when it comes to wind erosion;

$$E = I * K * C * L * V \tag{2}$$

where:

- E = Soil loss due to wind erosion
- I = Soil erodibility index
- K = Surface roughness
- C = Climate factor (wind speed and soil moisture)
- L = Length of the field
- V = Vegetation cover factor

K= range from [0.2 to 0.8]
C=range from [0.1 to 0.6]
I=0.1
L=65/10000
V=0.5 The figures 3 and 4 show the same ability of learning with WEQ

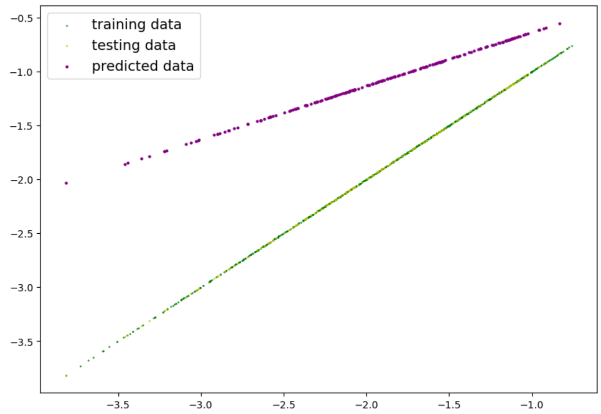

Figure 3: Wind erosion prediction-before training

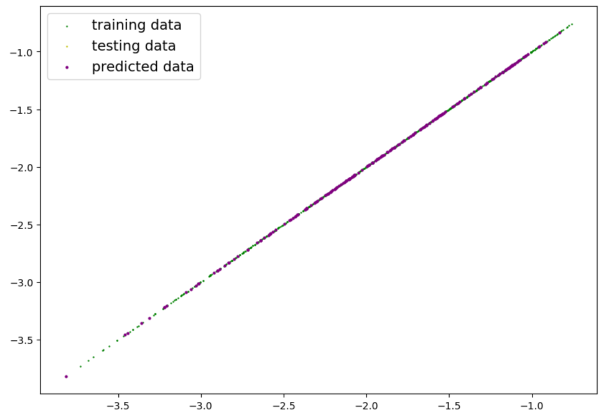

Figure 4: Wind erosion prediction-after training

4.3. Random forest model:

We fed the intervals of hazard classification to our model along with erosion prediction outputs the model to be be able classify the coming erosion hazards taking in consideration both features and their impact on the danger level. This phase can later help us predict the level of potential danger basing on the climate features which will impact the soil due to both wind and water.

Wind		Water		level of severity
lower	upper	lower	upper	
0	1	0	5	low
1	3	5	10	moderate
3	>3	10	20	high
>3	>3	20	50	severe
>3	>3	50	>50	very severe

Figure 5: Hazard classification levels

The process we went through went as follows:

- Training our model with the correspondent values as features
- Passing the input tests to our pre-trained model to get its prediction of the classification
- Testing the results of predictions with the real output test values with both accuracy_score and r2_score functions where both gave values higher than 0.98 corresponding to 98% accuracy

4.3.1. Random forest tree:

This figure below represents the random forest tree.
This shows the process which the model goes by when learning and trying to make the most accurate prediction using the necessary features, i,e, the model takes final decision in favor on the highest vote in the tree branches This process shows to be an easy learn for this case scenario because of the input simplicity

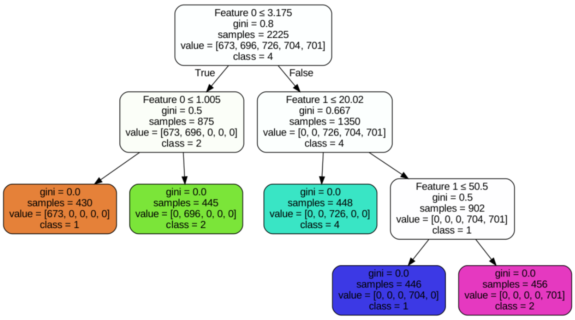

Figure 6: Random forest tree

4.3.2. The confusion matrix:

This confusion matrix shows the ease the model has learning the patterns of the classification The

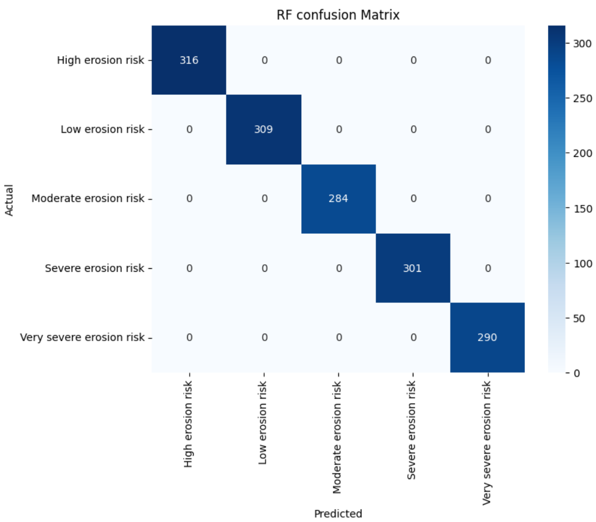

Figure 7: Random forest confusion matrix

confusion matrix of the random forest model shows how accurately it was predicting the classes where the:

- rows represent the actual classes
- columns represent the predicted classes
- diagonal cells are the correct predictions made by the model
- the rest of the cells are the mismatched; The wrong predictions

4.3.3. Final Classification:

The down-below table shows the model's attempt to classify the predicted data from both RUSLE and WEQ models after training. Those inputs were specifically input for difference classes to see the model's ability to distinguish the features; with that the figure 9 shows the probabilities that model based on to make the decision

Input	Predicted Class	Meaning
Input 1	0	Low erosion risk
Input 2	1	Moderate erosion risk
Input 3	4	Very severe erosion risk
Input 4	2	High erosion risk
Input 5	3	Severe erosion risk

Figure 8: RF Model classification output

	0	1	2	3	4
0	0.4	0.24	0.1	0.24	0.02
1	0.0	0.9	0.1	0.0	0.0
2	0.27	0.18	0.04	0.0	0.51
3	0.0	0.11	0.89	0.0	0.0
4	0.0	0.0	0.0	1.0	0.0

Figure 9: RF Table of probabilities

The previously shown results are mainly theoretical with predictions outputs as data due to our work limitations. Still it shows the ability and effectiveness of predictions and classifications

4.4. K_nearest neighbor model:

We repeated our work using the K_nearest neighbor model to test the difference of accuracy and decide which model would give us the best results After feeding the exact same data and evaluating the model with the same functions (r2_score and accuracy_score) we noticed that despite their high value, they were still lower than the accuracy reached by the random forest model
In the down_below figure, we display the accuracy matrix of the KNN model after training and using it for the same data

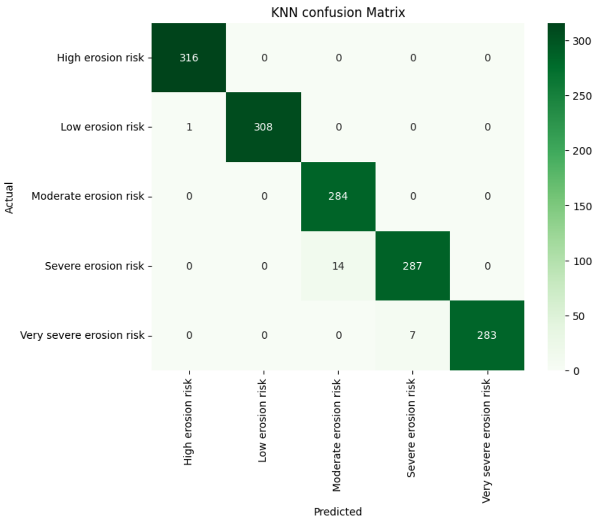

Figure 10: KNN model confusion matrix

Also, we tested the KNN trained model with the same new data to see the accuracy of its hazard level classification and we got the following output table along with the table of probabilities

Input	Predicted Class	Meaning
Input 1	3	Severe erosion risk
Input 2	1	Moderate erosion risk
Input 3	4	Very severe erosion risk
Input 4	2	High erosion risk
Input 5	3	Severe erosion risk

Figure 11: KNN Model classification output

	0	1	2	3	4
0	0.0	0.0	0.0	1.0	0.0
1	0.0	1.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	1.0
3	0.0	0.0	1.0	0.0	0.0
4	0.0	0.0	0.0	1.0	0.0

Figure 12: KNN Table of probabilities

5. Results observation and discussion:

1. Regression models can easily learn due to the simplicity of the inputs and patterns needed
2. When it comes to classification; random forest has better ability to learn and classify the potential hazard level of this context; This can be seen clearly in the both confusion matrices where the random forest matrix shows clear full ability to distinguish the classes when the KNN had less ease in that part

3. Good selection of models and their training data helps enormously in monitoring and predicting any coming danger before the bridge collapses and helps us react in the right or at least take measure to keep human life safe
4. Any wrong data or faulted estimation of any factor can lead to a completely wrong prediction (false alarm or false negative) which may result in serious consequences
5. For better application of the proposed idea, real concrete data of the climate and weather features is needed to be fed to the random forest model to be able to correlate it with erosion values and then give better erosion prediction basing on weather condition and classify the potential hazard

6. Remarks:

In an important note; works like [20] and [18] have mentioned that adding gravel-pebbles and rock fragments increase the level of coverage even more than vegetation which helps decrease the soil erosion and stabilize the area as well as the implementation of AI can estimate climate scenarios that can occur in the future [21] which gives us the upper hand to see the potential threat long before they happen

7. Work limitations:

1. Despite the importance of the situation there is not much work and researches done around the area which leads to scarcity in the data needed especially soil properties related data
2. scarcity of the data decreases the models ability to give accurate prediction specific to that location
3. It also might be an expensive measure to get the right values for either coverage factor, soil properties and other indexes
4. Lack of data was an obstacle in a huge part to test the solution when it comes to features correlation and pattern extraction with erosion estimated value
5. Prediction of coming threats is not enough but react actions need to be taken and studied

8. Conclusion

The sidi Rached bridge is an important heritage for the city but in order to continue being in its position doing its major role it needs to be monitored constantly; The landslide and soil erosion in its right bank threatens its standing and people around it which is why we suggested the application of artificial intelligence of things to predict any coming hazards due to the soil erosion highly impacted by the climate change. Our work emphasizes the ease of prediction using the simple equations of soil erosion in the regression models; by taking these two factors it is easier to get a proper estimation of the soil erosion value; These values can be then learned in patterns and classified to different levels of hazard. Different classification models exist but the performance proved that this case study gives better results when applying Random forest model.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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