Application of AI/ML in Tunnel Engineering: Prediction of Tunnel deformation over time

M. V. Karthikeya, Md. Adnan
Dr. Ankesh Kumar

***Abstract*—** Tunnelling in the Himalayan region of India is always challenging due to weak geological strata, higher overburden, and large shear zones. Tunnelling through such strata may often cause problems such as squeezing, rock bursting, heavy water ingress, and failure of the support system. Overall, tunnelling in the Himalayan region requires careful consideration of geological factors and precise interpretation of radial deformation around the tunnel to ensure safe and resilient tunnel construction. Traditional methods of predicting tunnel wall convergence rely on empirical formulas and numerical simulations, which may lack accuracy and require extensive computational resources. Hence, there is a need for more effective and efficient prediction techniques to mitigate the risks associated with tunnel construction. Therefore, developing reliable machine learning models capable of accurately predicting radial convergence of tunnel walls is critical for improving the safety, efficiency, and sustainability of tunnel construction projects. AI/ML algorithms can analyze large volumes of heterogeneous data, including geological surveys, historical tunnelling data, real-time monitoring data, and environmental factors. By considering a wide range of variables, these algorithms can provide more accurate predictions of ground behaviour, including the extent and rate of squeezing, compared to traditional empirical methods or numerical simulation.

I. Introduction

Several factors influence the long - term deformation of tunnels and these include the geological history, initial stress field, mineralogy, discontinuity orientation, construction technology and tunneling method, rate, support type, etc. We can measure deformation of area of cross section by calculating the net displacement of soil/rock around the tunnel. In long run rocks above the tunnel get displaced and exhibits creep like behaviour which deforms with time. This will cause a squeezing effect on tunnels and decreases its area of cross section. Which finally collapse the rock mass. So, it is important to keep track of displacements of soil and rocks above the tunnel to a certain depth.

One of the most common models to calculate these displacements is classic Burgers-creep visco-plastic model (Fig. 1). Which can be visualized as a spring, dashpot and plastic slider that are connected in parallel or in series. Here springs represent elastic deformation and dashpots represent plastic deformation.

II. Methodology

1. Data Collection:
We took a dataset of tunnel deformation over timer under different rheological parameters and at different depths.

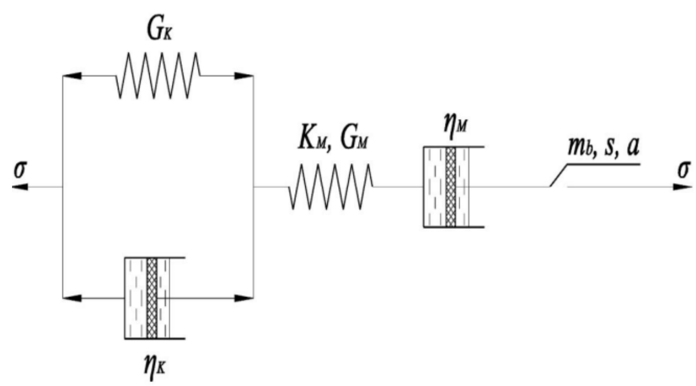

Fig. 1. classic Burgers-creep visco-plastic model

The data used for training consists of the following features:

Position, time (year), Gk/KM (ratio of Kelvin shear modulus and Maxwell bulk modulus), ηK(Kelvin viscosity), ηM(Maxwell viscosity), displacement (m)

Here position vary from 19m to 0m. We have trained some ML models and tested on data of tunnels in Himalayan regions.

2. Training:
We have trained multiple ML models to find out which model give better prediction and also combined models to check if that leads to even more accuracy.

Models used for training:
Linear Regression, Linear Regression with polynomial features, Neural Networks, K-Nearest Neighbours (KNN) and Bagging or Boosting Aggregation.

We have trained all these models for all different depths and all differnt kinds of rheological parameters. After training all these models with the training dataset, we have taken a new dataset of tunnels in Himalayan regions and tested these trained models on them. The results of training and testing will be shown in *Results* section.

3. Testing
After training all the models, we have tested these trained models on some new data to validate the accuracy. For testing data we have taken data of tunnels in Himalayan regions.

After testing we have plotted graph of predicted deformation vs original value. These plots and results of all the models were shown in *Results* section. Finally we have checked which model is better for prediction by comparing with the other models.

III. Results

In this section we will see results that we have obtained from training and testing.

Training Results:

1) For Position 19m:

- **Linear Regression Model:**
  - For position 19m, accuracy was around 99.680 with training error 0.0069 and testing error 0.0031. (Fig. 2).

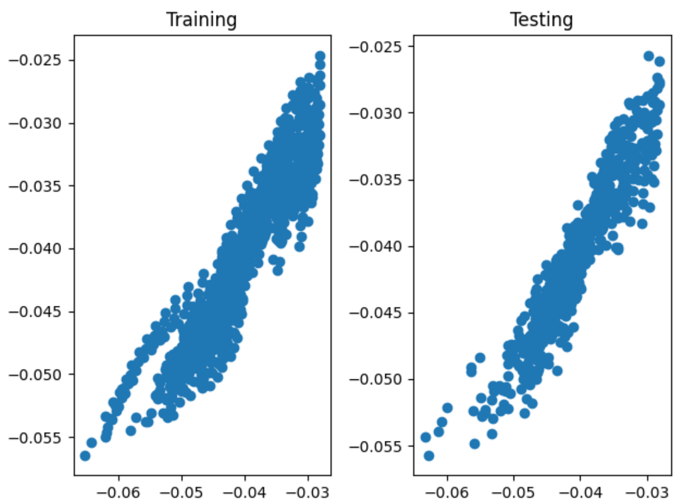

Fig. 2. Linear Regression for position 19m

- **Linear Regression with Polynomial Features Model:**
  - For position 19m, accuracy was around 99.879 with training error 0.00020 and testing error 0.00120 (Fig. 3).
- **Neural Network Model:**
  - For position 19m, accuracy was around 99.709 with training error 0.015 and testing error 0.0029. (Fig. 4).
- **K Nearest Neighbour:**
  - For position 19m, accuracy was around 99.951 with error 0.000492.(Fig. 5).
- **Bagging or Boosting Aggregation:**
  - For position 19m, accuracy was around 99.863846 with training error of 0.0022 and testing error of 0.0014.(Fig. 6).

Similarly for remaining depths (0m, 5m, 10m, 15m):

- **Linear Regression Model:**
  - For position 0m, accuracy was around 99.610 with training error 0.0113 and testing error 0.0039.

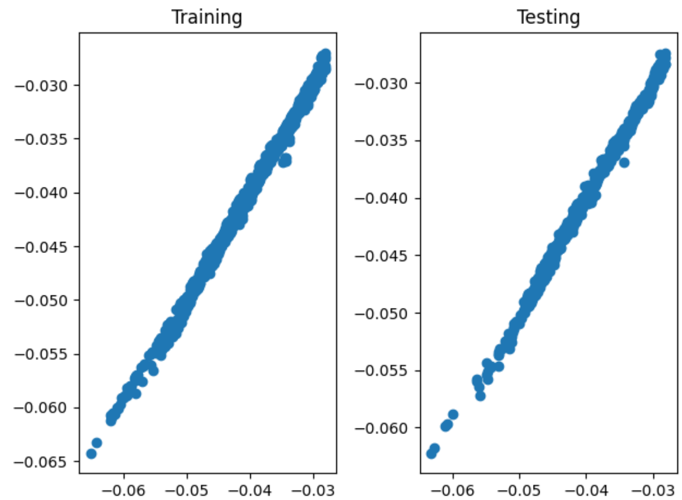

Fig. 3. Linear Regression with polynomial features for position 19m

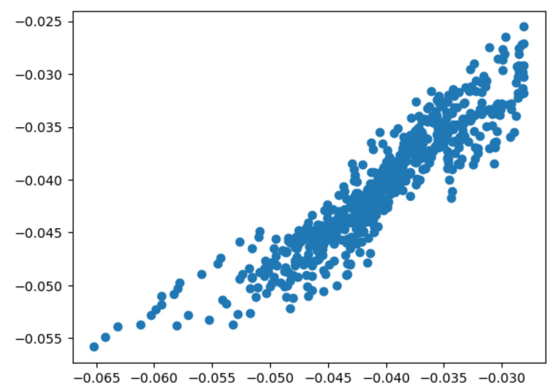

Fig. 4. Neural network for position 19m (testing)

  - For position 5m, accuracy was around 99.621 with training error 0.0106 and testing error 0.0038.
  - For position 10m, accuracy was around 99.639 with training error 0.0095 and testing error 0.0036.
  - For position 15m, accuracy was around 99.665 with training error 0.0081 and testing error 0.0031.
- **Linear Regression with Polynomial Features Model:**
  - For position 0m, accuracy was around 99.8576 with training error 0.00032 and testing error 0.00142.
  - For position 5m, accuracy was around 99.8605 with training error 0.00031 and testing error 0.00139.
  - For position 10m, accuracy was around 99.8657 with training error 0.00028 and testing error 0.00134.
  - For position 15m, accuracy was around 99.8733 with training error 0.00024 and testing error 0.00120.
- **Neural Network Model:**
  - For position 0m, accuracy was around 99.7845 with training error 0.023 and testing error 0.00215.
  - For position 5m, accuracy was around 99.6601 with training error 0.022 and testing error 0.00339.

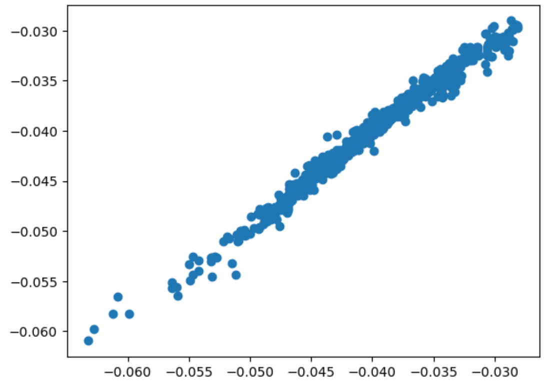

Fig. 5. KNN for position 19m (testing)

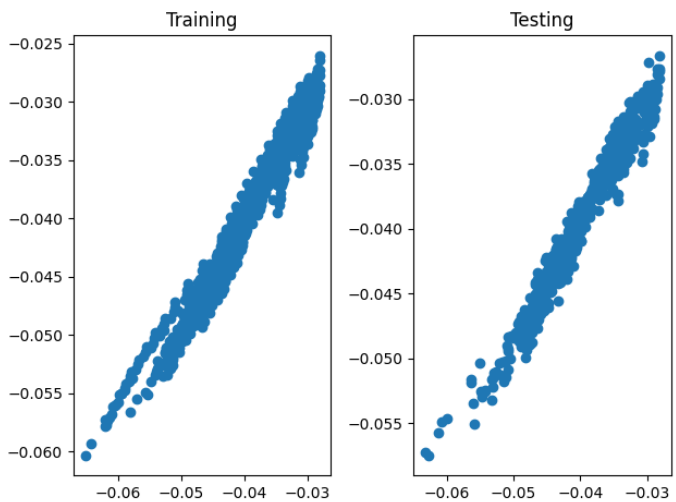

Fig. 6. Bagging for position 19m

- For position 10m, accuracy was around 99.6761 with training error 0.019 and testing error 0.00323.
- For position 15m, accuracy was around 99.6577 with training error 0.017 and testing error 0.00342.

Testing Results:

Observation: Among all the models, Linear regression with polynomial features has more accuracy.

Results of testing data: First we checked how our best model performed on new datasets There are 2 different test datasets. (Fig. 7) tells about how accurately our best model predicted the values for first dataset. And (Fig. 8) tells for second dataset.
In Fig. 7 and Fig. 8, blue plot indicates original data and orange indicates predicted ones.
Now, We will see how other models work for unseen data from second dataset (Fig. 9).
In Fig. 9, blue plot indicates original data and orange indicates predicted ones.

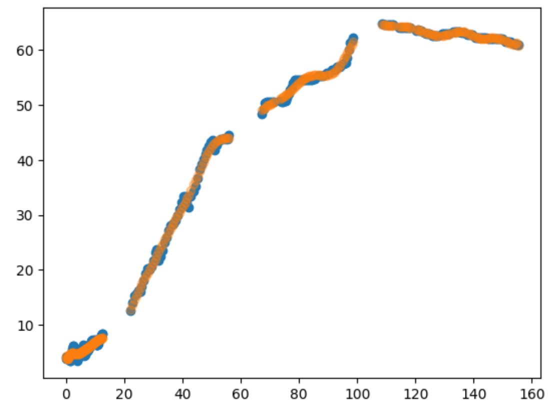

Fig. 7. First Dataset

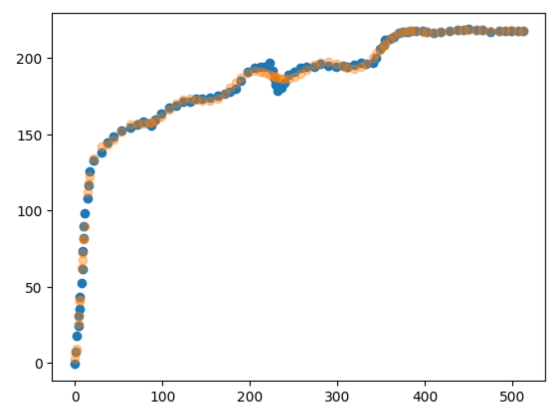

Fig. 8. Second Dataset

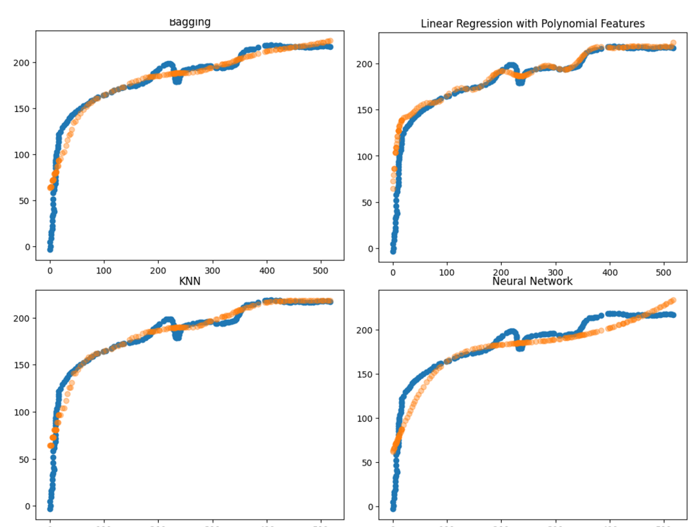

Fig. 9. Testing for all the models

IV. CONCLUSION

In this project, we focused on predicting the long-term deformation of tunnels using machine learning models and studying the time-dependent behavior of Creep. By incorporating the classic Burgers-creep visco-plastic model and rheological parameters such as the ratio of Kelvin shear modulus to Maxwell bulk modulus, Kelvin viscosity, and Maxwell viscosity, we were able to accurately predict the displacement of soil at different positions above the tunnels.

From our analysis of the following accuracies for different positions using machine learning models we can conclude that Linear Regression with polynomial features performed well in all the cases.

These results demonstrate the effectiveness of machine learning in predicting tunnel deformations over time and highlight the importance of continuous monitoring and predictive modeling in mitigating the long-term deformation of tunnels. By integrating advanced technologies and rheological principles, we pave the way for more resilient and sustainable tunnel infrastructure in the future.

REFERENCES

[1] https://www.frontiersin.org/articles/10.3389/fmech.2022.1003170/full
[2] https://www.sciencedirect.com/science/article/pii/S2666359722000695
[3] https://www.sciencedirect.com/science/article/pii/S0886779821000298
[4] https://www.sciencedirect.com/science/article/pii/S167477552200227X
[5] https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Creep+behavior+%2B+Tunnel&btnG=
[6] https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Creep+behavior+%2B+Tunnel%2BRock+mass&btnG=
[7] https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Creep+behavior+%2B+Concrete+%2B++AI+ML&btnG=
[8] https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Creep+behavior+%2B+Machine+learning&btnG=
[9] https://www.sciencedirect.com/science/article/pii/S1674775523000653
[10] https://www.hindawi.com/journals/mpe/2022/3241171/
[11] https://www.sciencedirect.com/science/article/abs/pii/S0886779821000298
[12] https://eprints.whiterose.ac.uk/123397/1/TUST_2016_719_Revision%201_V0.pdf
[13] https://downloads.hindawi.com/journals/ace/2021/4280139.pdf?_gl=1*10t4jfw*_ga*MTE4ODc4NzI0NS4xNzA5MzEyNjQ3*_ga_NF5QFMJT5V*MTcxNTYwOTk4OC4yLjAuMTcxNTYwOTk4OC42MC4wLjA.&_ga=2.200920169.67856945.1715609989-1188787245.1709312647
[14] https://link.springer.com/article/10.1007/s40515-023-00290-6

Github Link: https://github.com/Karthikeya-MV/OELP_S6