

Prediction of the Upward Movement of Tunnel Linings Using Machine Learning Algorithms and Field Monitoring Data Systematically

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Received date: February 01, 2023, Manuscript No. IPACSIT-23-16546; **Editor assigned date:** February 03, 2023, PreQC No. IPACSIT-23-16546(PQ);

Reviewed date: February 13, 2023, QC No. IPACSIT-23-16546; **Revised date:** February 22, 2023, Manuscript No. IPACSIT-23-16546(R);

Published date: March 01, 2023, DOI: 10.36648/ 2349-3917.11.3.4

Citation: Yang SY (2023) Prediction of the Upward Movement of Tunnel Linings Using Machine Learning Algorithms and Field Monitoring Data Systematically. Am J Compt Sci Inform Technol Vol: 11 No: 3: 004.

Description

With the improvement of urbanization and the further shortage of soil assets, safeguard burrow removal has turned into the best option in metropolitan underground designing in numerous nations and areas. However, in areas with soft soil, the tunnel lining frequently encounters the issue of local or overall upward movement during shield tunnel construction. This issue is especially unmistakable particularly when the safeguard machine crosses the stream base with shallow overburden soil. Excessive upward movement of the tunnel lining will result in lining dislocation, cracks, damage, and even axis deviation. During construction, this will put more stress on the tunnel lining and bolts, which will make the tunnel less waterproof and less durable for everyday use. As a result, it is necessary to anticipate and control the upward displacement of tunnel lining caused by shield tunneling. To investigate the vertical removal of passage lining incited by burrowing, many undertakings have been made to propose logical arrangements and direct mathematical recreations. The logical arrangement depends on the Winkler versatile establishment shaft hypothesis to anticipate the vertical development of the passage lining by improving on the heap size and appropriation of the encompassing soil and slurry. The simplified model, on the other hand, is a horizontal or vertical two-dimensional plane model that is unable to accurately calculate the upward displacement of the tunnel lining under the three-dimensional stress characteristics during construction. In addition, the supposition that the encompassing soil layer is homogeneous is conflicting with the real perplexing land circumstance. By restoring the distribution of the surrounding soil layers, the numerical simulation method can simulate the three-dimensional stress state of the tunnel during upward movement. A delicate three-dimensional soil-segments-bolts model can accurately predict the tunnel lining's upward displacement by taking into account the tunnel's interaction with the soil. However, the selection of the soil constitutive model parameters affects the simulation's outcomes, and it takes a significant amount of time to modify for various sections.

Machine Learning Algorithm Utilized in Tunnel Engineering

Machine Learning (ML) algorithms have been widely used to solve tunnel engineering's prediction issues over the past few decades. Machine learning algorithms have two significant advantages over the conventional approach. In theory, all relevant parameters can be input into the machine learning model without selection or assumption, and the model will automatically adjust the weight of input parameters during the training process because ML algorithms have excellent performance in solving non-linear problems with high dimensional variables. Then again, AI calculations have strong processing power and can rapidly foresee measures of information in a brief time frame, keeping away from numerous displaying in various segments. The first type of machine learning algorithm utilized in tunnel engineering to solve the prediction problem is the back-propagation neural network (BPNN). The General Regression Neural Network (GRNN) was developed by Jiang and Chen to predict tunneling-induced settlement in order to enhance BPNN's robustness and computational efficiency. Huang and co. proposed the Extreme Learning Machine (ELM), a new feed forward neural network learning method that performs better in terms of learning speed and generalizability. Zhang and co. compared ELM's prediction of the maximum settlement caused by shield tunneling to that of other conventional algorithms. To predict displacement, Support Vector Machines (SVMs) and other SVM-derived algorithms have also been used. However, in each of the aforementioned algorithms, the parameters are chosen either manually or discretely through trial and error. This method is inefficient, and the outcome may not even be the best value. As a result, Hasanipana et al introduced Particle Swarm Optimization (PSO) to efficiently determine the ML algorithm's optimal hyperparameters. The Genetic Algorithm (GA) was also proposed by Aryanezhad and Hemati as a means of improving prediction accuracy. Be that as it may, there is little examination work on the correlation of the streamlining execution of the improvement calculations for taking care of the anticipating issues.

Systematic Use of Machine Learning Algorithms and Field Monitoring Data

Additionally, the fact that a robust ML prediction model must go through three phases raises additional concerns: train, validate, and test; however, the majority of the aforementioned research does not include a validation phase to evaluate prediction accuracy. Algorithms for machine learning have been shown to be useful and effective, as was mentioned earlier. However, current research focuses on predicting the worst-case scenario, so they are rarely used to predict the upward displacement of tunnel lining. while ignoring the development process, which makes it hard to use machine learning algorithms to figure out how engineering problems work. This paper elaborates on the systematic use of machine learning algorithms and field monitoring data to predict the upward movement of tunnel linings caused by shield tunneling in order to address the aforementioned issues. The optimal hyper-parameters of ML algorithms are determined in conjunction with k-fold cross validation and optimization algorithms to predict the upward displacement of twelve output variables over a 48-hour period.

These output variables represent the process of the upward movement of tunnel linings. Back Propagation Neural Network (BPNN), General Regression Neural Network (GRNN), Extreme Learning Machine (ELM), and Support Vector Machine (SVM) prediction performance were compared using PSO and GA optimization. A type of feedforward neural network known as a Back-Propagation Neural Network (BPNN) is a nonlinear function. Its feedback and expectation worth of the organization are the free factor and ward variable of the capability separately. In this review, the PSO calculation and the GA calculation are picked for enhancing hyper-boundaries of four unique ML calculations. In both of the optimization algorithms, the fitness function is the mean prediction error of 5-fold CV. The systematic use of machine learning algorithms and field monitoring data to predict the upward movement of tunnel linings is elaborated upon in this paper. Twelve output variables, which represent the process of upward movement of the tunnel lining over the course of 48 hours, were considered to predict the upward displacement of fourteen input variables, which included shield operational parameters, tunnel geometry, geological conditions, and anomalous condition.