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Comprehensive deformation study in the new Austrian tunneling technique tunnel utilising artificial neural network model

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***Abstract*—** Ground deformation during tunneling projects is one of the complicated concerns that must be constantly monitored to prevent unanticipated damages and human losses. In addition to conventional approaches, several intelligent methods, like ANN, have recently been used for different tunnel challenges. Geological elements such as thrust zones, folded rock sequences, shear zones, rock cover, in-situ tensions, water ingress, gas ingress, geothermal gradient, and significant seismicity all present difficulties during digging. These difficulties have a substantial influence on the routine functioning of the tunnel as well as traffic safety. To address these issues, the authors recommended using ANNs from many elements of tunnel engineering. The new Austrian tunneling technique (NATM) has shown to be a highly affordable and versatile mode of construction, and as a result, it has become the most common tunneling construction method utilized in the building of the double-arched tunnel. In this work, the MATLAB program was utilized to generate the results, which comprised training and testing datasets. The experimental results demonstrate that the suggested model's values for R2, Bias, Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE), with training data are 18.56, 0.98, 1.05, and 0.08, respectively. The suggested RMSE, R2, Bias, and MAPE values for the test dataset were 19.89, 0.98, 1.05, and 0.09.

Keywords: new austrian tunnelling technique, root mean squared error, artificial neural network, tunnel, mean absolute percentage error.

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I. INTRODUCTION

Predicting the deformation of rock masses is one of the most important aspects of assessing the stability of underground excavation operations. Tunnel construction has recently grown at a quick pace in difficult geological formations, particularly in metropolitan locations where the low construction depth and external loads from structures exacerbate risk circumstances [1]. However, if these characteristics are not identified before the tunnel is excavated, construction delays and an increase in cost can occur. Therefore, accurate soil deformation forecast around the tunnel is essential for avoiding project setbacks [2], [3].

The NATM, one of several tunnel-building techniques, is the most often utilized technique (figure 1) employed in the structure of the double-arched tunnel since it is both exceedingly versatile and cost-effective. The NATM is a technology that uses the drilling and blasting process to construct a tunnel in the rock, with a shotcrete liner and rock bolts serving as the primary support system [4]. The NATM is the most important because it includes constant monitoring of the geological state of excavation faces and the efficiency of subsurface structural support like linings. It is based on the idea of an "as-built or during-excavation categorization system." These observed data are translated using the most popular rock mass categorization systems, Rock Mass Rating (RMR) system and Q, to produce an assessment of the necessary excavation techniques and support system components during tunneling [5]. As it can be seen, field monitoring is essential to NATM and is the only reliable way to assess the soundness and safety of supporting structures as well as the stability of the rocks around the tunnel site [6,7]. NATM was used to construct the tunnel in Figure 2 [8].

Figure 1: New Australian tunneling method [9].
Source: Own elabotation.

The NATM liner construction procedures are shown in Figure 2 below. The tunnel's longevity and stability are guaranteed by this method's three-layer construction. The initial layer, known as the shotcrete lining, is a thin coating of concrete sprayed over the excavated tunnel surface, typically roughly 5-10 cm in thickness. This secondary layer acts as an anchor to keep the earth below from collapsing. After that, a layer of reinforcement is added, usually in the form of steel mesh or rebar that is inserted into the shotcrete lining to add strength and stiffness to the structure. The reinforcing layer is then covered with a second shotcrete layer (the C-line) of around 10-20 cm thickness. The C-line tunnel's outside is protected from rain and other moisture by a waterproof covering. This methodical procedure is repeated until the whole tunnel is lined, following the initial excavation with a tunnel boring machine (TBM) or other excavation methods. The NATM uses this methodical approach to building to guarantee a strong and waterproof tunnel lining.

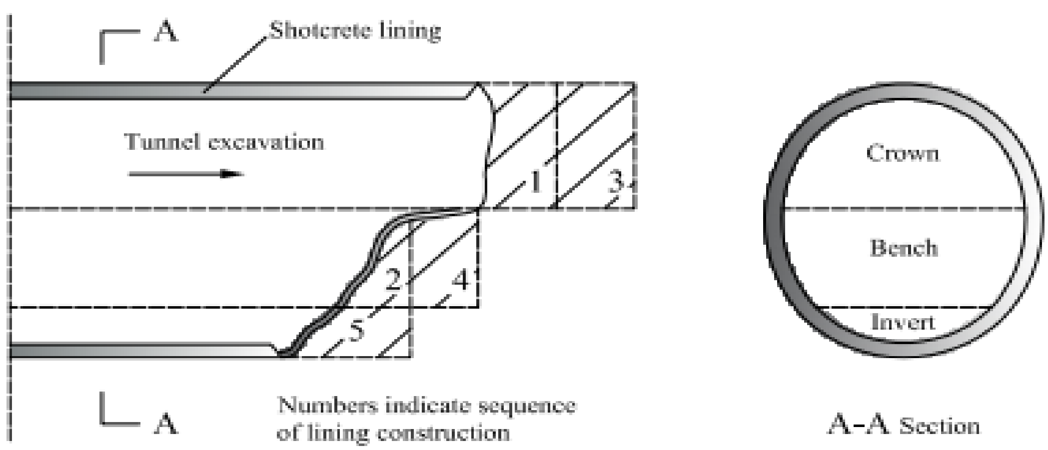


Figure 2: Tunnel built with NATM, as a schematic.
Source: Own elaboration based on contributions from [10]-[11].

The difficulty in producing correct findings comes from the fact that many computations need certain external factors and precise predictions. Big data driven ANNs are regarded as an emerging technique in tunnel engineering and have been utilized to address these issues.

ANNs, which can assist tunnel engineers in establishing correlations among input parameters and output parameters, are motivated by studies on the biological behavior of neurons and the human brain [12,13].

a. Tunneling method

Tunnels are long, flat, or hardly sloping subterranean tunnels having an excavated cross-section of more than 20 m2 [14-15]. Numerous ways are often used for tunneling, however, the technique to be chosen is the NATM. It is based on the examination and evaluation of the immediate surroundings. NATM is based on the following principles: (1) Application of rock mass strength; (2) Shotcrete protection using flexible support; (3) Size; (4) Inverted closure; (5) Rock mass classification steps; (6) Dynamic design during tunnel construction; and (7) Excavated and supported in sequential order. Figure 3 indicate the different method of tunnel construction and Table 1 indicate the advantages and disadvantages of the tunnel construction method.

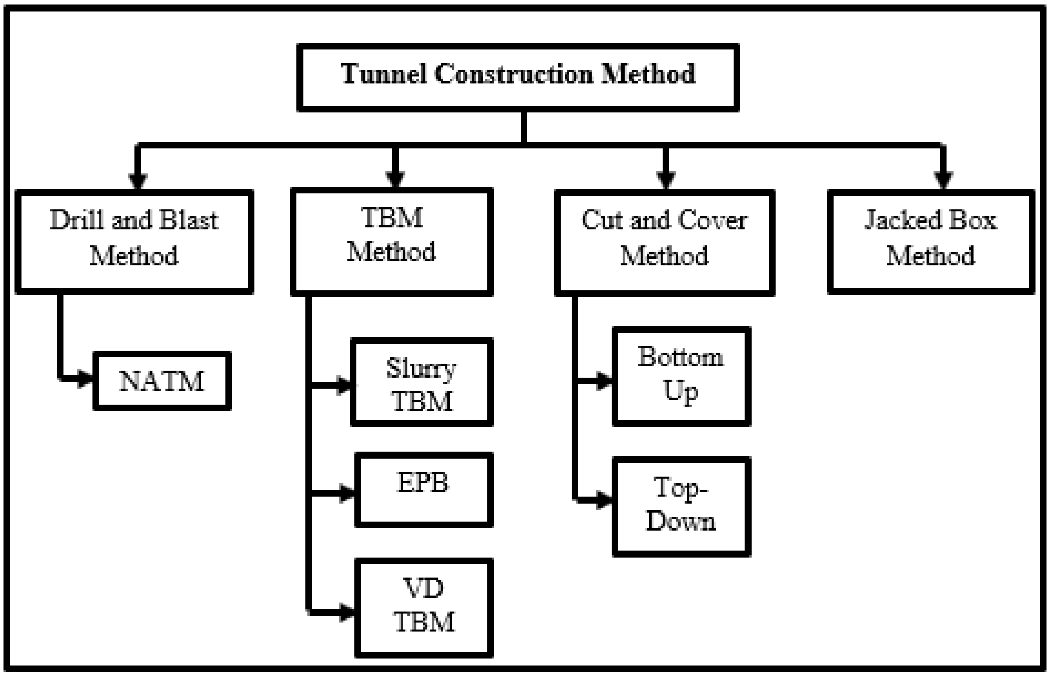


Figure 3: Different types of tunnel construction methods.
Source: Own elaboration based on contributions from [16].

Table 1: Benefits and Drawbacks of Various Kinds of Methods [17].

Methods	Advantages	Disadvantages
Drill and Blast	Flexible and adaptable, requiring little mobilization time, allowing for the installation of primary rock supports, any desired form tunnel cross-section, and a lower overall investment cost. Along the length of the drive, the tunnel form can change.	Workers' safety is a key concern, and advance excavation is performed at a lesser pace. Labor costs overall are expensive and involve heavy and arduous physical effort. Low degree of task automation and mechanization.
TBM	High performance, cheap labor costs, and rapid advancement, particularly in the soft ground soil. The greatest method for building deep and lengthy tunnels, with excellent cost-effectiveness and high automation levels, little noise, continuous operation, and disruption to nearby buildings.	A lack of flexibility in the presence of extreme geologic circumstances Significant investment costs and high backup system requirements. It takes a long time for TBMs to be mobilized. The tunnel remains round and have the same diameter. Capital expenses rise, and mobilization takes longer.
Jacked Box	cheaper, better-quality control, and quicker finish. saving on labor and equipment. No use of a crane or other heavy machinery Less engagement from other Departments	need competent supervision and qualified personnel. For a longer time, a caution order has been imposed. No night-time working scope. When the box's vertical and lateral alignment is altered, correction is very difficult.
Cut and Cover	Environmental protection. Safe tunnel construction and opening for roads. Safe work progress on unstable work grounds. In the event of the worst geotechnical circumstances, the sequential building could be used. Cheaper and more useful than other subterranean tunneling. Comparatively less dangerous compared to other building methods.	Not appropriate for excavations that go extremely deep. There could be increased noise and dust effects. Interfere with other urban activities and traffic.
Sequential Excavation	Only localized possible environmental consequences would be produced, similar to the drill-and-blast and bored tunneling approaches.	The possible environmental repercussions would last longer than with the other methods because the process is rather slow.

Source: Own elabotation.

1. NATM Method

The NATM is a technique of support that makes use of anchors, sprayed concrete, and other forms of support to sustain the tunnel's perimeter and relies on constant monitoring to control the tunnel's stability. The tunneling method was developed in 1948 by Rabcewicz [18].

Mobilization of rock mass strength, shotcrete flexibility, deformation evaluation, quick inversion closure, rock class-based support system design, sequential excavation, and contract management are the cornerstones of NATM's methodology. The NATM Method excels in situations with very variable geology; it can be used to any type of rock, even under extreme ground pressure, and may be modified as needed [19]. There are several processes involved in tunnel excavation, including planning, installing steel supports, drilling, dynamite blasting, ventilation, mucking, scaling, shotcreting, and rock bolting (figure 4). [20].

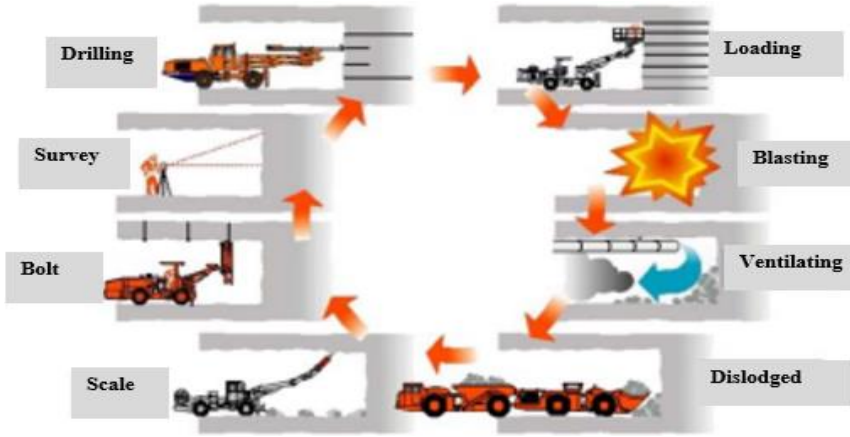
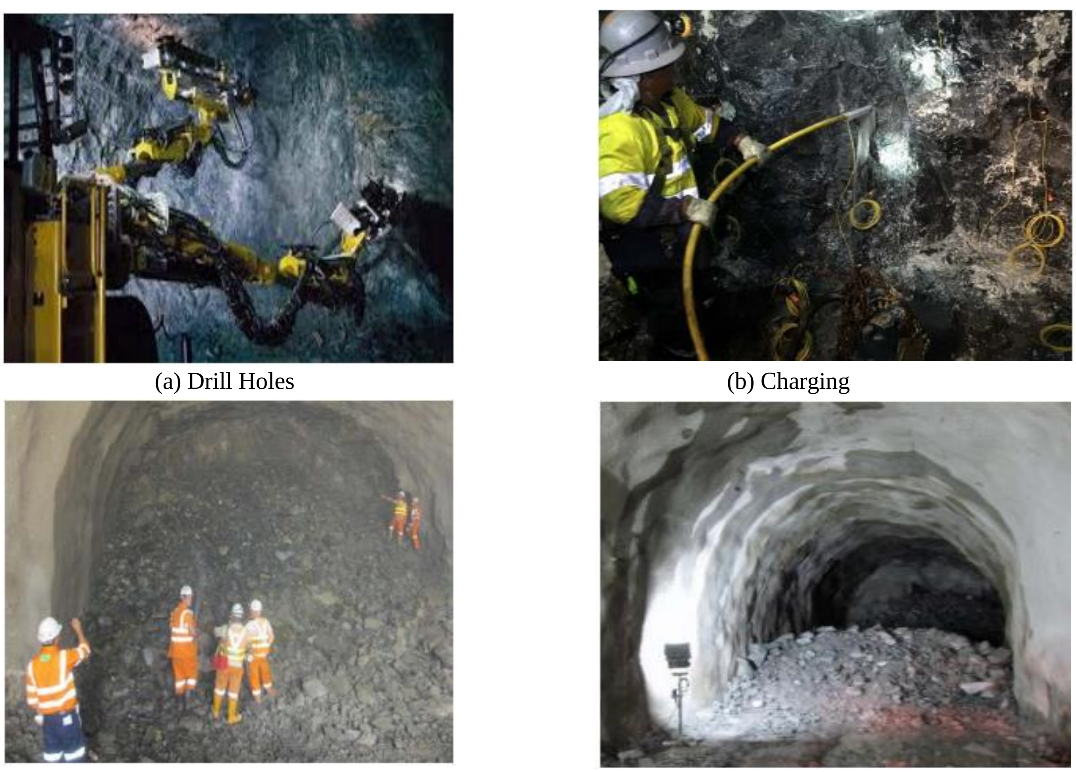


Figure 4: Sequence of NATM
Source: Own elaboration based on contributions from [21].

Marking of Drill Holes: Drilling is indicated on the tunnel face according to the blasting pattern. Whether it's a wedge cut or a burn cut.

Charging and Blasting: Charging and blasting refer to the insertion of explosives and preparation for detonation. Professional personnel manually charge the holes. The Drill Jumbo's basket is employed to hoist the labor force to charge the holes on the top section of the working face.

Mucking: The whole process of collecting and removing muck is known as mucking. Figure 5 (d) shows the material acquired from blasting and the fragmented rock that comes from blasting. The equipment used for mucking is dependent on the amount of workspace that is available within the tunnels [22]. Figure 5 indicate the different sequence of NATM.



(a) Drill Holes
(b) Charging
(c) Blasting
(d) Mucking

Figure 5: Sequences of NATM [23].
Source: Own elaboration.

b. Cavity Opening Reason with Treatment

A cavity in a tunnel's lining construction is hard to see with the naked eye and requires special equipment to locate. Block falls and other accidents are a constant threat to high-speed vehicles and their passengers, which is bound to result in catastrophic losses [24]. Cavity in tunnel lining is widespread due to the geological environment and building technologies. Table 2 below explains the reasons and how to fix the holes in the tunnel ceiling.

Table 2: Problems with tunnel lining and how to fix them [25].

Causes	Solutions
Causing a void due to concrete shrinkage.	The water reducer can be employed to decrease the amount of water in the concrete mix, hence increasing the concrete's workability.
The absence of concrete because the pumping pressure was too low, or the concrete didn't flow fast enough to fill the void.	Make sure there is enough pumping pressure before beginning construction.
A vacuum developed because the pumping was done in the incorrect location.	Pour with a skew-pumping mouth; if there is a slope, a high-pumping mouth is required.
Void formed by the waterproofing layer's insufficient loose paving.	i) The main support's flatness should be examined, and the qualifying one should be levelled. ii) Provide a suitable coefficient of loose pavement material.
Void formed by insufficient sealing.	Use the valve for sealing.

Source: Own elaboration.

The lining structure is more likely to fracture and eventually fall block because of the cavity's stress concentration or reduced bearing capacity. The research into the treatment technology of tunnel lining structural cavities, as well as the proposed countermeasures and assessment methodologies, is of tremendous practical importance [26,27].

Cavity development of this kind can occur in almost every metropolitan region due to the prevalence of various subsurface structures. The invention describes a method for fixing a collapsed void in a tunnel using backfilling techniques, such as surface drilling and grouting or backfilling. The procedure consists of three stages: (1) locating and drilling, (2) filling up the hole, and (3) removing the debris. The construction difficulty is decreased, rapid construction is achieved, and the method is equivalent to tunneling under normal geological conditions by first filling the collapse cavity with various backfill components to create a force bearer that bears the unstable load of a collapse area to prevent much farther collapse and serves as a force implementation point for subsequent support [28].

II. LITERATURE REVIEW

In this section, the author defines the Literature review based on the deformation study of NATM tunnel utilized ANN.

An et al., (2022) [29] developed an intelligent neural network model with a more precise estimate, and simulation tests on tunnel excavation of diverse terrains are carried out, and the model's accuracy for forecasting the deformation amount is measured. According to the findings of the experiments, the prediction error range of the model is less by a factor of 10 compared to the conventional neural network. This model's prediction accuracy is more than 95%, and its volatility rate is less than 11%, while the volatility rate of conventional prediction accuracy is greater than 365%. Intelligent tunnel deformation can be predicted with high precision using the neural network model.

Ngamkhanong et al., (2022) [30] used ANN to foretell the stability of a planar tunnel heading in the rock mass, based on the well-defined Hoek-Brown (HB) yield criterion. The proposed solutions would increase confidence in the stability of rock tunnel headings. The statistical solutions of the stability of tunnel heading may be estimated more accurately with the ANN approach than with the more traditional linear regression method because of the ANN methodology's use of machine learning to enhance prediction.

An et al., (2022) [31] created a smart neural network model to forecast and compute the amount of ground deformation brought on by tunnel excavation. An intelligent neural network model with better prediction is suggested; simulation tests are run on tunnel excavation in various terrain types; and the model's accuracy in estimating the amount of deformation is computed. The experimental findings demonstrate that the model has a prediction error range that is 10 times less than that of a conventional neural network.

Huo et al., (2021) [32] designed a BP ANN model with a 4102 tri-layer architecture to predict the Mises stress and transverse deformation of tunnel liners subjected to seismic loadings. The tunnel on Guangzhou Metro Line 4 was employed as a parametric case study, and 70 literature data sets were used for training and testing. The relative error between the BP ANN and the ABAQUS FEA findings is found to be within 15%, indicating a high degree of agreement. Therefore, the BP ANN-based technique offers a fresh perspective on the seismic analysis of tunnels and has some illustrative importance for real-world engineering.

Zhang et al., (2021) [33] presented a description of the Guangzhou, China karst ground and its karst tunneling, as well as measurements and predictions of the resulting surface reaction. It examines the differences and similarities of four deep learning approaches: ANN, 1d Convolutional Neural Networks (Conv1d), Long Short-Term Memory (LSTM) neural networks, and Gated Recurrent Unit (GRU) neural networks. Kinetic correlation analysis is built from the static Pearson correlation coefficient to evaluate the impact of input data factors on ground settling. Results show that tunneling-induced ground settling can be accurately predicted using the expanding Conv1d model.

Nsubuga et al., (2021) [34] Examine the Finite Element Models (FEM) and ANN models to see whether they can predict tunnel convergence. An in-depth analysis of the developed ANN and its results are presented. We conclude by comparing the deformation results from the ANN tool, the FEM models, and the real field measurements, and discussing how the proposed ANN technique may be used as a quick tool for predicting tunnel deformation.

Wu et al., (2020) [35] develops an easily comprehensible Artificial Intelligence (AI) system for detecting NATM construction projects using low-site surveillance images. The analysis results of four NATM tunneling projects' Site Closed-Circuit Television (CCTV) surveillance videos are obtainable to show its ability to i) classify NATM tasks according to project phases, ii) classify NATM tasks using the project timetable and (iii) organize NATM work according to the project schedule. The suggested methodology produces encouraging results on an actual NATM tunneling project.

Balta et al., (2021) [36] created a risk assessment approach for Tunnel Boring Machine (TBM) tunnel projects based on a Bayesian Belief Network (BBN). The BBN model served as the foundation for the creation of BBN Tunnel, a decision-support tool designed to evaluate the effects of various risk-mitigation measures on latency. Conclusions showed that modeling interrelationships between risk components, building a risk network, predicting delay, and assisting decision-makers in developing cost-effective risk mitigation methods were all possible using BBN Tunnel and the risk assessment approach.

Mousivand et al., (2019) [37] explore how excavation patterns and tunnel cross-section design affect stress reduction factors. To estimate the stress reduction factor, conventional tunnel cross sections (circular, horseshoe, and double arch) were analyzed using FLAC 2D and FLAC 3D and full-face and multi-face excavation types, considering depth, radius, and dissimilar points around the tunnel. Final investigations were done between 2D and 3D analysis and Karaj subway experiments to corroborate the 2D results. Radius, depth, point position around tunnel cross-section, and form significantly affect stress reduction factors, according to this study. The circle, double arch, and horseshoe tunnel walls have 27, 10, and 7% inaccuracy, respectively.

Table 3 demonstrates the comparison of the literature of review.

Authors	Techniques Used	Outcomes
An et al., (2022) [29]	Intelligent neural network	The model has a prediction accuracy of over 95%, with a volatility rate of about 11%, compared to as much as 3.65 times the volatility rate of conventional methods.
Ngamkhanong et al., (2022) [30]	ANN	High values of R2 (0.9982), Mean Absolute Error (0.624), and RMSE (0.7740) obtained during performance evaluations point to a reliable neural network prediction model.
An et al., (2022) [31]	ANN	The experimental findings demonstrate that the model has a prediction error range that is 10 times less than that of a conventional neural network
Huo et al., (2021) [32]	BP ANN	Based on these findings, it can be concluded that the BP model is consistent with the existing literature to an error of less than 15% relative.
Zhang et al., (2021) [33]	DL	The Conv1d model's predictions are the most accurate, with an R2 of 0.78 and RMSE of 7 mm.
Nsubuga et al., (2021) [34]	FEM and ANN	The ANN's mean squared error is 24.7 and its root mean squared error (RMSE) is 4.9 mm when compared to the findings obtained from FEM analysis; the regression R2 is 87%.
Balta et al., (2021) [35]	BBN	The findings confirmed that BBN Tunnel and the risk assessment approach could be used to model relationships among risk components, build a risk network, estimate delay, and aid decision-makers in developing cost-effective risk mitigation methods.
Wu et al., (2020) [36]	AI	Four NATM tunneling projects' Site CCTV surveillance recordings were analyzed, yielding results of 71.4% for Excavation/Mucking, 43.3% for Profiling, 79.1% for Shotcrete, and 70.2% for Bolting.
Mousivand et al., (2019) [37]	FLAC 2D and FLAC 3D	The findings show a range of errors in tunnel walls, ranging from roughly 27 to 10 to 7 percent for circles, arches, and horseshoes, respectively.

Source: Own elaboration.

III. BACKGROUND STUDY

A backpropagation (BP) neural network model with a 4×10×2-layer, three-layer is built to determine horizontal deformation and the maximum Mises stress of circular tunnels under seismic loadings. From these 12 input parameters describing the tunnel lining, surrounding soil, and seismic properties, the four common input factors F1-F4 are calculated. After training and testing using 70 sets of literature data, we use three seismic movements in the tunnel of Guangzhou Metro Line 4 as a parametric case study. The relative error between the BP ANN and the ABAQUS FEA findings is found to be within 15%, indicating a high degree of agreement. Therefore, the BP ANN-based technique offers a fresh perspective on the seismic analysis of tunnels and has some illustrative value for real-world engineering [32].

IV. PROBLEM FORMULATION

Tunnel construction is expanding rapidly in difficult geological formations, particularly in metropolitan regions where the low construction depth and external loads from buildings raise risk circumstances. One of the many complicated challenges that must be carefully monitored throughout tunneling operations is ground deformation, which can cause costly and perhaps deadly surprises. Challenges to tunneling arise from geological features such as thrusting zones, cracks, folding rock sequence, in-situ stresses, rocky cover, water ingress, thermal gradient, gas ingress, strong seismicity, and so on. These issues have a significant impact on the tunnel's regular operation and transportation safety. The NATM is the most common tunneling construction method utilized in the building of the double-arched tunnel, which has shown to be a highly affordable and adaptable mode of production. The NATM is a method of tunneling through rock that primarily makes use of drilling and blasting, with a shotcrete liner and rock bolts as support systems.

V. CASE STUDY

a. Rohtang Tunnel

The South Portal of the Rohtang Tunnel, which is situated in Dhundi, 25 km from Manali, at an elevation of 3060 m, and the North Portal, which is situated close to Teling Village, Sissu, in Lahaul, at an elevation of 3071 m, are the sources of data utilized to train the ANN. The tunnel has a modified horseshoe shape. The Rohtang Tunnel is being built using drilling and blasting as well as the NATM. Figure 6 indicates the location of the Rohtang tunnel.

Figure 6: Location of Rohtang Tunnel.
Source: Own elaboration based on contributions from [38].

The Rohtang Tunnel's design is exceptional since the Emergency Egress Tunnel is a component of the main tunnel, underneath the roadway, increasing the tunnel's total cross-sectional area (137 sq m) [39]. The tunnel has an 8 m-wide highway and a sidewalk that is 1 m broad on each side. The finished concrete lining has a thickness of 500 mm and a 0.5% gradient from both entrances for efficient drainage. The tunnel's construction began on August 29, 2010, and a breakthrough was made on October 15, 2017. Figure 7 indicates the cross-section area of the Rohtang tunnel.

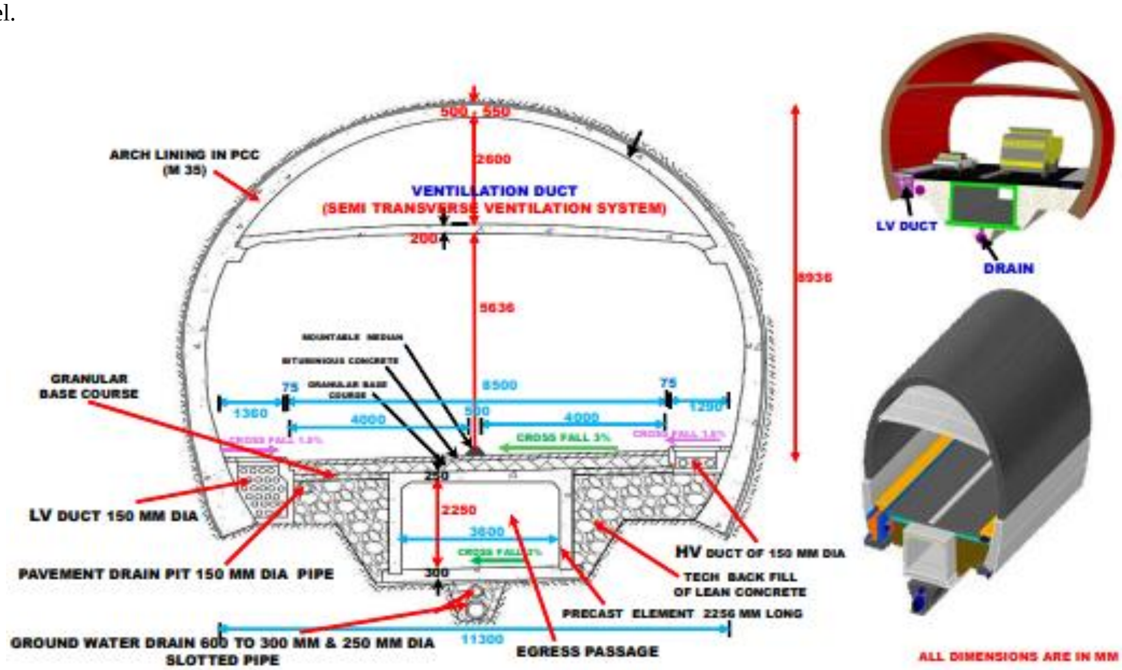


Figure 7: Cross-Section of Rohtang Tunnel.
Source: Own elaboration based on contributions from [40].

117 data sets with seven parameters are collected in this scenario. In the current research, three different varieties of Rohtang Himalayan rocks were considered. These rocks are phyllitic quartzite (PQ), migmatic gneiss (MG), and quartzitic phyllite (QP). Tables 4 and 5 display these rocks' input characteristics. Physical input characteristics are shown in Table 4 whereas mechanical input qualities are shown in Table 5. The characteristics of PQ and QP are extremely similar. These rocks, PQ, MG, and QP have relative densities of 2730, 2690, and 2680 kg/m3. The Poisson's ratio, Friction angle from, Young's modulus, and Cohesion, [41].

Table 4: Input Index Properties of PQ, QP, and MG [42].

Rock type	Specific gravity	Sonic wave velocity (km/s)	Density (kg/m^3)
Migmatic Gneiss (MG)	2.73	2.52	2680
Quartzitic Phyllite (QP)	2.73	3.99	2730
Phyllitic Quartzite (PQ)	2.77	3.65	2690

Source: Own elaboration based on contributions from [42].

Table 5: Input Mechanical Properties of PQ, QP, and MG.

Rock type	Brazilian tensile strength (Mpa)	Uniaxial compressive strength (Mpa)	Shear strength		Modulus of elasticity (GPa)	Poisson's ratio
			C (MPa)	Friction angle (^{0})		
MG	6.06	46.36	2.99	38.88	15.05	0.24
QP	11.71	112.18	3.33	37.64	43.57	0.24
PQ	12.28	105.96	4.02	34.73	42.91	0.26

Source: Own elaboration based on contributions from [43].

VI. TECHNIQUES USED

In this part, the author discussed the technique used in this study for tunnel deformation which is ANN.

a. Artificial Neural Network (ANN)

Neural networks (NN) are non-linear numerical data modeling techniques that use a group of linked nodes to mimic the operation of the human brain. The use of neural networks in the classification and clustering processes has the following advantages. In the first place, it is flexible; in the second, it can construct robust models; and in the third, it can be refreshed by the application of new training weights. Neural networks have found applications in fields as varied as credit card fraud, auto insurance, and corporate theft. Neural networks can be built for supervised and/or unsupervised learning. The user defines the number of secret passages or levels and the number of nodes included within each hidden layer. The output layer of a neural network could include one or more nodes depending on the application. An increasing number of statistical and numerical analysis techniques have recently been incorporated into neural network studies. Neural networks can learn and summarize the fundamental assumptions of data even if they have no prior knowledge of the data principles [44].

b. Biological Architecture of NN

NNs are biologically inspired computer programmers who are supposed to mimic how the human brain processes information. There are several NNs out there, but they are all based on organic nerve systems, such as the brain. To develop meaningful predictions on a given data set, NNs use the information paradigm to gain knowledge from prior learning experiences (via examination of training data). Layers of artificial processing components, such as nodes that link to coefficients or weights of processing elements, are assembled into an NN by combining a small number to hundreds of single units. Similar to more complex networks, which may have several hidden layers and numerous input and output layers, a basic NN consists of an input layer, a hidden layer, and an output layer. When presented with complicated and imprecise data, NNs are able to discern patterns and trends that would otherwise go unnoticed by the human brain or other computer systems. In contrast to conventional computers, which rely on predetermined algorithms and programming, neural networks are capable of real-time learning and adaptation. Various regions of the brain have different types of biological neurons, but they all have the same fundamental structure, as seen in Figure 8 [45].

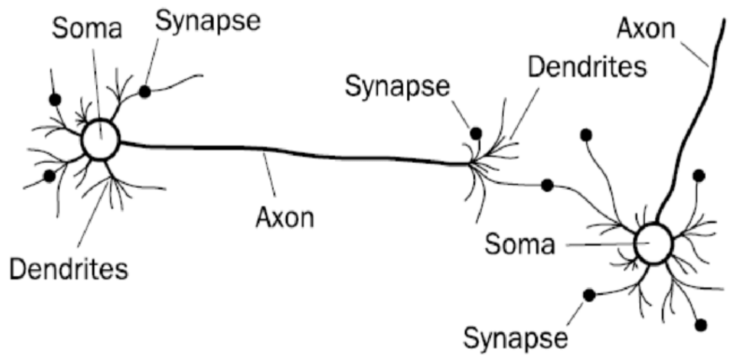


Figure 8: Biological NN.
Source: Own elaboration based on contributions from [45].

- Working on a Biological Neuron Network

An average neuron is depicted in the picture above to have the following four components, which can be used to describe how it works:

- **Dendrites** − Their function is to receive information from other neurons to which they are attached, much like a tree branch. In another way, it can compare them to the neuron's ears.
- **Soma** − It is the cell body of the neuron, and it is liable for the administering of data that has been obtained from the dendrites of the nerve cell.
- **Axon** − It functions in the same way as a cable, transmitting information between neurons.
- **Synapses** − It is the link that exists between the axon and the dendrites of other neurons.

VII. INPUT PARAMETERS AND COMMON FACTORS

Input parameter selection is an important phase in the creation of ANN models since it improves model performance. The selected parameters emphasize the most important aspects of the issue. Impertinent input rejection could also speed up model prediction outcomes while cutting down on training, testing, and assessment time.

The Rohtang Tunnel's excavation area has a constant value, and the suggested ANN model's surface settlement forecast hardly notices its impact. According to Table 5, the standard penetration test (SPT), moisture content, cohesiveness, and other geological characteristics of the research region were determined by field and laboratory testing. The input parameter and common variables utilized for training and testing in the ANN model are shown in Tables 6 and 7, respectively.

Table 6: The input parameter of an ANN model used for training and testing.

Items	Description	Value		Unit
		Minimum	Maximum	
	Tunnel depth	8	14	m
Input parameters	SPT	226	74	$-$
	Moisture Content	8	25	%
	Cohesion	14	60	kPa
	Friction Angle	19	43	°
	Unit Weight	17.2	21.6	kN/m^3
	Poisson Ratio	0.5	0.6	$-$
	Elasticity Modulus	42	82	MPa

Source: Own elaboration.

Table 7: The common factors in the ANN model

Input parameter		3 Common factors	
	F1	F2	F3
Tunnel depth (m)	.255	-.112	-.015
SPT	-.055	.214	.774
Moisture Content	.782	-.116	-.234
Cohesion	.642	.026	.298
Friction Angle	.866	-.062	-.105
Unit Weight	-.115	.049	.855
Poisson Ratio	-.148	-.040	-.254
Elasticity Modulus	-.055	.214	.774

Source: Own elaboration.

VIII. RESULT AND IMPLEMENTATION

Using MATLAB software, the studies were carried out, and encouraging findings were obtained. 117 data sets had been produced and split into three parts: 70% for training, 15% for assessing, and 15% for testing. This was done to train and test the suggested network. During training, the network was given training data, and the network adjusted itself depending on the computed error. Network generalization was measured using validation data, and training was stopped when generalization stopped improving. Testing information did not influence training, therefore it could be used to gauge network performance both during and after training independently. Figure 9 provides a summary of the trained ANN model's prediction capabilities. The outcomes show that the network has achieved negligible error and noticeably desirable regression, 1 for training, 0.99942 for validation, and 0.99976 for testing. Additionally, the total regression score of 0.99727 shows that the model can accurately predict surface settlement throughout the whole range of training data.

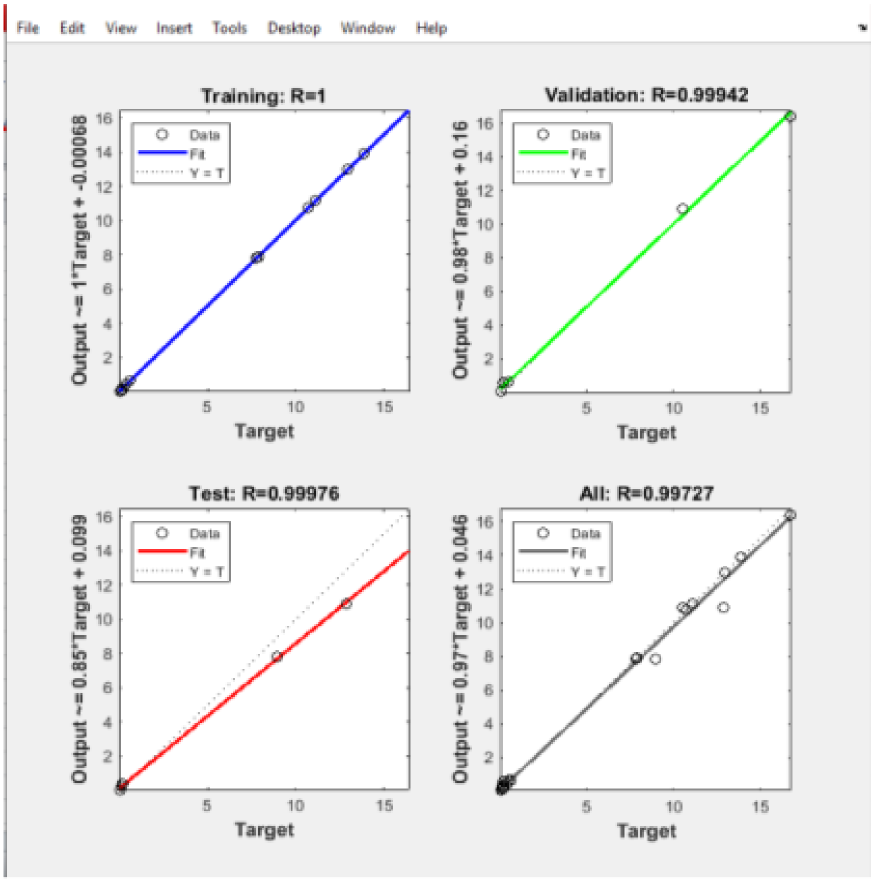


Figure 9: Predictive performance of the suggested ANN model.
Source: own elaboration.

c. Comparison analysis

The comparison of ANN, XG-Boost, and SVM is shown in Table 8. Table 8 shows the comparison in terms of RMSE, MAPE, Bias, and R^2 between ANN, XG-Boost, and SVM.

An RMSE value that is closer to zero or equal to zero suggests a minor error in prediction [46].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(\widehat{y_i} - y_i)^2} \tag{1}$$

The fact that the coefficient of determination R^2 values should be closer to 1 and near one another indicating that the model took advantage of the majority of the variability in soil parameter variation [47].

$$R^2 = \frac{\sum_{i=1}^{n}(\widehat{y_i}-\bar{y})^2-\sum_{i=1}^{n}(\widehat{y_i}-y_i)^2}{\sum_{i=1}^{n}(\widehat{y_i}-\bar{y})^2} \tag{2}$$

The bias factor is a variable whose value is more than unity to represent an overstated model, less than unity to represent an underestimated model, and whose value of unity represents an unbiased forecast [48].

$$Bias\ Factor = \frac{1}{N}\sum_{i=1}^{n}\frac{y_i}{\widehat{y_i}} \tag{3}$$

Prediction accuracy is good when the MAPE value is near 0 [49].

$$MAPE = \frac{1}{N}\sum_{i=1}^{n}\left|\frac{\widehat{y_i}-y_i}{\widehat{y_i}}\right| \tag{4}$$

N is the total amount of data, y_i and $\widehat{y_i}$ are the FEM value and the SCM estimates, respectively, and $\bar{y}$ i s the mean of the FEM findings in the following equations.

Table 8: Performance indicators of the models

Techniques	**Evaluation index**							
	RMSE		**R^2**		**Bias**		**MAPE**	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**	**Training**	**Testing**
XG-Boost	5.52	7.90	0.99	0.99	1.00	1.00	0.03	0.04
SVM	16.61	17.40	0.94	0.94	1.01	1.01	0.05	0.06
Proposed	**18.56**	**19.89**	**0.98**	**0.98**	**1.05**	**1.05**	**0.08**	**0.09**

Source: own elaboration.

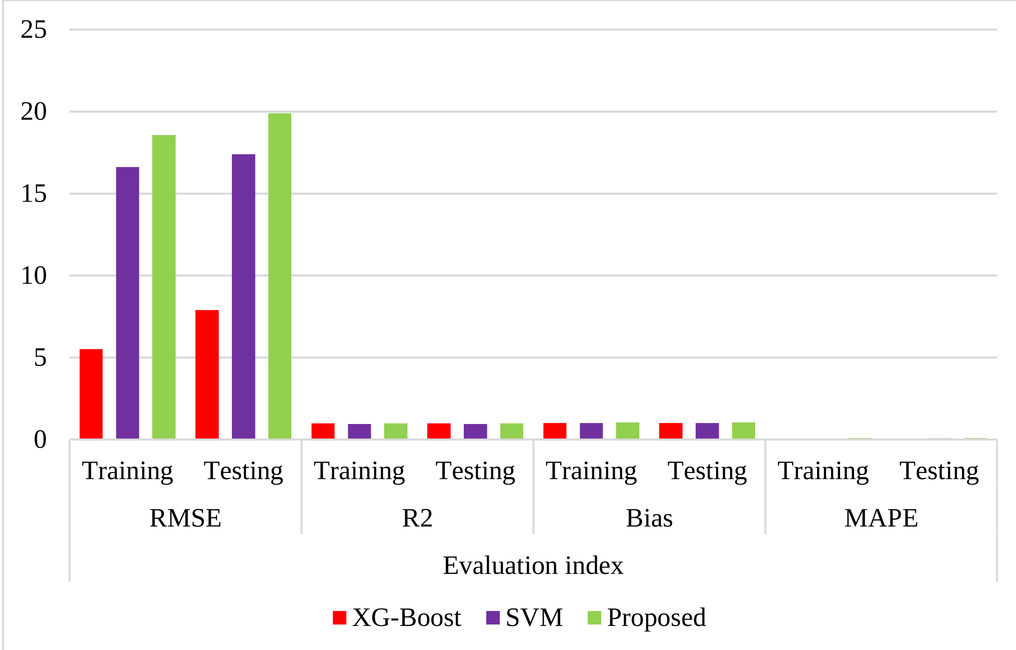


Figure 10: Graph of comparative analysis of methods.
Source: Own elaboration.

Table 8 lists the method's performance indicators, including XG-Boost, SVM, and the suggested model. The suggested model is more valuable than the other comparison techniques in the table. The suggested model's values are 18.56, 0.98, 1.05, and 0.08 based on RMSE, R2, Bias, and MAPE using training data. RMSE, R2, Bias, and MAPE values for the test dataset were 19.89 0.98, 1.05, and 0.09 respectively. The value of another technique is determined by the training and test datasets in Table 8 above. The graph of the comparative analysis of the suggested approach with other methods is shown in Figure 10.

IX. CONCLUSION

Tunnel wall convergences should be forecasted and established precisely before excavation to enable a safe and cost-effective tunnel excavation medium. Rock mass behaviors in the tunnel should be estimated before excavation. Today, the NATM is being used to create an increasing number of urban tunnels with little overburden. According to experimental findings, the suggested model's values for RMSE, R2, Bias, and MAPE when applied to training data are 18.56, 0.98, 1.05, and 0.08. With the test dataset 19.89, the suggested RMSE, R2, Bias, and MAPE values were 0.98, 1.05, and 0.09 respectively.

Authors predict that the future of tunnel deformation detection equipment would include a more streamlined data-collecting process as well as a speedier installation process. In other words, it assists decision-makers in spending less time gathering data so that they have more time to analyze the data they acquire.

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