An empirical study on the best prediction model of water inflow into drill and blast tunnels among several machine learning techniques

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Abstract— *The main aim of this paper is to perform an empirical investigation on the best prediction model for water input into drill-and-blast tunnels among multiple machine learning techniques. A water influx during tunnel construction is one of the most frequent and complicated geological catastrophes, and it has a significant influence on both safety and the timeliness and efficiency of the project [1]. In tunnel construction, major water inflows may result in significant economic losses and deaths. In order to assure safety and schedule throughout the subterranean building process, it is essential that this phenomenon's forecast be made. Additionally, tunnels must be designed and constructed in a way that minimizes the environmental effect of groundwater inputs. Before beginning to dig deep rock tunnels, especially those constructed in saturated medium, adequate planning is usually necessary [1]. Water transportation, reservoir emptying, hydropower plants, sanitary drainage, and transportation networks are just a few of the many uses for tunnels that have emerged as a result of the increased need for subterranean space. Managing groundwater infiltration into tunnels is a major problem for designers and construction crews. In reality, by interfering with the excavation's short- and long-term stability, the latter may raise failure risk. Most groundwater inflows happen when and after digging deep tunnels, and they change how rocks behave [1]. Furthermore, they cause general instability and decrease rock strength and shear. Consequently. It's also possible that the unexpectedly high groundwater flow rate might cause catastrophic harm, including deaths and equipment failure.*

Keywords: Prediction model, Tunneling, Machine learning, Water inflows, Thermodynamics and physics

I. INTRODUCTION

In the fields of hydrology, geotechnical engineering, structural geology, rock engineering, and other associated disciplines, groundwater ingress into tunnels is usually an issue that receives significant attention. As it turns out, tunnels, especially those constructed below the groundwater table, are typically plagued by groundwater inflows during and even after construction. Unpredictable geological dangers, these floods induce instability in the underlying rocks of tunnels and inflict significant harm, such as injuries and deaths, along with enormous financial costs. Groundwater conditions have been claimed to be critical to the construction and operation of tunnels [1]. As a result, it is critical that groundwater inflows into tunnels be accurately predicted or evaluated. Despite the fact that making such a forecast is still difficult, numerous academics have attempted it using a variety of methodologies. However, there hasn't been a comprehensive analysis of these approaches to far[1,2].

Groundwater inflows into rock tunnels have been the subject of several studies during the last few decades, according to a review of the literature. There are, in fact, a variety of ways to do this. Some examples of these methodologies are analytical (including semi-analytical), empirical, and numerical. Despite this, precisely estimating groundwater inflows into tunnels remains a difficult undertaking due to several possible causes. That's because rock masses tend to be complex and diverse, making it difficult to pin down their key qualities with any precision. Consequently, assumptions are often used to minimize important factors and true characteristics of rocky medium. It's not always easy to determine which strategy or strategies are best for a given situation. groundwater intrusion into tunnels dug through rock medium will be examined in this research [3]. Groundwater inflows into subterranean constructions have been the subject of several investigations. A lack of awareness has prevented a thorough comparison and analysis of various methodologies for monitoring groundwater inputs into tunnels. As a way of addressing this problem, this article provides a brief summary of recent research findings in the area. As a result, it serves as a concise roundup of the most recent findings in the subject [4]. The purpose of this study is to examine several machine learning algorithms that may be used to determine the amount of water that enters drill and blast tunnels.

II. RESEARCH PROBLEM

The main problem that will be solved by this study to explore machine learning algorithms for assessing water input in drill and blast tunnels. One of the most difficult but crucial jobs in tunnel design and construction is to accurately predict the groundwater intake to a tunnel. Because most numerical or analytical methods fail to account for changes in material qualities and hydraulic-head positions along the tunnel's path during excavation, reliable predictions of inflow rates are impossible. If water inrush occurs during tunnel construction, it will have a significant influence on both the timeline for completion and the overall safety of the work. Moreover, major water inrushes during tunnel building might result in enormous financial losses as well as human tragedies. In order to assure the safety and on-time completion of the subterranean construction project, accurate groundwater inflow predictions must be made before and during excavating the tunnel[4,5]. Additionally, groundwater inflows to tunnels are routinely used to determine pumping needs and groundwater management methods.

III. LITERATURE REVIEW

A. Groundwater flows into rock tunnels

The entrance of groundwater into rock tunnels has been the subject of several definitions and descriptions in the scientific literature. They often draw inspiration from a variety of methods and viewpoints. However, even though they all aim to anticipate groundwater infiltration into tunnels, only the most relevant of these models should be presented[7]. This might lead to a better knowledge of groundwater inflows into tunnels and subterranean excavations.

B. Groundwater flow and its impacts

Thermodynamics and physics govern the movement of groundwater. The surrounding ecosystems and climate change have an impact on groundwater flow patterns throughout time. Because of the area's geological history, it is difficult to identify the natural characteristics that influence groundwater recharge. Over the last several years, effective water management has been achieved by the use of process-based, numerical, and conceptual models to address the complicated variability of groundwater flow[8]. This strategy has shown to be quite effective. However, this is a constant issue for water management to deal with, and it varies depending on the local hydrogeological circumstances. This is not the only reason why groundwater levels are decreasing due to construction on and under the earth. Reduced groundwater levels are a result of surface-level impermeable structures such as roads, pavements, tunnels, and deep foundations, among other things. As a result, stormwater drainage systems are installed to channel rainwater from the surface into the earth. Leaks from drinking water systems can contribute to enhanced recharging of the groundwater. When it comes to dealing with the groundwater implications of deep foundations and subterranean structures such as tunnels, these are challenging tasks. Permeability, hydraulic qualities, groundwater flow direction, waterproofing ability, aquifer type, and other important features all play a role in the effects of groundwater on subterranean projects[8,9]. Data-driven GWL time series analysis may also be used to assess groundwater consequences. This makes it easier to picture the height of the groundwater head in wells in relation to time. The visual representation of groundwater levels in various aquifers is produced by charting the connection between observed GWL data and time in 2D. In addition, stressors on aquifers generated by precipitation, evapotranspiration, pumping, infiltration rates, and surface water levels affect fluctuations in groundwater head. Using time series analysis, it is possible to locate the locations of desirable groundwater heads. Drought recovery, well head levels, and the effects of climate change are just a few examples of drawdown circumstances in a well caused by pumping [9].

Triggers and processes for groundwater infiltration into rock tunnels

It is highly helpful for a better assessment of groundwater inflows into tunnels to have a solid grasp of the actions that might induce groundwater inflows as well as the process by which they occur. When tunnels are excavated, the rocks that are around them go through a complicated process of unloading and loading. As a result, there is a redistribution of the stress field that was already present. Thus, the EDZ and the EDZ are generated, which are the two primary zones that are affected by excavation (EdZ). The EDZ is the zone where the rocks in the surrounding area retain their deformed shapes. Rocks in the EDZ have significantly different physical, mechanical, hydraulic, and geochemical characteristics than those rocks outside of the EDZ[10]. It is also important to keep in mind that, depending on the circumstances, excavations might result in the release of strain elastic energy, which can then lead to rockbursts being produced. Underground water is disturbed when tunneling occurs below the water table. A potential reaction to this disruption may be groundwater flowing into tunnels. Groundwater inflows into tunnels may be made easier with the use of EDZ[11]. Because of the discontinuities, this facilitation is enhanced in fractured rocks. Predicting flow routes with precision is still a challenge. Reactivation of fault zones may be caused by stress redistribution, which increases the permeability of these zones. As a result, groundwater inflows have routes to travel between the fault and the damaged areas. A safe groundwater inflow thickness into tunnels was simulated by Liu et al. based on an analysis of rock porosity and permeability. These experts say there are three phases of groundwater ingress progression below safety thicknesses of 4 or 5 meters (slowly, mutation and stable stages) [11].

Groundwater may enter rock tunnels in a variety of ways, depending on the qualities of the rock mass and the circumstances in which it occurs. Hydraulic conductivity, the availability of groundwater aquifers and storage, the permeability of underlying rocks, and the hydraulic gradient all affect the amount of water that enters tunnels. Some fractured rocks and lithology may enhance rock permeability due to karstification, as can rock solubility[11,12].

C. Artificial Intelligence (AI)-aided prediction

Methods of teaching computers to learn: some considerations Many attempts have previously been made to enhance the accuracy of estimating groundwater inflows into tunnels. In this work, a variety of methods and tactics are discussed. Groundwater inflows into tunnels may now be predicted using Machine Learning approaches. Despite this, many approaches need a large quantity of relevant data in order to achieve high levels of accuracy [13]. Similarly, numerical methodologies, financial considerations, and time commitment might be seen as roadblocks in the quest for exact prediction. The accuracy of groundwater inflow predictions into tunnels might be improved using hybrid machine learning approaches. According to Liu and colleagues80, a hybrid model can accurately estimate groundwater infiltration into karts tunnels. A thorough examination of how these techniques may be used in a variety of environments would be worthwhile.

When it comes to groundwater infiltration into rock tunnels, there are several factors to consider. Such inflows into tunneling may vary in size depending on four different variables: hydrological slope, permeability of the underlying rocks, accessibility of groundwater sources, and storage [14]. Rock permeability may be increased when soil type, rock solubility, and certain fractured rocks are present. This is because karstification is a characteristic of certain rock types.

D. Machine-Learning Algorithms

i. Long-Short-Term Memory (LSTM) Algorithm

Recurrent Neural Networks (RNNs) can learn long-term dependent information, and the LSTM method may be used to analyze and forecast key events with relatively long intervals and delays in time series [35]. When using the LSTM method, the vanishing gradient issue may be solved by introducing the function of "gate operation" and adding three control units: an input layer, one or more hidden layers, and an output layer [14,15]. The LSTM algorithm uses control units to evaluate the information that is fed into it, and either the information that complies with the rules is retained or it is discarded. It is possible to overcome the neural network's long-sequence reliance by just keeping the useful information. The storage unit's input activation flow is controlled by the input gate. The forgetting gate determines whether or not the preceding step's information is retained. When a memory block is full, it sends data to the next one through the output gate. Surface settlement at engineering measurement stations may be anticipated using the LSTM model delay unit and feedback structure's features, which can be used to create a time series array from the duration data of the settlement [15].

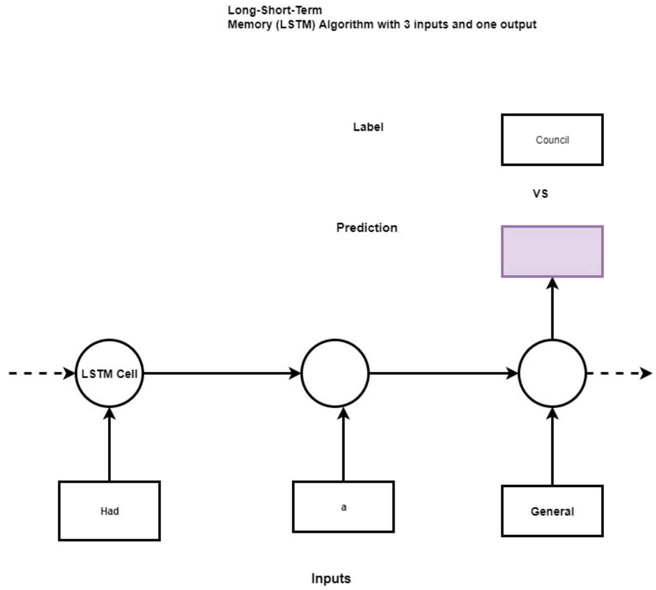

Fig i: An illustration for Long-Short-Term Memory (LSTM) Algorithm

ii. Gated Recurrent Unit (GRU) Algorithm

An RNN called a GRU is a specific kind of RNN. Long-term memory gradients and backpropagation issues were also addressed by GRU. In order to simplify the model, it merges the forgetting gate and input gate into a single update gate, merges the cell state and hidden state, and makes additional improvements. The vanishing gradient issue is addressed by the GRU method using the update and reset gates [15]. When a new input is paired with a prior memory, the update gate specifies how many previous memories are used.

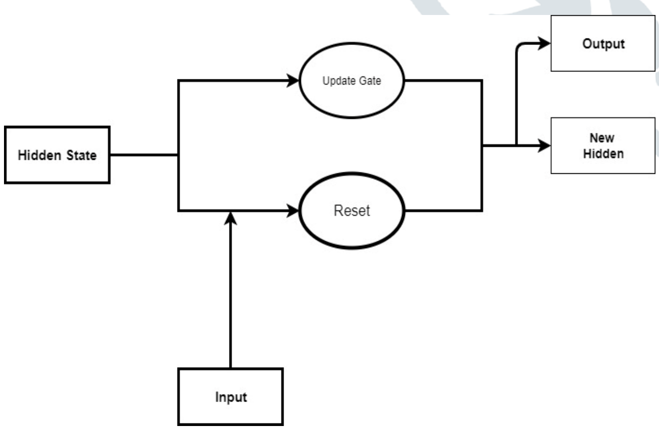

Fig ii: Gated Recurrent Unit (GRU) Algorithm

iii. The Random Forest Algorithm (RF).

The random forest generates a new sample set by taking part of the previous samples and putting them back together. For each sample set, you may create a decision tree by repeating the method [16,17]. Some characteristics are chosen at random to participate in the branches of the decision tree and subsequent recursive branches during the generation of each decision tree. As a result of recursive branching, some of the remaining traits are picked at random. A number of decision trees will be constructed as a result of this. Predicting fresh input samples, each tree generates a prediction result. Finally, additional input samples will be categorized according to the concept of minority following majority [17].

IV. SIGNIFICANCE

Numerous sectors of engineering and science are considering the use of numerical techniques as possible tools. Much more fruitful in terms of science, technology, and economics would be an investigation into the entry of groundwater into rock tunnels. Also utilized extensively in the forecast and computation of groundwater flow through tunnels constructed of varied rocky medium [17]. A water influx during tunnel construction is one of the most frequent and complicated geological catastrophes, and it has a significant influence on both safety and the timeliness and efficiency of the project. In tunnel construction, major water inflows may result in significant economic losses and deaths. In order to assure safety and schedule throughout the subterranean building process, it is essential that this phenomenon's forecast be made. An accurate estimate of both the time and money needed to build a tunnel is critical to its success [18,19]. However, for a variety of geological and geotechnical reasons, most estimates fall short of the real time and money required. Uncertainty is introduced into tunnel construction due of this. Continuous update strategies are described in this article as a means of reducing the impact of geological and geotechnical uncertainty on tunnel construction time and expense.

V. ITS FUTURE

Machine learning (ML) technologies are becoming more popular because of their capacity to analyze complex correlations between settlements and probable triggering conditions. Modeling and technical knowledge in geo-material parameters isn't required for ML techniques, unlike traditional methods. The use of intelligent models to estimate water intake into drill and blast tunnels has become widespread. ML approaches are based on the idea that computers can learn from past experiences autonomously and logically[19]. As a result, individuals are able to use what they have learned to solve new issues, which is known as generalization. In geotechnical engineering, the ML has been extensively employed as an alternate tool to uncover and manage the uncertainty and unpredictability that many engineers and researchers commonly encounter.

VI. CONCLUSION

Water input into drill and blast tunnels may be accurately predicted using machine learning algorithms, as explained in this study. Additionally, tunnels must be designed and constructed in a way that minimizes the environmental effect of groundwater inputs. Prior to excavating deep rock tunnels, especially those created in saturated medium, adequate planifications are always necessary. Water transportation, reservoir emptying, hydropower plants, sanitary drainage, and transportation networks are just a few of the many uses for tunnels that have emerged as a result of the increased need for subterranean space. Managing groundwater infiltration into tunnels is a major problem for designers and construction crews. In reality, by interfering with the excavation's short- and long-term stability, the latter may raise failure risk. Groundwater may enter rock tunnels in a variety of ways, depending on the qualities of the rock mass and the circumstances in which it occurs. The amount of water that flows through tunnels is determined by four possible parameters, including the groundwater levels of the subsurface, the accessibility of underground water and reservoirs, the permeability of the rocks that are in the area, and the pressure gradients.

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