Deep Learning-Based Hazard Evaluation for Resource Network Setting Up via Horizontal Directional Drilling

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Abstract. A pipeline and another utility are transported through the underground tunnel construct utilizing horizontal directional drilling (HDD). This method includes a drilling tunnel under a river or other specified location. It is crucial to ensure the safety and dependability of HDD operations, particularly while drilling in areas with significant resource networks. Ensuring data accuracy and high quality in dynamic drilling circumstances that could impact the efficiency of the system was challenging. The study presented the Red Deer Optimized Bidirectional RNN algorithm (RDO-Bi-DRNN) method to examine and predict the possible hazards related to HDD operations in the resource network. The RDO-Bi-DRNN method assesses hazard evaluation by developing resource networks through HDD. The research collected a dataset of 3,082 data of different drilling input parameters and pre-processed the data using the min-max normalization to generate a high-quality dataset for analysis. To evaluate the performance of the proposed method by using the Python tool. This study examines the significant performance indicators, such as Accuracy (95%), Recall (97%), Precision (94%), and F1-Score (98%). This method provides professionals and planners of projects with the knowledge and skills that are necessary to ensure the security, dependability, and sustainability of resource network development.

Keywords: Hazard evaluation · Drilling input · horizontal directional drilling (HDD) · resource network · tunnel construction

1 Introduction

Subterranean pipes are installed in a relatively shallow deposit using the Horizontal Directional Drilling (HDD) method that includes launching drill equipment from the surface. HDD is a method used to lay underground cables, pipes, and conduits. The process involves accurately drilling along the chosen path and enlarging the required pipe by utilizing a directional drilling machine and associated equipment [1]. The advantages of HDD encompass expedited construction, minimal ground disturbance, reduced

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construction expenses, enhanced installation efficiency, fewer external limitations, and improved stability management for various applications such as oil and water pipelines, highways, and gas pipelines [2]. The HDD has become a prevalent trenchless construction technology for the installation of conduits and pipelines in areas with obstructions where traditional open-cut methods were impractical. The installation procedure consists of three steps such as drilling small-diameter piloting holes along the anticipated location, enlarging the first hole to the necessary diameter for the product pipe, and subsequently drawing the product pipe into the expanded borehole [3]. The implementation of energy infrastructure by HDD has significantly transformed the process of establishing and maintaining crucial utilities. HDD offers a trenchless technique for underground installation of cables, pipes, and conduits, avoiding the negative environmental impact and disturbance caused by traditional open-cut technologies [4]. The technique enables accurate and regulated drilling underneath obstacles such as rivers, highways, and fragile ecosystems. The complexity of the system is influenced by the characteristics of the mud, operational conditions, and pipeline requirements. Consequently, the situation is hard to accurately ascertain the exact retraction power [5]. Despite its numerous advantages, Horizontal Directional Drilling does present certain challenges and considerations. The accuracy of the drilling process relies on accurate mapping and surveying of the subsurface conditions. Any discrepancies in the data can lead to deviations from the planned pathway, potentially causing conflicts with existing utilities or geological features [16]. The environmental impact of HDD must be carefully managed. While the method reduces surface disruption, the drilling fluids used in the process, typically composed of water mixed with bentonite or polymers, need proper disposal or treatment [17]. The potential for inadvertent returns, where drilling fluids escape to the surface, must be mitigated to prevent environmental contamination. Therefore, thorough pre-drilling surveys and subsurface investigations are crucial to the success of an HDD project [18]. Although currently a prominent topic in this field, several scholars have examined this issue. With this incentive, we analyzed and forecasted potential risks linked to HDD operations in resource networks via the RDO-Bi-DRNN technique.

Horizontal Directional Drilling (HDD) faces several limitations that warrant careful consideration. One significant challenge in machine learning is the potential for subsurface uncertainties and variations, leading to difficulties in accurately predicting the geology and geotechnical conditions along the drill path. Limited accessibility to certain areas may also restrict the deployment of advanced drilling technologies, further complicating hazard assessment.

2 Related Works

The study [6] used the improved radial movement optimization (IRMO) method toward merging five segments in addition to catenary trajectories and used each trajectory's benefits. The objective of this study is to increase the effectiveness of HDD design preparations by designing and testing an automated system for predesigning and modifying drilling career paths. The experimental findings demonstrated the set of restrictions possesses an important function in determining the accuracy and feasibility of the algorithmic production. The paper [7] implemented an Ant Colony Optimization (ACO) to optimize the entry angle, alignment depth, and exit angle to achieve the shortest possible drill path duration, prevent collapse or instability, and stay within the construction field. The experimental outcomes demonstrate the ability of predictive algorithms, such as the ACO execution, to recognize the requirement of the architectural engineer's individual repetitions despite the automated HDD alignment phase of design. The study [8] used the HDD to carry out both experimental and theoretical analysis to evaluate the grout hydraulic conductivity as well as the characteristics of these mining-induced fractures. As a result of extraction, the rock mass became fractured, as evidenced by the data that revealed the HDD drill had progressed through the initial rock mass inside the extraction zone. Numerous fracture types subsequently emerged due to varied fracture morphology in distinct industrial burden areas. The paper [9] described the laboratory-level creation of pumps depending on scheduled the axial blade propeller intended philosophy used in turbomachinery. An axial rotor generator placed in the pump hub powered each annular pump. The study [10] investigated the rheological characteristics of drilling fluids with varying betonies concentrations. Drilling fluid shear stresses and shear rate correlations were determined using a six-speed rotating viscometer, and rheological parameters were described using the Herschel-Bulkley (HB) and Bingham plastic (BP) models. The results demonstrated the contrast between the traditional BP method, and the H-B system was capable of producing precise forecasts regarding rheological activity. The paper [11] enhanced the unloading arch and winch calculation methods using ground pressure to develop a new model and perform an example calculation using the revised formula and enhanced the step resistance and retraction effort computation technique. The experimental findings indicate domestic and international research on pipeline departure power occurs on a global scale, with very little attention paid to regional contexts.

Problem Statement

In the domain of resource network development, specifically in the context of Horizontal Directional Drilling (HDD), there exists a critical need for an advanced hazard evaluation system. Traditional hazard assessment methods in HDD projects often rely on manual inspection and rule-based approaches, leading to limitations in accuracy, efficiency, and adaptability. As the complexity and scale of resource network installations increase, there is a growing demand for a sophisticated hazard evaluation system that can harness the power of Deep Learning techniques.

3 Methodology

Initially, we gathered 3082 datasets in this article from various drilling input parameters and pre-processed them using the min-max normalization method to create a high-quality dataset for analysis. To investigate and predict possible hazards associated with HDD operations in resource networks the RDO-Bi-DRNN method in this study. The RDO-Bi-DRNN method is used to assess hazard evaluation by developing resource networks through HDD, as shown in Fig. 1.

3.1 Dataset

This research consists of 3082 datasets pertaining to diverse drill settings and their corresponding actual Rates of Penetration (ROP). The data is sourced from an oil well situated

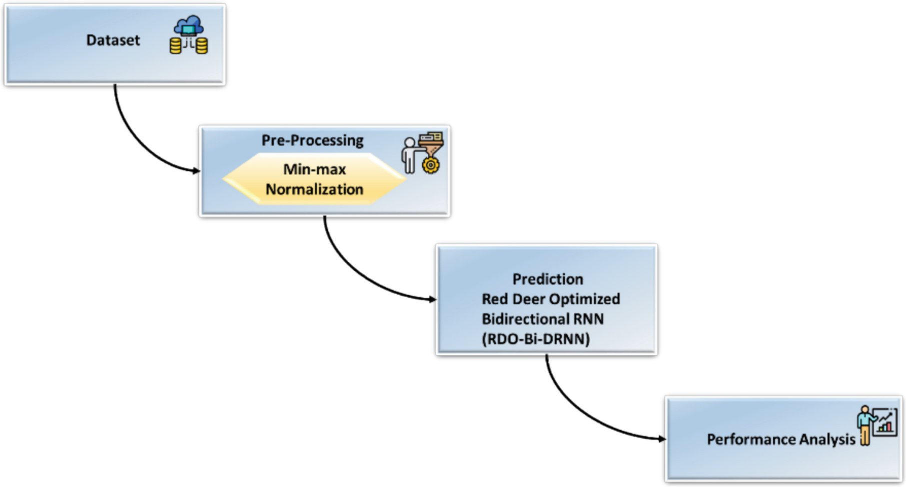

Fig. 1. Graphical representation of a proposed method

in the Central East region. The primary objective is to facilitate precise predictions of ROP during drilling operations. Notably, all input parameters in the existing dataset are surface-measurable, enhancing the feasibility of accurate predictions [12]. Furthermore, an additional 4662 input and ROP datasets have been acquired from the second well within the same oil field. This expanded dataset contributes to the richness and diversity of the research, potentially uncovering deeper insights into drilling dynamics. The inclusion of data from a different well within the same field introduces variability and allows for a more comprehensive understanding of the factors influencing ROP [13].

3.2 Pre-processing Using Min-Max Normalization

Min-max normalization is a crucial technique employed in the setup of resource networks utilizing Horizontal Directional Drilling (HDD). In this context, HDD serves as a method for installing pipelines, conduits, or cables underground with minimal surface disruption. Normalization allows for the standardization of variables such as drilling depth, angle, and distance, ensuring that each component of the network is optimized within predetermined boundaries. Each value decreases by the minimum value of the feature before being divided by the feature's range during the pre-processing step of min-max normalization. The HDD hazard evaluation pipeline includes an essential Min-Max normalization stage that encourages more accurate and responsible choices for the security and sustainability of resource network development. The Min-Max normalization process entails making linear alterations to the original data to achieve equilibrium between the values comparisons among the data before and after the procedure.

1. **Original Value:** This is the individual data point that you want to normalize. It represents the original value of the feature.
2. **Minimum Value:** This is the smallest value present in the dataset for the specific feature. It is used as the reference point to scale the original values.

3. **Maximum Value:** This is the largest value present in the dataset for the specific feature. It is also used as a reference point to scale the original values.

3.3 Red Deer Optimized Bidirectional RNN (RDO-Bi-DRNN)

The Red Deer Optimized Bidirectional Recurrent Neural Network (RDO-Bi-DRNN) stands as a pioneering solution tailored for hazard assessment in the deployment of resource networks through Horizontal Directional Drilling (HDD). This cutting-edge neural network model addresses the challenges inherent in HDD processes, where traditional trenching methods are bypassed, but hazards like ground instability, underground utilities, and environmental concerns persist. The RDO-Bi-DRNN distinguishes itself through its utilization of a bidirectional recurrent neural network (RNN) architecture, strategically fine-tuned by the red deer optimization algorithm. This specialized design enables the model to comprehensively evaluate and effectively mitigate risks associated with HDD operations. Drawing upon diverse data sources, including geophysical surveys, soil composition analyses, and insights from prior drilling experiences, the RDO-Bi-DRNN demonstrates its capability to assimilate complex information. It offers invaluable insights for ensuring the secure and efficient establishment of resource networks through HDD. The model's sophisticated analysis contributes to informed decision-making, allowing stakeholders to navigate potential threats such as ground instability or underground utilities with greater precision. In essence, the RDO-Bi-DRNN emerges as a key technological advancement, leveraging artificial intelligence to enhance safety and efficiency in the deployment of resource networks via Horizontal Directional Drilling, thus revolutionizing the landscape of underground infrastructure development. The RDO-Bi-DRNN can provide valuable insights to ensure safe and efficient resource network setup via HDD.

4 Result and Discussion

The recommended task is executed on open-source Anaconda 2024, Python (3.12.1), and is required to be installed alongside Python to carry out the procedure. The hazards assessment process for resource network development by HDD utilizes the RDO-Bi-DRNN. The method's ability to adapt and change in real-time, along with its progressive identity, enables it to effectively handle the dynamic challenges associated with HDD operations. The development of resource infrastructure that is safer, more efficient, and more sustainable is eventually facilitated by that. The results demonstrate that improved the proposed approach as compared with existing methods. A comparative outcome of the existing techniques of Convolutional neural networks (CNN) [15], Artificial neural networks (ANN) [13], and Support Vector Machine (SVM) [14]. This study examines the significant performance indicators, such as recall (97%), precision (94%), Accuracy (95%), and F1-score (98%).

Accuracy to reduce hazards that improve the general safety and dependability of HDD operations it is essential to make sure that hazard assessments are accurate as shown in Eq. (1). The accuracy of the proposed system and the existing system are both displayed in Table 1 and Fig. 2.

$$Accuracy = (Tp + TN)\Big/(Tp + Tn + Fp + Fn) \tag{1}$$

Table 1. Numerical outcomes of accuracy

Accuracy (%)	
Methods	Percentage
ANN [13]	81
SVM [14]	71
CNN [15]	85
RDO-Bi-DRNN [Proposed]	95

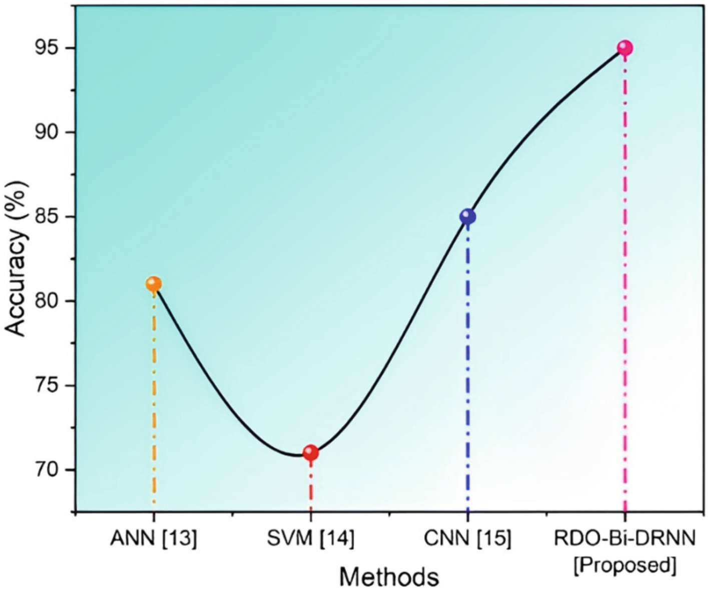

Fig. 2. Graphical representation of Accuracy

RDO-Bi-DRNN achieved (95%), comparatively with ANN attained (81%), SVM attained (71%), and CNN attained (85%). It proves that the accuracy of the proposed process approach has higher rates than the existing methods.

Precision requires a solid understanding of geological and environmental conditions, historical data, and real-time monitoring that, while combined, allow for educated decision-making as shown in Eq. (2). The Precision of the proposed system and the existing system are both displayed in Table 2 and Fig. 3.

$$Precision = Tp/Tp + Fp \tag{2}$$

RDO-Bi-DRNN achieved (94%), comparatively with ANN attained (73%), SVM attained (82%), and CNN attained (72%). It proves that the Precision of the proposed process approach has higher rates than the existing methods.

Table 2. Numerical outcomes of precision

Precision (%)	
Methods	Percentage
ANN [13]	73
SVM [14]	82
CNN [15]	72
RDO-Bi-DRNN [Proposed]	94

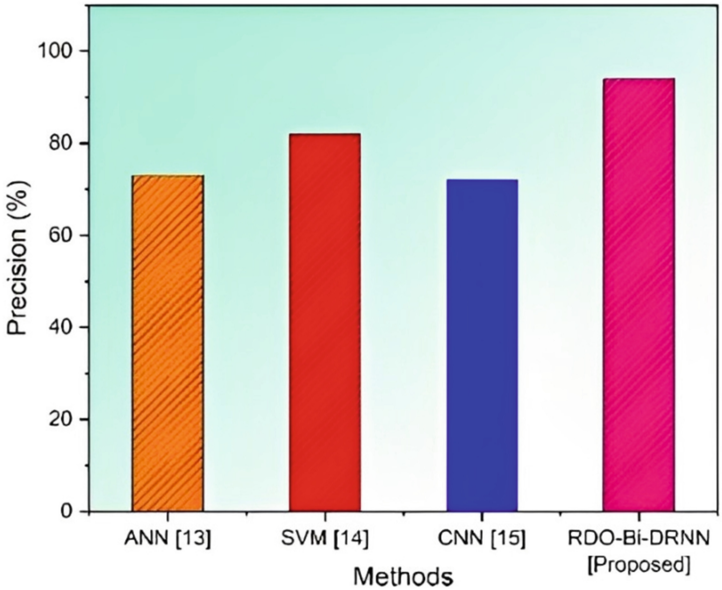

Fig. 3. Graphical representation of precision

Recall measures to determine whether a system can identify and recover hazardous detects in a drilling environment as shown in Eq. (3). The Recall of the proposed system and the existing system are both displayed in Table 3 and Fig. 4.

$$Recall = TP \big/ TP + FN \tag{3}$$

RDO-Bi-DRNN achieved (97%), comparatively with ANN attaining (86%), SVM attained (74%), and CNN attained (84%). It proves that the Recall of the proposed process approach has higher rates than the existing methods.

The F1-score demonstrates that the model recognizes and reduces possible dangers while avoiding incorrect assessments in the context of HDD, as safety and risk

Table 3. Numerical outcomes of recall

Recall (%)	
Methods	Percentage
ANN [13]	86
SVM [14]	74
CNN [15]	84
RDO-Bi-DRNN [Proposed]	97

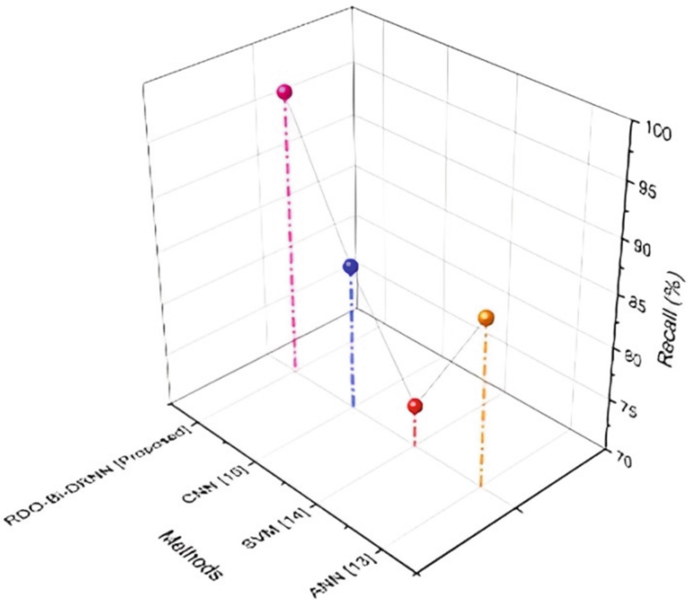

Fig. 4. Graphical representation of Recall

Mitigation is crucial as shown in Eq. (4). The F1-score of the proposed system and the existing system are both displayed in Table 4 and Fig. 5.

$$F1 - score = 2x[(PrecisionxRecall)/(Precision + Recall)] \tag{4}$$

RDO-Bi-DRNN achieved (98%), comparatively with ANN attained (83%), SVM attained (75%), and CNN attained (87%). It proves that the F1-score of the proposed process approach has higher rates than the existing methods.

Discussion

CNNs may struggle when dealing with imbalanced datasets, where certain hazard classes are underrepresented. Addressing class imbalance through techniques like oversampling, under-sampling, or weighted loss functions is crucial. ANNs require large amounts of

Table 4. Numerical Outcomes of F1-score

F1-score (%)	
Methods	Percentage
ANN [13]	83
SVM [14]	75
CNN [15]	87
RDO-Bi-DRNN [Proposed]	98

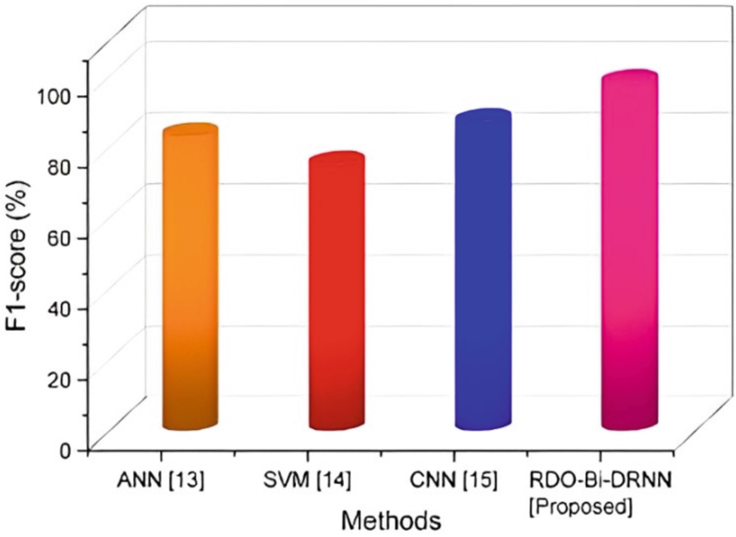

Fig. 5. Graphical representation of F1-score

labeled data for training. In scenarios with limited or noisy data, the model's performance may suffer, leading to inaccurate hazard predictions. SVMs are sensitive to noisy data. When the dataset contains significant noise or outliers, the SVM model may struggle to find an optimal hyperplane that separates classes effectively. Our novel red deer-optimized bidirectional RNN (RDO-Bi-DRNN) combines the power of bidirectional RNNs with optimization techniques to enhance hazard prediction accuracy. By analyzing geological and environmental factors, it aims to identify potential risks during HDD operations, ensuring safer and more efficient resource network installations. The RDO-Bi-DRNN model can contribute significantly to minimizing hazards, optimizing drilling paths, and improving overall project success rates.

5 Conclusion

The underground tunnel was built using HDD, a construction technique that entails digging a tunnel beneath a river or another designated place to deliver a pipeline and another service. It is essential to guarantee the reliability and safety of HDD operations, especially drilling in regions with a sizable resource network. The hazards assessment procedure for resource network development by HDD leverages the RDO-Bi-DRNN. The method's capacity to adapt and alter in real-time, together with its progressive identity, allows it to address the dynamic issues connected with HDD operations efficiently. Creating a resource network that is safer, more efficient, and more sustainable is eventually aided by that compensation. F1-score (98%), recall (97%), Accuracy (95%), and precision (94%), are some of the important performance measures that are examined in this study. Geological and environmental elements display a substantial amount of unpredictability, and unanticipated subterranean circumstances provide significant difficulty. Future studies are focused on integrating the real-time environmental and geological data from IoT devices and sensors that allow the hazard assessment system to continuously adjust and react to changing drilling operations circumstances.

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