Leveraging Machine Learning for Subsurface Geothermal Energy Development

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Abstract. Geothermal energy, which derives heat from the Earth's core, presents a promising renewable resource for meeting sustainable global energy needs. Nevertheless, challenges including high initial costs, technical risks, and complex underground conditions have limited its widespread adoption. Recent advancements in Machine Learning (ML), a subset of Artificial Intelligence (AI), offer innovative solutions to these challenges. This paper presents a comprehensive review of the application of ML techniques in geothermal energy development, focusing on exploration, drilling, reservoir characterization and engineering, as well as production/injection engineering. Various ML algorithms including neural networks, clustering methods, and decision trees, have been employed to analyze complex geological and operational data. These applications have led to improved identification of geothermal resources, optimized drilling operations, enhanced reservoir management, and increased production efficiency. While ML integration offers significant advantages, limitations like data quality issues and computational demands persist. This paper highlights the need for interdisciplinary collaboration, data sharing, and increased investment in research and development to overcome these challenges. The ongoing advancement of AI technologies is anticipated to drive innovation in geothermal exploration and development, enhancing the efficiency, reliability, and economic viability of geothermal energy as a cornerstone of sustainable energy systems.

Keywords: Geothermal Energy, Artificial Intelligence, Machine Learning.

1. Introduction

The term "geo" denotes earth, and "thermal" signifies heat; thus, geothermal energy refers to energy derived from the Earth's core. Approximately 80% of this heat originates from the radioactive decay of isotopes, whereas the remaining 20% comes from residual heat from the Earth's formation [1, 2]. Given that the rate of human utilization of geothermal energy is significantly lower than its natural replenishment rate, it is considered a renewable energy source.

Humanity possesses a long history of utilizing geothermal energy. For instance, hot springs were employed during the Paleolithic era for bathing, and the Romans used geothermal energy for heating purposes [1-4]. In modern times, geothermal energy is also used in agriculture, especially for greenhouse heating [1-4].

Geothermal resources are primarily classified into two types: hydrothermal (steam or hot water) and hot dry rock. Hydrothermal resources are easier to utilize, as they consist of naturally occurring steam or hot water that can be directly accessed. Hot dry rock, on the other hand, requires more advanced technological methods to extract heat from deep within the Earth's crust, necessitating ongoing technological advancements for more efficient utilization [1-2].

Geothermal energy can be applied directly for heating purposes or converted into electricity. Direct utilization includes six major categories: geothermal heat pumps, bathing and swimming, space heating, greenhouse heating, aquaculture pond heating, and industrial applications [1, 3]. These categories are ranked from the largest to the smallest in terms of the proportions of usage. As of the end of 2019, the global installed capacity for geothermal direct utilization reached 107,727 MWt, marking a significant increase from under 10,000 MWt three decades earlier [3]. This rapid growth is mainly driven by heightened awareness and the increasing popularity of geothermal (ground-source) heat pumps [3]. The leading countries in terms of installed capacity for direct use include China, the USA, Sweden, Germany, and Turkey [3].

In contrast, the use of geothermal energy for electricity generation commences much later, in the early 20th century [1-3]. Electricity generation typically involves the use of steam or other forms of heat to drive a turbine, which subsequently generates electricity [1-2]. There are three main types of geothermal power plants: dry steam, flash steam, and binary cycle [1-2]. By 2021, the total global installed capacity for electricity generation from geothermal energy reached approximately 15.96 gigawatts electric (GWe), marking an annual growth rate of approximately 3.5% [2].

Geothermal energy is among the most promising renewable sources capable of replacing fossil fuels for sustainable global development, offering several distinct advantages. First, geothermal energy is environmentally sustainable. Unlike fossil fuels, geothermal power plants generate minimal greenhouse gas emissions, as they do not involve combustion [1, 3, 5, 6]. Second, geothermal energy is stable and reliable. Unlike solar or wind energy, geothermal energy is independent of weather conditions, relying instead on the consistent heat from the Earth's core, thus serving as a reliable source of base-load power generation [1, 2, 4]. Third, geothermal energy shows immense potential. The untapped global capacity is estimated to exceed 100 GW, yet humanity has only explored approximately 6-7% of this potential [2]. Fourth, geothermal energy is highly effective for both heating and cooling applications, rendering it versatile for a wide range of industrial and residential uses [1-3].

However, geothermal energy is not always perfectly "green." Certain geothermal reservoirs contain naturally occurring non-condensable gases (NCG), such as CO_2 and hydrogen sulfide, which may be released during extraction, thereby diminishing the environmental benefits [5]. Secondly, geothermal projects often require high initial costs for exploration, drilling, and plant construction, making it a financially challenging option for certain regions [1, 3, 5]. Furthermore, geothermal energy is highly location-dependent, as it requires specific geological conditions, which limits its widespread applicability to regions with suitable geothermal resources and increases the risk of earthquake, as it is most abundant near plate intersection areas [1, 3, 5].

The disadvantages also represent challenges within the geothermal sector, characterized by the highest technical and financial risks from the project beginning, which deter the development of geothermal energy in numerous areas [7, 8], as shown in Fig 1. The successful application of artificial intelligence in the oil and gas sectors to overcome technical difficulties has prompted scientists to explore the potential of leveraging AI in geothermal, a renewable resource of immense potential. Okoroafor et al. identified a steady increase in AI applications over the past 20 years in subsurface geothermal resource development, spanning exploration to injection engineering [7]. Abrasado et al. verified the practicability of AI in above-ground geothermal operations for optimizing plant performance [4]. Hossain et al. specifically focused on the exploration stage, demonstrating a systematic approach to different AI applications in innovative geoscience and subsurface engineering [8]. The integration of AI within the geothermal sector, from subsurface to surface operations, spans the whole process of geothermal energy development, including the interpretation of complex geological data, optimization of drilling operations, and prediction of reservoir behavior, thereby further aiding decision-making and problem-solving.

Despite an exponential increase in the number of published papers on machine learning applications in geothermal energy post-2018, as shown in Fig 2, this category still represents a low ratio relative to all published papers. Therefore, this paper aims to analyze the recent applications of machine learning in geothermal, along with current challenges and future perspectives. The following structure of this paper will focus on recent advancements in ML applications within geothermal energy, particularly in resource exploration, drilling optimization, reservoir characterization, reservoir engineering, and production engineering. It will highlight specific ML models that have shown promise in geothermal energy, including neural networks, clustering and dimensionality reduction, as shown in Fig. 3. The paper will also explore the challenges and opportunities associated with ML application and will conclude with future trends and emerging technologies that could further improve the efficiency and sustainability of geothermal energy operations.

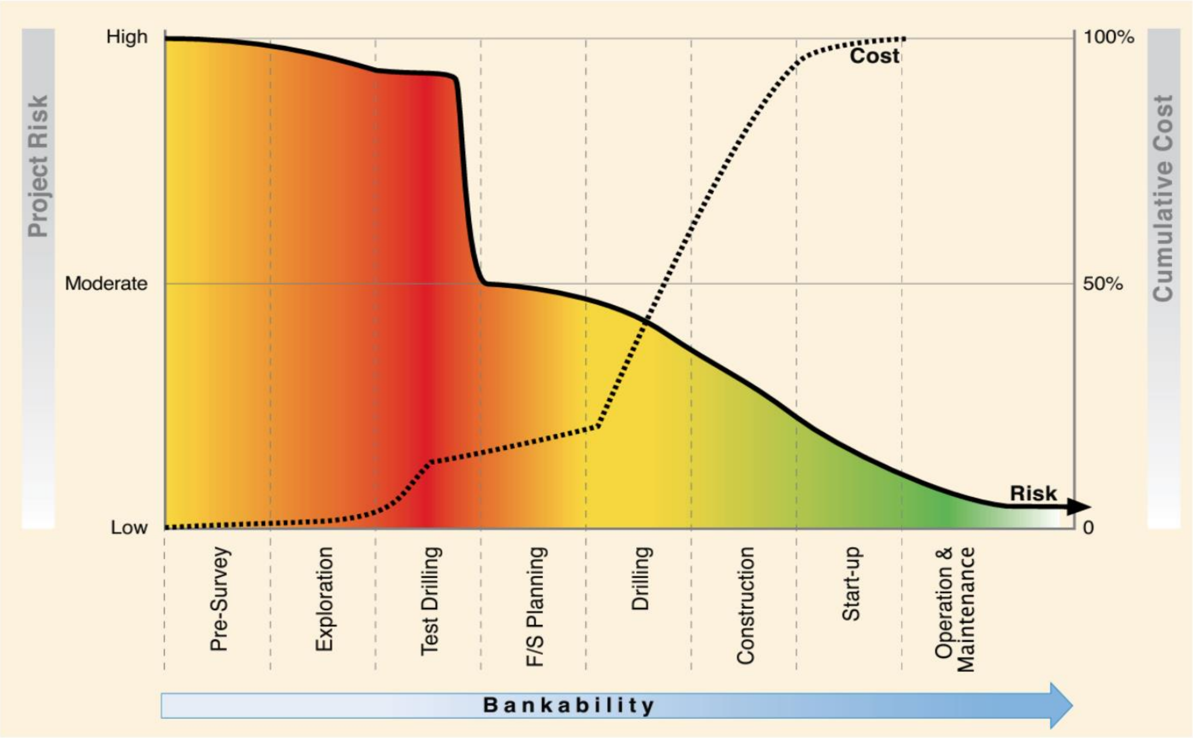

Figure 1. Cost and risk profile of a geothermal development project at different phases [8].

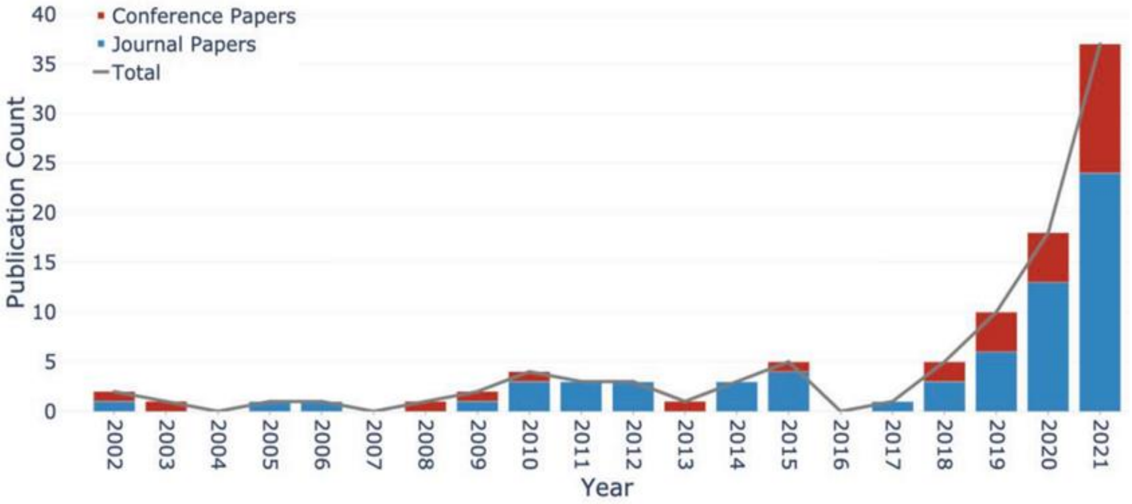

Figure 2. Histogram illustrating the annual publication frequency about machine learning applications in subsurface geothermal resource development [7].

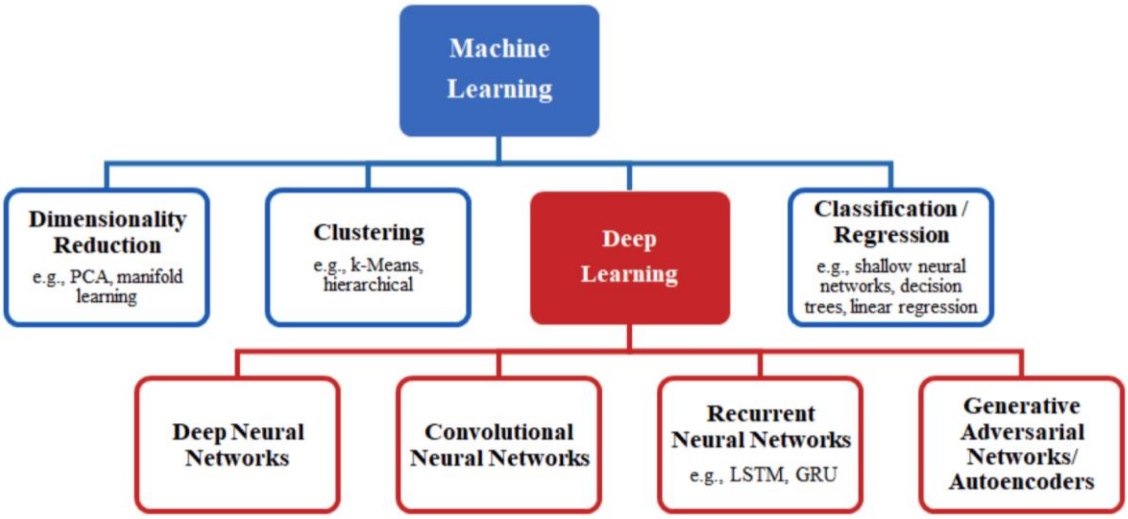

Figure 3. Classification of machine learning methodologies employed in this research [7].

2. Geothermal and Machine Learning

2.1. Core knowledge in the field

2.1.1. AI, ML, DL

Artificial Intelligence (AI) refers to technologies that enable computers or robots to perform tasks historically associated with intelligent beings, such as problem solving, decision making, or autonomy [7]. Machine Learning (ML), a subset of AI, allows computers to learn from statistical techniques without explicit programming [7, 9]. This includes Deep Learning (DL), which specifically refers to using multiple layered neural networks to simulate human thought processes for analyzing sophisticated patterns [7, 9]. In this paper, ML will be used as a broad term that includes DL.

2.1.2. Geothermal

A geothermal energy exploitation program operates in sequential stages. First, geothermal energy prospectivity mapping is conducted using collected spatial or field data [10]. This is followed by a surface survey of potential sites, and subsequently exploration drilling to confirm the reservoir. If the reservoir is verified, delineation drilling follows to confirm productivity and the subsequent development plan. The development often involves production wells, reinjection wells, a steam gathering system, and power plant construction, all of which require continuous financial investment. The final task is the operation and maintenance of the power plant until it retires [8]. The integration of AI could be applied throughout the whole process of geothermal development, improving the locating accuracy, extraction, and operation efficiency, while reducing costs and risks [11].

This paper focuses on 4 main categories of study interests: exploration, drilling, reservoir characterization and engineering, and production/injection engineering. For the purpose of this review, exploration refers to the processes of identifying prospective reservoirs prior to firm confirmation of their presence. Drilling involves exploratory drilling to confirm the resource, and subsequent drilling activities based on evaluations and decisions made for the exploration. Reservoir characterization and engineering involve describing the reservoir rocks or fluids that may affect productivity and relating model buildings used to monitor the dynamics of the resource and its characterizations to ensure sustainable extraction. Finally, production/injection engineering includes activities related to heat flux within the geothermal wells.

2.2. Application of ML algorithms

Machine learning techniques are increasingly used throughout all stages of geothermal energy development. They help to identify hidden geothermal reserves and reduce machine wearing, substitute for hazardous and labor-intensive human tasks, and assist in prediction and maintenance. These advancements hence significantly improve the efficiency of the entire project. Table 1 lists the most commonly used machine learning algorithms across exploration, drilling, reservoir characterization and engineering, and production/injection engineering.

Table 1. ML algorithms used in different research subjects.

Study Subject	ML algorithms	The problems being treated
Exploration	NMFk, Shallow NN, deep NN	Interpreting and inverting geophysical data, analyzing gravity and seismic anomalies, prospective mapping
Drilling	Shallow NN, multi-layer perceptron, artificial NN	Predicting ROP and drilling depth, Estimating SFTs
Reservoir characterization and engineering	Shallow NN, deep NN, decision trees, random forest, long-short term memory, clustering	Depicting fractures and interwell connectivity - Predicting reservoir temperatures from fluid compositions, permeability distributions and fault detection; Optimizing well placement, estimating pressure and thermal drawdown, modeling tracer returns
Production/injection engineering	Shallow NN, deep NN, artificial NN, long-short term memory, decision trees	Modeling production and injection rates, estimating missing data and well performance, predicting well temperature and pressure profiles

2.2.1. Exploration

In the area of exploration, common ML algorithms, such as neural networks—including convolutional neural network (CNN) and artificial neural network (ANN)-and k-means clustering (NMFk), are employed to analyze complex geological and geophysical data to detect patterns, correlations and anomolies for subsurface characterizations, aiding in the building of reservoir prospective mapping [12]. ML techniques can also integrate with specific seismic or gravity data to generate more accurate information on reservoir location, dimensions, and quality [13, 14]. Other studies also show the combination of geochmical data to identify thermal properties, temperature gradients, and heat transport models, which can help identify hidden geothermal resources [14].

2.2.2. Drilling

Drilling occupies the major cost and risk factor in geothermal projects due to the complex structures of hard rocks. To reduce the cost, the most effective way is to estimate the rotation of penetration (ROP) and static formation temperatures (SFTs). ML techniques, such as ANN, shallow NN and MLP, are employed to predict drilling rates by adjusting surface controllable parameters in real time to predict optimal drilling paths. For example, ML algorithms can forecast the likelihood of encountering hard rock formations or high-pressure zones, enabling operators to make data-driven decisions to adjust drilling speed, pressure, and bit type, thereby reducing the risk of drill bit damage and unplanned delays [15, 16]. Additionally, static formation temperature, which represents the stabilized temperature of subsurface rocks, is essential for evaluating in-situ thermophysical rock properties and optimizing drilling strategies [8]. Studies also show that the application of ANN effectively improves the accuracy of predicting SFTs, achieving errors of less than 5% [17], while traditional methods encounter significant inaccuracies.

2.2.3. Reservoir characterization and engineering

Reservoir characterization runs through all stages of geothermal development, especially in exploration, drilling, and production, as it involves properties associated with a geothermal resource, such as permeability, porosity, fracture distribution, etc [7]. Throughout these phases, extensive engineering work—such as numerical reservoir modeling, production forecasting, well testing, tracer testing, chemical analysis of reservoir fluids, and economic modeling—is required to generate reserve estimates and methods for maximum economical production [7]. The extensive use of various data sources indicates the majority of publications of ML techniques in this area [7-9].

Techniques such as Artificial Neural Networks (ANN), Deep Neural Networks (DNN), and k-means clustering are widely used to characterize fractures, predict reservoir temperatures, and estimate permeability distributions. For instance, ML models can process gas-phase fluid compositions and identify discrete fractures, which are critical for assessing interwall connectivity and understanding fluid flow dynamics within a reservoir [18-20]. This enhances the ability to predict the thermal and structural properties of reservoirs, facilitating the identification of optimal drilling sites and improving overall resource evaluation.

In reservoir engineering, ML algorithms, such as decision trees, Random Forests, and Long Short-Term Memory (LSTM) networks, are applied to optimize well placement, forecast temperature and pressure changes, and estimate production enthalpy in geothermal wells. These models leverage historical and real-time data to predict thermal drawdown and pressure decline, both of which are crucial for maintaining reservoir performance over time [20-23]. Additionally, ML-driven predictive modeling of tracer returns and vertical permeability profiling enables more precise management of reservoir stimulation and flow control strategies [24, 25]. By integrating ML techniques, geothermal reservoir characterization and engineering gain improved accuracy in subsurface predictions, reduced operational costs, and enhanced decision-making capabilities, ultimately maximizing the efficiency of geothermal energy extraction.

2.2.4. Product engineering

Production and injection wells serve as channels for characterizing and tracking the reservoir; they reflect the proper operation of the reservoir. Therefore, although they occur at a later stage of the project, the information obtained can aid in the early diagnosis of any problems, enhancing development efficiency [7]. ML techniques, such as neural networks, LSTM, and decision trees, are employed as predictive tools for modeling different production and injection quantities to estimate missing production data, forecast future flow rates and assess well conditions to reduce machine downtime and save operational costs. For example, studies have shown the use of ANN with experimental and historical data to predict wellbore pressure drop and temperature profiles [26]. Other studies demonstrate the combination of ANN with LSTM or decision trees to predict well production and decline rates [24, 27, 28].

3. Geothermal Oppoutunities and Challenges

The application of ML approaches spans the different phases of geothermal projects, with an increasing number of publications each year. It helps overcome various traditional challenges in geothermal energy, such as the carcity of exploitable sites, remote locations often far from load centers, and complex underground conditions, thereby largely reducing the technical, financial and practical obstacles to commissioning a project. Through this review, it is indicated that reservoir characterization and engineering is the most active research area, with the highest number of publications, while exploration drilling, which involves the greatest financial and technical risks in the early stages, has relatively fewer publications. As an emerging and transformative technique, ML has benifited the development of geothermal energy but also has its limitations that requires a significant number of future scholars to continue tackling and advancing this area.

3.1. ML Application Pros

ML models, such as ANN, DNN, and CNN, are capable of handling complex, high-dimensional datasets [9], making them ideal for predicting subsurface properties, identifying geothermal reservoirs, and optimizing drilling and production strategies.

Secondly, ML algorithms can automate data analysis and decision-making, significantly reducing human intervention and associated costs [29]. By leveraging historical and real-time data, ML models improve the accuracy of drilling predictions, optimize well placement, and enhance reservoir management, leading to better resource utilization and lower operational costs.

Thirdly, ML enhances risk assessment and management in geothermal operations by predicting equipment failures, identifying potential drilling hazards, and optimizing maintenance schedules [9]. This proactive approach minimizes unplanned downtime and enhances the safety and reliability of geothermal systems.

Finally, ML models, especially DNNs, are highly adaptable and can be retrained with new data, enabling continuous improvement as more operational data becomes available [29]. This adaptability is crucial in geothermal systems, where conditions can change rapidly, necessitating flexible and responsive analytical tools.

3.2. ML Application Cons

The effectiveness of ML models heavily relies on the quality and quantity of available data [7-10, 29]. Poor data quality, missing data, or limited datasets can lead to inaccurate predictions and unreliable model performance, adversely affecting decision-making in geothermal development.

Secondly, advanced ML techniques, particularly deep learning models, require substantial computational resources, specialized hardware, and expertise in algorithm design and data processing [29]. This complexity can pose a barrier to implementation, especially in resource-limited settings or smaller geothermal operations.

Thirdly, many ML models, especially ANNs and DNNs, function as "black boxes," making it difficult to understand or interpret the underlying decision-making process [9]. This lack of transparency can be problematic in critical applications where understanding the rationale behind a model’s predictions is vital for regulatory compliance and operational decision-making.

Fourthly, training ML models, especially deep learning algorithms like CNNs and RNNs, can be time-consuming and require extensive tuning of hyperparameters [9]. Fine-tuning these models for optimal performance often involves a trial-and-error process that can delay deployment in practical geothermal applications.

Finally, ML models can occasionally overfit to training data, performing well on known data but failing to generalize to new, unseen scenarios [29]. This issue is particularly relevant in geothermal development, where subsurface conditions can vary significantly, making it crucial to develop models that are robust and can generalize across different geological settings.

4. Future outlook

With growing public awareness and appreciation of its internal vast potential, geothermal energy shows promise as one of the cheapest and most competitive renewable resources for meeting sustainable development goals set by the United Union. As the geothermal industry evolves, ML is expected to play an increasingly critical role in enhancing data-driven decision-making, reducing operational costs, and improving the overall efficiency of geothermal systems. With considerable investment in advanced research and development, the sector has substantial potential to increase the annual generation capacity rate to 6%-7%, surpassing the steady annual growth rate of 3%-4% observed over the past decade [2].

However, to fully realize these benefits, challenges such as the limited availability and quality of geothermal data, data handling and preprocessing, as well as logistic and financial obstacles, need to be addressed. To address poor data quality, collective data sharing from the gas and oil industries, which face similar challenges, is necessary for testing algorithms, or exploring alternative open-source options such as the Geothermal Data Repository, a collection node mainly used by researchers funded by the U.S. Department of Energy’s Geothermal Technology Office [7]. Developing standardized geothermal datasets and explainable ML models that can be readily adopted requires regular updates of hardware and facilities, as well as the recruitment of multidisciplinary talent [7]. Hence, it proves that successful geothermal development needs interdisciplinary collaboration among geoscientists, the public, and industry stakeholders. At the technical level, more geothermal experts should study AI instead of relying on computer science expertise lacking energy knowledge. On a social level, increased awareness of safety issues and resolution of environmental disputes are essential for improving public acceptance. From an economic perspective, increased investment in R&D is the basis for enhancing the development of AI applications. More studies on drilling are highly desirable to reduce early uncertainty and shorten project gestation time.

The ongoing advancement of AI technology is anticipated to foster further innovation in geothermal exploration and development. Future research should focus on refining AI models, investigating novel AI applications, and integrating AI with other emerging technologies. A digital twin model of the drilling tool head was programmed to precisely match the operations of the physical system in real time to avoid breakage and wearing [30]. AI-powered IoT enhances all stages of geothermal power processing by enabling real-time thermodynamic modeling, thus saving manpower, time, and money [31].

5. Conclusion

The integration of machine learning techniques into geothermal energy development has demonstrated substantial potential in overcoming traditional challenges associated with geothermal projects. ML applications have enhanced exploration accuracy by more effectively identifying and characterizing reservoirs, optimized drilling operations through predictive modeling of optimal paths and conditions, and improved reservoir management and production efficiency via advanced data analysis. Despite these benefits, challenges such as data scarcity, computational resource requirements, and the need for transparent and generalizable models remain. Addressing these obstacles requires interdisciplinary collaboration among geoscientists, data scientists, industry stakeholders, and policymakers. Increased investment in research and development, standardized data sharing practices, and the advancement of interpretable ML models are crucial for progress. As AI technologies continue to evolve, their integration with geothermal operations is expected to drive significant innovations, reduce environmental impacts, and enhance the economic viability of geothermal projects. Ultimately, the continued advancement of ML technologies promises to solidify geothermal energy's role as a vital component of global sustainable energy systems.

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