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A Review based Investigation of Exploratory analysis in AI and Machine Learning for a Variety of Applications

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Abstract
In recent years, the number of production settings that make use of machine learning (ML) and other types of AI has grown significantly. The research presents a comprehensive review of where machine learning (ML) applications stand in industrial contexts at present. The development of smart mining tools has allowed for the generation, collection, and exchange of data in near-real time. This is why there is so much interest in machine learning (ML) studies in the mining industry. Additionally, this study provided a thorough evaluation of data sciences and ML's applications in a variety of petroleum engineering and geosciences domains, such as petroleum exploration, reservoir characterization, oil well drilling, production, and well stimulation, with a focus on the rapidly developing area of unconventional reservoirs. Future directions for data science and ML in the oil and gas industry are discussed, and the properties of ML that are necessary to enhance prediction are analysed. This study provides a detailed comparison of various ML techniques that can be used in the oil and gas industry. New possibilities for analysing and predicting medical data have emerged thanks to the development of artificial intelligence and machine learning, which were covered in this article. Multiple recent studies have shown that AI and ML can be used to fight the COVID-19 pandemic. This article's goal is to offer reviewers with an overview of recent studies that have made use of AI and ML in a variety of contexts.

Key words: Artificial Intelligence, Machine Learning, Oil Industry applications, Health care related applications, Mining based applications.

I. INTRODUCTION

Several studies have taken a retrospective look at the history of AI and related fields like machine learning and data mining; for example, HARDING ET AL. presents an overview of AI applications from 1987 to 2005[1]. The inevitable ascent of AI and ML is being fueled by the expanding reach of digitalization. Large monetary rewards have been provided in recent online competitions, indicating that companies see considerable promise in data-driven tactics (e.g., Kaggle.com). GOODFELLOW claims that the best use of AI is in solving problems that cannot be reduced to code but can be addressed by intuition alone [2].

This article demonstrates the recent transition of machine learning (ML), a subfield of artificial intelligence, from the academic world to the business sector. More datasets are accessible for use by an ML application to learn from the past as data generation increases thanks to the fast digitalization of industry. Deep learning (DL) is a branch of machine learning and AI that has been applied to issues like image recognition and object localization, with the help of techniques like convolutional neural networks (CNNs) and other types of deep neural network designs (NNs) (e.g. [3]). The focus will shift from theoretical models to practical applications beginning in 2015. This article provides a comprehensive overview of different areas and demonstrates their utility with several examples.

People are rational creatures, so they learn both formally and informally, from themselves and others. However, unlike humans, computers can learn by following a set of rules called an algorithm. The term "machine learning" is used to describe this approach. Researchers in the field of artificial intelligence developed a method called machine learning (ML) to help computers better understand and take advantage of their environments. ML is based on a set of algorithms that attempt to mimic the learning processes of humans. The term "machine learning" (ML) is often defined as follows: "A computer programme is said to learn from

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experience E relating to given class of tasks T and performance measure P, if its performance at tasks T, as measured by P, improves with experience E." Although ML's conceptual roots can be traced back to the 1950s, it was not officially recognised as a field of study until the 1990s. ML algorithms are used in many different fields, including computer science [4], healthcare [5], the environment, medicine, energy, services, and more.

II. REVIEW OF LITERATURE

The SLR follows the framework of posing a research question, identifying the traits to be emphasised, narrowing the focus to the appropriate literature, and then drawing conclusions and synthesising the findings. These recommendations were adapted from KITCHENHAM ET AL. [6]. To begin, here is the formal research question that guided the structured review that was carried out:Finding the manufacturing industry's use of machine learning applications during the past five years. Additional criteria for primary attention in a typical factory or especially a learning factory environment include manufacturing applications such as manufacturing process planning, quality control, predictive maintenance, logistics, robotics, assistance and learning systems, ML-training concepts in learning factories, and process control and optimization. An overview of each work is provided, along with a mention of the algorithm that was implemented or used to address the issue raised in the study.

2.1 A Machine learning illustration for medical

More over 1.6 million people have lost their lives as of December 22, 2020 due to the SARS-COV-2 pandemic, which has also put a significant burden on the global economy and healthcare systems. A global death toll of around 6,000 per day, with no cure in sight and the chance of novel virus emergence, might kill around 2.2 million people annually. Global mortality and prevalence curves have not decreased [7] despite continued attempts at prevention and social isolation. More focus on clinical therapy in the earliest stages could help reduce fatality rates. A patient in critical condition requires immediate transfer to the intensive care unit (ICU) and insertion of a ventilator. About 54% of critically ill patients in China did not have fast access to the Intensive Care Unit [8], and 30% of those who did not survive did not get prompt mechanical ventilation. In cases where there are numerous patients, medical staff is overworked, and not enough resources to treat each patient, rapid identification of those at high mortality risk becomes critical.

When COVID-19 patients are admitted to the hospital, it is generally too late for doctors to give an accurate diagnosis. To add insult to injury, the course of COVID-19 can take unexpected twists, in which a previously stable patient's status abruptly deteriorates to a critical state [9]; this could surprise even the most seasoned doctors off guard. As AI models are able to spot intricate patterns in massive datasets, they may prove to be invaluable helpers in clinical prediction, a task at which the human brain excels not. From large-scale epidemiological modelling to fine-grained individual diagnosis and prognosis prediction, AI techniques have been used in the fight against COVID-19 [10]. Although a number of prognostic models for COVID-19 have been presented [11], the predictive ability of non-invasive and invasive characteristics has not been systematically examined.

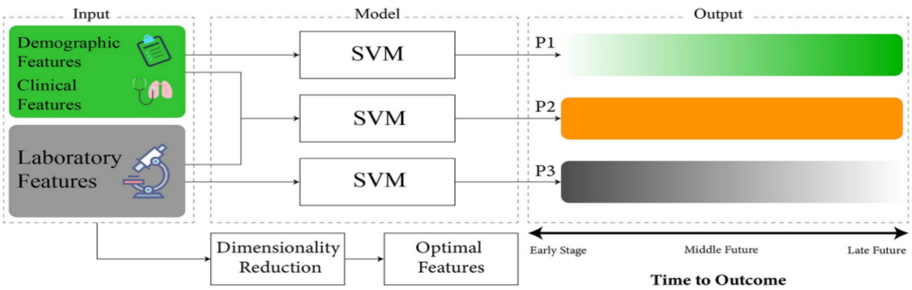

Fig 1. Illustration of the modeling framework.

This study aimed to develop a mortality prediction model using routine clinical data from the first day of admission, investigate the feasibility of predicting COVID-19 mortality outcome using non-invasive patient features, and provide a direct comparison of the mortality prediction powers of non-invasive and invasive features. The invasiveness of laboratory testing and other distinguishing features were used to classify patients into distinct groups. A total of three machine learning models were developed, two using each feature group individually and one using them all together, to evaluate and contrast the projected efficacy of the aforementioned features (Fig 1). Numerous COVID-19 patients have been reported to have experienced an exacerbation episode during the hours of 24 and 48

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following hospital admission [12].As a result, we built our model using information collected on the first day of patients' stays in order to give a practical resource.

III. EXPLORATION, EXPLOITATION OF MACHINE LEARNING APPLICATIONS IN MINING:

The mining sector is beginning to examine adopting "smart mining" practises. The term "smart mining technology" refers to the utilisation of cutting-edge ICTs such the Internet of Things (IoT), big data, mobile, AI, augmented reality, and virtual reality in the extraction of mineral resources. A massive amount of information is being generated, gathered, and disseminated in real time as a result of the evolution of smart mining technologies. Several factors have contributed to the recent surge in popularity of data science in mining. These include the emergence of novel data types (such as drilling data, sensor data, and measurement data), the maturation of AI methods, the enhancement of computers' processing power, and the advent of machine learning (ML).

Application of ML in the mining industry is the focus of a number of ongoing initiatives. In order to extract more gold from Canada's Red Lake mine, Goldcorp's geologists employed IBM's Watson AI Supercomputer to analyse exploration data and locate previously unknown amounts of the precious metal. Heavy equipment manufacturers like Komatsu and NVIDIA have collaborated on projects to improve the mining industry's ability to track its employees and their machinery. New technologies allow for the detection of inefficient machinery and the maintenance of a secure working environment. Pilot projects are being conducted by the Canadian artificial intelligence research institute IVADO and the underground mining safety and operations management services provider Newtrax to collect big data from sensors installed in mining equipment, analyse the data using ML, and predict when the equipment has failed and needs maintenance.

The use of ML in mineral processing, the application of soft computing technology in exploration, the latest developments in digitalization, and the automation of the mining sector are only some of the subjects discussed. The study covers mineral exploration, mining, and mine reclamation; nevertheless, a more thorough introduction of ML's applications in the mining industry would be helpful.

Structured data (such as tables of numbers) and unstructured data (such as images and papers) make up the bulk of what is commonly referred to as "big data". In other words, it's a data-intensive technology. By their very nature, ML algorithms get better as more data is fed into them. In this way, data plays an important role in ML studies. Data in abundance is useful and transferable to other settings like hospitals and universities. We looked at research with big data-related discussions or comments.

IV. MACHINE LEARNING APPLICATIONS TO THE OIL AND GAS INDUSTRY

The most common problem addressed by ML petroleum researchers is how to generalise the results of ML models, which are typically exclusive to the data set evaluated. Overfitting, coincidence, excessive training, lack of interpretability of outcomes, and bias are only a few of the ML applications' widespread limits and problems that prevent the globalisation of the produced models. Furthermore, these models call for a substantial amount of data that is often lacking.

When there is no predetermined point at which training should end, overtraining can occur. It's possible that changing the model structure, including the weights, will continue the trend of decreasing error. The true danger then is that the model becomes overfit to a particular dataset, making further generalisation unfeasible. Early stopping is a training strategy that employs a control set to keep an eye on how things are going during the training process and stop when it looks like enough is enough. The training process will be terminated prematurely if the rate of error increases. To conserve time and energy, reinforcement learning with instream supervision is utilised. Generative adversarial networks, which take a look at the development of two rival networks to comprehend the model concept, are conceptually similar to this method.

Generalizability issues in existing AI models are a major hurdle to AI's mainstream adoption in the oil and gas industry. Many models struggle when applied to conditions outside of those used to create them. When training on new datasets, additional resources should be used even if the dataset is comparable to one previously trained. Further complicating matters is the fact that reusing ML models is quite difficult. In most cases, the performance of models trained on one geological field suffers when applied to another. When the given dataset's input parameters are within the range of the input parameters on which the model is to be built, it is strongly advised to do so.

V. CONCLUSION

The relevant SLR examined the state of the art during the past few years (2015-2022), with a particular emphasis on concrete examples and the specific nomenclature of applied machine learning algorithms in the manufacturing context of each piece of literature. Numerous publications make use of these technologies to create novel applications that improve upon existing industrial methods. With regards to the machine learning approach, supervised approaches are now considered state-of-the-art, while reinforcement learning approaches have received greater research attention over the past few years. Simply two references were found to unsupervised approaches, which may be because many papers only explained the implemented regression or classification job in detail, leaving out the actual data preparation and investigation. The authors believe that unsupervised approaches are used extensively throughout the data analysis process, even if they are not specifically specified. Researchers in the mining, oil, and gas industries, as well as those working in the medical field, have all done systematic assessments of the most up-to-date ML research to determine where the field is headed. The review serves as a summary of previous studies and a guide for additional studies.

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