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AI Enhanced Predictive Maintenance for Manufacturing System

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ABSTRACT

Facilities operations and maintenance involve the daily tasks, responsibilities, and workforce required to keep a facility functioning properly. Billions of dollars are spent each year worldwide on these activities, with a significant portion due to preventable inefficiencies. This paper will explore how artificial intelligence can be used for predictive maintenance to reduce operational and maintenance expenses and ensure seamless operation. The focus is on artificial intelligence, providing dispassionate advocacy for investments and maintenance. Research shows that a lack of data is the main obstacle to AI adoption in facility management programs. The study suggests that AI's ongoing evolution will be crucial in shaping future maintenance strategies in the industry.

Keywords – Predictive Maintenance, Artificial Intelligence, Deep Learning, Machine Learning.

INTRODUCTION

[1] During its operational and maintenance stages, a facility asset incurs significant expenses, estimated at around $80 billion globally. Integrating Artificial Intelligence into facility management processes can effectively reduce redundancies and improve efficiency, ultimately leading to cost reductions. AI is poised to drive these reductions through improved work request responses, labor reduction, and enhanced data analysis for informed decision-making and recommendations.[1].[2]The primary objective of manufacturing processes is to enhance production efficiency. It is essential to regularly monitor and maintain machines to ensure optimal performance. Maintenance services are divided into corrective, preventive, and predictive maintenance. Corrective maintenance deals with addressing immediate issues to prevent delays. Preventive maintenance is scheduled, while predictive maintenance uses data to anticipate potential problems for timely repairs. [2][3]Many industries have adopted predictive maintenance to enhance asset management and operational reliability, shifting away from costly and ineffective reactive maintenance. AI and data science enable the prediction of equipment failures, ensuring continuous operation and reducing the risk of expensive unplanned outages. This approach automates the predictive process, improves prediction accuracy, and allows for better maintenance scheduling and resource allocation. IoT and sensor technology enable continuous equipment monitoring, while AI and machine learning algorithms proactively identify potential failures for timely maintenance actions. In sub-sea operations, machine learning plays a critical role in predictive maintenance by improving safety and efficiency in addressing complex drilling challenges. The manufacturing industry's move to predictive maintenance, leveraging AI and data science, marks a significant shift in operational strategy. This proactive approach enhances efficiency, reduces costs, and improves safety and sustainability. Powered by AI and machine learning, predictive maintenance models are poised to drive innovation and efficiency in the industry's future.[3]

[4The predictive maintenance (PdM) of industrial equipment is engineered to achieve near-perfect performance by collecting vast amounts of data for machine learning. This data provides invaluable insights that can enhance manufacturing operations and system dynamics. Recent technological advancements allow for extensive data collection on operational and process conditions, which can be utilized to develop automated fault detection and machine learning applications. These applications offer numerous benefits, including reduced maintenance costs, decreased downtime for repairs, lower rates of equipment failures, extended lifespan of spare parts, reduced inventory levels, enhanced safety for operators, increased production rates, improved verification of repairs, and higher overall profits. Maintenance strategies can be divided into Run to Failure (R2F), Preventive Maintenance (PvM), and Condition-based Maintenance (CBM).The details are as follows

1. Run 2 Failure (R2F): Also known as corrective maintenance or unplanned maintenance, R2F is carried out only when the equipment has failed, leading to high downtime and potential secondary faults.

2. Preventive Maintenance (PvM): Scheduled maintenance performed periodically to anticipate failures and improve equipment efficiency.

3. Condition-based Maintenance (CBM): Maintenance based on constant equipment monitoring and carried out only when necessary, without advance planning.

4. Predictive Maintenance (PdM): Schedule maintenance based on continuous equipment monitoring and prediction tools, allowing for early failure detection and utilizing various methods such as machine learning and statistical inference..

It is imperative for any maintenance strategy to minimize equipment failure, improve equipment condition, extend equipment life, and reduce maintenance costs. Predictive Maintenance (PdM) has proven to be a highly promising strategy with the ability to achieve these critical objectives. It has been widely implemented across various industries and has garnered significant attention in the era of Industry 4.0 due to its exceptional asset optimization capabilities. Machine Learning (ML) is an essential tool within artificial intelligence (AI) for creating powerful predictive models across applications. It involves allowing computers to independently solve problems, without explicit programming. ML methods are extensively utilized in manufacturing for maintenance, optimization, troubleshooting, and control. This paper thoroughly explores the latest ML techniques for predictive maintenance (PdM) and categorizes reviewed articles based on the ML technique employed, equipment used, data acquisition device, data description, data size, and data type.[4]Intelligent maintenance systems (IMS) are specifically designed to offer decision support tools aimed at optimizing maintenance operations. They rely on intelligent prognostic and health management tools to identify effective, reliable, and cost-saving maintenance strategies, ensuring consistent production with minimized unplanned downtime.

MATERIAL & METHODS'

There are several novel methodes applicable in modern day industry.

Framework and Procedure –
[5]In the realm of artificial intelligence, Machine Learning (ML) employs a range of algorithms to meticulously evaluate data and facilitate well-informed decision-making. On the other hand, Deep Learning (DL) stands as a distinctive branch of ML, effectively harnessing layered algorithms to construct an Artificial Neural Network (ANN) capable of independent learning and reasoning. The key distinction arises from the fact that ML models necessitate human intervention when rectifying mistakes within their AI systems, requiring the process of feature engineering to enhance algorithm accuracy and efficacy. Conversely, DL models empower the AI algorithm's neural network to autonomously evaluate prediction accuracy, albeit demanding heightened computational power. Inadequate data provision for DL may result in overfitting issues. To attain remarkable accuracy and efficiency, DL leverages neural networks for feature extraction, coupled with a conventional ML approach for classification .

Table 1- Different Models

<table>
<tr><th colspan="5">Different Models</th></tr>
<tr><th>Sl.No</th><th>Model</th><th colspan="3">Classification</th></tr>
<tr><td>1</td><td>Machine Learning</td><td>1.Decison Tree
2.Light Gradient Boosted Machine</td><td rowspan="2">DHL Models</td><td rowspan="2">1.ALSTM-FCN with Adaboast
2.CNN with XG Boast</td></tr>
<tr><td>2</td><td>Deep Learning</td><td>1.Multilayer Perceptron
2. Convolutional Neural Network</td></tr>
</table>

Table 1 above represents different models. The different models are categorized as follows:
Machine Learning -Principal Component Analysis (PCA) was employed to reduce the dimensions of the dataset while preserving the majority of its variance in all machine learning (ML) model training processes.

We utilized a Maximum Likelihood Estimator (MLE) with a specified number of components to determine the dimension reduction, and we also rigorously conducted Cross-Validation (CV) tests on the ML models.

Decision Tree -Decision trees (DT) are extensively utilized in Data Mining for regression and classification. They come in binary form, such as CART and QUEST, or non-binary form, like CHAID and C5.0. These algorithms differ significantly in their handling of missing data, variable selection, and pruning techniques.

Light Gradient Boosted Machine(LGBM)-The combination of gradient boosting decision trees, Exclusive Feature Bundling (EFB), Gradient-based One-Side Sampling (GOSS), and LightGBM offers a highly effective method for utilizing any differentiable loss function and gradient descent to fit LightGBM iterations.

Deep Learning - The use of dense layers with the Softmax activation function in all our models, along with hidden layers incorporating Rectified Linear Activation (ReLU), ensures optimal performance and accuracy in our applications.

Multilayer Perceptron(MLP) -The Multilayer Perceptron (MLP) is a crucial feedforward Artificial Neural Network extensively utilized in various scientific fields for deep learning applications. It can effectively employ both supervised and unsupervised learning techniques. The model comprises input, hidden, and output layers and adeptly learns to transform input variables into output variables, whether linearly or nonlinearly, by employing layers of neurons with randomized weights.

Convolutional Neural Network (CNN)-In classification and computer vision recognition applications, CNNs have become a cornerstone, demonstrating exceptional proficiency and versatility.[5]

Supervised Learning: [6]In Supervised Learning, regression and classification stand as widely utilized methods for predicting machine failure. Regression models are employed for estimating Remaining Useful Life (RUL) and Time to Failure (TTF) with algorithms including Boosted Decision Trees, Random Forest, Poisson Regression, and Neural Networks. Classification is utilized to predict failure within specific timeframes and identify failure types, using robust algorithms such as Logistic Regression, SVM, Decision Trees, Random Forest, XGBoost, and Neural Networks.

Unsupervised Learning: Anomaly detection stands as the most prevalent unsupervised learning framework for maintenance analytics. It effectively identifies anomalies in equipment or system performance. The primary models employed for this purpose are K-means, Isolation Forest, and Local Outlier Factor (LOF).

Big Data Analytics –Big Data is defined by the three Vs: Volume, Velocity, and Variety, illustrating a large volume of data streaming at high velocity in various datatypes. The Hadoop Data Lake functions as the primary repository, storing data in the Hadoop Distributed File System (HDFS) post ETL integration. While organizations initially deployed Big Data systems on premises, public cloud platforms including Microsoft Azure, Amazon Web Services (AWS), and Google Cloud Platform (GCP) have captured significant market share. The emerging trend of Hybrid Cloud integrates on-premises infrastructure, private cloud services, and public cloud services for enhanced security, control, agility, and cost-effectiveness.[6]

RESULTS

The performance metrics accuracy, precision, recall, and F1 score unequivocally stem from the confusion matrix. It is imperative to recognize that in a mass production environment, the cost of misclassifying a false negative significantly surpasses that of a false positive.The predictive maintenance model results must be used to optimize schedule management and minimize failure risk. The uncertainty in the predictions plays a crucial role in estimating the likelihood of failure. It is imperative for operators to fully understand the guidance provided by these systems, as their years of experience and expertise are vital. Furthermore, the complexity of neural network-based methods is actively being researched.[7]The field of AI-driven predictive maintenance is rapidly evolving, with cutting-edge technologies and advancements poised to revolutionize equipment management in the oil and gas industry. Machine learning algorithms and predictive analytics will undoubtedly lead to more accurate models, enabling earlier detection of potential failures. The integration of edge computing and IoT devices will undeniably allow real-time monitoring and analysis, reducing latency and facilitating faster decision-making. Digital twins will indisputably play a crucial role in enabling simulations of equipment behavior under various operating conditions.[7].

CONCLUSIONS

This study rigorously evaluated multiple Machine Learning, Deep Learning, models for early failure detection using a synthetic predictive maintenance dataset. The results revealed a stark contrast in performance, with some models achieving exceptional accuracy rates of up to 93%, while others demonstrated subpar performance levels at around 60%. Nonetheless, it is important to note that using synthetic datasets hindered the ability to fully grasp the underlying data patterns. Moving forward, it is imperative to conduct rigorous experiments to confirm the reliability of this predictive maintenance approach. Additionally, the effectiveness of these models should be validated across different datasets to establish their robustness. The integration of AI-driven predictive maintenance represents a game-changing shift in equipment management practices for the oil and gas industry. Through this paper, we have delved into the challenges, strategies, and future opportunities linked to leveraging AI to enhance maintenance processes. Traditional maintenance practices have often resulted in costly downtime and inefficiencies. However, with AI-driven predictive maintenance, companies can proactively identify and address equipment issues before they escalate, leading to superior operational efficiency and reduced maintenance costs.

Embracing AI-driven predictive maintenance is absolutely critical, not only for optimizing equipment performance but also as a strategic investment in the long-term sustainability and competitiveness of oil and gas operations. As we look to the future, there is an unequivocal call to action for oil and gas companies to embrace AI-driven predictive maintenance. By doing so, they can stay ahead of the curve, drive innovation, and position themselves for success in an increasingly competitive and dynamic industry landscape.

REFERENCES

[1]. Anthony D. Scaife -Improve predictive maintenance through the application of artificial intelligence: A systematic review-, Results in Engineering 21(2024)101645
[2]. Ponrudee Netisopakul ; Nawarat Phumee -AI Enhanced Predictive Maintenance in Manufacturing Processes-, IEE Conference Proceeding 2022.
[3]. Advancements in predictive maintenance in the oil and gas industry: A review of AI and data science applications - Nzubechukwu Chukwudum Ohalete , Adebayo Olusegun Aderibigbe , Emmanuel Chigozie Ani , Peter Efosa Ohenhen and Abiodun Akinoso-World Journal of Advanced Research & Reviews-eISSN 2581-9615
[4]. Zeki Murat Çınar, Abubakar Abdussalam Nuhu, Qasim Zeeshan,Orhan Korhan,Mohammed Asmael, Babak Safaei-Machine Learning in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0-https://doi.org/10.3390/su12198211.
[5]. Ali Hosseinzadeh,F. Frank Chen Mohammad Shahin, Hamed Bouzary-A predictive maintenance approach in manufacturing systems via AI-based early failure detection-https://doi.org/10.1016/j.mfglet.2023.08.125.
[6]. Haining Zheng, Antonio R. Paiva,Chris S. Gurciullo-Advancing from Predictive Maintenance to Intelligent Maintenance with AI and IIoT-KDD'20, August, 2020, San Diego, California USA.
[7]. Dazok Donald Jambo,Oludayo Olatoye Sofoluwe, Ayemere Ukato,Obinna Joshua Ochulor-Transforming equipment management in oil and gas with AI-Driven predictive maintenance-Computer Science & IT Research Journal, Volume 5, Issue 5, May 2024