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ENHANCING AND EXPLAINING ENERGY MANAGEMENT IN SMART MANUFACTURING PRODUCTION VIA ML WITHIN THE CONTEXT OF INDUSTRY 4.0

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ABSTRACT

Objectives: This study aims to explore the integration of big data and machine learning to enhance energy efficiency in manufacturing, focusing on the opportunities presented by Industry 4.0 and cyber-physical production systems.

Theoretical Framework: The research leverages supervised learning techniques to analyze and predict machine-specific energy consumption patterns, utilizing energy disaggregation as a foundational concept.

Method: Various machine learning algorithms, including Lasso regression, Linear regression, and Decision Tree, will be employed to develop predictive models for energy usage. Additionally, Explainable Machine Learning (XML) techniques will be utilized to ensure interpretability and clarity in the prediction outcomes.

Results and Discussion: The proposed framework aims to elucidate the relationship between equipment utility and energy consumption, providing comprehensible explanations that enhance decision-making processes within intelligent industrial environments.

Research Implications: This work highlights the significant potential of XML in transforming machine learning applications in manufacturing, paving the way for improved energy efficiency and operational effectiveness.

Originality/Value: The introduction of an innovative framework that combines machine learning with explainability in the context of energy consumption marks a valuable contribution to the fields of manufacturing and sustainable industry practices.

Keywords: Smart Manufacturing, Industry 4.0, ML, Shapley Value, XML.

MELHORAR E EXPLICAR A GESTÃO DA ENERGIA NA PRODUÇÃO INTELIGENTE DE MANUFATURA ATRAVÉS DO ML NO CONTEXTO DA INDÚSTRIA 4.0

RESUMO

Objetivos: Este estudo tem como objetivo explorar a integração de big data e aprendizagem de máquina para melhorar a eficiência energética na fabricação, com foco nas oportunidades apresentadas pela Indústria 4.0 e sistemas de produção ciberfísicos.

Estrutura Teórica: A pesquisa utiliza técnicas supervisionadas de aprendizagem para analisar e prever padrões de consumo de energia específicos da máquina, utilizando a desagregação de energia como um conceito fundamental.

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Método: Vários algoritmos de aprendizagem de máquina, incluindo regressão de laço, regressão linear e árvore de decisão, serão empregados para desenvolver modelos preditivos para o uso de energia. Além disso, serão utilizadas técnicas de XML (Explainable Machine Learning) para garantir a interpretabilidade e clareza nos resultados da previsão.

Resultados e Discussão: A estrutura proposta visa elucidar a relação entre a utilidade do equipamento e o consumo de energia, fornecendo explicações compreensíveis que melhoram os processos de tomada de decisão em ambientes industriais inteligentes.

Implicações da pesquisa: Este trabalho destaca o potencial significativo do XML na transformação de aplicativos de aprendizagem de máquina na fabricação, preparando o caminho para uma melhor eficiência energética e eficácia operacional.

Originalidade/valor: A introdução de um quadro inovador que combina aprendizagem de máquina com explicabilidade no contexto do consumo de energia marca uma contribuição valiosa para os campos de fabricação e práticas industriais sustentáveis.

Palavras-chave: Smart Manufacturing, Industry 4.0, ML, Shapley Value, XML.

MEJORA Y EXPLICACIÓN DE LA GESTIÓN DE LA ENERGÍA EN LA PRODUCCIÓN DE FABRICACIÓN INTELIGENTE A TRAVÉS DE ML EN EL CONTEXTO DE LA INDUSTRIA 4.0

RESUMEN

Objetivos: Este estudio tiene como objetivo explorar la integración de big data y aprendizaje automático para mejorar la eficiencia energética en la fabricación, centrándose en las oportunidades presentadas por la Industria 4.0 y los sistemas de producción ciberfísica.

Marco teórico: La investigación aprovecha técnicas de aprendizaje supervisado para analizar y predecir patrones de consumo de energía específicos de las máquinas, utilizando la desagregación de energía como concepto fundamental.

Método: Se emplearán varios algoritmos de aprendizaje automático, incluyendo la regresión de Lasso, la regresión lineal y el árbol de decisiones, para desarrollar modelos predictivos para el uso de energía. Además, se utilizarán técnicas de aprendizaje automático explicable (XML) para garantizar la interpretabilidad y claridad de los resultados de la predicción.

Resultados y Discusión: El marco propuesto tiene como objetivo dilucidar la relación entre la utilidad de los equipos y el consumo de energía, proporcionando explicaciones comprensibles que mejoran los procesos de toma de decisiones dentro de entornos industriales inteligentes.

Implicaciones de la investigación: Este trabajo destaca el importante potencial de XML para transformar las aplicaciones de aprendizaje automático en la fabricación, allanando el camino para una mejor eficiencia energética y eficacia operativa.

Originalidad/Valor: La introducción de un marco innovador que combina el aprendizaje automático con la explicabilidad en el contexto del consumo de energía constituye una valiosa contribución a los ámbitos de la fabricación y a las prácticas sostenibles de la industria.

Palabras clave: Fabricación Inteligente, Industria 4.0, ML, Valor Shapley, XML.

1 INTRODUCTION

The conventional categories of energy users include residential, commercial, manufacturing, transportation, and others like agriculture and fishing [1]. Among these, the industrial sector is notably diverse, comprising approximately 30% of global energy consumption, with manufacturing industries alone accounting for nearly 50% [1]. Industrial machinery and equipment, essential components across all manufacturing sectors, are identified as responsible for over 75% of energy usage within manufacturing [2]. To reduce energy consumption, process-manufacturing firms often adopt strategies such as optimizing production planning and scheduling, refining machining operations, and mitigating power surges during extended production cycles [3].

Understanding and quantifying energy consumption is crucial for optimizing manufacturing operations, managing facilities effectively, and reducing energy usage in process manufacturing. In pursuit of this goal, analyzing and monitoring energy load patterns within workshop environments is commonly practiced to track energy consumption throughout various stages of production [4]. Process manufacturing involves a complex network of essential machinery, support equipment, and materials, characterized by dynamic interactions between energy and materials throughout the production process.

In process and industrial manufacturing, there has been a notable surge of interest in energy profiling and management in recent years, resulting in significant advancements. Rodrigues and colleagues [5] combined discrete event simulation with optimization techniques to analyze energy usage within manufacturing systems, examining both individual machines and the overall process. Seow et al. [6] utilized data encompassing direct and indirect energy usage to develop models that depict energy flow in manufacturing environments and enable energy consumption predictions at each stage of production. Herrmann et al. [7] developed a specialized modelling platform tailored for energy optimization in industrial settings, offering a highly adaptable, scalable, and modular framework. Meanwhile, Kohl et al. [8] integrated an energy module into an existing material flow modelling system, Plant Simulation, to establish machine and process load profiles for calculating energy consumption across specific equipment and the entire manufacturing process from start to finish.

The advent of Industry 4.0 has spurred exploration into intelligent manufacturing methodologies that leverage manufacturing big data, industrial IoT, and data-driven predictive analytics through machine learning. Machine learning applications in manufacturing are typically categorized into three main areas: process monitoring and control, predictive maintenance, and optimization of production and supply chain operations, as highlighted in various studies [9]. Integrating technologies that enhance energy efficiency in process manufacturing, facilitated by modern digital advancements such as big data, IoT, and machine learning, can result in reduced energy consumption compared to traditional operational excellence programs [10]. Numerous frameworks have been proposed to harness industrial big data and machine learning for achieving specific objectives. This study introduces an innovative three-phase framework designed to address energy management across all stages of process manufacturing, from planning to execution. This framework is adaptable for implementation in manufacturing facilities where machinery and processes heavily rely on electricity for operations. The initial phase involves forecasting energy consumption patterns of individual machines by analyzing centralized load data. Subsequently, energy consumption profiles specific to each machine are computed to assess production capacity and operational status. To validate the framework, a real-world pilot-scale production facility known as the Model Factory was chosen, equipped with advanced technologies like CPPS, IoT, and AI.

AI holds the potential to revolutionize the manufacturing industry entirely. It promises benefits such as heightened productivity, reduced costs, improved quality, and minimized downtime. While large factories are already leveraging this technology, it's crucial for smaller businesses to recognize how accessible high-value, cost-effective AI solutions have become.

With the vast amount of data generated daily by industrial IoT and smart factories, artificial intelligence has numerous potential applications in manufacturing. Manufacturers are increasingly adopting AI solutions such as machine learning (ML) and deep learning neural networks to analyze data more effectively and enhance decision-making processes.

Predictive maintenance stands out as a prominent application of artificial intelligence in manufacturing. AI can be employed to analyze production data, leading to improved predictions of equipment failures and more efficient maintenance planning. As a result, downtime can be minimized.

AI indeed offers accurate predictions, particularly in applications such as predictive maintenance. However, ensuring the reliability and interpretability of these predictions is crucial. Methods like SHAP (SHapley Additive exPlanations) play a significant role in this validation process. SHAP provides explanations for individual predictions from machine learning models, helping to understand the contribution of each feature to the model's output. This interpretability not only enhances trust in AI-driven predictions but also allows stakeholders to make informed decisions based on AI recommendations in manufacturing and other domains.

The article is structured in the following manner: Section 2 presents the literature review. Section 3 outlines the modelling energy consumption using machine learning. Section 4 details the model. Section 5 discusses the numerical result and application for industrial manufactory. Section 6 provides a summary of the work and a brief discussion of future directions.

2 LITERATURE REVIEW

In the realm of energy systems and manufacturing, several studies have examined the application of machine learning models. Mosavi et al. (2019) [11] conducted a literature review on this topic, while Walther and Weigold (2021) [12] focused on research pertaining to predicting electricity consumption in the manufacturing sector. Morariu et al. (2020) [13] proposed a method using Long Short-Term Memory neural networks to predict real-time energy consumption patterns, and Ribeiro et al. (2020) [14] used deep learning for forecasting demand-side power usage. Tan et al. (2021) [15] developed machine learning methods to forecast equipment-specific energy consumption patterns in a chemical plant. Similarly, Essien et al. (2020) [16] extended predictive intelligence from smart manufacturing to forecast energy use using historical data.

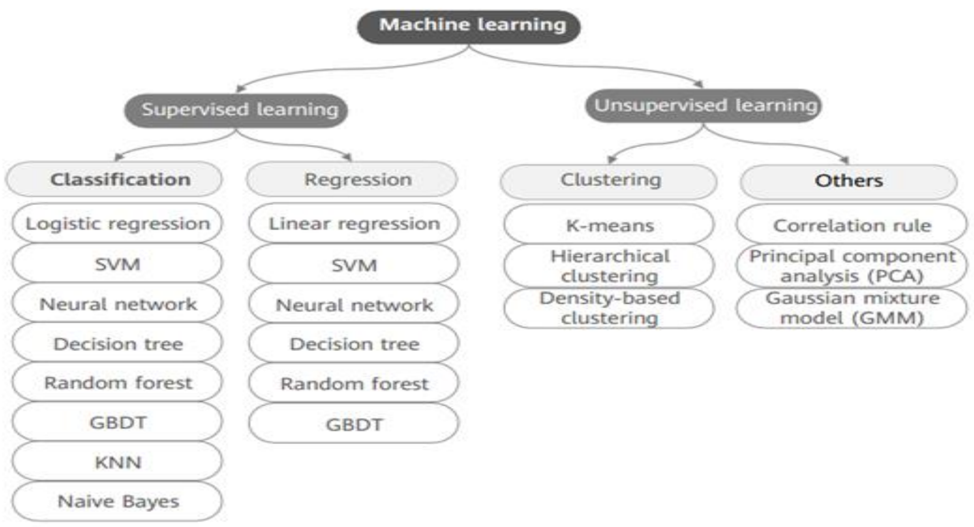
Mirandola et al. (2021) [17] employed machine learning models to estimate energy consumption in metal shaping processes, while Li et al. (2021) [18] proposed a hybrid machine learning strategy for additive manufacturing systems. Kuo-Hao Chang et al. (2021) developed predictive models for machine energy efficiency and optimization tools in the semiconductor sector, and Milczarski et al. (2020) [19] validated food processing manufacturing processes using classification machine learning models. Finally, Willenbacher et al. (2021) [20] applied machine learning to optimize energy usage and reduce defects in plastic parts production within small and medium-sized enterprises.

3 MODELING ENERGY CONSUMPTION USING MACHINE LEARNING

3.1 PREDICTION METHODS

Figure 1

Different machine learning algorithms



According to Fig 1, there are several machine learning algorithms (supervised and unsupervised)

In this article, we discuss our learning framework and explore why we chose a supervised learning approach.

Supervised learning involves predicting outcomes based on labeled training data. In classification tasks, where the target variable is discrete (e.g., identifying sentiment in text), the model learns to assign labels to input data based on patterns in the training set. For regression tasks, where the target variable is continuous (e.g., predicting salary based on education, work experience, location, and seniority), the model predicts numeric values by establishing relationships between predictors and the target.

Classification is a supervised learning method where the model is trained on labeled data and assessed on unseen test data before making predictions on new data.

To predict energy usage, we utilize various established regression methods: multiple linear regression, decision tree regression, random forest regression, and extreme gradient boost regression.

Multiple linear regression models the relationship between the dependent variable (e.g., energy usage) and several predictor variables (e.g., industry type, production output, employee count, facility size) assuming a linear association among them.

This approach allows us to estimate energy consumption effectively by leveraging these predictive models.

A decision tree (see Fig 2) is structured like a tree, which can be either binary or non-binary. In this structure:

Each non-leaf node represents a test on a feature attribute.

Each branch emanating from a node represents the outcome of the test for a particular value or range of values of the feature attribute.

Each leaf node contains a category or a class label.

To utilize a decision tree for classification:

Begin at the root node of the tree.

Evaluate the feature attributes of the item to be classified based on the tests at each node.

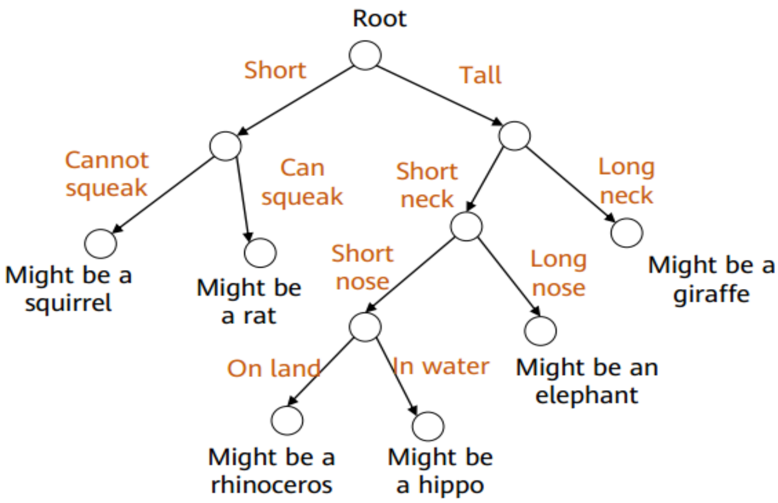
Traverse down the tree by following the appropriate branches based on the outcomes of these tests.

Eventually, arrive at a leaf node, which contains the category or class label that corresponds to the final classification result.

This method allows decision trees to effectively categorize or classify items by sequentially evaluating different attributes until a definitive decision (category) is reached at the leaf nodes of the tree.

Figure 2

Explanation of decision tree



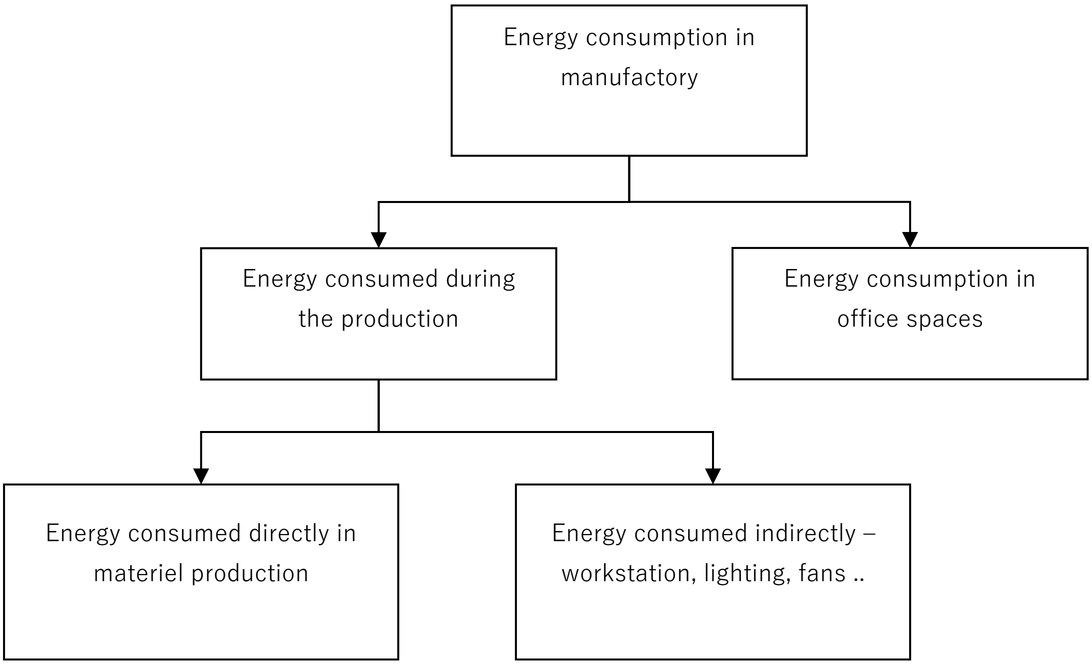
- Random forest regressor: A development of Decision Tree Regression, this method combines the output of various decision trees by generating them randomly.
- Extreme gradient boost regressor: This method creates ensembles using decision tree models as a starting point. It incorporates trees incrementally while making simple utilization and fitting to minimize the gradient loss, thereby fixing the inaccurate predictions made by previous models.

4 MODEL

4.1 DIFFERENT ENERGY CONSUMPTION IN MANUFACTORY

Figure 3

Energy use in a manufacturing facility



This framework outlines a structured approach to effectively develop models that can accurately estimate the potential energy consumption resulting from various interventions or initiatives.

This preliminary analysis also involves gathering general data about the facility, including details like its products, shift schedules, workforce size, floor space, and yearly utility consumption. This information helps energy assessors understand the facility's energy service rate structures and its day-to-day operations patterns throughout the day, week, and year, prior to conducting the audit. During the audit, the energy assessors conduct a comprehensive facility tour to gather additional information about the equipment and practices employed throughout the plant. Based on the information acquired during the tour, the auditors provide recommendations for energy-efficient practices that the facility could adopt to conserve energy and reduce costs. The final stage of the audit process entails the creation of a comprehensive report. The conclusive report consolidates all information obtained during the audit, comprising the foundational analysis & suggestion. The particular suggestions outline the proposed measures, present economic and environmental benefits calculations, and discuss implementation costs and internal rates of return. The ultimate document succinctly compiles all suggested measures for the facility's improvement.

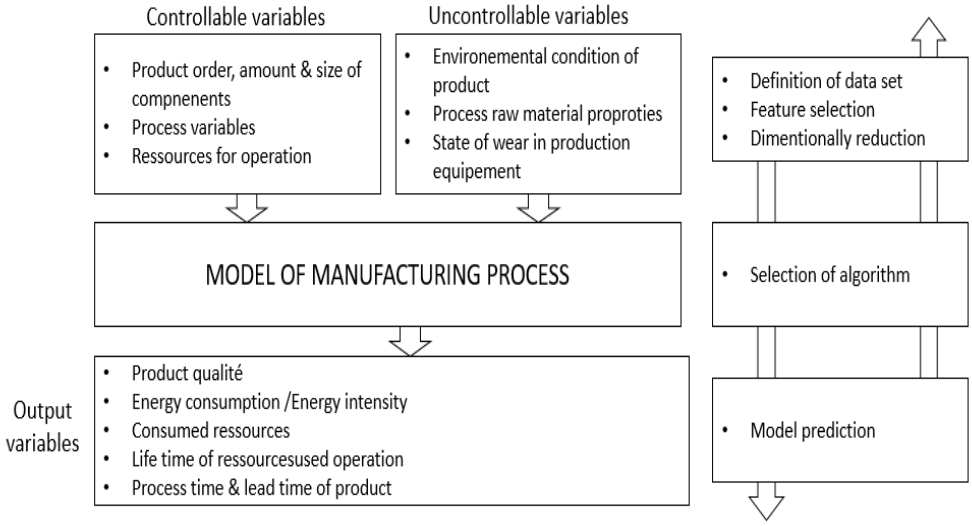
Fig 4 illustrates a data-driven modeling approach that leverages both product and process data.

The process of modeling, particularly in selecting a suitable machine learning (ML) model, is greatly influenced by the challenges posed, the amount, diversity, and speed at which data is gathered. (Sen et al., 2016) [21]. Consequently, there exists an intimate connection between the "Data integration" and "Modeling" steps. Often, data issues become apparent during the modeling stage or provide insights when new data is collected.

In the demonstrated modeling approach depicted in Fig 4, factors associated with the characteristics of the procedure and product are carefully selected. This selection process can be performed automatically or with the assistance of an expert (Goodfellow et al., 2016) [22]. For instance, choosing certain features of a product, such as its edge, while disregarding its color, involves feature selection. The identification and elimination of irrelevant and redundant features help reduce data dimensionality, enabling ML models to operate more efficiently and effectively (Yu & Liu, 2004) [23]. Representative sensor readings from a specific product type are retained, preserving their key characteristics (features of the product type), while irrelevant correlations are eliminated or excluded.

Figure 4

Approach to broad data-centric manufacturing process modeling.



In manufacturing plants, there are no models grounded in fundamental physical principles accessible for many interrelationships. However, in many cases, there exists a vast and extensive database of information. To address this, a unified approach is presented in Fig 4 to model the behavior of products within the manufacturing process. This model represents a fundamental contribution made by this article.

From a data-driven perspective, Fig 4 presents a comprehensive view of a manufacturing process, incorporating both product and process data. The influences within the process are categorized them into distinct input and output categories. The primary objective of this data-driven modeling approach is to enable the application of machine learning (ML) methods, specifically to enhance energy efficiency.

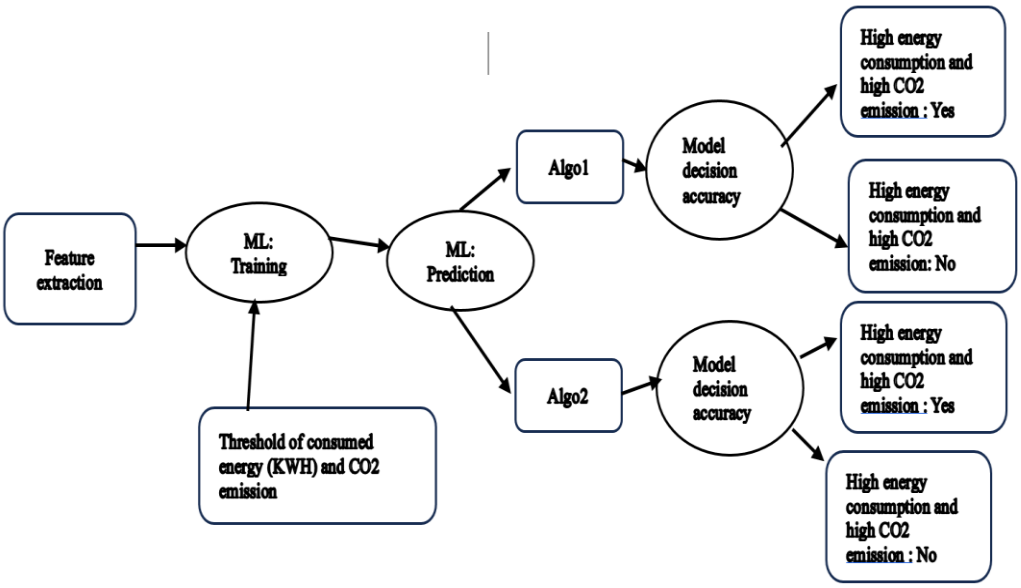
In Fig 4, the input section is further divided into two categories: controllable and uncontrollable parameters. In this data-driven model, parameters are considered as variables. Controllable variables refer to those that is subject to active adjustments or modified during the processing phase of the product. On the other hand, uncontrollable variables are measurable variables that cannot be directly influenced but serve as sources of information within the model.

To effectively utilize this generalized modeling approach for presenting the process behavior and reducing energy consumption while maintaining product quality, process should be included as output variables in the model. This allows the specific model to learn and understand the influence of input variables based on manufacturing data. It is crucial to encompass all relevant information that impacts the output variables within the input variables, whether they are controllable or uncontrollable.

Without adequately capturing all pertinent information, it becomes challenging to train a model with precision. The performance of the model plays a critical role in this approach and subsequent steps within the suggested framework. Insufficient model effectiveness can hinder the effectiveness of subsequent steps such as optimization or process control, thus limiting their potential to positively impact the energy efficiency of the manufacturing process.

Figure 5

Process involving machine learning (ML) algorithms for classification based on energy consumption and CO2 emissions.



It is a flowchart (Fig 5) representing a process involving machine learning (ML) algorithms for classification based on energy consumption and CO2 emissions.

The overall structure suggests a decision-making process where algorithms are trained and then used to predict outcomes, and the accuracy of these predictions is evaluated to determine whether the result is "yes (high energy consumption with CO2 emissions)" or "no (low energy consumption with no CO2 emissions)," based on specific steps:

1: Feature Extraction: In the first step, Feature Extraction, raw data is transformed into meaningful features that can be used to train a model.

2: Training: The next step involves training the model to recognize whether the equipment to be built will require significant electrical energy and thus result in high CO_2 emissions ("yes") or the opposite ("no"). In our case, supervised learning algorithms such as decision tree algorithm or linear regression are used for this purpose.

3: Prediction: After being trained, the model will use prediction algorithms.

4: Decision Tree Algorithm (Algo1): The decision tree algorithm is a supervised learning model used for classification and regression. It recursively divides the dataset into homogeneous subsets based on the most discriminative features. Linear Regression Algorithm (Algo2): Linear regression is a supervised learning algorithm used to predict the value of a continuous variable based on other variables.

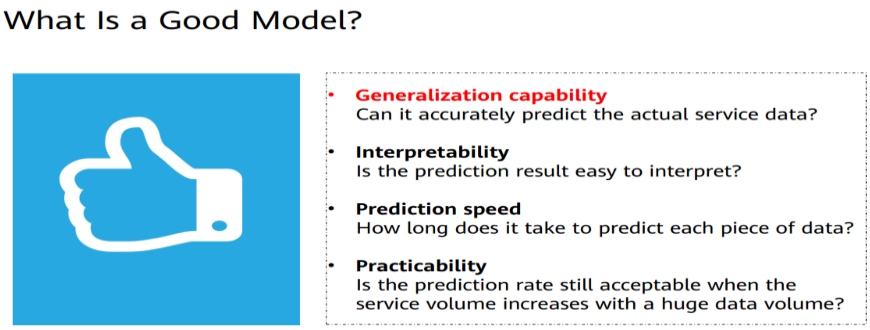
6: Decision: Using the model's prediction results, a decision is made to determine whether the observed behavior is desirable or not. If the model predicts that the equipment will require a lot of energy for its construction, an alert is triggered to notify industrial engineers so that they can investigate and take corrective actions.

4.2 EXPLAINING ML WITH SHAPLY

4.2.1 XML

Figure 6

What is a good model?



Explainable Machine Learning (XML) [24] refers to a range of methodologies and processes designed to help humans understand and trust the outcomes generated by machine learning (ML) models. Its importance lies in providing clarity and insight into how these models function, which becomes increasingly crucial as ML models become more complex.

In practical terms, XML serves to elucidate the decision-making processes of ML algorithms. This transparency is essential for companies aiming to build trust in the use of ML models within their operational systems. As ML algorithms evolve and grow more sophisticated, understanding the reasoning behind their predictions poses a significant challenge due to their often opaque "black box" nature.

In the realm of traditional machine learning, where computations stem from data, XML addresses the opacity associated with intricate algorithms. Even for data scientists developing these models, explaining the exact rationale behind a model's outputs can be challenging. Therefore, the demand for XML is pivotal in ensuring accountability, fostering trust, and facilitating the practical integration of ML models into real-world applications.

The benefits of understanding how ML arrives at specific results include:

Assisting developers in confirming that systems operate as intended.

Providing explanations to stakeholders about why ML produces certain outputs.

Allowing affected parties to influence or modify outcomes based on these explanations.

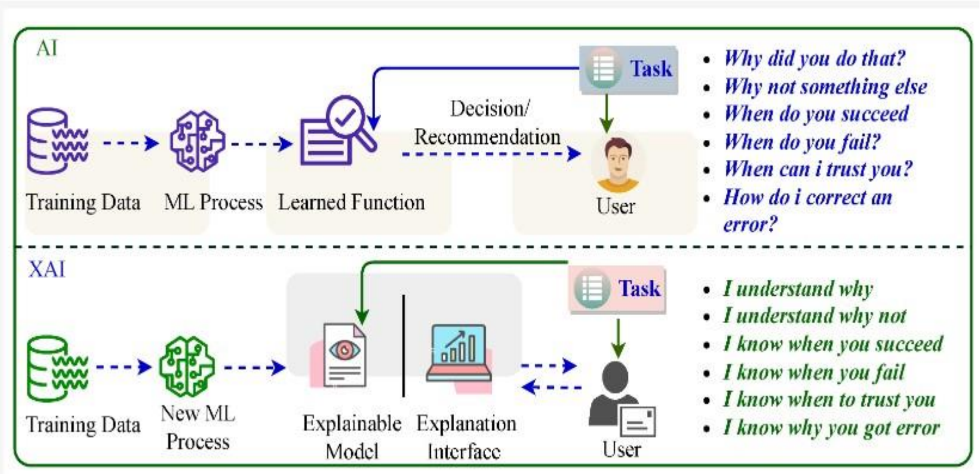
In summary, Explainable ML (XML) [25][26] comprises frameworks aimed at comprehending and interpreting predictions made by ML models. This capability aids in debugging and improving model performance while enhancing understanding of their behavior among stakeholders (refer to Fig 6)

4.2.2 XML for smart industry

In contemporary industries, the concept of "smart industry" is evolving rapidly, largely driven by advancements in Machine Learning (ML) [27][28]. Figure 7 delineates the advantages of Explainable Machine Learning (XML) within industry.

Figure 7

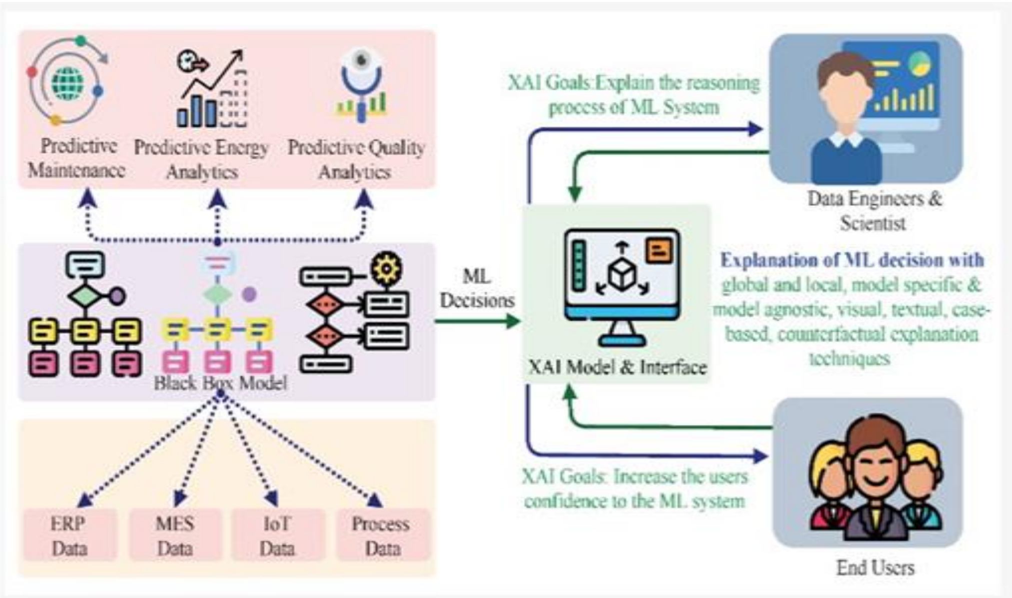
Difference between AI (ML) and XAI (XML)



In smart manufacturing, data analysis plays a crucial role in enhancing the efficiency and effectiveness of manufacturing processes [29]. The integration of Machine Learning (ML) is particularly significant in Industry 4.0 [30] and Industry 5.0 , where ML provides predictions for machine failures, safety improvements, and quality enhancements.

Figure 8

XML for smart industry



5 NUMERICAL RESULT: AI APPLICATION FOR INDUSTRIAL MANUFACTORY

In this section we will present a numerical result for a case of an application of AI in industrial manufactory. for this purpose, we will use an open dataset in Kaggle.

This dataset is about energy consumption and Co2 emission in steel industry.

Figure 9

Energy consummation on kWh in one day

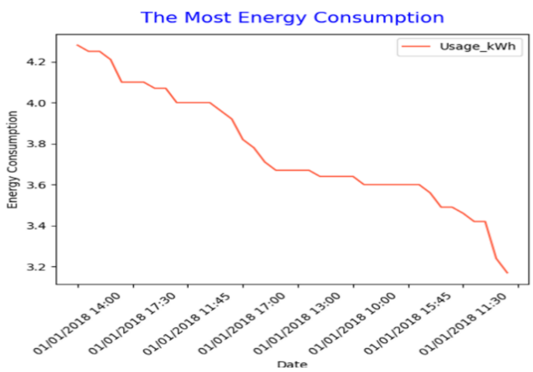


Figure 10

Distribution of each variable building the model: by selecting the best algorithm.

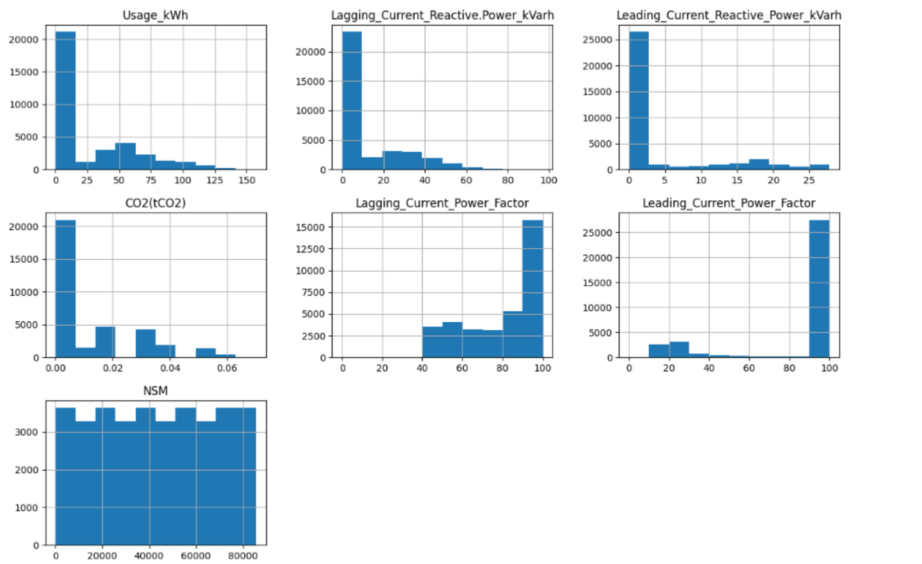
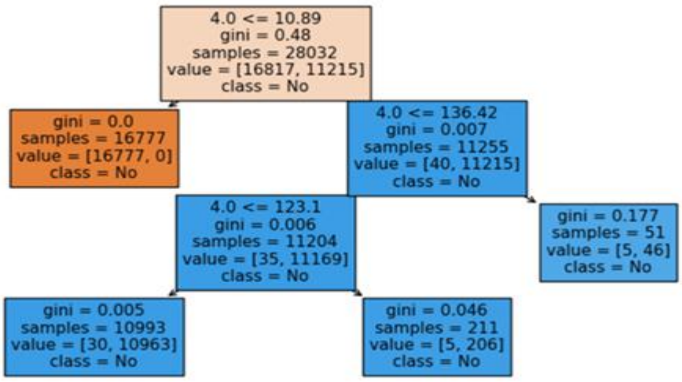


Figure 11

Decision tree graph



Let's contrast three algorithms: linear regression, lasso regression and decision tree. The precision of the linear regression model (refer to Fig 11) is provided by:

#Linear regression Model

CPU times: user 32.9 ms, sys: 10 ms, total: 43 ms

Wall time: 142 ms

Linear regression model gives 98%

The precision of Lasso agressor model gives the precision below:

#Lasso Regression Model

CPU times: user 70 ms, sys: 11 ms, total: 81 ms

Wall time: 27.6 ms

Lasso regression model gives 90%

#Decision tree model (see Fig 10) gives the precision below:

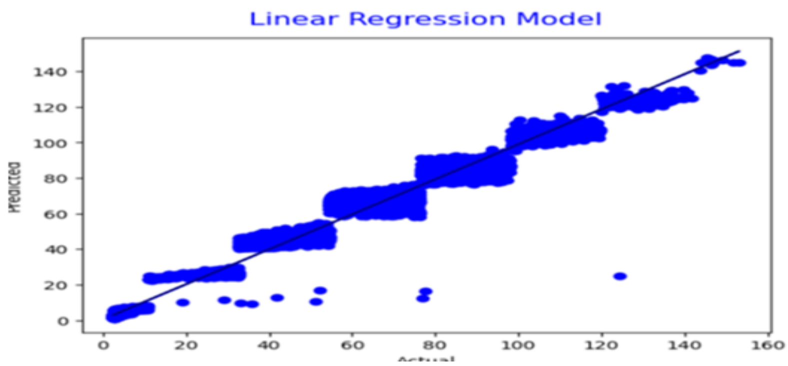
accuracy_score(y_pred,y_test)

0.9990011415525114 (99%)

We've decided to employ a decision tree for this dataset due to its superior accuracy compared to other models such as linear regression, among others. The decision tree model is highly suitable for predicting energy consumption in the Steel Industry, boasting an impressive accuracy score of 99.9%.

Figure 12

Linear regression model



After using the decision tree as the machine learning model, we explain the results using SHAP (SHapley Additive exPlanations). You can refer to the program already implemented on Matlab Online for this purpose.

We will explain the impact of features using SHAP values to understand which feature has the most significant impact.

Feat_1= usage_Kwh

Feat_2= Lagging_Current_Reactive.Power_kVarh

Feat_3 = Lagging_Current_Power_Factor

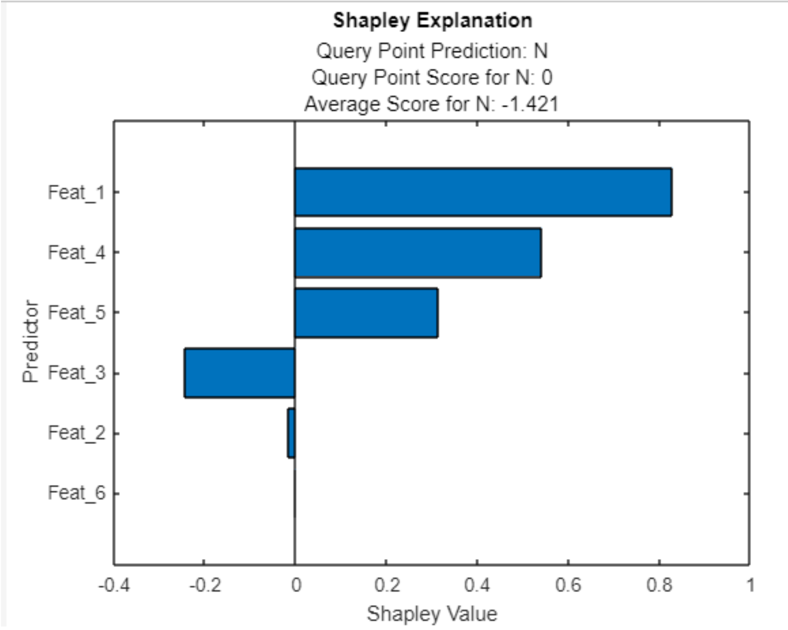
Feat_4= Leading_Current_Power_Factor

Feat_5= NSM

Feat_6=Leading_Current_Reactive_Power_kVarh

Figure 13

Shapley explanation



The SHAP framework is a powerful tool for model interpretation, providing valuable insights into global understanding via feature importance plots. As shown in Fig 12, the plot indicates that feature1 has a more significant impact compared to other features. This suggests that changes in the feature1 usage_Kwh can exert a more pronounced influence relative to other variables, emphasizing its critical role in evaluating the model. The other feature that impact is feature 4 and feature 5.

6 CONCLUSION

In conclusion, this study underscores the transformative potential of big data and machine learning within Industry 4.0 to enhance energy efficiency in manufacturing. By employing supervised learning techniques such as Lasso regression, Linear regression, and Decision Tree, the research aims to predict machine-specific energy consumption patterns through energy disaggregation. The integration of Explainable Machine Learning (XML) further enhances interpretability and decision-making capabilities, enabling detailed insights into equipment utility and energy consumption relationships. This innovative framework not only contributes to intelligent industrial settings but also sets a precedent for future advancements in optimizing energy usage through transparent and comprehensible machine learning models.

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