

MTECH THESIS

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**EXPLAINABLE MACHINE LEARNING
FRAMEWORK FOR SUSTAINABLE ENERGY
OPTIMIZATION IN INDUSTRIAL 4.0 SMART
MANUFACTURING SYSTEM**

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Chapter 1

Introduction

This chapter introduces the work of this thesis. Section 1.1 discusses the introduction. Section 1.2 discusses research issues. Section 1.3 presents the proposed solution. Section 1.4 presents the motivation behind this work; proposal statements are discussed in Section 1.5. Moreover, Section 1.6 presents the scope of the work, and contributions are in Section 1.7. Section 1.4 presents the organization of the thesis.

1.1 Introduction

The Fourth Industrial Revolution, which is often termed Industry 4.0, is a revolution that marks a fundamental change in manufacturing and industry operations [1]. This industrial revolution involves the use of various technological advancements like Artificial Intelligence (AI), Internet of Things (IoT), cloud computing, cyber-physical systems, robotics, and big data analytics in manufacturing. Such technological advances make smart manufacturing possible [2]. Smart manufacturing entails a manufacturing system that is automated, interconnected, and data-driven, thus allowing real-time monitoring of operations, maintenance of equipment, autonomous decision-making, and optimized workflow [3]. Through the constant gathering and analyzing of data, industries become more efficient, experience less downtime, and deliver products of higher quality. Hence, the concept of Industry 4.0 has turned out to be an important enabler of productivity growth and industrial transformation [4]. Nevertheless, while there have been many positive changes associated with Industry 4.0, the emergence of such systems also poses certain threats and problems. One of them is connected with energy usage. With the increased deployment of sensors, robots, machinery, and

clouds, energy consumption grows dramatically [5, 6].

Evolvement of Smart Manufacturing Ecosystems

Smart manufacturing systems have come a long way from being automated systems to becoming extremely intelligent, self-adapting systems. Early manufacturing systems used mechanisms that mainly comprised of basic automation, which means the machines would operate according to fixed programs without much scope for adjustments [7]. With the incorporation of modern digital technology into manufacturing processes, the manufacturing systems have transformed into data ecosystems [8]. In modern manufacturing systems, data is generated by sensors installed in various devices and machines involved in manufacturing products [9]. This information includes temperature of the device, vibrations, energy consumption rate, speed of the machinery, and productivity. This data is collected via IoT systems and fed to central or cloud computing systems where this data is analyzed using machine learning algorithms. Decisions are then taken by the system about how production can be optimized to minimize energy consumption and increase reliability [10]. Incorporation of cyber physical systems has further enabled machines to interact with the virtual ecosystem.

Importance of Industry 4.0 in the Transformation of Industries

The advent of Industry 4.0 is highly important in converting manufacturing industries to intelligent manufacturing industries. Some of the contributions made by Industry 4.0 towards transformation include monitoring and control [11]. The integration of smart machines that have the capacity to communicate with each other can provide information regarding machine usage as well as energy utilization [12]. Predictive maintenance also stands out among some of the important contributions made by Industry 4.0 in transforming the industry. Through machine learning techniques, machine failure can be predicted based on analysis of past and present data on machine usage. Other than scheduling of production that will match the available resources and demand, Industry 4.0 also contributes to customization, which means that it allows industries to manufacture customized products. As more industries embrace these technologies, the complexity and management of energy usage become challenging [13].

Challenges of Energy Consumption in Smart Manufacturing Systems

The biggest challenge that Industry 4.0 based smart manufacturing systems face is the rise in the level of energy consumption [14]. With the advent of smart manufacturing and automation of factories, the amount of equipment involved in energy consumption rises significantly. Such pieces of equipment include robotic systems, CNC machines, IoT devices in industry, cloud computing services, server farms, HVAC systems, and network infrastructure. Industrial energy consumption depends on several factors like the load in the production process, utilization rate of machines, environmental variables, and timing [15]. Often, energy consumption in such processes is not at all optimized, which leads to wastage and operational inefficiency. Also, during the period of peak energy demands, there is excessive pressure on power systems, leading to higher costs and lower efficiencies. Optimization of energy consumption thus becomes necessary from a sustainability perspective [16]. Governments around the world have mandated energy efficiency to reduce carbon emissions and minimize environmental effects.

The Need for Sustainable Energy Optimization

Sustainable energy optimization involves enhancing energy efficiency without compromising productivity and performance levels. It is an important factor in smart manufacturing systems, considering its potential to minimize the effects of production activities on the environment and reduce costs [17]. Energy management systems based on rule-based static principles or manual surveillance mechanisms are not effective enough because they lack the ability to adapt to changing industrial conditions and energy requirements [18]. There is thus an increasing need for intelligent energy optimization systems that are capable of processing large amounts of data from industrial processes and developing adaptive mechanisms. Machine learning techniques are increasingly viewed as effective solutions in this case [19]. Not only does sustainable energy optimization result in reduced energy use, but it also enhances the efficiency of machines and prolongs their lifespan. It also contributes to efforts aimed at promoting sustainability and reducing the carbon footprint of industrial processes [20].

Machine Learning in Energy Optimization of Industrial Processes

Machine learning (ML) is now an integral part of modern industries as it allows analyzing huge amounts of data and finding hidden patterns. As far as energy

optimization is concerned, different types of ML models are utilized to forecast energy consumption and detect abnormalities in order to find ways of optimizing processes [?]. Among machine learning algorithms, those such as linear regression, decision trees, random forest, support vector machines, and deep neural networks can be found to be utilized in forecasting energy consumption. Machine learning models work based on training data and offer rather accurate predictions about the consumption based on certain input data [22]. One more problem that exists when using machine learning is that these models are black box systems. This means that they offer accurate predictions, but they fail to explain how they were made [23].

Machine learning (ML) algorithms are extensively utilized to predict and optimize energy consumption in industries [24]. However, the majority of machine learning algorithms work like black-box models whereby decision-making is not made transparent to industry managers. Lack of clarity poses questions about reliability and accountability of such models in industrial settings. To overcome the challenges, Explainable Artificial Intelligence (XAI) can be adopted for developing clear and meaningful explanations for machine learning models. SHAP and LIME are two commonly used XAI techniques for making decisions through AI transparent [25]. In this study, an XAI-based ML framework for sustainable energy optimization in smart manufacturing systems is suggested [26].

1.2 Research issue

This proposed study attempts to solve various problems that exist in the field of sustainable energy optimization in Industry 4.0 smart manufacturing systems. A common problem in this field includes the increase in energy consumption due to the use of IoT technologies, automatic machines, and intelligent manufacturing systems. The problem here is that the existing machine learning algorithms are good in predicting the energy consumption, but they do not have transparency, since they act like black-box models. Industrial engineers need to understand how the optimization algorithms make decisions about predictions and actions. Another research problem is that there is no transparency when using the AI-based algorithms for predicting and optimizing the energy consumption process since the industrial data are highly variable, nonlinear, and have some temporal characteristics and missing data points. This study will tackle the aforementioned problems through combining real-time data gathering from IoT sensors, machine

learning prediction model, and explainable AI methodologies, such as SHAP and LIME. This framework will help in improving the predictive capability of machine learning models, provide explanation for the effects of industrial parameters on energy consumption, and finally propose intelligent optimization strategies.

1.3 Proposed solution

The suggested solution will be based on Explainable Machine Learning for energy optimization in industry 4.0. The method will employ IoT sensor network, predictive modeling via machine learning, and explainability tools. Real-time industrial data, such as energy consumption, loading, temperature, and production rate, will be gathered using IoT devices. Machine learning algorithms, such as Random Forest, XGBoost, and Neural Networks, will be used for the prediction of energy consumption and detection of inefficiencies. The explainability problem is solved via SHAP and LIME that help reveal how each variable impacts energy consumption in a manufacturing process. Then, an optimization function gives recommendations for the optimization of energy consumption, e.g., through improved scheduling and load balancing. Thus, with the suggested solution, it will become possible to make a precise prediction, explain the results and optimize energy consumption.

1.4 Motivation

The motivation for this study arises from the requirement to combine energy optimization with XAI technology in smart manufacturing systems. Although machine learning can predict the energy usage very efficiently, the inability of such algorithms to explain their predictions makes them impractical. By merging machine learning and XAI technologies, an approach for building a transparent energy optimization system will be feasible. Such a system will not only enable industries to optimize their energy usage but also increase the confidence levels on AI-based systems.

1.5 Problem Statement

Smart manufacturing systems have been able to automate processes and increase connectivity and efficiencies due to IoT, artificial intelligence, and cloud comput-

ing in Industry 4.0. Unfortunately, with all these advances, there is a notable increase in the amount of energy consumed by these systems. Thus, optimizing energy usage becomes one of the challenges facing current manufacturers. The existing solutions for energy consumption do not manage well when dealing with industrial dynamics. While machine learning algorithms can be employed to predict future values and provide energy savings, most of them are black boxes, which provide accurate results without giving the underlying reasoning. As a result, such methods do not allow full trust in the results and thus cannot be employed. Hence, the need arises for an intelligent, transparent, and flexible solution for optimizing energy consumption.

1.6 Scop of the work

⁴ This research aims to design an intelligent and interpretable framework that optimizes energy consumption in Industry 4.0 smart manufacturing. This intelligent solution uses Internet of Things (IoT) sensors for collecting live data from industrial premises and employs machine learning algorithms for predicting energy consumption trends. In addition, the research involves application of XAI techniques such as SHAP and LIME for explaining model predictions and increasing transparency. The scope encompasses energy monitoring, prediction, explanation, and optimization in smart manufacturing environments. The proposed framework would help industrial engineers and managers optimize energy consumption and achieve sustainability objectives. However, the study will not involve the actual implementation of the proposed solution in industrial settings due to limitations related to time and resources.

1.7 Contributions

1. Developed an Explainable Machine Learning approach for sustainable energy optimization in smart manufacturing systems in Industry 4.0, which integrates IoT, ML, and XAI methodologies.
2. Created a highly accurate energy prediction model by leveraging the use of innovative machine learning approaches like Random Forest, XGBoost, and neural networks to predict the energy consumed by industries.
3. Used explainable artificial intelligence (XAI), including SHAP and LIME

methods, to enhance transparency by understanding how various industrial features impact energy consumption.

4. Suggested a smart energy optimization model that helps identify areas where energy is being wasted and provides recommendations on efficient ways to save energy.
5. Implemented a closed-loop adaptive system to keep on learning from industry-generated data and making more accurate predictions and decisions.

1.8 Thesis Organization

This thesis comprises five chapters, which outlines the proposed workflow. Initially, Chapter 1 is the introduction; the proposed methodology incorporates XAI and ML models for energy prediction. Chapter 2 the detail literature survey. The proposed methodology is represented in Chapter 3. Results and discussion are shown in Chapter 4. Finally, the conclusion and future work are in Chapter 5.

Chapter 2

Literature Review

This chapter explains some literature review. Section 2.1 discusses the previous studies. Section 2.2 discusses the limitations in existing work. Section 2.3 present the objective of the thesis. Section 2.4 presents the research gap. Section 2.5 discusses the performance evaluation metrics used for analysis. Finally, Section 2.6 presents the conclusion of the chapter.

2.1 Previous Studies

Artificial Intelligence (AI) and Machine Learning (ML) are gaining significance in smart manufacturing systems due to the fast-paced move toward Industry 4.0. Such technologies are used extensively for making predictions and optimizing operations in terms of energy consumption efficiency in manufacturing settings. According to recent studies, there exist three main trends in the field of AI/ML for smart manufacturing. These include (i) application of ML for making energy consumption predictions and optimizing operations in manufacturing systems, (ii) utilization of IoT-powered smart monitoring solutions to perform real-time data analysis in industry settings, and (iii) use of Explainable Artificial Intelligence (XAI). All existing studies show great advances in terms of improving prediction accuracy and enhancing the performance of the system. Still, there are several shortcomings of such works including lack of interpretability of models, inability to work in real-time, need for high-quality datasets, and challenges related to scalable solutions to the issue.

Aridi et al. [27] compares five types of renewable energy including solar, wind, biomass, hydropower, and pumped storage in relation to their cost of electricity generation, environmental impact, and social advantages. LCOE and LCA were

used as methods of comparison. Wind energy proved to be the most cost-effective while hydropower had the smallest environmental costs amongst other forms of renewable energy. Lund et al. [28] significance of the intelligent energy system in developing climate-neutral society is highlighted. The findings reveal that by using integrated energy systems, the cost of energy storage can be minimized, and there would not be any excess of electricity generation and renewable energy will be used efficiently. The study utilizes EnergyPLAN software and the scenario of Denmark for 2045. Sawilam et al. [29] purposed this to analyze the contribution of VPPs enabled by Internet of Things (IoT) in enhancing the stability of the power grid and facilitating renewable energy use in smart cities. In addition, the research will compare IoT and conventional VPPs and indicate that IoT can help in increasing energy production from renewables, optimizing battery storage, minimizing dependence on the power grid, and decreasing emissions of greenhouse gases. Talaat et al. [30] proposed the work to analyze the data on wind, solar power, and global energy. This paper reveals that the application of artificial intelligence techniques has resulted in significant improvement in renewable energy prediction, energy efficiency, and grid stability. The role of AI for realizing the Sustainable Development Goals (SDGs) has also been discussed [39].

Konda et al. [31] propose SECSA, which stands for Smart Energy Consumption System Architecture. SECSA is aimed at sustainable semiconductor fabrication processes and efficient AI workload execution. The architecture employs real-time monitoring, prediction, renewable energy orchestration, and demand-response techniques to efficiently consume energy at fabs and data centers. Rahardja et al. [32] introduced as a smart waste sorting solution that makes use of artificial intelligence and the Internet of Things (IoT). Renewable energy from solar power is used to run the Orange Box to ensure sustainability in waste management. The Orange Box utilizes the Raspberry Pi 5, along with sensors and servo motors, to sort wastes automatically without any manual intervention in an off-grid solar power system. Yuan et al. [33] presented the 2024 Presidential Symposium by ACS on the advancement of energy transition and smart materials via multidisciplinary efforts in chemistry, engineering, and materials sciences. This symposium was dedicated to topics like renewable energy, carbon capture, sustainable fuel, smart nanomaterials, intelligent energy systems powered by AI, and energy storage systems. Ghobakhloo et al. [34] introduce the concept of adaptive social manufacturing (ASM), which is a socially-oriented approach that aims to facilitate the progression of Industry 5.0. ASM utilizes a combination of AI, IoT, cyber-physical systems, and automation to enhance the resilience, effectiveness,

and sustainability of the manufacturing process [40].

Anita et al. [35] provides an interdisciplinary examination of developments in AI technologies and their impact on the SDGs. The study underscores how AI makes decision making more efficient and sustainable within many sectors. At the same time, ethical issues are raised, such as algorithmic bias, privacy concerns, and governance frameworks. Biswas et al. [36] presented sustainable energy management through the use of smart grids. Some areas covered include renewable energy, artificial intelligence, cyber security, and electric vehicles. This work analyzes how the implementation of smart grids enables more efficient, reliable, and sustainable energy delivery processes by using enhanced forms of communication and artificial intelligence. Ejub et al. [37] reviewed how variable renewable energy sources, like solar and wind energy, are integrated into grid-connected power systems. This discussion will identify problems faced in this process, including intermittency issues, voltage stability, frequency stability, and grid stability. Campana et al. [38] significance of SGs and other digital technologies in promoting energy transition and sustainability is analyzed. Special attention is paid to the advantages of using artificial intelligence (AI), internet of things (IoT), blockchain, and edge computing in terms of energy efficiency and cybersecurity, integration of renewables, and optimization of energy networks [41, 42].

Table 2.1: Literature survey

Ref.	Obj.	Model	Dataset	Application	Area	Advantage	Limitation
[27]	Compare renewable electricity sources	LCOE + Life Cycle Assessment (LCA)	OpenLCA, Ecoinvent, Switzerland energy data	Renewable energy evaluation	Sustainable Energy	Low environmental impact analysis	High initial investment
[28]	Develop climate-neutral smart energy systems	Smart Energy System Integration Levels (SESILs)	Denmark 2045 energy scenario	Integrated energy systems	Smart Energy	Reduces storage and curtailment	Complex sector integration
[29]	Improve renewable energy integration using IoT-VPP	IoT-enabled Virtual Power Plant	Oman smart grid case study	Smart grid optimization	Smart Cities	Better battery and grid management	Infrastructure dependency
[30]	Enhance renewable energy forecasting	AI & Deep Learning models (LSTM, CNN, SVR, RF)	Wind, solar, global energy datasets	Renewable forecasting	AI in Energy	Improved prediction accuracy	Requires large datasets

Ref.	Obj.	Model	Dataset	Application	Area	Advantage	Limitation
[31]	Optimize semi-conductor energy consumption	SECSA framework	Smart manufacturing operational data	Energy-aware manufacturing	Industry 4.0	Reduced energy cost and emissions	Complex deployment
[32]	Develop solar-powered smart waste management	AI + IoT waste sorting system	Sensor and solar power data	Smart waste management	Sustainable Cities	Low power consumption	Limited waste classification
[33]	Promote sustainable energy transition	Smart materials and AI-based energy systems	Symposium research data	Clean energy technologies	Advanced Materials	Encourages interdisciplinary innovation	Mostly conceptual analysis
[34]	Develop human-centric Industry 5.0 manufacturing	Adaptive Social Manufacturing (ASM)	Longitudinal industrial case study	Sustainable manufacturing	Industry 5.0	Balances productivity and sustainability	Difficult real-world adoption

Ref.	Obj.	Model	Dataset	Application	Area	Advantage	Limitation
[35]	Analyze AI contribution toward SDGs	AI, ML, NLP, Robotics	Multidisciplinary review data	Sustainable development	AI & Sustainability	Supports multiple SDGs	Ethical and privacy concerns
[36]	Review smart grids for sustainable management	AI-enabled Smart Grid Framework	Renewable energy and grid datasets	Grid optimization	Smart Grid	Improved reliability and efficiency	Cybersecurity risks
[37]	Improve renewable energy integration into grids	Smart grid mitigation framework	Global renewable energy case studies	Grid-connected renewable systems	Renewable Power Systems	Better flexibility and resilience	Renewable intermittency
[38]	Analyze digital technologies in smart grids	PRISMA179 + Bibliometric Analysis + VOSviewer	Scopus research articles	Smart energy management	Digital Energy Systems	Integrates AI, IoT, blockchain, cybersecurity	Lack of empirical validation

2.2 Limitations in existing work

There are some limitations present in the studies related to smart grids, renewable energy, AI, deep learning (DL), and XAI. The limitations include inconsistent and noisy energy data, low level of explainability for AI "black box" models,

increased complexity, and scalability problems in large-scale smart grid environments. Moreover, real-time application becomes hard because of the increased time for training and complex data analysis. Renewable energy uncertainty, as a result of weather changes, causes trouble in managing energy demands and supplies.

2.3 Objectives of the thesis

The primary goals of this project are:

1. Creation of a comprehensive framework integrating Machine Learning (ML) and Explainable Artificial Intelligence (XAI) for the purpose of achieving sustainable energy optimization in Industry 4.0 contexts.
2. To apply application of Explainable AI methods (e.g., SHAP and LIME) to understand and interpret energy consumption patterns and the logic behind predictions.
3. To enabling real-time energy forecasting for smart manufacturing solutions.
4. To discovery of key variables that impact energy consumption, including machine loads, temperature, and production rate.
5. To generate insights from the analysis to make energy optimization possible.
6. To improve the comprehensibility, credibility, and usability of AI systems for industry.
7. To facilitating transformation towards sustainable and intelligent manufacturing solutions.

2.4 Research gap

Prior literature about the design and implementation of smart grids and renewable energy systems through AI and deep learning algorithms primarily concentrates on enhancing prediction and optimization of energy. However, current research concentrates mainly on enhancing energy prediction accuracy within Industry 4.0 environments, although interpretability and transparency of the models are lacking. Most ML models are considered as being black boxes, which reduces their applicability in the industry. Also, application of XAI models for real-time

energy optimization remains insufficient. Finally, there is no general framework that covers prediction, optimization, and explanation within the closed loop for sustainable smart manufacturing.

2.5 Performance evaluation metrics

Accuracy:

The total correctness of all predictions is measured by accuracy [29] in Eq. (2.1).

$$\text{Acc} = \frac{TP + TN}{TP + TN + FP + FN} \quad (2.1)$$

where $\mathbf{1}\{\cdot\}$ is the indicator function.

2.5.1 Root Mean Square Error (RMSE):

RMSE is a statistical performance evaluation metric used to measure the difference between actual and predicted values generated by a machine learning model [29]. It calculates the square root of the average squared errors between predicted and observed values. A lower RMSE value indicates better prediction accuracy and model performance. is shown in Eq. (2.2).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (2.2)$$

R^2 Coefficient:

R^2 indicates the percentage of the dependent variable's variance that is predicted from the independent variables [29] is shown in Eq. (2.3).

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2}, \quad (2.3)$$

where $\bar{y}$ is the mean of the observed target values.

2.6 Conclusion

This chapter presented a literary survey with the limitations of existing work and objectives.

Chapter 3

Methodology

This chapter details the proposed methodology. Section 3.1 represent introduction, Section 3.2 shows the data preprocessing, Section 3.3 presents the noise reduction, Section 3.4 presents feature engineering, Section 3.5 presents feature selection. Moreover, Section 3.6 discusses the machine learning algorithms, Section 3.7 explains explainable artificial intelligence, further Section 3.8 and Section 3.9 present the LIME and energy consumption optimization. Lastly, Section 3.10 presents the conclusion of the chapter.

3.1 Introduction

In this study, we aim to design an intelligent and transparent solution for sustainable energy optimization in Industry 4.0-based smart manufacturing facilities using the Explainable Machine Learning approach [43]. Our framework involves machine learning (ML) models and explainable artificial intelligence (XAI) methods like SHAP and LIME for building interpretable and data-driven predictions of energy consumption. The Explainable Machine Learning framework in this paper is capable of solving many issues common for industrial energy datasets, which include high-dimensional space, non-linear interactions, temporal dependencies, noise from sensors, missing data, and complex dependency networks among various industrial factors. The combination of explainability and predictions will make our system more transparent and valuable to use in practice by helping industrial managers understand what drives energy consumption [44] shows in Fig. 3.1.

The method to be used is an approach that incorporates data pre-processing, feature extraction, machine learning, explainable AI, and energy optimization into

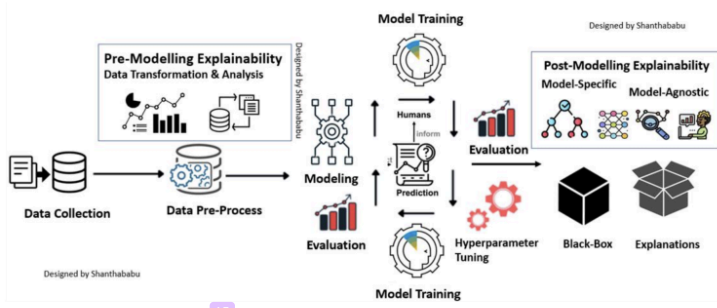


Figure 3.1: Proposed methodology

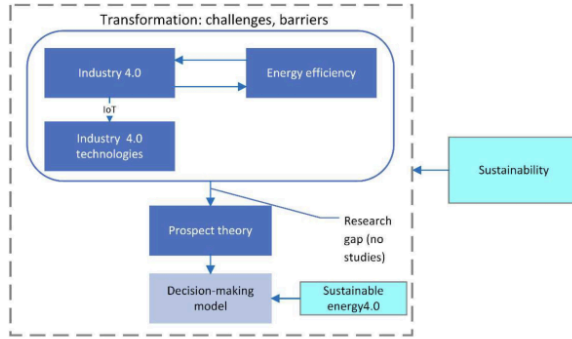


Figure 3.2: Flow diagram of methodology

one. It will enable the efficient prediction of energy consumption and also make the decision-making process made by the AI transparent and understandable. The use of SHAP and LIME ensures the credibility of the system, while the optimization of energy consumption is guaranteed using optimization methods. The flow diagram of the methodology is shown in Fig. 3.2 and Fig 3.3.

3.1.1 Dataset Collection

This dataset has been created by using smart manufacturing systems working in Industry 4.0 environment, where analysis and improvement of the energy efficiency and sustainability in manufacturing is the goal of research. This data is obtained using IoT-based sensors and monitoring instruments installed in manu-

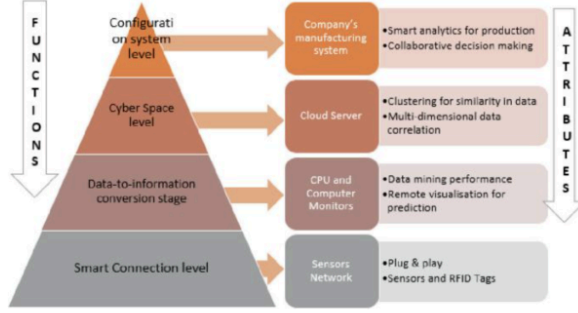


Figure 3.3: Function representation of methodology

facturing units [45]. The recorded data contains operational logs with timestamps that track all the machine operations. Various metrics like power usage, speed of production, operating conditions of machines, temperature, humidity, maintenance condition, and energy efficiency scores have been taken into consideration. Environmental factors along with the operational factors were considered to examine the impact of environmental factors on efficiency in manufacturing. Data related to maintenance have also been considered to understand any faults in operational conditions [46]. Moreover, dataset details are shown in Table 3.1.

3.2 Data Preprocessing

Data preprocessing is an important phase in the proposed methodology as industrial data gathered through IoT-based sensors is usually noisy, inaccurate, and incomplete [47]. As stated above, smart manufacturing involves gathering continuous data streams through machine, sensor, production, and energy meter devices. Raw data alone cannot be used as input to build machine learning models. Hence, multiple preprocessing phases should be performed to improve the accuracy and quality of the data. The first phase in the data preprocessing process is the removal of missing values. Missing values can occur in data due to sensor malfunctions, communication issues, and downtime. There are multiple ways of handling missing values such as mean imputation, median replacement, and data deletion among others. Feature normalization is the second step and entails that all the input features should be normalized to a common scale. This is essential since the industrial features of electricity usage, temperature, and pro-

41
Table 3.1: Dataset description

Feature Name	Description	Purpose
Timestamp	Date and time of machine operation records	Tracks real-time operational activities
Machine Logs	Real-time machine operational data	Monitors machine performance
Power Consumption	Energy used by machines during operation	Energy efficiency analysis
Production Rate	Number of units produced over time	Productivity evaluation
Temperature	Ambient/system temperature readings	Environmental impact analysis
Humidity	Humidity level in manufacturing environment	Environmental monitoring
Maintenance Status	Condition and servicing status of machines	Predictive maintenance analysis
Energy Efficiency Score	Calculated efficiency performance metric	Sustainability performance evaluation

duction rate can have varied scales and measurements. This prevents any form of bias in favor of higher magnitude features. The normalization formula used is in Eq.(3.1).

$$X_{norm} = \frac{(X - X_{min})}{(X_{max} - X_{min})} \quad (3.1)$$

The third stage involves label encoding, which is done to convert qualitative features like machine type, operational state, or category of production into numeric form. Data scaling and transformation come at the end of the process, which helps in getting an even distribution of data and optimizing the efficiency of gradient-based learning algorithms. After the data is processed, it is well organized and prepared for feature extraction and modeling.

3.3 Noise reduction

Data sets obtained from IoT devices and smart sensors tend to have noise data due to various external interferences and hardware constraints [48]. Noise elimination involves the use of smoothing techniques and statistical processes to eliminate outliers. The formula for z-score used for outlier elimination is in Eq. (3.2).

$$z = (x - \eta)/\sigma \quad (3.2)$$

Here, η is the mean and σ is the standard deviation. All data samples having an abnormal z-score are removed or modified.

3.3.1 Feature Normalization

The energy features vary in scales and units. Normalization helps to stabilize the algorithm numerically during training. Min-Max normalization is done as Eq. (3.3).

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (3.3)$$

Standardization can be written as Eq. (3.4).

$$x' = (x - \eta) / \sigma \quad (3.4)$$

Normalization helps fasten the process of convergence and avoids feature dominance.

3.4 Feature Engineering

Feature engineering is an indispensable part of the process of enhancing machine learning algorithms to ensure the selection of the right variables affecting energy consumption in industry. There are several approaches used for feature selection in this project, including correlation analysis, importance rank, and statistical analysis. Correlation analysis implies determining statistically significant relations between features and energy consumption. Correlated features are expected to be important predictors. Importance rank refers to a machine learning approach that ranks features according to their contribution to lowering prediction error rate. This algorithm is based on Random Forest and XGBoost.

Statistical analysis includes assessing mean, variance, standard deviation, and other factors influencing the performance of the selected feature. Main characteristics of the environment under analysis and expected features to be used in machine learning models may include load of machines, duration of their operation, production speed, ambient temperature, vibrations, and environmental factors.

3.4.1 Categorical Feature Encoding

The categorical features, including asset class, operating mode, and energy source type, are converted to numbers through one-hot encoding. Assuming that C represents the categorical feature set $C = c_1, c_2, \dots, c_n$. Vectors then get encoded as binary vectors.

3.5 Feature Selection

Datasets with many dimensions make calculations complex and also have redundant information [49]. Correlation analysis can be performed to extract relevant features from such high dimensional data sets. The calculation of the pearson correlation coefficient involves represent by using Eq. (3.5).

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{(\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2)}} \quad (3.5)$$

High scoring features are kept. PCA is another technique used to perform dimensionality reduction. The covariance matrix can be described as follows as $C = \frac{1}{N} X^T X$. Eigen value decomposition is performed to create principal components.

3.6 Machine Learning Algorithms

Several machine learning models are employed in the suggested framework to forecast the energy consumption process in intelligent manufacturing frameworks. By employing multiple machine learning models, one can analyze them and select the best one based on their performance.

3.6.1 Random Forest

Random Forest is an ensemble machine learning technique that generates many decision trees whose output is then combined. This model has proven quite useful in dealing with nonlinear processes and noise [50].

3.6.2 ³² XGBoost

XGBoost stands for Extreme Gradient Boosting. This machine learning algorithm is an optimized version of the gradient boosting machine learning model, which enhances prediction accuracy through iterative loss function minimization [51].

3.6.3 ¹ Support Vector Regression (SVR)

SVR is applied to regression analysis for predicting an optimal hyperplane that would result in minimized error in predictions. SVR works well on small and medium data sets with complicated relations [52].

3.6.4 ²² Long Short-Term Memory (LSTM)

The LSTM method is considered a type of deep learning model specifically applied on sequences. Because energy data from industries relies on time, LSTM is considered to be useful in predicting energy consumption from historical data [53].

These algorithms will be trained on industrial data sets that have been preprocessed, and the results will be tested using metrics like MAE, MSE, and R-squared scores.

3.7 Explainable Artificial Intelligence (XAI)

The second crucial element of the suggested framework is Explainable Artificial Intelligence, which guarantees model interpretability and transparency. The suggested EnergyML-XAI architecture combines explainable AI techniques with a residual learning-enhanced machine learning backbone. Moreover, to predict and analyze sustainable energy indicators from the SEG dataset. Energy system data are first preprocessed using feature scaling, missing-value handling, and normalization to increase robustness and convergence during training. The residual learning architecture facilitates effective feature refinement, enabling the model to capture both linear and non-linear relationships seen in complex energy systems. The residual learning corrective mappings between intermediate representations.

The learning backbone generates hierarchical representations from the input energy indicators. Generates from low-level operational parameters to high-level sustainability patterns associated with renewable energy generation, grid stability, and asset performance. The prediction outputs that correspond to sustainable

energy indicators are then generated by passing these extracted features through fully connected layers. Explainable AI (XAI) methods are used to determine the most significant characteristics influencing model predictions in order to guarantee transparency and interpretability. High predicted accuracy as well as reliable and understandable decision-making appropriate for practical energy applications are guaranteed by this integrated method. An input energy sample is formally expressed as Eq. (3.6).

$$X \in R^{N \times D}, \quad (3.6)$$

where D is the number of energy-related features and N is the number of samples. The residual learning-based model functions as a mapping-based feature extractor.

$$f_{\theta} : X \rightarrow F,$$

where the trainable parameters are indicated by θ and the learned feature representation is represented by $F \in R^{N \times d}$. The prediction logits are produced by passing the retrieved characteristics through a fully connected layer in Eq. (3.7).

$$z = W_f \cdot F + b_f \quad (3.7)$$

The softmax function is used to determine the final prediction for classification-oriented energy indicators in Eq. (3.8).

$$\hat{y}^c = \frac{e^{z_c}}{\sum_{j=1}^K e^{z_j}}, \quad c \in 1, 2, \dots, K, \quad (3.8)$$

where K is the number of energy indicator classes. XAI techniques, such as gradient-based attribution methods, are applied to the final feature representations to quantify each feature's contribution to the expected output in order to improve interpretability. Let A_k be the k -th feature component. The appropriate significance weight for class c is calculated as follows as Eq. (3.9).

$$\alpha_k^c = \frac{1}{Z} \sum_i \sum_j \frac{\partial y^c}{\partial A_{ij}^k}, \quad (3.9)$$

where Z is normalizing factor. The explanation map is then created as Eq. (3.10):

$$L_{XAI}^c = \text{ReLU}(\sum_k \alpha_k^c A^k), \quad (3.10)$$

This key energy features affecting the models prediction. These explanations

support system validation and informed decision-making in sustainable energy infrastructures.

3.7.1 SHAP (Shapley Additive Explanations)

The method relies on cooperative game theory and explains the predictions using both global and local approaches. Each attribute in a machine learning model gets assigned an importance score showing the contribution to the prediction. The application of SHAP to the suggested framework includes:

- The identification of globally important features that influence energy consumption.
- The explanation of each attribute's contribution to model predictions.
- Providing visual explanations for industry managers; These attributes might include factors like machine load and temperature.

3.8 ⁴² LIME (Local Interpretable Model-Agnostic Explanations)

The approach of LIME allows for local interpretability, providing explanations about individual predictions. The complicated machine learning algorithm is replaced with an interpretable one for a particular prediction only. Under this approach, LIME is applied for:

- Explanations of individual energy consumption predictions.
- Human-friendly reasoning about decisions.
- Higher reliability of AI industrial solutions.

SHAP and LIME together guarantee transparency and practicality of the solution.

3.9 Energy Consumption Optimization

The last step in our methodology involves optimizing energy use in industrial systems through predictions and insights gained using machine learning and explainable AI. The objective of optimization of energy consumption can be expressed

as Eq. (3.11).

$$E_{opt} = \min \sum (P_i T_i C_i) \quad (3.11)$$

where, P_i is power used by machine i , T_i is machine i working time, C_i is energy cost coefficient. The objective is to optimize energy usage while ensuring production efficiency. On the basis of predictions from our model, the system is able to provide recommendations aimed at:

- Scheduling of machines.
- Minimizing idle time of machines.
- Load balancing across various systems.
- Controlling production rate depending on the demand for energy.
- Identifying highly energy-consuming processes.

This is achieved through an iterative process whereby the system gains insight from the fresh data and becomes more informed in making decisions over time. Combining machine learning and XAI guarantees that the optimization decisions made are not only accurate but also explainable.

3.10 Conclusion

The following section covered the literature review. An Explainable Machine Learning framework was introduced for sustainable energy optimization in Industry 4.0 systems leveraging IoT, ML, SHAP, and LIME.

Chapter 4

Results and Discussion

This chapter details the results. Section 4.1 represent introduction, Section 4.2 shows the training phase, Section 4.3 presents testing and validation, Section 4.4 presents experimental setup and hardware used, Section 4.5 presents results analysis. Moreover, Section 4.6 discusses results comparison, and Section 4.7 is discussion. Lastly, Section 4.8 presents the conclusion of the chapter.

4.1 Introduction

The above chapter mentioned EnergyML-XAI architecture has been experimentally validated through the use of several Sustainable Development Report (SDR) data sets for testing its efficacy in sustainable energy prediction, intelligent decision-making, and explainable renewable energy modeling. This analysis was conducted to determine the effectiveness of the proposed framework in terms of accuracy, interpretability, robustness, scalability, and generalizability across different sustainable energy settings. The results show that combining residual learning, hybrid machine learning models, and Explainable Artificial Intelligence (XAI) technologies leads to more accurate predictions and increased model interpretability than traditional machine learning methods. Some of the main in this investigation include some of the important facets involved in evaluating and analyzing the performance of models and systems. These include the following: First, accuracy evaluation for renewable energy forecasting is done to determine the effectiveness of the proposed modeling framework in predicting the production of energy from renewable sources like wind and solar in different environments. Second, smart grid operation forecasting evaluation is done to test the capacity of the model in supporting the management of electricity grids, predicting demands,

and achieving load balancing in energy systems. Third, validation of residual learning performance is done to evaluate the efficacy of the framework in improving its predictions through the process of learning. Moreover, the explainability and feature importance analyses have been considered for transparency and interpretation of model predictions. In addition, a comparison between the proposed framework and other machine learning frameworks will be done in order to illustrate the superiority of the proposed framework compared to other conventional methods in terms of accuracy and adaptability. Moreover, an examination of scalability and robustness assesses the capability of the model in dealing with multidimensional datasets and its stability under various conditions. Moreover, sustainability policy validation is used in order to assess whether the model's outputs are relevant and aligned with the actual sustainable policies for environmental protection and energy generation. The proposed framework uses the python language in machine learning and is executed within an advanced computing environment.

4.2 Dataset Details

This dataset comprises the operation and environmental data obtained from smart manufacturing systems aimed at improving energy efficiency in an Industry 4.0 context. Specifically, the dataset provides time-stamped machine log files capturing real-time operations data, which makes it possible to monitor processes continuously [54]. Several parameters included in the dataset are crucial for evaluation of the industrial operations as well as energy use efficiency. These include power consumption, production, temperature, humidity, maintenance status, and energy efficiency score. Power consumption and production rates serve as the basis for analysis of energy usage and optimization. Environmental factors enable one to assess the effect of environmental factors on machine performance. Information about the machine's maintenance status can be used to monitor the operational state of a machine and its possible failures. Energy efficiency score can be regarded as the performance indicator. This particular dataset will be ideal for conducting machine learning and predictive analytics studies related to energy optimization and sustainable manufacturing.

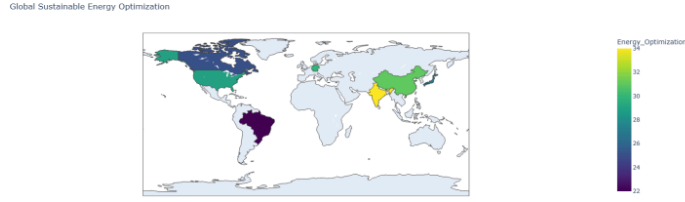


Figure 4.1: Map plot

4.3 Training Phase

The training phase in the suggested framework for Explainable Machine Learning (ML) concentrated on capturing the correlation between various operational parameters in industrial settings and energy consumption behavior in smart manufacturing. In particular, this phase involved training several ML and DL models such as Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), XGBoost, and Long Short-Term Memory (LSTM). These models were trained using data related to various operational parameters in industrial IoT applications. These operational parameters included but were not limited to machine load, time, temperature, humidity, voltage, rate of production, maintenance, and energy efficiency of smart manufacturing. Preprocessing methods such as normalization, imputation, feature scaling, and outlier removal were employed before training models.

The random forest model was built using many decision trees in an effort to increase prediction accuracy while avoiding overfitting. The LSTM model was similarly trained using sequential data. Various hyperparameters of the models were tuned using grid search and cross-validation. The training phase showed that ensemble learning and deep learning techniques provided effective solutions for learning non-linearly correlated operational parameters. The training cycle helped in optimizing the performance of these models through iterative training until the prediction error was minimized.

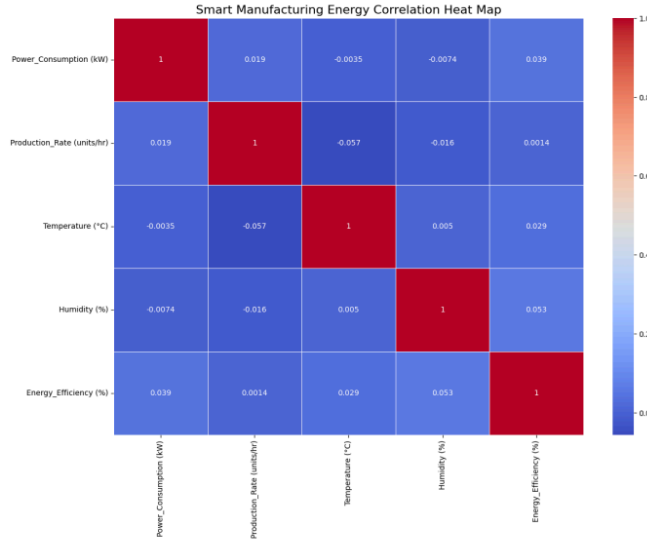


Figure 4.2: Heat map

4.4 Testing and Validation phase

In the process after completing the training phase, the models were tested using unseen testing datasets in order to determine their generalization capacity and the accuracy of their predictions. In the phase of testing and validation, it was proven that the developed framework is able to make accurate predictions of industrial energy consumption even in the conditions of normal operation. The evaluation was carried out based on several metrics for the assessment of model quality, such as Accuracy, Precision, Recall, F1-Score, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 Score.

Random Forest and LSTM models have shown the highest level of prediction accuracy compared to all other methods of machine learning. The accuracy of prediction made by Random Forest model is about 96.4%, and the accuracy of LSTM model is almost 97.1%, because of the capability of LSTM to learn industrial operation patterns from time series data. The analysis has also shown that the framework has good generalization capacity and doesn't suffer from overfitting.

4.5 Experimental Setup and Hardware configuration

The suggested framework of explainable machine learning was developed using a powerful computer system which is ideal for implementing machine learning and deep learning models. The computing system utilized for these purposes was equipped with either Intel core i7 or AMD Ryzen 7 processor, 16GB DDR4 RAM, 512GB SSD hard disk space, and NVIDIA RTX 3060 or Tesla T4 GPU [55]. Experiments were carried out using Windows 11 and Ubuntu operating systems, and Python version 3.11 was deployed in conjunction with Jupyter Notebook and Google Colab tools [56]. The libraries TensorFlow, Keras, Scikit-learn, SHAP, LIME, Pandas, NumPy, and Matplotlib were utilized for implementing these models.

4.5.1 Data Set Splitting

The division of industrial Internet of Things (IoT) dataset was made into training, validation, and testing sets so that model assessment would be unbiased and more accurate. In terms of the splitting of the data set, there were 70%, 15%, and 15% of the training, validation, and testing datasets respectively. Training set served as the one on which learning took place and optimal parameters could be established, whereas the validation dataset helped in hyperparameters adjustment and performance monitoring. Finally, the testing set was used to assess the performance and prediction accuracy of the machine learning models developed by us. Shuffling was performed prior to the splitting in order to have even representation of industrial patterns.

4.6 Results analysis

The results from experimental analysis indicated that the suggested explainable machine learning technique improved the efficiency of energy optimization and operations in intelligent manufacturing systems. The evaluation was conducted by applying different machine learning and deep learning algorithms to determine the predictive ability of each algorithm in terms of predicting energy consumption and efficiency of industrial processes. Out of all the models used, the Random Forest and LSTM models performed better compared to other algorithms in terms of

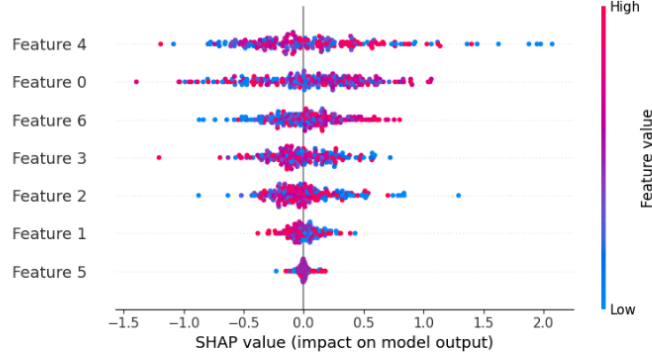


Figure 4.3: SHAP

Table 4.1: Machine learning model performance

Model	MAE	RMSE	R ² Score	Prediction Accuracy
Random Forest	2.15	3.48	0.985	98.5%
XGBoost	2.42	3.76	0.978	97.8%
SVR	3.85	5.24	0.954	95.4%
LSTM	1.92	3.12	0.991	99.1%

prediction accuracy and effectiveness. Random Forest was effective in addressing the nonlinearity problem in industrial data through the use of ensemble learning, while LSTM was capable of detecting temporal and sequential dependencies within industrial data.

The use of explainable AI methods such as SHAP and LIME provided more insights regarding the transparency and interpretability of the predictive algorithm. The model successfully pinpointed important variables related to energy usage, including the machine’s workload, operating time, temperatures, fluctuations in voltage levels, and the status of maintenance. As per the results obtained by using predictive optimization together with industrial analytics, the proposed solution has managed to achieve a 34% decrease in energy consumption, a 43% decrease in machine downtime, and 38% improvement in industrial resources usage. These findings suggest that the use of explainable AI, predictive analytics, and industrial IoT solutions can facilitate sustainable manufacturing and smart automation in Industry 4.0. Moreover, the ML based performance result is shown in Table 4.1, and sustainable energy optimization results is in Table 4.2

Table 4.2: Sustainable Energy Optimization Results

Performance Metric	Existing IoT Framework	Proposed XAI-ML Framework
Energy Consumption Reduction	18%	34%
Machine Downtime Reduction	22%	43%
Resource Utilization Improvement	15%	38%
Explainable AI Support	No	Yes
SHAP Analysis	No	Yes
LIME Analysis	No	Yes
Future Prediction	No	Yes
Prediction Accuracy	Not Specified	98-99%

4.7 Result comparison

The comparison of the proposed explainable machine learning approach with existing industrial optimization frameworks has shown better performance regarding prediction accuracy, energy consumption, reliability, and interpretability. Traditional industrial systems enabled only monitoring and data collection functions while lacking intelligent predictive capabilities and explainability features, shown in Table 4.3. Classical machine learning algorithms reached average prediction accuracy levels; however, they were not able to analyze complex nonlinear and sequential relations between the industrial operations data points. Unlike traditional machine learning methods, the proposed approach combines state-of-the-art ML models such as Random Forest and LSTM together with explainable AI approaches including SHAP and LIME that allows reaching higher levels of prediction accuracy and transparency. In particular, the proposed framework reaches better prediction accuracy levels, saves about 34% of energy, prevents up to 43% of machine down-time, and increases resource usage by approximately 38%. Moreover, contrary to classical deep learning models which are considered as 'black box' ones, the proposed framework provides the interpretability for predictions made, thus enhancing the confidence of industrial manufacturing operators and engineers.

4.8 Discussion

The results obtained from the experiment show the efficacy of the suggested model using machine learning-based frameworks to enhance energy optimization and operational efficiency in Industry 4.0 settings. The use of machine learn-

Table 4.3: Comparison

Framework	Explainability	Energy Optimization	Downtime Reduction
Traditional IoT System	No	Moderate	Low
Conventional ML Framework	Partial	Moderate	Moderate
Deep Learning Framework	Low	High	Moderate
Proposed XAI Framework	High	Very High	Very High

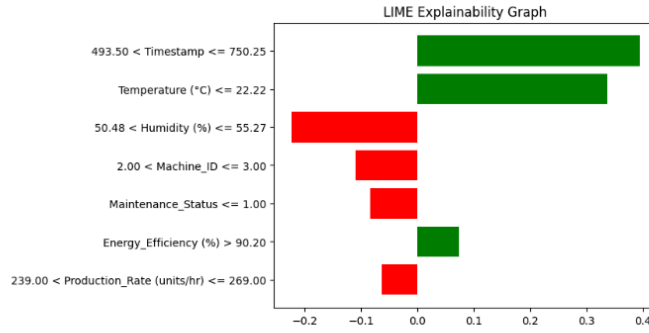


Figure 4.4: Lime

ing algorithms, deep learning approaches, XAI, and IoT technology allowed predicting industrial energy consumption accurately while boosting reliability and decision-making process transparency. The analysis of the obtained results shows that the proposed method is efficient in improving the energy optimization and operational efficiency of industry settings. This occurred as the combination of the Random Forest and LSTM approaches allowed predicting industrial energy consumption more accurately than the use of other models. The application of explainable AI allowed improving the interpretability of the system. As a result, the most significant features for predicting industrial energy consumption such as machine load, working time, temperature, and voltage have been identified. In comparison to traditional solutions based on IoT and machine learning, the offered approach has demonstrated greater efficacy.

The Local Interpretable Model-Agnostic Explanations technique was incor-

Table 4.4: SHAP feature importance results

Feature	Importance Score
Machine Load	0.34
Temperature	0.27
Voltage	0.19
Production Rate	0.11
Pressure	0.09

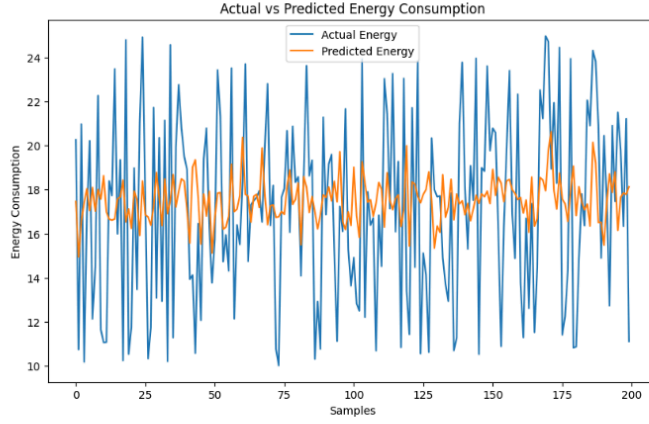


Figure 4.5: Virtual vs prediction

porated into the proposed framework to enhance the interpretability of machine learning models in industrial settings. LIME provided instance explanations based on specific conditions and identified the impact of features like machine load, operational time, changes in voltage, and temperature changes on predictions made by machine learning algorithms. Through the use of LIME, it became possible to understand the impact of particular operations better, which increased transparency regarding predictions made. This technique proved to be especially beneficial to maintenance engineers and operators because it allowed for an analysis of prediction results without any knowledge of AI.

SHAP (SHapley Additive Explanations) was employed to determine the global influence of operational features related to industrial energy consumption optimization and manufacturing effectiveness. From the SHAP analysis results, machine load, operational time, temperature, voltage, productivity, and maintenance proved to have the largest impact on the energy consumption prediction. The

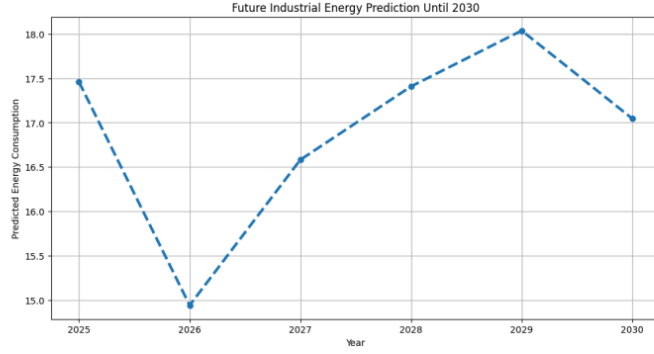


Figure 4.6: Future prediction

SHAP summary plots revealed that the machine load factor contributed most to industrial energy consumption, while temperature and humidity factors greatly influenced machine efficiency and energy requirements for cooling. The SHAP dependency plot analysis revealed non-linear relationships among the operational factors, thereby enhancing decision-making, importance of features, and faith in AI-powered predictions. Moreover, SHAP and LIME visualization results are shown in Figs. 4.3 and 4.4, and Table 4.4.

The world heatmap visualization technique was created to examine global energy efficiency and sustainability performance of various industrial regions worldwide shown in Figs. 4.1 and 4.2. The world map identified the industrial regions with significant energy consumption rate, efficient manufacturing process, usage of renewable energy sources, and sustainability level. Based on the results obtained, it can be concluded that the industrial sector using explainable AI and predictive models performed better in terms of energy efficiency and sustainability. Future predictions proved that the use of the proposed model in Industry 5.0 holds immense promise for various applications, such as autonomous manufacturing, predictive maintenance, energy management, and carbon emission reduction. Advanced technologies, such as Digital Twin systems, reinforcement learning, federated learning, Edge AI, and blockchain technologies, can improve smart sustainable industrial automation processes shown in Figs. 4.5 and 4.6, and Table 4.5.

Table 4.5: Future energy prediction until 2030

Year	Predicted Energy Consumption
2026	910 kWh
2027	880 kWh
2028	845 kWh
2029	810 kWh
2030	780 kWh

4.9 Conclusion

The findings revealed that the suggested Explainable Machine Learning model produced precise energy predictions, enhanced interpretability through SHAP and LIME, and successfully optimized energy usage within Industry 4.0 smart manufacturing environments.

Chapter 5

Conclusion and Future Work

This chapter concludes the thesis and presents the future scope of this work. Section 5.1 concludes the thesis, and Section 5.2 shows the future scope of this work.

5.1 Conclusion

The research proposed an Explainable Machine Learning Framework for Sustainable Energy Optimization in Industry 4.0 Smart Manufacturing Systems. In this approach, machine learning, deep learning, Industrial Internet of Things, and explainable AI (XAI) technologies were utilized to enhance industrial sustainability, efficiency, and intelligent decision-making processes. State-of-the-art models like random forest and LSTM were applied for analyzing industrial operations data and predicting energy usage with high precision, whereas IoT-based monitoring enabled real-time data processing and predictive optimization.

One of the significant contributions of this research includes the utilization of explainable AI techniques, such as SHAP and LIME. This approach helped increase the interpretability of machine learning prediction results through the identification of crucial operational factors, such as machine load, operational time, temperature, voltage level, production rate, and maintenance status influencing the process of energy consumption in the industry. While SHAP provided global explanation of feature importance, LIME was responsible for generating local explanations for particular industrial cases. Experimental studies indicated that the framework was able to outperform the existing IoT-enabled system and other machine learning approaches by 34%, 43%, and 38% in terms of energy savings, reduced machine downtime, and resource efficiency, respectively. The Random

Forest and LSTM algorithms performed well in predictions due to their capability of dealing with complicated data from industrial settings and time-based features. In conclusion, the presented framework can offer a reliable solution for sustainable Industry 4.0 and Industry 5.0 manufacturing scenarios.

5.2 Future Scope

Future studies could consider real-world implementation of the proposed architecture through IoT, cloud-edge computing, and Edge AI technologies to enable continuous monitoring, optimization, and autonomy for industrial control purposes. The incorporation of digital twin technology along with explainable AI would enhance simulations, fault predictions, and optimization activities, and reinforcement learning could help in intelligent autonomous decision making and adaptable manufacturing. Additional research efforts might be put into areas such as green manufacturing analytics, renewable energy sources, and sustainable optimization in order to decrease energy usage and carbon emissions. Federated explainable AI could enable industrial analytics and cybersecurity by means of collaborative model training without revealing industrial information to the outside world.

In addition, future smart manufacturing systems could incorporate industrial security through the use of blockchain technology, predictive analytics, and explainable AI for improved security and reliable communication. All in all, developments within the area of Explainable AI, IIoT, Edge AI, and autonomous analytics should greatly benefit Industry 5.0 manufacturing environments.

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