Advancing Manufacturing Energy Efficiency: The Role of AI and Web-Based Tools

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***Abstract*—This paper introduces a web-based application that simplifies the data analysis processing chain by automating the analysis of arbitrary variables. In particular, our application allows users to easily upload and process data for the analysis of a target variable by exploiting machine learning and evolutionary algorithms for precise forecasting and optimization. We demonstrate the system's efficacy using a dataset from a textile company, where our application successfully predicted the target variables with a high level of R-squared of 0.78, using the best regression model. These results not only highlight its real-world applicability but also played an important role in enhancing sustainable manufacturing practices. This innovative application offers a significant step towards sustainable and efficient manufacturing, addressing the challenges of high energy consumption and environmental impact in the industry.**

***Index Terms*—Artificial Intelligence, Machine Learning, Energy Efficiency, Manufacturing Sector, Web-Based Application, Data Analysis, Optimization, Genetic Algorithms, Industrial Energy Management, Sustainable Manufacturing**

I. Introduction

The manufacturing sector plays a crucial role in driving economic growth, fostering innovation, and boosting production. It is, however, a significant consumer of energy. For instance, in 2022, industrial activities in Portugal accounted for approximately 34% of the nation's total energy consumption [1]. Such extensive energy demands lead to various challenges, including environmental concerns, escalating costs, and the potential depletion of resources [2].

In our digitally-driven era, the application of data science and artificial intelligence (AI) has proven to be highly effective in addressing these issues. Data science is instrumental in analyzing large datasets to identify patterns and pinpoint areas of energy wastage. AI leverages these data to forecast future energy requirements, devise strategies to curtail waste and enhance the energy efficiency of production processes [3]–[6].

In this work, we have developed an innovative application that automates the entire data science workflow for monitoring energy consumption, operating independently of human oversight. This application, designed to be user-friendly, allows for the effortless uploading and processing of datasets. It is versatile, capable of forecasting any target variable, be it categorical or numerical, and is equipped to handle a variety of structured datasets. The application's development involved the use of AI algorithms for the training phase and React-Native.js for the web interface design. It enables users to upload diverse data types for forecasting and adeptly manages training, prediction, and optimization tasks based on the dataset. The system also integrates evolutionary algorithms for enhanced optimization capabilities.

To demonstrate the efficacy of our application, we tested it with a dataset provided by a manufacturing company that uses cutting-edge technology for energy management and forecasting.

II. Related Works

In the evolving field of energy management, researchers have increasingly turned to advanced computational techniques to optimize energy consumption. This section is divided into two approaches: those using genetic algorithms (GAs) and those using non-genetic AI and ML methodologies. Each method offers unique insights and solutions to the challenges of efficient energy use.

A. Genetic Algorithms for Energy Optimization

The domain of genetic algorithms stands out for its ability to mimic evolutionary processes, offering robust solutions in energy management. Studies such as [18], and [20] explore the synergy between GAs and Artificial Neural Networks

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(ANNs) in optimizing energy consumption in office buildings. These investigations reveal how the adaptive nature of GAs can fine-tune ANNs for superior energy efficiency. Exploring beyond traditional applications, [15] extends the use of GAs to the energy optimization of wireless sensor networks. In the innovative work of [17], GAs are used to develop a novel PID controller for office buildings, highlighting the potential of GAs in creating sophisticated and efficient control systems. A notable hybrid approach is presented in [22], where the integration of machine learning with GAs offers enhanced prediction accuracy in energy consumption within Iran. Moreover, [19] leverages GAs for optimized feature engineering in hybrid machine learning models. The GAs is showcased in [21], where they are utilized to design complex structures of deep neural networks for electricity consumption prediction. The usability of genetic programming is further highlighted in [24] and [23], where it is applied to forecast building energy consumption and predict natural gas usage, respectively.

B. Diverse AI and ML Approaches in Energy Management

Apart from genetic algorithms, other AI and ML techniques have also been widely adopted in energy management; works like [3] and [6] utilise traditional machine learning models for insightful analysis and predicting energy consumption. Advancing into more complex domains, [12] proposes a deep reinforcement learning method, showcasing the potential of cutting-edge ML techniques to respond to complex energy management challenges. In [7], authors rely on deep convolutional neural networks for predicting electricity consumption in buildings. In another work [25], ANNs are combined with model predictive control for energy optimization. Big data analytics and AI are used in [8] and [9] for industrial energy consumption analysis. Exploring broader technological horizons, [4] used AI, Big Data, IoT, and Blockchain in smart energy management. Finally, [14] and [5] methods focus on LSTM networks for energy consumption prediction and reviewing AI and ML applications in emerging markets.

III. Methodology

This section outlines the methodology adopted in the development of our application, designed for accurate forecasting of a target variable from dataset features. The process encompasses several stages, from initial data collection and preprocessing to the application of machine learning models and optimization techniques.

A. Data Collection

We collected data from a textile production company in Portugal. The dataset included detailed records of energy consumption in relation to machine operations and material usage from July 1st, 2021, to July 1st, 2023. It comprised 5562 entries with various categorical and numerical attributes, including machine type, material, and energy consumed.

B. Pre-Processing

The pre-processing stage involved several steps:

- **Data Cleaning:** Addressing missing values, duplicates, and errors to ensure data integrity.
- **Outlier Removal:** Employing z-score and Interquartile Range (IQR) methods to identify and eliminate outliers.
- **Categorical to Numerical Conversion:** Transforming categorical variables using label encoding for compatibility with machine learning algorithms.
- **Normalization:** Standardizing numerical features to have a mean of 0 and a standard deviation of 1.

C. Machine Learning Model Training

We experimented with various models, evaluating their performance based on Mean Squared Error (MSE) and R-squared metrics:

- **Decision Tree:** Employing criteria like max_depth to prevent overfitting.
- **XGBoost:** Optimizing parameters like learning_rate, max_depth, and n_estimators.
- **Random Forest:** Utilizing parameters like n_estimators and random_state for robust predictions.
- **Artificial Neural Network:** Configuring layers, neurons, and activation functions for effective learning.

D. Feature Importance Assessment

To understand the influence of features on model predictions, we used:

- **SHAP (Shapley Additive explanations):** Assessing individual feature contributions to predictions.
- **LIME (Local Interpretable Model-Agnostic Explanations):** Identifying key features affecting model outcomes in a local context.

E. Evaluation Metrics

Our models were evaluated using:

- **Mean Squared Error (MSE):** Calculating the average of squared differences between predicted and actual values.
- **R-squared (Coefficient of Determination):** Measuring the proportion of variance in the dependent variable explained by the independent variables.

F. Optimization Using Genetic Algorithm

To optimize target predictions, we employed:

- **Data-Based Algorithm:** Computing lower or higher energy consumption based on user-input features.
- **Genetic Algorithm:** Iteratively improving solutions using selection, crossover, and mutation, guided by ANN predictions as a cost function.

Algorithm 1 Data-Based Optimization Algorithm

Input: input_data: Data path, feature columns, user-input feature values, target column, min_max (min or max), standard deviation (std) entered by user

Output: row: Row with the optimal target value

if *input_data is empty* **then**
  if *min_max = 'min'* **then**
    Compute and return minimum target in dataset
  else
    Compute and return maximum target in dataset
  end
end
else
  Select rows matching user-input values **if** *no match found* **then**
    if *mismatch in categorical values* **then**
      Prompt for valid categorical values
      return *empty row*
    else
      Select rows within [value - std, value + std]
      return *row matching min_max target*
    end
  end
end

Algorithm 2 Genetic Algorithm

Input: input_data: Data path, feature columns, user-input feature values, target column, min_max (min or max), standard deviation (std) entered by user

Output: row: Row with the optimal target value

1) Preprocess, encode, and scale data.
2) Train ANN model.
3) Initialize population.
4) Define fitness function using ANN predictions.
5) Implement tournament selection for parent selection.
6) Apply crossover and mutation functions.

for *each generation* **do**
  Calculate fitness for each solution
  Select parents based on fitness
  for *each pair of parents* **do**
    Perform crossover and mutation
    Add offspring to new population
  end
  Update population
end
Identify the optimal row based on min/max fitness value.

IV. Experiment Results and Discussion

A. *Dataset*

Our study relied on a dataset comprising the functioning of different fabric producing machines and their energy consumption. The dataset, in CSV format, contained eleven features targeting energy consumption across 5562 instances.

B. *Implementation Details*

*a) **Dataset Splitting**:* The dataset was strategically divided into three subsets for training, validation, and testing, with proportions of 70%, 15%, and 15% respectively. This division was necessary for effective machine learning model training and evaluation.

Fig. 1: Traning history of ANN. The figure illustrates the history of Artificial Neural Networks (ANNs) training by showcasing loss by epochs or iterations to visualize the learning process and convergence of a neural network during training.

*b) **Model Training**:* The models that are training in our application:

Decision Tree. The Decision Tree model was trained by iteratively partitioning the dataset based on influential features. We optimized performance using parameters max_depth = 3 to prevent overfitting.

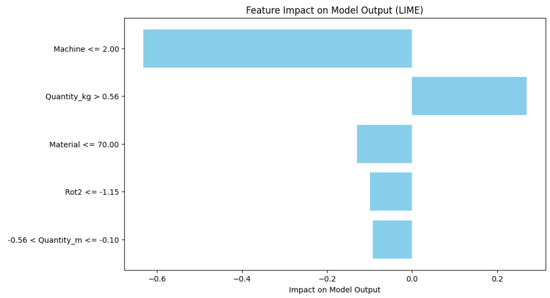
XGBoost. We employed a gradient descent approach to minimize loss functions. Key parameters included 'learning_rate' (set to 0.01), 'max_depth' (set to 3), and 'n_estimators' (set to 2000), crucial for optimizing the model's predictive capacity.

Random Forest. The Random Forest model, consisting of multiple decision trees, was trained on randomized subsets of data. Each tree independently predicted an outcome, and the model aggregated these predictions for a final result. We used 'n_estimators' = 200 and a random_state of 42 to ensure reproducibility and robust predictions.

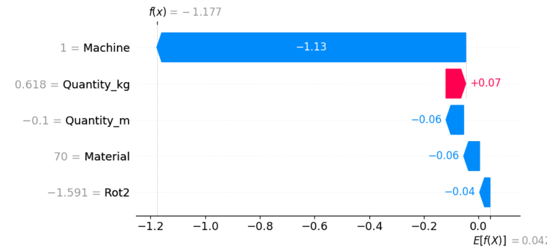
Artificial Neural Networks (ANNs). The ANNs had three hidden layers and one output layer, with varying neurons per layer (100 in the first, 50 in the second, and 25 in the third), and used ReLU activation functions. The Adam optimizer was employed for loss function minimization with a learning rate of 0.001. We implemented 'early stopping' with a default patience of 10 epochs, which is configurable in our application. This method halts training when no improvement is observed on the validation set after 100 epochs which is also configurable, preventing overfitting and guiding the selection of the best-performing model.

TABLE I: Evaluation of regression models

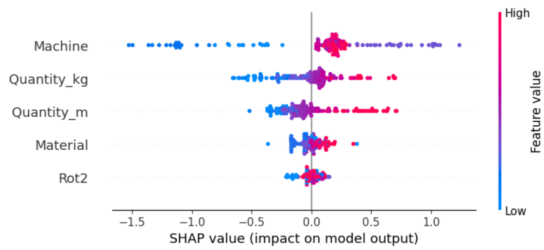
Model	MSE	R-squared(R^2)
Decision Tree	0.32	0.69
XGBoost	0.24	0.77
Random Forest	0.24	0.77
ANN	0.23	**0.78**



(a) Feature importance on model target (LIME)



(b) Feature importance on model target



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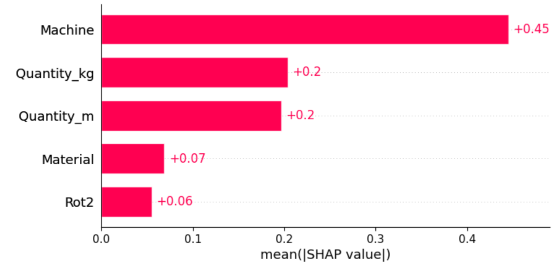
(c) Feature importance on model target (Shap value)



(d) Feature importance on model target (mean of Shap value)

Fig. 2: Feature importance on model output (energy consumed). (a) shows the importance of features(Machine MAterial, Quatity in meters and kilograms and Rot2) on the target variable(Energy) using LIME (Local Interpretable Model-agnostic Explanations) (b) and (c) showes the importance of features(Machine Material, Quatity in meters and kilograms and Rot2) on the target variable(Energy) using SHAP value and mean of SHAP value

C. Machine learning model results

The performance of each model was evaluated using Mean Squared Error (MSE) and R-squared (R^2) values, as summarized in the table (I). The results, as depicted, reveal that the Artificial Neural Network (ANN) exhibited the highest predictive accuracy and variance explanation, followed closely by the XGBoost and Random Forest models. The Decision Tree, while effective, showed slightly less accuracy in comparison. These insights are pivotal for understanding the efficacy of different machine learning models in predicting energy consumption and guiding future optimizations and applications in similar research areas. Fig. (1) depicts loss of ANN per epoch, allowing to visualize the learning process and convergence of the neural network during training. Fig. (2) shows the importance of features used in the ANN model obtained using SHap. Fig.(3) presents the best energy predicted for each generation in the genetic algorithm.

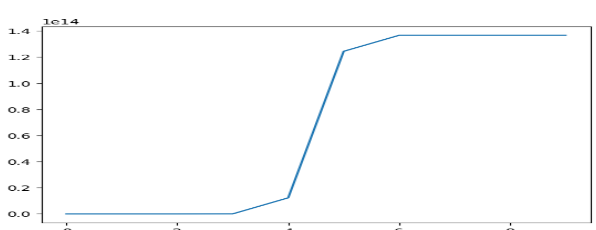


Fig. 3: The graph represents the best fitness values of each generation

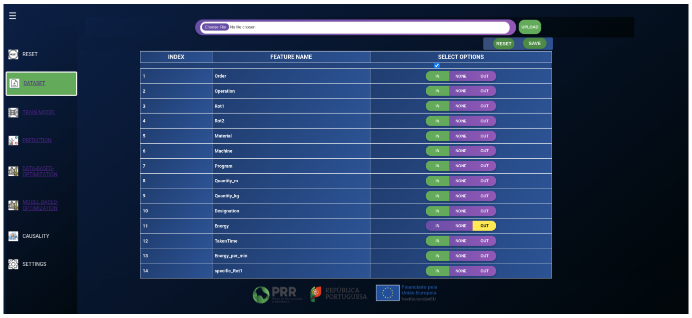
D. Application Development

We have developed a comprehensive web-based application designed to streamline the entire process outlined in our methodology. This application simplifies the user's role to merely uploading the dataset and choosing the relevant input and target variables. It efficiently manages numerous steps autonomously, offering user-configurable parameters including patience, learning rate, and the number of epochs. Figure (4) illustrates a screenshot of the application interface.

Beginning with (4a), the user is prompted to upload a CSV dataset. Subsequently, based on their specific objectives, the user selects the input features and the output (target) feature. This functionality is particularly advantageous in cases where the user intends to focus on a subset of features, allowing for customized feature selection. Upon saving their choices, the user is seamlessly directed to the training module.

In (4b), following the selection of input and output features, the user progresses to model training. Here, the user has the flexibility to configure hyperparameters such as the learning rate, patience, and epochs. The application dynamically displays training logs, enhancing user engagement and insight. Upon completion, the optimal model is automatically selected and stored on the server for future reference.

In (4c) presents the prediction interface of the application. The system intelligently identifies the type of features and accordingly suggests appropriate input values for ease of use. For categorical variables, it retrieves and displays all categories for the given column from the server. For numerical features, a user-friendly sliding tool is provided, enabling selection



(a) Data Upload Screen

(b) Train Screen

(c) Prediction Screen

(d) Optimization Screen

Fig. 4: Application Overview

among basic statistical values like mean, median, maximum, and minimum. The prediction module then transmits this data to the server via an API. The server, utilizing the trained model, generates prediction results and sends them back to the prediction module through the API.

In (4c), the application showcases the optimization module. This module's primary function is to identify the optimal configuration concerning the target variable. For instance, consider a manufacturer who wishes to determine the ideal energy consumption for producing 40 meters of fabric. In this scenario, the user inputs '40 meters' as the target output in the module. This information is then transmitted to the server via an API, which subsequently leverages the optimization module to calculate the most efficient settings configuration. Once determined, this information is relayed back to the user through the module, where a detailed report is presented. This report can be immensely beneficial in the production process, enabling manufacturers to adjust their machine settings accordingly for optimal efficiency and output. This functionality not only enhances operational effectiveness but also aids in resource optimization and cost reduction.

V. Conclusion

In this paper, we successfully demonstrate the potential of integrating Artificial Intelligence and Machine Learning into the field of energy management within the manufacturing sector. The development and implementation of our web-based application represents a significant advance in this domain. By automating the machine learning workflow, the application simplifies the complex process of energy consumption analysis, making it accessible and efficient for users. The use of advanced AI algorithms, combined with the strategic application of genetic algorithms for optimization, has proven effective in our application, not only in forecasting energy requirements but also in identifying the most efficient operational settings. Specifically, our application demonstrated promising results in predicting energy consumption based on provided features, achieving an R-squared value of 0.78. This facilitates the optimization of machine settings in real-time, enhancing efficiency and performance. These results highlight the practical benefits of our approach in optimizing energy consumption using genetic algorithms with ANN as fitness function and operational efficiency, thereby contributing to more sustainable manufacturing practices. This is particularly beneficial for industries aiming to reduce their energy consumption and optimize production processes, thereby contributing to both economic and environmental sustainability. Our application's real-world efficacy was validated using a comprehensive dataset from a Portuguese textile company. The results obtained evidence the application's capability in accurately predicting and optimizing energy consumption, thereby aiding in informed decision-making and resource management. This study not only provides a practical solution for energy management in the manufacturing sector but also paves the way for future research and development in the integration of AI and ML for sustainable industrial practices. It stands as a testament to the transformative power of technology in addressing some of the most pressing challenges of our time.

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