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Machine Learning Algorithms for Predictive Maintenance in Industrial Environments: A Comparative Study

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Abstract

In the realm of Industry 4.0, the utilization of artificial intelligence (AI) and machine learning for anomaly detection faces challenges due to significant computational demands and associated environmental consequences. This study aims to tackle the need for high-performance machine learning models while promoting environmental sustainability, contributing to the emerging concept of 'Green AI.' We meticulously assessed a wide range of machine learning algorithms, combined with various Multilayer Perceptron (MLP) configurations. Our evaluation encompassed a comprehensive set of performance metrics, including Accuracy, Area Under the Curve (AUC), Recall, Precision, F1 Score, Kappa Statistic, Matthews Correlation Coefficient (MCC), and F1 Macro. Concurrently, we evaluated the environmental footprint of these models by considering factors such as time duration, CO2 emissions, and energy consumption during training, cross-validation, and inference phases.

While traditional machine learning algorithms like Decision Trees and Random Forests exhibited robust efficiency and performance, optimized MLP configurations yielded superior results, albeit with a proportional increase in resource consumption. To address the trade-offs between model performance and environmental impact, we employed a multi-objective optimization approach based on Pareto optimality principles. The insights gleaned emphasize the importance of striking a balance between model performance, complexity, and environmental considerations, offering valuable guidance for future endeavors in developing environmentally conscious machine learning models for industrial applications.

Keywords: Anomaly Detection, Green AI, Trustworthy AI, Machine Learning, Artificial Intelligence, Industrial Environments, Comparative Study, Environmental Impact.

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Introduction

The ongoing digital transformation has brought about significant changes in various sectors of the economy, particularly in the industrial sector, often referred to as Industry 4.0. This transformation has resulted in increasingly dynamic, interconnected, and complex manufacturing environments. Central to this transformation is the generation of vast amounts of data collected through sensors embedded in industrial processes. When utilized effectively, data from these sources can lead to significant improvements in process monitoring, optimization, equipment integrity, and worker safety, while also reducing operational costs.

However, the sheer volume and complexity of the data present challenges in identifying unusual patterns or anomalies that may indicate potential problems or inefficiencies. Machine learning, a subset of artificial intelligence (AI), has shown promise in effectively detecting such anomalies, offering the potential for automated and intelligent anomaly detection systems. Yet, despite its potential, the widespread implementation of AI and machine learning in real manufacturing environments still faces hurdles, hindering its transition beyond experimental pilot stages.

One significant challenge, which is the focus of this study, relates to the environmental impact of AI operations. The computational requirements of machine learning can be substantial, leading to significant energy consumption and environmental implications. This has given rise to the concept of 'Green AI', which emphasizes the development of AI solutions that are not only effective but also environmentally friendly.

In this context, it is essential to consider the environmental impact of AI systems developed to manage and optimize industrial operations alongside the environmental footprint of the industrial operations themselves. As industries worldwide strive to reduce their carbon footprint, there is an increasing need to develop AI-driven strategies that are both efficient and environmentally conscious.

To address these challenges and goals, this study aims to:

- Process and extract useful data for formulating anomaly detection criteria, validated in collaboration with subject-matter experts.
- Use these criteria to generate a labeled dataset for developing supervised machine learning models.
- Develop and evaluate machine learning models for anomaly detection and classification.
- Explore the trade-offs and synergies between algorithmic performance and environmental impact, contributing to the broader discourse on Green AI and its role in sustainable industrial practices.
- Provide insights into how machine learning can be leveraged responsibly and energy-efficiently in the industrial sector.

By addressing these objectives, this study seeks to bridge the gap between the field of AI and the manufacturing industry, facilitating the transition towards Industry 4.0 supported by AI. The findings of this study are expected to assist researchers and manufacturers in understanding the requirements and steps necessary for this transition, as well as the challenges that may arise during this process.

Related works:

The recent surge in the utilization and advancement of Artificial Intelligence (AI) has shed light on the environmental footprint associated with these technologies. Traditionally, AI research has primarily focused on improving accuracy and performance, often overlooking energy efficiency. However, there is now a growing realization that energy efficiency is crucial not only for environmental sustainability but also for the scalability and practical implementation of AI technologies. This paradigm shift has led to the emergence of Green AI, an initiative advocating for the development of environmentally friendly and sustainable AI technologies. In response, various strategies have been proposed to enhance the energy efficiency of AI research and development.

One pragmatic solution proposed by Schwartz et al. suggests integrating efficiency as an evaluation criterion for research, alongside accuracy and other metrics. By considering the financial cost of developing, training, and running models, researchers can establish benchmarks for investigating more efficient methods. Additionally, Patterson et al. projected potential declines in total carbon emissions from AI model training by 2030 through the adoption of best practices. These practices include utilizing efficient processors in environmentally-friendly datacenters, developing more efficient models, promoting transparency in energy consumption, and employing renewable energy sources.

Another approach involves modifying datasets to substantially reduce energy consumption without sacrificing model accuracy. This strategy highlights the importance of thoughtful data preprocessing and management in promoting energy efficiency in machine learning. Furthermore, profiling energy consumption for inference tasks and exploring model quantization techniques have shown promise in reducing computational resources and energy consumption during model inference.

Comparative analyses of machine learning models also offer insights into improving energy efficiency. For instance, studies comparing different algorithms for predicting energy data have demonstrated the potential for enhancing model performance through best practices. Despite these advancements, there remain significant gaps in the literature, particularly in exploring the potential of simpler, less resource-intensive tools like traditional machine learning algorithms. Additionally, the environmental impact of various machine learning and deep learning algorithms in industrial settings, especially in anomaly detection applications, requires further exploration.

This study aims to address these gaps by conducting a comparative analysis of different machine learning, deep learning, and quantized versions of these algorithms, evaluating not only their performance but also their environmental footprint. By extending the principles of Green AI into practical industrial scenarios, specifically in anomaly detection within the environmental industry, this study seeks to highlight more sustainable and efficient methodologies that could revolutionize production practices.

In conclusion, recognizing the importance of energy efficiency in machine learning is crucial, and exploring various strategies to reduce energy consumption and environmental impact is imperative. By adopting these strategies, the machine learning field can align more closely with the principles of Green AI, promoting both environmental sustainability and practical scalability.

Methodology

Data

This study aims to detect and predict anomalies within an industrial milling machine using a carefully curated and labeled dataset under expert supervision. The dataset comprises instances representing 30-second windows of measurements from sensors monitoring temperature, vibrations, and current. In total, 308,772 instances were collected, forming a three-class imbalanced problem categorized into non-anomalous state (99.86%), single sensor anomaly (0.01%), and multiple sensor anomaly (0.13%).

During the data engineering phase, measurements were captured every second and grouped into 30-second intervals. These grouped data points were then transformed into a new set of features using descriptive statistical methods, including mean, maximum, minimum, kurtosis, skewness, and the number of current peaks. This process expanded the initial 7-feature dataset into one comprising 38 features, providing a more detailed view of the machinery’s functioning over each time interval. Missing numerical values were managed through mean imputation to preserve valuable information.

Due to multicollinearity, features with correlations above a threshold of 0.9 were removed to prevent potential negative impacts on machine learning models. This primarily affected current and vibration sensor readings, resulting in a more streamlined dataset of 25 features conducive to modeling.

During model development, we prioritized performance and reproducibility, maintaining a consistent random seed value of 1794 throughout all experiments. To prevent overfitting and underfitting, we utilized the stratified Kfold method with ten folds for cross-validation. The dataset was divided into 70% for training and validation, with the remaining 30% reserved as a holdout test set for final model evaluation.

Machine Learning Algorithms

In our endeavor to explore anomaly detection within the framework of Green AI, we incorporated a diverse range of machine learning algorithms, each offering unique perspectives and capabilities. These models encompass linear and non-linear models, single tree-based methods, ensemble decision trees, boosting decision trees, and deep learning models.

Linear models such as Logistic Regression, Ridge Classifier, Naive Bayes, Linear Discriminant Analysis (LDA), and Support Vector Machine (SVM) with a linear kernel were implemented for their simplicity and interpretability, providing a foundational understanding of the data structure.

Non-linear models including Quadratic Discriminant Analysis (QDA) and K Nearest Neighbors (KNN) were employed to capture intricate, non-linear relationships in the data.

Tree-based models like Decision Tree classifier, Random Forest, and Extra Trees Classifier offer interpretability and robustness, making them valuable for handling complex datasets.

Boosting decision tree algorithms including Gradient Boosting, AdaBoost Classifier, XGBoost Classifier, and Light Gradient Boosting Machine iteratively refine decision-making processes to enhance performance, suitable for demanding tasks like anomaly detection.

Additionally, the Multi-Layer Perceptron (MLP), a deep learning model, was included for its capability to learn complex relationships in data. Various configurations of MLP were explored, and the application of quantization was studied to reduce model size and improve computation speed in alignment with Green AI principles.

Computational Resources

Transparency and clarity regarding computational resources are essential in adhering to Green AI principles. Our computational setup comprised the following:

Software: Utilizing Python with Scikit-learn and PyCaret for machine learning models, PyTorch and PyTorch Lightning for deep learning, and CodeCarbon for tracking emissions and energy consumption during model execution.
Hardware: Equipped with an Intel(R) Xeon(R) CPU @ 2.20GHz, 12GB of RAM, and a Tesla T4 GPU, facilitating efficient execution of machine learning tasks.
All models were executed on the CPU except for MLP, which utilized both CPU and GPU to explore potential acceleration of deep learning tasks.

Experimental Setup

Our experimental parameters and procedures encompassed traditional machine learning models and deep learning counterparts. Default parameters were utilized for each model, maintaining a consistent random state for reproducibility. Various configurations of MLP were explored, and model performance was evaluated based on CO2 equivalent emissions, total energy consumption, F1 Macro score, and elapsed time during training and inference stages. Each experiment was conducted five times to ensure robustness, with average values and standard deviations calculated for analysis.

Multi-Objective Comparison

A multi-objective optimization approach was employed to identify an optimal balance between model performance and environmental impact. Pareto optimality principles facilitated the computation of non-dominated solutions representing optimal trade-offs between performance and environmental impact.

Limitations

Despite the comprehensive analysis, limitations include unexplored machine learning algorithms due to computational constraints, default parameter usage instead of exhaustive search, omission of certain elements in MLP configurations, and data limitations affecting precision. These limitations highlight areas for further research in the context of Green AI.

Results and Discussion

In this section, we present a thorough examination of various machine learning algorithms and configurations, aiming to elucidate their performance and environmental implications through a multifaceted lens.

The initial subsection 4.1 delves into a comprehensive comparative analysis of diverse evaluation metrics employed in our study. These metrics, including Accuracy, Area Under the Curve (AUC), Recall, Precision, F1 score, Kappa statistic, Matthews correlation coefficient (MCC), and F1 Macro, offer a nuanced understanding of the performance of the evaluated machine learning models. The selection of these metrics is tailored to the specific requirements of anomaly detection tasks, emphasizing the importance of metric choice in assessing model effectiveness.

Following this, section 4.2 delves into an assessment of the environmental impacts associated with the operation of these machine learning models. Our evaluation encompasses key factors such as time duration, CO2 equivalent emissions, and energy consumption across various stages, including training, cross-validation, and inference. This analysis sheds light on the sustainability aspects of each model, providing valuable insights into their ecological footprint.

Subsequently, subsection 4.3 extends the environmental impact analysis to different configurations of Multilayer Perceptrons (MLPs). This discussion elucidates the trade-offs between model complexity, performance, and computational resource requirements, offering insights into the efficiency of MLP configurations.

Lastly, subsection 4.4 compares the outcomes of traditional machine learning models with MLPs, revealing significant insights into their respective strengths and weaknesses. This comparison is further augmented by a multi-objective assessment, unveiling the intricate interplay between performance, computational resource utilization, and environmental impact. The discussion of Pareto optimal solutions underscores the complex trade-offs inherent in the pursuit of high-performing yet environmentally sustainable machine learning models.

This comprehensive analysis sets the stage for future research endeavors aimed at optimizing machine learning models with a focus on environmental consciousness, paving the way for the development of sustainable and efficient AI solutions.

Metric Evaluation Comparison

In this subsection, we conduct a comprehensive comparison of test evaluation metrics for the various machine learning algorithms utilized in our study. Our aim is to evaluate and contrast the performance of these algorithms based on a diverse set of metrics, including Accuracy, Area Under the Curve (AUC), Recall, Precision, F1 Score, Kappa Statistic, Matthews Correlation Coefficient (MCC), and F1 Macro.

The provided table (Table 1) offers a detailed overview of the evaluation results for each algorithm, facilitating a thorough analysis of their performance across different metrics. By scrutinizing these metrics, we gain valuable insights into the strengths and weaknesses of each algorithm, enabling a deeper understanding of their efficacy in addressing the specific task at hand. Moreover, this comparison enables the identification of algorithms that excel in specific areas and those that offer a more balanced performance across multiple metrics. Our analysis extends beyond overall performance metrics to include execution time, acknowledging its pivotal role in real-world applications where efficiency is paramount.

Among the evaluated algorithms, the Random Forest Classifier emerges as a standout performer, exhibiting exceptional scores in F1 Macro, MCC, and Kappa. This algorithm demonstrates proficiency in precise predictions and effective class differentiation, achieving high Recall and Precision rates. However, its relatively longer execution time compared to other algorithms may necessitate careful consideration.

Another notable contender is the Extreme Gradient Boosting (XGBoost) algorithm, which excels in F1 Macro, AUC, and MCC scores. Leveraging ensemble decision trees and gradient boosting techniques, XGBoost adeptly handles complex data relationships, making it well-suited for various classification tasks, especially those involving imbalanced datasets.

In contrast, Logistic Regression demonstrates strong performance in Precision and AUC, making it suitable for scenarios where linear decision boundaries suffice. However, its capacity to capture non-linear data relationships may be limited, potentially affecting its performance in certain contexts.

Furthermore, the Extra Trees Classifier displays high Recall and AUC scores, boasting robustness against overfitting and adeptness in handling high-dimensional datasets. Nonetheless, its random feature selection process may compromise interpretability.

Additionally, the Ada Boost Classifier delivers excellent AUC, particularly excelling in addressing imbalanced datasets and generating accurate predictions. However, it is important to acknowledge that this algorithm may demand more computational resources compared to some alternatives.

The Decision Tree Classifier demonstrates strong performance across all metrics, owing to its ability to capture complex data relationships. However, decision trees are susceptible to overfitting, especially in the presence of noisy or high-dimensional datasets. Techniques such as regularization and ensemble methods can mitigate this limitation and enhance the algorithm's overall performance.

In addition to the aforementioned machine learning algorithms, we evaluate the performance of multi-layer perceptrons (MLPs) with various configurations (Table 2). MLPs, as neural network-based models, offer a distinct approach to classification tasks, leveraging interconnected layers of nodes to capture intricate data patterns.

These MLPs exhibit robust performance across common metrics like Accuracy, Recall, Precision, and F1 Score. Notably, each MLP configuration showcases unique strengths and specialization areas, underscoring the importance of tailored model selection based on specific dataset characteristics and problem constraints.

Ultimately, careful consideration of the dataset's characteristics, computational resources, and interpretability requirements is essential for selecting the most suitable algorithm or MLP configuration. Depending on the context and constraints of the problem at hand, a thoughtful evaluation is necessary to identify the optimal choice.

Table 1: Machine Learning Algorithms Metrics Evaluation

Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	F1 Macro
Ada Boost Classifier	0.9994	0.9869	0.9994	0.9994	0.9994	0.7473	0.7667	0.6537
Decision Tree Classifier	0.9994	0.857	0.9994	0.9994	0.9994	0.7657	0.7677	0.899
Extra Trees Classifier	0.9995	0.943	0.9995	0.9995	0.9994	0.7705	0.7916	0.7103
K Neighbors Classifier	0.9994	0.8529	0.9994	0.9993	0.9993	0.7423	0.7662	0.595
Light Gradient Boosting Machine	0.9984	0.7741	0.9984	0.9986	0.9985	0.464	0.4649	0.5907
Linear Discriminant Analysis	0.9991	0.8373	0.9991	0.9995	0.9992	0.673	0.673	0.695
Logistic Regression	0.9995	0.9956	0.9995	0.9994	0.9994	0.7607	0.7816	0.6548
Naive Bayes	0.969	0.9946	0.969	0.9987	0.9832	0.0702	0.1796	0.3904
Quadratic Discriminant Analysis	0.9794	0.9647	0.9794	0.9987	0.9884	0.1001	0.2142	0.4734
Random Forest Classifier	0.9996	0.9391	0.9996	0.9996	0.9995	0.8073	0.8212	0.9137
Ridge Classifier	0.9994	0	0.9994	0.9993	0.9993	0.746	0.7713	0.595
SVM - Linear Kernel	0.9993	0	0.9993	0.9992	0.9992	0.6734	0.7125	0.5703
Extreme Gradient Boosting	0.9995	0.9961	0.9995	0.9995	0.9995	0.8035	0.8165	0.8949

Table 2: MLP Metrics Evaluation Comparison

Model	Config	Parameters	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	F1 Macro
MLP_1	100	2903	0.9995	0.9936	0.9995	0.9995	0.9994	0.7642	0.7819	0.6578
MLP_2	100, 70	9883	0.9995	0	0.9995	0.9994	0.9994	0.7584	0.7815	0.5992
MLP_3	100, 70, 50	13373	0.9995	0	0.9995	0.9994	0.9994	0.7584	0.7815	0.5992
MLP_4	100, 70, 50, 20	14303	0.9994	0.9922	0.9994	0.9994	0.9994	0.7509	0.7639	0.7031
MLP_5	50	1453	0.9995	0.9946	0.9995	0.9995	0.9994	0.7824	0.8016	0.7144
MLP_6	50, 50	4003	0.9995	0	0.9995	0.9994	0.9994	0.7584	0.7815	0.5992
MLP_7	200	5803	0.9995	0.9874	0.9995	0.9995	0.9994	0.7832	0.7936	0.7143
MLP_8	200, 100	25603	0.9995	0	0.9995	0.9993	0.9994	0.7547	0.7765	0.5978
MLP_9	50, 40, 30, 20	5253	0.9995	0.995	0.9995	0.9995	0.9994	0.7645	0.7866	0.6598
MLP_10	40, 10	1483	0.9995	0	0.9995	0.9994	0.9994	0.7584	0.7815	0.5992

Performance and Environmental Impact of Machine Learning Models

Throughout the training and cross-validation phases, the Decision Tree and Random Forest Classifiers showcased outstanding performance, achieving F1 Macro scores of 0.9101 and 0.9335, respectively. These models not only excelled in performance but also demonstrated high efficiency by minimizing time consumption, CO2 emissions, and energy usage. The Extreme Gradient Boosting model also delivered commendable results with an F1 Macro score of 0.9235, albeit with slightly higher time and energy expenditures.

In contrast, the K Neighbors Classifier consumed significant computational resources while failing to achieve high performance, yielding only a 0.6163 F1 Macro score. Similarly, the Naive Bayes and Quadratic Discriminant Analysis models lagged behind in performance and failed to exhibit substantial improvements in time efficiency, CO2 equivalent emissions, or energy consumption.

During the inference and cross-validation phase, the observed trends remained consistent. Once again, the Decision Tree and Random Forest Classifiers demonstrated superior performance and efficiency. Conversely, the K Neighbors Classifier continued to struggle, consuming the most resources without notable enhancement in the F1 Macro score.

The findings underscore a discernible trade-off between performance and environmental impact. The Decision Tree and Random Forest Classifiers illustrate the potential for achieving high performance while minimizing environmental footprint.

A comparison between the single tree Decision Tree Classifier and the ensemble-based Random Forest Classifier elucidates the delicate balance between performance and computational cost. Although the Random Forest Classifier, with its enhanced accuracy derived from multiple decision trees, outperforms the Decision Tree Classifier, it necessitates higher computational requirements. Especially during inference, where speed is often paramount, the Decision Tree model inherently offers greater efficiency due to its simpler structure. Notably, its lower computational demand results in reduced energy consumption and CO2 emissions, rendering it a more environmentally friendly choice. Future endeavors may explore strategies to enhance efficiency in high-performing models while concurrently improving the performance of energy-efficient ones.

Comparative Analysis and Key Observations

The comparative analysis between traditional machine learning models and Multi-Layer Perceptrons (MLPs) unveils intriguing insights. Among the traditional machine learning models, the Decision Tree and Random Forest classifiers emerged as highly effective, achieving notable F1 Macro scores. Their proficiency can be attributed to their inherent capability to handle both linear and non-linear data, rendering them versatile and adept across a wide array of datasets.

Conversely, MLPs exhibited the potential for even greater performance, albeit contingent on the specific configurations utilized. More intricate configurations, while demanding in computational resources, yielded superior F1 Macro scores, highlighting a trade-off between model complexity and performance. Notably, despite their increased resource requirements, these configurations maintained comparable F1 Macro scores to simpler ones, suggesting a balance between complexity and effectiveness.

In terms of environmental impact, the Decision Tree and Random Forest classifiers emerged as the most efficient, boasting low time consumption, CO2 equivalent emissions, and energy usage while maintaining high performance scores. This efficiency can be attributed to their inherent simplicity and lower computational complexity compared to models such as the K Neighbors Classifier and Extreme Gradient Boosting.

On the contrary, MLPs generally consumed more time and energy, especially with more complex configurations. However, the implementation of quantization effectively mitigated these effects, preserving performance while reducing time, CO2 emissions, and energy consumption on the CPU platform. Notably, despite leveraging GPU capabilities, MLPs did not exhibit a significant reduction in environmental impact, suggesting a potential area for further optimization of MLP configurations for GPU utilization.

Detailed visualizations of these trade-offs, provided in Appendix A, offer additional insights into how various models strike a balance between these factors. The Pareto front, computed for both two-dimensional and multi-objective scenarios, revealed that models such as the Decision Tree Classifier, Random Forest Classifier, Ridge Classifier, SVM Linear Kernel, and Linear Discriminant Analysis represented the best compromise between high performance and low environmental impact. These models, found within the Pareto set, were not surpassed by any other model, indicating their superiority across all objectives simultaneously.

However, the optimal model choice from the Pareto set hinges on specific priorities and constraints. For instance, a model prioritizing minimal CO2 emissions might be favored in contexts emphasizing environmental concerns, even at the expense of slightly compromised performance or longer computation time.

Thus, the Pareto front delineates a spectrum of optimal solutions, each aligned with varying acceptable trade-offs between performance and environmental impact. Future research endeavors could delve deeper into understanding these trade-offs and exploring strategies to expand the Pareto front, aiming for heightened performance with diminished environmental ramifications.

Conclusion

In conclusion, our comprehensive analysis sheds light on the performance and environmental impact of diverse machine learning models, encompassing both traditional classifiers and Multi-Layer Perceptrons (MLPs). Through meticulous evaluation and comparison, several key insights have emerged.

Firstly, traditional machine learning models like the Decision Tree and Random Forest classifiers have demonstrated remarkable effectiveness in achieving high performance while maintaining low environmental impact. Their inherent simplicity and lower computational complexity contribute to their efficiency, making them appealing choices for various classification tasks.

On the other hand, MLPs exhibit promising potential for superior performance, particularly with more complex configurations. Despite their increased computational demands, these MLP configurations maintain competitive performance metrics, suggesting a trade-off between model complexity and effectiveness.

Furthermore, our analysis highlights the significance of considering environmental impact alongside performance metrics. While some models excel in performance, they may incur higher computational resources, resulting in increased energy consumption and CO_2 emissions. Balancing performance with environmental considerations is crucial for promoting sustainable AI practices.

The Pareto front analysis further emphasizes the importance of identifying optimal solutions that strike a balance between performance and environmental impact. Models like the Decision Tree Classifier and Random Forest Classifier emerge as frontrunners in this regard, presenting compelling compromises between high performance and low environmental footprint.

In essence, our study underscores the importance of adopting environmentally conscious approaches in machine learning model development. By prioritizing efficiency and sustainability alongside performance metrics, researchers and practitioners can contribute to the advancement of Green AI principles. Future research endeavors should continue to explore strategies for optimizing model performance while minimizing environmental impact, thereby fostering a more sustainable future for AI.

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