Optimizing Industrial Production Processes Through AI-Based Anomaly Detection – An Investigation of Selected AI Methods

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Abstract: This research investigates the rising influence of Artificial Intelligence in industrial operations, specifically in anomaly detection and performance prediction. Seven methods (Random Forest Regression, Elastic Net Regression, Support Vector Regression, Gradient Boosting Machines, Extreme Learning Machines, Neural Network, Long Short-Term Memory) were strategically selected to perform a multidimensional regression task. The central investigation focuses on identifying the most efficient method, with Random Forest Regression emerging as the superior choice among the examined methods. The research further examines the factors contributing to the demonstrated efficiency of Random Forest Regression in the domain of predicting machine values for anomaly detection.

Keywords: Artificial Intelligence, Anomaly Detection, AI Methods, Industry, Process Optimizing

1 Introduction

This research study addresses the growing relevance of Artificial Intelligence (AI) in the context of industrial processes, with a specific focus on its application in anomaly detection and performance prediction in industrial environments. In an era dominated by Industry 4.0 and advancing automation, the proactive identification of irregularities in production workflows is becoming increasingly crucial (Merz et al. 2023). The Fourth Industrial Revolution, known as Industry 4.0, aims to establish an industrial setting that facilitates real-time, intelligent, and autonomous manufacturing environments to create smart factories (Angelopoulos et al. 2019). To represent this vision, Industry 4.0 relies on cutting-edge information and communication technologies, including cyber-physical systems, the Internet of Things, and Cloud Computing (Quadir et al. 2022). Therefore Industry 4.0, introduced by the German Federal Government in 2011, marks a transition into a data-driven, digitally interconnected industry (Schmalzried et al. 2023). Industry 5.0 builds upon the digital advancements of Industry 4.0 by shifting from a technology-driven focus to an industrial orientation centered around humanity, sustainability, and resilience (Barata/Kayser 2023). It views workers as investments, adapts technology to diverse needs, and aims to ensure industrial robustness in the face of disruptions and crises (Xu et al. 2021), with support from technologies like Big Data and AI (Pizoń/Gola 2023). In the context of Industry 5.0, time series analyses are playing an increasingly significant role, as they are required for interpreting patterns and trends of data (Tallat et al. 2023).

In the dynamic context of Industry 5.0, dealing with anomalies becomes a critical concern (Rožanec et al. 2022). Unlike quality monitoring, which typically has sufficient data on disruptions, optimizing pattern recognition methods in production and logistics requires the adoption of supervised learning approaches, including the creation of metrics for assessing anomalies in complex environments (Van Giffen et al. 2021). Effectively handling this task goes beyond a standard comprehension of AI techniques; it requires a familiarity with conventional production, combined with a practical, value-centric approach (Schmalzried et al. 2023).

In Industry 5.0, the collaborative evolution of the human-machine relationship aims to revolutionize manufacturing processes and optimize efficiency (Leng et al. 2022). The integration of advanced information system solutions reinforces the role of AI in monitoring and optimizing machine operations within this dynamic human-machine relationship (Rožanec et al. 2022). Therefore, AI acts as a crucial facilitator in Industry 5.0, fostering collaborative and innovative interactions between humans and machines to attain efficiency, flexibility, and sustainability in manufacturing (European Commission et al. 2021).

In large-scale manufacturing, where machine downtime can have significant consequences, automation is commonly employed to enhance efficiency and reduce costs (Saveliev/Savelieva 2019). Hence, efficiently reducing anomalies in the manufacturing process through data-driven anomaly detection and automated comparisons with similar incidents is essential for improving overall system efficiency and minimizing disruptions (Mohan et al. 2021).

The objective of this research is to investigate a range of AI methods to improve the predictability of anomalies in industrial environments, acknowledging the increasing importance of AI in industrial settings. With a specific focus on anomaly detection and performance prediction, the research undertakes a multidimensional regression task. This involves predicting an output variable by considering multiple dimensions. During this investigation, the primary focus is on addressing the following research question:

"Which of the presented AI methods proves to be the most efficient for performance prediction for anomaly detection in industrial environments?"

Additionally, the study aims to reveal the fundamental factors that contribute to the major efficiency of the identified AI method in the context of anomaly prediction.

The following graphical abstract illustrates the steps and resulting outcome of this research.

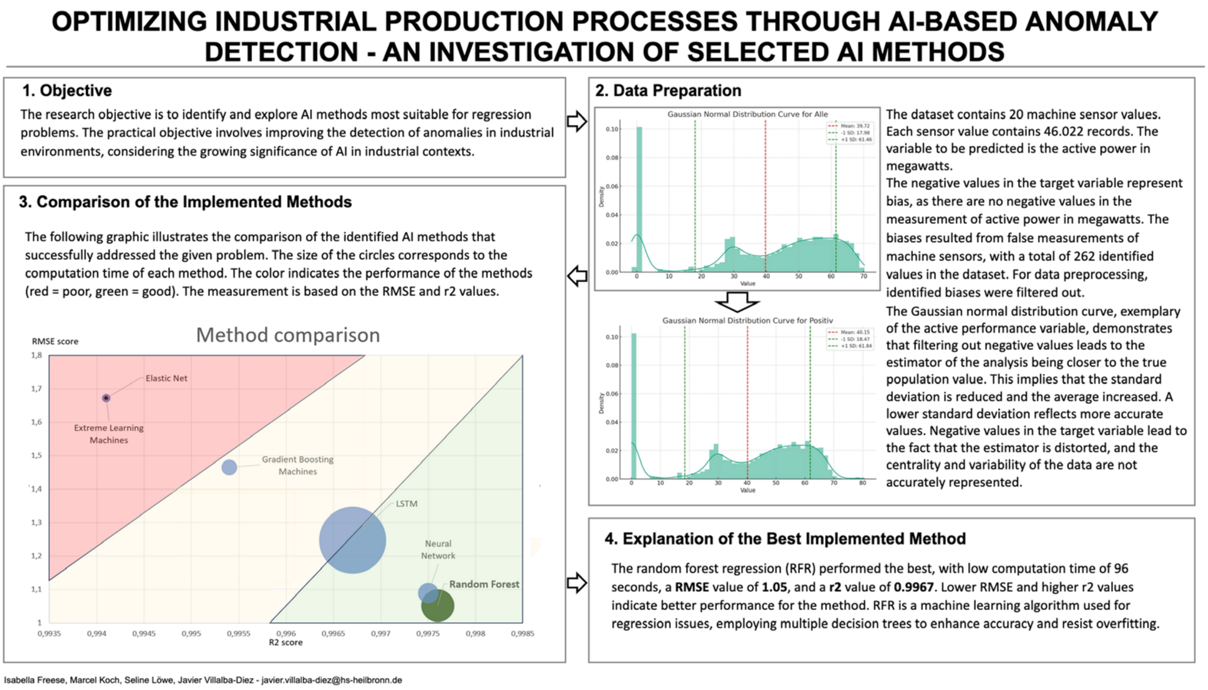

Image 1: Graphical Abstract (own illustration)

Step one was to identify AI methods for regression problems using a dataset of 20 machine sensor values, each with 46,022 data points. The target variable, active power in megawatts, presented biases with negative values, which were filtered out during step two, data preparation. Visualization through Gaussian distribution, mean, and standard deviation showed improved estimation. The graphic in step three compares AI methods based on computation time, RMSE and r2 scores. Random Forest outperformed, with a low computation time of 96 seconds, an RMSE of 1.05, and an R2 of 0.9967, efficiently addressing the objective of improving the predictability of anomalies in industrial environments.

2 Method Selection and Mathematical Backgrounds

Out of the most commonly used machine learning methods (Angelopoulos et al. 2019), (Nassif et al. 2021), (Shaukat et al. 2021), (Himeur et al. 2021), (Schmidl et al. 2022), (Peng et al. 2022), (Quadir et al. 2022), (Azevedo et al. 2023), seven were selected for implementation and training of the dataset. The selected methods are Random Forest Regression (Xue et al. 2021), Elastic Net Regression (Al-Jawarneh et al. 2021), Support Vector Regression (Parbat/Chakraborty 2020), Gradient Boosting Machines (Singh et al. 2021), Extreme Learning Machines (Wang/Niu 2023), Neural Network (Klüver/Klüver 2022) and Long Short-Term Memory (Mehedi et al. 2022). The selected methods will be evaluated by using the performance metrics Root Mean Square Error (RMSE) (Li et al. 2020) and R-square (R2) (Iqbal et al. 2021). RMSE is a commonly used metric to evaluate regression models (Hodson 2022) as it measures the average size of errors between predicted and actual values (Kim et al. 2022). A smaller RMSE value indicates better model performance, reflecting closer agreement between predictions and actual outcomes (Ağbulut et al. 2021). R2 measures how strong and reliable a model is and reveals how well the model explains the data overall (Maiti et al. 2021). Therefore, R2 reflects the model's accuracy where a score of 1 signifies perfect accuracy, while a score near 0 suggests random predictions (Klemme et al. 2020).

The Random Forest Regression (RFR) method is a popular machine learning algorithm (Speiser et al. 2019) and is used for classification (Liu et al. 2021), prediction (Wang et al. 2018) and regression problems (Singh et al. 2017). RFR is an ensemble learning algorithm as it combines multiple models to achieve robust and more accurate predictions (Louppe 2014). RFR adopts a modification of the bootstrap aggregation (bagging) (Alam/Vuong 2013). It means that multiple decision trees are trained on different subsamples of the input data, giving a prediction on their distinctive subsample (Singh et al. 2017). Then, all predictions are combined which results in the final output (Babar et al. 2020). During the training, the algorithm learns the ideal threshold to separate the data effectively and provide accurate predictions (Biau/Scornet 2016). The ensemble learning technique allows the RFR method to achieve an outstanding performance with a reduced risk of overfitting (Wu et al. 2017), (Ayyadevara 2018). Existent research approaches prove the good prediction rates when using the RFR method in different industries like forecasting incidences of infectious diseases in the medical sector (Fang et al. 2020) or forecasting production results (Xue et al. 2021).

The Elastic Net Regression combines the advantages of ridge regression and lasso regression within one method (A.Al-Jawarneh et al. 2020). Both models are based on the idea of regularization, which is a mechanism to control the complexity of a model (Melkumova/Shatskikh 2017). While both methods use a penalty term (Ghojogh/Crowley 2019) to achieve their objective, lasso regression uses the sum of the absolute values to set coefficients to zero (Tibshirani 1996), eliminating redundant or unnecessary variables within the dataset (Ranstam/Cook 2018). On the other hand, ridge regression reduces the magnitude of coefficients by taking the sum of their squares, minimizing their impact without forcing them to zero like the lasso regression (McDonald 2009). Ridge and lasso enable the reduction of predictors in a regression model, generating models with coefficients that are close or equal to zero (Giglio/Brown 2018), making the model more generalizable to new data and more suitable for datasets with a high number of different variables (Nikodinoska et al. 2022). Past research shows that the Elastic Net Regression is a good choice for predicting a continuous variable with changes over time (Tutun et al. 2016), (Nikodinoska et al. 2022).

Support Vector Machine (SVM), rooted in statistical learning theory (Cheng et al. 2017), uses a linear approach in a high-dimensional feature space that is non-linearly connected to the input space (Awad/Khanna 2015). This simple approach, coupled with top-tier performance in various learning tasks like classification (Brereton/Lloyd 2010), regression (Wu et al. 2004), and novelty detection (Hayton et al. 2000), has made SVMs widely popular (Karatzoglou et al. 2006). When used for a regression task, Support Vector Regression (SVR) aims to find a hyperplane that accurately represents the relationship between the given input variables and the target variable while introducing an epsilon tube that allows for flexibility to adjust to variations within the data

(Smola/Schölkopf 2004). By using a kernel function, SVR is enabled to handle non-linear relationships and therefore allows the method to capture complex patterns within the data (Karatzoglou et al. 2006). SVR was chosen as it was used for predicting values with time series data: a study from 2020 shows that the performance of SVR models can exceed an accuracy of over 90 % for predicting deaths and recoveries during the COVID pandemic in India (Parbat & Chakraborty, 2020). In addition, SVR models are especially used for the prediction of non-linear time series too, which matches the data this paper is based on (Lau/Wu 2008).

Like the previously presented RFR method, Gradient Boosting Machines (GBM) are also an ensemble learning algorithm (Lu et al. 2020) that can be used for classification (Fulton et al. 2019) and regression tasks (Singh et al. 2021). While the process of building decision trees is parallelized at the RFR method, GBM uses a sequential approach, iteratively improving the model by boosting the errors during each iteration (Ayyadevara, 2018). Additionally, GBM is known as a method that evolves from a weak to a stronger learner (Bentéjac et al. 2020). The iterative nature of boosting contributes to model refinement, involving the training of one decision tree after another, with the aim of reducing the mistakes made by the previous decision tree (Natekin/Knoll 2013). A study which compares various ensemble methods using time series data for forecasting electricity load reveals that the GBM achieves even better results than the RFR (Papadopoulos/Karakatsanis 2015). Another study marks the performance and computation time benefits of using the GBM algorithm to predict missing values within time series data (Körner et al. 2018).

Extreme Learning Machine (ELM) is a machine learning algorithm (Li et al. 2012) that belongs to the family of neural networks (Sun et al. 2017). It has been applied across various machine learning tasks, including regression (Huang et al. 2012), and classification (Aqel et al. 2021). Unlike traditional neural network training methods (Tan et al. 2020), ELM simplifies the training process by randomly initializing weights between the input and hidden layers, contributing to its rapid learning approach (Wang/Niu 2023) making it particularly suitable for generalization tasks (Huang et al. 2006). After randomly assigning weights between input features and hidden neurons layers (Wang et al. 2021), the output of each hidden neuron is determined using a chosen activation function applied to the weighted sum of inputs (Sattar et al. 2017). The ELM method proves useful for this paper as it utilizes the approach of sequential learning to predict values from time series data; particularly when dealing with incomplete training data at the outset, the model can initiate new sequences of training upon receiving additional data to enhance predictions (Nóbrega/Oliveira 2019). A study which uses extreme learning regression for wind speed predictions also highlights the good predictions while compressing the structure of the forecasting model (Yang et al. 2021).

Neural Networks (NNs) were inspired by the structure and function of the human brain (Goldberg 2016). The basic structure of a NN consists of various layers, including an input layer, possible hidden layers, and an output layer (Klüver/Klüver 2022). Within this network, artificial neurons are organized in layers and connected by weights (Choo et al. 2020). Each neuron in a NN receives inputs from previous neurons, weighs these inputs with individual weights, and forms the weighted sum (Bischoff/Luetkens 2022). Mathematically, the network input for a neuron in relation to its predecessor neurons is expressed as the sum of the products of the outputs of the predecessor neurons and the weights of the edges (Sonnet 2022). Overall, NNs enable complex pattern recognition and abstraction, making them particularly effective for tasks such as classification, prediction, and pattern recognition (Musser 2022). General Regression Neural Networks (GRNNs), as the simplest form of NNs for regression, enable the postulation of nonlinear relationships between a target variable and independent explanatory variables, offering advantages such as accuracy, modeling from small datasets, and outlier handling (Yip et al. 2013). A study about forecasting urban residential water demand in Saudi Arabia achieves a performance with a R2 score of 0.78 (Al-Zahrani/Abo-Monasar 2015).

The Long Short-Term Memory (LSTM) method was introduced by Hochreiter and Schmidhuber (Smagulova/James 2019) to overcome the weakness of remembering long-range time dependencies within a Recurrent Neural Network (RNN) (Hochreiter/Schmidhuber 1997). LSTM emerged as a powerful tool for tackling forecasting challenges and stands out in capturing long-term dependencies, connections among variables, and both chaotic and periodic behaviors inherent in time series data, distinguishing itself from conventional NNs (Mehedi et al. 2022), (Conti et al. 2023). Further studies with the LSTM method combined with a deep learning NN achieved good results with an RMSE of 0.025 (Sagheer/Kotb 2019).

3 Methodology of the Case Study

This research adheres to the methodological framework proposed by Eisenhardt (Eisenhardt 1989), employing a systematic approach as outlined below:

The study started with *Strategic Case Selection*, using an industrial dataset containing machine anomalies. Second, a *Research Question* was formulated with the aim of identifying an efficient AI method for reliably predicting machine performance in an industrial environment. *The Conceptual Framework* of the study was developed, focusing on AI methods suitable for regression problems. A literature review identified seven potential AI methods. The subsequent step involved *Data Collection*, whereas machine performance data were meticulously prepared, excluding any negative data that could potentially bias the results. After that, *Pattern-Matching* was conducted using the identified AI methods to identify patterns and anomalies in machine performance. Based on the performance of initial runs, the method parameters were adjusted, and influencing factors were identified, leading to the *Proposal of New Constructs and Relationships*. A systematic *Cross-Case Analysis* was conducted to compare results, facilitated by insights from the literature review. *Replication and Modification* were essential to ensuring result of robustness, with multiple tests conducted using different parameters. *Theoretical Sampling* guided further runs based on gained insights. The methodology attempted to attain *Data Saturation and Theoretical Consistency* through the prevention of overfitting and the maintenance of consistent metrics. The *Finalization of the Theory* involved consolidating and summarizing derived insights. Finally, the research findings were documented in the present research paper and prepared for *Dissemination*. The implementation of these methodological steps facilitated a systematic examination and comparison of the performance of different AI methods in predicting anomalies in an industrial environment. The clear structuring of research steps following Eisenhardt's (Eisenhardt 1989) methodology ensured a comprehensive and comparable analysis.

4 Implementation and Evaluation

4.1 Dataset Description and Pre-Processing

The given dataset contains 20 machine sensor values, each with 46,022 data records, including an exact date and time. The variable to be predicted is specified in the column "Active Performance (MW)" and represents the active power in megawatts. The relevant data are available as a spreadsheet in an xlsx file and are converted into a CSV format for further processing.

The pre-processing of the data and the implementation of the machine learning models are done almost equally for every implemented method with the programming language, Python (Freese et al. 2024). First, the dataset was imported, and the date column was set as the index column. Next, the column for the variable, which should be predicted, was analyzed in detail. After finding negative values for the active power in megawatts, those values were removed, as they were identified as incorrect measurements of the machine sensors. Out of 46,022 data records, 262 records with negative values of the target variable were removed.

After this step, the input variables (X) are separated from the target variable (Y) and stored within different data frames. In addition, the created data frames are split into 70 % training data, 15 % test data, and 15 % validation data. The random state of the split-function was set to a fixed value to be able to reproduce and compare the results of the further model. An additional data scaling step was added to the pre-processing only for the NN and LSTM models. Therefore, the standardscaler from sklearn was used to transform and reshape the data frames.

After those pre-processing steps, the different models are created and trained with the training data frame and tested with the validation data frame. Next, the hyperparameters of the models were optimized, and the improved model was tested with the test data frame. Lastly, some prediction results are visualized, and different performance scores are calculated.

4.2 Method Comparison

The final optimized models and their results are compared by their R2 and RMSE score and their computation time. With an R2 score of 0.5057, an RMSE score of 15.287 and a computation time of 481 seconds, the SVR method is far behind every other method and was therefore excluded within the following comparison.

Comparing the R2 score of the models, the Elastic Net Regression and ELM Model have the lowest score with 0.9941, while the GBM model is in the center of the compared methods with an R2 score of 0.9954. The RFR model has the highest score with an R2 score of 0.9976 directly followed by the NN with an R2 of 0.9975. The LSTM model is ranked in third place, aligning itself almost halfway between the NN model and the GBM model with an R2 score of 0.9967.

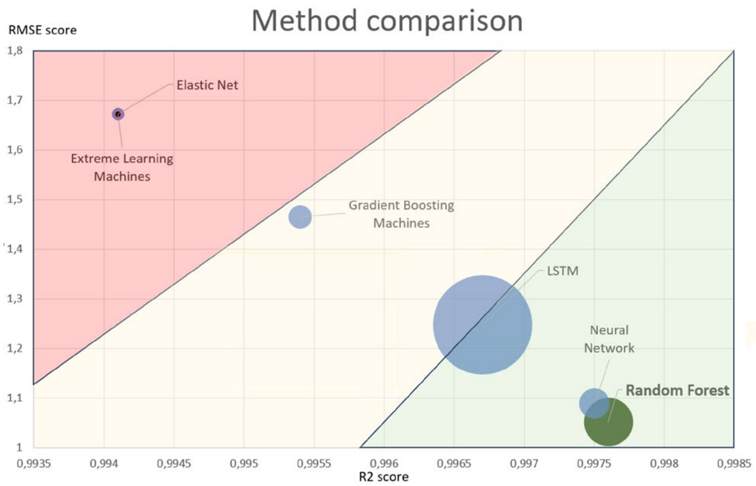

Image 2: Comparison of the identified AI methods, where red indicates a poor performance while green represents a good performance (own illustration)

As a second performance score for the comparison, the RMSE score was chosen. The Elastic Net Regression model and ELM model achieved the worst RMSE score with 1.67 in both. With an RMSE score of 1.05, the RFR model outperformed all other models in this performance metric too. The distribution of the other implemented models is like the distribution of the R2 scores with the GBM model almost in the center at 1.465. The NN model directly follows the RFR model with an RMSE of 1.089 while the LSTM model is in third place with an RMSE of 1.247.

The methods' comparison was extended by the computation time as the third factor. Compared to the ranking of the R2 score and RMSE score, the results of the computation time place the methods differently. With a computation time of just one second, the ELM method was the fastest machine learning algorithm. Followed by Elastic Net Regression (6 seconds), GBM (21 seconds) and NN (37 seconds). The slowest machine learning algorithms within this comparison were the RFR method with 96 seconds, and lastly the LSTM with 395 seconds of computation time.

4.3 Evaluation of Methodological Approaches

In the present case study, Eisenhardt's (Eisenhardt 1989) roadmap was used as a guiding framework for conducting a comprehensive investigation into anomaly detection in industrial environments using AI methods.

The use of strategic case selection and the formulation of the research question enabled a focused exploration of industrial machine data with anomalies, laying the foundation for the following research steps and providing a clear research direction. Furthermore, the conceptual framework and conducting cross-case analysis allowed for a deep understanding by using literature reviews to learn about AI for regression problems and to find out about similarities and differences between the AI methods. Also, the steps of data collection and pattern-matching helped prepare the data and eliminate biases as well as implement the AI methods to detect patterns and deviations. Finally, the roadmap gave insights on how to do theoretical sampling and consistency. Overall, the clear steps and guidelines of this methodology contributed to systematic research.

4.4 Result Interpretation

The method of comparison clearly determines the RFR as the best method for predicting the target variable of the dataset with the best R2 score and RMSE score at an acceptable computation time. With nearly the same R2 score and slightly higher RMSE score, but lower computation time, the NN method can also be seen as a great choice for the prediction task. Especially if lower computation time is more important than the loss of accuracy. The results of those two methods show that their complex algorithm structure can store the correlations of the independent input variables and the changes over time nearly completely. In contrast, the results of the SVM method disqualify this algorithm for predicting the target variable, because the created hyperplane cannot map the complex correlations of the input variables. The Elastic Net Regression model and the ELM model achieve very low computation time but cannot compete with the R2 and RMSE scores of the other methods. Also, the slightly better GBM model and the LSTM model with the second highest computation time of all compared methods were not able to solve the prediction task satisfactorily.

5 Conclusion and Outlook

This research explored the application of AI in performance prediction for anomaly detection within the context of Industry 5.0. Focusing on the growing significance of AI in industrial settings, the case study investigated various AI methods to enhance anomaly predictability. The primary objective was to identify the most efficient AI method for detecting anomalies in industrial environments. To achieve this goal, seven AI methods, capable of solving regression tasks, were implemented, and compared based on their R2 and RMSE scores, as well as their computation time. The results show the effectiveness of the RFR method in predicting performance for detecting anomalies in industrial environments as this method outperforms others.

Future research could explore optimizing the RFR algorithm for specific industrial contexts and expanding the study to include real-time anomaly detection applications. Additionally, exploring hybrid models may further enhance anomaly detection capabilities. Furthermore, it is advisable to conduct a more extensive exploration of hyperparameter tuning for individual models. To make findings more applicable across various situations, researchers should diversify their data sources. This could involve investigating anomalies in different types of machines or industrial setups, ensuring that proposed AI methods are adaptable to a high number of contexts. Moreover, exploring additional AI methods beyond those selected in this paper is recommended, as it could offer diverse perspectives and contribute to a more comprehensive understanding.

In conclusion, the research highlights the importance of selecting appropriate AI methods for predicting performance for anomaly detection in Industry 5.0, with the RFR method emerging as the most efficient and robust choice for the provided dataset. Future research should focus on optimizing AI methods for specific industrial applications, exploring hybrid models, delving deeper into hyperparameter tuning, and utilizing varied data sources. This approach will contribute to the development of effective performance prediction for anomaly detection solutions in the evolving field of Industry 5.0.

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