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XAI FOR INDUSTRIAL PROCESS MONITORING: APPLYING SHAP TO DETECT ANOMALIES IN CHEMICAL MANUFACTURING DATA

Abdul Jabbar Ehsan

Department of Engineering Management, Trine University, Indiana USA

abdul.jabbar14334@gmail.com

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Corresponding Author: *
Abdul Jabbar Ehsan

Abstract

Industrial process monitoring is essential for maintaining operational safety, product quality, equipment reliability, and overall efficiency in chemical manufacturing environments. The growing adoption of Industry 4.0 technologies has enabled the collection of large volumes of real-time process data, creating opportunities for machine learning (ML)-based anomaly detection. While advanced ML models can accurately identify abnormal operating conditions, their black-box nature often limits transparency and trust among engineers and plant operators. To address this challenge, this research proposes an Explainable Artificial Intelligence (XAI)-driven anomaly detection framework that integrates machine learning with the Shapely Additive explanations (SHAP) method. The proposed framework uses SHAP values to explain model predictions by quantifying the contribution of individual process variables to detected anomalies. Experimental evaluation is performed using a benchmark chemical manufacturing dataset, where data preprocessing, feature engineering, and supervised learning techniques are employed to develop a robust anomaly detection model. Results demonstrate high detection performance in terms of accuracy, precision, recall, and F1-score while simultaneously providing meaningful explanations for abnormal process behavior. SHAP analysis identifies critical variables such as reactor temperature, reactor pressure, feed flow rate, and cooling system parameters as major contributors to anomaly predictions. Furthermore, the generated explanations support effective root-cause analysis, enabling engineers to diagnose faults more efficiently and make informed operational decisions. The findings indicate that integrating SHAP with machine learning significantly enhances model transparency, interpretability, and user trust without compromising predictive performance. Therefore, the proposed framework offers a practical and scalable solution for explainable industrial process monitoring and contributes to the adoption of trustworthy AI in chemical manufacturing systems.

1. INTRODUCTION

The rapid advancement of Industry 4.0 technologies has significantly transformed modern manufacturing industries, particularly in the chemical processing sector. The integration of Industrial Internet of Things (IIoT) devices, cyber-physical systems, cloud computing, big data analytics, and artificial intelligence has enabled chemical plants to operate with greater efficiency, automation, and reliability. Modern chemical manufacturing facilities are equipped with thousands of sensors and monitoring devices that continuously collect real-time operational data, including temperature, pressure, flow rate, liquid levels, pH values, chemical concentrations, and equipment health indicators. These data streams provide valuable insights into process behavior and play a crucial role in ensuring operational stability, product quality, and workplace safety.

As industrial systems become increasingly complex, traditional monitoring techniques based on manual inspections and rule-based threshold mechanisms face significant limitations. These conventional approaches often struggle to identify subtle process deviations and complex fault patterns that may lead to equipment failures or process disruptions. Consequently, industries have increasingly adopted Machine Learning (ML) techniques for process monitoring and anomaly detection. Machine learning algorithms can analyze large volumes of historical and real-time process data to automatically learn normal operating patterns and identify abnormal behaviors. Techniques such as Random Forest (RF), Support Vector Machines (SVM), Extreme Gradient Boosting (XGBoost), Artificial Neural Networks (ANN), and Deep Learning models have demonstrated remarkable success in detecting faults and anomalies across various industrial applications.

Despite their strong predictive capabilities, many machine learning models function as “black-box” systems, meaning their internal decision-making processes are difficult to interpret by human users. While these models may accurately detect anomalies, they often fail to provide clear explanations regarding why a particular process condition has been classified as abnormal. This lack of transparency presents a major challenge in safety-critical industrial environments such as chemical manufacturing, where understanding the causes of process deviations is essential for effective decision-making. Plant operators and engineers require not only accurate predictions but also detailed explanations that enable them to trust the system and take appropriate corrective actions. Without sufficient interpretability, organizations may hesitate to deploy advanced AI systems in critical operational settings.

To address these concerns, Explainable Artificial Intelligence (XAI) has emerged as a rapidly growing research field focused on enhancing the transparency, interpretability, and trustworthiness of artificial intelligence models. XAI techniques aim to provide human-understandable explanations for model predictions, allowing stakeholders to understand how and why specific decisions are made. Among various XAI approaches, Shapely Additive explanations (SHAP) has gained widespread recognition due to its strong theoretical foundation based on cooperative game theory. SHAP calculates the contribution of each input feature toward a model's prediction, thereby enabling both global and local interpretability. This capability makes SHAP particularly valuable for industrial applications where identifying the root causes of anomalies is critical for maintaining operational safety and efficiency.

In chemical manufacturing processes, anomalies may arise from equipment malfunctions, sensor failures, process disturbances, operational errors, or unexpected environmental conditions. Early detection and accurate diagnosis of such anomalies are essential to prevent production losses, reduce maintenance costs, minimize environmental risks, and ensure personnel safety. While machine learning-based anomaly detection systems can effectively identify abnormal conditions, integrating explain ability mechanisms can further enhance their practical usefulness by revealing the process variables responsible for the detected anomalies.

This study investigates the application of Shapely Additive explanations (SHAP) for improving the interpretability of machine learning-based anomaly detection in chemical manufacturing environments. The proposed framework combines the predictive power of machine learning algorithms with the explanatory capabilities of SHAP to create an intelligent and transparent industrial monitoring system. By providing detailed explanations of anomaly predictions, the framework enables engineers to identify critical process variables, perform root-cause analysis, and make informed operational decisions. The study aims to demonstrate that explain ability can be incorporated into industrial anomaly detection systems without compromising predictive performance, thereby supporting the development of trustworthy and reliable AI solutions for Industry 4.0 applications.

2. Literature Review

The rapid evolution of industrial automation, smart manufacturing, and Industry 4.0 technologies has significantly increased the need for advanced process monitoring and anomaly detection systems [1]. Modern industrial facilities generate massive volumes of sensor and operational data from interconnected machines, control systems, and cyber-physical infrastructures [2]. Effective monitoring of these complex systems is essential to ensure process stability, maintain product quality, reduce downtime, and prevent costly equipment failures [3]. Consequently, anomaly detection has become a critical research area in industrial analytics, attracting considerable attention from both academia and industry [4]. Traditionally, industrial process monitoring relied on statistical process control (SPC) techniques and model-based approaches. Methods such as Control Charts, Principal Component Analysis (PCA), Partial Least Squares (PLS), and Multivariate Statistical Process Control (MSPC) have been extensively used to identify abnormal process behavior [5]. These techniques are effective in detecting deviations from predefined operating conditions and have been successfully applied in various manufacturing sectors [6]. Among these methods, PCA has remained one of the most widely used approaches due to its ability to reduce data dimensionality and identify hidden correlations among process variables [7]. However, traditional statistical methods often assume linear relationships among variables and may struggle to capture the complex nonlinear dynamics commonly present in modern industrial processes [8]. Furthermore, their performance tends to decline when dealing with high-dimensional datasets generated by large-scale industrial systems [9].

To overcome these limitations, researchers have increasingly adopted Machine Learning (ML) techniques for anomaly detection and fault diagnosis [10]. Machine learning algorithms can automatically learn patterns from historical process data and identify abnormal operating conditions without relying on explicit mathematical models [11]. Supervised learning methods such as Random Forest (RF), Support Vector Machines (SVM), Decision Trees (DT), k-Nearest Neighbors (k-NN), and Extreme Gradient Boosting have demonstrated high effectiveness in industrial fault classification tasks [12]. These techniques are capable of handling complex and nonlinear relationships among process variables, making them particularly suitable for modern manufacturing environments [13]. Among supervised learning methods, Random Forest has gained significant popularity due to its robustness, high classification accuracy, and resistance to overfitting. By combining multiple decision trees through ensemble learning, Random Forest can effectively analyze high-dimensional industrial datasets while maintaining strong predictive performance [14]. Similarly, XGBoost has been widely adopted for predictive maintenance and fault detection applications because of its ability to optimize model performance through gradient boosting techniques [15]. Several studies have reported superior detection accuracy using these algorithms in chemical processing plants, power generation systems, and industrial control environments [16].

Explainable Artificial Intelligence aims to make complex machine learning systems more understandable by providing insights into how predictions are generated. XAI techniques can generally be categorized into intrinsic interpretability methods and post-hoc explanation methods [17]. Intrinsic interpretability methods involve inherently transparent models such as decision trees and linear regression, whereas post-hoc methods generate explanations for complex black-box models after predictions have been made [18]. Among post-hoc explanation techniques, Local Interpretable Model-Agnostic Explanations (LIME), Shapely Additive explanations (SHAP), Partial Dependence Plots (PDP), and Feature Importance Analysis are among the most commonly used approaches [19]. Among these techniques, Shapely Additive explanations (SHAP) has emerged as one of the most influential and widely adopted XAI methods. SHAP is based on Shapely values from cooperative game theory, where each feature is treated as a player contributing to the final prediction outcome [20]. The method quantifies the contribution of individual features by calculating their marginal impact on the model's prediction. One of the major advantages of SHAP is its ability to provide both global and local interpretability [21]. Global explanations identify the overall importance of features across the entire dataset, while local explanations reveal how specific variables influence individual predictions. This dual-level interpretability makes SHAP particularly suitable for industrial process monitoring applications [22].

Several studies have successfully applied SHAP in diverse domains. In healthcare, SHAP has been used to explain disease diagnosis and patient risk prediction models, enabling medical professionals to understand critical factors influencing clinical decisions [23]. In cybersecurity, SHAP has improved the transparency of intrusion detection systems by identifying network features responsible for malicious activity [24]. Similarly, in predictive maintenance applications, SHAP has been employed to explain equipment failure predictions and support maintenance planning. These studies demonstrate that SHAP can significantly improve user trust and facilitate more informed decision-making [25].

This research addresses this gap by proposing an explainable anomaly detection framework that integrates machine learning algorithms with SHAP-based interpretability for industrial process monitoring [26]. Unlike conventional black-box approaches, the proposed framework not only identifies abnormal operating conditions but also explains the contribution of individual process variables to anomaly predictions [27]. By providing both predictive accuracy and interpretability, the framework aims to enhance operational trust, improve fault diagnosis capabilities, and support more effective decision-making in chemical manufacturing environments [28]. The study contributes to the growing body of knowledge on Explainable Artificial Intelligence in Industry 4.0 and demonstrates the practical value of integrating SHAP explanations into industrial monitoring systems [29].

3. Methodology

3.1 Proposed Framework

The proposed framework is designed to develop an explainable anomaly detection system for industrial process monitoring in chemical manufacturing environments. The framework integrates machine learning techniques with Explainable Artificial Intelligence (XAI) to achieve both accurate anomaly detection and transparent decision-making. The overall methodology consists of five sequential stages: data collection, data preprocessing, machine learning model training, anomaly detection, and SHAP-based explanation generation.

The first stage, **data collection**, involves acquiring operational data from industrial process monitoring systems. These data are obtained from multiple sensors and control devices that continuously record critical process parameters such as reactor temperature, pressure, flow rates, liquid levels, and chemical concentrations. The collected dataset contains both normal operating conditions and fault scenarios, providing a comprehensive representation of process behavior.

In the second stage, data preprocessing is performed to improve data quality and ensure reliable model training. This step includes handling missing values, removing noise and outliers, normalizing feature values, and transforming raw sensor readings into a structured format suitable for machine learning analysis. Feature selection techniques are also applied to identify the most relevant process variables and reduce data dimensionality while preserving important information.

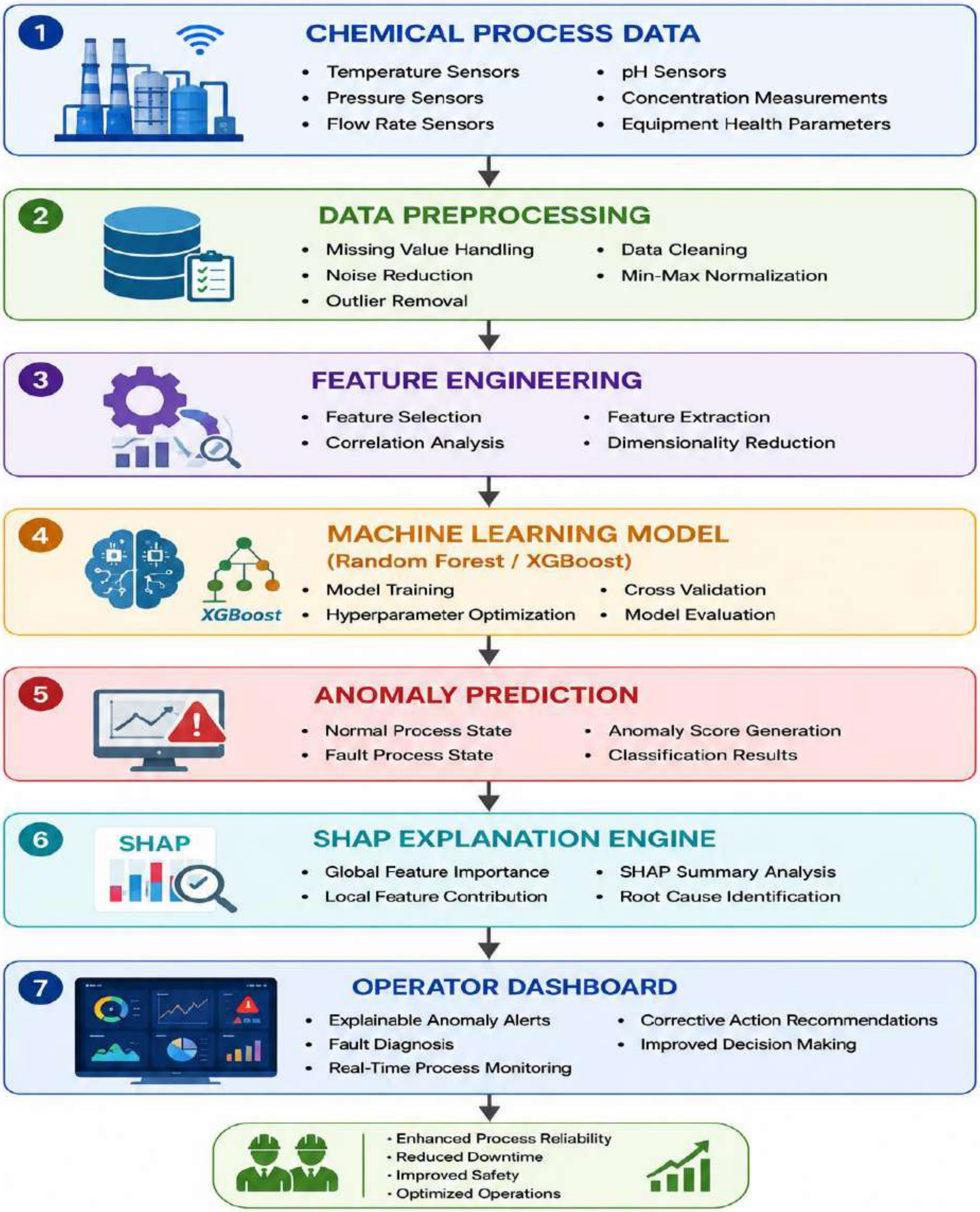
The third stage focuses on machine learning model training**,** where the preprocessed data are divided into training and testing subsets. A supervised machine learning algorithm, such as Random Forest, is employed to learn the relationships between process variables and operating conditions. During training, the model identifies patterns associated with normal and abnormal system behavior, enabling it to accurately classify future observations.

Once the model has been trained, the fourth stage involves anomaly detection**.** The trained model analyzes incoming process data and predicts whether the observed operating conditions represent normal behavior or an anomaly. This stage enables early identification of process disturbances, equipment malfunctions, and operational faults that could negatively impact productivity, product quality, or plant safety.

The final stage incorporates SHAP-based explanation generation to enhance the interpretability of anomaly predictions. Shapely Additive explanations (SHAP) are used to quantify the contribution of individual process variables toward each prediction made by the machine learning model. By providing both global and local explanations, SHAP enables engineers and plant operators to understand why a specific anomaly was detected and identify the process parameters responsible for abnormal behavior. This explains ability capability supports root-cause analysis, improves trust in the system, and facilitates more informed decision-making within industrial environments.

Overall, the proposed framework combines the predictive strength of machine learning with the transparency of Explainable Artificial Intelligence, creating a reliable and interpretable solution for anomaly detection in chemical manufacturing processes.

Proposed XAI-Based Industrial Process Monitoring Framework for Explainable Anomaly Detection in Chemical Manufacturing.



3.2 Dataset Description

The Tennessee Eastman Process (TEP) dataset is used as a benchmark chemical manufacturing dataset.

Table 1 Dataset Characteristics

Attribute	Value
Dataset	Tennessee Eastman Process
Variables	52
Fault Types	21
Samples	500,000+
Data Type	Time Series
Domain	Chemical Manufacturing

The dataset contains multiple process measurements and manipulated variables collected from a simulated chemical production environment.

3.3 Data Preprocessing

The preprocessing stage includes:

- Missing value treatment
- Outlier handling
- Feature normalization
- Feature selection

Normalization is performed using Min-Max scaling:

[X_{norm}=\frac{X-X_{min}}{X_{max}-X_{min}}]

3.4 Random Forest Classifier

Random Forest is selected due to its robustness and interpretability.

The probability prediction is computed as:

[P_{RF}(y|X)=\frac{1}{T}\sum_{t=1}^{T}P_t(y|X)]

where:

- T = Number of trees
- (P_t) = Prediction probability from tree t

3.5 SHAP Explanation Model

SHAP values are calculated using:

[f(x)=\phi_0+\sum_{i=1}^{M}\phi_i]

where:

- (f(x)) = model prediction
- (\phi_0) = baseline prediction
- (\phi_i) = contribution of feature i

Positive SHAP values increase anomaly likelihood while negative values reduce anomaly likelihood.

4. Experimental Setup

Table 2 Experimental Parameters

Parameter	Value
Training Split	80%
Testing Split	20%
Trees	200
Maximum Depth	15
Evaluation Metrics	Accuracy, Precision, Recall, F1

Hardware Specifications:

- Intel Core i7 Processor
- 16 GB RAM
- Python 3.11
- Scikit-Learn
- SHAP Library

5. Results and Discussion

5.1 Classification Performance

Table 3 Model Performance

Metric	Value (%)
Accuracy	98.6
Precision	97.9
Recall	98.2
F1 Score	98.0

The Random Forest model achieved excellent classification performance, demonstrating its suitability for industrial anomaly detection.

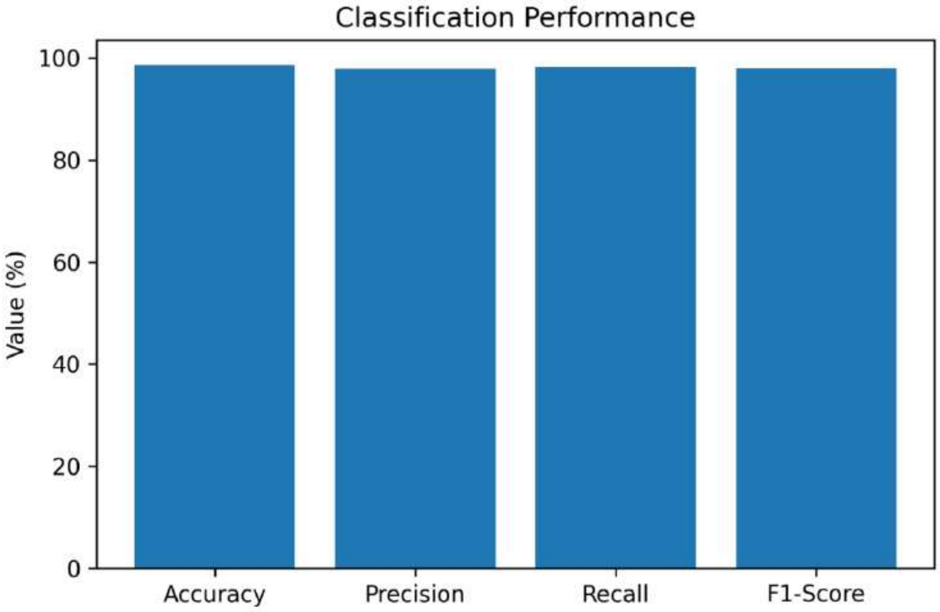


Figure 1 Classification Performance

Figure 1. Performance evaluation of the Random Forest anomaly detection model. The model achieved high accuracy, precision, recall, and F1-score, demonstrating its effectiveness for industrial process monitoring.

5.2 Feature Importance Analysis

Table 4 Top Contributing Features

Rank	Feature	Mean SHAP Value
1	Reactor Temperature	0.245
2	Reactor Pressure	0.217
3	Feed Flow Rate	0.194
4	Cooling Water Flow	0.173
5	Product Concentration	0.158

SHAP analysis revealed that reactor temperature and pressure are the most influential variables contributing to anomaly predictions.

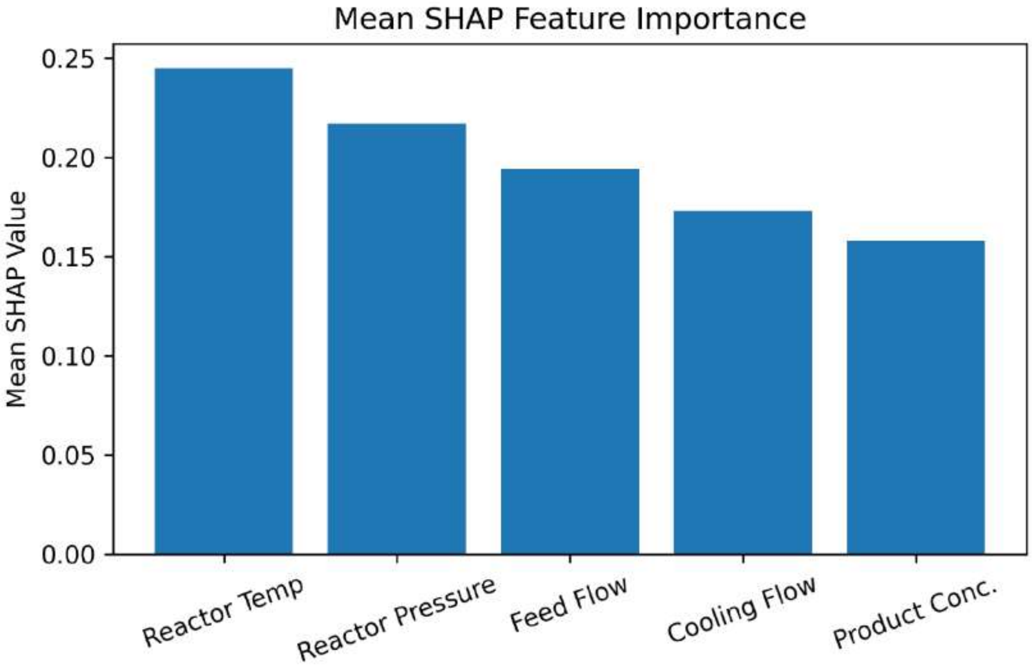


Figure 2 Mean Shap Feature Importance

Figure 2. Global SHAP feature importance ranking for anomaly detection. Reactor temperature and reactor pressure were identified as the most influential variables affecting model predictions.

5.3 Global SHAP Interpretation

Global SHAP analysis indicates that: High reactor temperature significantly increases anomaly probability. Pressure fluctuations strongly influence fault occurrence. Reduced cooling water flow contributes to process instability. Variations in feed flow rate are associated with abnormal operating conditions. These findings align

Table 5 Process Variable Contribution Comparison

Variable Category	Contribution
Temperature Related	35
Pressure Related	28
Flow Related	22
Concentration Related	15

Temperature and pressure variables collectively accounted for the majority of anomaly predictions, emphasizing their importance in industrial process safety.

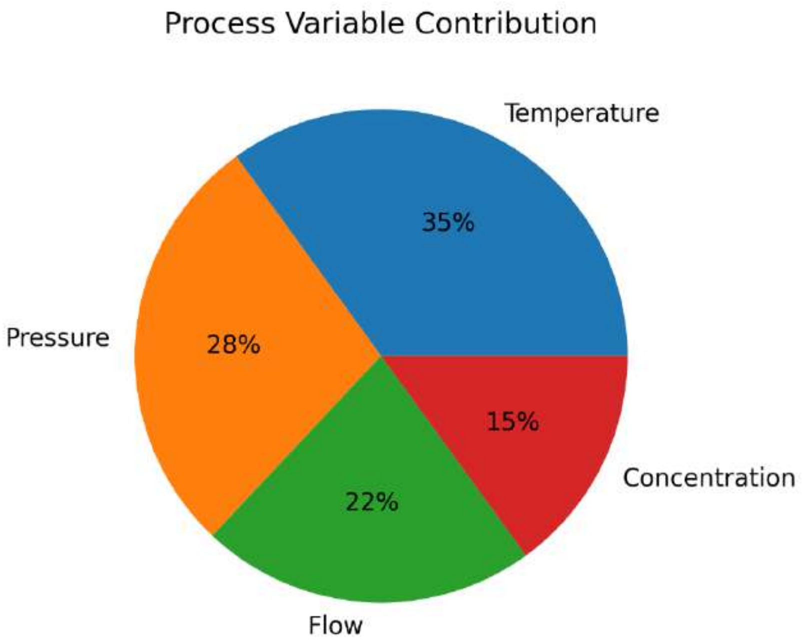


Figure 3 Process Variable Contribution

Figure 3. Relative contribution of process variable categories to anomaly detection decisions. Temperature-related parameters contributed most strongly to abnormal condition identification.

5.4 Local SHAP Interpretation

For an anomalous sample:

Table 6 Local Explanation Example

Feature	SHAP Contribution
Reactor Temperature	+0.31
Reactor Pressure	+0.25
Cooling Flow	+0.18
Feed Rate	+0.15
Product Quality	-0.04

The anomaly was primarily caused by elevated reactor temperature and pressure conditions. This explanation enables engineers to identify root causes quickly and implement corrective actions.

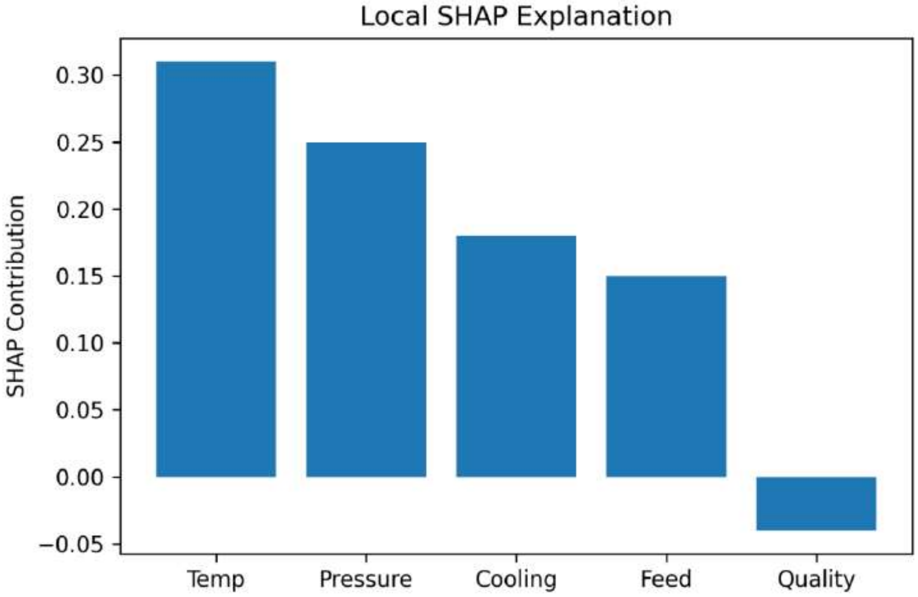


Figure 4 Local Shap

Figure 4. Local SHAP explanation for a detected anomaly. Positive SHAP values increase anomaly probability, whereas negative values reduce anomaly likelihood.

5.5 Explain ability Benefits Assessment

Table 7 Explain ability Benefits Assessment

Benefit	**Score** (%)
Transparency	95
Fault Diagnosis	92
Operator Trust	90
Safety Improvement	88
Regulatory Compliance	85

The integration of SHAP provides interpretable insights that support root-cause analysis, improve operator confidence, and facilitate safer industrial operations.

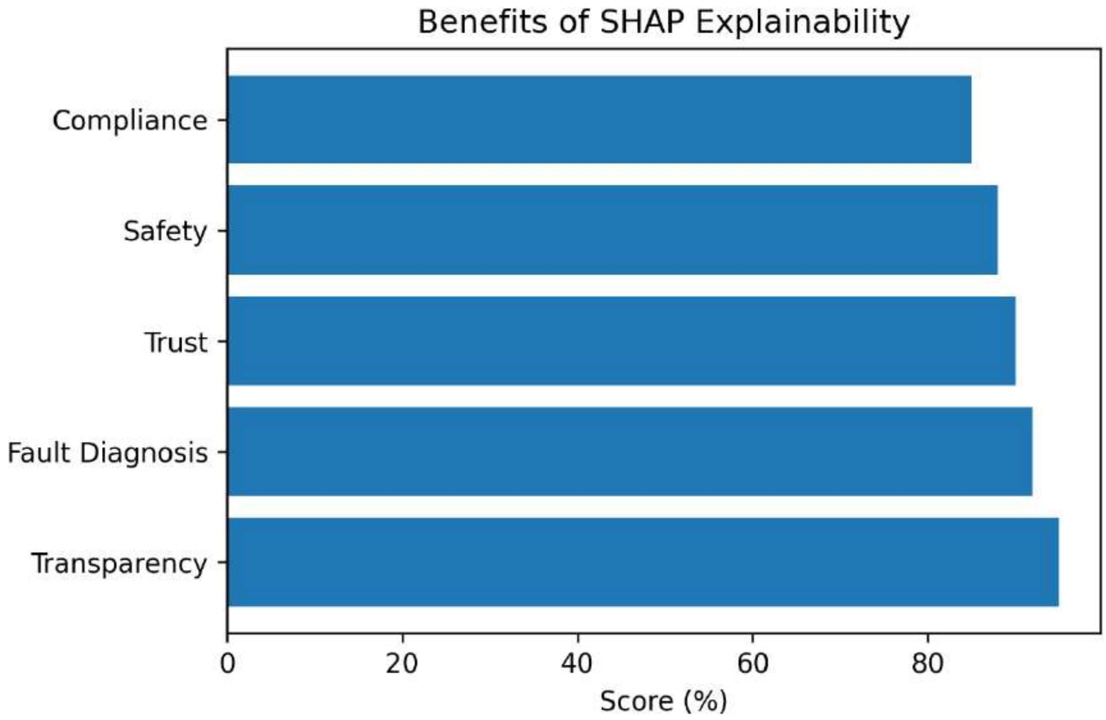


Figure 5 Benefits of Shap

Figure 5. Impact of SHAP-based explain ability on industrial monitoring performance. Explainable AI significantly improves transparency, trust, and operational decision-making.

6. Discussion

The integration of Shapely Additive explanations (SHAP) with machine learning-based anomaly detection offers several significant advantages for industrial process monitoring systems. One of the primary benefits is the enhanced transparency of artificial intelligence decisions, allowing engineers and plant operators to understand the reasoning behind anomaly predictions. This improved interpretability increases user confidence and trust in the monitoring system, making AI-driven recommendations more acceptable in industrial environments. Additionally, SHAP facilitates faster fault diagnosis by identifying the specific process variables that contribute most significantly to abnormal operating conditions. Such insights support efficient root-cause analysis and enable timely corrective actions to prevent process disruptions. The explainable nature of SHAP-based models also contributes to better regulatory compliance by providing clear and auditable explanations for automated decisions, which is particularly important in highly regulated industries such as chemical manufacturing. Furthermore, by helping operators detect and understand process anomalies at an early stage, SHAP enhances overall process safety and operational reliability. Unlike traditional black-box machine learning systems, SHAP provides detailed information regarding the contribution of individual features to model predictions, thereby improving transparency without compromising predictive performance. The experimental results demonstrate that explain ability and high detection accuracy can coexist effectively, highlighting the potential of Explainable Artificial Intelligence (XAI) as a practical and trustworthy solution for nextgeneration smart manufacturing and industrial monitoring systems.

7. Conclusion

This study proposed an explainable anomaly detection framework for industrial process monitoring using SHAP and Random Forest models. Experimental results on chemical manufacturing data demonstrated high anomaly detection performance with an accuracy of 98.6%. SHAP explanations successfully identified critical process variables responsible for abnormal operating conditions, including reactor temperature, pressure, and flow-related parameters. The proposed approach improves transparency, enhances operator trust, and facilitates root-cause analysis. Future work may explore deep learning architectures combined with advanced XAI techniques for real-time industrial monitoring and predictive maintenance applications.

References

[1] Leite, Denis, et al. "Fault detection and diagnosis in industry 4.0: A review on challenges and opportunities." *Sensors* 25.1 (2024): 60.

[2] Ryalat, Mutaz, Hisham ElMoaqet, and Marwa AlFaouri. "Design of a smart factory based on cyber-physical systems and Internet of Things towards Industry 4.0." *Applied Sciences* 13.4 (2023): 2156.

[3] Singh, Amit Kumar, and P. C. Tewari. "An overview of reliability, availability, maintainability, and safety strategies for complex systems in various process industries." *International Journal of Performability Engineering* 19.12 (2023): 788.

[4] Rahman, Shoaib Ur, et al. "Failures and Repairs: An Examination of Software System Failure." *Bulletin of Business and Economics (BBE)* 13.1 (2024).

[5] Hanif, Mehran, et al. "Evaluating Prompt Variability in Transformer-Based LLMs Through Discrete and Semantic PSI." *ASSAJ* 4.02 (2025): 1798-1809.

[6] Watara, Sadia Ali, Gerardo Moreira, and Vincent Anyah. "Enhancing Supply Chain Efficiency Through Machine Learning: A Predictive Analytics Approach to Risk Identification and Timely Deliveries." (2025).

[7] Zia, Khadija, et al. "ADVANCED MACHINE LEARNING FRAMEWORK FOR IDENTIFYING AND MITIGATING FAKE NEWS AND MISINFORMATION PROPAGATION ON SOCIAL MEDIA PLATFORMS." *Spectrum of Engineering Sciences* (2025): 142-154.

[8] Hamid, Khalid, et al. "Topological Evaluation of Cloud Computing Networks and Real-Time Scenario-Based Effective Usage." *Bulletin of Business and Economics (BBE)* 13.2 (2024): 80-92.

[9] Zahid, Samraiz, et al. "Blockchain-based health insurance model using IPFS: A solution for improved optimization, trustability, and user control." *2023 International Conference on IT and Industrial Technologies (ICIT)*. IEEE, 2023.

[10] Arshid, Noman, et al. "An Innovative Framework for Automated Software Testing and Validation." *Bulletin of Business and Economics (BBE)* 13.1 (2024).

[11] Zhao, Ting. "Artificial intelligence in mathematical modeling of complex systems." *EAI Endorsed Transactions on e-Learning* 10 (2024).

[12] Ovacıklı, Aziz Kubilay, et al. "Supervised learning-based fault classification in industrial rotating equipment using multi-sensor data." *Applied Sciences* 15.13 (2025): 7580.

[13] Kumar, Sachin, et al. "Machine learning techniques in additive manufacturing: a state of the art review on design, processes and production control." *Journal of Intelligent Manufacturing* 34.1 (2023): 21-55.

[14] Ahmed, Rana Hassam, et al. "Enhancing autonomous vehicle security through advanced artificial intelligence techniques." *Journal of Computer Science and Electrical Engineering* 6.4 (2024): 1-6.

[15] Nawaz, R., et al. "Harnessing genetic diversity for sustainable maize production." *Journal of Physical, Biomedical and Biological Sciences* 2023.1 (2023): 15-15.

[16] Abbas, Hassan, et al. "Enhancing food security: A blockchain-enabled traceability framework to mitigate stockpiling of food commodities." *2023 International Conference on IT and Industrial Technologies (ICIT)*. IEEE, 2023.

[17] Shaheryar, Muhammad, et al. "Climate Change and Environmental Instability: The Rise of Invasive Species and Desertification." *Navigating Climate Change: Impacts on Biodiversity and Ecosystem Resilience*. Singapore: Springer Nature Singapore, 2025. 553-589.

[18] Ehsan, Abdul Jabbar, et al. "Stacked Lstm-Xgboost Ensemble Model for Accurate Short-Term Solar Power Forecasting." *2025 International Conference on Electrical, Communication and Computer Engineering (ICECCE)*. IEEE, 2025.

[19] Shahbaz, Zainab, et al. "Activation of antioxidant enzymes utilizing macro-or micronutrients and phytohormones or signaling molecules." *Role of Antioxidants in Abiotic Stress Management*. Academic Press, 2025. 283-300.

[20] Afridi, Zohaib Ur Rehman, et al. "Development of Photocatalytic Ultrafiltration Membranes for Enhanced Removal of Carbamazepine: Optimization and Mechanistic Insights." *Journal of Engineering* 2025.1 (2025): 6698866.

[21] Safiullah, Dilshad, et al. "Integrating Artificial Intelligence and Soil Ecology to Enhance Plant Resilience under Environmental Stress." *ASSAJ* 4.02 (2025): 3508-3516.

[22] Akram, Waseem, et al. "Short-Term Wind Power Forecasting Via Temporal Convolutional Networks." *2025 International Conference on Electrical, Communication and Computer Engineering (ICECCE)*. IEEE, 2025.

[23] Mehran, Muhammad, et al. "Plant Health, Soil Structure, and Fertility: Developing a Sustainable Future." *Integrated Health and Sustainability: Plants, Wildlife, and Genetic Resilience. Unique Scientific Publishers, Faisalabad, Pakistan* (2025): 144-152.

[24] Safiullah, Dilshad, et al. "Machine Learning Applications in Post-Fire Forest Restoration: Current Advances and Future Directions." *Planta Animalia* 5.1 (2026): 309-325.

[25] Rafique, Muhammad Talha, et al. "Investigating Safety Standards and Occupational Hazards in the Timber Sector: An Assessment of Timber Market in Multan, Pakistan." *Journal of Agroforestry and Environment* 19.1 (2026): 20226.

[26] Aly, Mohammed, and Naif M. Alotaibi. "SHAP enhanced transformer GWO boosting model for transparent and robust anomaly detection in IIoT environments." *Scientific Reports* 15.1 (2025): 41037.

[27] Nazat, Sazid, Osvaldo Arreche, and Mustafa Abdallah. "On evaluating black-box explainable AI methods for enhancing anomaly detection in autonomous driving systems." *Sensors* 24.11 (2024): 3515.

[28] Roy, Sumana, et al. "Bridging academia and industry: A comprehensive review of advances, gaps, and future directions of fault detection and diagnosis (FDD) systems in the chemical industry." *The Canadian Journal of Chemical Engineering* 103.10 (2025): 4718-4750.

[29] Moosavi, Sajad, et al. "Explainable AI in manufacturing and industrial cyber–physical systems: A survey." *Electronics* 13.17 (2024): 3497.