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(**Research Article**)

Enhancing Predictive Maintenance in Industrial IoT: A Machine Learning Approach for Real-time Anomaly Detection in Pressure Switches

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Predictive Maintenance,
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Real-time Sensor Data,
Pressure Switch Monitoring

Abstract: This study investigates the real-time integration of machine learning techniques with Internet of Things (IoT) data to monitor and predict the behavior of pressure switches in an industrial environment. Predictive maintenance in industrial IoT systems is critical to increase operational efficiency and minimize unexpected failures. The increasing complexity of industrial processes has made integrating machine learning algorithms and IoT data a powerful solution for proactive maintenance. In this context, the study aims to perform anomaly detection and failure prediction in pressure switches by analyzing real-time sensor data and applying Random Forest, Isolation Forest, and Local Outlier Factor algorithms. The performance of the models is evaluated using the MetroPT-3 Train Dataset. Performance metrics like accuracy, precision, recall, and F1 score assess the models' effectiveness. The Random Forest Classifier showed the highest performance in anomaly detection with an accuracy rate of 99.92%. The findings emphasize the significant potential of machine learning and the Internet of Things in enhancing predictive maintenance, improving system reliability, and contributing to the broader field of industrial IoT.

(**Araştırma Makalesi**)

Endüstriyel IoT'de Tahmini Bakımın Geliştirilmesi: Basınç Anahtarlarında Gerçek Zamanlı Anomali Tespiti için Bir Makine Öğrenmesi Yaklaşımı

Anahtar Kelimeler:
Öngörücü Bakım,
Makine Öğrenimi,
Anomali Algılama,
Gerçek Zamanlı Sensör Verileri,
Basınç Anahtarı İzleme

Özet: Bu çalışma, endüstriyel bir ortamda basınç anahtarlarının davranışını izlemek ve tahmin etmek için makine öğrenimi tekniklerinin Nesnelerin İnterneti (IoT) verileriyle gerçek zamanlı entegrasyonunu araştırmıştır. Endüstriyel IoT sistemlerinde öngörücü bakım, operasyonel verimliliği artırmak ve beklenmeyen arızaları en aza indirmek için kritik öneme sahiptir. Endüstriyel süreçlerin artan karmaşıklığı, makine öğrenimi algoritmalarını ve IoT verilerini entegre etmeyi proaktif bakım için güçlü bir çözüm haline getirmiştir. Bu bağlamda çalışma, gerçek zamanlı sensör verilerini analiz ederek ve Rastgele Orman, Yalıtım Ormanı ve Yerel Aykırı Değer Faktörü algoritmalarını uygulayarak Basınç anahtarlarında anormallik tespiti ve arıza tahmini yapmayı amaçlamıştır. Modellerin performansı MetroPT-3 Tren Veri Seti üzerinde değerlendirilmiştir. Modellerin etkinliği, doğruluk, hassasiyet, geri çağırma ve F1 puanı gibi performans ölçütleriyle değerlendirilmiştir. Rastgele Orman Sınıflandırıcısı, %99,92'lik bir doğruluk oranıyla anormallik tespitinde en yüksek performansı göstermiştir. Bulgular, makine öğreniminin ve Nesnelerin İnterneti'nin öngörücü bakımı geliştirmede, sistem güvenilirliğini iyileştirmede ve daha geniş endüstriyel IoT alanına katkıda bulunmada önemli potansiyelini vurgulamıştır.

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1. INTRODUCTION

The Internet of Things (IoT) is essential in monitoring and maintaining equipment and systems in the modern industrial environment. IoT technology provides real-time data from various sensors, providing more accurate and timely information on the operational status of critical components. One such application is monitoring pressure switches in industrial environments where reliable operation is vital to ensure safety and efficiency.

This study aims to monitor and predict the behavior of a pressure switch in an industrial environment using machine learning techniques. The pressure switch sensor in trains plays a critical role in monitoring and controlling the pressure levels in various systems. These sensors detect pressure changes and send signals to activate or deactivate systems based on preset thresholds to ensure safety and efficiency.

This research uses the MetroPT-3 Train Dataset [1] to analyze real-time sensor data collected from IoT devices. MetroPT-3 Train Data consists of 15 data types, as shown in Table 1 and Figure 1. The MetroPT-3 Train Dataset includes comprehensive sensor readings such as pressure, temperature, engine current, and air intake valve readings. These data are critical to understanding the behavior of the pressure switches under various operating conditions.

The main goal of this study is to improve proactive maintenance activities, thereby optimizing industrial equipment's operational efficiency and reliability. The methods in this study include applying multiple machine learning algorithms to predict pressure switch status. Specifically, Random Forest Classifiers, Isolation Forests, and Local Outlier Factor algorithms are used to identify anomalies and predict potential failures. These methods were chosen for their robustness and efficiency in processing high-dimensional and complex IoT data applications.

Basic performance metrics such as accuracy, precision, recall, and F1 score are used to evaluate the effectiveness of the models. These measurements provide a comprehensive evaluation of the performance of the models, ensuring that they can accurately and reliably predict the condition of the pressure switch. The findings from this study underscore the significant potential of combining machine learning and IoT in industrial applications. The analysis using these technologies highlights improvements in predictive maintenance strategies and overall system reliability.

This research aims to contribute to the literature by providing a practical application of machine learning techniques in the context of industrial IoT. It demonstrates how advanced analytics can be seamlessly integrated with IoT data to achieve better operational results. The results underscore the importance of adopting innovative technologies to increase the efficiency and reliability of industrial systems. This work is a significant step forward in the field of industrial IoT, showing how real-time sensor data and machine learning can be used to monitor and predict the behavior of critical components. Integrating the Internet of Things and advanced analytics offers a promising approach to improving maintenance practices, reducing downtime, and increasing industrial equipment's overall efficiency and reliability.

2. LITERATURE REVIEW

Anomaly detection is essential for railway operations' safety, efficiency, and reliability [2][3]. Survey studies show a rapid increase in publications because research in this field is still developing [4][5]. While IoT devices generate large amounts of data that can be monitored for anomalies, trains equipped with sensors and monitoring systems also provide rich time series data for analysis [6].

Anomaly detection in trains highlights innovative technologies such as the Internet of Things and directed waves to improve railway systems' safety, reliability, and maintenance practices [7]. Large-scale implementation is recommended in the long term to ensure better safety standards for railway lines and achieve better results in the future [8].

Thanks to sensor data, possible malfunctions or maintenance needs in train components can be identified in advance, anomalies related to safety concerns can be detected, and deviations in operational efficiency can be corrected [9]. By integrating anomaly collections with IoT technologies, performance operators can improve the reliability of train units in intelligent cities [10].

Various studies have been conducted on train abnormality detection, including pantograph-catenary systems and locomotive conditions [11][12][13]. Abnormalities are detected by monitoring irregularities in tracks using MEMS accelerometers and other sensors and real-time data monitoring [12]. Field experiments conducted on the Datong-Qinhuangdao Railway line have demonstrated the system's ability to monitor 24-hour real-time monitoring with minimal use of track resources and high accuracy in detecting speed and carriage amount [13].

IoT technologies are critical in improving railway system safety, reliability, and operational efficiency. These technologies can predict maintenance needs and take proactive measures. IoT-based Rail Transportation Security Comprehensive Detection and Tracking Method is critical in anomaly detection [14][15]. The experiments aim to detect anomalies on railway tracks and vehicles through the sensor system mounted on the wagon [16].

Early detection of faults and reduced operational disruptions improve train safety, reliability, and efficiency [12]. Its effectiveness and applicability on an IoT-based distribution monitoring system called RailMon focuses on specific parameters within a certain range of representation. This system reduces temperature changes in the beams, allowing crack damage to be detected or fixed features to be determined from a long distance [17].

In the case of trains, anomalies can indicate potential safety risks, equipment malfunctions, safety breaches, or operating inefficiencies [18]. Principles and machine learning methodologies for IoT applications can be directly applied to train anomaly detections. Just as IoT devices generate large amounts of data that require real-time processing and analysis, trains also generate rich data about their operations, performance, and status [19].

Researchers frequently explore machine-learning techniques to analyze real-time sensor data and detect anomalies [20]. Extensive simulations performed on Sydney Trains, Australia, show that the use of anomaly detection shows efficiency increases ranging from 21% to 165% in ten different scenarios, and the study demonstrates the potential to transfer over 250 Gigabits of data via T2W communications using widespread Wi-Fi networks [21].

This study analyses sensor data collected from various sensors for anomaly detection in pressure switches. There are studies on anomaly detection using sensor data on trains. For instance, The IoT-based Railway Control System developed in Egypt detects train anomalies and improves safety. This system detects and responds to anomalies using real-time data monitoring and analysis. This enables early detection and response to problems such as train fires, train breakages, or derailments [22][23]. Using a real-world dataset obtained from a public transport service in Porto, Portugal, focusing specifically on the Air Production Unit (APU) of trains, various sensor signals and digital signals are analyzed for anomaly detection and fault prediction in trains and GPS information [24].

Using data collected from various sensors located on trains and train stations, researchers can create robust anomaly detection systems to improve railway operations' overall safety and reliability [25]. The concept of anomaly detection with IoT in trains aligns with the discussed research on anomaly detection in IoT environments using machine learning [26]. Both areas highlight the need to identify deviations from expected patterns or unusual events in data collected from IoT devices.

There are studies on the MetroPT-3 Train Dataset that apply machine learning classification algorithms for fault prediction and diagnosis [27][28][29]. However, these studies do not specifically focus on anomaly detection in pressure switches.

3. MATERIALS AND METHODS

In this study, machine learning techniques were used to attempt to predict the pressure switch's status. Real-time sensor data collected from IoT devices is investigated to monitor and predict the behavior of a pressure switch in an industrial environment.

Table 1. MetroPT-3 Train Data Set

DATA	EXPLANATION
TP2	The pressure on the compressor data
TP3	The pressure data generated at the pneumatic panel
H1	The pressure data generated due to pressure drop when the discharge of the cyclonic separator filter occurs
DV_pressure	The pressure data drop generated when the towers discharge the air dryer
Reservoirs	The downstream pressure data of the reservoirs
Oil_temperature	The oil temperature data of the compressor
Motor_current	Data related to motor current.
COMP	The electrical signal data of the air intake valve on the compressor
DV_eletric	The electrical signal data that controls the compressor outlet valve
Towers	The electrical signal data that defines the tower responsible for drying the air and draining the humidity removed from the air
MPG	The electrical signal data for starting the compressor under load
LPS	The electrical signal data that detects and activates when the pressure drops a threshold
Pressure_switch	The electrical signal data that detects the discharge in the air-drying towers
Oil_level	The electrical signal data that detects the oil level on the compressor
Caudal_impulses	The electrical signal data that counts the pulse outputs

In this study, multiple machine learning algorithms have been used to predict the state of the pressure switch. These include the Random Forest Classifier, Isolation Forest, and Local Outlier Factor. The Random Forest Classifier is a supervised learning algorithm used for classification tasks. Isolation Forest and Local Outlier Factor (LOF) are unsupervised learning algorithms primarily used for anomaly or outlier detection. These algorithms were chosen because they can deal with high-dimensional and complex data and have proven effectiveness in industrial IoT applications.

Random Forest Classifier: This algorithm is robust to noise and handles complex data distributions. It requires labeled data for supervised learning and it is intensive computationally.

Isolation Forest: This algorithm was used for anomaly detection. It is efficient for large datasets and doesn't require labeled data. It may miss anomalies with complex relationships.

Local Outlier Factor: This algorithm is used for anomaly detection. It detects local anomalies based on data density. It is sensitive to the choice of neighbors and struggles with high-dimensional data.

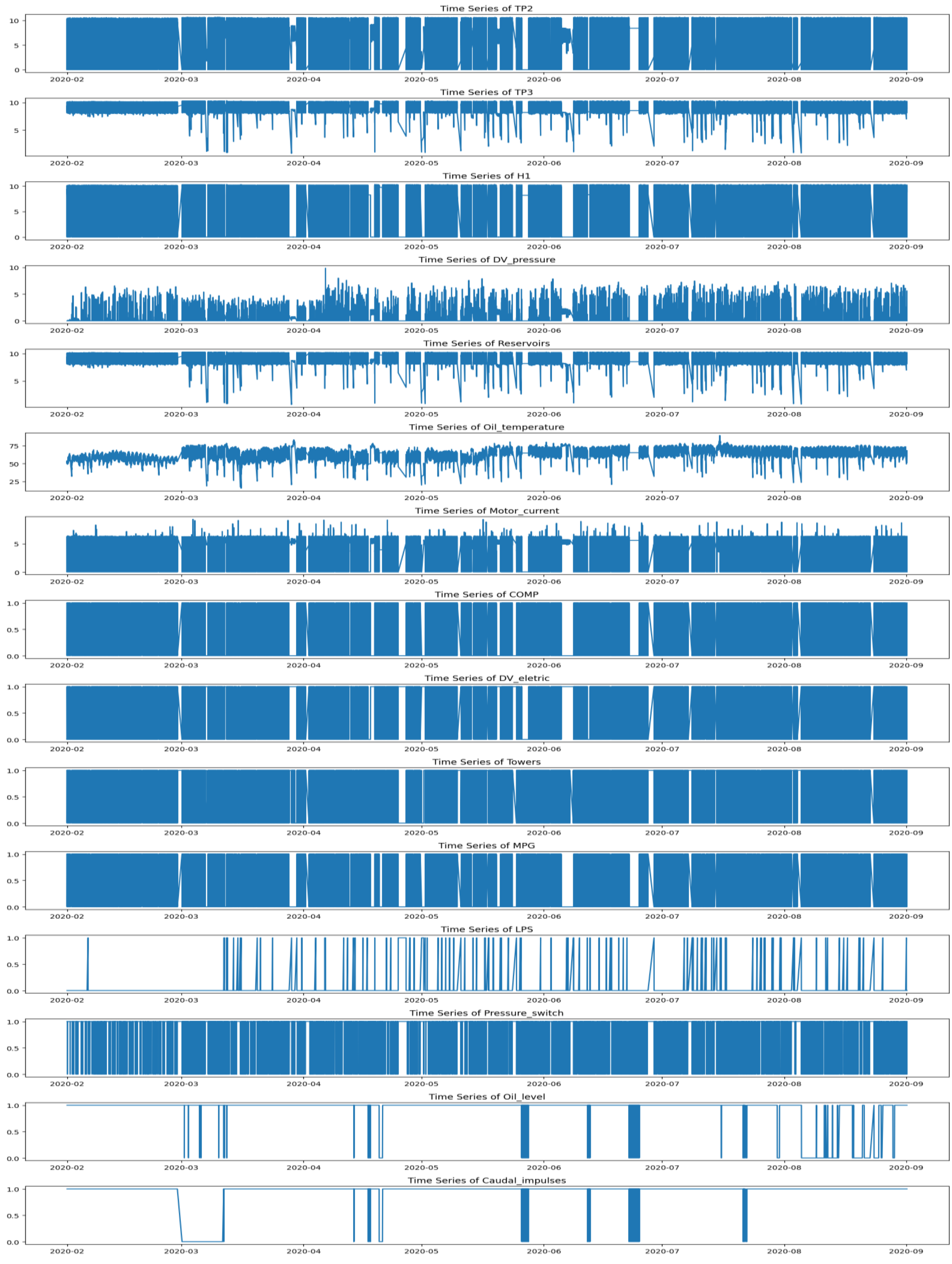

Figure 1. Time Series of Features

Pressure_switch data shows the electrical signal that detects the discharge in the air-drying towers and takes values as 0 or 1, as shown in Figure 1. The 1516948 line of Pressure_switch data consists of 12990 data of 0s and 1503958 data of 1s. 0s represent an anomaly, and 1s represent no anomaly in this data.

Various metrics were used to evaluate model performance, including accuracy, precision, recall, and F1 score [30][31]. These metrics are essential to determine how accurate and reliable the model is. For the explanation of these metrics, we use the abbreviations below.

TP: True Positive
TN: True Negative
FP: False Positive
FN: False Negative

Accuracy: Calculated as the ratio of the model's correct predictions in the test data to the total predictions.

$$Accuracy = (TP+TN)/(TP+TN+FP+FN)$$

Precision: Calculated as the ratio of the positive samples correctly predicted by the model to the total positive predictions.

$$Precision = TP/(TP+FP)$$

Recall (Sensitivity): Calculated as the ratio of positive samples correctly predicted by the model to the total true positive samples.

$$Recall = TP/(TP+FN)$$

F1 Score: Calculated as the harmonic mean of precision and sensitivity. This was used to evaluate the overall performance of the model.

$$F1\text{-}Score = 2*((Precision*Recall)/(Precision+Recall))$$

Performance metrics are calculated based on the model's predictions on test data. Additionally, the confusion matrix, which visually represents the model's correct and incorrect predictions, was used to visualize the model's performance.

4. RESULTS

4.1. Observed Anomalies

The analysis of the features from February to September 2020 reveals key patterns and anomalies. Anomalies in data cannot be observed at first glance. In this study, anomalies on pressure_switch are analyzed using several features and anomaly detection models. Based on these models, we predicted anomalies with respect to Class 0 and Class 1; Class 0 represents anomalies, and Class 1 represents data with no anomalies.

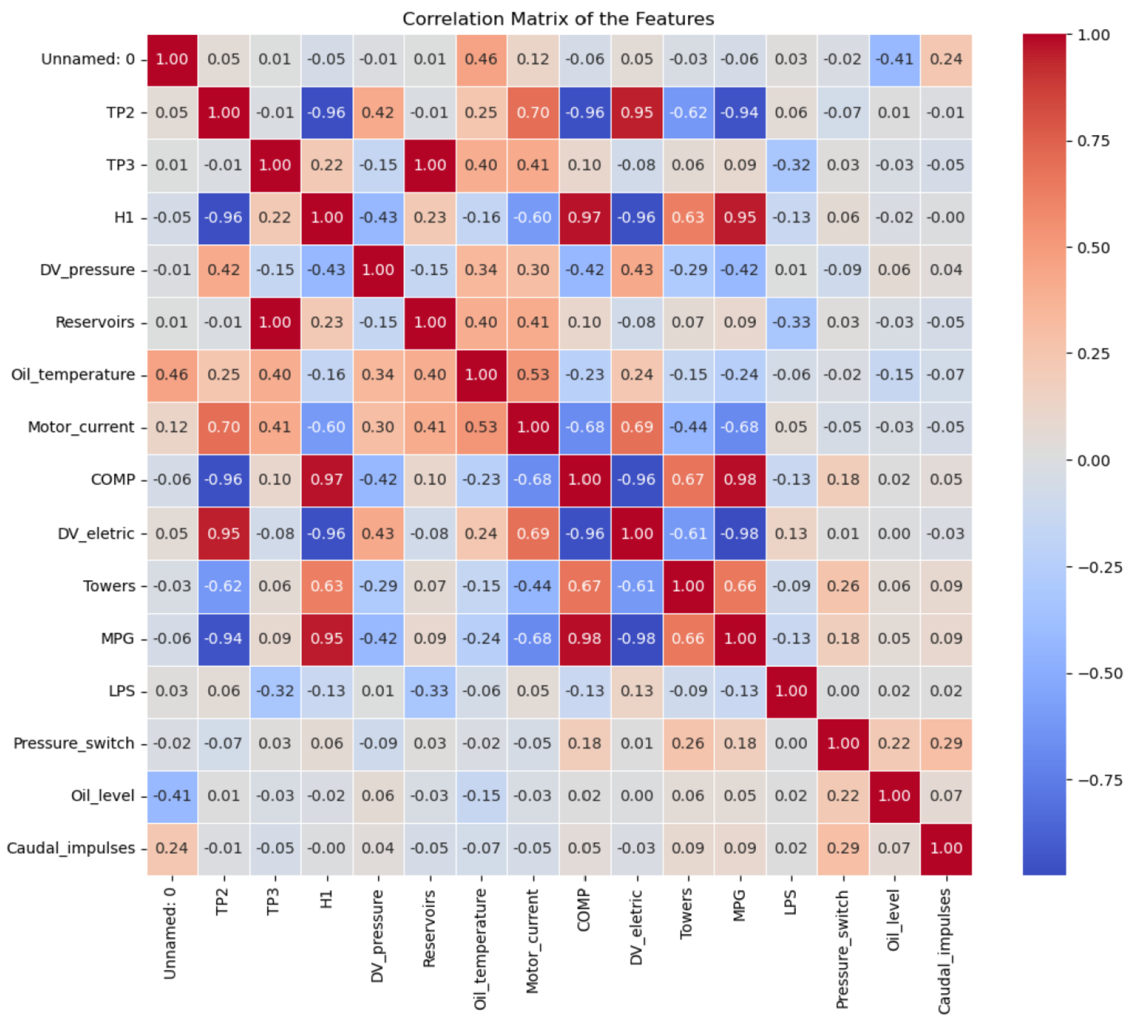

Figure 2. Correlation Matrix of the Features

Table 2. Model Parameters

ML Algorithm	Parameter	Description	Value
Random Forest	n_estimators	Number of trees in the forest	100 (default)
	criterion	Function to measure the quality of a split	gini (default)
	min_samples_split	Minimum number of samples to split an internal node	2 (default)
	min_samples_leaf	Minimum number of samples at a leaf node	1 (default)
	max_features	Number of features for the best split	sqrt (default)
Isolation Forest	contamination	Proportion of anomalies expected in the dataset	0.1
	n_estimators	Number of base estimators in the ensemble	100
	max_features	Number of features to pull from the dataset for training each base estimator	1.0 (all features)
Local Outlier Factor (LOF)	contamination	Proportion of anomalies expected in the dataset	0.1
	n_neighbors	Number of neighbors for calculating the LOF score	20
	leaf_size	Leaf size for the KDTree or BallTree algorithms for fast neighbor searches	30 (default)

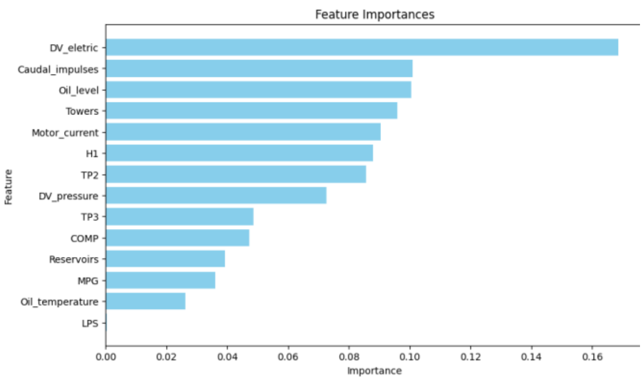

Figure 3. The importance values of features based on Random Forest

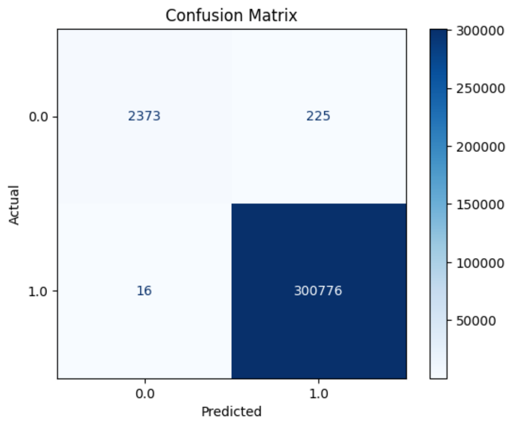

Figure 4. Random Forest Classifier Confusion Matrix for Anomaly Detection on Pressure Switch

4.2. Anomaly Detection Models

The correlation matrix in Figure 2 shows in detail the relationships between various features in the data set. Correlation coefficients range between -1 and 1, with 1 indicating perfect positive correlation, -1 indicating perfect negative correlation, and 0 indicating no correlation. For example, there is a moderate positive correlation between Pressure_switch and Caudal_impulses (0.29), implying that they tend to increase together. A weak negative correlation between Pressure_switch and MPG (-0.13) shows that these two variables tend to move slightly in opposite directions. There is a negligible or very weak correlation between Pressure_switch and some features like TP2 (-0.07), TP3 (0.03), and H1 (0.06), indicating no significant relationship.

While the correlation matrix in Figure 2 finds the linear correlation between some features and Pressure_switch is weak, the relationship might be strong nonlinear. The feature importance chart based on the Random Forest model, as shown in Figure 3, highlights the importance of each feature in predicting Pressure_switch. Figure 3 shows a strong nonlinear relationship between Pressure_switch and some features like DV_electric, Caudal_impulses, and Oil_level.

Based on all features, Random Forest, Isolation Forest, and Local Outlier Factor models are developed for anomaly detection on pressure switches, using the parameters shown in Table 2. For these models, 20% of the data was used for testing, and the remaining 80% was used for training. The seed for the random number generator is selected to be 42.

The performance of the Random Forest Classifier model was evaluated as relatively high. The accuracy rate of the model was calculated as 99.92%, precision as 99.93%, recall (sensitivity) as 99.99%, and F1 score as 99.96%. These results show that the model correctly identifies positive classes (high sensitivity) and keeps the number of false positives to a minimum (high sensitivity). In particular, the sensitivity rate is 99.99%, showing that the model detects positive samples almost without error.

Table 3. Model Performances

METRİC	RANDOM FOREST	ISOLATION FOREST	LOCAL OUTLIER FACTOR (LOF)
Accuracy	0.9992	0.8999	0.9000
Precision	0.9993	1.0000	1.0000
Recall	0.9999	0.8999	0.9000
F1 Score	0.9996	0.9473	0.9474

Table 3 shows the results of the algorithms. The Random Forest Classifier model's accuracy rate is 99.92%. The Random Forest Classifier model can correctly detect

99.92% of real anomalies, which reveals that the model produces very few false positives and false negatives. Random Forest outperforms Isolation Forest and LOF across all metrics, making it the best-performing algorithm for this anomaly detection task. It provides the most reliable results with minimal trade-offs between precision and recall. Isolation Forest and LOF show comparable performance, with identical precision and nearly identical F1 scores, though LOF has a slight edge in recall. The perfect precision of Isolation Forest and LOF indicates they are excellent at avoiding false positives but may underperform in detecting all anomalies compared to Random Forest.

Using Random Forest to achieve the best possible balance across all metrics is critical for pressure switch anomalies based on the results. It is better to consider Isolation Forest or LOF if avoiding false positives (high precision) is the priority, with trade-offs on the recall and accuracy.

The high metric results reflect the performance of the majority class, which is the normal case, but the confusion matrix shown in Figure 4 highlights poor anomaly detection. This is due to class imbalance. Because most data is in the normal class, metrics like accuracy and precision are heavily influenced by how well the model performs in the normal class.

5. DISCUSSION

The study focuses on enhancing predictive maintenance in industrial Internet of Things (IoT) systems through real-time anomaly detection in pressure switches using machine learning techniques. This approach is critical in improving operational efficiency and reducing unexpected failures in industrial environments. The work integrates IoT data with advanced machine learning models like Random Forest, Isolation Forest, and Local Outlier Factor to predict failures in pressure switches, which are vital for industrial and railway safety systems.

Random Forest is a supervised classifier algorithm, while Isolation Forest and Local Outlier Factor are unsupervised anomaly detection algorithms. Random Forest requires labeled data for supervised learning. Isolation Forest may miss anomalies with complex relationships, and the Local Outlier Factor algorithm struggles with high-dimensional data. The Random Forest Classifier demonstrated superior performance with an accuracy of 99.92%, precision of 99.93%, recall of 99.99%, and F1 score of 99.96%. Both Isolation Forest and Local Outlier Factor achieved a precision of 100%, but their recall and overall performance were lower compared to Random Forest.

Random Forest effectively balanced precision and recall, making it the best choice for detecting pressure switch anomalies. Isolation Forest and Local Outlier Factor showed strengths in avoiding false positives but struggled with false negatives due to the class imbalance in the dataset.

The study focused on pressure switches in a specific industrial and railway context using the MetroPT-3 Train Dataset, which might limit the applicability of the findings to other industrial components or systems. Features such as pressure levels, motor current, and oil temperature are analyzed in the study. The feature importance analysis highlighted key predictors like electrical signals (e.g., DV_electric) and caudal impulses for anomaly detection. The dataset had an imbalance between normal (class 1) and anomalous (class 0) data, affecting the models' ability to detect anomalies effectively.

Future research can expand on this work by addressing class imbalance through advanced sampling techniques or ensemble methods. In the future, more efforts can focus on optimizing computational efficiency to enable real-time anomaly detection in larger and more diverse IoT systems. Other than pressure switches, the methodology can be adapted for other critical components in various industrial domains, enhancing safety and efficiency across different domains. Future studies can integrate other deep learning techniques to improve reliability and transparency, providing insights into model decisions and anomaly detection.

6. CONCLUSION

This study examined advanced technologies such as sensor systems, IoT integration, and machine learning techniques for anomaly detection in pressure switches of railway systems. The findings of this study show that sensor and IoT-based systems are practical tools for early anomaly detection in rails and vehicles. These systems can detect potential problems early by monitoring speed, temperature, and vibration.

Machine learning models are powerful tools for detecting anomalies in railway operations. This study highlighted the role of sensor systems in detecting train anomalies, revealing the importance of IoT in safety and maintenance processes by analyzing real-time sensor data and applying Random Forest, Isolation Forest, and Local Outlier Factor machine learning algorithms. Random Forest is a supervised classifier algorithm, while Isolation Forest and Local Outlier Factor are unsupervised anomaly detection algorithms.

Performance metrics like accuracy, precision, recall, and F1 score evaluated these models' effectiveness. The Random Forest Classifier showed the highest performance in anomaly detection with an accuracy rate of 99.92% in detecting anomalies of pressure switches in the train.

Ethical Consideration

Compliance with ethical guidelines

Ethical guidelines were followed in this study.

Conflict of interest

The authors declare that they have no conflict of interest in this research.

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