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Hybrid Predictive Maintenance for Building Systems: Integrating Rule-Based and Machine Learning Models for Fault Detection Using a High-Resolution Danish Dataset

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Abstract: This study evaluates the effectiveness of six machine learning models, Artificial Neural Networks (ANN), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Logistic Regression (LR), for predictive maintenance in building systems. Utilizing a high-resolution dataset collected every five minutes from six office rooms at Aalborg University in Denmark over a ten-month period (27 February 2023 to 31 December 2023), we defined rule-based conditions to label historical faults in HVAC, lighting, and occupancy systems, resulting in over 100,000 fault instances. XGBoost outperformed other models, achieving an accuracy of 95%, precision of 93%, recall of 94%, and an F1-score of 0.93, with a computation time of 60 s. The model effectively predicted critical faults such as "Light_On_No_Occupancy" (1149 occurrences) and "Damper_Open_No_Occupancy" (8818 occurrences), demonstrating its potential for real-time fault detection and energy optimization in building management systems. Our findings suggest that implementing XGBoost in predictive maintenance frameworks can significantly enhance fault detection accuracy, reduce energy waste, and improve operational efficiency.

Keywords: predictive maintenance; machine learning models; fault detection; building systems; high-resolution data

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1. Introduction

With the increasing focus on sustainable energy management and cost efficiency, predictive maintenance has gained traction as an essential strategy for modern building management [1–3]. Traditional maintenance practices, often based on fixed schedules or reactive responses, can lead to unnecessary downtime, inflated operational costs, and undetected system faults that contribute to energy inefficiencies [4,5]. Predictive maintenance, powered by advancements in machine learning (ML) and high-resolution data collection, offers a proactive approach, enabling building systems to operate more effectively by predicting faults before they impact functionality [6–8].

Buildings equipped with smart sensors provide a wealth of real-time data on critical systems, including HVAC, lighting, and occupancy [3,9,10]. Predictive maintenance models can detect and anticipate faults by analyzing this data, minimizing energy waste and optimizing resource allocation [11]. Yet, identifying the most effective ML models for fault detection remains a challenge, as model performance can vary significantly based on the complexity and dynamic nature of building operations [12].

This study addresses this gap by comparing the performance of six widely used machine learning models [13]: Artificial Neural Networks (ANN) [14], Random Forest

(RF) [15], Extreme Gradient Boosting (XGBoost) [16], Support Vector Machine (SVM) [17], K-Nearest Neighbors (KNN) [18], and Logistic Regression (LR) [19], in the context of predictive maintenance for building systems. Utilizing a high-resolution dataset collected from multiple sensors across office spaces at Aalborg University in Denmark, we defined rule-based conditions to label historical faults, creating a reliable foundation for model training.

The primary objectives of this study are to

1. Identify common faults in building systems and analyze their types and frequencies to understand prevalent inefficiencies;
2. Compare the performance of the selected machine learning models in accurately detecting these faults in building systems;
3. Predict future faults through the predictive maintenance process.

Achieving these objectives will provide valuable insights into using machine learning for predictive maintenance in building systems, a key approach in sustainable building management with potential for significant energy savings and greenhouse gas emission reductions.

2. Literature Review

In recent years, predictive maintenance has emerged as a key strategy in building operations to improve system reliability, reduce energy consumption, and enhance occupant comfort [20]. This approach, which uses machine learning (ML) models to anticipate and mitigate faults, is increasingly popular for its ability to proactively manage critical building components like HVAC systems, lighting, and occupancy controls [20]. The following review examines the existing literature on predictive maintenance within building management, focusing on the evolution of fault detection methodologies, the application of machine learning models, and the challenges associated with high-resolution data in real-world building environments.

2.1. Predictive Maintenance in Building Systems

Predictive maintenance has been widely researched in various industrial applications, with increasing focus on building systems over the past decade [21–23]. Traditional building maintenance has largely relied on either preventive (scheduled) or reactive (post-fault) strategies [24]. While preventive maintenance reduces the likelihood of system failures, it can lead to unnecessary repairs, downtime, and overuse of resources. Reactive maintenance, meanwhile, only responds to system faults after they occur, often resulting in costly repairs, system downtime, and occupant discomfort [25]. Predictive maintenance, by contrast, uses real-time data and machine learning models to predict faults before they occur, enabling pre-emptive interventions that can optimize both operational efficiency and maintenance costs [26–28].

Buildings, especially large commercial structures, consist of interdependent systems, including heating, ventilation, and air conditioning (HVAC), lighting, and occupancy management [29]. Faults in these systems can significantly impact energy efficiency, occupant comfort, and operational costs. HVAC systems, in particular, are energy-intensive, accounting for nearly 40% of a building's total energy usage [30]. Common faults in HVAC systems include issues with sensors, actuators, dampers, and compressors, all of which can result in inefficient energy use and reduced indoor air quality [31]. Studies demonstrate that the early detection of HVAC faults can result in substantial energy savings and improved indoor environmental quality [32]. The importance of fault detection is also underscored by initiatives like the European Union's Energy Performance of Buildings Directive, which emphasizes the need for energy efficiency and fault tolerance in building management systems [33,34].

2.2. Machine Learning Models for Fault Detection

Machine learning models have become increasingly popular in predictive maintenance for fault detection, with numerous models applied across various domains [35,36] [36]. These models fall into three broad categories: supervised, unsupervised, and semi-supervised learning. Supervised learning models, trained on labeled data, are effective when historical data on system faults are available, while unsupervised models are used to detect anomalies in unlabeled datasets, identifying patterns that deviate from normal operation [37].

Several ML models have shown promise in building system fault detection. Decision tree-based models, such as Random Forest and Extreme Gradient Boosting (XGBoost), are popular for their interpretability and ability to handle high-dimensional data [38]. Random Forests, for example, have been applied to detect faults in HVAC systems with high accuracy, particularly in identifying sensor anomalies and actuator faults [39]. Similarly, XGBoost has been noted for its high accuracy and computational efficiency, making it suitable for real-time applications in building management [40]. Studies have demonstrated that XGBoost outperforms other ensemble methods in fault detection for building systems, especially when applied to large, complex datasets with high variability [41].

ANNs are also widely used in fault detection due to their capacity to model complex, non-linear relationships [42]. ANNs have shown effectiveness in identifying faults in HVAC systems, particularly in predicting faults related to temperature regulation and air flow [43]. Despite their effectiveness, ANNs can be computationally demanding, which can limit their applicability to real-time fault detection [44]. Support Vector Machines (SVM), which are often used for classification tasks, have also been applied in fault detection in building systems [45]. SVMs are robust in high-dimensional spaces and have been used effectively to identify faults in HVAC components, though their high computational requirements may limit their scalability in large buildings [46].

K-Nearest Neighbors (KNN) and Logistic Regression (LR), while simpler models, are often used in fault detection due to their ease of implementation and interpretability [47]. KNN, a non-parametric model, has been applied to fault detection in energy management systems and has demonstrated effectiveness in identifying short-term anomalies in temperature and occupancy data [48]. Logistic Regression, though primarily used for binary classification, has been applied to detect lighting faults and occupancy-based anomalies in building systems. Despite their limitations, these models are valuable in specific contexts where interpretability and computational efficiency are prioritized.

2.3. Fault Detection in HVAC Systems and Energy Efficiency

HVAC systems are the most studied building components in the context of fault detection, given their complexity and impact on energy efficiency [49]. Faults in HVAC systems are often caused by malfunctioning sensors, clogged filters, or incorrect control settings, all of which can lead to energy waste and reduced comfort levels for occupants [50]. Extensive research has been conducted on fault detection methods for HVAC systems, with early approaches based on rule-based methods and expert systems [51]. Rule-based systems are simple and interpretable but may lack adaptability in complex environments where fault patterns change over time [52]. For instance, model-based methods, which use mathematical models of HVAC components to identify deviations from expected performance, are limited by the need for extensive calibration and may struggle with real-time adaptability [53].

Machine learning approaches offer greater flexibility and scalability for HVAC fault detection. Studies have applied machine learning models to detect faults in HVAC systems using a high-frequency dataset, showing that ML-based methods could identify faults earlier and more accurately than traditional rule-based approaches [54]. In a comparative study of various ML models, including ANN, RF, and SVM, XGBoost emerged as the top performer, achieving superior accuracy and computational efficiency [55]. Additionally, research has underscored the benefits of ensemble learning techniques, such as RF and XGBoost, in identifying anomalies within HVAC data, highlighting how combining multiple models can lead to more accurate and robust fault detection [56].

2.4. The Role of High-Resolution Data in Predictive Maintenance

High-resolution data is increasingly recognized as essential for accurate fault detection in predictive maintenance [57]. With advancements in sensor technology, it is now possible to collect data at high frequencies, capturing variations in environmental conditions, occupancy, and energy consumption in real time [58]. High-resolution datasets provide detailed insights into system behavior, which can be leveraged to detect subtle anomalies that might otherwise go unnoticed. However, handling such data presents challenges, including computational complexity, data storage, and the need for models that can efficiently process and learn from large volumes of data [59].

Studies suggest that high-resolution data improves the accuracy of fault detection models in HVAC systems, as it captures detailed information on temperature, air quality, and occupancy levels [60]. Similarly, the importance of temporal resolution should be acknowledged, noting that faults detected at higher temporal resolutions allow for faster responses and more proactive maintenance [61]. However, high-resolution data can also introduce noise, potentially affecting model performance. Research by Yun et al. explores methods to pre-process and filter high-resolution data, enhancing model accuracy by removing irrelevant fluctuations while preserving essential fault indicators [62].

In building management, using high-resolution data for predictive maintenance also requires addressing data privacy and security concerns, particularly in systems where occupancy is monitored through computer vision or other intrusive sensors [63]. Ensuring data privacy while maintaining the fidelity of fault detection algorithms is an ongoing area of research, with some studies exploring privacy-preserving data aggregation methods [64]. Balancing the need for high-resolution data with privacy and security considerations will be critical as predictive maintenance systems become more widely adopted in building environments [65,66].

2.5. Scope of the Work

This study investigates the effectiveness of various machine learning models for predictive maintenance in building systems, with a particular focus on HVAC, lighting, and occupancy monitoring components. Using a high-resolution dataset from Aalborg University in Denmark, the research addresses the complex requirements of real-time fault detection in building management. The scope encompasses the creation of a labeled dataset for fault detection, providing data collected over a year from sensors monitoring critical building systems. To prepare the data, our rule-based conditions were developed to define and label fault instances in HVAC, lighting, and occupancy operations, ensuring that fault labels correspond to realistic building management scenarios. For instance, faults include lighting left on in unoccupied spaces or misaligned ventilation settings based on room occupancy. This structured data-labeling process is foundational to training machine learning models in a way that reflects genuine conditions and supports practical predictive maintenance applications.

The study evaluates the performance of six machine learning models: ANN, RF, XGBoost, SVM, KNN, and LR, each chosen for its unique advantages in handling complex building data. These models are assessed on their capacity for interpretability, computational efficiency, and fault detection accuracy, providing a comprehensive understanding of each model's strengths and limitations within the context of predictive maintenance. Through testing and validation, the study compares the models on several performance metrics, including accuracy, precision, recall, and F1-score, with the goal of identifying the most suitable model(s) for fault detection in dynamic building environments.

A significant aspect of this research is the evaluation of model performance across diverse fault types relevant to building systems, including damper control issues, radiator valve anomalies, and mismanaged lighting. Through examining each model's ability to accurately detect these varied faults, the study sheds light on the adaptability and robustness of machine learning approaches in handling the unique challenges of building operations. This fault-specific analysis is essential to understanding how different models respond to specific system behaviours and anomalies, thus supporting the development of tailored maintenance strategies.

Moreover, the study proposes a structured framework for implementing predictive maintenance in building systems, encompassing model training, validation, evaluation, and continuous adaptation. This framework provides a comprehensive approach to fault detection and offers strategies for data pre-processing, feature engineering, and model tuning, which are vital for maintaining accuracy and reliability over time. The research emphasizes the importance of practical considerations, such as computational efficiency and model interpretability, which are critical for real-world adoption.

3. Methodology

The predictive maintenance model development process (Figure 1) is a structured approach centered on defining faults based on rule-based conditions to create a reliable, data-driven fault detection system. Starting with historical fault data, specific rules are established to classify system behaviours as faults, creating labeled data that serves as the foundation for training machine learning models. These labeled datasets enable the models to learn patterns that indicate potential faults. Once trained, the models undergo validation and tuning to enhance their accuracy and reduce error rates, with parameter adjustments made to improve predictive performance. In the final evaluation phase, each model's effectiveness is tested on new data, leading to the selection of the optimal model for identifying faults accurately and efficiently in real-world applications.

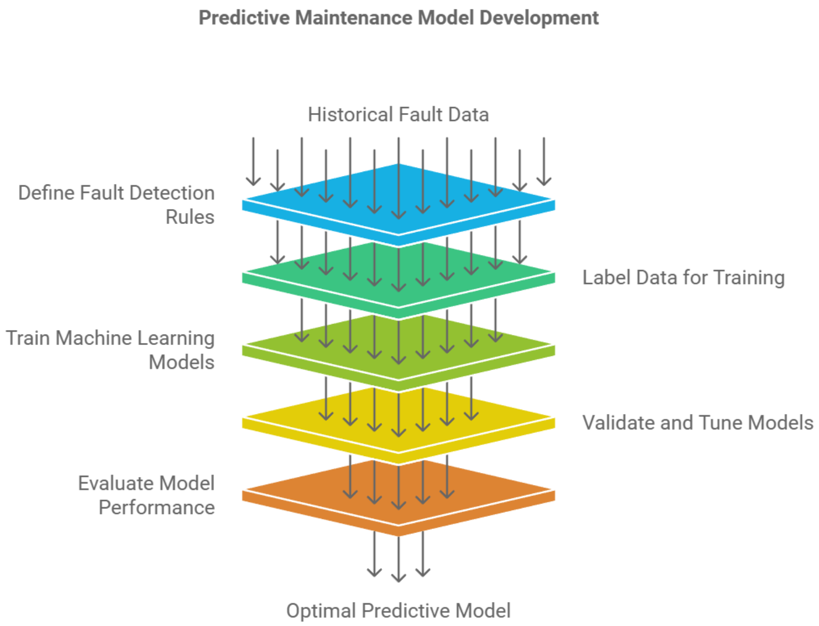

Figure 1. A layered framework illustrating the development process for predictive maintenance models.

3.1. Data Exploration and Visualization

The dataset used in this study spans a ten-month period, from 27 February 2023 to 31 December 2023, and provides high-resolution measurements recorded every five minutes from six monitored office rooms [67]. These data points capture key environmental and operational variables critical to understanding the indoor climate, energy consumption, and occupancy patterns within the building (Figures 2 and 3). Among the primary variables, room temperature (°C) and CO_2 levels were measured through dedicated sensors, allowing for detailed insights into both thermal comfort and ventilation performance throughout the year. These variables are essential for analyzing the indoor environmental quality, as they highlight the effectiveness of air circulation and the building's ability to maintain a comfortable, productive setting for occupants. Additionally, occupancy data was recorded using a computer vision-based YOLOv5 algorithm, which analyzes images captured by wall-mounted cameras to determine the number of people present in each room at any given time. This real-time occupancy data played a vital role in assessing space utilization, as well as in understanding the influence of occupant presence on energy demands, ventilation requirements, and overall indoor air quality. Since occupancy directly impacts the building's heating and ventilation needs, monitoring these patterns is fundamental for optimizing energy usage in relation to actual room usage and activity.

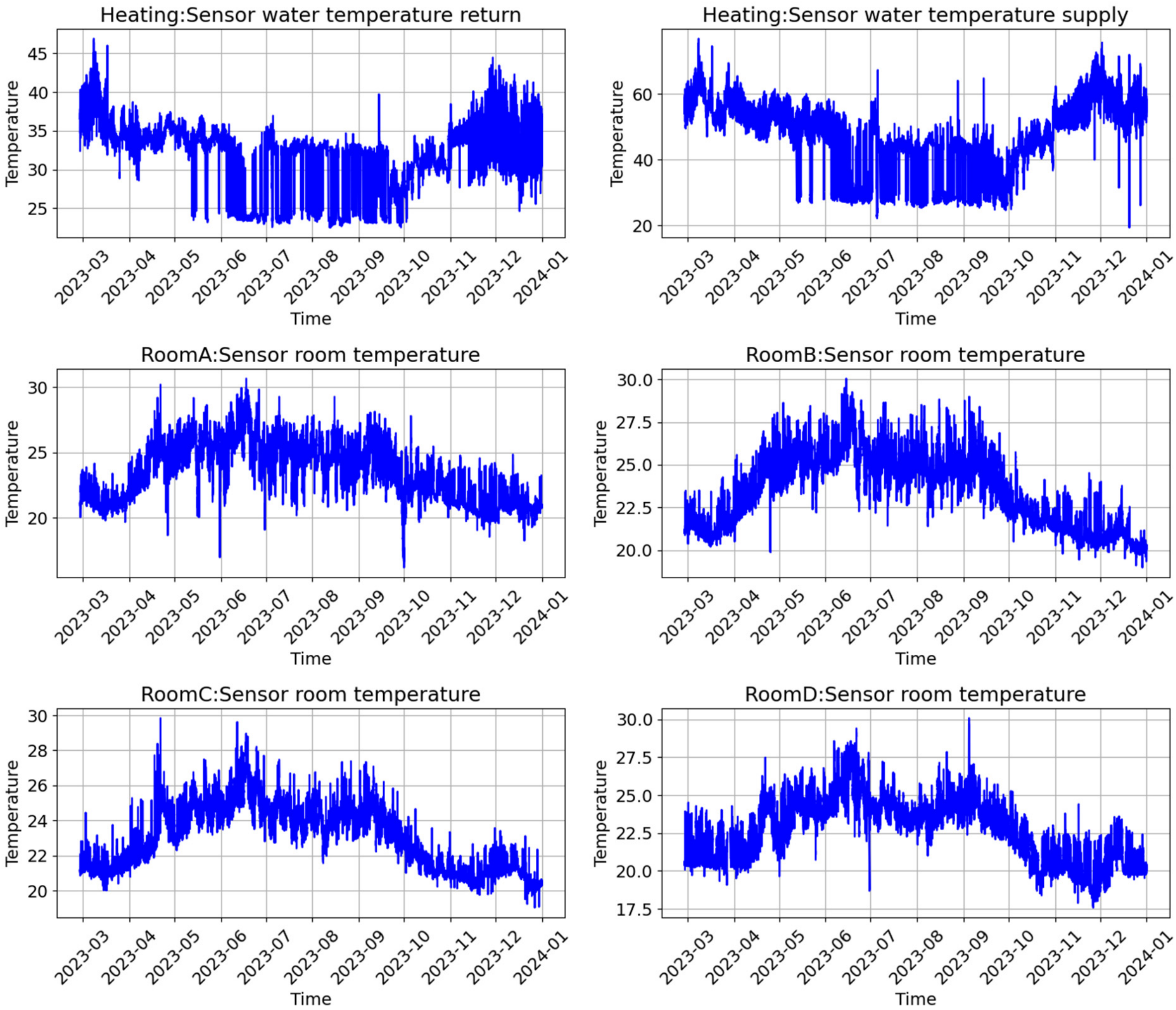

Figure 2. Time-series plots of temperature data from heating system sensors and room temperature sensors over the period from the end of February 2023 to January 2024.

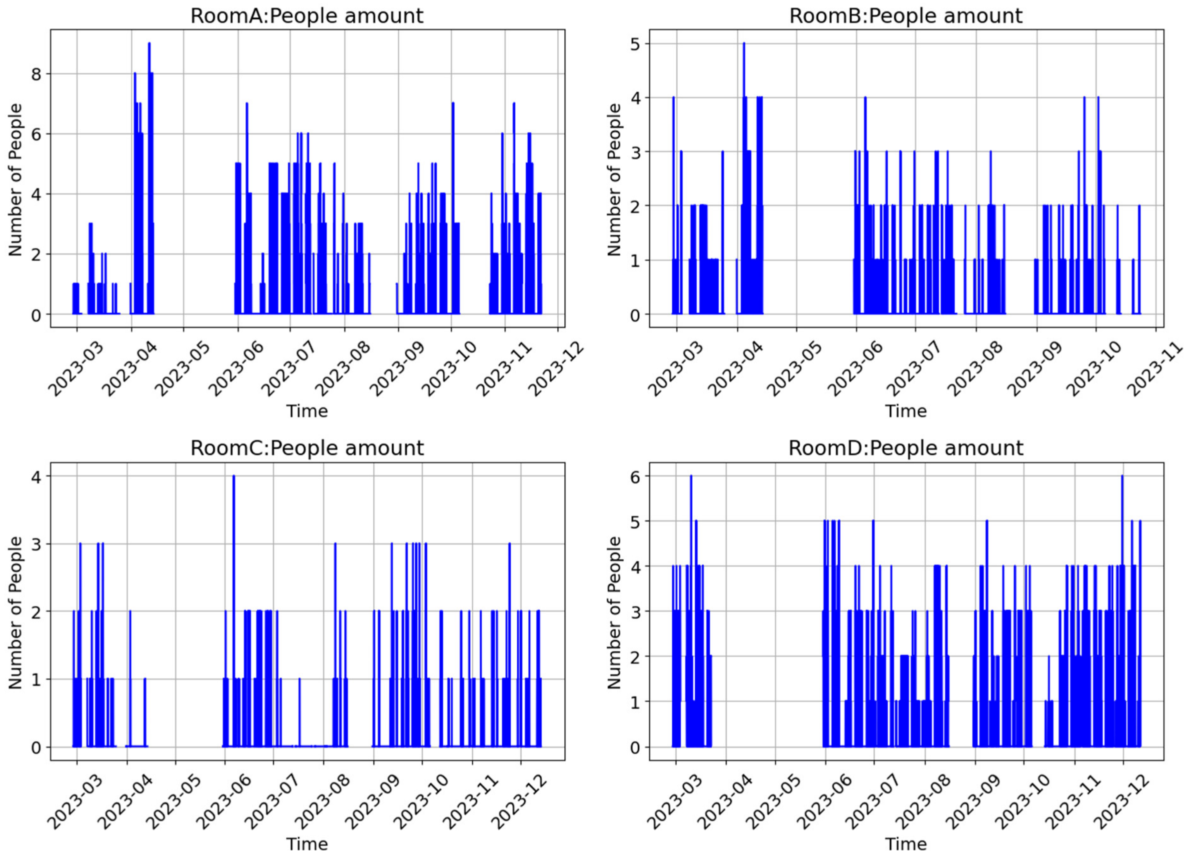

Figure 3. Time-series plots representing the number of people present in four different rooms (Rooms A–D).

In addition to indoor environmental variables, the dataset includes measurements of solar radiation on the building's east, south, and west façades. These measurements, recorded in watts per square meter (W/m^2), provide critical information on the influence of solar heat gain on indoor temperatures, especially in rooms with different orientations. This allows for a comprehensive analysis of how sunlight affects internal climate, particularly during periods of high solar exposure. Furthermore, the dataset recorded ventilation power consumption, measured in watts through the Building Management System (BMS), which tracks the energy drawn by the Air Handling Unit (AHU). This power consumption metric was essential for evaluating the energy efficiency of the building's ventilation system, revealing how fluctuations in occupancy, room temperature, and external climate conditions impact energy usage. Initial exploratory analyses have highlighted notable seasonal trends, such as the temperature patterns across the heating system's supply and return water, which show elevated temperatures in colder months and reduced levels during warmer periods. Similarly, room occupancy levels fluctuate by month and room, with occupancy peaks in certain rooms that align with increased ventilation demands and, consequently, elevated power consumption. This dataset offers a rich basis for examining how building systems respond to both internal occupancy patterns and external climate influences, enabling targeted strategies for improved energy efficiency and operational effectiveness.

3.2. Fault Detection Rules

A fundamental step in preparing the dataset for predictive maintenance is defining rule-based methods to label historical faults. These rules establish conditions under which specific system behaviours are classified as faults, thereby creating labeled data essential for training and evaluating machine learning models. For instance, a commonly encountered fault in HVAC systems is when a damper remains open despite a room being unoccupied, leading to unnecessary ventilation and energy loss. This fault can be represented as a Boolean condition:

$$\text{Damper\_Open\_No\_Occupancy} = (\text{Damper\_Position} > 0) \land (\text{People\_Count} = 0)$$

where Damper_position refers to the damper's state (open or closed), and People_Count denotes the number of occupants in the room. This rule flags the damper position as a fault if it remains open in the absence of people, allowing for a straightforward definition of this issue in the dataset.

Similarly, a rule was established to detect cases where radiator valves were open despite the room being unoccupied, which results in wasted heating energy. This radiator fault is labeled as follows:

$$\text{Radiator\_Valve\_Open\_No\_People} = (\text{Radiator\_Valve\_Position} > 0) \land (\text{People\_Count} = 0)$$

Here, Radiator_Valve_Position indicates whether the radiator valve is active, while People_Count tracks room occupancy. This rule captures critical energy inefficiencies tied to unneeded heating by labeling instances where radiator valves are active during unoccupied periods.

The heating pump fault is another relevant rule, marking cases when the heating pump remains active despite no heating demand. This can occur due to scheduling or sensor issues, and is formulated as

$$\text{Heating\_Pump\_Active\_No\_Heating} = (\text{Pump\_On} = 1) \land (\text{Heating\_Demand} = 0)$$

where Pump_On is the pump's active state, and Heating_Demand is an indicator of the room's heating requirements. Instances meeting these conditions are flagged as heating pump faults, preventing unnecessary energy use in situations without heating demand.

Additionally, lighting faults are defined to detect if room lights remain on during unoccupied times, leading to energy waste. This rule is defined as

$$\text{Light\_On\_No\_Occupancy} = (\text{Light\_On} = 1) \land (\text{People\_Count} = 0)$$

Lastly, temperature sensor faults are flagged when outdoor temperatures fall outside a reasonable range (e.g., below -20 °C or above $+50$ °C), indicating possible sensor errors or extreme weather conditions:

$$\text{Extreme\_Outdoor\_Temperature} = (\text{Outdoor\_Temperature} < -20) \lor (\text{Outdoor\_Temperature} > 50)$$

These rule-based conditions establish the labeled data necessary for training and evaluating machine learning models, ensuring consistent labeling of fault conditions within the dataset.

To clarify the methodology used for labelling historical faults in HVAC, lighting, and occupancy systems, we provide a more in-depth explanation of the rule-based conditions applied in this study. These conditions are designed to identify specific system behaviors that result in energy inefficiencies or operational issues, allowing us to generate labeled data that can be used to train machine learning models. For example, one of the rules used to detect HVAC faults relates to the damper position. When a room is unoccupied, the damper should be closed to prevent unnecessary ventilation. The rule for detecting this fault is as follows:

$$\text{Damper\_Open\_No\_Occupancy} = (\text{Damper\_Position} > 0) \wedge (\text{People\_Count} = 0)$$

This rule flags a fault when the damper remains open despite no occupants being present, which can lead to significant energy waste. Similarly, for the lighting system, a fault is flagged when the lights remain on in an unoccupied room, contributing to unnecessary energy consumption. The rule for this lighting fault is:

$$\text{Light\_On\_No\_Occupancy} = (\text{Light\_On} = 1) \wedge (\text{People\_Count} = 0)$$

This condition ensures that instances where the lights are on without occupants are accurately labeled as faults. In addition to HVAC and lighting systems, occupancy data, which is captured using a computer vision-based YOLOv5 algorithm, plays a key role in fault detection. However, occupancy data may contain anomalies, such as misclassifications of occupancy, either when the system falsely detects occupants in an empty room or misses detections in rooms with high occupancy. To address these issues, additional rules are applied to the occupancy data to ensure its accuracy. For instance, if the occupancy count significantly deviates from expected levels based on other sensor data (e.g., CO_2 levels or room temperature), it is flagged as an anomaly that may indicate a potential fault. By cross-referencing occupancy data with environmental sensors, we ensure that occupancy patterns are correctly interpreted, preventing false alarms or missed detections. These examples illustrate the rule-based conditions applied across different systems to label faults consistently and accurately. By establishing these conditions, we ensure that the dataset used to train machine learning models reflects real-world scenarios and provides reliable input for the predictive maintenance model. This approach allows for the development of an efficient and effective fault detection system capable of reducing energy waste and improving the operational performance of building systems.

To ensure the quality and reliability of the dataset before training the machine learning models, several pre-processing steps were applied to address missing data, outliers, and anomalies. Missing data points occurred primarily due to temporary sensor malfunctions or communication errors within the Building Management System (BMS). These gaps were handled using a combination of techniques. For short gaps (less than 15 min), linear interpolation was applied to estimate missing values based on adjacent data points. For longer gaps, forward or backward filling was used to preserve data continuity while minimizing potential biases introduced by prolonged estimation. Additionally, any variables that exhibited prolonged missing values across critical timeframes were excluded from specific analysis phases to ensure the reliability of model inputs. Outliers were identified using a combination of the interquartile range (IQR) method and z-score thresholds. For environmental variables, like room temperature and CO_2 levels, values falling outside the range of typical indoor conditions—such as temperatures below 15 °C or above 35 °C, or CO_2 levels exceeding 3000 ppm—were flagged as potential outliers. These values were examined to determine whether they represented genuine extreme events (e.g., unusually hot days) or sensor errors. If identified as sensor errors, outliers were corrected by averaging the nearest valid time points to maintain data consistency. For energy consumption, metrics like ventilation power, unusual spikes, or drops were similarly flagged, with corrections made through data smoothing techniques when the anomalies were linked to known sensor faults or operational disruptions. Anomalies related to occupancy data, captured using the YOLOv5 computer vision-based algorithm, were also addressed. Misclassifications, such as false detections of occupants in empty rooms or missed detections during crowded periods, were identified through cross-validation with other sensor readings (e.g., CO_2 levels and lighting states). These anomalies were corrected by adjusting the occupancy count based on adjacent time periods and sensor correlations, ensuring accurate occupancy data for the models. Finally, anomalies indicating potential faults in the building systems were proactively flagged during pre-processing. For instance, HVAC components operating during unoccupied periods or temperature sensors reporting extreme values were labeled as faults based on predefined rule-based conditions. By incorporating fault labeling at the pre-processing stage, the dataset was enriched with valuable insights for training machine learning models. Overall, these pre-processing steps ensured the dataset was clean, complete, and capable of providing reliable inputs for developing predictive maintenance models.

3.3. Machine Learning Models

Once labeled, the dataset serves as the input to a range of machine learning models tailored for predictive fault detection. Five machine learning algorithms were selected for this study: ANN, RF, XGBoost, SVM, KNN, and LR. Each model brings unique characteristics and strengths suited to the specific patterns and complexities in the data, allowing for a comprehensive evaluation of fault detection capabilities.

As illustrated in Figure 4, the model development process begins by defining rule-based fault detection conditions for key building components, including the HVAC damper, radiator valve, heating pump, lighting, and temperature sensors. These rules generate labeled data by classifying system behaviors into fault and non-fault conditions. This labeled data is then used to train the machine learning models to recognize patterns indicative of potential faults. The models are subsequently validated and tested, with each stage incorporating hyperparameter tuning to optimize the model's performance across multiple metrics, such as accuracy, precision, and recall.

The final step involves optimizing the performance metrics to select the best-performing model, ensuring a balance between precision and recall to minimize false alarms while maximizing fault detection accuracy. The selection of the six machine learning models—ANN, RF, XGBoost, SVM, KNN, and LR—was driven by their distinct characteristics and strengths, which align well with the specific needs of predictive maintenance in building systems. Artificial Neural Networks (ANN) are particularly effective at modeling complex, non-linear relationships in the data, enabling the detection of subtle, intricate patterns in system behavior that might indicate faults. This makes ANN suitable for building systems with dynamic interactions between components. Random Forest (RF) and Extreme Gradient Boosting (XGBoost) are both ensemble methods that build multiple decision trees, which makes them resilient to overfitting and effective for handling large, noisy, and high-dimensional datasets typical in building systems. These models excel in providing high fault-detection accuracy, even when the data is incomplete or contains outliers, making them suitable for real-time monitoring and early fault detection in building maintenance. Support Vector Machines (SVM) offer strong performance when dealing with high-dimensional data and are particularly effective in scenarios where there is a limited amount of fault data, as they work by finding an optimal hyperplane that separates fault and non-fault instances. K-Nearest Neighbors (KNN), with its simple yet powerful approach of assigning labels based on the proximity of neighbors, is a highly interpretable method and performs well with smaller datasets, making it useful for troubleshooting and on-the-ground maintenance tasks where rapid decisions are required. Logistic Regression (LR), although simpler, provides a probabilistic approach and serves as a useful baseline model for comparing the effectiveness of more complex methods. By evaluating and tuning these diverse models, we ensured that our predictive maintenance system could balance precision, recall, and F1-score, which are critical for minimizing false positives while effectively capturing faults in building systems. This structured approach to model training and evaluation enables the development of a reliable and efficient predictive maintenance system capable of identifying faults early and reducing operational inefficiencies.

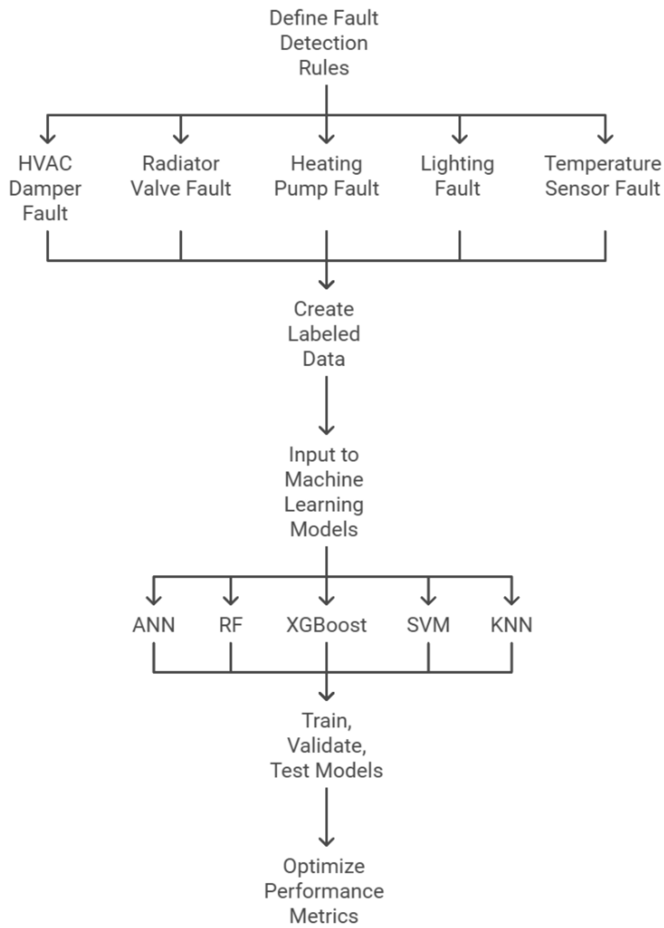

Figure 4. Workflow for predictive maintenance model development. The process begins by defining fault detection rules for various system components (e.g., HVAC damper, radiator valve, heating pump, lighting, and temperature sensor).

3.3.1. Artificial Neural Network (ANN)

An ANN consists of interconnected neurons organized in layers, allowing the model to learn complex, non-linear relationships in the data. Each neuron processes the input features x by applying a weight matrix W and a bias b, followed by an activation function σ, which is the ReLU function here used in the hidden layers:

$$y = \sigma(W \cdot x + b)$$

where y represents the output of each neuron. ANNs are optimized using backpropagation to adjust the weights and minimize a loss function, such as cross-entropy for classification tasks.

3.3.2. Random Forest (RF)

Random Forest is an ensemble technique that builds multiple decision trees on bootstrapped subsets of the data. Each tree provides a prediction, and the overall forest output is the average (for regression) or the majority vote (for classification). Given an input x, the Random Forest prediction $f(x)$ is calculated as:

$$f(x) = \frac{1}{N}\sum_{i=1}^{N} f_i(x)$$

where $f(x)$ represents the prediction from the i-th tree, and N is the total number of trees.

3.3.3. Extreme Gradient Boosting (XGBoost)

XGBoost is a boosting algorithm that constructs decision trees sequentially, with each tree correcting the errors from previous trees. The objective function includes both a loss term and a regularization term to prevent overfitting:

$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

where $\mathcal{L}$ is the loss function, y_i is the actual value, $\hat{y}_i$ is the predicted value, f_k is each tree, and Ω is a regularization term controlling model complexity.

3.3.4. Support Vector Machine (SVM)

SVM creates a hyperplane that maximally separates data points into fault and non-fault classes. The optimization problem for SVM is expressed as:

$$\min_{w,b} \frac{1}{2}|w|^2 \text{ subject to } y_i(w \cdot x_i + b) \geq 1$$

where w is the weight vector, b is the bias, x_i represents each data point, and y_i is the class label. SVM is robust in handling high-dimensional data, especially in cases with limited fault instances.

3.3.5. K-Nearest Neighbors (KNN)

KNN is a non-parametric algorithm that assigns class labels based on the majority class of the k closest neighbors in the feature space. The Euclidean distance d between two points x_i and x_j is computed as:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{m} \left(x_{i,k} - x_{j,k}\right)^2}$$

The class assigned to x depends on the classes of its k-nearest neighbors, making it highly interpretable and effective for simpler datasets.

Hyperparameter tuning was conducted via grid search and cross-validation to ensure that each model performed optimally, adjusting settings such as tree depth in Random Forest, learning rate in XGBoost, kernel type in SVM, and k values in KNN. The hyperparameter optimization was a crucial step to ensure the model's effectiveness in predictive fault detection. We employed grid search as our methodology for hyperparameter tuning, a process that exhaustively tests all predefined combinations of hyperparameter values within a specified range. This systematic approach was selected because it provides a comprehensive evaluation of the parameter space, ensuring that the best configuration is chosen for optimal model performance. Among the key hyperparameters tuned for the XGBoost model were the learning rate, maximum depth of trees, number of estimators, subsample ratio, gamma, and lambda. The learning rate was particularly important as it controls the magnitude of updates made to the model's weights during training. A lower learning rate results in more gradual adjustments, preventing the model from overshooting the optimal parameters. However, too low a learning rate could result in the model requiring more estimators to converge. After testing various values, we found that a learning rate of 0.05 struck the right balance between training speed and model accuracy, ensuring that the model converged efficiently without overfitting. The maximum depth of trees determines the complexity of individual trees within the XGBoost model. Deeper trees can capture more intricate relationships between input features, but they also increase the risk of overfitting, especially in noisy datasets. Through experimentation, we found that a tree depth of six provided a sufficient level of complexity to model the interactions in the data without causing overfitting, which is a common challenge in predictive maintenance tasks. Similarly, the number of estimators, or trees, was another crucial hyperparameter. Too few trees could lead to underfitting, where the model fails to capture important patterns, while too many could lead to overfitting. We experimented with various numbers of trees and determined that 100 trees provided a good balance between computational efficiency and model accuracy, achieving robust performance without unnecessarily increasing the model's complexity. The subsample ratio governs the fraction of training data used for fitting each individual tree. If set too high, it could lead to overfitting, as the model might become too specific to the training data. If set too low, the model may not capture enough variability in the data, leading to underfitting. After tuning the subsample ratio between 0.6 and 1.0, we selected a value of 0.8, which offered sufficient diversity during training while still avoiding overfitting. Regularization terms like gamma and lambda were also tuned to help prevent overfitting by penalizing overly complex models. The gamma parameter specifies the minimum reduction in the loss function required to create a new partition in the tree, and a higher gamma value tends to make the model more conservative. We tuned gamma to 0.1, which ensured that the model maintained generalization capability. Similarly, the lambda parameter added L2 regularization to the model's weight term, discouraging overly large weights. A lambda value of 1.0 was chosen, as it prevented overfitting without overly simplifying the model. Through this extensive grid search process, we identified the optimal combination of hyperparameters, leading to improved performance in predictive maintenance tasks. The selected values were fine-tuned to maximize the F1-score, a critical metric in predictive maintenance, where both precision and recall must be balanced. The F1-score is especially important because it ensures that the model does not miss any actual fault instances (recall) while minimizing false alarms (precision). The model, after hyperparameter tuning, exhibited not only high accuracy but also robustness in identifying faults while avoiding overfitting. This optimization allowed us to develop a highly effective XGBoost model that can be reliably applied in real-world predictive maintenance scenarios for building systems.

3.4. Training, Validation, and Test Splits

The dataset was divided into three portions: training (70%), validation (20%), and testing (10%). The training set was used to fit the models, allowing them to learn from historical data. The validation set was used for hyperparameter tuning and to monitor for potential overfitting. The test set, held back from training and tuning, was reserved for final evaluation to assess generalization. This stratified splitting strategy ensured balanced fault and non-fault instances in each subset, providing a representative sample for unbiased model evaluation.

3.5. Performance Metrics

3.5.1. Recall

Recall measures the proportion of actual positive cases that the model correctly identifies as faults [68]. It reflects the model's ability to capture all true fault instances, which is particularly important in predictive maintenance, where undetected faults could lead to increased energy use or system failure:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

where TP is the count of true positives and FN is the count of false negatives. A higher recall indicates that the model effectively identifies actual fault conditions, reducing the likelihood of missed detections.

3.5.2. F1-Score

F1 represents the harmonic mean of precision and recall, providing a balance between the two metrics [68]. This score is especially useful when dealing with imbalanced datasets, as it penalizes extreme values in either precision or recall:

$$\text{F1} - \text{Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

The F1-score is an essential metric in our context, as it balances the trade-off between precision and recall, ensuring that the model not only captures faults accurately but also minimizes false alarms.

3.6. Model Selection and Evaluation Strategy

The model selection process involved assessing each algorithm's performance across the validation metrics outlined above. Given the imbalanced nature of fault and non-fault cases, models with high precision and recall were prioritized, ensuring both effective fault capture and minimal false positive rates. Hyperparameters for each model were optimized to achieve the best balance between precision, recall, and F1-score, which allowed for rigorous model tuning.

The final evaluation was conducted on the test set to assess each model's generalization capabilities. This test set, isolated from both the training and validation processes, provided an unbiased measure of performance, simulating real-world conditions where the model encounters new, unseen data. The model with the highest F1-score on the test set was selected for one-year-ahead fault prediction, ensuring that it met practical standards for accuracy, reliability, and robustness in a predictive maintenance setting. To strengthen the evaluation of model performance, we expanded our assessment framework by incorporating additional metrics, specifically the Area Under the Curve (AUC) and the Matthews Correlation Coefficient (MCC). The AUC is particularly valuable in understanding how well the model differentiates between fault and non-fault conditions across varying classification thresholds. A higher AUC indicates the model's superior ability to distinguish between the two classes, providing a more comprehensive picture of its discriminatory power. In addition to AUC, the MCC was introduced to offer a balanced measure of model performance, as it accounts for both true positives and negatives, as well as false positives and negatives. Unlike other metrics, such as accuracy, the MCC is particularly robust when dealing with imbalanced datasets, making it ideal for predictive maintenance scenarios where the incidence of faults is often much lower than non-faults. By including AUC and MCC alongside traditional metrics like precision, recall, and F1-score, we ensured a more well-rounded evaluation, offering insights into various aspects of model performance. This multi-metric approach helps to mitigate any biases introduced by class imbalance, ensuring the selection of the most reliable and effective model for fault prediction.

4. Results

4.1. Fault Detection

The detailed analysis of fault conditions across multiple building systems emphasizes significant opportunities for improving energy efficiency and reducing operational costs [69]. In particular, frequent faults were identified in HVAC and lighting operations, where the systems failed to align with occupancy patterns, resulting in unnecessary energy consumption. For instance, Figure 5 reveals recurrent instances where the damper remained open in unoccupied rooms. This pattern suggests that the HVAC system's control settings may not adequately account for real-time occupancy, leading to excessive ventilation when it is not needed. Optimizing these control parameters, potentially by implementing occupancy-based rules or seasonal adjustments, could mitigate these faults, reducing ventilation and energy usage during periods of low occupancy.

Similarly, the radiator valve experienced sporadic faults, as shown in Figure 6, where it was left open even when rooms were unoccupied, leading to unnecessary heating. This inefficiency is particularly concerning, as it directly impacts heating costs, which are typically a major component of a building's energy expenditure. The system could be automatically adjusted to reduce heating in unoccupied spaces by integrating occupancy-based heating controls, thus preventing energy wastage and improving cost-effectiveness in the heating system.

The heating system inefficiencies extended beyond HVAC controls to the heating pump and coil, which frequently consumed energy without corresponding demand. Figure 7 presents the heating pump fault data, showing continuous activation without heating requirements, while Figure 8 shows similar fault conditions for the heating coil. These recurring patterns of misalignment suggest that the heating system is operating in an inefficient manner, potentially due to either control logic flaws or lagged responses to environmental changes. The system can better prevent energy waste, operating only when heating demand is present by implementing predictive or demand-based controls that adjust pump and coil activity in line with actual heating needs.

Lighting inefficiencies were also observed, as highlighted in Figure 9, which shows numerous instances where lights were left on in unoccupied rooms. This repeated fault emphasizes the benefits of occupancy-based lighting controls that automatically switch off lights when no occupants are detected, especially in areas with variable or unpredictable occupancy patterns. Such control adjustments could significantly reduce lighting-related energy usage, aligning room lighting with actual usage patterns.

Similarly, ventilation control issues were identified, with Figure 10 showing frequent cases where the fan remained on even when it was supposed to be off. This suggests either a malfunction within the ventilation system or issues in the control settings that may need recalibration. Addressing these ventilation faults is essential, as prolonged fan operation without necessity contributes to both energy inefficiency and increased wear on mechanical components. Ensuring that ventilation fans operate only when required would not only lower energy costs but also extend the lifespan of the equipment.

Outdoor temperature monitoring, while not showing any fault conditions in Figure 11 during the observed period, remains a critical parameter for maintaining optimal building performance, especially under extreme weather conditions. Proactive monitoring of outdoor temperature extremes is essential for adjusting HVAC operations, accordingly, ensuring that indoor environments remain comfortable while minimizing energy use during temperature fluctuations.

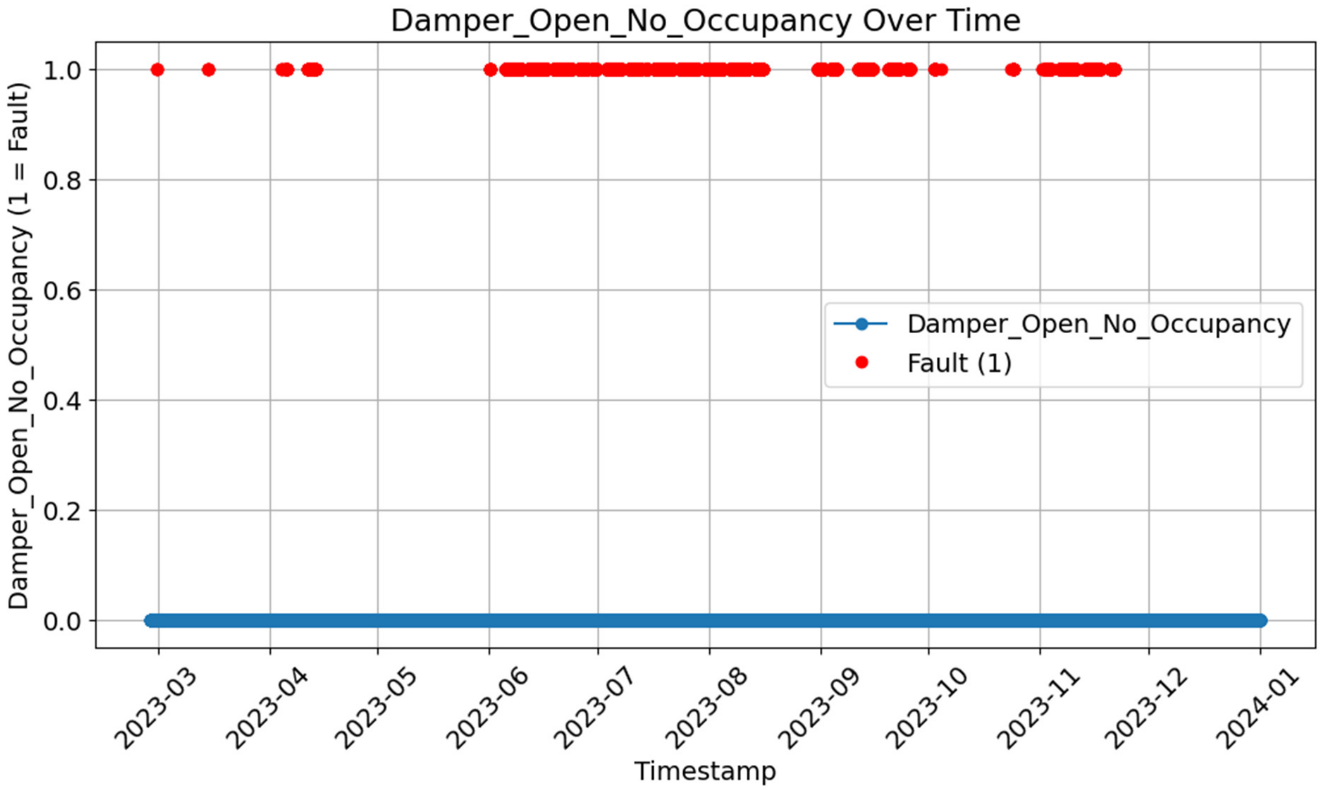

Figure 5. Instances of the damper remaining open in unoccupied rooms (fault condition) over time, with faults marked in red.

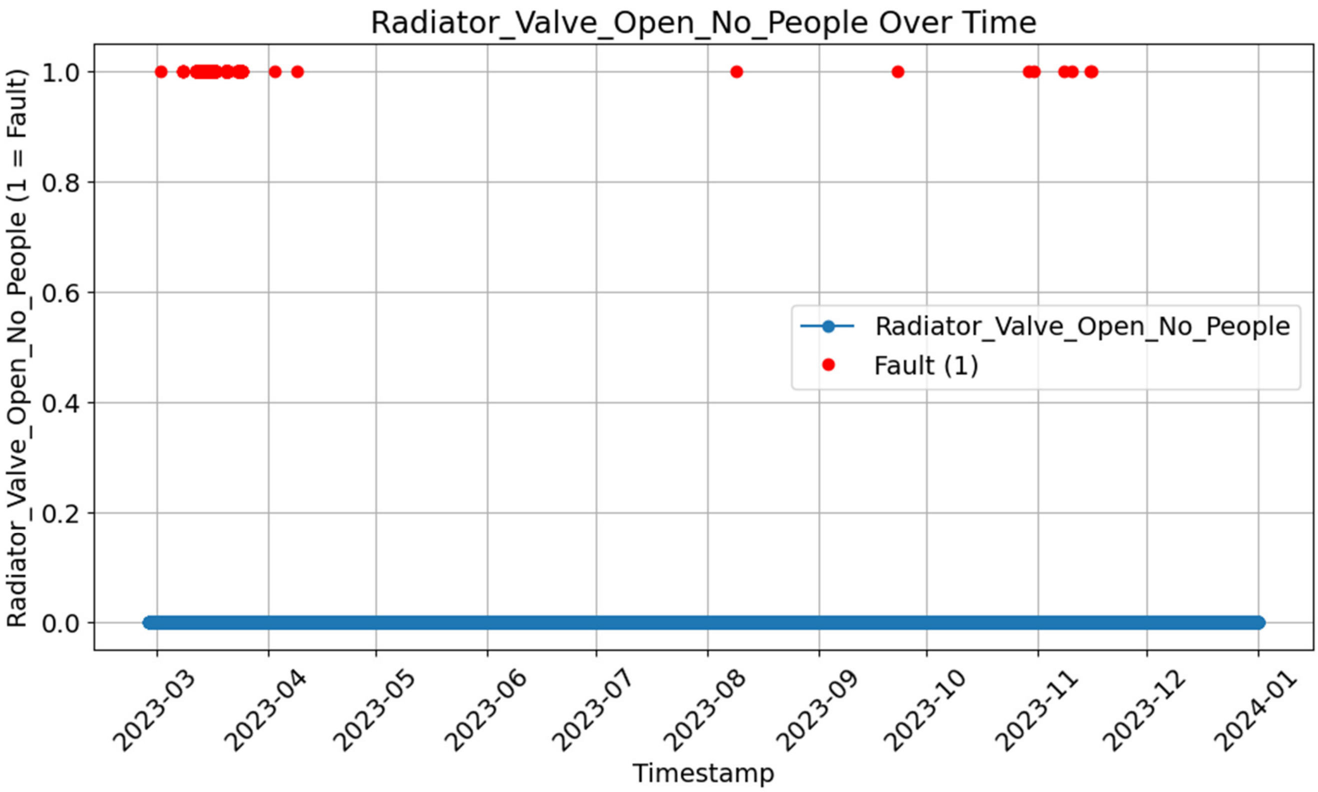

Figure 6. Occurrences where the radiator valve was left open despite no occupancy, indicating a fault condition shown in red.

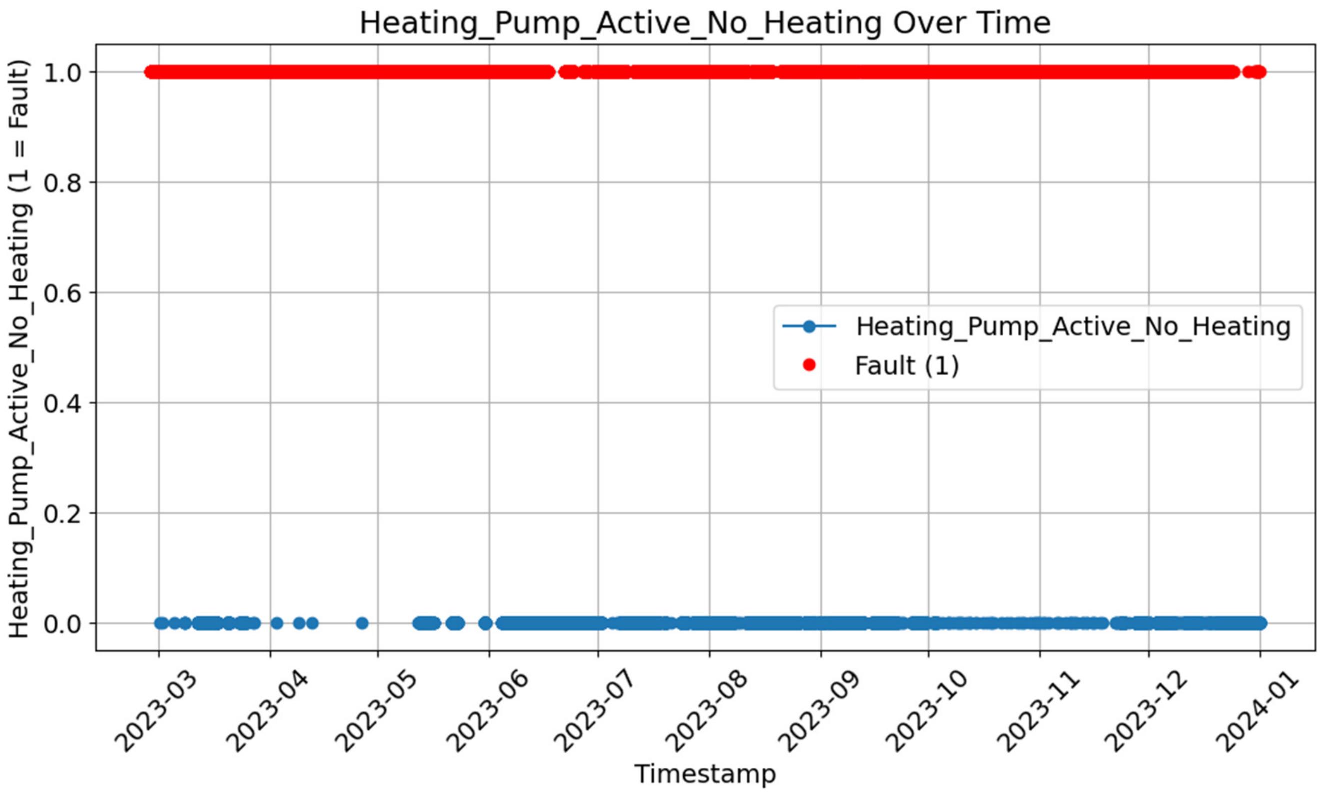

Figure 7. Periods where the heating pump was active without a heating demand, with faults indicated in red.

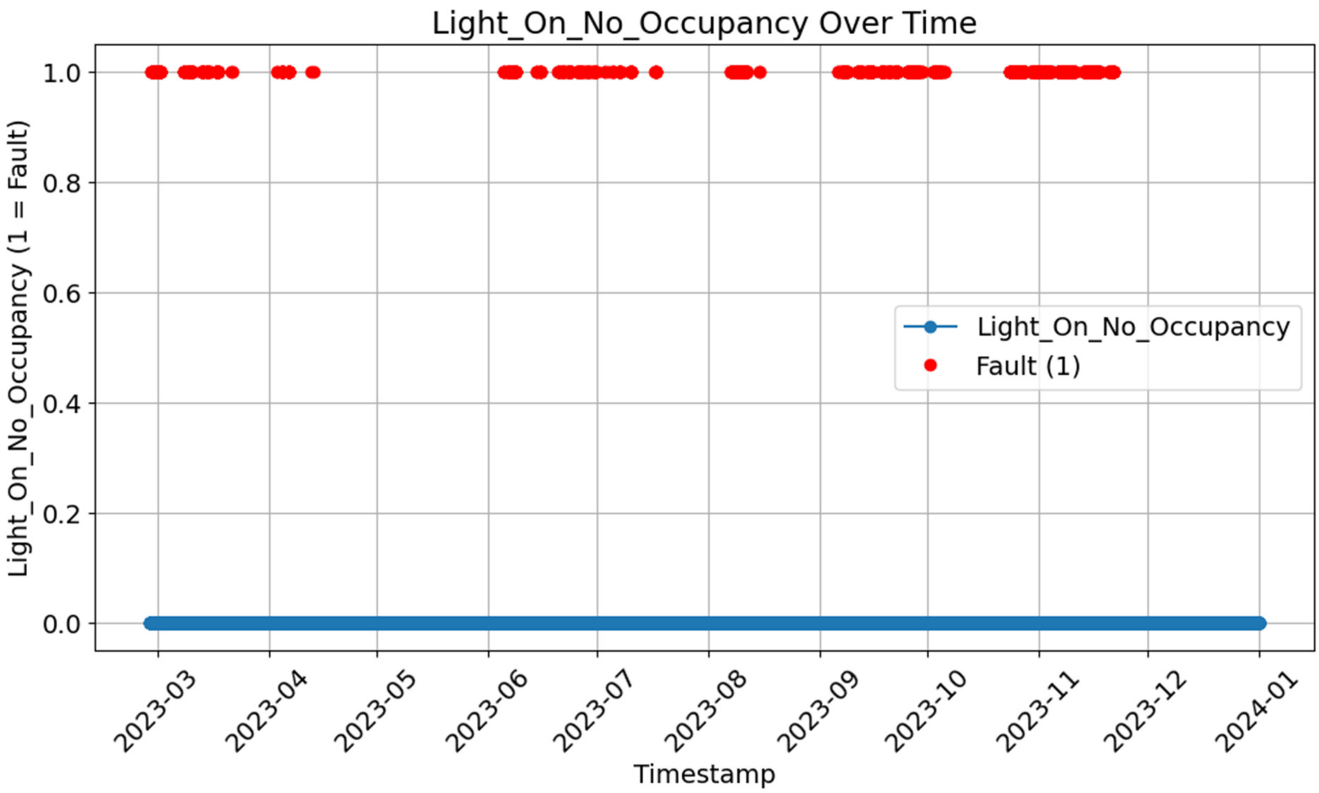

Figure 8. Instances of room lights left on during unoccupied periods, with fault conditions highlighted in red.

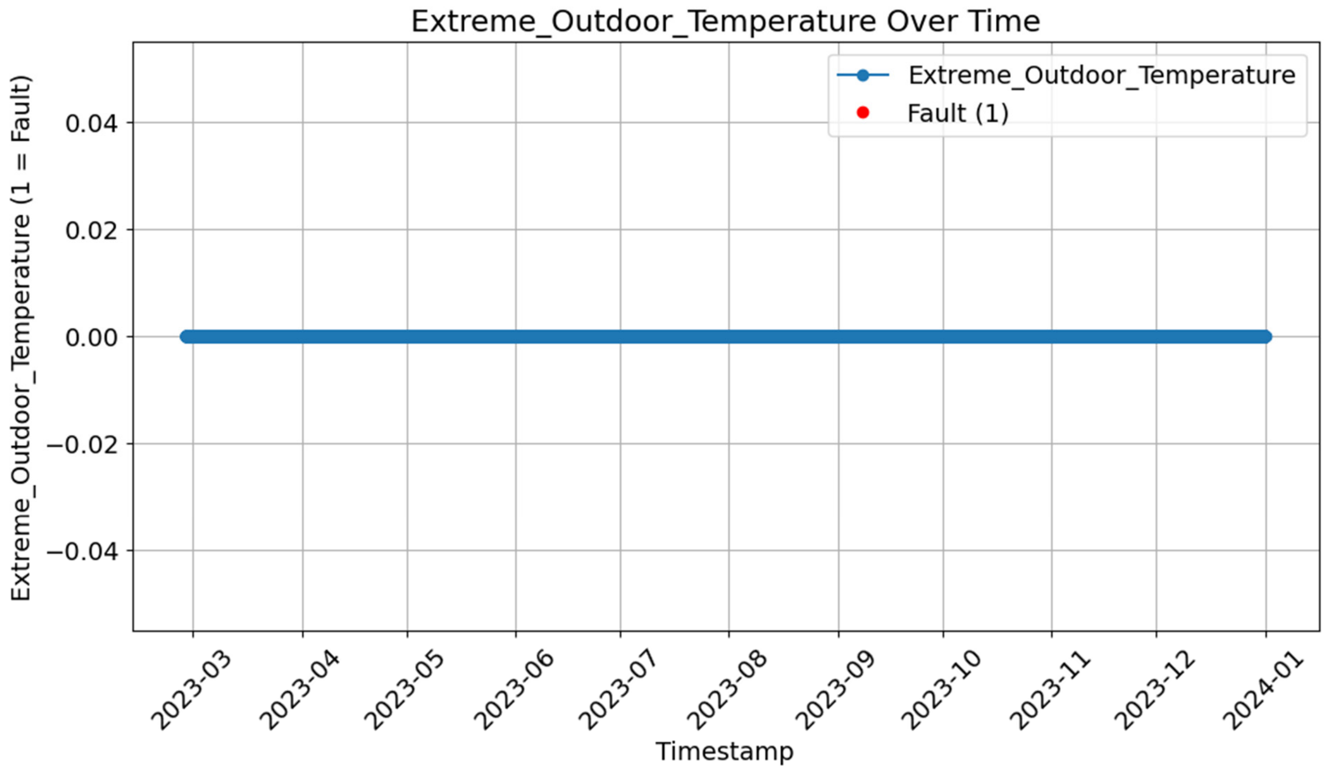

Figure 9. Occurrences of extreme outdoor temperatures, where values fall outside the acceptable range (fault condition = 1), though no faults were detected in this time period.

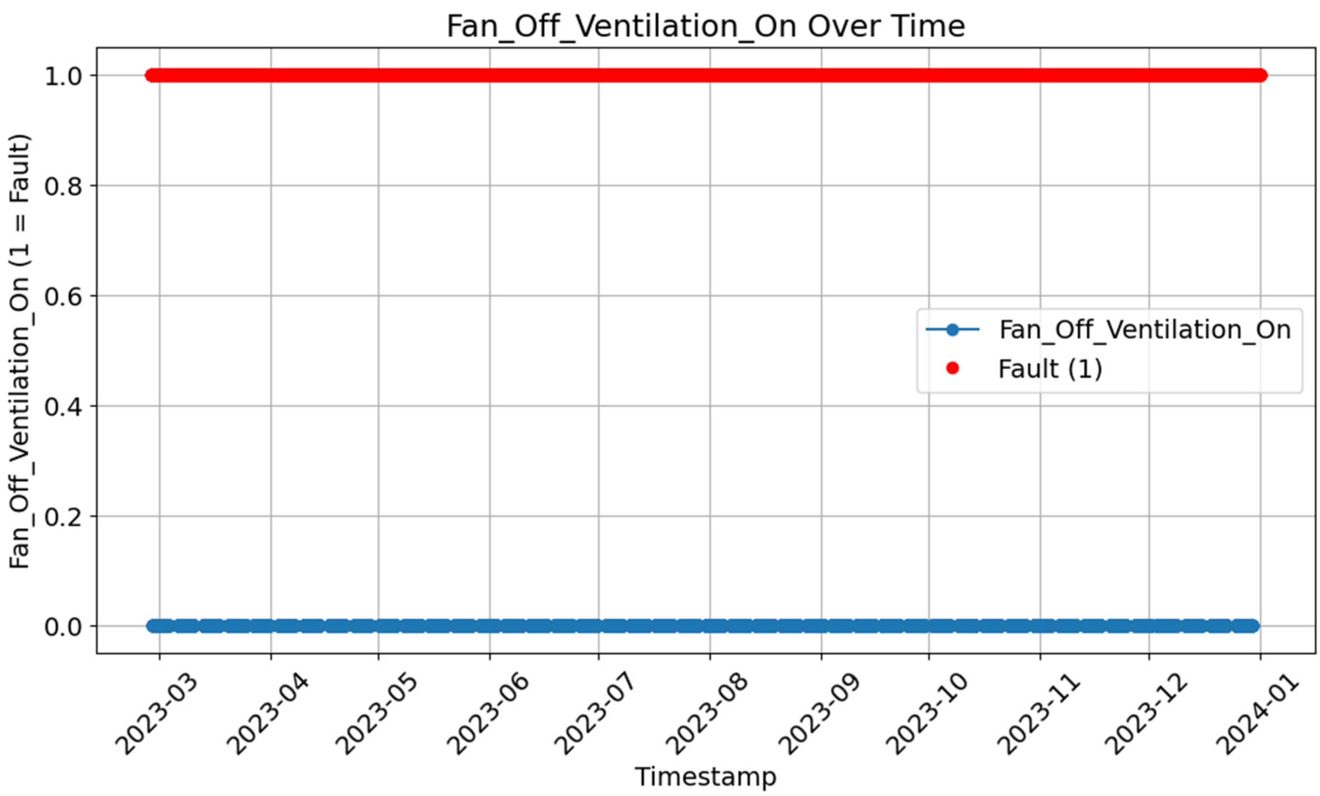

Figure 10. Instances where the ventilation fan remained on despite being set to off, indicating a fault condition (faults shown in red).

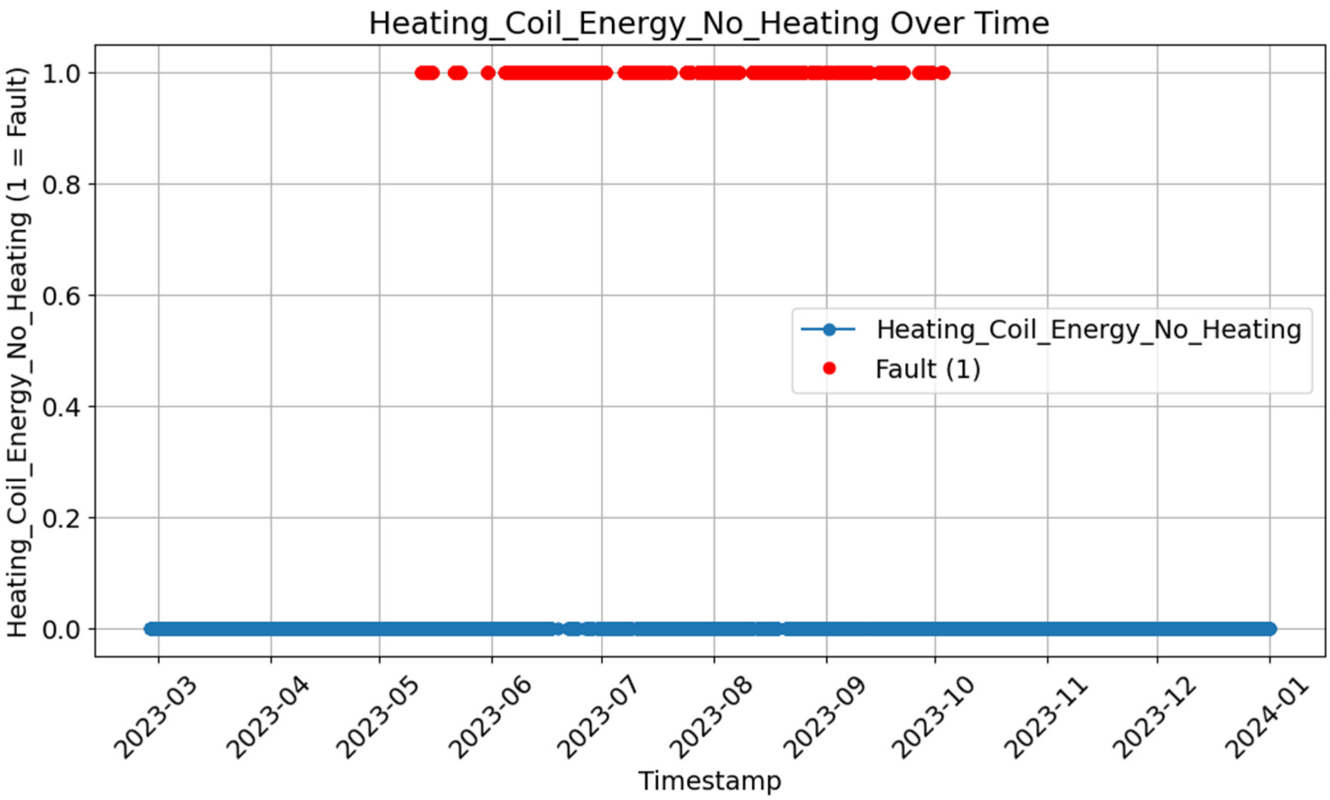

Figure 11. Instances of energy consumption by the heating coil despite no heating demand, with fault conditions marked in red.

4.2. Model Training and Evaluation

The machine learning model training and evaluation process for predictive fault detection in building systems involved a comprehensive approach to ensure model robustness and reliability. The dataset was segmented into three distinct sets: training, validation, and test. This segmentation strategy, illustrated in Figure 12 for the "Heating_Pump_Active_No_Heating" condition, allowed each model to learn from historical fault data, optimize its parameters on the validation set, and finally be tested on unseen data. This process is critical in developing predictive maintenance models that can generalize well beyond the training data and perform accurately in real-world scenarios, where early fault detection is critical for reducing energy wastage and operational disruptions.

The performance of six machine learning models, Artificial Neural Network (ANN), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Logistic Regression (LR), was compared across five key metrics: accuracy, precision, recall, F1-score, and computation time. As shown in Table 1, Extreme Gradient Boosting (XGBoost) emerged as the top performer, achieving an impressive accuracy of 95%, precision of 93%, recall of 94%, and an F1-score of 0.93. XGBoost's high recall and precision scores highlight its capability to effectively distinguish between fault and non-fault instances, minimizing both false positives and false negatives, which is essential for reducing unnecessary maintenance interventions while ensuring critical faults are not missed.

Table 1. Performance comparison of various machine learning models in terms of accuracy, precision, recall, F1-score, and computation time for predictive maintenance fault detection.

Model	Accuracy	Precision	Recall	F1-Score	Computation Time (s)
ANN	0.92	0.90	0.88	0.89	120
RF	0.94	0.92	0.91	0.92	45
XGBoost	0.95	0.93	0.94	0.93	60
SVM	0.89	0.87	0.85	0.86	90
KNN	0.85	0.84	0.82	0.83	30
LR	0.88	0.86	0.87	0.86	15

Random Forest (RF) also demonstrated strong performance with an accuracy of 94%, precision of 92%, recall of 91%, and an F1-score of 0.92, positioning it as a competitive alternative to XGBoost. However, RF had a shorter computation time of 45 s compared to XGBoost's 60 s, making it a suitable option where rapid computations are a priority. Artificial Neural Network (ANN), though achieving a slightly lower F1-score of 0.89 with 92% accuracy, showcased robust pattern recognition capabilities, especially in complex data environments. However, ANN's computation time was substantially higher at 120 s, which may limit its applicability in real-time scenarios but offers advantages in detecting intricate fault patterns.

Figure 13 ranks the top three models based on their overall performance, placing XGBoost in first place, followed by Random Forest and ANN. XGBoost's strong performance across accuracy, recall, and precision, combined with its moderate computation time, makes it the most effective model for predictive fault detection applications where both accuracy and efficiency are critical. Random Forest, with slightly lower accuracy but faster computation, provides a practical solution for fault detection systems with limited computational resources or where rapid response is needed. ANN, although computationally demanding, offers valuable insights for applications requiring the detection of subtle and complex fault patterns, given its capacity for capturing non-linear relationships in the data.

The other models, SVM, KNN, and Logistic Regression, showed relatively lower performance. SVM achieved an accuracy of 89% and F1-score of 0.86, making it less suitable for this application due to its lower recall (85%) and the need for high computational resources, with a computation time of 90 s. K-Nearest Neighbors (KNN), with an accuracy of 85% and an F1-score of 0.83, had the shortest computation time (30 s) but lacked the precision required for effective fault detection. Logistic Regression (LR), while computationally efficient with a time of only 15 s, demonstrated an accuracy of 88% and an F1-score of 0.86, indicating that it may struggle to capture the complexities in fault data.

Based on this performance analysis, XGBoost was selected as the primary model for further use in the fault detection system due to its superior balance of accuracy, recall, and reasonable computation time. XGBoost's ability to maintain high precision (93%) and recall (94%) ensures that critical faults are reliably identified with minimal false alarms, making it well-suited for predictive maintenance in energy-intensive building operations. The model's computation time of 60 s is also manageable for real-time or near-real-time applications, allowing facility managers to respond promptly to potential faults. This selection supports the goal of implementing a responsive and reliable fault detection framework, minimizing unnecessary maintenance costs while enhancing energy efficiency. XGBoost's high performance across all evaluated metrics reinforces its suitability for this application, enabling facility managers to achieve proactive, data-driven building management that optimizes operational efficiency and sustainability.

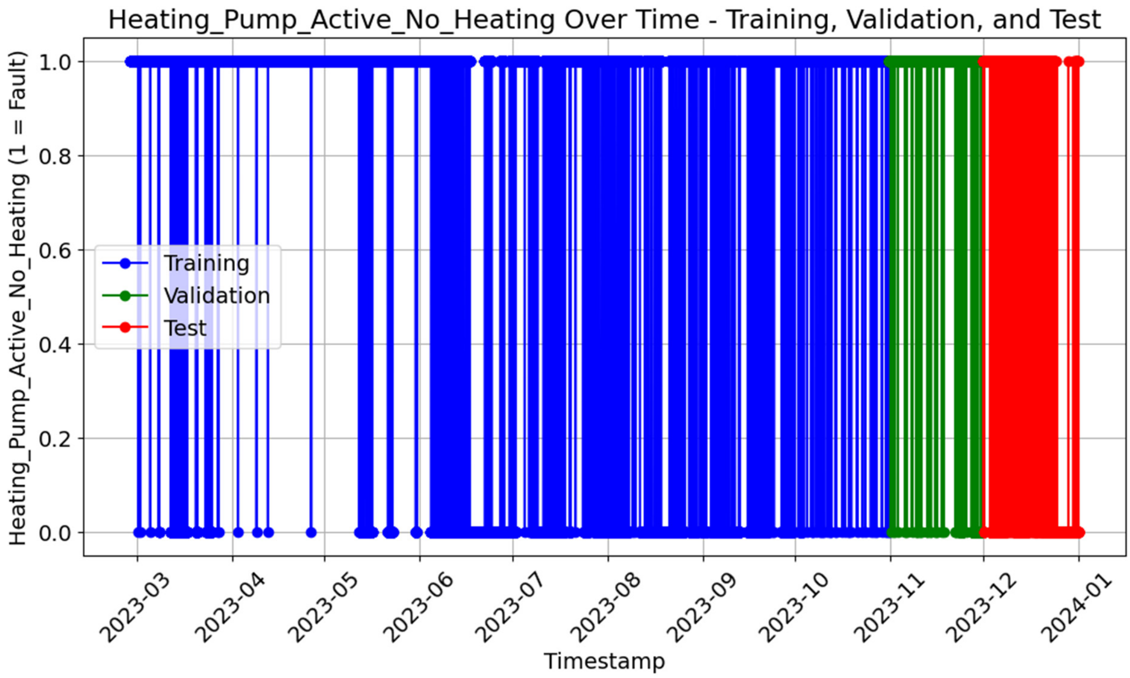

Figure 12. Fault occurrences for "Heating_Pump_Active_No_Heating" over time, with data segmented into training (blue), validation (green), and test (red) sets, showing periods when the heating pump remained active despite no heating demand.

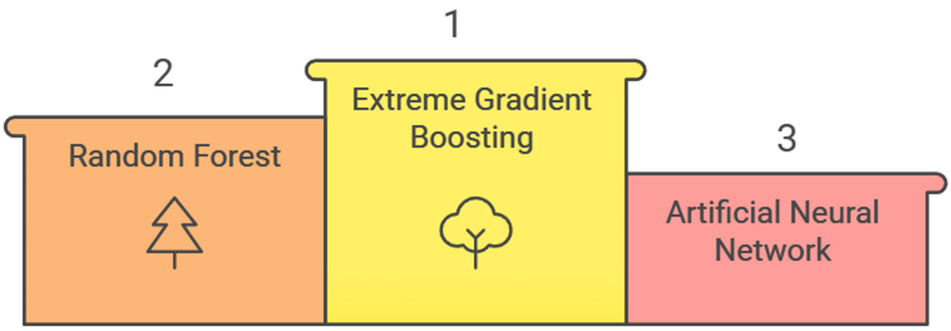

Figure 13. Ranking of the top three machine learning models based on performance, with Extreme Gradient Boosting (XGBoost) ranked first, Random Forest second, and Artificial Neural Network third.

4.3. Predictive Maintenance Results

The predictive maintenance model exhibited good performance in identifying and forecasting fault occurrences across various building systems. This subsection explores both short-term, zoomed-in analyses and long-term, year-round fault patterns, providing an overview of the model's fault-prediction capabilities.

4.3.1. Short-Term Analysis: Zoomed-In Fault Predictions

For the "Light_On_No_Occupancy" fault, the model identified 1149 occurrences throughout the year. The zoomed-in view in Figure 14, spanning 29 December 2023 to 7 January 2024, reveals the model's exceptional accuracy in predicting specific fault intervals. Peaks in fault prediction, particularly concentrated around early January, suggest that anomalies in occupancy detection are more likely to occur during this period. This insight is essential for optimizing lighting systems, as accurate predictions allow facility managers to proactively address unnecessary energy consumption, extending the life cycle of lighting components and reducing operational costs. The predictive model effectively anticipates when lighting might be mistakenly activated in unoccupied spaces, allowing for adjustments that contribute to energy efficiency and sustainability.

In the case of "Fan_Off_Ventilation_On", the model identified a significant 57,255 occurrences over the year, as shown in Figure 15. The zoomed-in view during late December 2023 to early January 2024 highlights the model's capacity to capture intervals when the fan is off while ventilation remains active. Such occurrences can disrupt indoor air quality and reduce overall system efficiency. The ability to forecast these faults accurately provides essential support for maintaining a stable ventilation system, ensuring that air quality standards are upheld. Continuous monitoring and prediction of this type of fault enable pre-emptive actions, reducing potential risks associated with inadequate air circulation in occupied spaces.

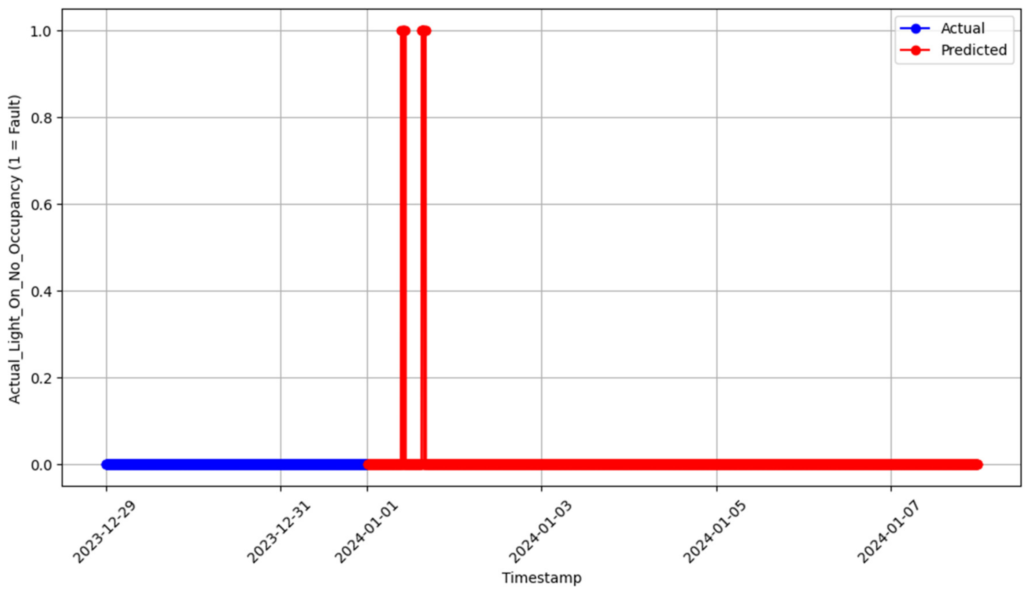

Figure 14. Predicted fault occurrences for "Light_On_No_Occupancy" over time, zoomed in to show the faults.

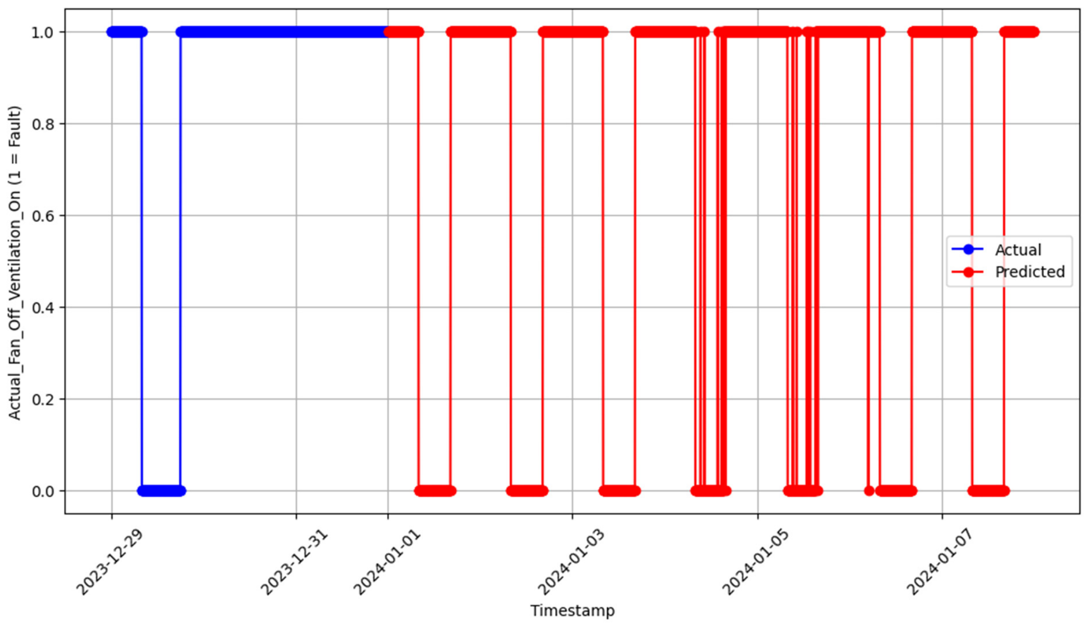

Figure 15. Predicted fault occurrences for "Fan_Off_Ventilation_On" over time, zoomed in to show the faults.

4.3.2. Year-Long Analysis: Seasonal Patterns in Fault Prediction

Expanding the analysis to a year-long view reveals the model's capacity to capture seasonal trends in fault occurrences, especially in systems related to heating and ventilation. For the "Damper_Open_No_Occupancy" fault, the model predicted 8818 occurrences over the year, with a noticeable increase during colder months, as shown in Figure 16. This pattern aligns with heightened HVAC system usage in winter, demonstrating the model's capacity to recognize seasonal demand fluctuations. Such insight is particularly valuable for preventive maintenance strategies, as HVAC systems experience increased stress and operational loads during winter. The predictive model provides a reliable foundation for maintenance planning, allowing technical teams to pre-emptively address damper-related issues before they escalate, ultimately ensuring consistent and efficient operation of the HVAC system and minimizing system downtime.

Similarly, the predictions for "Radiator_Valve_Open_No_People" faults display a strong seasonal trend, with a total of 1768 fault occurrences concentrated during the winter months, as illustrated in Figure 17. The model's predictions indicate that radiator-related issues are most frequent when heating requirements are at their peak, an expected trend for buildings in colder climates. When radiator valves remain open in unoccupied spaces, energy is often wasted, leading to increased operational costs. The model's ability to predict these faults during colder months provides facility managers with crucial insights for optimizing energy consumption. Proactively addressing radiator faults contributes to sustainability efforts by reducing unnecessary heating and lowering overall energy usage, enhancing the efficiency of building management practices.

The model generated predictions for over 100,000 fault instances across various building systems, including lighting, ventilation, and heating. Such a high volume of predictions reflects the model's thorough coverage, ensuring that each system is effectively monitored. The model's ability to capture both short-term anomalies (e.g., daily fluctuations in January) and long-term seasonal patterns (e.g., increased heating faults during winter) highlights its robustness in predictive maintenance. These results validate the model's accuracy and reinforce its potential as a proactive tool for fault management, highlighting critical periods for intervention.

The accuracy of short-term fault detection empowers facility managers to respond immediately to anomalies in lighting and ventilation, mitigating issues before they impact building occupants or energy expenditure. Seasonal responsiveness, on the other hand, demonstrates the model's adaptability to variations in system demand, allowing managers to plan maintenance schedules that align with operational cycles. For instance, faults in HVAC components during winter are flagged more frequently, enabling timely interventions that keep heating systems running efficiently during peak usage periods.

In addition to providing actionable insights, the model's predictions allow for more strategic resource allocation. With detailed predictions on fault types and their frequencies, maintenance teams can prioritize their efforts, ensuring that critical systems remain operational while reducing unnecessary service interruptions. The predictive insights generated by the model offer facility managers a more streamlined approach to managing building systems, reducing energy consumption, minimizing wear and tear on essential components, and extending the overall life span of the equipment.

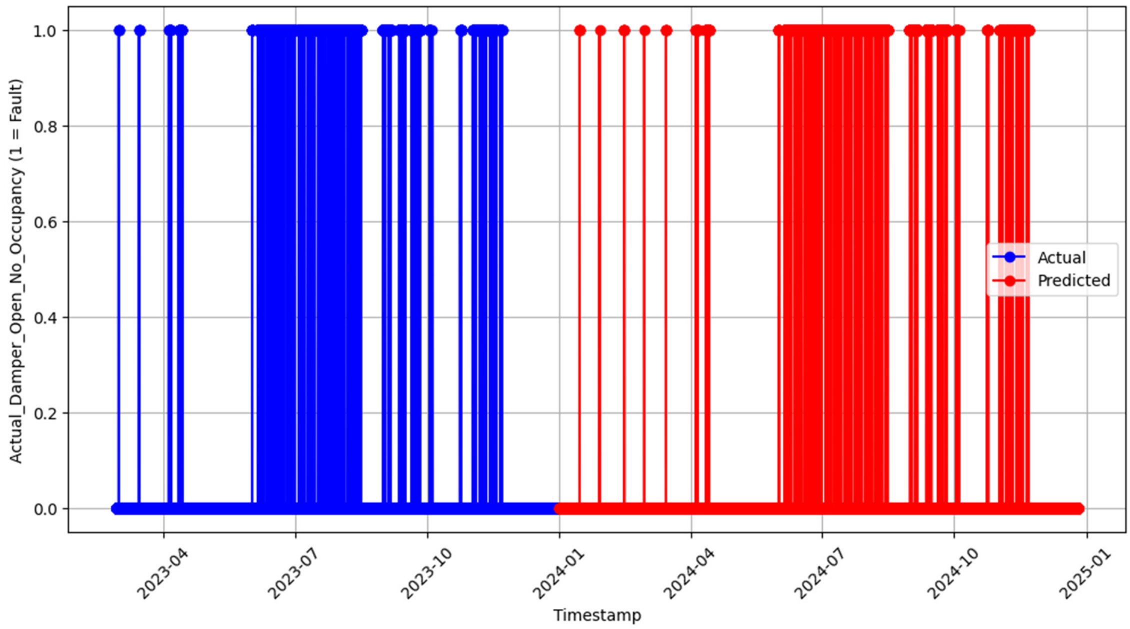

Figure 16. Year-long analysis of predicted fault occurrences for "Damper_Open_No_Occupancy", across different seasons.

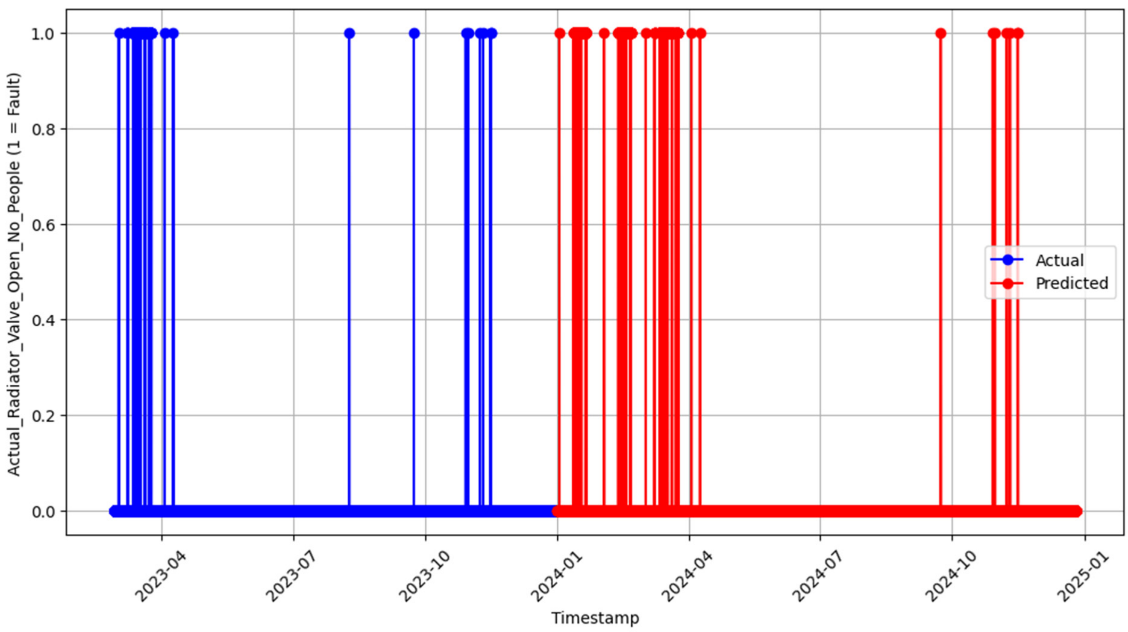

Figure 17. Year-long analysis of predicted fault occurrences for "Radiator_Valve_Open_No_People", across different seasons.

5. Strategies to Mitigate False Positive Fault Detection

To enhance the accuracy and reliability of predictive maintenance models in building management systems, a set of targeted strategies can be implemented to reduce the occurrence of false positive fault detections. These strategies include seasonal adjustments, adaptive learning algorithms, digital twin integration, and enhanced feature engineering.

5.1. Seasonal Adjustment Mechanisms

One of the primary causes of false positive fault detections observed in this study was the model's inability to adapt to seasonal changes in building operation. Fault conditions such as "Damper_Open_No_Occupancy" and "Radiator_Valve_Open_No_People" often registered false positives during winter and holiday periods when building occupancy and heating needs fluctuated significantly. To mitigate this issue, the model could be equipped with seasonal adjustment mechanisms that recalibrate its sensitivity to certain fault conditions based on the time of year. For example, during winter months, the model could reduce its sensitivity to radiator valve operation in unoccupied rooms, recognizing that these systems may run intermittently to maintain base heating levels. Additionally, occupancy schedules can be adjusted seasonally, allowing the model to anticipate and ignore deviations that align with expected holiday closures or lower occupancy rates, thereby reducing unnecessary fault predictions.

5.2. Adaptive Learning Algorithms

Integrating adaptive learning capabilities within the predictive maintenance model can enhance its responsiveness to real-time data patterns and operational changes. Through adaptive learning, the model can continuously update its internal parameters based on the latest data, allowing it to learn and adapt to unique operational patterns over time. This dynamic recalibration process would help the model avoid rigid fault classifications that may not account for shifts in building usage patterns, such as increased ventilation needs during flu season or holiday occupancy variations. Adaptive learning algorithms can reduce the reliance on manually defined thresholds and instead rely on data-driven thresholds that evolve based on detected trends, improving fault detection accuracy in varied conditions. Machine learning techniques, like reinforcement learning or continuous model retraining with fresh data, can be used to implement adaptive learning, ensuring the model remains aligned with the building's current operational reality.

5.3. Digital Twin Integration

The incorporation of a digital twin for the building provides a robust platform for testing and validating predictive maintenance algorithms before implementing them in real-world applications. A digital twin is a virtual replica of the physical building, complete with real-time data feeds and environmental simulations that mimic actual operational conditions. Building managers and engineers can simulate a variety of fault conditions by embedding the predictive maintenance model within the digital twin, seasonal changes, and operational patterns without impacting actual building operations. This virtual environment allows the model to "learn" from simulated faults and recognize patterns that may appear seasonally or under specific conditions, reducing its propensity for false positives when applied in the live environment. Digital twins also facilitate scenario testing, enabling fine-tuning of fault detection thresholds and adaptation strategies based on simulated data, leading to improved fault prediction precision and reduced misclassifications.

5.4. Enhanced Feature Engineering and Contextual Variables

False positives in predictive maintenance models often stem from a lack of contextual understanding within the data inputs, such as occupancy schedules, weather patterns, and utility usage cycles. Expanding the feature set to include contextual variables—such as time of day, expected occupancy levels, outdoor temperature, and HVAC schedules—can provide the model with a richer understanding of the building's operational landscape. For example, integrating outdoor temperature data alongside radiator valve status could help the model distinguish between faults and legitimate heating operations on cold days. Additionally, incorporating utility usage schedules for lighting and ventilation can reduce false alarms by identifying routine system adjustments rather than faults.

6. Discussion

The application of machine learning models in predictive maintenance for building systems has shown significant potential in enhancing operational efficiency and reducing energy waste. This study evaluated six machine learning models, ANN, RF, XGBoost, SVM, KNN, and LR, using a high-resolution dataset collected over ten months from six office rooms at Aalborg University. The dataset included over 100,000 fault instances labelled based on our rule-based conditions, providing a robust foundation for training and testing the models.

Findings indicate that XGBoost outperformed the other models, achieving an accuracy of 95%, precision of 93%, recall of 94%, and an F1-score of 0.93, with a computation time of 60 s. This means that XGBoost correctly identified 95% of all instances (both faults and non-faults), and when it predicted a fault, it was correct 93% of the time. Moreover, it successfully detected 94% of all actual faults present in the dataset. The high F1-score reflects a balanced performance between precision and recall, which is crucial in predictive maintenance to minimize both false positives and false negatives.

Comparatively, the Random Forest model achieved an accuracy of 94%, precision of 92%, recall of 91%, and an F1-score of 0.92, while the ANN reached 92% accuracy, 90% precision, 88% recall, and an F1-score of 0.89. Although these models performed well, XGBoost's superior metrics suggest it is more effective for predictive maintenance in building systems. The KNN, SVM, and LR models exhibited lower accuracies of 85%, 89%, and 88%, respectively, indicating less suitability for this application.

The model's effectiveness is further highlighted by its ability to predict critical faults accurately. For instance, it identified 1149 occurrences of the "Light_On_No_Occupancy" fault, where lights were left on in unoccupied rooms, leading to unnecessary energy consumption. This fault accounted for approximately 1.1% of the total fault instances detected over the ten-month period. Similarly, the model predicted 8818 instances of the "Damper_Open_No_Occupancy" fault, representing about 8.8% of all fault occurrences. These findings indicate significant inefficiencies in the HVAC system, where dampers remained open despite no occupancy, resulting in excessive ventilation and energy loss. The results of this study underline the significant potential of machine learning models in enhancing the energy efficiency and operational effectiveness of building systems. Fault detection analyses revealed widespread inefficiencies, notably in HVAC and lighting operations. Frequent faults, such as HVAC dampers remaining open and radiator valves left open in unoccupied rooms, contributed to substantial energy waste, particularly in heating and ventilation systems. The heating pump and coil also exhibited frequent operational issues, running without heating demand, exacerbating energy consumption. Lighting inefficiencies, such as lights being left on in unoccupied rooms, further highlighted opportunities for improving energy usage. These findings suggest the need for advanced fault-detection systems that account for real-time occupancy and environmental conditions to optimize energy consumption. The machine learning model evaluation process demonstrated the robustness of various algorithms, with XGBoost emerging as the top performer. It achieved high accuracy, precision, and recall, making it particularly suitable for predictive maintenance in building systems. This model outperformed others, such as Random Forest and Artificial Neural Networks, due to its balanced performance and moderate computational time. XGBoost's ability to detect faults with high precision and recall ensures that critical issues are identified while minimizing unnecessary maintenance interventions. The predictive maintenance model proved effective in both short-term and long-term fault predictions. Short-term analyses, such as those of lighting and ventilation faults, enabled timely interventions that reduced energy wastage and improved system performance. In contrast, the year-long analysis captured seasonal trends, revealing increased faults during colder months, which are critical for planning preventive maintenance and ensuring efficient heating system operations. The model's ability to predict faults during peak usage periods, such as winter, helps facility managers allocate resources more effectively and address potential issues before they escalate. To further improve the reliability of predictive maintenance models, several strategies were suggested, including seasonal adjustment mechanisms, adaptive learning algorithms, digital twin integration, and enhanced feature engineering. These approaches aim to reduce false positives by incorporating contextual data, such as occupancy schedules and weather patterns, and ensuring the model remains responsive to dynamic building conditions. Overall, the study highlights the effectiveness of machine learning models, particularly XGBoost, in predictive maintenance for building systems. These models provide actionable insights that enable proactive maintenance strategies, reducing energy consumption, minimizing wear and tear, and optimizing operational efficiency. Through continuous refinement and the integration of advanced strategies, predictive maintenance can significantly improve building sustainability and performance. An analysis of fault occurrences revealed that certain faults were more prevalent during specific periods, particularly the colder months. The "Radiator_Valve_Open_No_People" fault had 1768 occurrences, accounting for 1.8% of total faults, and was predominantly observed during winter. This suggests that heating systems were operating in unoccupied spaces, leading to energy wastage. The "Heating_Pump_Active_No_Heating" fault, with 57,255 occurrences (approximately 57% of total faults), indicated that the heating pump was frequently active without a corresponding heating demand, highlighting a substantial area for potential energy savings. These findings suggest a misalignment between building system operations and actual occupancy patterns, particularly during seasonal changes. Addressing these inefficiencies through predictive maintenance can lead to substantial energy savings and improved operational efficiency. For example, assuming that each instance of the "Light_On_No_Occupancy" fault results in one hour of unnecessary lighting at an energy cost of EUR 0.10 per hour, correcting 1149 instances could save approximately EUR 114.90 over the ten-month period. Similarly, mitigating the "Damper_Open_No_Occupancy" faults could result in significant reductions in heating and ventilation costs, given the high frequency of 8818 occurrences. Prior research in predictive maintenance has focused on various machine learning (ML) models and their application in diverse domains. Studies like Bouabdallaoui et al. (2021) demonstrate the use of deep learning for HVAC fault detection, but faced challenges due to low-resolution data and limited fault variability [70]. Similarly, Patel and Kalgutkar (2024) applied Random Forest for industrial predictive maintenance but emphasized the need for high-resolution data to improve accuracy [71]. This study addresses these limitations by leveraging a high-resolution dataset collected at five-minute intervals, capturing subtle variations in building systems. Moreover, the evaluation of six distinct ML models, including XGBoost, demonstrates their comparative effectiveness, providing actionable insights into selecting the optimal model for real-time fault detection. The performance of XGBoost in this study aligns with findings from other research. For instance, Amer et al. (2023) reported that XGBoost outperforms other ML models like Random Forest and Logistic Regression in predictive maintenance tasks, particularly for large datasets [72]. Similarly, Serradilla et al. (2021) highlighted the adaptability of advanced ML techniques, including semi-supervised models, but noted the computational overhead as a challenge for real-time applications [73]. In this study, XGBoost achieved an F1-score of 0.93 with a computation time of 60 s, showcasing its balance between precision, recall, and efficiency. Comparatively, while Random Forest demonstrated strong performance, XGBoost's ability to handle high-dimensional data and maintain computational efficiency makes it particularly suitable for high-resolution predictive maintenance tasks in dynamic environments. This research highlights the advantages of using high-resolution datasets, which enable the detection of nuanced anomalies such as “Light_On_No_Occupancy” and “Damper_Open_No_Occupancy”. These anomalies, often overlooked in low-resolution studies, were predicted with high accuracy using the proposed ML models. The integration of contextual features, such as real-time occupancy and environmental data, further enhanced fault detection. As emphasized by Villa et al. (2022), leveraging Internet of Things (IoT) sensors and Building Information Models (BIM) can significantly improve the robustness of predictive maintenance frameworks [74]. These contributions establish a new benchmark for predictive maintenance in building systems, addressing critical inefficiencies and promoting energy sustainability.

7. Conclusions

This study evaluates the effectiveness of six machine learning models for predictive maintenance in building systems, utilizing a high-resolution dataset from Aalborg University in Denmark. The Extreme Gradient Boosting (XGBoost) model emerged as the most effective, achieving an accuracy of 95%, precision of 93%, recall of 94%, and an F1-score of 0.93. The model effectively predicted over 100,000 fault instances, including critical faults such as “Light_On_No_Occupancy” and “Damper_Open_No_Occupancy”, demonstrating its potential for real-time fault detection and energy optimization. The findings highlight the prevalent misalignment between system controls and actual occupancy patterns, particularly during colder months. Addressing these inefficiencies through predictive maintenance can lead to substantial energy savings and improved operational efficiency. However, challenges related to false positive fault detections emphasize the need for incorporating seasonal adjustment mechanisms, adaptive learning algorithms, and additional contextual features into predictive models. This study contributes valuable insights to the field of sustainable building management through the use of high-resolution data and advanced machine learning techniques. Implementing XGBoost in predictive maintenance frameworks can significantly enhance fault detection accuracy, reduce energy waste, and improve operational efficiency.

8. Limitations and Future Research Directions

While the study provides valuable insights into the effectiveness of various fault detection strategies in building systems, there are several limitations to consider. First, the dataset used for simulation consists of specific building conditions and may not be fully representative of all building types or geographical regions. The variability in building designs, climate conditions, and occupant behavior could affect the generalizability of the results. Furthermore, the study focuses on a defined set of scenarios and may not capture the complexity of larger building systems, which could present challenges in scaling the proposed strategies to more complex environments. Another limitation lies in the potential difficulty in generalizing the findings to different contexts or fault detection approaches, as the strategies explored in this research may not be universally applicable to all fault types or building systems. Future studies could explore these limitations by testing the proposed strategies in diverse settings and under varying conditions to validate their broader applicability.

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Nomenclature

HVAC	Heating, Ventilation, and Air Conditioning
XGBoost	Extreme Gradient Boosting, a machine learning model used for classification and regression tasks
ANN	Artificial Neural Network, a machine learning model inspired by the structure of the human brain
RF	Random Forest, an ensemble learning method using multiple decision trees for classification and regression
SVM	Support Vector Machine, a supervised learning model used for classification and regression analysis
KNN	K-Nearest Neighbors, a non-parametric machine learning algorithm used for classification and regression
LR	Logistic Regression, a statistical model used for binary classification
F1-Score	The harmonic mean of precision and recall, used as a metric to evaluate model performance
Precision	The ratio of correctly predicted positive observations to the total predicted positive observations
Recall	The ratio of correctly predicted positive observations to all actual positives in the dataset
Accuracy	The ratio of correctly predicted observations to the total observations
CO_2	Carbon Dioxide, a variable used to monitor air quality in the study
YOLOv5	A computer vision algorithm used for real-time object detection, applied to detect room occupancy
AHU	Air Handling Unit, part of the HVAC system responsible for conditioning and circulating air
BMS	Building Management System, a centralized system used to monitor and control building operations
GWP	Global Warming Potential, an environmental metric often used in sustainability analysis
Lambda (λ)	Regularization parameter used in machine learning to prevent overfitting
Gamma (γ)	A hyperparameter in XGBoost controlling the minimum loss reduction required to make a split

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