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Fault Detection and Diagnostics of Air Handling Unit in Hospital Building Using Machine Learning

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***Abstract*—Fault Detection and Diagnostics (FDD) in Air Handling Units (AHUs) are vital for ensuring optimal indoor air quality and operational efficiency in hospital buildings. AHUs play a critical role in regulating temperature and humidity, which directly impacts patient care and staff comfort. Effective FDD can prevent system malfunctions that lead to increased energy consumption, higher operational costs, and potential health risks due to poor air quality. This study explores the application of machine learning techniques for FDD in hospital HVAC systems. Utilizing comprehensive datasets from the Lawrence Berkeley National Laboratory (LBNL), we focused on various classifiers, including Random Forest and K-Nearest Neighbors, which achieved accuracies of 99.85% and 99.77%, respectively, in fault identification. These models demonstrated exceptional precision, highlighting their suitability for complex environments where accurate diagnostics are essential. Our findings emphasize the importance of integrating machine learning into building management systems. By enabling early fault detection, these advanced models significantly reduce operational costs and enhance system reliability. This approach not only improves indoor air quality but also supports sustainable healthcare environments by minimizing energy waste. The research contributes to the development of smarter, more efficient building management solutions, paving the way for real-world applications of data-driven FDD methods. The insights gained provide a strong foundation for future implementations, promoting safer and more sustainable healthcare facilities through enhanced HVAC system performance and fault management. This study underscores the potential of machine learning in revolutionizing building management and improving the overall hospital environment.**

***Index Terms*—Air handling units ahus, Building management systems, Fault detection and diagnostics, Hospital building, Machine learning, Real time monitoring**

I. Introduction

In recent years, the importance of maintaining optimal indoor air quality in hospital buildings has become increasingly evident, as it directly impacts patient health, staff well-being, and overall operational efficiency [1]. Air Handling Units (AHUs) play a crucial role in regulating air quality, temperature, and humidity within these environments. However, the complex nature of AHUs and their continuous operation make them susceptible to various faults and inefficiencies, which can compromise indoor air quality and increase energy consumption [2].

Traditional methods of Fault Detection and Diagnostics (FDD) in AHUs often rely on manual inspection and rule-based systems, which are time-consuming, labor-intensive, and prone to human error [3]. With the advent of advanced machine learning techniques, there is an opportunity to enhance the reliability and efficiency of AHU operations by implementing automated, data-driven approaches for FDD.

Smart buildings leverage IoT to automate and connect devices, simplifying control processes and enhancing the implementation of FDD algorithms [4]. In our research, we adopt an IoT architecture and employ various supervised learning algorithms on labeled HVAC datasets to identify the most efficient and accurate data-driven FDD method. The significance of smart buildings extends beyond energy efficiency; they also play a vital role in reducing maintenance costs, which account for over 65% of annual Facility Management (FM) expenses. Effective building management systems (BMS) are essential for monitoring and controlling building systems through sensor data, ensuring optimal operational states [5].

Hospitals, as examples of complex buildings, utilize various specialized systems to provide safe and sustainable healthcare services [6]. HVAC systems in hospitals are critical for maintaining good Indoor Air Quality (IAQ), a key determinant of human health. Potential HVAC failures can affect economic, environmental, and performance aspects, making advanced FDD methods essential to prevent failures and optimize operational costs [7].

Over the past three decades, the expansion of the Internet and the advent of IoT have transformed building management. The integration of smart devices and systems into the IoT ecosystem enables real-time monitoring and fault detection, bridging the gap between the physical and information worlds [8]. Despite the advantages, challenges remain, such as the need for frameworks capable of processing large volumes of data and delivering real-time results.

Our research aims to address these challenges by employing data-driven FDD methods to enhance the reliability and efficiency of HVAC systems in hospital buildings. Through performance analysis of various algorithms on labeled datasets, we strive to identify the most effective

FDD approach, ultimately contributing to the development of smarter, more efficient building management systems.

Major Contributions

- **Integration of Machine Learning:** Implemented advanced machine learning techniques for automated fault detection in AHUs, improving accuracy and reducing human error.
- **IoT Architecture:** Developed an IoT-based framework for real-time monitoring and diagnostics of HVAC systems in hospital buildings.
- **Comparison of Classifiers:** Evaluated multiple supervised learning algorithms to determine the most effective approach for fault detection in complex environments.
- **Comprehensive Dataset Analysis:** Utilized extensive datasets from LBNL, providing a robust basis for analysis and model validation.
- **Practical Implications:** Highlighted the potential for energy savings and operational efficiency in hospital HVAC systems through data-driven FDD methods.

The remainder of this paper is structured as follows: Section 2 reviews existing research on predictive maintenance and FDD methods. Section 3 outlines our proposed IoT-based architecture and supervised learning algorithms. Section 4 describes the datasets used and their preparation. Section 5 presents the performance results and analysis of various machine learning algorithms. Finally, Section 6 provides the conclusions with future research directions.

II. Literature Review

Different types of faults can affect a building system's components, ranging from a single component to an entire system. These faults not only lower performance but also increase energy consumption, making early detection crucial. Many previous works have focused on predictive maintenance and fault detection and diagnostics (FDD) algorithms to address these issues. These algorithms are designed to monitor building systems, detect irregularities or faults, and subsequently reduce the operational costs of the systems. By identifying faults early, FDD algorithms help maintain the efficiency and reliability of building systems, ensuring optimal performance and energy use.

Albayati *et al.* (2023) [9] developed a novel semi-supervised ML method, combining supervised learning with unsupervised k-nearest neighbors (k-NN) labeling, was developed to enhance fault classification accuracy while minimizing the requirement for extensive labeled training data of rooftop. The researchers demonstrated high accuracy, up to 95.7%, using this approach, showcasing its potential to improve the reliability and efficiency of building management systems through enhanced FDD capabilities. However, it was primarily tested on specific RTU system specifications and fault types, limiting their generalizability to other RTU types and multiple simultaneous faults.

Malik *et al.* (2024) [10] examined examines the methodologies and findings related to the reliability of datasets used for early fault diagnosis in air handling units (AHUs) of HVAC systems, focusing on fan degradation and return air duct leakage faults. Data was generated using OpenStudio (OS) and real-world measurements, with sensitivity analysis performed to identify the most responsive parameters to fault conditions, ranging from zero to 30% deviation from the healthy state. The analysis revealed the consistency of parameter behaviors under fault conditions, including increasing, decreasing, both, or no correlation with fault severity.

Al-Aomar *et al.* (2024) [11] presented a data-driven predictive maintenance model of a hospital's HVAC system with a focus on the Air Handling Units (AHUs). The developed model adopted machine-learning using the sensor data acquired by the BMS and the database of the hospital's CMMS. Support Vector Machine (SVM), Decision Trees (DT), and K-Nearest Neighbours (KNN) algorithms used for the prediction of AHU's short-term conditions. However, the dependency on the quality and availability of real-time sensor data, which may affect the accuracy and reliability of the predictions if the data is incomplete or noisy.

In light of these previous studies, our research addresses several key challenges identified in the literature. Our approach not only improves the fault detection accuracy but also ensures the model's applicability and scalability to diverse HVAC systems, contributing to more efficient and reliable building management solutions.

III. Methodology

Our proposed model for fault detection and diagnostics (FDD) in air handling units (AHUs) in hospital buildings starts by obtaining data from IoT-based sensors deployed in the system. This generates a large amount of data, which is stored in the cloud for extraction and analysis. Using various machine learning algorithms, the model identifies potential flaws in the system. Even minor faults are predicted by the model, allowing users to take preventative maintenance actions. This approach enhances the reliability and performance of hospital HVAC systems, contributing to better air quality and operational efficiency.

A comprehensive model for fault detection and diagnostics in building systems, focusing particularly on HVAC systems is shown in Fig. 1.

Here's a detailed description of the proposed model:

- **Building System:** The model starts with the building system, which includes various types of buildings such as hospitals, offices, and potentially other facilities. These buildings are the primary sources of data for the fault detection and diagnostic process.
- **Fault Detection:** This stage focuses on identifying any anomalies or faults within the building systems by analyzing data collected from various sensors and monitoring devices.
- **Fault Diagnostic:** This stage is crucial for understanding what specific issues are affecting the building systems.

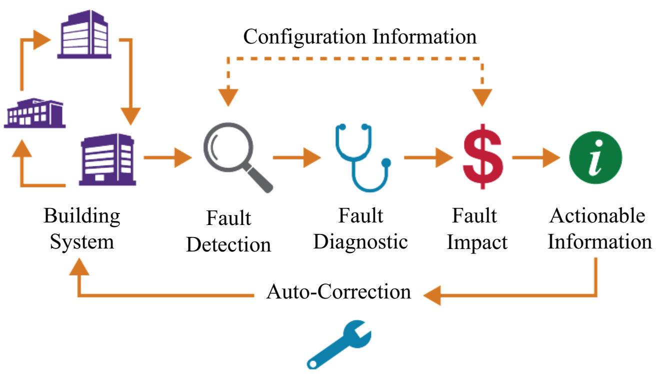

Fig. 1. Work flow of the proposed model system

- **Fault Impact:** The implications of the diagnosed faults are assessed in terms of their impact on the system's efficiency, operational costs, and potential risks.
- **Actionable Information:** This phase involves communicating the findings and recommended actions to relevant stakeholders, enabling them to make informed decisions and take necessary measures.

The model includes feedback loops back to the building system, showing that the process is continuous. The outcomes of the fault detection, diagnostic, impact assessment, and auto-correction phases are fed back into the system to enhance its ongoing operations. It emphasizes the importance of real-time data analysis and feedback mechanisms to maintain optimal system performance and reduce operational costs.

IV. Data Representation

A. Dataset Description

Although IoT is widely utilized in building management systems, there is a lack of publicly available data for fault detection and predictive maintenance. We chose building fault detection data for our model due to its emphasis on fault detection and diagnostics (FDD). This dataset, provided by the Lawrence Berkeley National Laboratory (LBNL), categorizes occupancy as "occupied" (humans present) or "vacant" (no humans present), which is crucial for monitoring building operations via IoT sensors [12]. The dataset includes both simulated data, generated through computer simulations, and experimental data, derived from real-world building experiments. The simulated data offers theoretical insights, while the experimental data provides practical insights from real building environments, as shown in Table I.

TABLE I
USED DATASETS AND THE APPROACH OF CREATION

Set	**Dataset Name**	**Data Provenance**
SZVAV	Air handling unit: single zone variable air volume	Experimental
SZCAV	Air handling unit: single zone constant air volume	Simulated

B. Exploratory Data Analysis

The sensor data were collected from September 1 to 30, 2017, from field devices and processed in the Direct Digital Control (DDC) system for a hospital's Air Handling Unit (AHU). This data includes parameters such as supply air temperature, outdoor air temperature, mixed air temperature, return air temperature, fan status, fan speed control signal, damper control signals, cooling coil valve control signal, heating coil valve control signal, and occupancy mode indicator. These parameters are critical for assessing the AHU's operational conditions and are retrieved from the Building Management System (BMS). A sample of the extracted sensor data, including temperature and fan speed, is shown in Table II.

TABLE II
SAMPLE EXTRACT OF SENSOR DATA FROM AHU FOR SEPTEMBER 2017

Date	**Supply Air**	**Outdoor Air**	**Mixed Air**	**Return Air**	**Supply Air Fan Status**	**Fan Speed Control Signal**	**Air Damper Control Signal**
9-01-2017	72.29	81.11	78.56	76.38	1	0.1	0.5
9-12-2017	72.30	80.22	77.89	76.39	1	0.1	0.5
9-18-2017	72.37	81.09	78.56	76.37	1	0.1	0.5
9-24-2017	72.29	81.06	78.51	76.38	1	0.1	0.5
9-30-2017	71.82	82.94	78.41	76.36	1	0.1	0.5

C. Data Prepossessing

The data pre-processing phase is crucial for preparing the datasets for effective Fault Detection and Diagnostics (FDD) in Air Handling Units (AHUs). The workflow, as shown in Fig. 2, consists of four main steps:

1) **Data Gathering:** Data gathering is the initial step, where sensor data from the AHUs is collected. This data includes various parameters such as temperature readings, fan speeds, control signals, and occupancy indicators.
2) **Processing:** In the processing step, two critical substeps are involved: feature engineering and normalization. Feature engineering creates new features from raw data, such as differences between temperature readings and interaction terms between sensor measurements, to improve model performance. Normalization ensures features are on a similar scale. Min-max scaling transforms data within a range of [0, 1], ensuring equal contribution from all features, which is crucial for distance-based algorithms.

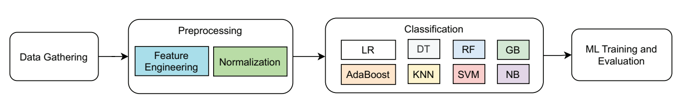

Fig. 2. Steps of Data Pre-processing

3) **Classification:** After processing, the data is classified using various machine learning algorithms: Logistic

Regression (LR), Decision Tree (DT), Random Forest (RF), Gradient Boosting (GB), Adaptive Boosting (AdaBoost), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Naive Bayes (NB). These algorithms are selected for their robustness and effectiveness in complex classification tasks.

4) **ML Training and Evaluation:** Finally, the preprocessed data is used to train and evaluate the machine learning models. This involves splitting the data into training and testing sets, training the models on the training data, and assessing their performance on the test data to ensure accurate fault detection and diagnostics.

D. Data Analysis Metrics

A confusion matrix is used to evaluate the performance of a classification model by comparing the actual target values with the model's predictions [13]. This provides us with a comprehensive picture of how well our classification model is working and the types of errors it makes. Positive or Negative are the two possible values for the target variable.The target variable in this context has two possible values: Positive or Negative. The confusion matrix is presented in Table III, where:

TABLE III
CONFUSION MATRIX FOR CLASSIFICATION MODEL PERFORMANCE

Classification	Actual "Yes"	Actual "No"
Classified as "Yes"	TP	FP
Classified as "No"	FN	TN

- **True Negative (TN)** represents the number of correctly identified negative cases.
- **False Positive (FP)** denotes the number of actual negative cases incorrectly classified as positive.
- **False Negative (FN)** indicates the number of actual positive cases incorrectly classified as negative.
- **True Positive (TP)** reflects the number of correctly identified positive cases.

E. Performance Metrics

To evaluate the effectiveness of our machine learning models in Fault Detection and Diagnostics (FDD) for Air Handling Units (AHUs), it is employed a comprehensive set of performance metrics. These metrics provide a detailed assessment of each model's accuracy, precision, recall, and other important characteristics. The following table IV summarizes the performance metrics used.

These metrics will be applied to each of the eight machine learning algorithms used in our study: LR, DT, RF, GB, AdaBoost, KNN, SVM, and NB. By comparing these metrics across different models, it is aimed to identify the most effective algorithm for FDD in AHUs, ensuring optimal indoor air quality and operational efficiency in hospital buildings is shown in Table IV.

TABLE IV
SUMMARY OF PERFORMANCE METRICS FOR MACHINE LEARNING MODELS

Performance Metric	Formula
Precision	TP / (TP + FP)
Accuracy	TP + TN / TP + TN * FP + FN
Recall	TP / TP + FN
F1 Score	(2 TP) / (2 TP + FP + FN)
Specificity	TN / (TN + FP)
ROC Curve	TPR = Recall and FPR = Specificity

V. RESULTS AND DISCUSSION

This section evaluates the performance of various machine learning algorithms for fault detection in air handling units (AHUs) using the SZVAV and SZCAV datasets. The analysis includes metrics such as accuracy, ROC, precision-recall curves, and confusion matrices to assess each model's effectiveness. By comparing these metrics, the most suitable model for fault detection in AHUs is identified.

A. Classifier Performance

Accuracy in classifier performance is vital for Fault Detection and Diagnostics (FDD) in Air Handling Units (AHUs) as it affects the reliability and efficiency of HVAC system management [14]. High accuracy ensures timely fault identification, reducing energy wastage, operational costs, and maintaining optimal indoor air quality, which is crucial in hospital settings for patient care and staff comfort. Among the classifiers, decision tree and random forest models excelled with accuracies around 0.99, indicating strong effectiveness in diagnosing AHU faults. Support Vector Machine (SVM) and Gradient Boosting also performed well with accuracies close to 0.98, while K-Nearest Neighbors (KNN) achieved approximately 0.96, demonstrating its effectiveness in pattern recognition. The accuracy of these classifiers is illustrated in Fig. 3.

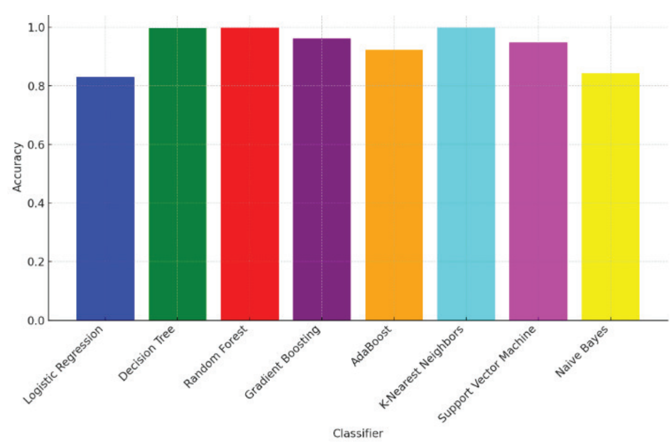

Fig. 3. Accuracy Comparison of Various Classifiers

On the other hand, models like logistic regression and Naive Bayes, while still achieving relatively high accuracies of around 0.89, did not perform as well as the more advanced algorithms. The AdaBoost classifier showed an accuracy of around 0.92, which, although lower than gradient boosting, still indicates strong performance in fault detection. These results underscore the significance of selecting the appropriate classifier for effective FDD in AHUs, with decision tree, random forest, gradient boosting, and SVM emerging as the top performers in our study.

B. Confusion Matrix Analysis

Confusion matrices are a critical tool for evaluating the performance of classification models, providing insight into not only the accuracy but also the types of errors a model makes. In the context of Fault Detection and Diagnostics (FDD) in Air Handling Units (AHUs), understanding these errors is crucial for improving system reliability and operational efficiency.

The confusion matrices for the various classifiers used in our study are presented in Fig. 4. Among the classifiers, Random Forest exhibits the highest performance with the fewest mis-classifications. Specifically, the Random Forest model correctly classifies 1426 instances of the 'no fault' class and 5920 instances of the 'fault' class, with only 9 false positives and 15 false negatives. This indicates that the Random Forest model is highly effective in both identifying actual faults and minimizing false alarms, making it the most reliable classifier in our study for FDD in AHUs.

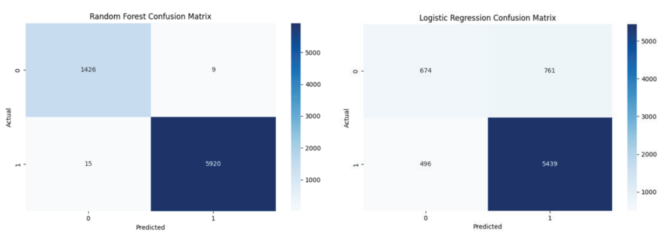

Fig. 4. Confusion Matrix with highest and lowest value algorithm

Conversely, the Logistic Regression model exhibits the lowest performance with many misclassifications. It correctly identifies 674 'no fault' instances and 5439 'fault' instances but generates 761 false positives and 496 false negatives. This high misclassification rate indicates that Logistic Regression may be less suitable for FDD tasks in AHUs, where the costs of false positives (unnecessary maintenance) and false negatives (missed faults) are significant.

C. ROC Curves Analysis

ROC curves are crucial for evaluating classifiers in Fault Detection and Diagnostics (FDD) for Air Handling Units (AHUs), as they measure a model's ability to distinguish between true and false positives. Fig. 5 shows that Random Forest and K-Nearest Neighbors achieve perfect performance with an AUC of 1.00, indicating they effectively differentiate between normal and faulty conditions with a true positive rate of 1.00 and a false positive rate of 0.00. This makes these models highly reliable for critical FDD applications.

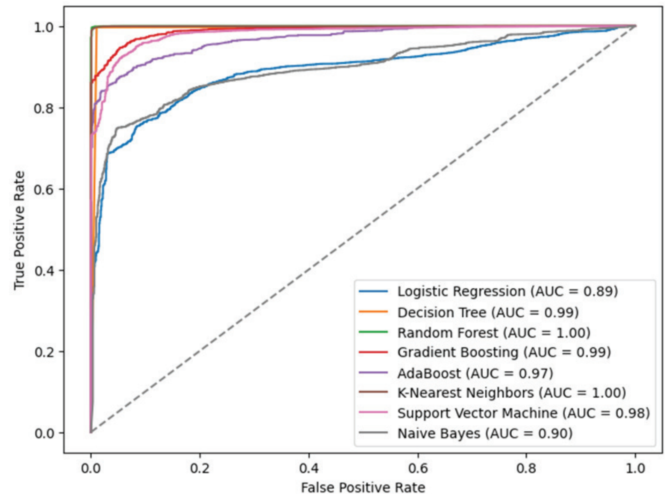

Fig. 5. ROC Curves for Various Classifiers

On the other hand, the Logistic Regression classifier shows the lowest performance with an AUC of 0.89. While this is still relatively high, it is notably lower than the other classifiers. The curve indicates that the Logistic Regression model has a higher false positive rate at various threshold settings compared to the other models, which may lead to more frequent false alarms or missed fault detections. This highlights the importance of model selection based on specific performance metrics like AUC in the context of FDD, where the cost of errors can significantly impact system efficiency and maintenance costs.

D. Precision-Recall Curve Analysis

Precision-Recall (PR) curves are essential for evaluating classifiers, especially with imbalanced datasets in Fault Detection and Diagnostics (FDD) for Air Handling Units (AHUs). Fig. 6 displays the PR curves and Average Precision (AP) values for our classifiers. Decision Tree, Random Forest, Gradient Boosting, K-Nearest Neighbors, and Support Vector Machine achieve an AP of 1.00, indicating perfect precision and recall. These classifiers effectively balance identifying true positives while minimizing false positives, making them well-suited for critical FDD tasks.

In contrast, the Logistic Regression and Naive Bayes classifiers exhibit lower AP values of 0.97, while AdaBoost achieves an AP of 0.99. These classifiers, although still performing well, show a slight decline in either precision or recall at certain thresholds compared to the top-performing models. This emphasizes the importance of selecting classifiers with optimal PR characteristics to ensure robust and accurate fault detection in AHUs, thereby enhancing system reliability and operational efficiency.

E. Model Comparison and Selection

To determine the best algorithm for Fault Detection and Diagnostics (FDD) in Air Handling Units (AHUs), we compare various classifiers using metrics such as accuracy,

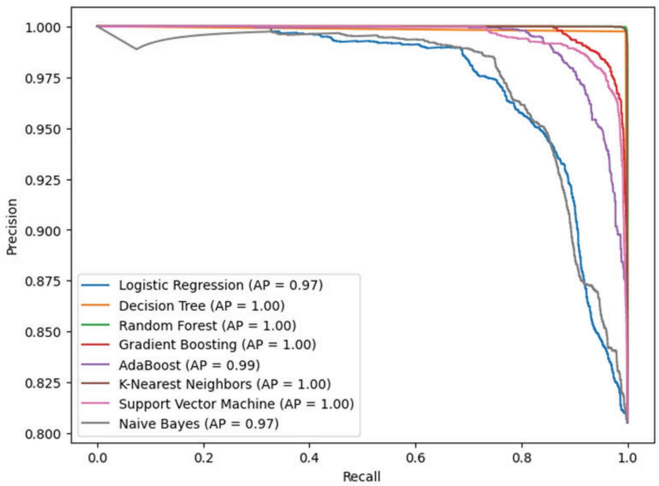

Fig. 6. Precision-Recall Curves for Various Classifiers

confusion matrix, ROC curve, and precision-recall curve. These metrics help identify the strengths and weaknesses of each classifier. Table V presents the comparison of classifiers to aid in model selection.

TABLE V
COMPARISON OF CLASSIFIERS FOR MODEL COMPARISON AND SELECTION

Classifier	Accuracy	AUC	AP	TP	TN	FP	FN
LR	87%	0.89	0.97	5439	674	761	496
DT	99%	0.99	1.00	5915	1420	15	20
RF	99%	1.00	1.00	5920	1426	9	15
GB	99%	0.99	1.00	5794	1268	167	141
AdaBoost	96%	0.97	0.99	5620	1142	293	315
KNN	99%	1.00	1.00	5921	1418	17	14
SVM	98%	0.98	1.00	5692	1290	145	243
NB	92%	0.90	0.97	4998	1175	260	937

The table compares classifiers based on accuracy, AUC, AP, and confusion matrix components. Random Forest, K-Nearest Neighbors, and Decision Tree show exceptional performance with 99% accuracy, AUC of 1.00 (for Random Forest and K-Nearest Neighbors), and AP of 1.00. These models demonstrate high precision and recall, indicating superior fault detection and minimal false alarms.

Conversely, Logistic Regression and Naive Bayes, though still effective, have lower accuracy (87% and 92%), AUC (0.89 and 0.90), and AP (0.97). They exhibit higher false positives and negatives, making them less reliable for critical FDD applications. Thus, Random Forest is identified as the best model for Fault Detection and Diagnostics in Air Handling Units, offering the highest accuracy and performance across all metrics.

VI. CONCLUSION

This study on fault detection and diagnostics (FDD) of air handling units (AHUs) in hospital buildings using machine learning reveals that classifiers such as Decision Tree, Random Forest, and K-Nearest Neighbors achieved high accuracy and effectiveness. These models excel in real-time monitoring and predictive maintenance, demonstrating their suitability for improving operational efficiency and safety in critical healthcare environments. The analysis highlights the importance of selecting robust models to enhance air quality and system reliability within hospital HVAC systems. By effectively identifying faults, these machine learning techniques contribute to reducing energy consumption and ensuring optimal indoor conditions. The findings emphasize the role of advanced machine learning in promoting sustainable and efficient healthcare environments. Future research should focus on integrating real-time monitoring systems to enhance fault detection. Additionally, evaluating model performance across various operational scenarios will be crucial. Expanding datasets to include a broader range of fault types will further improve model generalizability and practical effectiveness.

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