Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 21s (2025)
https://www.jneonatalsurg.com

OPEN ACCESS

Novel Approach for Predictive Maintenance of Air Handling Units Using Machine Learning Algorithms

Sushopti Gawade[1], Swati Chopade[2], Kavita Shirsat[3], Shankar Patil[4], Prathamesh Palatshaha[5], Vaishnavi Badgujar[6]

[1]Email ID: sushoptiekrishimitra@gmail.com

[2]Email ID: schopade@mc.vjti.ac.in

[3]Email ID: kavita.shirsat@vit.edu.in

[4]Email ID: smpatil2k@gmail.com

[5]Email ID: prathamesh.palatshaha@gmail.com

[6]Email ID: badgujarvaishnavi3@gmail.com

Cite this paper as: Sushopti Gawade, Swati Chopade, Kavita Shirsat, Shankar Patil, Prathamesh Palatshaha, Vaishnavi Badgujar, (2025). Novel Approach for Predictive Maintenance of Air Handling Units Using Machine Learning Algorithms. *Journal of Neonatal Surgery*, 14 (21s), 481-488.

ABSTRACT

Traditional maintenance of Air Handling Units (AHUs) in buildings is often reactive or time-based, resulting in unexpected failures, downtime, and higher costs. This paper explores Machine Learning (ML) for predictive maintenance (PrM) of AHUs, using user-provided data. A dataset from Granderson and Lin (2019) demonstrates how ML models can classify AHU conditions as faulty or normal. This research discusses suitable ML algorithms for AHU PrM, including supervised learning, and highlight benefits such as reduced downtime, cost savings, improved efficiency, and enhanced occupant comfort. The methodology covers data acquisition, preprocessing, model selection, training, and evaluation.

Keywords: *Predictive maintenance, Air Handling Units (AHUs), HVAC systems, Fault detection, Anomaly detection, Machine learning, Data preprocessing, Exploratory data analysis, Model training, Energy efficiency, Facility management.*

INTRODUCTION

Air Handling Units (AHUs) are crucial components of Heating, Ventilation, and Air Conditioning (HVAC) systems in commercial and industrial buildings, playing a key role in controlling indoor air quality and distributing air. Proper maintenance of AHUs is vital for occupant comfort, energy efficiency, and sustainable operations [12]. Traditionally, AHU maintenance relies on reactive or time-based approaches, often leading to unexpected failures, increased costs, and safety risks [1]. Predictive maintenance (PrM) has emerged as a valuable strategy for enhancing HVAC performance, reducing downtime, and lowering maintenance costs. AHUs particularly benefit from PrM, which uses data-driven methodologies and advanced technologies like Machine Learning (ML) to preempt equipment failures [13, 14, 15]. While existing ML-based PrM solutions typically depend on sensor data to detect anomalies [6, 8, 16], sensor installation can be costly and impractical in certain contexts [9]. This paper introduces a novel ML-based PrM approach for AHUs that leverages user-provided data from building occupants or maintenance personnel, rather than sensor data. This data includes observations of abnormal temperatures or airflow changes. By analyzing these inputs, ML models can detect patterns suggesting potential AHU malfunctions, enabling proactive maintenance actions that reduce disruptions, optimize energy consumption, and ensure optimal performance.

LITERATURE REVIEW

Sensor-Based Predictive Maintenance (PrM)

Sensor-based predictive maintenance (PrM) helps keep Air Handling Units (AHUs) working well by using sensors to track things like temperature and airflow. This data is analyzed with advanced computer techniques to predict problems before they happen, which helps save money on repairs. Zhao et al. [1] show that using AI for fault detection improves how building energy systems work. Schmidt and Wang [2] explain that PrM in manufacturing can prevent machine failures, reducing downtime and costs. Singh et al. [3] combine sensors with machine learning to better manage HVAC systems, while Kim et al. [4] use simulations and sensor data to improve system performance. Hosamo et al. [11] use digital twins, which are virtual models of AHUs, to predict maintenance needs. Zhang et al. [8] use mixed data models to make fault detection more accurate.

Challenges in Sensor-Based Prm

Implementing sensor-based PrM has some challenges. Integrating different sensors and dealing with data quality can be tough [1]. Yu et al. [5] mention that AHU operations are complex, making fault detection difficult. Granderson and Lin [7] point out that managing and analyzing large amounts of data is necessary for effective PrM. Babadi Soultanzadeh et al. [15] discuss that current systems have limitations in handling various conditions. The high cost of installing and maintaining sensors [6] and ensuring cybersecurity [13] are also significant issues.

User-Driven PrM and Its Advantages

User-driven PrM involves getting feedback from users to improve maintenance. This approach helps make predictions more accurate and maintenance more aligned with user needs. Ahern et al. [6] show that including user input leads to better fault predictions and maintenance plans. Wang et al. [17] note that user-driven methods can also help save energy. Combining user feedback with machine learning improves maintenance strategies and collaboration between facility managers and occupants. Trivedi et al. [14] demonstrate that using user feedback with machine learning makes predictions more reliable. Digital twins [11] also help by adjusting maintenance based on user behavior, which boosts system performance. In summary, while sensor-based PrM has many benefits like improved predictions and cost savings, it also faces challenges with integration, data management, and costs. Adding user feedback can make these systems even better.

METHODOLOGY

The aim of this study is to:

1. Identify the Most Effective Classification Technique: Determine which machine learning model offers the highest accuracy in predicting faults in Air Handling Units (AHUs).
2. Assess Data Splitting Impact: Examine how different training and testing data ratios affect prediction accuracy.

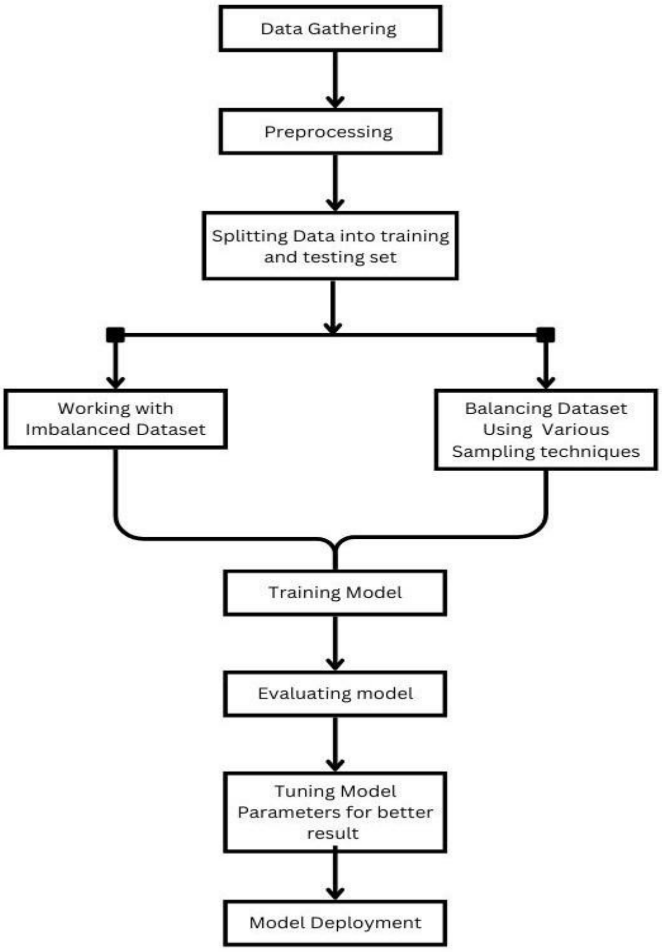

Figure 1: System Flow

These objectives will help optimize the predictive maintenance system for better performance and reliability.

Data Gathering

Data gathering involves collecting operational data from Air Handling Units (AHUs) through a user interface. Users input various parameters such as fan status, temperature, and control signals. This data is crucial for the predictive models to generate accurate forecasts and manage potential faults effectively.

Data Preprocessing

Data preprocessing prepares the raw dataset for analysis by:

Cleaning the Data: Handling missing values and removing duplicates.

Normalizing Features: Applying Min-Max Scaling to bring feature values into a [0, 1] range using:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad \textbf{Eq.1}$$

and Robust Scaler to handle outliers, using:

$$X_{scaled} = \frac{X - median}{IQR} \quad \textbf{Eq.2}$$

These methods ensure that all features contribute equally to the model training.

Splitting Data into Training and Testing Sets

The dataset is divided into training and testing subsets. This separation allows the models to be trained on one portion of the data while being evaluated on another, helping to assess their performance and generalization ability.

Working with Imbalanced and Balanced Datasets

i. Working with Imbalanced Dataset: Initially, models are trained on the imbalanced dataset to establish a performance baseline and identify any issues related to class imbalance.

ii. Working on Balanced Dataset Using Sampling Techniques: Techniques such as oversampling the minority class or undersampling the majority class are applied to balance the dataset and address class imbalance issues

Algorithm Description:

A key challenge in ML for AHU predictive maintenance (PrM) is class imbalance, with scarce fault data compared to normal data. This can lead to biased models favoring the majority class and missing faults [11]. To address this, specialized algorithms and sampling techniques are used to improve ML model performance on imbalanced datasets.

Balanced Bagging Classifier

Balanced Bagging Classifier combines bagging with random undersampling to address class imbalance. Each bootstrap sample is balanced by undersampling the majority class, ensuring equal representation of both classes during training.

Mathematically, for a dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$ with classes $y \in \{0,1\}$:

- Bootstrap samples D_b are created with undersampling:

$$D_b = D_{minority} \cup Resample\left(D_{majority}\right) \quad \textbf{Eq.3}$$

- The final prediction is an aggregation of predictions from individual models $f_m(x)$:

$$\hat{y} = majority\ vote\ (\{f_m(x)\}_{m=1}^{M}) \quad \textbf{Eq.4}$$

RUSBoost

combines random undersampling (RUS) with AdaBoost, where RUS reduces the majority class in each iteration, and AdaBoost adjusts weights to focus on misclassified instances.

For each boosting iteration (t):

- Update sample weights (α_i):

$$[w_i^{(t+1)} = w_i^{(t)}\ exp\ exp\left(-\alpha_t y_i f_t(x_i)\right)] \quad \textbf{Eq.5}$$

- The classifier adjusts with random undersampling:

$$[D_t = D_{minority} \cup RUS(D_{majority})] \quad \textbf{Eq.6}$$

Easy Ensemble Classifier

Easy Ensemble creates multiple balanced subsets by repeatedly undersampling the majority class, then trains a boosting classifier on each subset. The ensemble combines predictions from all boosted classifiers.

- For each subset (s), train a boosting classifier (f_s) on balanced data:

$$[D_s = D_{minority} \cup RUS(D_{majority})] \quad \textbf{Eq.7}$$

- Aggregate predictions from all classifiers:

$$[\hat{y} = majority\ vote(\{f_s(x)\}_{s=1}^{S})] \quad \textbf{Eq.8}$$

Balanced Random Forest (RF) Classifier

Balanced Random Forest modifies the standard Random Forest algorithm by incorporating random undersampling of the majority class within each tree. This ensures each decision tree is trained on balanced data, improving fault detection.

- For each tree (t), create a balanced bootstrap sample:

$$[D_t \ = D_{minority} \cup Resample(D_{majority})] \quad \textbf{Eq.9}$$

- Aggregate predictions from all trees:

$$[\hat{y} = majority\ vote(\{f_t(x)\}_{t=1}^{T})] \quad \textbf{Eq.10}$$

These algorithms effectively address class imbalance by balancing training data, leading to improved performance in detecting minority class faults.

Sampling Techniques
To further improve the performance of these algorithms, various sampling techniques can be applied:

Never miss: This technique ensures that no minority class instance is missed during sampling. It involves oversampling the minority class to ensure adequate representation in the training dataset. By doing so, Never miss improves the detection of faults in AHU systems.

Tomelink: Tomelink is a hybrid sampling technique that combines Tomek links (pairs of instances from different classes that are each other's nearest neighbors) with oversampling. By removing Tomek links and oversampling the minority class, Tomelink enhances the model's ability to distinguish between classes and improves fault detection accuracy.

Random Oversample: This technique involves randomly duplicating instances from the minority class to balance the dataset. Random Oversample is straightforward to implement and effectively addresses class imbalance by ensuring the minority class is adequately represented during training. It enhances the detection of faults in AHU systems by reducing the bias towards the majority class.

Borderline: Borderline is a sophisticated oversampling technique that focuses on instances near the decision boundary. By oversampling minority class instances close to the majority class, Borderline improves the classifier's ability to distinguish between classes and enhances fault detection accuracy in imbalanced datasets.

By integrating these algorithms and sampling techniques, the performance of machine learning models in detecting faults in AHU systems can be significantly improved, leading to more effective and reliable predictive maintenance strategies.

Model Evaluation

Models are evaluated using performance metrics such as accuracy, precision, recall, and F1-score. A baseline model is developed to provide a reference performance level. Multiple advanced classifiers are tested, including Bagging Classifier, Balanced Random Forest Classifier, RUSBoost Classifier, and Easy Ensemble Classifier, to identify the most effective approach.

Parameter Tuning for Better Performance

The selected models are fine-tuned using parameter optimization techniques such as grid search or random search. This process adjusts hyperparameters to improve model performance. The refined model is then re-evaluated to ensure it meets the desired performance metrics.

Predictive System

The final step involves integrating the trained model with a user interface (UI) for practical application. This process includes:

· Model Loading: The pre-trained model, saved in a pickle file, is loaded and initialized for inference.

·Data Feeding and Prediction: Preprocessed data is fed into the model to generate predictions. The predictions are displayed through the UI in a user-friendly format, showing fault detection results and additional insights.

RESULTS AND DISCUSSION

Table 1: Performance metrics of every algorithm used

The following table summarizes the performance metrics of various ensemble classifiers and random forest models evaluated on the dataset

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
BalancedBagging Classifier	0.991014664	0.999436465	0.990081142	0.994736808	0.993359308
BaggingClassifier_Borederline	0.99711623	0.999271573	0.997364492	0.998317122	0.996492693
BaggingClassifier_nevermiss	0.917617717	0.999211311	0.904654333	0.949584699	0.950176713
BaggingClassifier_randomsampler	0.99845234	0.998961659	0.999234015	0.999097819	0.996489075
BaggingClassifier_tomelinks	0.99800697	0.998935203	0.998740669	0.998837926	0.996164204
Randomforest_Borderline	0.996203222	0.99721192	0.998364167	0.997787711	0.990775765
Randomforest_nevermiss	0.837484551	0.998164669	0.811996105	0.895507002	0.90150165
Randomforest_randomsampler	0.996526115	0.997393503	0.998558909	0.997975866	0.991420524
Randomforest_tomelinks	0.996192088	0.99697987	0.998584875	0.997781727	0.990182334

• Highest Accuracy: The Bagging Classifier Borederline model achieves the highest accuracy at 0.9971, indicating it performs exceptionally well in correctly predicting both positive and negative cases.

• Best Precision: The Balanced Bagging Classifier and Bagging Classifier Borederline models both demonstrate high precision, with values of 0.9994 and 0.9993 respectively, showing that they have a low rate of false positives.

• Top Recall: The Bagging Classifier Randomsampler has the highest recall at 0.9992, indicating its effectiveness in identifying true positive cases, minimizing false negatives.

• Highest F1-Score: The Bagging Classifier Randomsampler and Bagging Classifier Tomelinks models have the highest F1-scores at 0.9991 and 0.9988 respectively. The F1- score balances precision and recall, highlighting these models' strong overall performance.

• Best ROC-AUC: The Balanced Bagging Classifier leads in ROC-AUC with a value of 0.9934, which measures the model's ability to distinguish between classes across various thresholds.

• Lower Performances: The Random forest Nevermiss model shows lower performance across all metrics, with notably lower accuracy (0.8375) and F1-score (0.8955), indicating it may not be as effective as the other models in this dataset.

As shown in Figure 2, Figure 3, Figure 4, Figure 5 overall, ensemble classifiers such as Bagging Classifier variants tend to outperform Random Forest models, with the Bagging Classifier Randomsampler showing particularly strong overall performance in terms of accuracy, recall, and F1-score.

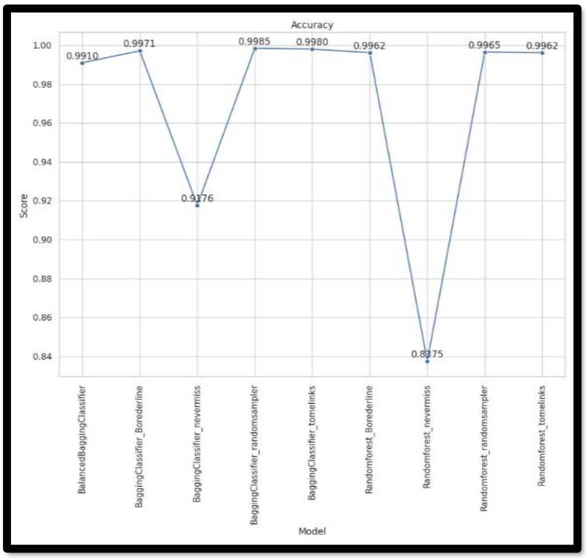

Figure 2: Accuracy

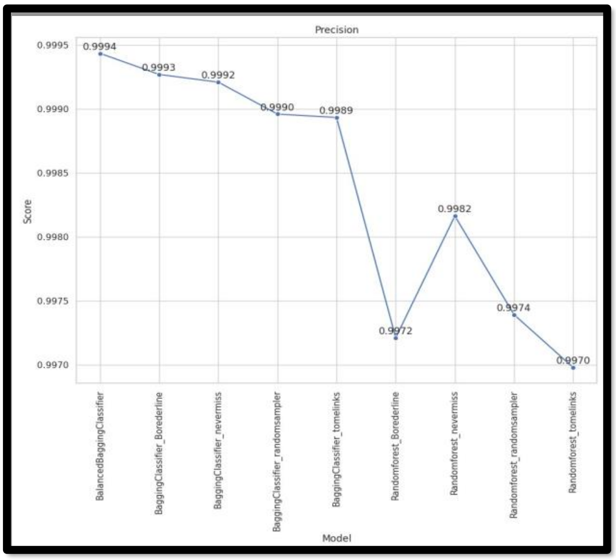

Figure 3: Precision

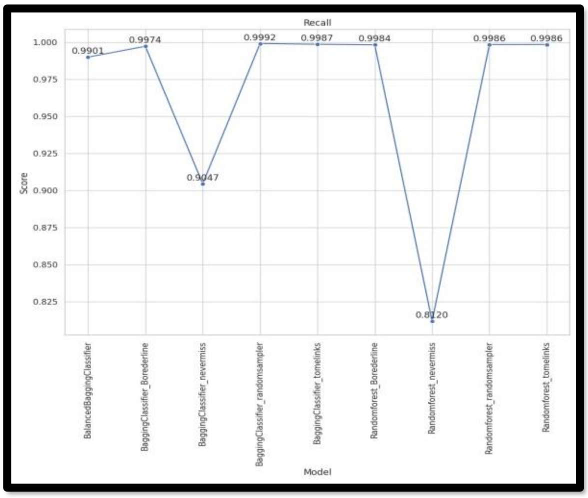

Figure 4: Recall

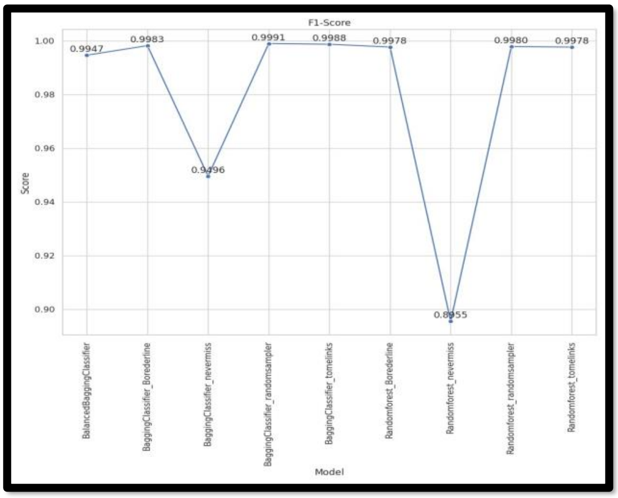

Figure 5: F1 Score

CONCLUSION:

This research paper investigates a machine learning-based predictive maintenance (PrM) system for Air Handling Units (AHUs) using user-provided data. The study aimed to identify the most effective classification techniques for fault prediction and to evaluate the impact of different data splitting ratios on model accuracy.

Key Findings:

1. Model Effectiveness: As shown in Figure 2, Figure 3, Figure 4, Figure 5, among the tested models, the Bagging Classifier variants demonstrated superior performance. The Bagging Classifier Randomsampler achieved the highest accuracy (0.9985), recall (0.9992), and F1-score (0.9991), while the Balanced Bagging Classifier excelled in precision (0.9994) and ROC-AUC (0.9934). These results indicate that ensemble methods, particularly Bagging Classifiers, are highly effective for predicting AHU faults.
2. Data Handling: The study underscores the importance of addressing class imbalance through specialized algorithms and sampling techniques. Models trained on balanced datasets showed improved performance, with techniques like oversampling and undersampling enhancing the detection of faults.
3. Implementation: The research highlights the benefits of integrating machine learning models into a user-driven interface. This approach allows for real-time fault detection and maintenance recommendations based on user inputs, which can lead to reduced downtime, cost savings, and optimized energy usage.
4. Challenges: The study also notes the challenges of working with imbalanced datasets and the need for comprehensive preprocessing to ensure model accuracy and reliability.

In conclusion, the research demonstrates that a well-designed predictive maintenance system using advanced machine learning models can significantly enhance the performance and reliability of AHUs. Future work should focus on refining data splitting techniques and further optimizing model parameters to maximize predictive accuracy and operational efficiency.

REFERENCES

[1] Zhao Y, Li T, Zhang X, Zhang C. Artificial intelligence-based fault detection and diagnosis methods for building energy systems: advantages, challenges and the future. Renewable Sustainable Energy Rev 2019;109:85–101

[2] Schmidt, B., Wang, L., 2018. Predictive maintenance of machine tool linear axes: a case from manufacturing industry. Proc. Manuf. 17, 118–125.

[3] Divyansh Singh , Mohd. Arshad , Bhaumik Tyagi , Garv Kalia "Predictive Maintenance Strategies for HVAC Systems: Leveraging MPC, Dynamic Energy Performance Analysis, and ML Classification Models" Iconic Research And Engineering Journals, 7(4)

[4] W. Kim, Y. Jeon, Y. Kim, Simulation-based optimization of an integrated daylighting and HVAC system using the design of experiments method, Appl. Energy 162 (2016) 666–674.

[5] Y. Yu, D. Woradechjumroen, D. Yu, A review of fault detection and diagnosis methodologies on air handling units, Energy Build. 82 (2014) 550–562.

[6] Ahern, M., O'Sullivan, D. T. J., & Bruton, K. (2023). Implementation of the IDAIC framework on an air handling unit to transition to proactive maintenance. Energy and Buildings, 284.

[7] Granderson, J., & Lin, G. (2019). Inventory of Data Sets for AFDD Evaluation. Lawrence Berkeley National Laboratory. (https://catalog.data.gov/dataset/data-sets-for-evaluation-of-building-fault-detection-and- diagnostics-algorithms-2de50)

[8] Zhang, B., Wang, P., Liu, G., Ma, Z., & Zhao, T. (2024). AHU sensor fault diagnosis in various operating conditions based on a hybrid data-driven model combined energy consumption, Journal of Building Engineering, 87.

[9] A.U. Ackley, C. Teeling, E. Atamewan, Factors Affecting the Shortage and or Provision of Sustainable Affordable Housing in Developing Countries - A Case-Study of Cross River State, Nigeria, Journal of Sustainable Architecture and Civil Engineering 22 (1) (2018) 27–38, number: 1. doi:10.5755/j01.sace.22.1.20573.

[10] L. Yu, Z. Xu, T. Zhang, X. Guan, D. Yue Energy-efficient personalized thermal comfort control in office buildings based on multi-agent deep reinforcement learning Building and Environment, 223 (2022), Article 109458, 10.1016/j.buildenv.2022.109458

[11] H.H. Hosamo, P.R. Svennevig, K. Svidt, D. Han, H.K. Nielsen A Digital Twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics Energy and Buildings, 261 (2022),Article 111988, 10.1016/j.enbuild.2022.111988 [12] About —— IEA EBC (2021). URL: https://www.iea-ebc.org/ebc/about.

[13] Hosamo, H. H., Nielsen, H. K., Kraniotis, D., Svennevig, P. R., & Svidt, K. (Year). Improving building occupant comfort through a digital twin approach: A Bayesian network model and predictive maintenance method.

Energy and Buildings, 288.

[14] Trivedi, S., Bhola, S., Talegaonkar, A., Gaur, P., & Sharma, S. (2019). Predictive Maintenance of Air Conditioning Systems Using Supervised Machine Learning. In 20th International Conference on Intelligent System Application to Power Systems (ISAP).

[15] Milad Babadi Soultanzadeh, Mohamed M. Ouf, Mazdak Nik-Bakht, Pierre Paquette, Steve Lupien, Fault detection and diagnosis in light commercial buildings' HVAC systems: A comprehensive framework, application, and performance evaluation,Energy and Buildings,Volume316,2024,114341,ISSN0378-7788, https://doi.org/10.1016/j.enbuild.2024.114341. (https://www.sciencedirect.com/science/article/pii/S0378778824004572)

[16] for Tian, R.; Gomez-Rosero, S.;Capretz, M.A.M. Health Prognostics Classification with Autoencoders Predictive Maintenance https://doi.org/10.3390/en16207094

[17] of HVAC Systems. Energies 2023, 16, 7094. Wang, Z., Liu, J., & Wang, W. (2020). A review of building energy efficiency improvement using machine learning. Renewable and Sustainable Energy Reviews, 131, 110040.