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Recent Advancement of Predictive Maintenance Based Data-Driven Strategies for HVAC Equipment Health Monitoring

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Abstract: *HVAC systems play a vital role in supporting the comfort and energy efficiency of indoors, as well as in safeguarding and ensuring the reliability of indoor air; however, the sensors and sensors constantly have challenges related to wear, sensor noise, environmental variations, and the operating conditions of the system, which is why data-driven and artificial intelligence (AI) techniques are invaluably helpful to change the situation. Some of the functionalities enabled include monitoring of performance in real time, system operation optimization based on the real time sensor data and Fault detection and diagnostics based on the abnormal patterns that were identified to enable timely maintenance and hence reliability. Neural networks, autoencoders, and time-series machine learning (ML) and deep learning (DL) models are highly beneficial in fault detection, anomaly detection, and Remaining Useful Life (RUL) prediction processes, allowing identifying when equipment is getting old and can be detected sooner and more accurately. In addition to equipment diagnostics, the emergence of new technologies, including digital twins, blockchain-based data integrity models, and intelligent control systems, leads to a higher level of reliability, transparency in the functioning of devices, and automated decision-making. interpretability, hardware limitations, and inability to generalize in a variety of HVAC environments.*

Keywords*:* HVAC Systems, Predictive Maintenance, Data-Driven Monitoring, Machine Learning, Fault Detection, Remaining Useful Life, Digital Twins

I. INTRODUCTION

The new technology of the Internet of Things (IoT), cyber-physical systems and cloud computing have made automation and data exchange achievable in the manufacturing industry, where it is increasingly important to have operational reliability and energy efficiency, as well as ensure the health and safety of engineering systems in real-time, with the help of real-time, data-driven analytics [1]. This is due to continuous monitoring which is made possible by real-time information to detect defects, deterioration trends, and abnormalities that could affect the performance of the system in an early fashion. In this respect, smart health monitoring has turned out to be a ground-breaking approach that evaluates the condition of the equipment by combining sensor data gathering, signal processing and smart analytics. Turning raw data into actionable insights makes it possible to enhance the dependability of the system, minimize downtime, and make well-informed decisions regarding maintaining the schedule of maintenance [2].

The energy consumption of commercial buildings is dominated by heating, ventilation, and air conditioning (HVAC) systems, which are directly related to indoor air quality, occupant comfort, and asset reliability maintenance techniques that have a first-order effect on energy and reliability performance [3]. Because of their widespread usage, reactive repair and fixed-interval preventative regimens frequently ignore the presence of slow-growing degradations (such as refrigerant undercharge, fouling heat exchangers, and pump wear), and latent faults reduce efficiency and result in sporadic outages [4][5]. The reason why Pd.M. has become an indispensable approach in contemporary industrial environments is because of the rapid growth of Industry 4.0 technologies [6][7]. With the help of ML methods, Pd.M.

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could make the shift of reactive to proactive maintenance policies, minimizing the number of unforeseen failures, minimizing costs, and enhancing the efficiency of the whole operational process though some buildings were also equipped with mechanical ventilation systems where the fans were used to facilitate the distribution of air [8].

HVAC predictive maintenance can be an excellent alternative to the conventional reactive or schedule-based maintenance systems [9][6]. Predictive maintenance can indicate any possible failures and also provide the parts' remaining useful life (RUL), which may be determined by using machine learning, statistical models and data-driven algorithms to forecast the presence of failures, hence the parts can be replaced before the failure occurs and is costlier [9]. Therefore, health monitoring incorporated with the predictive maintenance makes a holistic system of HVAC equipment health management [10][11]. This step conforms to the idea of intelligent buildings and Industry 4.0, in which the machines themselves perform the maintenance, depending on the insights gained in the data, and that also leads to energy saving and improved lifecycle management.

A. Structure of the Paper

The paper structure is as follows: Section I provides the introduction to the topic and describes the development of the maintenance strategies. In Section II, the authors cover data acquisition technologies, sensor technologies in HVAC systems. Section III discusses predictive maintenance systems in HVAC systems. Section IV offers the AI-enhanced predictive maintenance of HVAC. Section V contains a thorough overview of the literature in question, and Section VI is the conclusion of the study, which outlines the future study directions.

II. DATA ACQUISITION AND SENSOR TECHNOLOGIES IN HVAC SYSTEMS

The process of energy or load forecasting involves an essential procedure of data acquisition before implementing machine learning techniques [12]. Figure 1 depicts the improper organization and division of the HVAC system's optimization and monitoring into three primary layers: the sensor layer, the processing layer, and the prediction layer. The sensing layer is a group of sensors that are positioned to control the HVAC system's operating and environmental parameters, including airflow, pressure, temperature, and humidity. These sensors are used to gather real time information and send this information to the gateway device. The gateway is the central node in the processing layer where it collects sensor data, carries out an early stage of filtering as well as normalization and storage of the data in a structured data store. System administrators may see data in real-time, check on HVAC components' status, and handle warnings efficiently using the dashboard interface that is component of this layer [13].

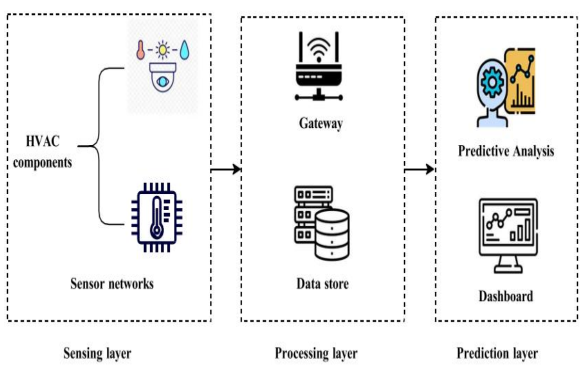

Fig. 1.HVAC Maintenance System

Purpose of data acquisition of HVAC System In HVAC systems, data collection is essential to achieve comfort, safety, dependability, and energy efficiency. Through constant data-gathering from sensors, HVAC systems are able to make and keep their operations:

- **Performance monitoring:** Data capture enables the real-time monitoring of several HVAC parameters, including humidity, airflow, pressure, temperature, and humidity. it guarantees the specified limits of performance. Typical HVAC systems include a distributed data collecting system that requires wiring, maintenance, and calibration.

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- **Energy optimization:** Energy optimization of HVAC systems means the system operation is adjusted based on real-time sensor data. The sensors detect occupancy and environmental conditions. No energy is wasted, the machine is more efficient, and thermal comfort is guaranteed all at the same time.
- **Fault detection and diagnostic:** In HVAC, fault detection and diagnostics are methods that use sensor data to examine anomalous trends or early equipment problems [14][15]. As a result, this makes it possible the timely maintenance, system failures are avoided, the time during which the system is not functioning is reduced, and the overall reliability and safety of the operations are enhanced.
- **Outdoor Air Intake and Air Exhaust Ducts and Controls:** Dampers provide for room-by-room management of the air supply and the ability to switch off the central air conditioning in unoccupied rooms [16]. The supply, relief, and return components of the HVAC system can benefit from these energy-saving devices. Louvres are used to keep water out of buildings.
- **Air Handling Units (AHU):** The air it takes in from the outside is reconditioned and then supplied as fresh air.

A. Sensor Systems For Predictive HVAC Control:

The indoor and outdoor temperatures, along with their predicted changes across a Prediction Horizon (PH), are necessary inputs for IMBPC. In addition to detecting the aforementioned three factors and providing energy-autonomous communications based on the IEEE 802.15.4 standard, the authors developed and evaluated an intelligent weather station that can also predict these variables over a user-specified PH. Internal air temperature and relative humidity readings are readily obtained by use of SPWS sensors. The IMBPC HVAC method requires the SPWS devices to acquire a signal for motion detection in every room. Predictions of PH-related weather variables are computed by the smart weather station. The SPWS collects the indoor climatic variables and the movement signal [17].

B. Data collection and Feature Engineering

Data pre-processing is a crucial preliminary step prior to implementing machine learning techniques for energy or load forecasting. Typical methods include data imputation, data resolution processing, data normalization, outlier detection, and data smoothing. When it comes to managing operational data that is lacking values, there are two main approaches. Since the majority of data mining algorithms are unable to process data that contains missing values, the first option is to just remove the samples from the dataset associated with those values. As with the second, inferenced values can be used in place of missing data using missing value imputation methodology. Classify the most common approaches to missing value imputation as either univariate (such as the filter, wrapper, or embedding techniques) or multivariate (such as the aforementioned methods). In feature extraction, the goal is to build new features using either linear or nonlinear [18]. Data is collected from many system components, including sensors, Internet of Things devices, maintenance records, and processes listed in Table I.

Table 1: Types of Data Collected from HVAC Systems

Data Type	Source	Frequency of collection	Purpose
Temperature Data	Thermostats, Sensor	Continous	Monitoring system performance
Vibration Data	Vibration sensors	Continous	Detecting mechanical failure
Energy consumption	Smart meters	Hourly/Daily	Analyzing energy efficiency
Maintenance Logs	Service reports	After each maintenance	Historical analysis

C. Key Features of HVAC System Predictive Maintenance

A preventative method, HVAC systems use data analytics, Internet of Things (IoT) sensors, and ML algorithms to track the status of HVAC systems in real-time. Proactive maintenance systems can anticipate a component's failure and suggest remedies in a timely manner by evaluating data like as temperature, vibration, pressure, and energy usage.

- **Real-Time Monitoring:** Data on system performance, such as energy use, humidity, airflow, and temperature, is continually collected by sensors.

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- **Data Analytics:** Patterns and outliers may be found in both historical and real-time data by using advanced algorithms.
- **Failure Prediction:** Machine learning predicts failures in machine, which can be maintained in time.
- **Remote Diagnostics:** System data can be accessed remotely by technicians and therefore, it does not require on-site inspections.
- **Integration with Building Management Systems (BMS):** Predictive maintenance solutions may be easily included into BMS to offer centralized oversight and management.
- **Custom Alerts:** Immediate response is guaranteed as notifications are sent to stakeholders whenever specific thresholds are violated.

III. PREDICTIVE MAINTENANCE APPROACHES FOR HVAC SYSTEMS

The traditional methods of maintenance are becoming less efficient with the emergence of HVAC systems of higher complexity. Reactive maintenance involves worrying failures and only addresses them when they arise and therefore is more of an emergency maintenance. The major drawback is that it causes over-maintenance by scheduling maintenance operations even when the equipment doesn't really need them. Because it acts only when equipment fails or malfunctions, the conventional method of corrective maintenance is inefficient and ineffective. Predictive maintenance (PdM) uses AI and ML to anticipate potential issues and proactively address them. This method decreases the likelihood of unscheduled downtime while simultaneously making better use of available resources, making the system more dependable, and reducing energy consumption [19].

A. Ml-Based Hvac Degradation Detection

The three main components of the HPC-AE framework are data pre-processing, autoencoder degradation analysis, and health state categorisation, as seen in Figure 2[20]

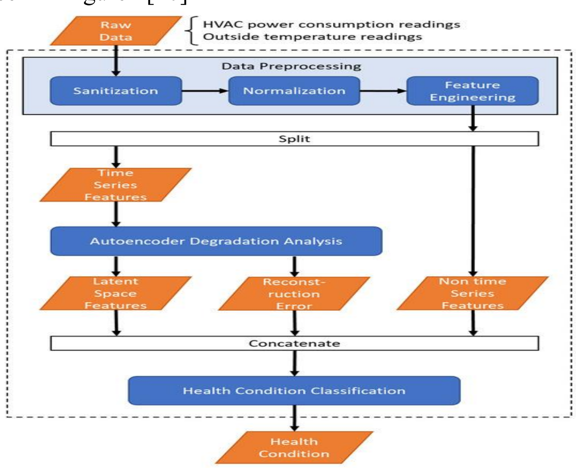

Fig. 2. HVAC Health Prognostics Framework.

The outside temperature trends have a significant impact on HVAC power consumption, according to previous study on HVAC power consumption patterns (r=0.91). The average yearly power usage of the HVAC system might rise by 28.2% while operating under deteriorated circumstances. Therefore, the goal of this study is to classify the daily health of an HVAC system only on the basis of power consumption and the pattern of outside temperatures. The suggested model classifies the daily health state using a neural network (NN) and an autoencoder. The autoencoder model analyses the HVAC system's relative deterioration data while taking outside temperature trends into account. It then generates new features to help the NN classifier classify the daily health state.

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B. Machine Learning for Anomaly Detection

This section summarizes the generally utilized anomaly detection methods. Unsupervised global anomaly detection using k-NN (k-nearest-neighbours) is the most popular and easiest approach[21]. Using the k-nearest-neighbours distance as its basis, this distance-based method seeks out data points that are out of the ordinary. The Local Outlier Factor (LOF) is one unsupervised method for local density-based anomaly identification methods. Cluster-Based Local Outlier Factor (CBLOF) clusters data using the k-means clustering approach to identify abnormalities. Malhotra et al. proposed a supervised technique based on stacked LSTM architecture to identify abnormalities in time series data. A model that is trained on data that is not abnormal is utilized as a predictor by the network. Situational outliers are illustrated in Figure 3 of HVAC time series datasets [22].

IV. AI-ENABLED PREDICTIVE HVAC MAINTENANCE

Artificial intelligence has made a lot of progress in many areas, and HVAC systems are no different. Unless integrated technology like data analytics, neural networks, and ML are used, it is feasible to diagnose and run HVAC systems in real time with an analysis of what is likely to go wrong. By analyzing the massive amounts of data generated by sensors and IoT devices, HVAC systems can be kept running at peak efficiency with the help of AI. This allows for continuous monitoring of the machine's health and potential fixes to any issues that may arise [19].

A. Integration with HVAC system

The sensor readings are sent into the Data Pipeline, a set of procedures intended to process the data, as shown in Figure 3, HVAC predictive maintenance system architecture. The Real-time Data Collection module must first collect these data in real time. Due to the presence of noise or other irrelevant data in the raw sensor data, data pre-processing is necessary to clean, filter, or convert the data before analysis. The step of pre-processing is especially useful in ensuring that the information that is being fed to the predictor models is of the best quality.

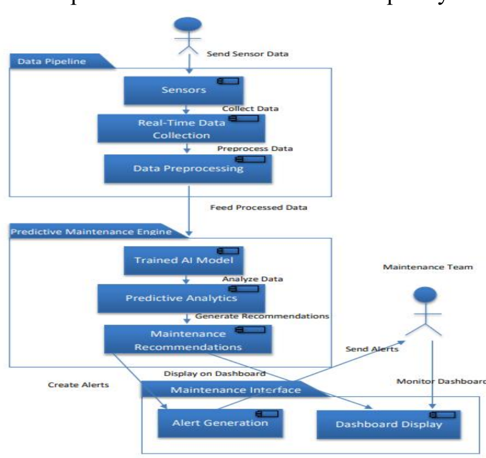

Fig. 3. Predictive Maintenance System Architecture for HVAC

This system is used by the maintenance team through monitoring the dashboard and responding to the alerts. They work on introducing preventive actions that can be aligned with what AI can offer in terms of the HVAC functioning and, therefore, ensured a stable operation with no failures [23]. This building exemplifies the ideal of a contemporary maintenance process, where data provided by AI facilitates a shift from reactive to proactive maintenance, cutting down on breakdowns and increasing equipment lifespan.

B. Condition Monitoring For Hvac Maintenance:

The purpose of condition monitoring is to continuously track a set of contextual parameters that may show signs of degradation or wear and tear on the monitored object. This allows users to identify the system's health state [24]. If no remedial action is performed, condition monitoring can reveal when the failure mode is likely to occur. As a diagnostic-

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oriented strategy, the suggested maintenance decision diagram suggests condition-based maintenance wherever possible. For example, in the case when detection is "Almost Certain—AC," the recommended process recommends setting up condition monitoring to determine the system's health-state. This allow for optimization of the maintenance strategy according to the system's real circumstances[25].

C. IoT Enable HVAC system setup

IoT and cloud platform integrations allow HVAC systems to gather, locally save, and analyze in real-time sensor data of several devices from a remote location [26]. Connectivity of this sort is the enabler of advanced analytics, centralized monitoring, automated fault detection, and uninterruptible control throughout various places [27][28]. Besides extending the system's capabilities, it also makes the energy use more efficient and enables the prediction of maintenance through AI-powered instruments without the need for a direct interaction with the location.

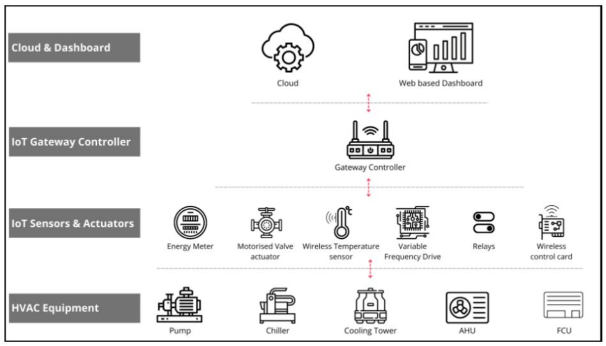

Fig. 4. Iot Enable HVAC System

HVAC system with the addition of IoT and electronics, IoT devices such as energy meters, motorized valve actuators, wireless temperature sensors, variable frequency drives, relays, and wireless control cards are shown above the HVAC equipment such as pumps, chillers, cooling towers, AHU, and FCU from which they collect operational data in Figure 4. These sensors are linked to an IoT gateway controller that sends the data to the cloud a cloud and a web-based dashboard for remote monitoring, analytics, and control through a single platform.

V. LITERATURE REVIEW

In this section, recent studies data-driven and machine-learning approaches are improving predictive maintenance for HVAC systems, particularly in fault detection, RUL enhance reliability and efficiency, further research.

Biswas et al. (2025) humidity ventilation air conditioning (HVAC) systems keep these indoor space elements stable. The air filter reduces the particulate, which improves breathability. The capacity of the HVAC system to maintain temperature and humidity is impacted by the state of the filter. An innovative Field Programmable Gate Array (FPGA) implementation of an air filter health detection system using feature-based machine learning (ML). The air filter's condition is ascertained using the sensor's real-time data. The detecting system used only 161 mW of dynamic power and produced an outstanding 96.7% accuracy[29].

Sahil and Urvashi (2025) a number of methods for estimating Remaining Useful Life (RUL), such as hybrid approaches, statistical methods, and ML models. CNNs and LSTM networks of DL techniques that make sensor data, while physics-based models improve accuracy by taking consideration of actual conditions. Planning maintenance for complex systems is improved when these approaches are included into hybrid models still exist without technological developments, such as high processing power requirements, handling real-time data, and ability to understand predictions produced advanced techniques like Bayesian neural networks, particle filtering is required for real-time implementation[30].

Mehta et al. (2025) blockchain-based architecture to secure Digital Twins and ensure data integrity, transparency, and trustworthiness in predictive maintenance workflows. This framework leverages smart contracts for secure event triggering, tamper-proof logs for maintenance actions, and decentralized identity (DID) mechanisms for authentication

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an autonomous industrial robotic arm demonstrates the effectiveness in ensuring secure, resilient, and reliable predictive maintenance[31].

Afolalu et al. (2024) maintenance planning and scheduling, was also carried out maintenance is important as it aids in understanding the reason for such maintenance strategy, and when to effectively utilize them evolved from pre-world War II. Due to increase in technology, there has been a great advancement in maintenance procedures and practice, therefore different modern technology and analysis different failure mechanisms were analysed in order to know their causes and detection[32].

Rustambekov et al. (2024) Using real-time data analysis for Smart Grid component predictive maintenance methods. By analyzing industry reports and conducting comparative and inductive analyses, delve into the ways in which traditional maintenance techniques can be enhanced by sophisticated analytics and ML. also discuss the ways in which the IoT and edge computing can integrate DL algorithms for time series analysis, which could lead to continuous monitoring. Finally, discuss about how to use predictive analytics to optimise maintenance operations, such as prioritising repair tasks according to failure risk prediction, and dynamic maintenance scheduling based on risk assessment. Data infrastructure investment and standardization continue to be obstacles, despite the fact that predictive maintenance demonstrates potential for lowering operational costs and increasing dependability [33].

Hamayat et al. (2023) A data-driven method for predictive maintenance utilising machine learning to identify issues with HVAC systems in contemporary buildings. To be more precise, several machine learning approaches are used to establish a data-driven architecture that accurately detects faults. For every type of error classification, the highest-performing machine learning models were Random Forest, Cat Boost, Extra Tree, and Extra Tree, which had the best overall performance across all criteria. When compared to Extra Tree, two machine learning based data-driven frameworks for HVAC system problem detection, Cat Boost and Random Forest perform better [34].

Palaić et al. (2023) A critical concern is the need for energy. The biggest user of energy is HVAC systems, which contribute significantly to both resource depletion and environmental degradation. Building HVAC system performance may be better understood with the assistance of enormous volumes of data made available by the growth of IoT devices. ANN model for commercial building interior temperature forecasting that uses data-driven approaches to improve productivity, analyse performance, and generate model behaviour. The data-driven model may forecast interior temperatures with a root-mean-squared error (RMSE) of 0.85 °C. Using the developed model in a predictive control system might be another strategy to reduce energy use[35].

Table II provides a summary of recent studies on AI and ML applications in predictive maintenance and HVAC system health monitoring, highlighting the approaches adopted, important conclusions, current issues, and possible avenues for further research.

Table 2: Summary of Recent Studies on AI, Ml and Predictive

Author	Study Focus	Key Findings	Limitations	Future Work
Biswas et al. (2025)	Air filter health detection in HVAC using ML & FPGA	Suggested a new ML-based hardware (FPGA) system based on real-time sensor data in order to identify air filter health. The highest success rate of 96.7% at 161 mW dynamic power consumption..	Limited to feature-based ML; scalability and integration with larger HVAC systems not addressed.	Explore deep learning-based models, multi-sensor fusion, and integration with building management systems.
Sahil & Urvashi, (2025)	Remaining Useful Life (RUL) estimation using hybrid ML models	Reviewed CNNs, LSTMs, physics-based and Bayesian approaches for RUL prediction. Highlighted benefits of hybrid models for maintenance planning.	High computational requirements, difficulty in real-time implementation, interpretability issues.	Real-time deployment using Bayesian neural networks, edge computing, particle filtering, explainable AI.

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Mehta et al. (2025)	Predictive maintenance using a secure digital twin powered by blockchain	Developed blockchain framework with smart contracts, DID authentication, and tamper-proof logs. Demonstrated secure and resilient predictive maintenance on industrial	High system complexity and computational overhead; blockchain latency issues.	Optimization of blockchain integration, lightweight protocols for real-time maintenance, scalability across industries.
Afolalu et al., (2024)	Maintenance planning and scheduling using modern technologies	Reviewed evolution of maintenance strategies and analysis of failure mechanisms to improve detection and planning.	Lack of real-time implementations and automated decision-making frameworks.	Integration of AI tools, predictive scheduling, and real-time maintenance advisory systems.
Rustambekov et al. (2024)	Predictive maintenance for Smart Grid using ML & IoT	Proposed use of IoT, edge computing, deep learning, and dynamic scheduling to enhance grid reliability and efficiency.	Challenges in data standardization, infrastructure cost, and large-scale deployment.	Development of unified data standards, risk-based maintenance prioritization frameworks, scalable predictive models.
Hamayat et al.(2023)	Fault detection in HVAC systems using ML	Implemented data-driven ML framework CatBoost & Random Forest were most effective for individual fault detection.	Limited fault categories; model interpretability and real-time deployment challenges.	Expand dataset, implement explainable AI (XAI) and deploy real-time fault detection systems.
Palaić et al. (2023)	Energy efficiency & temperature prediction in HVAC systems	Developed ANN-based model predicting indoor temperature with RMSE of 0.85 °C, suitable for predictive control.	Focused only on temperature prediction; energy optimization not fully explored.	Integration with predictive control systems, multi-parameter energy optimization, adaptive learning models.

VI. CONCLUSION AND FUTURE WORK

The application of data-driven predictive maintenance has become a major technology in contemporary HVAC system management, with unprecedented possibilities of analyzing complex operation data undertakings in an attempt to guarantee reliable performance of the equipment in light of the fact that the traditional methods of maintaining equipment are mostly constrained by a set timetable or intervention performed after failure. ML and DL approaches to the improvement of HVAC condition and failure forecasting, which is essential to increase the lifespan of the system and minimize energy waste. In addition to fault detection, data-driven frameworks support decision-making in maintenance through unifying multi-source sensor data and using digital-twin settings to predict and monitor the performance. Although it has been confirmed that automation of diagnostics and optimization of maintenance have improved, many challenges have remained, including the lack of real-time data, inaccessibility of black boxes, and the lack of validation on a variety of HVAC installations. The way forward in future workers should focus on large-scale real-world testing, explainable and transparent AI systems, and curated multi-building data to turn the mentioned innovations into a practical change in HVAC reliability. It will require further development of sensor integration, lightweight inference models, and strong anomaly interpretation as well as the solutions to deployment and interoperability limitations

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