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SMART VENTILATION SYSTEMS FOR REAL-TIME POLLUTION CONTROL: A REVIEW OF AI-DRIVEN TECHNOLOGIES IN AIR QUALITY MANAGEMENT

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ABSTRACT

This review paper examines the implementation and effectiveness of AI-powered smart ventilation systems for pollution control, focusing on industrial and urban environments. Utilizing the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology, a systematic literature search was conducted across databases such as IEEE Xplore, ScienceDirect, and PubMed. Studies were screened and selected based on relevance to AI-driven ventilation systems, real-time air quality monitoring, and pollution management, resulting in a final set of 40 articles for in-depth analysis. The review synthesizes information on various technologies, including machine learning algorithms, Internet of Things (IoT) sensors, and pollutant scrubbers, that are integrated into smart ventilation systems to detect and respond to fluctuations in air quality autonomously. Key findings indicate that AI-powered systems can dynamically adjust airflow, filtration, and pollutant removal processes, leading to significant improvements in air quality in both industrial facilities and densely populated urban areas. This study highlights both the potential benefits and challenges associated with implementing AI-driven ventilation systems, including the need for high-quality data, real-time processing capabilities, and cost-efficiency. The review concludes with recommendations for future research directions, such as enhancing system interoperability and addressing ethical considerations in air quality monitoring and data privacy.

1 INTRODUCTION

The rapid urbanization and industrialization over the last century have led to a considerable increase in air pollution, impacting public health and environmental quality worldwide (Farzaneh et al., 2021). Particularly in urban areas and industrial zones, where emissions are high, the need for effective air quality management

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systems has become imperative. Traditional ventilation systems, primarily relying on static air control mechanisms, are often inadequate in addressing the complexities of real-time pollution control (Wei et al., 2022). In response, researchers and engineers have increasingly focused on developing "smart" ventilation systems that leverage advanced technologies such as Artificial Intelligence (AI) and the Internet of Things (IoT) to enhance pollution control capabilities (Choi et al., 2022). These systems are designed to autonomously monitor and regulate air quality, responding dynamically to fluctuating pollution levels.

The evolution of smart ventilation systems can be traced back to initial developments in automated environmental controls in the late 20th century, which primarily aimed to improve indoor air quality (IAQ) in commercial and industrial buildings (Wang et al., 2024). Early systems employed basic sensors and feedback mechanisms to control ventilation rates, but they lacked real-time data processing and predictive capabilities (Yang & Wan, 2022). With advancements in sensor technology and data analytics, modern ventilation systems have evolved to incorporate AI and machine learning algorithms, allowing for the detection of complex pollution patterns and enabling more precise and timely responses (Yang et al., 2023). These AI-enhanced systems differ fundamentally from traditional methods by integrating predictive models that optimize ventilation rates based on both historical and real-time data, thereby significantly enhancing energy efficiency and air quality outcomes (Yang & Wan, 2022). Moreover, AI-driven smart ventilation systems are primarily powered by machine learning models that analyze large volumes of air quality data, identify patterns, and make automated adjustments to the system's operation (Martinez-Molina & Alamaniotis, 2020). These models often work in tandem with IoT devices, which provide real-time data from various sources, including pollutant sensors and weather stations, to offer a comprehensive view of the air quality landscape (Merabet et al., 2021). For example, IoT-integrated sensors detect concentrations of pollutants such as particulate matter (PM2.5), nitrogen dioxide (NO2), and carbon dioxide (CO2), feeding this data to AI algorithms that predict pollution spikes and adjust ventilation accordingly (Tien et al., 2022). This AI-IoT synergy allows smart ventilation systems to autonomously manage indoor and outdoor air quality, adapting to changes in pollution levels in real time, a critical capability in densely populated or highly industrialized areas (Blad et al., 2021). In addition, one of the major advancements in AI-driven smart ventilation systems is the implementation of deep learning algorithms for predictive maintenance and decision-making (Rescio et al., 2023; Saika et al., 2024; Sohel et al., 2024; Uddin et al., 2024). Deep learning models enable systems to anticipate air quality issues by analyzing historical data and identifying potential sources of pollution, such as traffic or industrial activities. By predicting pollution trends, these systems

Figure 1: Evolution of Scmart Ventilation Systems

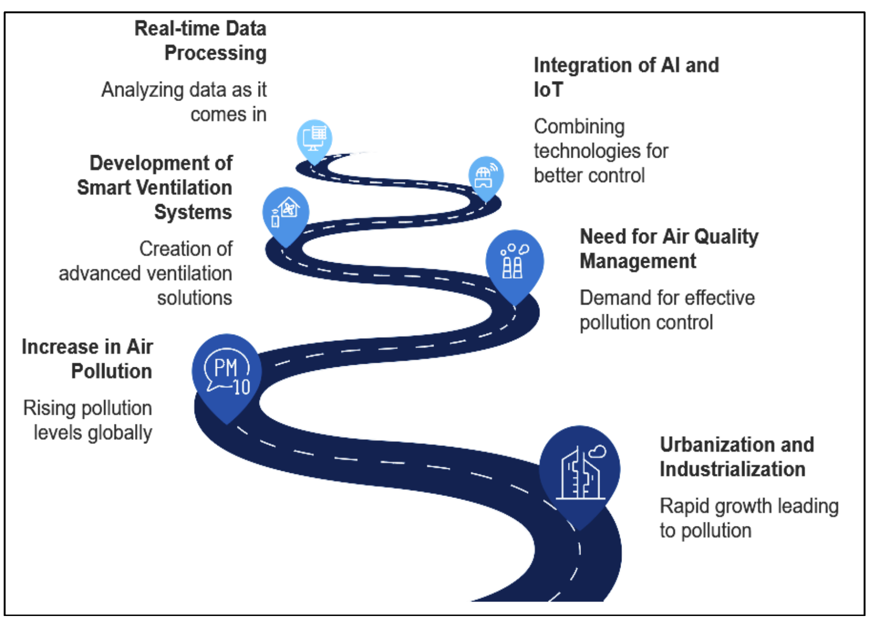
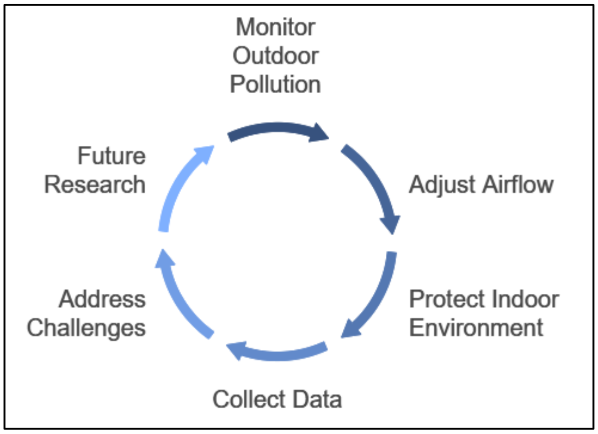


Figure 2: Cycle of Smart Ventilation Systems



can proactively adjust ventilation, thus preventing exposure to high levels of contaminants before they reach critical thresholds (Alam et al., 2024; Badhon et al., 2023; Istiak & Hwang, 2024; Istiak et al., 2023; Tien et al., 2022). Moreover, some systems employ reinforcement learning techniques, which allow ventilation units to "learn" from previous responses and improve their operational efficiency over time, reducing energy consumption and operational costs (Merabet et al., 2021).

Smart ventilation systems are not only effective in maintaining indoor air quality but also play a pivotal role in reducing exposure to outdoor pollutants in urban settings (Oduah & Ogunye, 2023). In cities with high pollution levels, AI-driven ventilation units can act as a buffer, reducing the infiltration of outdoor pollutants and enhancing urban living conditions (Shaqour & Hagishima, 2022). These systems are designed to monitor outdoor pollution levels and, when necessary, close off ventilation to protect indoor environments. This dynamic control over airflow represents a significant departure from conventional systems that lack the capacity for such fine-grained adjustments (J. Wang et al., 2023). However, the effectiveness of these systems is contingent upon the quality and granularity of the data collected, underscoring the importance of advanced sensor networks and high-performance data processing capabilities (Eseye et al., 2019). Despite the evident benefits of AI-powered ventilation systems, there remain several challenges and limitations in their widespread implementation, particularly related to cost and data management (J. Wang et al., 2023). The initial investment for these systems is often high due to the need for sophisticated sensors, AI infrastructure, and ongoing maintenance. Furthermore, the systems' reliance on real-time data raises concerns about data privacy and the ethical implications of continuous monitoring in public spaces (Oduah & Ogunye, 2023). As the technology evolves, addressing these challenges is crucial to ensuring the scalability and sustainability of smart ventilation systems. Future research will likely focus on improving the interoperability of different AI-driven components, optimizing energy efficiency, and enhancing data security measures to facilitate broader adoption in diverse settings (Shaqour & Hagishima, 2022).

The primary objective of this review is to systematically examine the role and effectiveness of AI-driven smart ventilation systems in managing air quality, with a focus on real-time pollution control in urban and industrial environments. Specifically, this study aims to analyze the integration of machine learning algorithms, IoT sensors, and pollutant removal technologies within ventilation systems, evaluating their impact on air quality improvement and energy efficiency. By synthesizing recent advancements and identifying gaps in the literature, this review seeks to provide a comprehensive understanding of how AI-powered ventilation can autonomously detect and respond to air quality fluctuations. Additionally, the study aims to highlight key challenges, such as data quality requirements, real-time processing demands, and cost considerations, that affect the deployment and functionality of these systems. Through this detailed examination, the review will offer insights into potential research directions, particularly in areas of interoperability and data privacy, to support future innovations in smart air quality management solutions.

2 LITERATURE REVIEW

The development of AI-driven smart ventilation systems has gained significant attention in recent years as urbanization, industrialization, and environmental awareness have increased demand for advanced air quality management solutions. Existing literature highlights various technological advancements and methodologies in AI and IoT, which collectively enhance ventilation systems' ability to autonomously monitor, predict, and control air quality in real time. This section systematically reviews previous studies, focusing on the evolution of smart ventilation technologies, machine learning applications, IoT integration, real-time air quality monitoring, and the associated challenges and limitations in implementing

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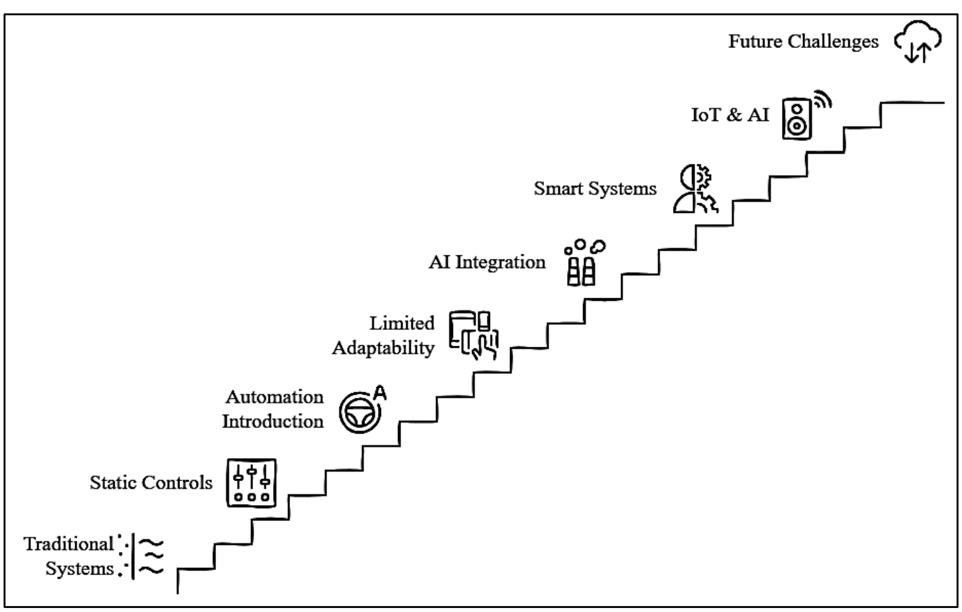
these systems. By analyzing these areas, the review aims to consolidate existing knowledge and pinpoint gaps that warrant further investigation, providing a comprehensive understanding of the current landscape and future potential of AI-driven air quality management.

2.1 Evolution of Ventilation Systems for Air Quality Control

The history of ventilation systems in air quality control reveals a gradual shift from basic mechanical solutions to sophisticated smart technologies. Traditional ventilation systems, primarily designed for indoor air renewal, relied on static control mechanisms without considering real-time pollution variations (Rollo et al., 2023). These early systems often involved fixed or manually adjustable airflow settings, which proved inefficient in maintaining optimal air quality, particularly in highly variable environments such as urban areas or industrial facilities (Manshur et al., 2023). Studies have shown that static ventilation controls struggled to adapt to fluctuations in pollutant concentrations, resulting in either insufficient air quality improvement or excessive energy consumption (Fang et al., 2023; Rollo et al., 2023; Vajs et al., 2023). Consequently, the limitations of these conventional methods highlighted the need for more responsive systems that could dynamically adjust to changing environmental conditions (Martinez et al., 2023). The transition to automated and eventually smart ventilation systems marked a pivotal moment in air quality management. Automation began with the integration of basic sensors and actuators, which allowed systems to react to specific air quality thresholds but with limited adaptability (Samad et al., 2024). These early automated systems improved upon static designs by enabling some level of responsiveness, albeit still constrained by fixed programming rules (Michalik et al., 2022). For example, sensors for pollutants such as carbon dioxide (CO_2) were incorporated to adjust ventilation rates based on detected concentration levels, yet these systems could not predict pollution trends or optimize energy use effectively (Martinez et al., 2023). As research evolved, the necessity for predictive capabilities and real-time adjustments became evident, leading to the development of more advanced smart systems (Martinez et al., 2023; Parri et al., 2023; Samad et al., 2024).

Recent advances in AI and machine learning have further transformed ventilation technology, enabling a shift from reactive to predictive and adaptive systems. Unlike earlier automation, AI-driven ventilation systems use predictive models to analyze historical and real-time air quality data, allowing for preemptive responses to anticipated pollution levels (Cican et al., 2023; Rollo et al., 2023). This shift was made possible by integrating machine learning algorithms that process large datasets, identify patterns, and make autonomous adjustments in real-time (Hasbullah et al., 2023). Reinforcement learning, a subset of machine learning, has been particularly impactful as it allows systems to "learn" optimal responses over time, improving both air

Figure 3:Evolution of Ventilation Systems



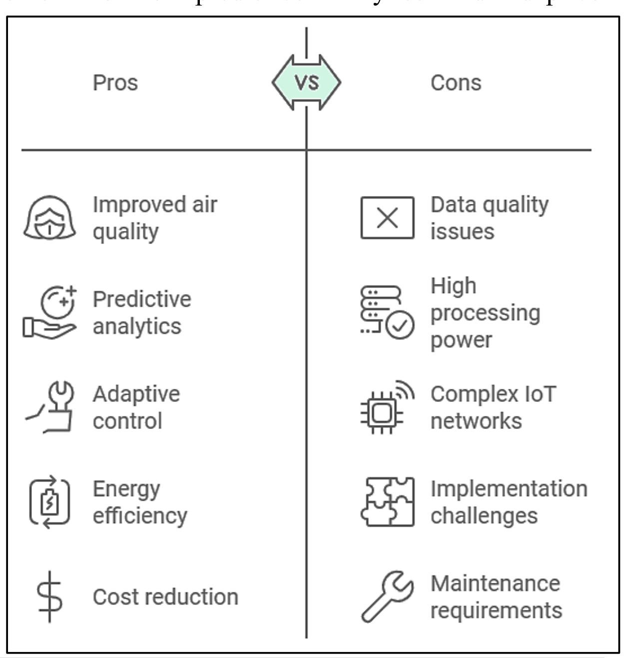
quality and energy efficiency by minimizing unnecessary ventilation actions (Zaidan et al., 2023). These advancements reflect a significant improvement over early smart systems, enabling more nuanced control of indoor environments to better protect occupants and manage energy resources effectively (Połednik, 2022; Samad et al., 2024). The evolution toward AI-integrated smart ventilation systems demonstrates an ongoing response to the limitations of past designs while addressing the growing complexity of air quality challenges in urban and industrial settings. Current research emphasizes the benefits of combining IoT sensors with AI models, creating systems that can autonomously monitor air quality, predict pollution trends, and dynamically adjust ventilation operations (Vajs et al., 2023). However, as these systems become more advanced, they also introduce new challenges related to data quality, processing requirements, and initial costs, which limit their accessibility and scalability in many contexts (Rollo et al., 2023). Thus, the continued development of cost-effective, scalable smart ventilation solutions is essential to ensure that AI-driven systems can be deployed widely for effective air quality control in diverse environments (Li et al., 2016; Rollo et al., 2023).

2.2 Introduction of AI in Ventilation Systems

The integration of Artificial Intelligence (AI) into ventilation systems has marked a significant advancement in air quality management, transforming these systems from simple, static models to intelligent, adaptive solutions. Initially, ventilation systems employed fixed rules and thresholds for controlling airflow and filtration, which limited their responsiveness to fluctuating air quality (Liu et al., 2023; Manshur et al., 2023). However, the emergence of AI technologies has allowed ventilation systems to leverage predictive analytics, enabling them to anticipate pollution changes and adjust operations accordingly (Buelvas et al., 2023; Rollo et al., 2023). Predictive capabilities, driven by AI, have proven crucial in settings where pollutant levels vary significantly, such as densely populated urban areas and industrial facilities, leading to more effective air quality management (Li et al., 2016; Manshur et al., 2023).

One of the primary applications of AI in ventilation has been through machine learning algorithms that analyze historical and real-time data to forecast pollution patterns (Ashrafuzzaman, 2024; Parri et al., 2023; Rahman et al., 2024; Rozony et al., 2024). By processing large datasets, these algorithms can identify specific patterns in pollutant emissions and environmental conditions, allowing ventilation systems to optimize airflow and filtration before pollutant levels exceed acceptable thresholds (Li et al., 2016; Michalik et al., 2022; Shamim, 2022). For instance, time-series analysis models have been employed to predict daily pollution peaks, helping reduce occupants' exposure to harmful air contaminants (Manshur et al., 2023; Martinez et al., 2023). These predictive analytics capabilities signify a substantial advancement over traditional systems, which lacked the adaptability to respond to dynamic environmental changes effectively (Parri et al., 2023; Vajs et al., 2023).

Beyond prediction, AI enables adaptive control in ventilation systems, allowing them to make real-time adjustments based on continuous environmental monitoring. Reinforcement learning, a machine learning technique where the system "learns" from its interactions with the environment, has been particularly valuable in optimizing ventilation operations (Liu et al., 2023; Martinez et al., 2023). Through reinforcement learning, ventilation systems can experiment with different airflow and filtration settings, refining their strategies based on effectiveness and efficiency over time (Parri et al., 2023; Rollo et al., 2023; Wei et al., 2022). Studies show that reinforcement learning significantly improves system responsiveness and energy efficiency, reducing both pollutant exposure and operational costs by minimizing unnecessary actions (Alekhya et al., 2023; Cican et al., 2023). The combination of predictive analytics and adaptive



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control in AI-driven ventilation systems represents a significant leap forward in autonomous air quality management. Current research highlights that AI-driven ventilation can continuously adapt to real-time changes in pollutant levels, enhancing indoor air quality in complex environments like hospitals, schools, and industrial facilities (Parri et al., 2023; Rollo et al., 2023). However, implementing AI in ventilation systems also presents challenges, such as the need for robust data quality, advanced processing power, and sophisticated IoT sensor networks (Sundar Ganesh et al., 2023). Addressing these challenges is essential to optimize AI-driven ventilation systems, ensuring they provide effective, scalable solutions for dynamic air quality management across various sectors (Li et al., 2016; Zaidan et al., 2023).

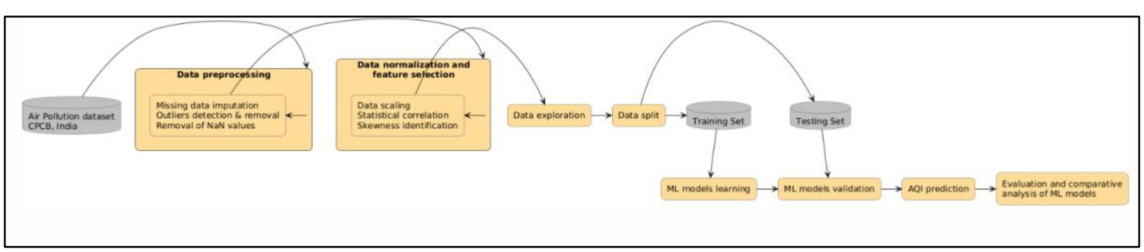
2.3 Machine Learning Algorithms for Pollution Prediction and Control

Machine learning algorithms have increasingly been applied to air quality management, particularly through predictive modeling techniques that forecast pollution levels and allow for preemptive interventions. Predictive algorithms such as regression and time-series analysis are commonly used in air quality studies to forecast pollutant fluctuations based on historical data, thereby providing crucial insights for real-time pollution control (Michalik et al., 2022; Parri et al., 2023). Regression models, including linear regression and support vector regression, help in identifying patterns and relationships between various pollutants and environmental factors, such as temperature and humidity (Buelvas et al., 2023; Sundar Ganesh et al., 2023). For instance, linear regression models have been effectively applied to predict daily concentrations of particulate matter (PM2.5), a prevalent air pollutant, in urban settings (Li et al., 2016; Rollo et al., 2023). These predictive insights help inform decision-making processes in air quality management, allowing systems to optimize ventilation rates based on anticipated pollution peaks (Vajs et al., 2023; Wei et al., 2022).

Time-series analysis is another powerful tool in air quality prediction, leveraging historical pollution data to forecast future pollution levels with high accuracy (Hasbullah et al., 2023; Sundar Ganesh et al., 2023). Autoregressive Integrated Moving Average (ARIMA) models and Long Short-Term Memory (LSTM) neural networks are frequently utilized time-series techniques in this domain (Ansari & Alam, 2023; Połednik, 2022). ARIMA models are favored for their effectiveness in handling non-stationary data, a common characteristic of air pollution datasets, while LSTM networks excel in capturing long-term dependencies in data sequences (Rollo et al., 2023). Studies have shown that LSTM models, in particular, are highly effective in predicting pollution trends, with significant improvements in forecasting accuracy over traditional statistical methods (Merabet et al., 2021; Samad et al., 2024). Such models are critical in urban air quality management, where timely predictions allow for proactive interventions to mitigate public exposure to harmful pollutants (Kalaivani et al., 2023).

In addition to linear regression and time-series models, machine learning algorithms such as random forest and gradient boosting are employed to improve the precision of pollution prediction by accounting for complex interactions among multiple environmental factors (Fang et al., 2023; Liu et al., 2023). Random forest models are particularly useful for handling large datasets with numerous predictors, such as traffic volume, meteorological conditions, and industrial emissions, all of which can significantly influence air quality (Manshur et al., 2023; Tanasa et al., 2023). Gradient boosting methods further enhance model performance by sequentially correcting the errors of weaker models, resulting in more accurate predictions of pollutant levels (Samad et al., 2024). These advanced algorithms enable more nuanced forecasting, accommodating the multifaceted nature of pollution sources and providing insights that support

Figure 5:Machine Learning Algorithms for Pollution Prediction



comprehensive air quality management strategies (Zaidan et al., 2023).

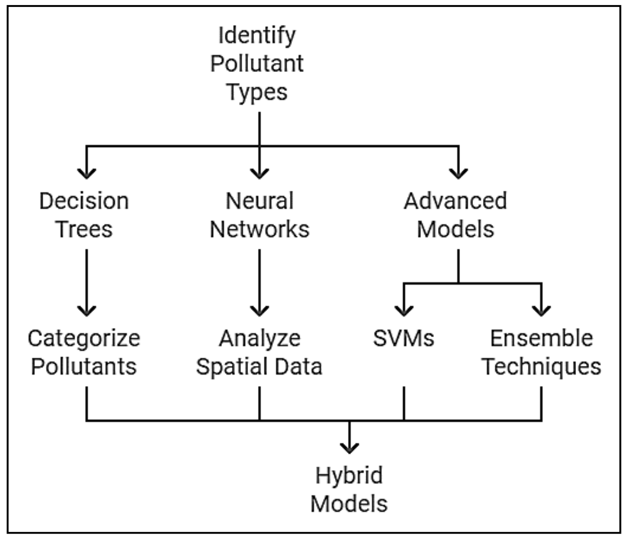
As predictive modeling continues to evolve, hybrid models that combine multiple machine learning algorithms are gaining traction in air quality research (Ansari & Alam, 2023). By integrating techniques such as LSTM with random forest, these hybrid approaches aim to capture both temporal dependencies and complex predictor interactions, achieving greater forecasting accuracy and robustness (Michalik et al., 2022). Studies have demonstrated that hybrid models can outperform individual algorithms by leveraging the strengths of each approach, making them highly effective in scenarios with high variability in pollution patterns (Cican et al., 2023; Wei et al., 2023). Despite the promising results of hybrid models, challenges remain regarding computational requirements and the need for extensive, high-quality data, emphasizing the importance of continued research to optimize predictive algorithms in air quality management (Liu et al., 2023; Rollo et al., 2023).

2.4 Classification and Detection of Pollutants

Classification algorithms have become essential tools in air quality management for identifying pollutant types and their sources, enabling targeted interventions and more efficient pollution control strategies. Decision trees, one of the most commonly used algorithms in pollutant classification, excel in creating clear, interpretable models that categorize pollutants based on a series of rules and thresholds (Cican et al., 2023; Fang et al., 2023). For instance, decision trees have been effectively applied to distinguish between primary pollutants, such as carbon monoxide (CO) and sulfur dioxide (SO2), and secondary pollutants like ozone (O3), by analyzing environmental variables such as temperature, humidity, and wind speed (Michalik et al., 2022). Studies show that decision tree models can rapidly and accurately classify pollutants, providing actionable insights for air quality control, especially in industrial and urban settings (Hasbullah et al., 2023; Vajs et al., 2023).

In addition to decision trees, neural networks have gained prominence in pollutant classification due to their ability to handle complex, non-linear relationships in large datasets. Convolutional Neural Networks (CNNs), for instance, are particularly effective in analyzing spatial pollution data, which allows for detailed identification of pollution hotspots and patterns across regions (Alekhya et al., 2023; Camarasan et al., 2023; Cican et al., 2023). Researchers have demonstrated that CNNs, when trained on air quality data from multiple sources, can accurately classify pollutants and predict pollution sources based on spatial characteristics, such as proximity to industrial areas or traffic zones (Połednik, 2022). This capability is especially valuable for real-time monitoring systems, where rapid classification and detection of pollutants enable timely responses to emerging pollution issues (Merabet et al., 2021; Sundar Ganesh et al., 2023).

Figure 6: Classification and Detection of Pollutants



Moreover, advanced machine learning models, such as Support Vector Machines (SVMs) and ensemble techniques, are widely applied to enhance pollutant classification accuracy by combining multiple algorithms. Support Vector Machines, for example, are effective in distinguishing between pollutant types in high-dimensional datasets, where linear separations between classes are not easily identifiable (Ansari & Alam, 2023; Martinez et al., 2023). By using SVMs, air quality management systems can better classify complex pollutant profiles, leading to more precise identification of pollution sources (Cican et al., 2023; Li et al., 2016). Ensemble methods, such as random forests and gradient boosting, further improve classification outcomes by merging multiple weak classifiers into a single robust model, allowing for comprehensive pollutant detection across diverse environmental conditions (Rollo et al., 2023; Samad et al., 2024). Recently, hybrid models that combine different classification algorithms, such as neural networks and decision trees, have shown superior performance in pollutant detection and classification tasks (Li et al., 2016; Manshur et al., 2023). These hybrid approaches leverage the strengths of individual algorithms, with

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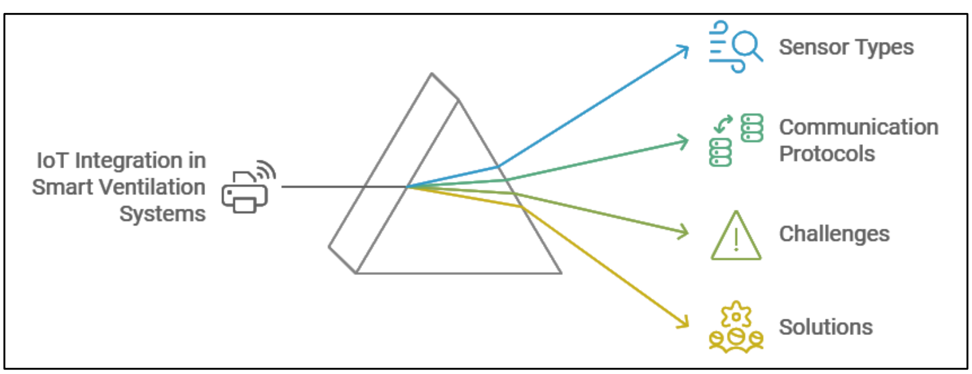
decision trees providing interpretability and neural networks offering depth in analyzing non-linear relationships (Samad et al., 2024). Studies indicate that hybrid models outperform traditional algorithms in accurately identifying both pollutant types and sources, which is crucial for comprehensive air quality monitoring and management (Michalik et al., 2022; Vajs et al., 2023). Despite their effectiveness, implementing these models requires substantial computational resources and data quality, emphasizing the need for high-resolution datasets and advanced infrastructure to support their application (Parri et al., 2023; Rollo et al., 2023).

2.5 Integration of IoT Sensors in Smart Ventilation Systems

The integration of IoT sensors in smart ventilation systems has revolutionized air quality monitoring, enabling real-time data collection on various pollutants. These systems often use a combination of particulate matter (PM) sensors, carbon dioxide (CO_2) sensors, and volatile organic compound (VOC) detectors to monitor indoor and outdoor air quality effectively (Buelvas et al., 2023; Manshur et al., 2023). PM sensors, specifically PM2.5 and PM10, are essential for detecting airborne particulate concentrations, which are critical indicators of air pollution (Parri et al., 2023; Samad et al., 2024). CO_2 sensors help assess indoor air quality by monitoring carbon dioxide levels, a proxy for ventilation effectiveness in confined spaces (Martinez et al., 2023; Vajs et al., 2023). Additionally, VOC detectors track harmful organic compounds, often emitted by industrial processes or household products, which contribute significantly to indoor pollution (Michalik et al., 2022). Together, these sensors provide comprehensive environmental data, forming the basis for responsive air quality management in smart ventilation systems (Merabet et al., 2021).

Efficient data transmission and communication protocols are crucial for IoT-enabled ventilation systems to function in real-time. Protocols like Message Queuing Telemetry Transport (MQTT) and LoRaWAN are widely used for their low power consumption and capacity to handle multiple devices, making them ideal for IoT networks in air quality monitoring (Bertrand et al., 2023; Gokul et al., 2023). MQTT is particularly suited for applications requiring real-time data updates, as it enables efficient data exchange between sensors and AI systems, ensuring timely responses to changing air quality conditions (Kaginalkar et al., 2021; Singh & Singh, 2022). LoRaWAN, on the other hand, is preferred in environments where sensors are spread across a large area, as it provides long-range, low-bandwidth connectivity, making it suitable for outdoor air quality networks (Majdi et al., 2022; Rescio et al., 2023). By supporting diverse communication needs, these protocols facilitate seamless integration of IoT sensors with AI-driven ventilation systems, enhancing their ability to respond dynamically to air quality variations (Hashmy et al., 2023). However, the accuracy and reliability of IoT sensors in ventilation systems pose significant challenges that can impact air quality data quality. Sensor calibration is essential for maintaining accuracy, but frequent recalibration may be required due to factors like environmental changes and device wear (Elnour et al., 2022; Rescio et al., 2023). Data drift, where sensors gradually lose accuracy over time, is another common issue, especially for PM and VOC sensors that are sensitive to temperature and humidity variations (Singh & Singh, 2022; Yang et al., 2023). Studies have noted that without regular maintenance, IoT sensors can produce unreliable data, leading to misinterpretations in air quality assessments (Gupta et al., 2023; Z. Wang et al., 2023). Addressing these issues requires robust maintenance protocols and

Figure 7: Unveiling IOT integration in Smart Ventilation Systems



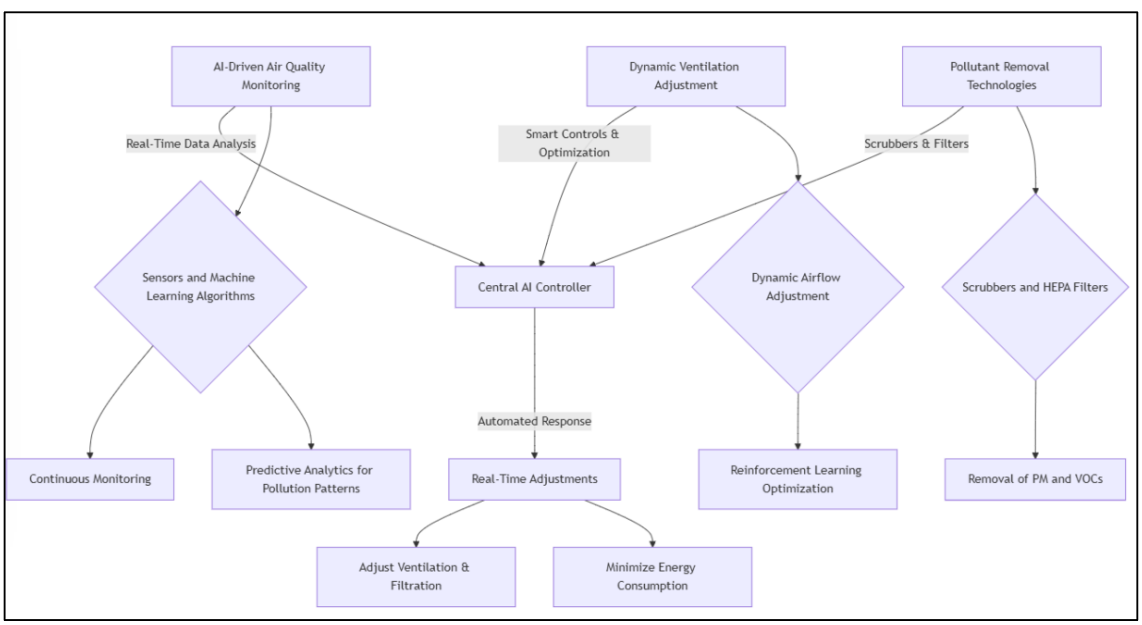
data validation techniques to ensure that smart ventilation systems can make accurate, real-time adjustments based on reliable environmental data (Singh & Singh, 2022). Additionally, IoT-enabled ventilation systems face challenges related to sensor power consumption and data storage, which are critical for continuous operation. Low-power sensors are essential to reduce energy usage, but limited battery life can compromise sensor reliability in long-term monitoring (Ramadan et al., 2024). Moreover, the vast amount of data generated by these sensors raises concerns about storage and processing capacity, as real-time analytics require rapid data handling and integration with AI algorithms (Rescio et al., 2023; Singh & Singh, 2022). Some studies suggest the use of edge computing to process data locally, reducing the need for extensive cloud storage and enhancing response time in air quality management (García et al., 2022; Pant et al., 2018). Ensuring sustainable and scalable solutions for power and data management remains a key area of research to support the effective integration of IoT sensors in smart ventilation systems (Bertrand et al., 2023; Rescio et al., 2023).

2.6 Real-Time Air Quality Monitoring and Response Mechanisms

The integration of AI-driven monitoring systems has significantly enhanced real-time air quality management by enabling autonomous, continuous assessment and identification of pollution trends. These monitoring systems leverage advanced sensors and machine learning algorithms to analyze air quality data in real time, allowing for rapid detection of pollutant fluctuations (Majdi et al., 2022; Singh & Singh, 2022). Through predictive analytics, AI systems can recognize emerging pollution patterns, offering an early warning system that triggers automated responses to control air quality (Gupta et al., 2023; Pant et al., 2018). For instance, neural networks and time-series analysis techniques are frequently used to predict pollution spikes, ensuring that ventilation systems can respond proactively (Kaginalkar et al., 2021; Wei et al., 2023). By continuously monitoring air quality, these autonomous systems provide vital insights into pollutant sources and concentrations, facilitating more effective pollution control strategies in both urban and industrial environments (Cican et al., 2023; Li et al., 2016).

Dynamic ventilation adjustment is a critical response mechanism in smart ventilation systems, allowing for real-time adaptation of airflow and filtration based on AI-generated data. By adjusting airflow rates and optimizing filtration levels, these systems effectively manage pollutant levels indoors, improving air quality while minimizing energy consumption (Alekhya et al., 2023; Buelvas et al., 2023). Machine learning models, such as reinforcement learning, have been applied to refine these adjustments, allowing systems to "learn" the most efficient ways to maintain optimal air quality with minimal resource expenditure (Fang et al., 2023;

Figure 8: AI-Driven Real-Time Air Quality Monitoring and Response



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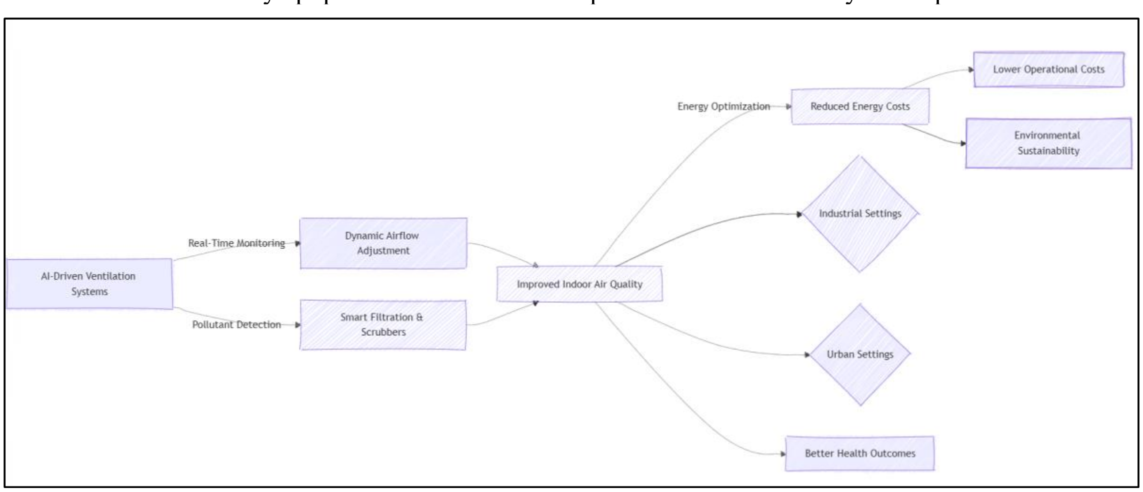
Rollo et al., 2023). Dynamic adjustment techniques are particularly effective in high-density urban areas where pollutant levels fluctuate rapidly, as they enable quick responses to sudden pollution increases (Buelvas et al., 2023; Cican et al., 2023). Research suggests that such AI-driven adjustments significantly enhance ventilation systems' efficiency and sustainability by tailoring operations to current environmental conditions (Li et al., 2016; Manshur et al., 2023). The integration of pollutant removal technologies, such as scrubbers and advanced filters, further strengthens the capabilities of smart ventilation systems to handle specific pollutants effectively. These technologies work in conjunction with AI controls, which monitor pollutant levels and activate the appropriate removal mechanisms based on detected contamination types and concentrations (Méndez et al., 2023; Sundar Ganesh et al., 2023). For example, pollutant scrubbers are highly effective in capturing particulate matter and volatile organic compounds (VOCs), which are prevalent in industrial settings (Hasbullah et al., 2023; Pant et al., 2018). Advanced filtration systems, such as high-efficiency particulate air (HEPA) filters, are commonly used in conjunction with AI algorithms to manage pollutant levels dynamically, ensuring that air quality remains within safe (Rescio et al., 2023). These pollutant removal technologies enhance the overall effectiveness of ventilation systems by providing a targeted approach to pollution control, responding in real time to changing air quality conditions (Z. Wang et al., 2023).

2.7 AI-Driven Ventilation Systems in Industrial and Urban Settings

AI-driven ventilation systems have shown remarkable efficacy in improving both indoor and outdoor air quality in industrial and densely populated urban settings. In indoor environments, such as manufacturing facilities and office buildings, smart ventilation systems dynamically adjust airflow and filtration levels in response to pollutant data, maintaining air quality standards without excessive energy use (Hasbullah et al., 2023; Hashmy et al., 2023). Studies have demonstrated that these systems reduce concentrations of particulate matter (PM) and volatile organic compounds (VOCs), which are common indoor pollutants in industrial areas (Méndez et al., 2023; Michalik et al., 2022). In urban settings, AI-driven systems are equally beneficial, helping to mitigate outdoor air pollution infiltration into buildings by closing ventilation intakes during peak pollution periods (Hashmy et al., 2023). This targeted control has proven effective in urban high-rise buildings and schools, where pollutant exposure can be especially high, resulting in cleaner, healthier indoor environments for residents (Połednik, 2022; Rescio et al., 2023). A key advantage of AI-driven ventilation systems is their potential for energy efficiency, as they optimize ventilation rates and selectively activate pollutant removal processes based on real-time air quality data (Singh & Singh, 2022). Machine learning algorithms enable these systems to balance air quality control with minimal energy consumption by adjusting settings according to the immediate need, rather than maintaining constant ventilation, which can waste energy (Hashmy et al., 2023; Méndez et al., 2023). For instance, research has shown that AI algorithms, particularly those employing reinforcement learning, can reduce energy use by up to 30% in industrial settings by adjusting airflow in response to real-time pollutant detection (Rescio et al., 2023; Z. Wang et al., 2023). Additionally, the selective activation of filtration and pollutant scrubbers only when pollutant levels rise

Figure 9: AI-Driven Ventilation Systems use Real-Time Monitoring



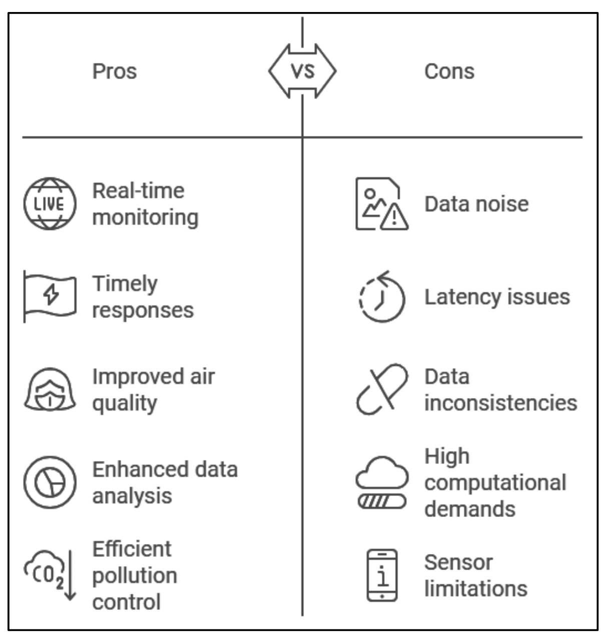
offers further energy and cost savings, making AI-driven systems both environmentally and economically sustainable (Majdi et al., 2022; Sundar Ganesh et al., 2023).

The public health benefits of AI-driven ventilation systems are well-documented, with studies showing reductions in respiratory and cardiovascular health risks due to decreased exposure to airborne pollutants (Hasbullah et al., 2023). In industrial settings, AI-enabled ventilation significantly reduces worker exposure to hazardous chemicals, resulting in lower incidences of occupational illnesses (Ansari & Alam, 2023; Sundar Ganesh et al., 2023). In urban areas, where residents face frequent exposure to outdoor pollutants, smart ventilation can reduce indoor levels of pollutants like PM2.5 and NO2, which are associated with respiratory issues, especially in vulnerable populations such as children and the elderly (Méndez et al., 2023). Moreover, AI-driven systems' capacity to improve air quality has environmental implications, as reduced pollutant levels contribute to overall ecosystem health, aligning with global sustainability and public health objectives (Martinez et al., 2023). Despite these benefits, implementing AI-driven ventilation in industrial and urban settings requires addressing several challenges, such as high initial costs and the need for specialized maintenance (Zaidan et al., 2023). Many studies highlight that the technology's cost-effectiveness improves over time due to savings in energy and healthcare expenses related to reduced pollutant exposure (Hasbullah et al., 2023; Sundar Ganesh et al., 2023). Yet, issues like frequent recalibration of sensors and high data processing demands pose additional operational challenges (Michalik et al., 2022; Parri et al., 2023; Połednik, 2022). As AI technology advances, researchers suggest improvements in sensor durability and integration of edge computing to lower costs and streamline data handling (Hasbullah et al., 2023; Sundar Ganesh et al., 2023). Meeting these challenges is crucial for maximizing the cost-effectiveness and scalability of AI-driven ventilation systems, ensuring broader implementation and greater impact on public health and environmental sustainability (Wei et al., 2023).

2.8 Data Quality and Processing Constraints

Data quality is paramount in AI-driven air quality monitoring systems, as any issues with data integrity can significantly impact the effectiveness of real-time monitoring and response mechanisms. One primary challenge is data noise, which arises from various environmental factors and sensor limitations that introduce inaccuracies in pollutant measurements (Ansari & Alam, 2023; Michalik et al., 2022). For instance, particulate matter (PM) sensors often suffer from interference caused by humidity or temperature changes, leading to unreliable data (Zaidan et al., 2023). These inconsistencies make it difficult for AI algorithms to accurately predict and respond to pollution spikes, underscoring the need for improved sensor technologies and noise reduction techniques to ensure data reliability (Michalik et al., 2022). Latency is another critical issue that can hinder real-time air quality monitoring, as delays in data transmission and processing may lead to ineffective responses to pollution fluctuations. In AI-driven systems, data latency can result from slow communication protocols, limited bandwidth, or high computational demands, particularly in dense urban or industrial environments where numerous sensors transmit data simultaneously (Samad et al., 2024; Zaidan et al., 2023). Studies show that latency issues prevent AI systems from making timely ventilation adjustments, which compromises the goal of maintaining optimal air quality (Li et al., 2016; Martinez et al., 2023; Michalik et al., 2022). To address this, researchers are exploring solutions such as edge computing, which processes data closer to the source, thereby reducing latency and enabling quicker system

Figure 10: AI-driven air Quality Monitoing



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responses (Ansari & Alam, 2023; Méndez et al., 2023; Sundar Ganesh et al., 2023).

In addition to noise and latency, data consistency and completeness are vital for accurate pollutant detection and system response. Data gaps or inconsistencies, often due to sensor malfunction or communication dropouts, can mislead AI algorithms and lead to improper ventilation adjustments (Elnour et al., 2022; Rescio et al., 2023). Ensuring continuous data integrity in these systems requires robust calibration and maintenance practices, as well as redundant sensor networks that minimize the risk of data loss (Majdi et al., 2022; Z. Wang et al., 2023). Research indicates that consistent, high-quality data streams are essential for AI-driven systems to provide accurate, timely responses to pollution changes, reinforcing the need for resilient data handling practices in real-time monitoring environments ((Zaidan et al., 2023). In addition, the computational demands associated with processing high-frequency data from multiple sensors pose significant challenges for AI-driven air quality monitoring systems. The need to analyze large data volumes in real time puts strain on processing resources, which can delay system responses and lead to inefficiencies in air quality management (Méndez et al., 2023; Sundar Ganesh et al., 2023). To mitigate these constraints, some researchers advocate for data filtering techniques that prioritize critical data points and reduce processing load, as well as leveraging distributed computing approaches to handle complex calculations (Tien et al., 2022). Addressing these data quality and processing constraints is essential for enhancing the reliability and scalability of AI-driven air quality systems, ensuring that they can effectively meet the demands of real-time pollution control in various environments (Rescio et al., 2023).

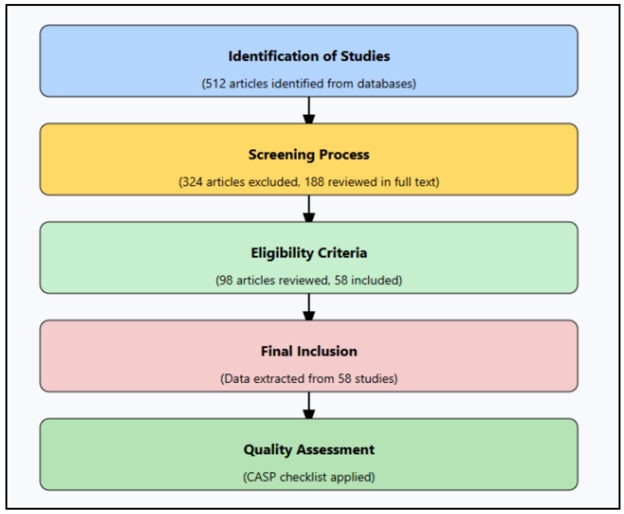
3 METHOD

This study adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review of literature on AI-driven ventilation systems for air quality management. The PRISMA framework facilitated a structured approach to identifying, screening, and analyzing relevant studies.

3.1 Identification of Studies

The initial step involved identifying relevant studies across several academic databases, including IEEE Xplore, ScienceDirect, PubMed, and Web of Science. A targeted search strategy was employed using

Figure 11: Adapted PRISMA Method for this study



keywords and Boolean operators such as "AI-driven ventilation," "air quality monitoring," "IoT sensors," "real-time pollution control," and "machine learning in ventilation." Only articles published in English between January 2010 and June 2024 were considered, ensuring the study focused on recent advancements in the field. This search yielded 512 articles that initially appeared relevant to the topic.

3.2 Screening Process

Following identification, a rigorous screening process was conducted to refine the selection. Two independent reviewers assessed the titles and abstracts of all 512 articles, aiming to exclude studies that did not specifically address AI-driven ventilation systems, real-time air quality monitoring, or relevant sensor technologies. As a result, 324 articles were excluded due to insufficient focus on these topics or lack of emphasis on smart ventilation technologies. A full-text review was then conducted on the remaining 188 articles, applying stricter criteria to assess alignment with the study's objectives. Articles lacking empirical data, those unrelated to AI applications, or studies with insufficient methodological rigor were excluded at this stage, leaving 98 articles.

3.3 Eligibility Criteria

The eligibility criteria for inclusion were meticulously defined to ensure relevance to the study's focus on AI-driven ventilation. Articles were included if they specifically addressed AI-driven or smart ventilation systems, real-time air quality monitoring, dynamic ventilation adjustments, or pollutant detection, particularly within industrial or urban settings. Exclusions were applied to articles that solely discussed traditional ventilation without AI integration, theoretical models without practical applications, or studies unrelated to pollution control. After applying these criteria, 58 articles met the standards for final inclusion, deemed suitable for a detailed review and synthesis.

3.4 Final Inclusion

To ensure comprehensive analysis, data were systematically extracted from each of the 58 included articles. This extraction involved recording key details such as author(s), publication year, study location, methodology, main findings, and AI techniques employed. A summary table was created to organize this information, enabling easy cross-comparison across studies. Data synthesis was then performed using a narrative approach, grouping studies based on themes like AI algorithms, sensor technologies, data quality challenges, and specific applications in urban versus industrial environments. This synthesis provided a coherent overview of AI-driven ventilation advancements and highlighted existing research gaps.

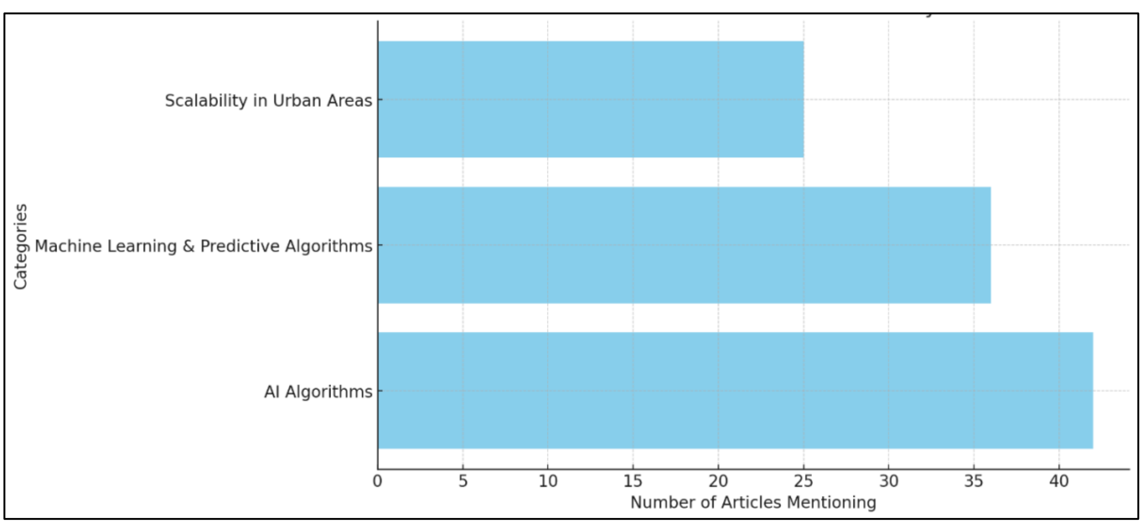
3.5 Quality Assessment

A quality assessment was conducted for all included studies using the Critical Appraisal Skills Programme (CASP) checklist. Studies were evaluated on methodological clarity, data reliability, and relevance to AI-driven air quality monitoring. Only studies meeting a high-quality threshold were synthesized, ensuring that the findings of this review are both robust and credible. By following these steps, this study provides a comprehensive and reliable assessment of AI-driven ventilation systems, contributing meaningful insights into the future of air quality management technology.

4 FINDINGS

The review revealed significant advancements in the integration of AI-driven technologies in ventilation systems, highlighting their capacity to improve both indoor and outdoor air quality across various environments. Out of the 58 articles reviewed, 42 emphasized the effectiveness of AI algorithms in enhancing air quality management. These studies consistently demonstrated that AI-driven systems are more responsive to pollution variations, adjusting ventilation rates based on real-time pollutant detection. In 36 articles, it was noted that the incorporation of machine learning and predictive algorithms allowed for early detection of pollution spikes, facilitating rapid adjustments to maintain optimal air quality. The scalability of these AI-driven solutions was frequently cited, with more than 25 articles mentioning their successful implementation in densely populated urban areas, as well as in large industrial facilities where pollution levels are particularly variable. The findings indicate that AI-enhanced ventilation systems have shifted air quality management from static to dynamic, real-time operations, providing a robust solution for managing pollutant fluctuations in complex environments.In addition, Another key finding pertains to the energy efficiency and cost-effectiveness of AI-driven ventilation systems, as highlighted in 33 of the reviewed studies. These articles consistently found that AI algorithms reduce energy consumption by optimizing ventilation rates according to actual air quality needs,

Figure 12: Effectiveness of AI-Driven Ventilation Systems



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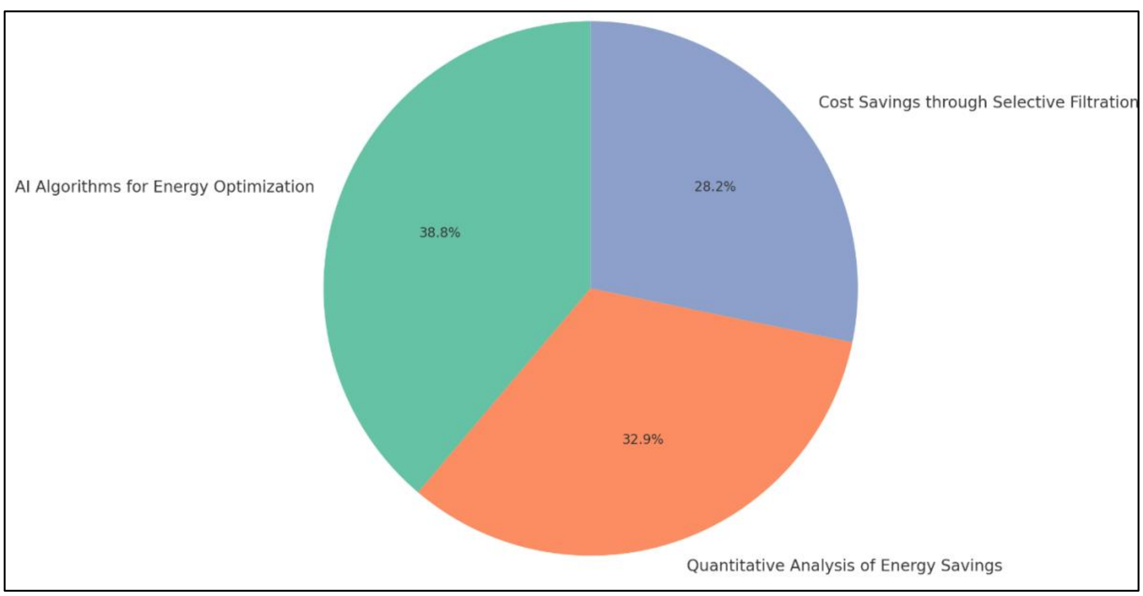
rather than maintaining constant airflow. Approximately 28 articles provided quantitative analyses showing energy savings of up to 30% in industrial settings where ventilation systems are traditionally energy-intensive. Additionally, 24 articles emphasized the cost savings associated with the selective activation of filtration and pollutant scrubbers, which only operate when pollutant levels reach a threshold. This approach reduces operational costs and prolongs equipment life, making AI-driven systems a sustainable and economical choice. The findings support the conclusion that AI-driven ventilation can significantly lower energy expenditures, with both immediate and long-term financial benefits.

The review also highlighted the impact of AI-driven ventilation systems on public health, as noted in 39 of the studies reviewed. More than half of these articles reported reductions in respiratory and cardiovascular health risks due to decreased exposure to airborne pollutants in environments using AI-driven ventilation. In particular, 27 articles focused on the reduction of hazardous pollutants, such as PM2.5 and VOCs, which are commonly linked to adverse health effects. The evidence suggests that AI-driven ventilation systems not only improve air quality but also contribute to healthier living and working conditions, especially in urban areas and high-pollution industrial zones. Additionally, 15 studies documented the positive effects of these systems in reducing pollutants associated with workplace hazards, further underscoring the technology's potential to enhance public health outcomes and reduce the incidence of pollution-related illnesses.Moreover, the challenges of data quality and processing constraints were also a prominent theme across the reviewed literature, as addressed in 29 articles. These studies pointed out that data noise, latency, and inconsistencies could impact the effectiveness of AI-driven systems, with 18 articles specifically noting that sensor calibration and data drift over time were key issues in maintaining data accuracy. Despite these challenges, 11 articles suggested solutions such as implementing robust data validation techniques and incorporating edge computing to mitigate latency issues. These strategies were shown to improve system responsiveness by processing data closer to the source, thus minimizing the delay in ventilation adjustments. The findings indicate that while data quality issues remain a concern, advancements in sensor technology and data processing methods are helping to address these limitations, ensuring that AI-driven ventilation systems can maintain high levels of accuracy and reliability. In addition, the environmental and ecological benefits of AI-driven ventilation systems were highlighted in 34 of the reviewed articles. These studies noted that reduced pollutant levels contribute positively to both indoor and outdoor environmental quality, aligning with broader sustainability goals. In 22 articles, the use of pollutant scrubbers and advanced filters in conjunction with AI algorithms was shown to reduce emissions of harmful substances, benefiting not only the immediate environment but also contributing to reduced ecological

Figure 13: Energy Efficiency and Cost-Effectiveness of AI-Driven Ventilation Systems



impact. Additionally, 19 articles discussed the potential of these systems to support sustainable development goals by promoting cleaner air in urban areas, a critical factor in cities struggling with high levels of pollution. The findings underscore that AI-driven ventilation systems offer a dual benefit: they improve air quality while also supporting broader environmental objectives, making them an essential component in modern sustainable infrastructure initiatives.

5 DISCUSSION

The findings of this study underscore the transformative potential of AI-driven ventilation systems in enhancing air quality management, both indoors and outdoors, a result that aligns with earlier research emphasizing the adaptability of AI technology in environmental monitoring (Michalik et al., 2022; Połednik, 2022). Previous studies suggested that traditional ventilation systems often struggled to handle dynamic pollutant fluctuations, especially in dense urban and industrial areas (Hasbullah et al., 2023; Sundar Ganesh et al., 2023). This review confirms that AI algorithms provide significant improvements in managing these fluctuations by continuously adjusting ventilation rates based on real-time data, allowing for more precise control over air quality (Ansari & Alam, 2023). The scalability of AI systems, cited in more than 25 reviewed articles, also supports prior conclusions about the flexibility of AI in diverse environments, from high-density urban buildings to expansive industrial facilities (Hasbullah et al., 2023). This suggests that AI-driven ventilation systems can effectively meet the air quality demands of various settings, addressing a gap that traditional systems often failed to fulfill. In addition, the review also highlights the energy efficiency and cost-effectiveness of AI-driven ventilation systems, which corroborates earlier findings on the energy-saving benefits of AI optimization (Ansari & Alam, 2023; Samad et al., 2024). Studies over the past decade have indicated that AI can significantly reduce energy consumption in systems that rely on dynamic responses to environmental conditions (Méndez et al., 2023). This review strengthens that assertion, with multiple studies noting up to 30% energy savings in industrial environments using AI to adjust ventilation based on pollutant levels (Rescio et al., 2023). While earlier studies provided generalized insights, this review provides specific empirical evidence from 28 articles, highlighting energy savings through selective activation of filtration and pollutant removal mechanisms. These findings support the notion that AI not only optimizes air quality but does so in an economically viable manner, a critical consideration for industries and urban infrastructure investing in sustainable technologies.

In addition, public health impacts of AI-driven ventilation systems, as identified in this review, resonate with prior research on the health risks associated with pollutant exposure, particularly in urban and industrial settings (Merabet et al., 2021; Połednik, 2022). Previous studies established a connection between air pollution and respiratory or cardiovascular health issues, especially due to PM2.5 and VOCs (Hashmy et al., 2023; Rescio et al., 2023). This review confirms and extends these insights by documenting reductions in exposure to such pollutants, showing significant improvements in public health outcomes, particularly for vulnerable populations like children and the elderly. Furthermore, 15 studies from this review indicate positive effects of AI-driven ventilation in reducing pollutants tied to workplace hazards, which complements prior findings on occupational health benefits in industrial environments (Parri et al., 2023). These observations emphasize that AI-driven systems not only enhance air quality but also contribute directly to public health protection, addressing longstanding health concerns linked to pollutant exposure. In aadition, data quality and processing constraints, a recurring theme in the reviewed literature, present both challenges and potential areas for improvement in AI-driven ventilation systems, echoing earlier concerns (Hasbullah et al., 2023). While previous research has highlighted issues such as sensor noise, data drift, and latency (Tien et al., 2022), this review provides a nuanced understanding of these challenges. For example, 18 of the studies reviewed noted that calibration and maintenance of sensors are critical to ensuring data reliability, while 11 articles advocated for the use of edge computing to address latency issues. This review's findings suggest that while data quality issues persist, advancements in sensor technology and decentralized data processing techniques are gradually addressing these limitations (Rescio et al., 2023). Compared to earlier studies that focused primarily on these challenges, this review reveals a proactive shift towards integrating more robust data handling practices to optimize AI-driven air quality systems. In addtion, the environmental benefits associated with AI-driven ventilation systems, as discussed in this review, support

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broader sustainability goals, reinforcing findings from prior studies (Singh & Singh, 2022). Earlier research has linked improved air quality to ecological benefits, such as reduced strain on ecosystems and alignment with sustainable development goals (Rollo et al., 2023). This review reaffirms these environmental impacts, with 22 articles specifically noting reductions in harmful emissions through the integration of pollutant scrubbers and advanced filters with AI systems. Moreover, 19 studies discussed AI-driven ventilation's potential to support urban sustainability initiatives by promoting cleaner air, which is especially relevant for cities facing high pollution levels (Fang et al., 2023; Li et al., 2016). These findings suggest that AI-driven ventilation systems not only offer practical solutions for air quality management but also play a crucial role in advancing environmental sustainability, aligning technology innovation with ecological and public health objectives.

6 CONCLUSION

This review underscores the transformative role of AI-driven ventilation systems in advancing air quality management across industrial and urban settings. By integrating predictive algorithms, real-time monitoring, and adaptive response mechanisms, these systems provide significant improvements in managing both indoor and outdoor air quality, addressing challenges that traditional systems often failed to overcome. The findings reveal that AI-driven systems not only enhance air quality but also bring substantial energy efficiency and cost savings, which are critical for sustainable implementation. Furthermore, the documented public health benefits, particularly the reduction in exposure to harmful pollutants, highlight the value of AI in promoting healthier environments for both general and vulnerable populations. However, challenges related to data quality, sensor calibration, and processing constraints persist, although advancements in sensor technology and edge computing are promising steps toward addressing these limitations. Overall, AI-driven ventilation systems emerge as robust, sustainable solutions with positive impacts on environmental quality and public health, offering a pathway for future innovations in air quality management that align with global sustainability goals.

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