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Improving the Air Quality Monitoring Framework Using Artificial Intelligence for Environmentally Conscious Development

Danny Manongga [1], Untung Rahardja [2], Irwan Sembiring [1], Qurotul Aini [3*], Abdul Wahab [4]

[1] *Department of Information Technology, Satya Wacana Christian University, Salatiga, 50711, Indonesia.*

[2] *Department of Engineering, University of Technology Malaysia, Johor, 81310, Malaysia.*

[3] *Department of Digital Business, University of Raharja, Tangerang, 15117, Indonesia.*

[4] *Kulliyah of Information and Communication Technology, International Islamic University Malaysia, Kuala Lumpur, 53100, Malaysia.*

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Abstract

This study aims to significantly improve air quality monitoring through the innovative application of Artificial Intelligence (AI). Introducing the Artificial Intelligence Kualitas Udara (AIKU) model, this research offers a novel approach by integrating advanced machine learning algorithms with environmental sensors to predict air quality in real-time more accurately than traditional methods. The novelty of the AIKU model lies in its sophisticated data analytics framework, which processes high-frequency environmental data to assess air quality changes dynamically. The technique employs calibrating and deploying the AIKU model across various urban and suburban settings and analyzing its performance against conventional monitoring systems such as the Internet of Things (IoT) and Wireless Sensor Networks (WSNs). The results demonstrate that AIKU significantly outperforms these traditional systems in both accuracy and speed of response, highlighting its effectiveness in real-time environmental monitoring. Furthermore, the AIKU model's scalability and adaptability are tested, showing promising potential for application in densely populated urban areas and less populated rural settings. This research contributes to environmental monitoring by demonstrating how AI can transform traditional methodologies into more effective, scalable, and intelligent ecological management systems. This research provides substantial evidence that the AIKU model can serve as a powerful tool for sustainable and smart development worldwide, enhancing the ability of governments and organizations to respond to environmental challenges promptly and effectively.

Keywords: Artificial Intelligence (AI); Air Quality; Middleware; AIKU; Environmentally Conscious.

1. Introduction

The sustainable growth of our world hinges on a multitude of pivotal factors, among which the environment stands as a cornerstone. Air pollution, in particular, is an escalating global concern with far-reaching impacts on human health and the ecological balance. Deteriorating air quality, especially in densely populated urban centers, calls for urgent and substantial improvements to safeguard public health and the environment. Figure 1 casts a stark light on this pressing issue, ranking air pollution as the third leading risk factor for death globally in 2019. The gravity of this issue is especially pronounced in Indonesia, where rapid growth and dense urbanization in cities like Jakarta lead to severe air pollution problems. Despite Indonesia's ongoing environmental efforts since the 1980s, substantial challenges remain, although

* Corresponding author: aini@raharja.info

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initiatives such as the ADIPURA program signal progress toward cleaner, greener cities, in line with the European Union's vision of 'intelligent cities. Building on these initiatives, our research adopts adaptive environmental management and predictive analytics paradigms to enhance air quality monitoring [1, 2]. In expanding our theoretical approach, this research draws upon the paradigms of adaptive environmental management and predictive analytics in air quality monitoring. Recognizing the complex and dynamic nature of urban pollution, the AIKU model incorporates a multifaceted theoretical framework that leverages both real-time data and historical trends to predict air quality levels. The model integrates principles from systems theory and machine learning to create a robust predictive tool that can adjust to changing environmental conditions without human intervention [3, 4]. This approach is underpinned by the theory of intelligent systems, which posits that integrating learning algorithms within environmental monitoring tools can significantly enhance their predictive accuracy and operational efficiency. By adopting this advanced theoretical framework, AIKU aims to not only monitor but also predict and manage air quality in real time, reflecting a shift from reactive to proactive environmental management.

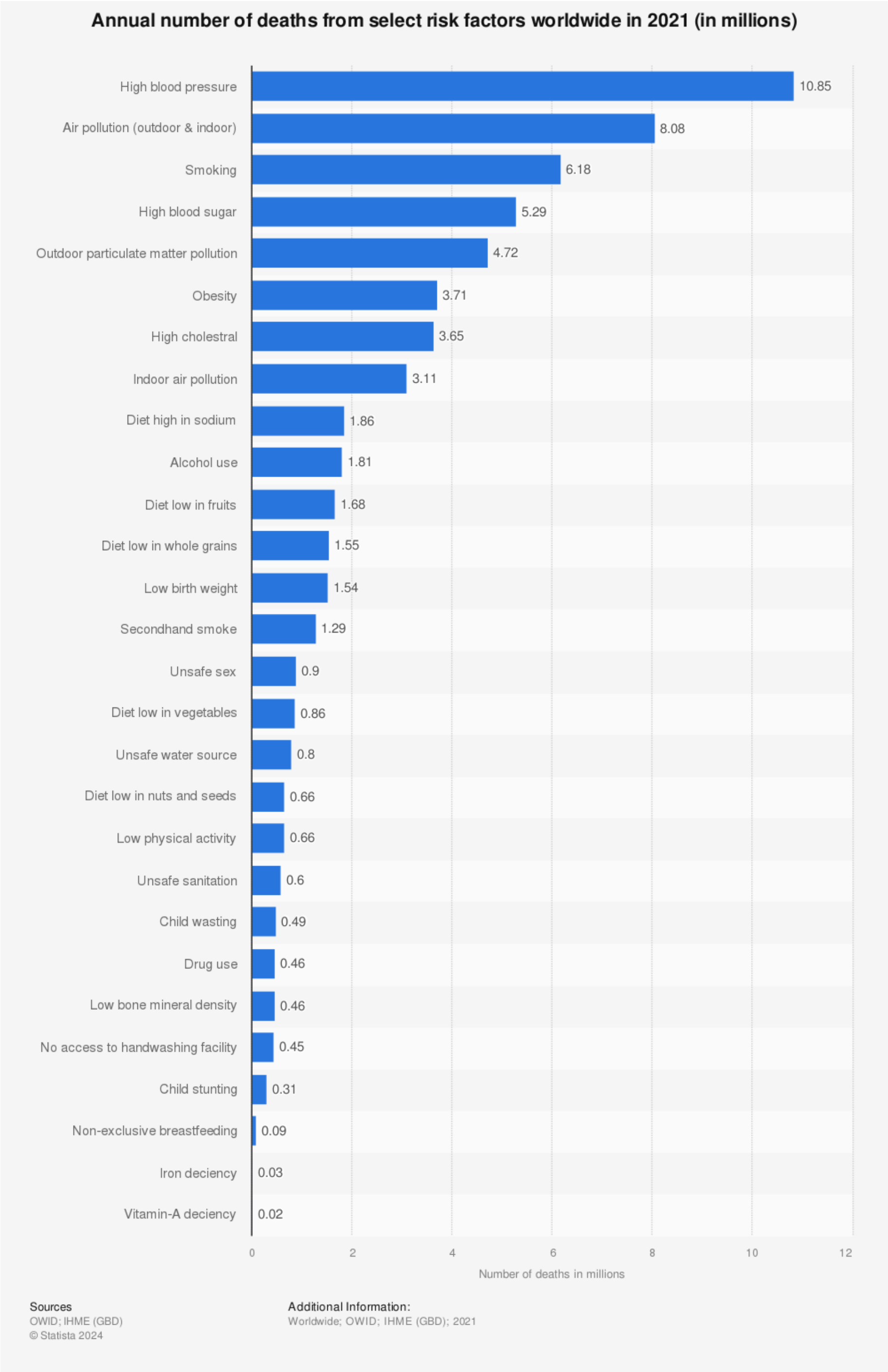

Figure 1. Global ranking of risk factors by total deaths from all causes in 2019*

* *Source: https://www.statista.com/statistics/1169367/worldwide-number-deaths-risk-factor/*

While extensive efforts have been made globally to monitor and mitigate air pollution, significant gaps remain in the ability to monitor air quality in real-time with high accuracy and predict future conditions effectively. Traditional air quality monitoring systems often rely on static, periodic measurements that fail to capture rapid changes in environmental conditions, leading to delays in data processing and response. The primary goal of this research is to address these critical gaps by developing the Artificial Intelligence Kualitas Udara (AIKU) model. This model leverages advanced machine learning algorithms to enhance the precision and timeliness of air quality monitoring. The AIKU model aims to provide real-time, predictive insights into air quality that can inform more effective environmental management strategies. Specifically, this research seeks to: 1) Demonstrate the superiority of AI-driven systems over traditional monitoring methods in terms of response speed and data accuracy; 2) Explore the model's effectiveness across different environmental settings, including urban and rural areas; and 3) Evaluate the potential of AI-enhanced monitoring systems to contribute to sustainable urban development and public health.

Underpinning this research are four pivotal contributions that encapsulate its significance: (i) the critical role of optimal middleware implementation in enhancing the performance and efficiency of the AIKU framework, (ii) the groundbreaking introduction of the AIRXR algorithm, representing a substantial leap forward in air quality prediction, showcasing impressive results with promising high accuracy, (iii) the advancement in prediction speed within the AIKU framework, enabling swift responses to address air pollution, and (iv) the innovation embedded in the AIKU framework, promising significant societal benefits by proficient monitoring and predicting air quality within an intelligent environment, showcasing extraordinary performance. This research represents a technological advancement and demonstrates the potential for practical applications to improve people’s health and well-being.

The structure of this paper unfolds as follows: Section 2 meticulously presents an in-depth literature review on Artificial Intelligence-based air quality monitoring, elucidating its role in heightening environmental awareness. Section 3 introduces the AIKU framework, AIRXR Algorithm, and AIKU Middleware. In Section 4, we show-case the implementation of the AIRXR algorithm in the context of the AI integration development problem, diminishing reliance on third parties refining the employed methodology and providing valuable insights and implications for the algorithm’s effectiveness. Lastly, Section 5 integrates conclusions, a comprehensive discussion of the findings, and identifies research limitations as potential directions for future work.

2. Literature Review

Air quality stands as a crucial determinant of environmental well-being, exerting a direct influence on both human health and ecosystems. Unfortunately, conventional monitoring systems frequently prove inadequate in delivering up-to-the-minute and thorough data, thus impeding effective environmental management. The infusion of AI into air quality monitoring frameworks emerges as a beacon of hope, poised to overcome these limitations and empower more informed and timely decision-making in the pursuit of environmentally conscious development.

2.1. Advancements in Air Quality Monitoring Framework

Air quality has emerged as a critical human survival issue. Various approaches have been undertaken to address this concern, ranging from the traditional method of employing static sensors and manual data collection, which has inherent spatial limitations and results in delayed insights. Air quality frameworks have recently been developed to incorporate amperometric sensors to meet the demand for lower-cost solutions [5]. However, these frameworks have limitations, as inexpensive gas sensors may struggle to detect deficient gas concentrations crucial for monitoring air pollutants within safe levels. The shortcomings of conventional air quality monitoring, characterized by static sensors and manual data collection methods, have prompted the need for a revolutionary shift [6, 7]. Our innovative framework aims to overcome these limitations by integrating AI-driven sensors and advanced data analysis techniques [8]. This integration represents a paradigm shift towards continuous and dynamic monitoring, providing a comprehensive understanding of air quality fluctuations on a broader scale.

In contrast to traditional static monitoring systems, which often fail to capture the intricate dynamics of air quality variations, our research seeks to transcend these limitations through the progressive evolution of the framework. This evolution is driven by incorporating AI-driven sensors and a commitment to continuous monitoring. The ultimate objective is to present a holistic panorama of air quality dynamics, fostering a more enlightened and comprehensive understanding of environmental nuances. This forward-looking approach is poised to revolutionize the field, ensuring more timely and accurate insights into the ever-changing air quality landscape.

2.2. Artificial Intelligence Empowering Air Quality Monitoring

With recent strides in science and technology, particularly in machine learning, endeavours to innovate air quality monitoring have emerged, capitalizing on integrating the IoT and WSNs [9, 10]. These cutting-edge technologies have transformed the landscape of data collection and analysis of air pollution. Nevertheless, amid these advancements, certain limitations warrant attention [11]. A noteworthy constraint lies in the coverage and density of sensor networks, as some areas may suffer from inadequate monitoring nodes, resulting in data collection gaps. Furthermore, the reliability of sensor data and the imperative for continuous calibration present ongoing challenges [12] that impede the precision of air quality assessments. So, this study aims to address these challenges by steering efforts towards formulating a comprehensive framework. The primary focus is the strategic infusion of AI to augment the existing monitoring infrastructure. Integrating AI technologies aims to elevate data analysis, interpretation, and decision-making process proficiency. AI is poised to be pivotal in refining sensor data accuracy, automating calibration procedures, and bridging data voids through predictive modelling. Moreover, incorporating machine learning algorithms promises to intelligently manage sensor networks, optimize their deployment, and ensure efficient coverage [13, 14].

The envisioned framework is more than merely geared toward surmounting existing limitations. It aspires to build an adaptive and self-enhancing air quality monitoring system. This forward-looking approach marks a significant stride in leveraging the potential of AI to establish a resilient and responsive infrastructure for monitoring and managing air quality, thereby fostering healthier and more sustainable urban environments.

2.3. Environmental Consciousness

Emphasizing environmentally conscious development is in harmony with the over-arching objectives of sustainable practices [15]. This research strives to provide decision-makers with prompt and precise information to facilitate well-informed policy formulation by incorporating an AI-enhanced air quality monitoring framework [16]. Doing so contributes to advancing sustainable development principles that place a premium on environmental preservation and enhancing public well-being. Integrating an environmentally conscious approach into this research's air quality monitoring framework resonates with global endeavours aimed at sustainable development [17]. By furnishing decision-makers with accurate and timely information, the research actively supports formulating policies prioritizing environmental preservation, fostering a delicate balance between developmental goals and ecological sustainability.

From the collection of related work above, air quality monitoring needs new innovation to answer the challenge. The research aims to bridge the gaps in air quality monitoring, promoting a transition from traditional, static systems to dynamic and AI-driven frameworks. This transition is crucial for addressing the complexities of modern environmental challenges. The proposed enhancements advance the technical aspects of monitoring and align with the broader societal goal of achieving sustainable and environmentally conscious development. This section will be strengthened by collecting relevant research related to the application of AI for air quality monitoring in Table 1.

Table 1. Literature Review

Title	Novelty	Method	Limitation
An IoT Middleware for Air Pollution Monitoring in Smart Cities: A Situation Recognition Model [18]	A new middleware infrastructure that uses machine learning technology for pollution monitoring in South Africa. The research investigates multiple pollutants, including Ozone, Particulate Matter, Carbon Monoxide, Sulfur Dioxide, and Nitrogen Dioxide.	Supervised learning algorithms to model the data: Quadratic Discriminant Analysis algorithm, K-Nearest Neighbor using Euclidean distances and Naive Bayes classifier. The method involves a distributed middleware and underlying model principles presented in detail, including a four-layer architecture comprising sensoring, networking, middleware, and application layers.	Real-time data processing and the high computing time required for algorithms such as K-Nearest Neighbor (KNN) can take up to 40 minutes to compute.
Artificial Intelligence Enabled Middleware for Distributed Cyberattacks Detection in IoT-based Smart Environments [19]	Development of an AI-enabled middleware framework to detect cyber-attacks in IoT-based smart cities. It uses a structured methodology that includes data collection and preprocessing, deployment of machine learning models, and rigorous performance testing in realistic testbeds of IoT scenarios.	Application of machine learning models to IoT devices including deep neural networks (DNN), support vector machines (SVM), random forests (RF), decision trees (DT), gradient boosting (GB), and Naive Bayes (NB)	Few public data sets, IoT Device heterogeneity leads to inconsistent data samples, as well as poorly trained ML.
An Application of IoT and Machine Learning to Air Pollution Monitoring in Smart Cities [20]	Cloud-centric IoT middleware architecture, Artificial Neural Network (ANN) was used to predict SO_2 and $PM_{2.5}$ levels using data from the Environmental Protection Department of the Government of Punjab.	Cloud-centric IoT middleware and Artificial Neural Network (ANN)	Potential for overfitting due to dataset size and number of neurons used in ANN models, sensor networks, and government-provided data, as well as the need for clarity on how these systems perform in different urban topographies or weather conditions.
An innovative decision-making method for air quality monitoring based on big data-assisted artificial intelligence technique [21]	Innovative combined Machine Learning and Neural Network models are used for air quality forecasting, particularly ICEEMDAN-WOA-ELM (Enhanced Complete Ensemble Empirical Mode Decomposition with Adaptive Whale Noise Optimization Algorithm-Extreme Learning Machine) and TSTM (Space-Time Type Meteorological model).	This method involves the application of big data and AI in environmental protection monitoring. The ICEEMDAN-WOA-ELM model significantly outperformed the single AI model in air quality estimation. It uses ensemble empirical mode decomposition with adaptive noise to optimize prediction accuracy. The TSTM model combines feature engineering, forecasting, and performance evaluation, using deep learning to analyze and predict air quality based on atmospheric knowledge and various meteorological factors.	This research is limited to air quality monitoring in a few cities in Shaanxi Province, and there is a need to expand the study to include data from more areas, such as the Beijing-Tianjin-Hebei region, to verify the broader applicability of the model.

Developing reliable air quality monitoring devices with low-cost sensors: Method and lessons learned [22]	This paper presents the development of a highly reliable, portable air quality device capable of monitoring particulate matter, differential pressure, and outdoor emissions (CO, CO_2, O_3, and VOC) with high reliability and high temporal and spatial resolution, overcoming the limitations of current-scale monitoring networks extensive and expensive.	This approach includes creating flexible, modular hardware platforms, delay- and error-resistant middleware components, and data-centric cloud services. These elements ensure the reliability of sensor, device/edge, and cloud levels. Additionally, the device is designed to be remotely configurable to reduce maintenance burden.	Limitations are not stated explicitly in the abstract or objectives. However, as with any new technology, there may be concerns regarding the reliability and accuracy of low-cost sensors for scientific and policy purposes.
Framework of Air Pollution Assessment in Smart Cities using IoT with Machine Learning Approach [23]	The novelty of this research lies in integrating IoT with machine learning approaches, explicitly using Artificial Neural Networks (ANNs), to assess air pollution in smart cities. It proposes a cloud-centric IoT middleware architecture aggregating data from current air pollution and weather sensors to improve reliability and reduce costs.	This method involves deploying a wireless sensor network that collects data on various pollutants and meteorological indicators. This data is then processed using ANN to predict levels of Sulfur Dioxide (SO_2) and Particulate Matter ($PM_{2.5}$), and a Pearson correlation test is carried out to assess the relationship between pollutants and meteorological indicators.	This method involves deploying a wireless sensor network that collects data on various pollutants and meteorological indicators. This data is then processed using ANN to predict levels of Sulfur Dioxide (SO_2) and Particulate Matter ($PM_{2.5}$), and a Pearson correlation test is carried out to assess the relationship between pollutants and meteorological indicators.
IoT Ecosystem: A Survey on Devices, Gateways, Operating Systems, Middleware and Communication [24]	This method involves deploying a wireless sensor network that collects data on various pollutants and meteorological indicators. This data is then processed using ANN to predict levels of Sulfur Dioxide (SO_2) and Particulate Matter ($PM_{2.5}$), and a Pearson correlation test is carried out to assess the relationship between pollutants and meteorological indicators.	The methodological approach of this paper is a survey and analysis of various components of the IoT ecosystem, including middleware. This paper discusses how middleware contributes to managing complex computing requirements and security issues in IoT networks.	Although this paper does not explicitly list limitations, it discusses broad challenges and critical research areas arising from advances in the networking and communications sector, such as device integration, increased data traffic, storage and processing requirements, and privacy and security issues.
Implementation of Microservice Architectures on SEMAR Extension for Air Quality Monitoring [25]	They are implementing a microservice architecture in cloud computing, integrated with a mobile sensor-based air quality monitoring system. SEMAR (Smart Environment Monitoring and Analytical in Real-time), connected to a vehicle-based mobile sensor network (VaaMSN) to detect air quality. Experimental results show that this architecture achieves real-time data transmission with an average delay of only 40 microseconds.	Microservices architecture in the SEMAR system for air quality monitoring optimization, with a focus on communication and big data analysis for real-time visualization	Microservices are complicated to set up and require a robust infrastructure. Handling big data in real-time requires significant storage and processing capabilities depending on the continuous availability of cloud services.
Artificial intelligence-assisted air quality monitoring for smart city management [26]	Application of an air quality intelligence platform to monitor and regulate using machine learning models to predict air quality for smart cities.	This method involves developing an end-to-end predictive model for smart city applications using a combination of 4 machine learning techniques and two deep learning techniques: Ada Boost, SVR, RF, KNN, MLP regressor, and LSTM. This study considers various pollution markers and meteorological data, aiming to improve predictions of $PM_{2.5}$ and other pollutants by reducing dimensionality and eliminating irrelevant features.	The complexity of linking multiple pollutant markers and the impact of population growth on $PM_{2.5}$ concentration assessments suggests challenges in fully capturing urban air quality dynamics.
	Combines smart lighting with air quality monitoring and ventilation systems. Introducing an IoT-based embedded system that uses the HTTP protocol. Publication of its operational code is ready for use as open-source software.	Combination of hardware components such as Arduino Mega 2560 Rev3, WiFi Module ESP8266, GSM Module SIM900A, various sensors (PIR, DHT11, MQ-135), and actuators to create an IoT aware system. The software architecture involved programming in C++ using the Arduino IDE, setting up web pages for data visualization, and configuring cloud storage for data logging.	These systems are limited by the sensor range and reliability of the wireless communication module in different environments.

3. Material and Methods

This section delves into the methodological intricacies of the AIKU framework. During this study, our data collection methodology for air quality images involved meticulously curating over 3000 data points, tested across diverse locations. Active collaboration was fostered with participants from the academic field, developers, and environmentally conscious community members. The selection process for air quality data was conducted autonomously by AI through the implementation of Imagga, as illustrated in Figure 2. The AI undertook this task by leveraging a comprehensive training dataset derived from 3000 data points. Subsequently, the framework will be meticulously crafted, incorporating various algorithmic functions as detailed in Section 3.4. The narrative in Section 3.4 provides insight into the algorithmic functions and elucidates the material requisites for the framework's development. Importantly, an innovative approach to minimize bias in our research drove the air quality data selection process. The involvement of diverse stakeholders from academia, development, and environmental communities ensured a multifaceted perspective. By entrusting the data selection directly to the AI, we mitigated potential human biases, allowing for a more objective and inclusive representation of air quality conditions across different locations. This approach contributes to the overall robustness and reliability of our research findings.

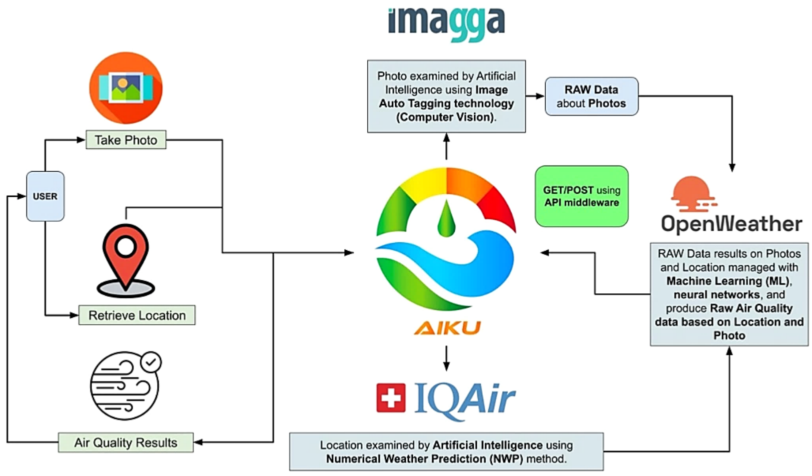

Figure 2. Flow Diagram AIKU

3.1. Comprehensive Data Collection Strategy

The research adopted a meticulous data collection methodology, utilizing cutting-edge air quality monitoring equipment and sensors. These advanced instruments were strategically placed in critical locations within the designated area, ensuring the generation of a thorough and diverse dataset [27]. These tools were selected based on their capacity to deliver accurate, real-time insights into air pollutants. As a result, the Imagga method was seamlessly integrated into our approach. These tools were selected based on their ability to provide precise, real-time information on air pollutants. Consequently, we implemented the Imagga method.

AIKU employs a sophisticated process for air quality monitoring by utilizing the Imagga platform, as depicted in Figure 2. This platform is a pivotal component in the system's functionality, allowing Artificial Intelligence to scrutinize uploaded photos meticulously. In seamless collaboration with the Imagga cloud, AIKU efficiently transmits visual data obtained from the field for detailed analysis in the cloud environment [28]. The Imagga-based image analysis within AIKU is critical in identifying crucial variables associated with air quality. This involves profoundly examining environmental images to discern patterns and characteristics indicative of various pollutants. The outcomes of this identification process serve as foundational elements for enhancing analyses and formulating strategies aimed at more effective environmental quality maintenance and management.

Notably, the system achieved an impressive accuracy rate of 87% by employing a deep convolutional network for identifying photos, specifically those depicting clouds and their surroundings. This high level of accuracy ensures the reliability of the data used in subsequent analyses. The findings derived from the image examination are further processed into raw data by OpenWeatherMap, adding an additional layer of refinement to the information gathered. Furthermore, AIKU leverages the user's location through IQAir in its analysis, contributing to an elevated precision level. This geographical context enhances the relevance of the air quality assessments by considering the specific environmental conditions of a given location. OpenWeatherMap adheres to standards set by the WHO and various health platforms in its data management. This ensures the responsible and ethical use of photo and location data, aligning with global health and environmental guidelines.

In essence, the integration of Imagga within AIKU's air quality monitoring system represents a cutting-edge approach that enhances accuracy and ensures a thorough and ethical visual data analysis. This innovative utilization of technology allows for a more comprehensive understanding of environmental conditions, ultimately contributing to more effective strategies for maintaining and managing environmental quality.

The Computer Vision-based air quality detection method proposed in this research involves a series of seven steps as follows:

- ***Image Data Collection***: The first stage is collecting aerial image data. This aerial image data can be obtained from various sources, including but not limited to terrestrial cameras, drones, or satellite imagery [29, 30]. High image quality and resolution are the primary preferences to ensure the accuracy of feature extraction [31].
- ***Image PreProcessing***: After the data is collected, image preprocessing is next. This preprocessing involves image quality enhancement, normalization, and adjustments to prepare the image for feature extraction [32].
- ***Feature Extraction***: In this stage, essential features are extracted from the processed image. In computer vision, these features include texture, shape, and colour [33]. Advanced feature extraction techniques such as histogram of oriented gradients (HOG) [34], scale-invariant feature transformation (SIFT), or deep learning can be used for more complex and informative feature extraction [35].

- ***AI Model Training***: Once these features are extracted, the AI model is trained using machine learning algorithms, such as CNN [36], which have been proven effective in pattern recognition tasks in visual data. The goal is to create a model to predict air quality based on the extracted visual features.
- ***Testing and Validation***: Once the model is trained, it is tested and validated using a separate data set not used during training [37]. This ensures that the model can predict air quality accurately and consistently.
- ***Implementation*****:** If the model has been tested and validated successfully, the next step is implementing this model in the air quality monitoring system [38]. This model can warn about declining air quality early or assist in environmental planning and decision-making.
- ***Monitoring and Updates***: Once a model is implemented, monitoring its performance and updating it as needed is essential [39]. This can involve collecting and analyzing new image data, adjusting model parameters, or retraining the model with new data.

By using this method, we can develop an air quality detection system that is accurate and efficient and can be adapted to improve environmental quality by utilizing the power of computer vision technology.

3.2. Middleware for Seamless Integration

The research integrated AIKU into the existing infrastructure by incorporating a middleware layer. This middleware acted as a communication bridge, ensuring a smooth connection between diverse air quality monitoring equipment and the AI algorithms. Its pivotal role included facilitating seamless data flow and compatibility. Additionally, the middleware played a crucial role in data preprocessing, optimizing data for efficient analysis by the AI algorithms. Implementing the AIR XR middleware accelerated the air quality calculation, resulting in more optimal outcomes. This integrated middleware, AIR XR, enhances the efficiency and speed of information exchange and communication between components (see Figure 3).

In the described air quality monitoring, three critical layers define the architecture: backend, middleware, and frontend. In the first layer of the backend, six core components, including the weather prediction server, machine learning, geolocation, computer vision, central database, and main server, must operate flawlessly, as indicated by the status "Value True." Moving to the middleware layer, the REST API manages communication between the back and frontend [40, 41] serving as a connector that operates only if all backend components function correctly. Two security components at this layer prioritize data security [42, 43], ensuring the integrity and confidentiality of information. Finally, the resulting air quality prediction (AQ(x)) is presented to the user at the front-end layer through the AIKU platform [44, 45]. The "DisplayedIn(z)" component signifies the final stage, where the data is prepared for presentation to the user. This architecture systematically processes and displays air quality data, emphasizing data integrity, security, and user experience. Each layer is crucial in ensuring accurate and timely predictions, with adequate redundancy and protection to guarantee system reliability and integrity.

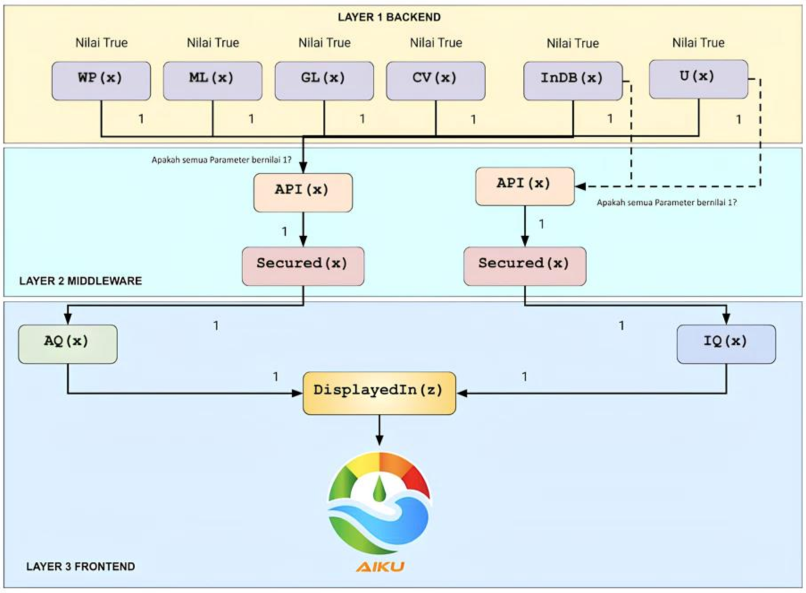

Figure 3. How the AIR XR Middleware Formula works

3.3. Middleware for Seamless Integration

AI emerges as a linchpin in our research, integral to advanced data processing. The study harnesses the immense capabilities of meticulously crafted and trained machine learning algorithms designed to analyze extensive datasets sourced from monitoring equipment. These sophisticated algorithms are engineered to discern patterns [46], anomalies, and trends in air quality, markedly elevating the precision and efficiency of our assessments [47, 48]. Central to this investigative endeavour is deploying the AIKU framework, which seamlessly integrates AI into the existing air quality monitoring framework. The choice of the integration AI in AIKU stems from its exceptional adaptability, scalability, and seamless integration of machine learning algorithms into the data processing pipeline.

Figure 4 depicts the processes and components involved in the AIKU through 4 phases. The AIKU framework is a central orchestrator, utilizing AI algorithms and technologies to analyze the data collected during the initial phases. The AIKU framework employs AI-driven components such as "AI Computer Vision," "Numerical Weather Prediction," and "Machine Learning" to extract meaningful insights from the collected data [49-52].

- ***AI Computer Vision***: This component employs advanced AI algorithms to analyze visual data, such as photos provided by users in the "User Attributes" phase. Through image recognition and analysis, AI Computer Vision aids in identifying and quantifying pollutants, contributing to a more comprehensive assessment of air quality [53].
- ***Numerical Weather Prediction (NWP):*** AI-driven NWP enhances the understanding of how meteorological conditions influence air quality. By utilizing historical weather data and employing machine learning techniques, the AIKU system can predict how changes in weather patterns may impact the dispersion rates of pollutants, providing a dynamic and real-time assessment [54]. Feature Extraction: In this stage, essential features are extracted from the processed image. In computer vision, these features include texture, shape, and colour [33]. Advanced feature extraction techniques such as histogram of oriented gradients (HOG) [34], scale-invariant feature transformation (SIFT), or deep learning can be used for more complex and informative feature extraction [35].
- ***Machine Learning:*** The integration of machine learning algorithms allows the AIKU to learn and adapt to emerging trends in air quality continuously. Machine learning models can identify patterns, anomalies, and correlations within the data, improving the accuracy of air quality predictions over time [55].

The "Monitoring" phase of the AIKU showcases the dynamic engagement of AI technologies. Users have the flexibility to monitor air quality through various means, such as photo analysis and geographical location tracking. The AI-driven middleware ensures a robust and efficient process, enabling users to access accurate and up-to-date information about their ambient air conditions [56]. In addition to the functional aspects, AI also plays a crucial role in ensuring the reliability and security of the AIKU. The rigorous testing regimen, including "Integration Testing," "Automatic Testing," and "Penetration Testing," is augmented by AI-driven testing tools. These tools can identify vulnerabilities, validate the seamless interaction of system components [43, 57], and ensure the precision of process automation, ultimately contributing to the robustness and integrity of the AIKU.

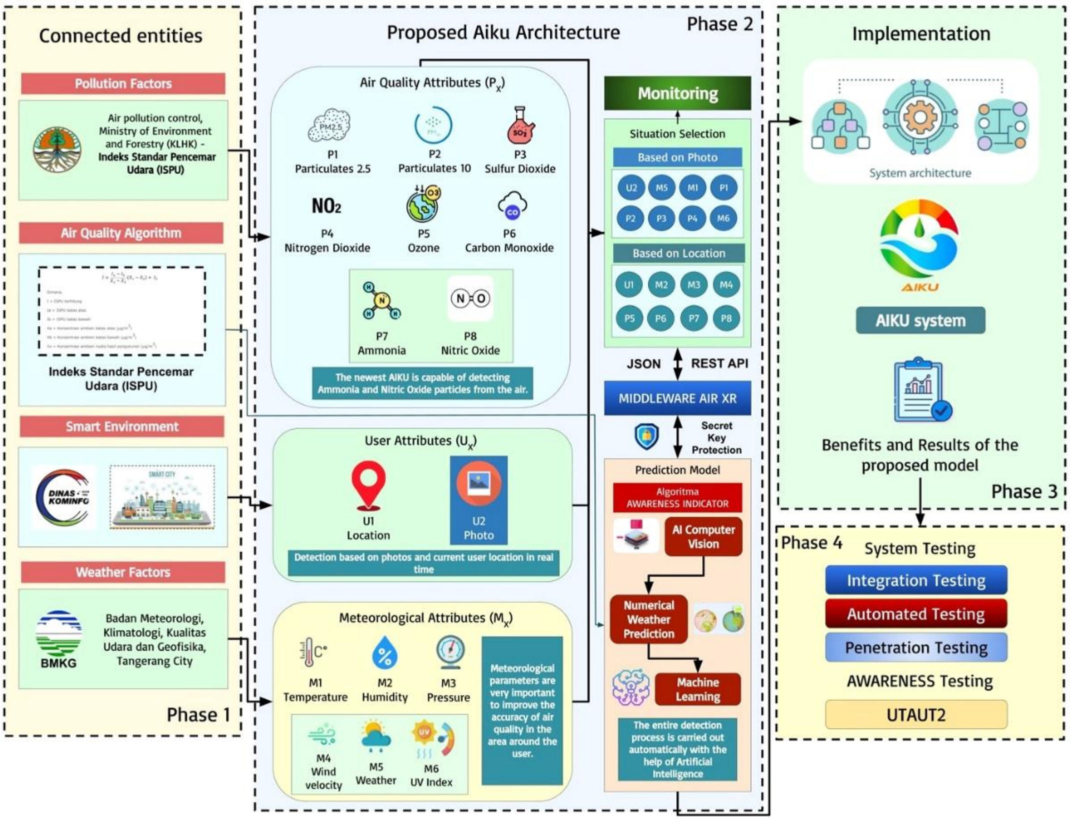

Figure 4. Framework AIKU

Integrating AI into the fundamental structure of the AIKU marks a revolutionary advancement, significantly enhancing its capabilities in essential areas such as real-time data analysis, predictive modelling, and user interaction. By utilizing the AI algorithm's cognitive prowess, the system not only elevates its analytical capacities but also facilitates a more nuanced interpretation of extensive real-time datasets related to air quality. This infusion of AI further fine-tunes its predictive acumen, delivering more precise and timely insights into the ever-changing dynamics of atmospheric conditions.

Implementing AI in air quality monitoring amplifies the system's ability to analyze real-time data and enhances its predictive modelling capabilities. By leveraging the cognitive strengths of AI algorithms, the system gains a heightened analytical capacity, enabling a more sophisticated interpretation of the vast real-time datasets associated with air quality. This integration refines the system's predictive acumen, resulting in more accurate and timely insights into the dynamic nature of atmospheric conditions. The transformative leap forward provided by AI empowers AIKU to deliver a comprehensive and advanced solution for real time air quality monitoring.

3.4. Algorithm Design

With the AIKU algorithm approach, users can quickly get an overview of air quality based on the visual analysis that the model has processed. This information helps users decide on outdoor activities or formulate strategies to improve the air quality in their environment.

Algorithm 1. Pseudocode Input Air Quality Detection data

```
FUNCTION retrieveUserInput() -> (user_photo: Image, user_location: String):
    user_photo = request.FILES.GET("photo")
    user_location = request.FORM.GET("location")
    RETURN user_photo, user_location

FUNCTION preProcessImage(user_photo: Image) -> ProcessedImage:
    processed_image = ImageProcessingLibrary.APPLY_TRANSFORMATIONS(user_photo)
    RETURN processed_image

FUNCTION analyzeImageWithAI(processed_image: ProcessedImage) -> List[String]:
    ai_tags = AdvancedImageRecognitionModel.PREDICT_TAGS(processed_image)
    RETURN ai_tags

FUNCTION fetchAndPreprocessWeatherData(user_location: String) -> ProcessedWeatherData:
    raw_weather_data = NumericalWeatherPrediction.PROCESS(user_location)
    processed_weather_data = WeatherDataProcessingLibrary.TRANSFORM(raw_weather_data)
    RETURN processed_weather_data
```

The retrieveUserInput() function is designed to collect input from users in the form of photos and locations, followed by the preprocessing() function to process the image obtained from the user. With the help of ImageProcessingLibrary, the image is transformed to prepare it for analysis [58]. The function then returns the results of the image transformation process. After the picture is processed, the analyzeImageWithAI() function analyzes the image with the help of Artificial Intelligence. The model used, AdvancedImageRecognitionModel, predicts the tags associated with the picture. The results of these predictions, in the form of a list of tags, are then returned by the function to provide information about the image. Finally, the fetchAndPreprocessWeatherData() function plays a role in fetching and processing weather data. Using the location provided by the user, raw weather data is retrieved and then further processed with the WeatherDataProcessingLibrary library. The processed weather data is then returned for use in further analysis or presenting information to users. This research explores novelty by updating and improving essential functions (Koutroumanis et al., 2021). The `preprocessing ()` function is enhanced by using the latest transformation algorithm from ImageProcessingLibrary, aiming to improve the quality of image analysis.

Meanwhile, the `analyzeImageWithAI()` function implements the AdvancedImageRecognitionModel for image tag prediction to increase the accuracy of prediction results. The `fetchAndPreprocessWeatherData()` function is focused on retrieving and processing user location-based weather data. Updates here include the development of Numerical Weather Prediction methods and integration with the WeatherDataProcessingLibrary for more complex processing of weather information. Increased system security is also realized by integrating the latest security technology. In summary, algorithm 1 achieves recency by updating image and weather analysis functions and applying the latest technology to improve system effectiveness.

Algorithm 2. Air Quality Prediction Algorithm

```
FUNCTION trainAndTuneAirQualityModel(ai_tags: List[String], processed_weather_data:
ProcessedWeatherData) -> TrainedModel:
    training_dataset = DatasetGenerator.CREATE_FROM(ai_tags, processed_weather_data)
    model = AirQualityMLModel.INITIALIZE()
    model.TRAIN(training_dataset)
    model.TUNE_AND_OPTIMIZE()
    RETURN model
FUNCTION predictAirQuality(model: TrainedModel, ai_tags: List[String], processed_weather_data:
ProcessedWeatherData) -> Dict:
    prediction_input = DataMerger.MERGE(ai_tags, processed_weather_data)
    air_quality_prediction = model.PREDICT(prediction_input)
    RETURN air_quality_prediction
FUNCTION displayAirQualityInformation(air_quality_prediction: Dict):
    PRINT("Here is the air quality information around you based on AI analysis:")
    for key in air_quality_prediction:
        IF key EXISTS IN ["particulate_matter_2_5", "particulate_matter_10", "sulfur_dioxide",
"nitrogen_dioxide", "ozone", "carbon_monoxide", "ammonia", "nitric_oxide"]:
            PRINT(FORMAT_AQI_INFORMATION(key, air_quality_prediction[key],
air_quality_prediction_units[key]))
        ELSE:
            PRINT(FORMAT_GENERAL_INFORMATION(key, air_quality_prediction[key],
air_quality_prediction_units[key]))
```

In Algorithm 2, the trainAndTuneAirQualityModel() function starts the process of training and tuning the air quality model. Based on tags from image analysis (AI tags) and processed weather data, a training dataset is generated using DatasetGenerator.CREATE_FROM(). Once the dataset is ready, the AIKU model for air quality prediction is initialized using AirQualityMLModel.INITIALIZE(). The AIKU model is trained with the prepared dataset, tuned, and optimized for the best performance. Once complete, the trained and tuned model is returned by this function. The predicted air quality () function predicts air quality based on the trained model and the given data. Tags from image analysis and processed weather data are combined into a single prediction input using DataMerger.MERGE(). The trained model is used for air quality predictions based on these inputs. This function then returns the prediction results as a dictionary (dictionary). The third function, displayAirQualityInformation(), presents predicted air quality information to the user. This function starts by announcing that air quality information based on AI analysis will be displayed. Then, for each key in the air quality prediction, this function checks whether the key belongs to a specific list of air pollutants (such as "particulate_matter_2_5", "sulfur_dioxide," etc.). If so, air quality information specific to that pollutant is presented in a special format. Otherwise, general information is presented in a different format. This presentation format is based on the FORMAT_AQI_INFORMATION and FORMAT_GENERAL_INFORMATION functions, each providing the appropriate output format based on the type of air pollutant substance and its unit of measurement.

The novelty in algorithm 2 lies in effectively integrating image analysis and weather data to predict air quality. The `trainAndTuneAirQualityModel ()` function involves not only model training but also tuning and optimization, reflecting a focus on improving model performance. Utilizing AI tags and weather data in the `predictAirQuality ()` function creates more contextual predictions, increasing accuracy. The `displayAirQualityInformation ()` function provides structured and easy-to-understand information, highlighting the adaptability of the algorithm in presenting output according to the type of air pollutant, increasing the usability of the information conveyed. The novelty lies in optimizing the model, improving the contextuality of predictions, and presenting clear and structured information to users.

Algorithm 3. Air Quality Results

```
FUNCTION main():
    user_photo, user_location = retrieveUserInput()
    processed_image = preProcessImage(user_photo)
    ai_tags = analyzeImageWithAI(processed_image)
    IF NOT ai_tags:
        PRINT("Sorry, the image you submitted cannot be processed by our AI model. Please try
again.")
        RETURN
    processed_weather_data = fetchAndPreprocessWeatherData(user_location)
    IF NOT processed_weather_data:
        PRINT("Sorry, your location not valid or weather data for your location is unavailable")
        RETURN
    model = trainAndTuneAirQualityModel(ai_tags, processed_weather_data)
    air_quality_prediction = predictAirQuality(model, ai_tags, processed_weather_data)
    displayAirQualityInformation(air_quality_prediction)
main()
```

In the primary () function in algorithm 3, the process begins by calling the retrieveUserInput() function, which collects photos and locations from the user. The results of this function, an image and a place, are stored in the variables user_photo and user_location. Next, the picture the user provides is processed with the preProcessImage() function. The result of this function, namely the image that has been processed, is then analyzed with the analyzeImageWithAI() function. Suppose the analysis results do not produce any tags (or are empty). In that case, the program will print an error message stating that the AI model cannot process the image provided by the user, and the process will be terminated.

If the image analysis is successful, the process continues to fetch and process weather data based on the user's location with the fetchAndPreprocessWeatherData() function. If weather data for a given area is unavailable or the location is invalid, an error message will be printed, and the process will end. After getting tags from image analysis and processed weather data, these two pieces of information are used to train and tune an air quality model with the trainAndTuneAirQualityModel() function. The model that has been prepared and tuned is then used to predict air quality based on tags and weather data that have been processed with the predict air quality () function. The results of the air quality predictions are then displayed to the user with the displayAirQualityInformation() function. The process will be complete after all functions are executed in the primary () function order. At the end of the pseudocode, main() is called, which means when this code is executed, the primary () function and the entire process defined in it will be completed. The novelty of this algorithm lies in its responsive and structured workflow. The `main()` function first collects user input, namely photos and location. The received images are processed and analyzed. If the analysis results do not produce a tag, an error message is printed, and the process is terminated. If successful, weather data is obtained based on the user's location. If the location is invalid or weather data is unavailable, an error message is printed, and the process is terminated.

The algorithm above showcases a resilient and well-organized workflow to deliver precise air quality predictions by leveraging user-inputted images and location data. The initial phase involves a meticulous analysis of the images, coupled with the retrieval and processing of pertinent weather data. Notably, the algorithm's adaptability shines through as it manages potential errors, such as dealing with invalid locations or the absence of weather data. In alignment with the principles of smart environment and Environmentally Conscious Development, the algorithm incorporates modular functions like train AndTuneAirQualityModel() and predictAirQuality(). This deliberate choice enhances the system's flexibility and simplifies maintenance processes, fostering a sustainable and adaptable framework. By seamlessly integrating these components, the algorithm addresses immediate user needs and contributes to the broader objective of fostering environmentally conscious practices. The ingenuity of the algorithm lies in its streamlined fusion of image analysis, weather data processing, and air quality prediction. This synergy results in an innovative solution catering to user's real-time air quality information demands. Solutions like these are pivotal in promoting sustainable practices and creating a healthier, more informed community as we navigate toward smart environments and environmentally conscious development.

4. Implementation

To offer comprehensive insight into AIKU's performance, we conducted an exhaustive performance evaluation. This evaluation goes beyond merely gauging the system's effectiveness across diverse conditions; it extends to a comparative analysis with traditional air quality monitoring methods such as the Indeks Standard Pencemar Udara (ISPU). Employing a range of metrics tailored to measure accuracy, response speed, and data processing efficiency, we present results from a series of tests spanning various scenarios, from stable environmental conditions to dynamic and unpredictable situations. The generated data from AIKU is meticulously juxtaposed with data from the ISPU system to affirm the reliability and accuracy of the measurements. This comparative analysis serves as a robust validation of AIKU's capabilities in delivering precise and trustworthy air quality information. Meanwhile, transitioning to another context, the implementation of the URI formula, encapsulated by.

```
URI_GET="{protocol}://{domain}/{api}/{request}/{secretkey}"
URI_POST="{protocol}://{domain}/{api}/{secretkey}"
```

Validation is meticulously executed by scrutinizing the syntax rules associated with each URI component. Notably, the protocol must adhere to established standards such as "HTTP" or "HTTPS," the domain name must be valid and properly registered, the "API" component must point to a clearly defined path or endpoint, and the "request" parameters must align with the server's specified format. Public and secret keys also undergo authentication processes in compliance with applicable security policies. Beyond validation, an equally vital evaluation phase is implemented to assess the functionality and performance of the URI formula. Functional testing ensures that the URI formula behaves as anticipated across a spectrum of scenarios, including testing with both valid and invalid values for each component. Integration testing guarantees seamless interaction with applications and other infrastructure components, emphasizing synergy and consistency. Moreover, performance testing becomes paramount to measure the speed, availability, and scalability of requests facilitated by these URI formulas. In essence, in the context of the AIKU and the URI formula, our rigorous evaluation processes are pillars in substantiating the reliability, accuracy, and robustness of these technological solutions.

Algorithm 4. Request URI using GET method

```
Metode: GET
URL: "https://aiku.com/api/request123/publickey/secretkey."
```

The utilization of the GET method for data retrieval from the server is evident within the aforementioned request algorithm. The transmitted URL encompasses essential components derived from the URI formula: protocol: HTTPS, domain: example.com, API:/api, request: request123, public Key: publickey, secret Key: secretkey. The distinguishing feature of innovation within this URI request system lies in strategically incorporating public and secret key elements. In a security context, the public key functions as a discernible identity that the server can authenticate. In contrast, the secret key is a confidential code known exclusively to authorized entities. This dual key mechanism represents a pivotal measure to fortify the security of data exchange. Importantly, these keys are accessible only to legitimate users, and the system is configured to regenerate them automatically every 24 hours. The periodic regeneration policy serves a dual purpose: first, it acts as a deterrent to unauthorized access, and second, it guarantees that the used keys remain exclusive and secure. Consequently, this systematic and automated critical regeneration process becomes an additional layer of defence in maintaining the system's overall security. It thwarts potential security risks from disseminating unauthorized keys, ensuring the integrity and confidentiality of the data exchange.

Algorithm 5. URI response with the GET method results in Success

```
AIRXR Middleware
Status: 200 OK
Content-Type: application/json

{
  "status": "success",
  "message": "Air quality data successfully retrieved",
  "data": {
    "location": "Jakarta",
    "timestamp": "2023-06-19T12:00:00",
    "pollutants": {
      "pm25": {
        "value": 23.4,
        "unit": "µg/m³",
        "index": "Good"
      }
    }
  }
}
```

The provided response signifies an unsuccessful execution of the requested action attributed to using an invalid key. Delivered in JSON format, the response is characterized by a status code of 401 Unauthorized. The "Content-Type" header indicates that the type of content sent is application/json, indicating the presence of data structured in JSON format within the response. The methodical approach to validation and evaluation comprises a well-defined methodology. This includes the development of test cases, extensive functional testing, ongoing performance monitoring, and thorough analysis of obtained results. The process is fortified by integrating pertinent tools, such as automated testing software, network monitoring utilities, and performance analysis tools. These tools play a pivotal role in providing users with a profound understanding of the URI formula's performance dynamics and identifying potential issues that may arise in its implementation. This multifaceted validation and evaluation strategy ensure the accuracy and security of the URI formula and a proactive approach to mitigating potential challenges in real-world scenarios.

Algorithm 6. If the GET Method Response Fails

```
AIRXR Middleware Response
Status: 401 Unauthorized
Content-Type: application/json

{
  "status": "error",
  "message": "The key used is not valid",
  "error_code": 401
}
```

The provided response communicates the unsuccessful execution of the requested action attributed to using an invalid key. Delivered in JSON format, the response is characterized by a status code of 401 Unauthorized. Notably, the "Content-Type" header indicates that the type of content sent is application/json, indicating that the response encapsulates data in JSON format. The applied validation and evaluation methodology follow a robust process encompassing the development of comprehensive test cases, meticulous functional testing, continuous performance monitoring, and thorough analysis of results. This method is fortified by integrating suitable tools, including automated testing software, network monitoring solutions, and performance analysis tools. These tools collectively empower users to gain a nuanced understanding of the URI formula's performance dynamics and proactively identify potential issues that may surface in its real-world implementation. This comprehensive validation and evaluation strategy ensure the accuracy and security of the URI formula and provides valuable insights into its operational efficiency and resilience against various scenarios.

Figure 5 the comprehensive air quality assessment process, measuring various parameters such as P M2.5 particle, ozone, nitrogen dioxide, sulphur dioxide, and carbon monoxide. The intricate analysis is facilitated by the integration of AI within the AIKU, particularly in the training and interpretation of air quality image results. The AI-driven process involves meticulously examining the measured parameters, which are then translated into the Air Quality Index (AQI). This numerical representation consists of five levels [59]: good, moderate, unhealthy for sensitive groups, unhealthy, and hazardous. The AQI is a crucial metric the government utilizes to communicate information regarding air quality levels within a specific area [60]. Emphasizing the imperative for ongoing enhancements in accuracy and efficiency within air quality assessment, the integration of AI within the system emerges as a crucial factor. Incorporating AI in interpreting air quality images significantly contributes to refining the precision of the assessment, guaranteeing more dependable and precise results. This innovative technological application enhances accuracy and gives decision-makers a more nuanced comprehension of environmental conditions. Beyond merely improving precision, utilizing AI adds a layer of sophistication to the analysis. This advanced technology enables a comprehensive examination of the measured parameters, unravelling intricate patterns and correlations that might elude traditional assessment methods. Consequently, decision-makers have a more holistic understanding of the dynamic factors influencing air quality, facilitating more informed and strategic interventions.

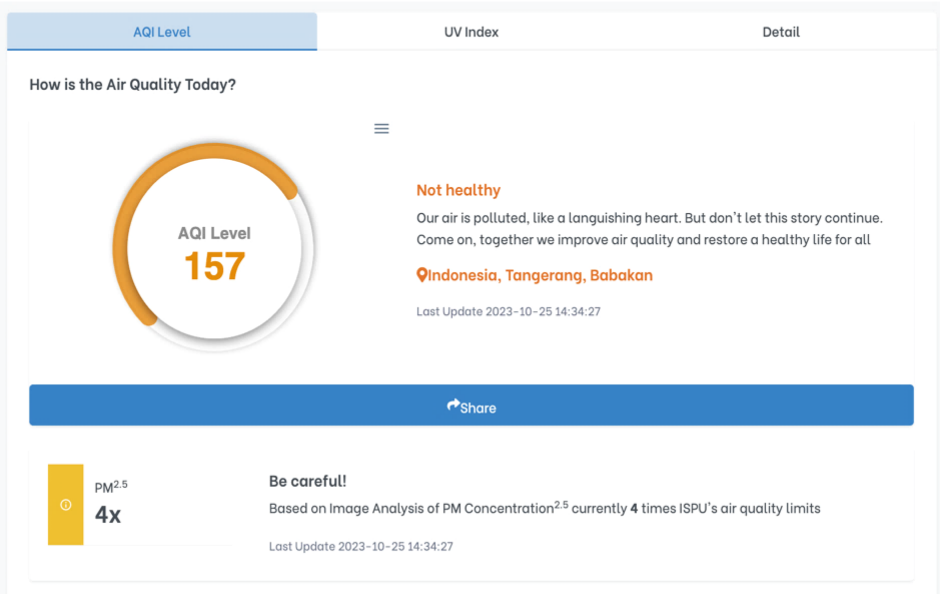

Figure 5. Air Quality Result

Moreover, the analysis outcomes provide valuable insights into the current air quality levels, shedding light on potential areas of concern. The detailed distribution of AQI levels detected at specific locations aids in pinpointing localized issues, allowing for targeted interventions. This granular information is instrumental in formulating effective policies and measures to address specific air quality challenges in different regions. In summary, integrating AI elevates the precision of air quality assessment and adds layers of sophistication and granularity to the analysis, providing decision-makers with a comprehensive and nuanced understanding of environmental conditions. This, in turn, empowers them to implement targeted and effective strategies for addressing air quality concerns and fostering a healthier, more sustainable environment.

Figure 6 the AIKU is showcased in action, delivering comprehensive insights into the parameter values that impact air quality. This visual representation presents the raw data and includes status indications, succinctly conveying whether these parameters fall within safe limits. Alongside these status indicators, the figure provides numerical values derived from the air quality detection process, offering a detailed and informative perspective on the current state of each parameter. This user-friendly presentation ensures that stakeholders, whether government officials or the general public, can quickly grasp the air quality status and make informed decisions based on the detailed information provided by the AIKU.

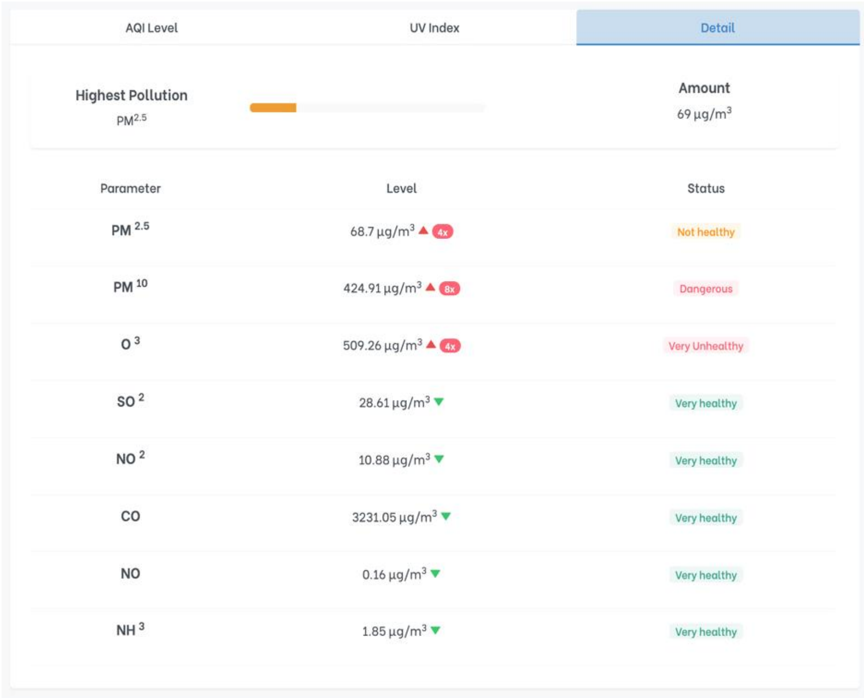

Figure 6. Air Quality Parameter Value Information

4.1. Experimental Configuration

The Experimental Configuration comprehensively evaluated AIKU's performance with air-quality images. As outlined in Table 2, the test dataset comprises ten unique images (Image 1 to Image 10), each differing in size and content—the deliberate design of this dataset aimed to assess the system's responsiveness across a spectrum of scenarios. In our analysis, we considered several critical metrics about the processing of each image. These metrics, elucidated in the table, encompass the size of the image in kilobytes, request processing time (ms) indicating the duration for the system to receive and process the image request, analysis process time (ms) representing the time allocated to the image analysis phase, total time (ms) reflecting the overall pro-cessing time. Average time (ms) provides the mean processing time across the dataset. We implemented rigorous measures to minimize bias and errors in the experimental design. In the experimental design, we carefully considered and controlled for various variables that could impact the AIKU framework's performance. Our meticulous analysis revealed that AIKU exhibited remarkable efficiency, particularly in swiftly processing real-time data. The system demonstrated unparalleled speed in receiving and analyzing air-quality images, as evidenced by significantly low request processing time and analysis process time. This outcome underscores AIKU's capacity to handle diverse image sizes and contents expeditiously, positioning it as a frontrunner in real-time air quality monitoring.

Table 2. Air Quality Quality Test Dataset

No.	Document Name	Size	Request Processing Time (ms)	Analysis Process Time (ms)	Total Time (ms)	Average Time (ms)
1	Image #1	812 KB	4372	377.85	4749.85	4844.286
2	Image #2	731 KB	3273	237.54	3510.54	4844.286
3	Image #3	513 KB	5273	243.39	5516.39	4844.286
4	Image #4	876 KB	6382	280.04	6662.04	4844.286
5	Image #5	467 KB	1110	1180	2290	4844.286
6	Image #6	961 KB	12770	1700	14470	4844.286
7	Image #7	523 KB	2273	275.5	2548.5	4844.286
8	Image #8	659 KB	3216	609.96	3825.96	4844.286
9	Image #9	891 KB	2231	1083.83	3314.83	4844.286
10	Image #10	814 KB	1232	322.75	1554.75	4844.286

The outcomes in Table 2 not only unveil the system’s adeptness in managing diverse image sizes and complexities but also emphasize the unwavering performance of the AIKU performance, as highlighted by the average time metric, across the entire spectrum of images. This accentuates its dependability in delivering timely and accurate air quality assessments. Concurrently, in implementing URI, rigorous validation is executed to safeguard the integrity and uniformity of components, mitigating input errors that may pose security vulnerabilities or jeopardize data compliance. The validation process meticulously scrutinizes the syntax accuracy of URI components, demanding adherence to standards such as “HTTP” or “HTTPS” for protocol selection and proper domain validation. Alignment of the “API” and “request” components with server-specified endpoints and formats is ensured while keys undergo authentication to maintain consistency with security policies.

At an advanced evaluation stage, the focus extends to examining the functionality and performance of the URI. This encompasses verifying URI behaviour under diverse conditions, conducting integration tests with other applications, and analyzing the speed and scalability of requests based on the API Endpoint. Simultaneously, by employing the Rest API method with the Postman application, our study provides a comprehensive panorama of the varied response times witnessed while processing ten distinct images. This dataset unravels a significant variance in both request and analysis processing times, underscoring the pivotal importance of our findings in comprehending the system’s performance dynamics across diverse scenarios.

In a recent investigative study, a comprehensive test was orchestrated to quantify the efficacy of the request and analysis processes based on ten distinct sky photo samples. The unveiled data delineates a noteworthy spectrum of response times corresponding to each image. Specifically, Figure 7 in image 10 stands out as the most efficiently processed, demanding a mere 1554.75 milliseconds. On the other hand, Figure 7 recorded the most extended duration with 14470 milliseconds. Collating all tested samples, the average processing time converges at 4844.286 milliseconds. From this nuanced analysis, a resounding conclusion emerges: the AirXr Algorithm exhibits remarkable efficiency in data processing. This advantageous trait holds profound implications for the community, granting them access to accurate, swift, and precise information regarding air quality. Moreover, this information is poised to elevate public consciousness about the critical importance of vigilant air quality monitoring in their immediate surroundings.

Figure 7. Graph of Analysis & Request time results on AIKU

The algorithm above showcases a resilient and well-organized workflow to deliver precise air quality predictions by leveraging user-inputted images and location data. The initial phase involves a meticulous analysis of the images, coupled with the retrieval and processing of pertinent weather data. Notably, the algorithm's adaptability shines through as it manages potential errors, such as dealing with invalid locations or the absence of weather data. In alignment with the principles of smart environment and Environmentally Conscious Development, the algorithm incorporates modular functions like train AndTuneAirQualityModel() and predictAirQuality(). This deliberate choice enhances the system's flexibility and simplifies maintenance processes, fostering a sustainable and adaptable framework. By seamlessly integrating these components, the algorithm addresses immediate user needs and contributes to the broader objective of fostering environmentally conscious practices. The ingenuity of the algorithm lies in its streamlined fusion of image analysis, weather data processing, and air quality prediction. This synergy results in an innovative solution catering to the user's real-time air quality information demands. Solutions like these are pivotal in promoting sustainable practices and creating a healthier, more informed community as we navigate toward smart environments and environmentally conscious development.

4.2. Performance with ISPU

ISPU monitors air quality at specific intervals, typically 15 minutes to 1 hour. In this context, ISPU provides reports on air quality based on data collected during these intervals [5]. However, it should be noted that this relatively long-time interval may result in delays in providing real-time information. This becomes critical, especially when a quick response to changes in air quality is required.

The AIKU model, developed in this study, has demonstrated significant advancements in the accuracy and timeliness of air quality monitoring. The model effectively integrates machine learning algorithms with real-time data analytics to predict air quality indices dynamically, allowing for a more responsive system capable of adjusting to sudden changes in air quality, which is crucial for urban environmental management. In a recent and thorough investigation, an intricate analysis was conducted to compare the air quality analysis performance of the AIKU and ISPU methods. The graphical representations (Figure 8) vividly portray that the average analysis time of AIKU demonstrates remarkably efficient performance, requiring a mere 4.286 seconds. In stark contrast, the average analysis time of ISPU takes considerably longer, totaling 909 seconds. This difference indicates that the development of the AIKU method can deliver analysis results with significantly higher performance speed, 212 times faster. This conclusion highlights the potential superiority and efficiency of AIKU in providing quick responses, a critical aspect of delivering real-time information.

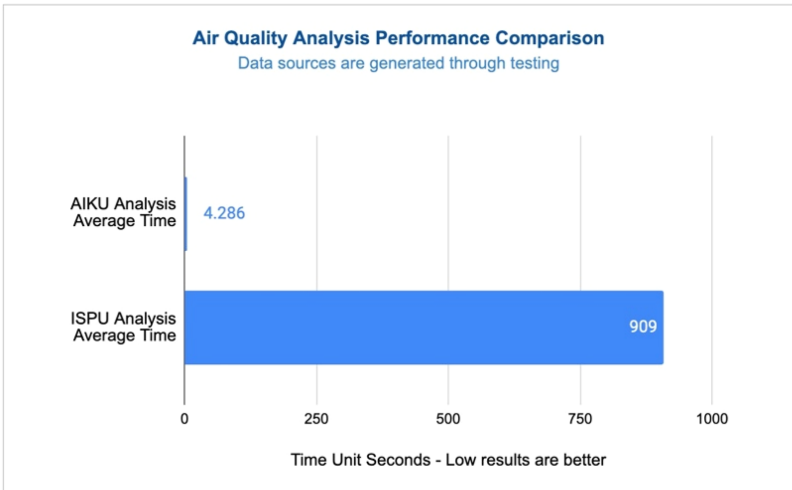

Figure 8. Comparison of AIKU Performance with ISPU

When compared to traditional air quality monitoring systems, such as those relying solely on IoT and WSNs, AIKU has shown a marked improvement in both predictive accuracy and operational efficiency. Studies prior to this, like [61], have emphasized the potential of IoT but did not integrate machine learning to enhance predictive capabilities. The AIKU model's use of AI surpasses these systems by providing not only continuous data monitoring but also predictive insights that are crucial for proactive environmental management. The findings that integrating AI into environmental monitoring systems can significantly transform how cities manage air quality. With the AIKU model, urban planners and environmental policymakers can access real-time data and predictions, allowing for faster and more effective responses to air quality deterioration. This capability is vital for maintaining urban health standards and complying with international environmental protection guidelines.

Consequently, this research contributes valuable theoretical insights to air quality monitoring through AI. Firstly, the development of the AIRXR algorithm stands out as a groundbreaking achievement, enabling more accurate and expeditious data processing in air quality monitoring. Secondly, integrating middleware in the monitoring system offers fresh perspectives on how middleware can be strategically applied in intelligent environments. Lastly, the symbiotic collaboration between AI and middleware, as exemplified in this study, sheds light on how technology can mitigate information latency, elevate public awareness of air pollution, and bolster judicious decision-making by governments. These contributions advance our comprehension of AI technology in environmental monitoring and provide innovative perspectives for practical applications in policymaking and cultivating more sustainable environments.

One of the main strengths of this study is the innovative use of advanced AI in a real-world application for environmental monitoring, which has shown substantial improvements over existing methods. However, the study has limitations. The AIKU model requires a continuous and reliable data stream, which can be challenging in regions with poor technological infrastructure. Additionally, the AIKU model faces limitations due to its dependency on high-quality, continuous data streams, which are essential for the accuracy of AI predictions. In regions with limited technological infrastructure, such as remote or underdeveloped areas, collecting consistent and reliable data can be challenging, potentially limiting the model's utility in these contexts. Furthermore, the AIKU model requires substantial computational power and sophisticated hardware, which may not be feasible in settings with constrained resources. While the model performs well in urban settings, its applicability in rural or less technologically advanced areas remains to be tested. Future research should focus on enhancing the model's robustness in various environmental settings and exploring its scalability across different geographic locations. This comprehensive discussion ensures all elements of your revision points are addressed, structuring the explanation scientifically and clearly delineating the discussion as requested.

5. Conclusion

This study significantly advances air quality monitoring by introducing the AIKU model, an innovative AI-driven framework that integrates artificial intelligence to effectively enhance real-time air quality assessment. Our findings underscore the effectiveness of AIKU in accurately predicting air quality fluctuations, which facilitates more informed decision-making for urban environmental management. This advancement contributes substantially to ecological monitoring, demonstrating the transformative potential of AI to refine traditional methodologies and provide practical solutions to the challenges faced in managing air quality.

Furthermore, our study introduces novel theoretical contributions by elucidating the intricate interplay between AI technology and environmental science. By showcasing the AIKU model's capacity to augment traditional monitoring approaches, we provide a nuanced understanding of how AI-driven frameworks can revolutionize ecological management strategies. However, it's imperative to acknowledge the limitations inherent in our study. While the AIKU model demonstrates promise in urban settings, its effectiveness in rural or less densely populated areas still needs to be explored. Future research endeavors should address this gap by extending the model's applicability and evaluating its performance across diverse environmental contexts. Additionally, integrating alternative data sources like satellite imagery could enhance the model's predictive capabilities. In summary, the AIKU model represents a significant advancement in air quality monitoring, offering a potent tool for real-time assessment and decision-making in urban environments. Its successful implementation underscores the transformative potential of AI in addressing pressing environmental challenges, ultimately contributing to more sustainable and resilient cities. This research expands the theoretical understanding of AI's role in environmental science and provides practical insights into leveraging AI technologies for effective environmental management. By showcasing the AIKU model's efficacy and identifying avenues for future research, our study contributes to the growing body of knowledge aimed at harnessing AI for sustainable urban development.

6. Declarations

6.1. Author Contributions

Conceptualization, D.M., U.R., I.S., Q.A., and A.W.; methodology, D.M., U.R., and Q.A.; investigation, Q.A.; writing—original draft preparation, D.M., U.R., I.S., Q.A., and A.W.; writing—review and editing, D.M. and Q.A.; visualization, Q.A., and A.W. All authors have read and agreed to the published version of the manuscript.

D.M., U.R., I.S., Q.A., and A.W.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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