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Developing Machine Learning Model to Predict HVAC System of Healthy Building: A Case Study in Indonesia

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Abstract. Sick Building Syndrome (SBS) is the health and comfort issues experienced by people during the time indoor. As urban dwellers typically spend 90% of the time indoor, Indoor Air Quality (IAQ) becomes essential. Consequently, ensuring appropriate air exchange in building is essential, with Heating, Ventilation, and Air-Conditioning (HVAC) system playing a crucial ole in maintaining indoor comfort. Therefore, this study aimed to develop a predictive machine learning (ML) model using Industry 4.0 technological advancements to optimize HVAC system design that meets IAQ parameters in Indonesia healthy building (HB). An extensive literature review was carried out to identify IAQ parameters specific to Indonesia HB. Furthermore, four ML models were developed using the RapidMiner Studio application, validated with the Mean Absolute Error (MAE), and confusion matrix methods. The results showed that the cooling load and the chiller-type prediction models had a relative error of 1.11% and 3.33%. Meanwhile, Air Handling Unit (AHU) type and filter area predictive model had a relative error of 10% and 1.22%, respectively. These errors showed the accuracy of ML model in predicting HVAC system of HB.

Keywords: Healthy building; Indoor air quality; Machine learning

1. Introduction

Sick Building Syndrome (SBS) is used to describe the sudden and severe discomfort or illness experienced by occupants after spending time in building (Babaoglu, Milletli-Sezgin, and Yag, 2020). Symptoms such as headaches, eye, nose, or throat irritation, dry or itchy skin, and nausea are reported, typically relieved upon leaving with unidentified causes. A 1984 World Health Organization Committee reported that approximately 30% of new and renovated buildings globally could elicit excessive Indoor Air Quality (IAQ).

IAQ is essential as humans spend 90% of the time indoor (US EPA, 2017), which is mostly affected by occupants, Heating, Ventilation, and Air-Conditioning (HVAC) system, pollutants pathways, and sources of contaminants. The perception of air quality includes temperature, humidity, odor, air movement, ventilation, bioaerosols, and volatile organic hydrocarbons (VOCs) contaminations. However, poor IAQ leading to respiratory issues, allergies, and cancer, requires improvement to safeguard human health, reduce work-related health issues, and minimize economic losses due to illness (Whulanza and Kusrini,

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2023; Mentese *et al.*, 2020).

Healthy building (HB) has become a promising solution to address various environmental and health-related concerns, minimizing adverse impacts on the health of occupants and the surrounding environment. Among the critical indoor environmental issues demanding attention, IAQ is important in preventing negative effects on the health and well-being of occupants (Sari *et al.*, 2022). Additionally, elements such as thermal quality, lighting, acoustics, privacy, security, and functional compatibility must be carefully considered during the design, construction, and operation. HB concept is not well-developed in Indonesia, as evident from the absence of specific standards and certifications, compared to the more established idea of green building promoted by Green Building Council Indonesia (GBCI). This concept has gained substantial growth in wealthier nations including China, Europe, and the United States, evidenced by the prominence of certifications such as WELL Building Standard, Fitwel, RESET, and LEED Indoor Air Quality Rating System, in ensuring building positively contribute to the health and well-being of occupants (Lin *et al.*, 2022).

All occupied buildings require an external air supply, which may need heating or cooling before distribution to the occupied spaces depending on outdoor conditions. Concurrently, as outside air is drawn into building, indoor air is exhausted or passively discharged, effectively removing airborne contaminants. HVAC system, including heating, cooling, outdoor air filtration, and humidity control, play a crucial role in maintaining the comfort of occupants. However, poorly designed HVAC system in building has become a significant source of poor IAQ.

In recent years, the development of digital technology has significantly impacted various industries, including building sector. Artificial Intelligence (AI) and Machine Learning (ML) models have also shown great potential for application in building construction industry (Hong *et al.*, 2020). Based on previous studies, ML can be effectively used in all stages of a construction project, including the design phase to optimize building performance (Triadji *et al.*, 2023). The implementation of the model was also discussed, such as ML prediction to optimize the operation of HVAC system by controlling the temperature setpoints (Li, 2020). HVAC load forecasting for energy conservation was predicted (Zheng *et al.*, 2021), including the development of anomaly detectors (Borda *et al.*, 2023). A limited report has been documented regarding ML use in HVAC system of HB. Consequently, this study aimed to explore ML application to build a predictive model that optimizes HVAC system design, ensuring the fulfillment of IAQ parameters in the context of HB.

2. Methods

This study aimed to identify IAQ parameters for HB in Indonesia and develop ML predictive models to assist the design process of HVAC system, optimizing compliance with IAQ parameters of HB. A literature review was conducted to identify relevant IAQ parameters for HB in Indonesia. This includes examining HVAC system features and design stages to determine components affecting IAQ. Subsequently, IAQ parameters data and HB were collected to achieve the first objective. The results were validated through interviews with experts in HVAC system and ML, gathering valuable insights and recommendations.

Several categories of individuals were included to ensure the credibility of the interview results. These included 1) HB professionals with a minimum of 15 years of experience and a master's degree, 2) Building HVAC professionals with at least 15 years of experience and a bachelor's degree in a related discipline, and 3) ML experts with a minimum of 15 years of experience and a bachelor's degree in relevant areas.

For the second RO, RapidMiner Studio was used for ML model development. This open-source data mining tool is known for the versatility and wide range of applications. It can be used as a standalone framework for data analysis or seamlessly integrated into other software for data mining (Dawangi and Budiyanto, 2021; László and Ghous, 2020). Furthermore, the user-friendly interface and high visualization capabilities facilitate data interaction and insight generation without extensive coding. In this study, the Auto Model function in RapidMiner was used to address prediction, clustering, and outlier detection, effectively handling classification and regression tasks.

Model development commenced with the collection of input and output data. Key building information was obtained to inform HVAC system planning, including floor area, window area, door area, occupancy, room height, etc. These data enabled precise calculation of IAQ-influencing HVAC components such as cooling load and filter area requirements. The chiller and air handling unit (AHU) selection was based on cooling capacity per building floor. Data were sourced from two sets, namely real building data in Greater Jakarta area and synthetic building data obtained using HB indicators, comprising 22 and 78 entries, respectively. Synthetic data integrated into the model involving climatic and building data ensured comprehensive and accurate building characteristics for robust HVAC system planning. Table 1 summarizes building data for cooling load calculations.

Table 1 Collected data for cooling load calculation

No.	Building Data	Description
1	The floor area of the air-conditioned space	Collected data
2	Height of the air-conditioned space	Collected data
3	Window area	Set at a minimum of 10% of the floor as per SNI 03-6572-2001
4	Door area	
5	Wall area	Collected data
6	Roof/ceiling area	Collected data
7	Number of occupants	Each person has a minimum of 7.5 m^2 of space as per Ministry of Health Regulation No. 28/2019
8	Electrical power used by other equipment	Energy Consumption Intensity standard for the very efficient category with a power usage of less than 8.5 kWh/m^2/month following Regulation of the Minister of Energy and Mineral Resources No. 13/2012

Cooling Load Temperature Difference (CLTD) method was used to calculate floor-specific cooling loads, determining HVAC components influencing IAQ as ML model output. The method included inputting climate data (location, outdoor and indoor temperatures, outdoor and indoor humidity, elevation, and latitude) and building data (windows, doors, walls, and ceilings) for heat gain calculations. Heat gain was calculated using U-value (U) and Shading Coefficient (SC), representing the material heat transfer rate and the thermal performance of single glass units in building, respectively. U-value of the triple glass with Opaque Roller Shade was 0.72 BTUh/ft^2, and SC was 0.36. Subsequently, Glass Load Factor (GLF) selection was evaluated based on window orientation and material. The formula for calculating heat based on window area (A) in each orientation is expressed in Equation 1:

$$q = A \ x \ GLF \qquad (1)$$

Where: q = heat addition from solar radiation through the glass (MBTu/h)
A = glass surface area (ft^2)
GLF = Glass Load Factor (MBTu/h/ft^2)

Heat gain from doors and walls was calculated using triple glass doors with U-value of 1.87 BTUh/ft^2 and plaster brick walls with U-value of 0.08 BTUh/ft^2. Heat gain from walls was determined using the formula in Equation 2:

$$q = U\ x\ A\ x\ CLTD \quad (2)$$

Where: q = heat addition from solar radiation through the door wall (MBTu/h)
U = heat transfer coefficient (MBTu/(h·ft^2·°F)
A = wall surface area (ft^2)
CLTD = wall coolant load temperature difference (°F)

Heat gain from infiltration, occupants, and electrical devices was calculated using the formula in Equation 3:

$$q = 1{,}23.Q.\Delta t \quad (3)$$

Where: q = sensible heat addition from infiltrated air (MBTu/h)
Q = ventilation in liters per second and infiltration (ft^3/s)
Δt = difference between the outside and indoor air temperature

Q is calculated by the formula in Equation 4:

$$Q = \frac{V.ACH}{3600} \quad (4)$$

Where: V = Conditioned room volume (ft^3)
ACH = Number of air changes in a room in 1 hour

Heat gain from humans is calculated by multiplying the number of occupants by the rate of heat gain, which is set at 475 Btu/hour according to SNI 03-6572-2001 for moderate activity office work, and the formula used is shown in Equation 5:

$$q = N.(heat\ gain\ rate) \quad (5)$$

Where: N = Number of occupants

As the model output, the minimum filter area is crucial for preserving indoor pressure stability and air quality. It is determined by considering the ventilation rate of the room. Based on ASHRAE recommendation, the maximum filter ventilation rate is 150 ft/min for a 1-inch thick HEPA filter (MERV13). The formula is expressed in Equation 6:

$$A = Q.Qf.60 \quad (6)$$

Where: A = Minimum filter area (ft^2)
Q = Room ventilation rate (ft^2/s)
F = Filter ventilation rate (ft/min)

RapidMiner, used for developing ML model, streamlines the process through Auto Model feature, automating various stages:

1) Data import: The initial stage is to import relevant data into RapidMiner.
2) Data cleansing: This includes tasks such as managing missing values, data normalization, feature selection, data partitioning for training and testing to ensure suitability for modeling.
3) Auto Model Configuration: Users specify the target variable and performance metric.
4) Model Selection: Auto Model explores various ML algorithms such as regression, classification, and clustering to identify the best model for the target variable and performance metric.
5) Model Training: Auto Model optimizes model parameters and hyperparameters.
6) Model Evaluation: After training, Auto Model assesses the performance of each model on the validation dataset, ranking based on the specified performance metric
7) Model Deployment: The best-performing model is selected for deployment, allowing prediction for new unseen data.

After developing the model to predict output values based on input data, the accuracy was assessed using Mean Absolute Error (MAE) and the confusion matrix to calculate performance. MAE was used to compute absolute errors for all predictions and calculate the mean. This process was carried out by evaluating the mean of the dataset, subtracting it from each data point, summing the results, and dividing by the total number of datasets (Lubis *et al.*, 2021). Moreover, MAE has been widely used as a metric in regression tasks for quantifying the average discrepancy between the predicted and actual values, with various advantages related to robustness to outliers and scale consistency (Hodson, 2022), and the MAE formula is expressed in Formula 7:

$$MAE = \frac{1}{n}\sum xi - x \tag{7}$$

Where: xi = the actual value
x = the predicted value
n = the total number of values

The confusion matrix visually represents the performance of the predictive model, detailing correct and incorrect predictions (Berawi *et al.*, 2021). Precision and Recall are key indicators for accuracy assessment. Precision measures accurate predictions among all predicted data, while Recall assesses successful predictions relative to actual data. These indicators offer insights into the classification performance and ability to make accurate class predictions. The workflow for achieving the objectives of this study is presented in Figure 1.

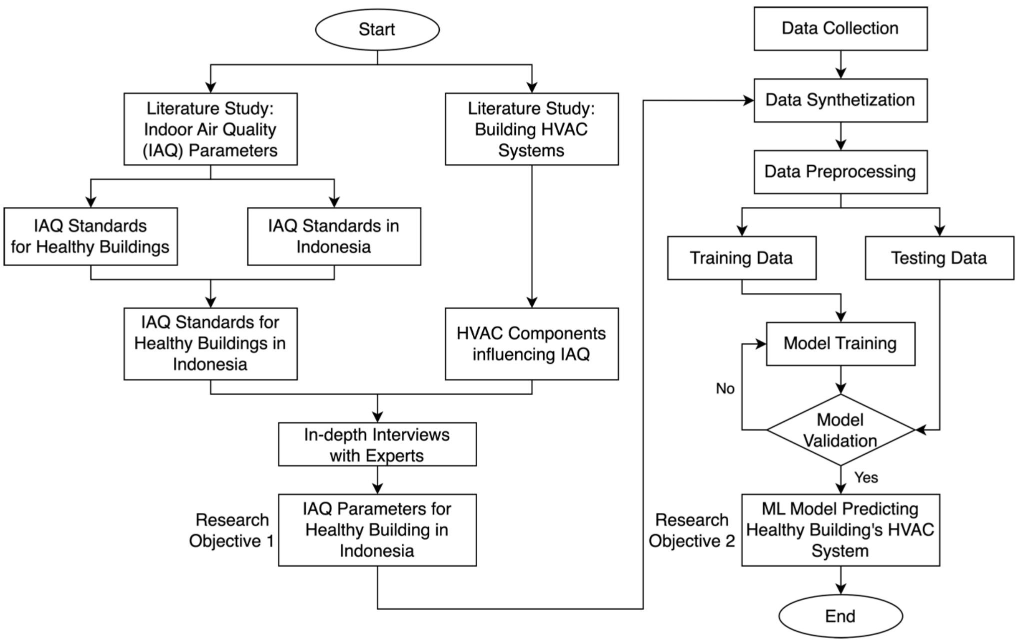

Figure 1 Study Workflow

3. Results and Discussion

3.1. Identifying IAQ Parameters for Healthy Building (HB) in Indonesia

A literature review conducted on related documents showed that there were various indicators used to measure IAQ of HB. Moreover, IAQ indicator in HB consisted of seven pollutants, namely Particulate Matter (PM10), PM2.5, Radon, Ozone, Volatile Organic Compound (VOC), Nitrogen Oxides (NO), and Carbon Monoxide (CO), negatively impacting human health (Allen *et al.*, 2017). The data of threshold values for these indicators, representing optimal air quality, were collected and validated through in-depth interviews with experts in the field of HB. Subsequently, the addition of several parameters was recommended including CO_2, temperature, and humidity as significant IAQ parameters. CO_2 was considered due to its presence in inhabited spaces from human respiration and recognition as an indoor pollutant in standards such as ASHRAE, along with PM_{10}, $PM_{2.5}$, and NO_2. Table 2 summarizes IAQ parameters for HB, integrating expert insights.

Table 2 IAQ parameters for HB in Indonesia

Indicators	Threshold	References
CO_2	1000 ppm (8h)	ASHRAE/EPA
PM_{10}	50 µg/m³ (24h)	WELL/LEED
$PM_{2.5}$	35 µg/m³ (24h)	WELL; EPA; PMK No. 1077
NO_2	100 ppb (1h) 53 ppb (1y)	ASHRAE/EPA
Radon	4 pCi/L	WELL/LEED; ASHRAE/EPA; OSHA
Ozon	0,07 ppm (8h)	WELL/LEED; ASHRAE/EPA
VOC	500 µg/m³	WELL/LEED
CO	9 ppm (8h)	WELL/LEED; ASHRAE/EPA; PMK No. 1077

Optimal IAQ in HVAC system can be achieved through ventilation and filtration. Ventilation, either natural or mechanical, supplies and removes air, while filters are key in removing particulates. Consequently, the impact of filters on room pressure is essential during the selection. In commercial and office buildings, a MERV13 filter is effective during the filtration of particles sized between 0.3-1.0 microns (NIOSH, 2003).

Temperature and humidity also play a significant effecting in determining IAQ. Indoor temperature affects air movement and pollutant dilution, with high temperatures potentially increasing VOC concentrations (Liu, 2018). Humidity significantly affects particulate matter, with higher levels leading to the settling of heavier particles, while lower humidity keeps particles airborne (Zhang *et al.*, 2017).

Based on a literature study and in-depth interviews with experts, chiller and Air Handling Unit (AHU) are key components affecting temperature and humidity. Chiller is responsible for cooling the rooms for comfortable temperatures, while AHU maintains humidity levels. Furthermore, the evaporator in AHU adds moisture to conditioned air, regulating indoor humidity. Well-coordinated chiller and AHU operation is essential for optimal temperature and humidity control for building of occupants.

3.2. Developing Machine Learning Models

3.2.1. Data Preprocessing

The result of the first Research Objective (RO) led to the development of predictive ML model for four key outputs, namely 1) Cooling load, 2) Chiller type, 3) AHU type, and 4) Minimum filter area. Initial preparation of building data facilitated air conditioning load calculation for each floor, enabling the selection of appropriate chiller and AHU types. focusing on a commonly used chiller brand in Indonesia based on cooling load capacity, as shown in Table 3.

The ventilation rate of the room determines the minimum filter area. According to ASHRAE recommendation, the maximum filter ventilation rate is 150 ft/min for a 1-inch filter thickness. After preprocessing the data, the modeling process included three stages, namely Importing, Auto Model, and Deployment. RapidMiner user-friendly interface and automation features streamline the creation and deployment of ML model efficiently.

Table 3 Cooling load capacity of several Chiller and AHU types

Chiller			AHU		
No.	Type	Capacity (kW)	No.	Type	Capacity (kW)
1	EWAQ040	43.4	1	AHUR16	47.5
2	EWAQ050	51.8	2	AHUR20	59
3	EWAQ064	64.5	3	AHUR32	95.1
4	EWAQ075	74.7	4	AHUR40	110.2
5	EWAQ085	84.2	5	AHUR48	140.2
6	EWAQ100	96.7	6	AHUR60	177.4
7	EWAQ120	117	7	AHUR80	236.1
8	EWAQ140	139			
9	EWAQ155	154			
10	EWAQ180	178			

3.2.2. Machine Learning (ML) Model Development

This section presents the development of predictive ML model, including 1) Cooling load, 2) Chiller type, 3) AHU type, and 4) Minimum filter area predictions. After the training data was accessed and the predictors were selected through task selection, the required attributes were imported to build the first prediction model for Cooling load. RapidMiner played a crucial role by providing attribute quality indicators based on correlation, ID-ness, stability, and missing values that significantly impacted model performance. However, poor data quality could lead to overfitting, limiting predictions to a narrow data range, or underfitting due to scattered data quality, impeding accurate predictions.

ML algorithms considered in developing the first model included the Generalized Linear Model (GLM), Deep Learning (DL), Decision Trees (DT), Random Forest (RF), Gradient Boosted Trees (GBT), and Support Vector Machine (CVM). As presented in Figure 2, model with the highest accuracy was identified through algorithm comparisons, assessing errors, standard deviations, and prediction times. For the first model, GLM outperformed others with a minimal relative error of 1.1%, while DT had the quickest prediction time.

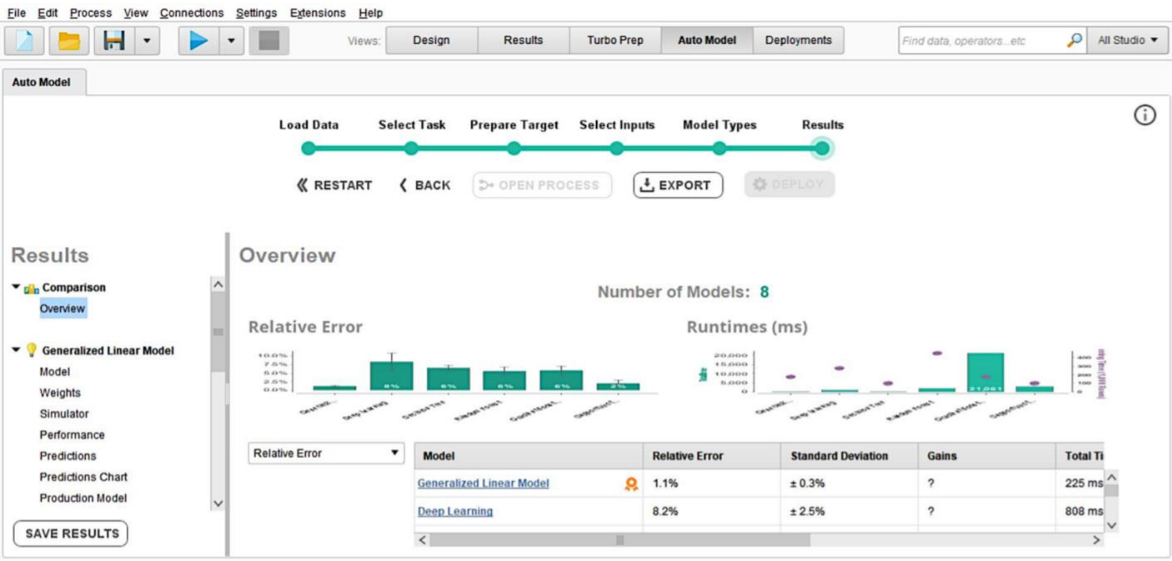

Figure 2 Prediction result of ML for cooling load

The second model followed the same procedures that were previously used. Algorithms considered included Naïve Bayes (NB), GLM, Logistic Regression (LR), Fast Large Margin (FLM), DL, DT, RF, GBT, and SVM. Naïve Bayes showed the best performance with a 3.3% relative error, while DL showed the fastest runtime of 5 seconds. Furthermore, Naïve Bayes proved the most accurate for the third predictive model for AHU types, with a 10% classification error. Regarding the fourth model for minimum filter area, floor area and ceiling height were used as inputs. Among models developed with algorithms including LR, FLM, DL, DT, RF, GBT, and SVM, GLM showed excellent performance with a 1.2% relative error and the fastest runtime. GLM was selected as the most suitable algorithm for models 1 and 4 due to the accuracy in predicting numerical values in these models. Furthermore, Naïve Bayes, a classification algorithm, yielded the best results for Models 2 and 3, as the output was in the form of classes.

3.2.3. Machine Learning (ML) Model Evaluation

The assessment of the regression model accuracy included relative error and MAE, providing insights into the prediction error magnitude. For example, in Model 1, MAE was 0.893, and 381.760 in Model 4. The accuracy for Models 2 and 3 was measured using the confusion matrix due to the classification nature. The confusion matrix showed that Model 2 achieved 100% accuracy in 9 out of 10 chiller types, with a 3.33% classification error. Model 3 achieved 100% accuracy in 4 among 7 AHU types, resulting in a 10% classification error. Table 4 summarizes the accuracy results of all developed models.

Table 4 The accuracy results for ML models

Model	Algorithm	Relative/Classification Error	MAE
1: Cooling Load	Generalized Linear Model	1.11%	0.893
2: Chiller Type	Naïve Bayes	3.33%	-
2: AHU Type	Naïve Bayes	10%	-
4: Filter Area	Generalized Linear Model	1.22%	381.760

The developed ML model was deployed to show the predictive capacity on new data. A particular building was used as the case study with several specifications, accommodating 175 occupants. These included a total area of 1850 m^2, ceiling height 3.1 meters, and ceiling area matching the total area. Window sizes are specified (north-facing: 15.5 m^2, east-facing: 16 m^2, south-facing: 16.5 m^2, west-facing: 15.7 m^2), door sizes (north-facing: 6.5 m^2, east-facing: 2.1 m^2, south-facing: 6 m^2, west-facing: 7.8 m^2), and wall areas (north side: 97 m^2, east side: 96.2 m^2, south side: 95.6 m^2, and west side: 94 m^2).

The cooling load prediction from Model 1 was 102.297 kW, which was Models 2 and 3 to determine chiller type (EWAQ120) and AHU type (AHUR48), respectively. Additionally, Model 4 predicted a minimum filter area of 4.084 m^2. As shown in Figures 3, 4, and 5, the implementation of these predictions can effectively optimize IAQ in Indonesian building, following HB concept.

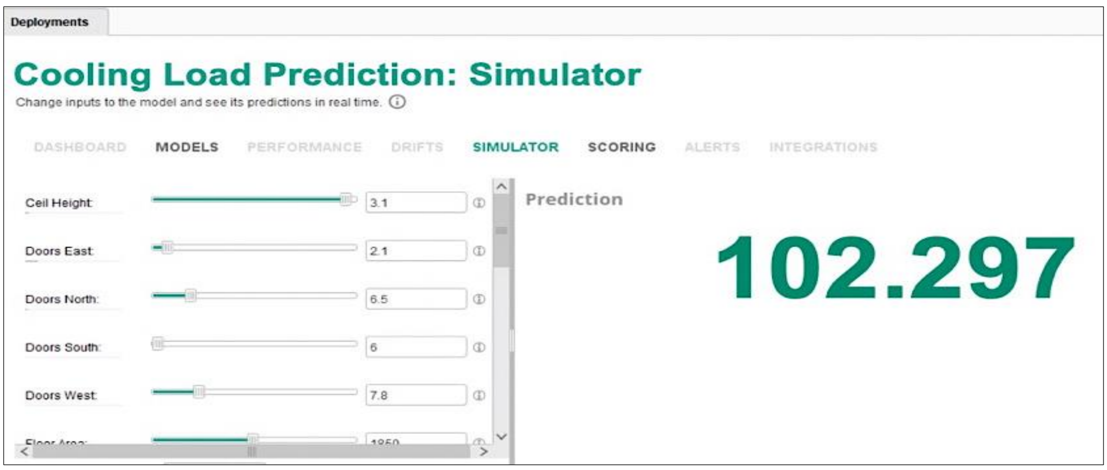

Figure 3 Model deployment: Cooling load prediction with ML Model 1

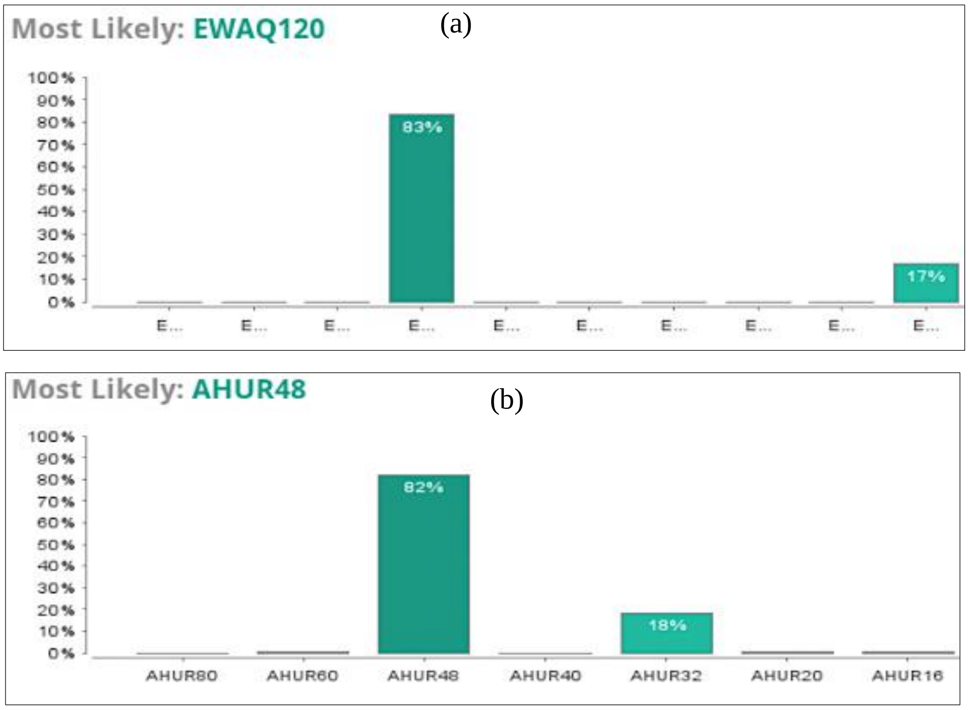

Figure 4 Model deployment: (a) Chiller and (b) AHU type prediction with ML Models 2&3

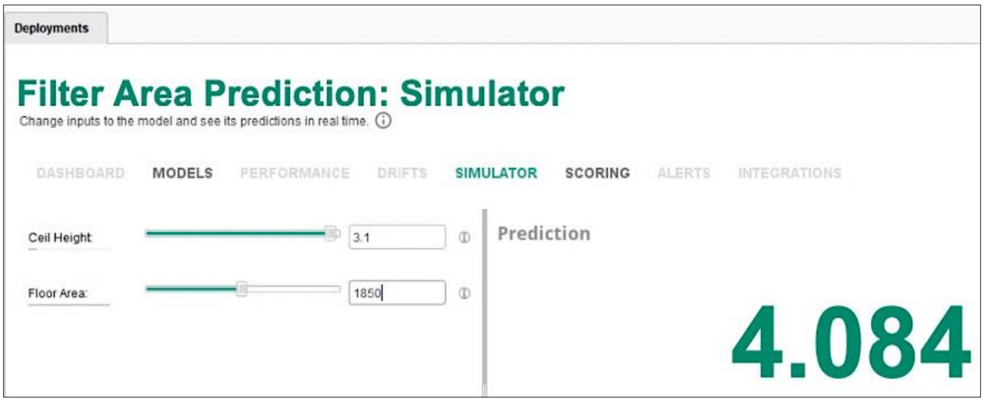

Figure 5 Model deployment: Filter Area prediction with ML Model 4

4. Conclusions

In conclusion, this study used ML to enhance HVAC system design, focusing on improving IAQ to achieve HB concept. The two main objectives included identifying IAQ parameters for Indonesian HB and developing ML model for HVAC system planning. Based on the results, ML model successfully predicted the cooling load, chiller type, AHU type, and filter area based on climate and building data. GLM algorithm was recommended to predict cooling load and minimum filter area, while Naïve Bayes performed best in forecasting chiller and AHU types. The implementation of these predictions could effectively optimize IAQ, contributing to the reduction of SBS incidence. This study did not specifically quantify the percentage by which the incidence was reduced. Consequently, future study was recommended to examine the reduction in SBS incidence resulting from the improved IAQ.

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