Indoor Air Quality Predictions For Automation

Kadir Gökdeniz*
*Ankara University, Computer Engineering Department
Email: kadirqokdeniz@hotmail.com, ORCID: https://orcid.org/0009-0004-0901-8642

***Abstract*—This study explores the application of home automation systems for indoor air quality prediction, leveraging real-time data on temperature, humidity, pressure, CO_2 levels, occupancy status, and window conditions. Despite potential challenges in data quality and responsiveness, the research employs deep learning techniques to predict air quality. Comparative analysis of GRU and LSTM models reveals GRU's superior performance across multiple metrics, emphasizing its generalization capability. However, model selection requires consideration of all scenarios. Additionally, the study introduces an Air-Smart Controller, enabling users to monitor predictions and control home automation systems. In conclusion, the research underscores the promise of home automation in air quality prediction, offering insights into neural network architectures and contributing to advancements in automation technology and air quality management.**

Keywords: Automation System, Air Quality, Deep Learning, Machine Learning

I. Introduction

The origins of automation systems can be traced back to before the Common Era. However, the Industrial Revolution is what mass-transformed human life. While the primary domain benefiting from automation systems has been industrial production, as we entered the 2000s, they began to transform our lives in many other areas. Automation systems are reshaping our lives in various fields such as automatic driving systems and transportation, energy management, smart grids, building automation and smart home technologies, telecommunications and communication management, healthcare, and medical technologies.

The emergence of COVID-19 has led to global quarantine and social distancing measures, which have forced people to stay at home more. These prolonged periods spent indoors have brought along comfort and health problems. Smart home technologies promise to address these comfort and health issues. Heating, ventilation, and air conditioning (HVAC) systems work seamlessly with smart home systems to automate indoor air quality. Using microcontrollers, information such as indoor and outdoor temperature, relative humidity, pressure, CO_2 levels, occupancy status, and window status (open/closed) is measured in real time.

The data obtained from sensors may encounter some potential problems. For example, sensors may produce erroneous results for any reason. The demands of homeowners may vary temporarily, and the automation process may struggle to respond to these demands. On the other hand, measurements of indoor air quality may provide information about potential disasters in the future, but the automation system may be inadequate in responding to them. For instance, high temperature may indicate a fire while high humidity levels may indicate a water leak or flooding. A simple automation system lacks foresight about future situations, hence it is insufficient in providing proactive solutions.

Model Predictive Control (MPC) is a structure developed to predict and analyze future states of automation systems and to provide energy savings. MPC systems integrate automation systems and prediction models to form a hybrid system. The mentioned system design necessitates a Human-machine interface (HMI) that enables users to understand how automation systems operate and what mode they are in. HMI simply refers to a software platform where people can intervene in the operation of automation systems and view data. Figure 1 illustrates the interaction of home automation systems with the environment.

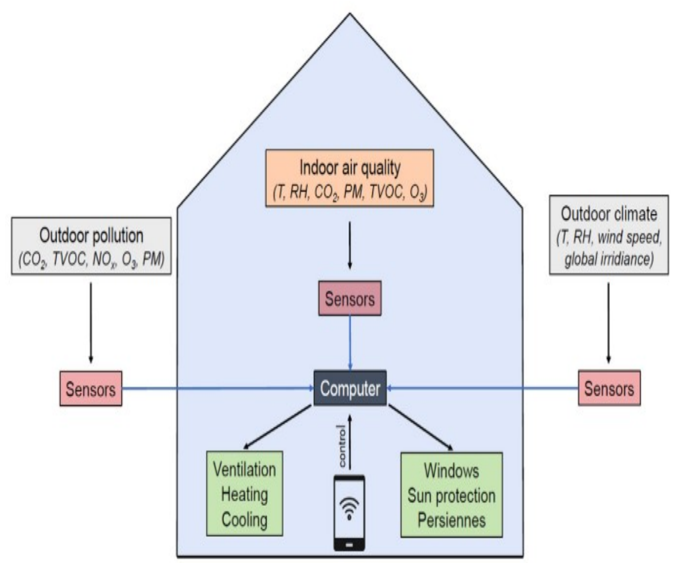

Fig. 1: Indoor Air Quality Automation [1].

Dynamics systems emerge as structures that enable systems to better understand user needs and facilitate the creation of smarter strategies. This approach allows for the development of faster and more effective strategies toward goals, which can improve living standards. However, during the installation phase of automation systems, they are tested, and test engineers may find the data quality low due to insufficient data and the presence of outlier values. Prediction data obtained with machine learning methods can help meet such needs. Additionally, the operation of the automation system can be automated with new data using prediction data. This is another benefit of generating prediction data.

Human-Machine Interface (HMI) systems developed in smart home technologies promote low energy consumption and utilize specialized technologies to enhance indoor air quality [2]. These systems also aid in developing new strategies to protect against the adverse effects of climate change. As noted in the study [3], modern sensor technologies not only diagnose climatic characteristics but also detect air pollutant particles and transmit this data to smart home systems. However, new smart homeowners need to adapt to situations like not being able to manually open windows, which is a significant adjustment that many find challenging.

According to the research, we will need to further investigate how to create healthy living environments [4]. In the United States, a group of health experts has extensively addressed how climate change affects our lifestyle [5]. Upon reviewing the report of this research, it was found that climate change significantly increases health risks for the elderly, children, and people with cardiac/respiratory diseases. Study [6] also focused on the impacts of climate change on indoor air quality and emphasized that systems regulating indoor air quality (HVAC) are a significant factor affecting the prevalence of diseases.

Health-based smart technologies form a complex network with various technological devices, introducing the concept of Ambient Assisted Living (AAL) into our lives. This network integrates with personal healthcare monitoring and telehealth systems [7]. In addition to helping reduce the increasing demands in the healthcare sector, this technology also supports improving energy efficiency and reducing negative environmental impacts.

The data collected by sensors also aims to enhance user comfort. A study [8] shows that the need for humidity and temperature sensors in smart home systems has increased over the years. The number and placement of sensors are crucial. Sensors placed inside the home can be of different types, and their measurement capacities and performances bring along various advantages and disadvantages [8]. To better understand this, a comparison of materials used in humidity sensors across different categories can be considered. Table 1 provides the necessary data for this purpose. For example, if a fast response time and a wide humidity range are required, P(VDF-TrFE)/GF would be a good choice. On the other hand, Reduced Graphene Oxide provides high linearity and a reasonable response time.

Another important issue is IoT protocols. In smart home systems, data collected from sensors should be securely, quickly, and comprehensively transported in an appropriate format. Protocols such as Wi-Fi (802.11), Bluetooth, Zigbee, and Z-Wave are commonly used technologies for transmitting data in smart home automation systems [10]. While Wi-Fi provides broad coverage and high bandwidth, Bluetooth is ideal for short-range communication. Zigbee and Z-Wave, on the other hand, are preferred for establishing wireless communication among devices with low power consumption. These protocols are selected based on the features of the devices and user preferences, each offering different advantages.

With all these mentioned details, IoT systems and automation systems emerge and are utilized alongside machine learning methods. These systems impact humans comprehensively, with effects ranging from health to security, and even entertainment areas. For these reasons, they will continue to be among the focus areas for researchers and

Sensing Material	RH Range	Response Time(s)	Recovery Time(s)	Linearity	Sensing Principle
Graphene Oxide	10-98	19	10	-	Piezoelectric
Reduced Graphene Oxide	30-90	28	48	Yes	Resistive
Tin(IV) Oxide/Reduced Graphene Oxide	11-97	102	6	-	-
Chitosan/Graphene Quantum Dots	11-95	36	3	No	-
Black Phosphorous	11-97	255	10	-	Resistive
Graphene Oxide/polyelectrolyte	11-97	-	-	No	Capacitive
Graphene-Polystyrene Sulfonic Sodium	30-95	3	22	No	Impedance Based
VS_2	0-100	30-40	12-50	No	Resistive
P(VDF-TrFE)/GF	8-98	0.8	2.5	No	Impedance Based

TABLE I: Performance Comparison of Humidity Sensor Materials [9] individuals in the near future.

II. Literature Review and Background

A. Literature Review

As an early study, a research conducted in 2011 used multivariate analysis of variance (MANOVA) to predict the indoor air quality of a metro system [12]. In this study, the data was divided into three categories: spring and fall as the first category, summer as the second category, and winter as the third category. The variance analyses were conducted separately for these categories. This study indicates that indoor air quality varies depending on the seasons.

Another study is based on an optimization work conducted by Gaurav Priyadarshi and B. Kiran Naik [13]. In this study, they perform regression prediction using the K-nearest neighbors (KNN) algorithm. For these predictions, they utilize a model called the Finite Difference Transient Model (FDM). The study thoroughly discusses the potential limits and advantages of this model.

The study conducted by T. Akilan and K.M. Baalamurugan [14] focuses on predicting indoor weather conditions in agriculture using GRU (Gated Recurrent Unit) and LSTM (Long Short-Term Memory) to develop a warning system that alerts before plants encounter unfavorable conditions. This IoT (Internet of Things) based study is significant for understanding how GRU and LSTM models are used in time series analysis and how sensor data interacts.

Another study conducted by Elnaggar and other researchers presents a risk analysis of the indoor air quality required for the preservation of artworks in a museum located in the Mediterranean region [15]. This study also provides a comprehensive examination of how risk analysis is conducted in the preparation of automation systems. By identifying the necessary indoor air quality parameters for the preservation of artworks, the study details how these parameters can be integrated into automation systems and how these systems can be managed effectively.

A. Gururaj and colleagues conducted a classification study on air quality prediction using artificial neural networks and gradient-boosting models, and they developed a website to present their findings [16]. This study is an important resource for our project to compare HMI (Human-Machine Interface) design with literature studies and to learn from current applications.

In another study conducted by Nyoman Kusuma Wardana and other researchers, a comprehensive study was presented on the simultaneous display of predictive and real-time data in SCADA (Supervisory Control and Data Acquisition) devices [17]. This study thoroughly explores how data can be integrated and presented simultaneously in SCADA systems.

B. Automation and Prediction Systems

The automation pyramid is used because it provides a better approach to explain automation processes [19]. Figure 2 presents the automation pyramid. The automation process has a hierarchical structure. If any part of the pyramid is missing or has significant problems, it can hinder the automation processes. From a general perspective, the fundamental parts of the automation process are hardware, software, and management levels. When we talk about hardware, we refer to various sensors, PLC (Programmable Logic Controller), and PLD (Programmable Logic Device) levels. The software part is the Supervisory level, which includes SCADA (Supervisory Control and Data Acquisition) devices. MES (Manufacturing Execution System) and ERP (Enterprise Resource Planning) are the management levels.

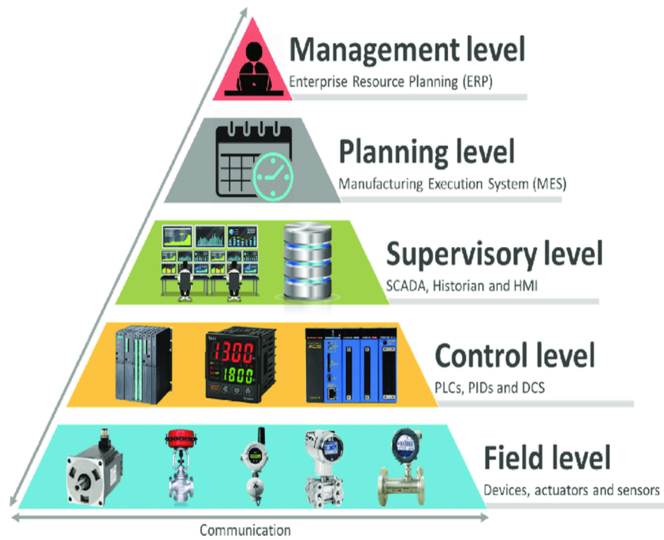

Fig. 2: Automation Pyramid [20].

ISA has a significant role in the creation, development, and adoption of the automation pyramid [21]. According to the hierarchy presented by the pyramid, a five-step process is adopted. Implementation starts from the bottom level. The bottom level is called the "field level," where various sensors interact. One of its most important features is the real-time acquisition and modification of data.

The second part is the control level. Here, the sensors are organized using a programmable logic controller (PLC), microcontrollers, automatic controllers, or a dedicated computer. Control devices can begin their tasks within milliseconds after receiving the information in the decision-making process [22].

The third part is the supervision level. In this part, data from the control level is received within a very short time and filtered. Filtering data is an important step because not all data needs to be sent to and processed by the control system; not all data is included in the higher-level processes. Supervision systems can interact with other devices in the field and ensure the execution of commands generated by certain decisions. However, if there is a discrepancy between the levels, the commands generated at the supervision level may lose their validity.

The planning level is the fourth tier, encompassing manufacturing execution and operation management systems. Compliance with the production plan is observed based on Key Performance Indicators (KPIs). Since the information comes from the control level, it has been filtered; additionally, data is updated in specific patterns. The frequency of data updates may vary; sampling of data is tightly dependent on ISA 95 standards.

At the apex of the pyramid is the management tier. Commercial systems such as Altai, SAP, and Oracle are utilized to actively operate Enterprise Resource Planning (ERP) systems. The management of all processes is organized from a central point. This can be likened to the main control center that encompasses all home systems for smart home systems. The aim is to easily account for data, and additional factors such as availability and corrective maintenance can also be integrated into the system at this stage.

Automation systems used in smart home setups provide automatic control in various areas of the house, including lighting, heating, ventilation, security, and entertainment. For instance, lighting automation adjusts room lights based on ambient light, promoting energy efficiency and offering homeowners a more comfortable environment. Heating systems optimize every room in the house through temperature sensors and programmable thermostats, enhancing comfort levels and lowering energy costs. Security systems continuously monitor the surroundings of the house through cameras and motion sensors, allowing users remote access. All these automation systems provide homeowners with the flexibility to remotely monitor and manage their homes, enabling a more comfortable, secure, and energy-efficient living experience.

In the study [23] that examines the potential negative effects and risks of systems in smart homes, possible automation system errors and reasons for user dissatisfaction were investigated comprehensively, and the results were presented in detail. According to the research findings, errors arising from a specific hierarchy in automation systems can affect other processes, and the automation system's response to such errors may take a long time or may not be effective.

If the mentioned problems arise from data-related issues, data security can be ensured, data quantity can be increased, and the system can gain foresight by using prediction data. Prediction data can be incorporated into both the management and control parts of the automation system. In the control part, supervisory devices can reduce response time by providing remote access, viewing, and intervention capabilities for data. This approach can be a crucial step in addressing data-based issues in automation systems and making the system more secure and effective.

Our primary objective within the project revolves around the prediction of indoor air quality, thus necessitating the handling of a regression problem concerning time series data. Within the existing literature, a range of machine learning methodologies including Dummy, Huber, Ada Boost, GBoost, Random Forest, XGBoost, KNN, Decision Trees, LSTM, and ARIMA are frequently employed [19]. The outcomes of the research indicate that among these machine learning models, Recurrent Neural Networks (RNNs) exhibit superior performance, particularly within short-term intervals. Consequently, our focus has been directed towards leveraging RNNs.

III. Material and Methods

In this section, factors affecting prediction ability will be explained while constructing the deep artificial neural network.

A. Dataset and Data Preparation

The study [24] aimed at examining household energy consumption, health, and security impacts, and providing support to researchers, presents an open-access dataset. The data were obtained from an apartment in Beijing, China. Using a cloud-based data collection platform called IDCP, the data were collected covering a period from May 31, 2021, to May 31, 2022. The data were collected on a minute-by-minute basis, including household behaviors, thermal environment information, device usage quantities, and also external weather data from the nearest national weather station. This dataset is significant for being the first publicly accessible dataset that concurrently records household behaviors and electricity usage in China. The dataset is made accessible under the title CN-OBEE.

The dataset includes data from 6 different rooms: cloakroom, home office, kitchen, living room, master bedroom, and secondary bedroom. Data for each room, such as temperature, relative humidity, pressure, window status (open/ closed), location, and occupancy status, are recorded at a minute-by-minute frequency. External weather data, on the other hand, are recorded at an hourly frequency and include dry-bulb temperature (°C), relative humidity (%), atmospheric pressure (hPa), wind speed (m/s), wind direction, ground temperature (°C), horizontal total solar radiation intensity (W/m^2), and horizontal diffuse solar radiation intensity (W/m^2). Energy consumption data for household appliances are stored at a minute-by-minute frequency and include data from an electric kettle, fridge, rice cooker, computer, TV, upstairs water heater, downstairs water heater, washing machine, and 6 different air conditioners.

Ensuring that the data is in numerical format is imperative before training the models. Categorical data such as wind direction in the dataset has been converted to numerical values using Label Encoder. However, dealing with missing values presents another challenge. While low rates of missing values may be tolerable, high rates can significantly compromise data quality. Therefore, missing values have been imputed with the median value. Due to the high rate of missing values, data from the master bedroom has been excluded from the analysis.

To optimize the processing of the data, it has been examined in 10-minute intervals. Since the external weather data is available at hourly frequency, it is assumed that the outdoor weather conditions remain constant within each hour. Therefore, the weather data for each hour is utilized to divide the data into 10-minute intervals.

B. Data Visualization and Feature Engineering

Examining the characteristic features of the data before training is essential for better management of the process. Data visualization can facilitate the analysis of statistical information such as arithmetic mean and standard deviation, as well as other problems. For example, anomaly detection is a crucial approach for analyzing automation systems. Upper and lower limits can be determined using Exponential Moving Averages, aiding in the analysis of abnormal behaviors. Figure 3 presents an analysis of abnormal behavior in some of the indoor temperature data in the living room.

The selection of data for training significantly impacts the performance of the training process. In some cases, meaningful potentials can be derived from the data, while in others, training with similar or identical data may exacerbate the tendency for overfitting. Guided by the insights provided by the study [12], we are incorporating seasonal information into the data numerically. The high interaction of this information, particularly with relative humidity data, suggests its potential to enhance predictive performance. Conversely, through the use of a correlation matrix, we investigate the interaction among the data, and some data with similar correlation values that are selected for prediction are excluded from the training process.

C. Data Preprocessing

In deep neural networks, normalization is a routine process applied to enhance training performance, as also mentioned in the study [25]. Normalization procedures reduce the effects of outliers while preserving the fundamental characteristic features of the data. An implementation such as MinMaxScaler rescales the data to a scale between the minimum and maximum values. This process brings the data distribution into a range between 0 and 1, allowing the model to be trained more effectively and converge more rapidly.

The function serves as a data preprocessor, designed to extract batches of samples from a time series dataset for training purposes. It generates sequential samples with a specified ”lookback” period, determining how far back each sample should consider, and a ”delay” period, indicating the time lag for target values. The function supports the shuffling of samples and allows customization of batch size and step size, providing flexibility in data preparation for model training.

Each sample is constructed by looking back over a period of 10 days, with a time interval of 30 minutes between consecutive data points. The time difference between input data and target values is 1 day. These parameters determine how the dataset will be processed and how far back and forward each sample will look. Thus, they play a crucial role in determining how the model will evaluate and predict time series data.

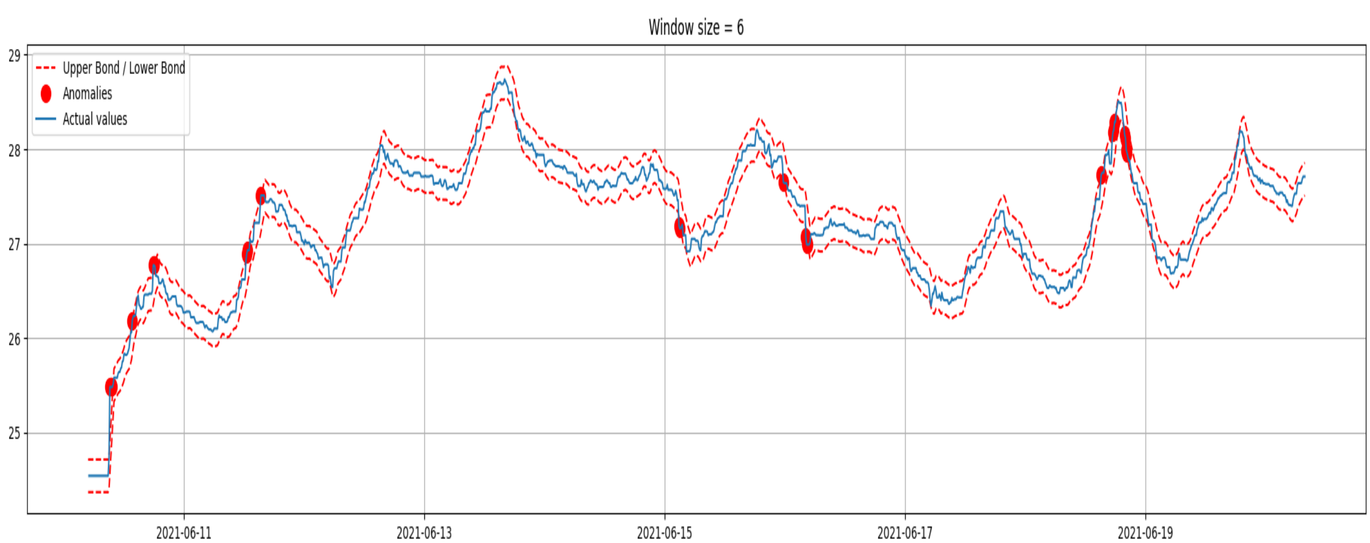

Fig. 3: Anomaly detection for living room interior temperature.

D. Air-Smart Controller

Air-Smart Controller is a web interface developed using Python's Streamlit library. This interface allows users to view forecast data at ten-minute intervals. These forecast data are connected to the control level of the automation system and work integrated with SCADA and MES systems.

Through this web interface, users can view data for the next 44 days at ten-minute intervals. Data is available for 5 different rooms. The data displayed includes temperature, relative humidity, and pressure information. Additionally, it shows which modes the automation system will operate in, synchronized with the data.

Users can request changes to the modes of the automation system. They can suspend the operation of the automation system or request it to operate in different modes. The manipulated data is evaluated by the automation system, and as a result of this evaluation, the request may be deemed valid or invalid. Figure 4 shows the deployment of the Air-Smart Controller device.

E. Deep Neural Networks

LSTM

When feedforward artificial neural networks are trained with time series data, recent data is learned strongly while the influence of older data diminishes over time. This problem is called vanishing gradients. Conversely, in situations where the influence of older data is amplified, the exploding gradients problem may occur. Recurrent Neural Networks (RNNs) are used in artificial neural networks to address these issues. RNNs mitigate this effect by feeding a representation of past data alongside new data into the input. This feature enables the prediction of the next data point by deciphering patterns between past and current data.

LSTM-based models can be thought of as an extension of RNNs and have the ability to learn longer-term dependencies. However, remembering longer-term dependencies also brings some challenges in updating the weights. LSTM can decide which gradients to forget and which ones to remember. This feature is often explained using the gate analogy. The core components of LSTM generally include three gates: the forget gate, the input gate, and the output gate. Figure 5 shows simple LSTM structure.

Forget Gate: This gate generally employs the sigmoid function to determine which information should be discarded from the LSTM memory. This decision is mainly based on the previous time steps, h_{t-1}, and the current input, x_t. The output of this gate, f_t, ranges between 0 and 1, where 0 signifies complete forgetting of the learned information and 1 signifies retaining all information. This output is calculated as:

$$f_t = \sigma(W_{fh}h_{t-1} + W_{fx}x_t + b_f) \tag{1}$$

, where b_f is a constant termed as bias.

Input Gate: In the LSTM model, the input gate decides whether new information should be added to the LSTM memory. This gate comprises both sigmoid and tanh layers. The sigmoid layer determines which values need updating, while the tanh layer generates new candidate values. The output of the sigmoid layer, i_t, indicates the update decision, while the output of the tanh layer, $\tilde{c}_t$, represents the new candidate values. These two outputs are then used to update the LSTM memory.

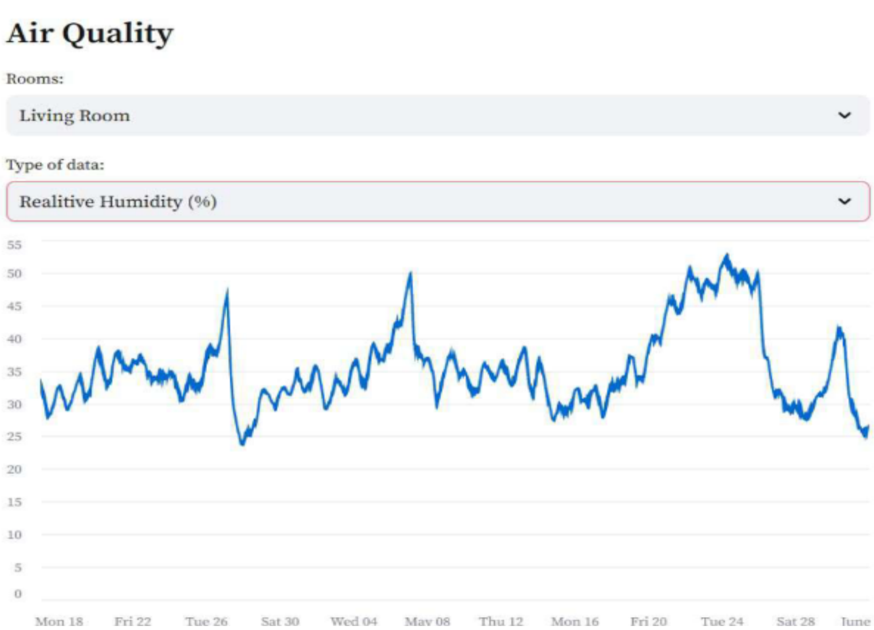

Fig. 4: Air-Smart Controller Data Visualisation.

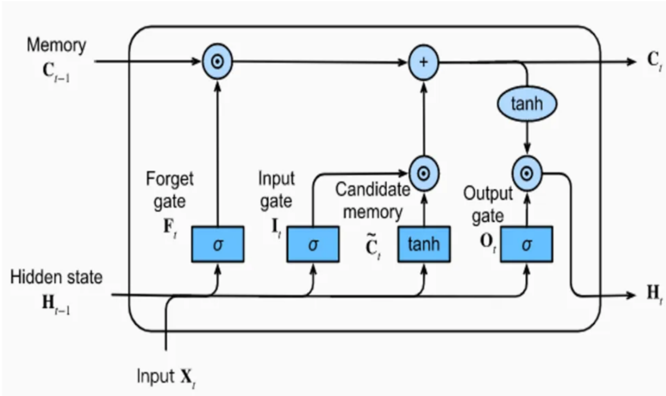

Fig. 5: LSTM structure [26].

The sigmoid layer is formulated as follows:

$$i_t = \sigma(W_{ih} \cdot h_{t-1} + W_{ix} \cdot x_t + b_i) \tag{2}$$

The tanh layer is formulated as follows:

$$\widetilde{c}_t = \tanh(W_{ch} \cdot h_{t-1} + W_{cx} \cdot x_t + b_c) \tag{3}$$

The combined formula for these layers is as follows:

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \widetilde{c}_t \tag{4}$$

Output Gate: This gate primarily uses a sigmoid layer to determine how the LSTM memory contributes to the output. It then applies a non-linear tanh function to map the values between -1 and 1. Finally, it obtains the result by multiplying this with the output of the sigmoid layer. The following equations are used to compute the output:

$$o_t = \sigma(W_{oh} \cdot h_{t-1} + W_{ox} \cdot x_t + b_o) \tag{5}$$

$$h_t = o_t \cdot \tanh(c_t) \tag{6}$$

GRU

The Gated Recurrent Unit (GRU) is another type of recurrent neural network (RNN) akin to LSTM but with a more straightforward cell structure. GRU comprises two gates: a reset gate and an update gate. The reset gate manages the flow of new input to the previous memory, while the update gate dictates the extent to which the previous memory is preserved.Figure 6 shows simple GRU structure.

The equations representing the single-cell structure of GRU are as follows:

Reset Gate:

$$r_t = \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r) \tag{7}$$

Update Gate:

$$z_t = \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z) \tag{8}$$

Candidate Activation:

$$\widetilde{h}_t = \tanh(W_{xh}x_t + W_{hh}(r_t \cdot h_{t-1}) + b_h) \tag{9}$$

Output:

$$h_t = z_t \cdot h_{t-1} + (1 - z_t) \cdot \widetilde{h}_t \tag{10}$$

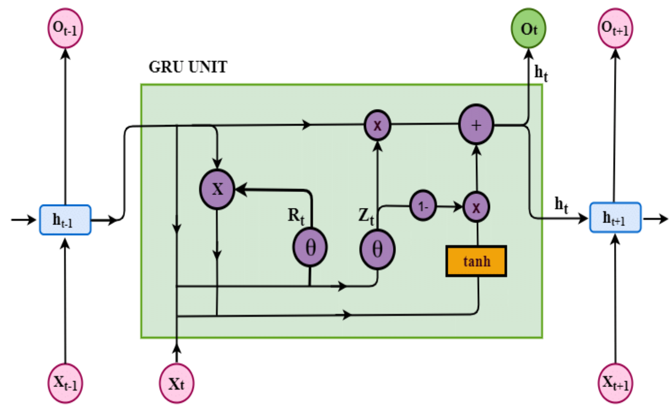

Fig. 6: GRU structure [27].

Here, x_t, h_t, r_t, and z_t represent the input vector, output vector, reset gate, and update gate, respectively. All W variables represent weight matrices, and b denotes biases. The activation functions utilized are the sigmoid function (σ) and the hyperbolic tangent ($\tanh$) function.

These equations define the single-cell structure and output of GRU. This architecture, designed similarly to LSTM, is suitable for modeling long-term dependencies.

F. Metrics

MAE:

MAE quantifies the extent of the disparity between observed and forecasted values. It does not consider whether the predictions are higher or lower than the actual values. Instead, it measures the average amount of error across all predictions.

Formula:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|P_i - O_i| \tag{11}$$

P_i is the predicted value at index i,
O_i is the actual value at index i,
N is the number of data points.

MAE is straightforward to calculate and interpret. Compared to RMSE, MAE is less affected by outliers, making it a more robust metric. The absolute value function is not differentiable at zero, making it challenging to incorporate into optimization problems.

MSE:

MSE is the mean of the squares of errors. Squaring the errors gives more weight to larger errors.

Formula:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2 \quad (12)$$

P_i is the predicted value at index i,
O_i is the actual value at index i,
N is the number of data points.

Employing MSE assists in handling larger error magnitudes, thereby enhancing the model's generalization performance. Additionally, its differentiability at every point extends its applicability to various domains. However, compared to MAE, MSE may become more sensitive to outliers.

RMSE:
RMSE is simply the square root of the MSE error metric. It measures the magnitude of the resulting error rates.

Formula:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \quad (13)$$

P_i is the predicted value at index i,
O_i is the actual value at index i,
N is the number of data points.

Similar to MSE, RMSE is sensitive to large error magnitudes. This characteristic is important to consider in certain applications. RMSE is sensitive to outliers. However, the combination of average error and variance in RMSE can complicate the application in some scenarios.

IV. Results And Discussion

Table II presents a comprehensive comparison of LSTM and GRU models across different rooms and air quality parameters. Let's analyze these results in detail:

A. Temperature Predictions

Mean Absolute Error (MAE):
GRU outperforms LSTM in all rooms except the kitchen, where they are tied. GRU's average MAE (0.57°C) is significantly lower than LSTM's (0.93°C), indicating more accurate predictions overall.

Mean Squared Error (MSE):
GRU consistently shows lower MSE values across all rooms. The average MSE for GRU (0.56) is nearly one-third of LSTM's (1.54), suggesting GRU's predictions have less variance and fewer large errors.

Root Mean Squared Error (RMSE):
GRU maintains lower RMSE values in most rooms. The average RMSE for GRU (2.98°C) is slightly better than LSTM (3.12°C), confirming GRU's superior performance in temperature prediction.

B. Relative Humidity Predictions

MAE:
GRU shows better performance in three out of five rooms. GRU's average MAE (5.41%) is lower than LSTM's (6.14%), indicating more accurate humidity predictions.

MSE:
Interestingly, LSTM shows a slightly lower average MSE (60.24) compared to GRU (61.98). This suggests that while GRU is more accurate on average, LSTM might handle some extreme cases better.

RMSE:
The average RMSE values are very close (GRU: 9.21%, LSTM: 9.02%), with LSTM showing a marginal advantage.

	Models	Metrics	Cloakroom	Home Office	Kitchen	Living Room	Secondary Bedroom	Average Result
Temperature (°C)	GRU	MAE	0.62	0.59	0.53	0.50	0.63	0.57
		MSE	0.61	0.62	0.52	0.43	0.63	0.56
		RMSE	3.06	3.10	2.70	3.24	2.81	2.98
	LSTM	MAE	1.50	1.35	0.59	0.63	0.59	0.93
		MSE	3.37	2.66	0.53	0.62	0.54	1.54
		RMSE	3.77	3.14	2.70	3.15	2.83	3.12
Relative Humidity (%)	GRU	MAE	4.60	5.56	5.56	6.14	5.19	5.41
		MSE	40.60	51.95	106.08	69.47	41.82	61.98
		RMSE	8.00	8.68	11.69	9.52	8.14	9.21
	LSTM	MAE	5.98	5.79	7.48	6.25	5.19	6.14
		MSE	56.18	51.83	51.95	70.58	70.64	60.24
		RMSE	8.78	8.53	8.68	9.37	9.72	9.02
Air Pressure (hPa)	GRU	MAE	627.83	607.42	607.42	583.51	596.27	604.49
		MSE	564 216.87	535 430.87	535 431.78	510 340.63	521 524.22	533,388.87
		RMSE	1 085.16	1 098.53	1 094.52	1 086.07	1 081.29	1,089.11
	LSTM	MAE	644.21	621.78	553.50	593.14	633.675	609.26
		MSE	612 609.11	604 939.58	488 360.060	540 417.29	609 777.93	571,220.79
		RMSE	1 117.023	1 113.87	1 036.33	1 067.38	1 110.68	1,089.06

TABLE II: Indoor Air Quality Predictions - Results

This further supports the observation that LSTM might be slightly better at handling extreme humidity cases.

C. Air Pressure Predictions

MAE:

GRU consistently outperforms LSTM across all rooms. The average MAE for GRU (604.49 hPa) is noticeably lower than LSTM (609.26 hPa).

MSE:

GRU shows significantly lower MSE values in all rooms. The average MSE for GRU (533,388.87) is much lower than LSTM (571,220.79), indicating more consistent predictions.

RMSE:

Despite the large difference in MSE, the average RMSE values are very close (GRU: 1,089.11 hPa, LSTM: 1,089.06 hPa). This suggests that while both models have similar overall error magnitudes, GRU's errors are more consistent across predictions.

D. Room-Specific Performance Analysis

Our results reveal interesting variations in prediction accuracy across different rooms. Let's examine these differences and explore potential reasons behind them:

1. Living Room: Best Overall Performance
The living room consistently shows the lowest error rates across all metrics for both temperature and humidity predictions.

Possible reasons:

Central location: The living room might be less affected by external factors, providing more stable and predictable conditions.

Consistent usage patterns: Regular occupancy and standardized activities could lead to more predictable environmental changes.

Optimal sensor placement: The sensors in the living room might be ideally positioned, capturing representative data for the entire space.

2. Kitchen: Mixed Performance
The kitchen shows relatively good performance in temperature prediction but higher error rates in humidity prediction.

Possible reasons:

Frequent temperature changes: Regular cooking activities might create predictable temperature patterns.

Irregular humidity spikes: Cooking, boiling water, and dishwashing can cause rapid and significant changes in humidity, making predictions more challenging.

Ventilation factors: Kitchen exhaust systems might introduce additional variability in air quality parameters.

3. Cloakroom and Secondary Bedroom: Higher Error Rates
These rooms generally show higher error rates across multiple metrics.

Possible reasons:

Irregular usage: Less frequent or more variable occupancy patterns could lead to less predictable environmental conditions.

Size and location: Smaller rooms or those located at the building's periphery might be more susceptible to external environmental influences.

4. Home Office: Average Performance
The home office shows moderate error rates, generally falling between the best and worst-performing rooms.

Possible reasons:

Predictable usage patterns: Regular work hours might contribute to more consistent environmental conditions.

Electronic equipment: Computers and other devices could introduce heat and affect air quality in ways that are challenging for the model to capture precisely.

5. Air Pressure Predictions: Consistent Across Rooms
Interestingly, air pressure predictions show relatively consistent error rates across all rooms.

Possible reasons:

Building-wide factor: Air pressure might be more influenced by building-wide or external factors rather than room-specific conditions.

Sensor quality: The consistency might indicate that air pressure sensors are of uniform quality and placement across rooms.

E. Overall Model Comparison

Consistency: GRU demonstrates more consistent performance across different rooms and air quality parameters.

Accuracy: GRU generally provides more accurate predictions, especially for temperature and air pressure.

Error Distribution: While GRU shows lower average errors, LSTM might handle some extreme cases better, particularly in humidity prediction.

Computational Efficiency: Although not directly measured in this study, GRU's simpler structure typically leads to faster training and inference times compared to LSTM.

In conclusion, our analysis suggests that the GRU model is generally more suitable for predicting indoor air quality parameters in home automation systems. However, the choice between GRU and LSTM may depend on specific requirements, such as the relative importance of different air quality parameters or computational constraints in the deployment environment.

V. Conclusion

This study has demonstrated the potential of deep learning techniques, specifically GRU and LSTM models, in predicting indoor air quality parameters within the context of home automation systems. Our comprehensive analysis across different rooms and air quality metrics (temperature, humidity, and air pressure) revealed that GRU models generally outperform LSTM models in terms of prediction accuracy and consistency. This superior performance was particularly evident in temperature and air pressure predictions, where GRU models showed lower error rates across multiple evaluation metrics (MAE, MSE, RMSE). These findings underscore the promise of GRU-based models for enhancing the predictive capabilities of smart home systems, potentially leading to more efficient and responsive indoor environment management.

Our room-specific analysis uncovered significant variations in prediction performance across different residential spaces. The living room consistently showed the best prediction accuracy, likely due to its central location and stable usage patterns. In contrast, spaces like the kitchen exhibited mixed performance, excelling in temperature predictions but struggling with humidity forecasts, possibly due to the rapid environmental changes associated with cooking activities. These insights highlight the complex dynamics of indoor environments and emphasize the need for nuanced, room-specific approaches in air quality modeling. Furthermore, the consistent performance in air pressure predictions across all rooms suggests that some air quality parameters may be more influenced by building-wide factors rather than room-specific conditions.

The development and implementation of the Air-Smart Controller interface mark a significant step towards practical application of our research findings. This user-friendly interface allows residents to view air quality predictions and interact with their home automation systems, bridging the gap between advanced predictive models and everyday user experience. By enabling users to monitor predictions and adjust system settings, the Air-Smart Controller enhances the adaptability and user-centricity of smart home systems. This integration of predictive analytics with user control exemplifies the potential for machine learning to enhance living environments while maintaining user autonomy and comfort.

While our study provides valuable insights, it also reveals areas for future research and development. The performance variations across rooms suggest that incorporating room-specific features or developing tailored models for different spaces could further improve prediction accuracy.

Additionally, exploring hybrid models that leverage the strengths of both GRU and LSTM architectures could yield even more robust predictive systems. Lastly, long-term studies on the real-world impact of these predictive systems on energy efficiency, occupant comfort, and overall air quality management would be invaluable in quantifying the practical benefits of this approach. As we continue to refine these technologies, the ultimate goal remains to create smarter, more responsive living environments that prioritize both human comfort and environmental sustainability.

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