






Machine Learning and Deep Learning for Predicting Indoor and Outdoor IoT Temperature Monitoring Systems

Nur Indah Lestari¹, Mahmoud Bekhit^{2,3} , Mohamed Ali Mohamed⁴,
Ahmed Fathalla² , and Ahmad Salah⁵ 

¹ 2 Messiter Street, Campsie, NSW 2194, Australia

² Department of Mathematics, Faculty of Science, Suez Canal University,
Ismailia 41522, Egypt

{mahmoud_bakhit, fathalla_sci}@science.suez.edu.eg

³ School of Electrical and Data Engineering, University of Technology Sydney,
Sydney 2007, Australia

⁴ 2P Perfect Presentation, Riyadh 105523, Saudi Arabia

⁵ Faculty of Computers and Informatics, Zagaizg University, Zagazig 44519, Egypt
ahmad@zu.edu.eg

Abstract. Nowadays, IoT monitoring systems are ubiquitous. These systems utilized sensors to measure the temperature indoors or outdoor. These sensors can be temporarily unavailable for several reasons, such as power outages. Thus, the server that collects the temperatures should find an alternative for predicting the temperature during the downtime of temperature sensors. In this context, there are several machine learning models for predicting temperature. This work is motivated to study the performance gap of predicting outdoor and indoor temperatures. In the proposed study, we utilized a deep learning recurrent neural network called Gated Recurrent Units (GRUs) and four machine learning models, namely, random forest (RF), decision trees (DT), support vector machines (SVM), and linear regression (LR) for predicting the temperature during the downtimes of the temperature sensors. Then, we evaluated the proposed models on a realistic dataset. The results show that predicting the indoor temperature is more predictable than the outdoor temperature. Moreover, the results revealed that the SVM model was the most accurate model for this task.

Keywords: Deep learning · Indoor · IoT · Machine learning
temperature prediction · Outdoor

1 Introduction

Many natural disasters are tied to weather patterns. Predicting and monitoring climate occurrences are critical challenges for society and numerous economic

sectors. Due to various reasons, such as a lack of region-specific parametrizations and data availability, numerical weather prediction models are currently unable to recreate precipitation patterns accurately. As machine learning models were reported to address various problems from different fields successfully [3, 12, 19], the machine learning models are compared to satellite-observed precipitation patterns for distinct climate seasons. These machine learning algorithms are capable of making exceptionally accurate climate predictions for the majority of the world's continents. [4, 14].

Climate effect studies on ecological, agricultural, environmental, and industrial sectors have used air temperature estimations as a crucial component. Accurate temperature forecasting aids in the protection of life and property and the planning of operations for the government, industry, and the general public. Machine Learning approaches can aid in the precise prediction of temperatures based on a collection of input characteristics, such as radiation, rain, relative humidity, prior temperature, solar, and wind speed observations, to name a few [9].

Several works proposed to address the outdoor temperature prediction. In [32], an Internet of Things (IoT) stand-alone system has provided a dynamic datasheet on city climate metrics like as temperature, humidity, pressure, Carbon Monoxide (CO), and dangerous air contaminants. The method aids in the design of pollution control measures as well as raising public awareness about the issue. An IoT-based climate monitoring system for rural areas was proposed in [27]. Every five minutes, the system was able to submit monitoring data. Wind speed and direction, rainfall, temperature, barometric pressure, and humidity were all part of the monitoring data. The system was used to mitigate natural disasters. In order to detect fires in outdoor situations such as woods, an IoT prototype was created. The system used a low power wide area network as well as sensors to detect heat, chemical compounds, and flame. The technology was designed to ensure that temperature and gas measurements were accurate when a fire started [31]. The authors of [24] described a low-cost method of monitoring and forecasting outside temperature using single-board computers as temperature sensors. The method models the association between device CPU temperature at each device and external temperature using linear regression.

The authors in [29] had designed an IoT system to remotely monitor and collect the greenhouse parameters such as temperature, light, soil, carbon dioxide (CO₂), and moisture. So, the system enabled controlling these parameters has led to good crops growth. Pressure and temperature were collected from a press machine in the industry's press shop assembly section using an IoT-based industrial monitoring and control system. The system was used to determine if a component was functional or not [30]. An IoT voltage management system linked with an Android smartphone was demonstrated to safeguard appliances and devices from overheating in a home or commercial setting. The system offered automated temperature ventilation and regulated the voltage of alternating current (AC)-supported equipment [16]. To acquire optimal clinker production, an industrial IoT based on an image processing system framework was built to

measure and manage the temperature of rotary kilns in the cement sector. To generate high-quality clinker, precise temperature mapping of flame pictures was used to manage the temperature within the rotary kiln [7].

Despite these several efforts for predicting indoor and outdoor temperatures, to the best of the authors' knowledge, there is no work that studied which task is easier to predict (i.e., an indoor or outdoor temperature prediction). In other words, this work answers the question of whether indoor or outdoor temperatures are more predictable. The temperature readings are collected using IoT devices fixed within rooms and outside these rooms. In addition to answering this question, this work investigates the performance gap between four machine learning-based temperature prediction methods against the well-known GRU architecture. The machine learning-based models and the deep learning-based models under comparison are evaluated on a real-life dataset on five different performance metrics. Besides, this study was conducted on tuning the models' hyperparameters and the lag value of the data which achieved the best results. The main contributions of this work can be summarized as follows:

- To our knowledge, this is the first study to compare the indoor against the outdoor prediction temperature prediction. We evaluated the performance of the predictive model on five different accuracy metrics.
- The proposed models are utilized to predict the temperature during the down times of the sensor.

The rest of the paper is organized as follows. Section 2 exposes the background of this work. In Sect. 3 the existing methods are discussed. Then, the utilized models are discussed in Sect. 4. Section 5 exposed the evaluation and results of the proposed system. Finally, the paper is concluded in Sect. 6.

2 Background

In the following, we will explain the basic ideas of the utilized machine learning models.

2.1 Random Forest

Random forest (RF) is described as a collection of tree predictors and a mechanism for aggregating the results of the individual tree predictors. Every tree predictor with a random subsample of the dataset, either in terms of observations or features. The RF algorithm used in this study develops a tree by picking or mixing characteristics at each node in a random manner. To generate a training dataset for each characteristic chosen, we used a strategy that included randomly picking replacement samples from the original training set, where N is the number of samples in the training set. The most often used aggregation methods are average probability and most common class, with the latter serving as an extension of the previous.

2.2 Decision Trees

The Decision trees (DT) model is one of the most frequently applied methods for predictive modeling in various applications, including classification and regression. The decision tree technique performs excellently and indefinitely well when discontinuous data is used, even when noise arises. Numerous strategies were explored to discover the optimal method for splitting the input data. One of the primary purposes of the decision tree approach is to locate the most critical splits between the tree's nodes, hence improving the categorization of the data. To do this, we must apply the appropriate decision rules to the given data, which substantially impacts the algorithm's performance.

The DT model takes advantage of Information Gain (IG); because a decision tree model's objective is to discover the optimal split node that ensures high accuracy. The IG approach looks for the most appropriate nodes that yield the greatest amount of information, which may be quantified using an Entropy factor. The Entropy factor is used to quantify the degree of disorder in a system. The following formula may be used to compute the entropy of the output:

$$E(s) = \sum_{i=1}^c -p_i \log_2 p_i. \quad (1)$$

2.3 Support Vector Machine

Support vector machine (SVM) is built on a statistical learning theory to determine the best decision boundaries for class separation. SVMs choose the linear decision boundary that leaves the most margin between the two classes in a two-class pattern recognition task. The margin is the sum of the distances from the two classes' nearest locations to the hyperplane. The margin is calculated using the data nearest to the hyperplane. These data points are called 'support vectors' and are always few. Initially, SVMs were developed to solve two-class (binary) issues. When numerous classes are involved, a multiclass method is required. Techniques such as 'one versus one' and 'one against the others' are frequently used for multiclass situations.

2.4 Linear Regression

Linear regression (LR) is considered the basic regressor. Its basic idea is to find a function to map the input to the output. The term linear comes from that the coefficients maintain the linear property. Meanwhile, the feature can be of non-linear order. The linear regression model is nothing but a linear line when the features in the equation are linear. The function curvature can be increased to fit the data shape by increasing the order of the feature from linear to non-linear. Thus, linear regression can be seen as a curve fitting method. The data should be split into two sets in linear regression, namely, training and test sets. The training data determine the shape of the curve, while the model accuracy is measured by computing the distance between the data points of the test set and

the curve. The linear regression can be applied when its assumptions are held. The assumptions are linearity, homoscedasticity, Independence, and normality.

3 Literature Review

Numerous comfort management techniques have been developed to use indoor and outdoor environmental conditions and maintain a specific comfort level for building occupants and managing to the optimal resources in the cloud [17, 18, 21, 22]. The ambient outdoor temperature has a considerable effect on the indoor temperature, as well as on the amount of energy consumed for cooling and heating.

Energy consumption is critical in remaining buildings, as most buildings use energy to maintain a particular level of comfort for inhabitants. Temperature control in a resident's area is a critical function of occupant buildings. The modeling approaches utilized in the literature have gotten increasingly complex over time to enhance prediction model performance [23]. According to previous research, such as in [2], the heating, ventilation, and air conditioning (HVAC) systems consume the most energy in a structure. As a result, controlling HVAC systems in existing buildings should be considered in order to increase energy efficiency through better energy strategies. Designing a model that takes environmental conditions into account is critical for configuring the optimal HVAC system settings. Literature has taken into account a variety of comfort factors, the most prominent of which are indoor air quality, visual comfort, and thermal comfort. These factors both affect user comfort, and energy consumption [11].

For forecasting, several machine learning methods have been suggested, including the artificial neural network (ANN), the support vector machine (SVM), the hidden Markov model (HMM), and several more as presented in [20, 33]. Nivine et al. [5] developed a novel method for forecasting the inside temperature up to four hours in advance using Artificial Neural Network (ANN) and considering the outdoor parameters. Additionally, the authors of [25] regulated the cooling load in a smart building by adding a Neural Network (NN) into an intelligent system that allows examination and prediction of the building's energy need as well as identification of essential elements affecting energy usage. The study demonstrates that the building's capacity is critical in predicting the HVAC system's cooling demand.

The authors of [28] examined the influence of users' behaviors and practices on the potential for energy savings in smart buildings. The authors identified the user as the primary element affecting energy demand and categorized the user's effect on energy needs into three major components: HVAC, plugging loading systems, and lighting. Additionally, Varick et al. [13] examined building occupancy and its effect on energy savings using real-time data. They suggested an occupancy model that could be incorporated effectively into the building's HVAC system through Markov Chains.

In [26], a novel model for predicting the hourly cooling load in office buildings was created using Support Vector Regression (SVR). The hyper-parameters of

the model were adjusted to obtain the most accurate temperature forecast. Additionally, authors of [10] investigated the possibility of forecasting building energy consumption using SVR and the effect of different SVR settings on prediction accuracy. According to the study, SVR achieved the best accuracy when compared to other comparable research techniques, including genetic programming and neural networks.

Researchers in [23] utilized deep learning to predict the ideal indoor temperature and then automatically regulate the air conditioner based on that forecast. In order to maximize the HVAC's thermal energy storage, Abdullatif et al. [6] developed a cooling load forecasting model that uses the generalized regression neural network (GRNN) and takes into account the building's orientational features and occupancy. With the use of neural networks and polynomial regression models, Catalina accurately forecasted the monthly heating demand for residential buildings based on the structure of the structures [8].

4 Methodology

4.1 Overview

Figure 1 shows that the prediction model requires a set of historical data for indoor and outdoor temperatures to forecast future temperatures for both cases. The model used these historical data as input to be trained for the prediction model. The prediction model is used to forecast indoor and outdoor environments considering many environmental surroundings and characteristics. The settings are subject to vary over time. As a result, the data must be continuous for both training and prediction. The input data is used to anticipate the next time, which might be a single data point or a data sequence from a previous point to the present point in time. The prediction model's output is a dataset containing the projected indoor and outdoor temperatures and environmental parameters. The main goal is to determine the forecasting indoor and outdoor temperatures value for the building, which can be used to determine the least amount of energy required to maintain a pleasant atmosphere. As a result, the actuators must provide a pleasant environment for the user while consuming the least amount of energy possible.

4.2 Feature Engineering and Model Building

We proposed applying the data differencing to the raw input temperature. Time series forecasting issues are traditionally turned into supervised learning problems using lag characteristics. The lag value of the proposed models is set by searching for the value that yields the best prediction accuracy. This happened through utilizing the grid search approach. Thus, the problem is framed as a time series analysis problem. The data is split into training, validation, and test sets.

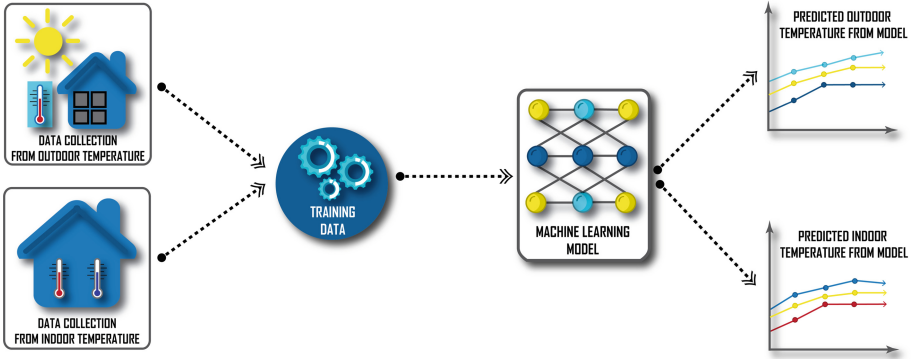


Fig. 1. The proposed temperature prediction system.

Regarding building the models, we proposed tuning the models' hyperparameters using the grid search method for the GRU model. A custom architecture is proposed to fit the nature of the data. The overfitting was checked by comparing the difference between the validation and training losses.

5 Experimental Results

5.1 Dataset

The dataset includes the temperature measurements from IoT sensors deployed outside and within a business building room (admin) that were randomly recorded in the dataset. At random intervals, this was recorded. The recording was accomplished at a rate of one second. The dataset contains different attributes, namely, room_id, noted_date, temperature, and IoT sensing device place (i.e., out/in), as listed in Table 1. These temperature measurements were

Table 1. Dataset features description.

No	Feature	Description
1	id	Unique ID for each reading
2	room_id	The room id at where the sensor was placed, inside and outside
3	noted_date	Date and time of temperature reading
4	temp	Temperature readings
5	out/in	Determine if the reading came from a source sensor within or outside the room

collected by IoT sensors that were placed outside and inside a private room. The dataset is publicly available online¹.

5.2 Setup

The utilized programming language was Python. The hyperparameters of the models are tuned using the grid search approach to obtain the best results. The proposed models used 10,000 observations for each indoor and outdoor data, where data are split into 80% and 20% for training and testing, respectively.

5.3 Evaluation Metrics

In order to assess the performance of the proposed models, we used five evaluation metrics used in various time series and regression applications [1, 15]. Evaluation metrics' equations (*i.e.*, Eqs. 2–6) define the utilized evaluation metrics where different patterns of error values are measured.

$$MAE = \frac{1}{N} \sum_{i=1}^N |Y_i - \hat{Y}_i| \quad (2)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (Y_i - \hat{Y}_i)^2 \quad (3)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (Y_i - \hat{Y}_i)^2} \quad (4)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^N \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \times 100\% \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (6)$$

where y_i represents the true values, N indicates the number of observations, \bar{y} represents the mean true values, and \hat{y}_i represents the predicted values.

5.4 Results and Discussion

Figure 2 depicts the MAE of the proposed five models for the indoor and outdoor temperature prediction. Apparently, for the five models, the prediction errors for the indoor temperature are less than the prediction errors for the outdoor temperature. Moreover, the best model for the temperature prediction was SVM and LR, where the former was slightly better than the latter. The deep learning model (*i.e.*, GRU) performance was an average, while the worst prediction rates

¹ <https://www.kaggle.com/atulanandjha/temperature-readings-iot-devices>.

were achieved by DT and RF models. In the same context, Table 2 lists the performance metrics for the five models on five different accuracy metrics. The listed results emphasize that the indoor temperature is more predictable than the outdoor temperature. The accuracy gap varies based on the utilized model. One can conclude that the more accurate the model is, the less the accuracy gap between the indoor and outdoor temperature prediction model and vice versa.

Table 2. The accuracy rates for the proposed models on five different metrics.

Model	Data	MAE	MSE	RMSE	R^2	MAPE
GRU	Indoor	0.44174	0.55045	0.73987	0.88591	1.40952
	Outdoor	0.69523	0.99453	0.99461	0.95875	2.39551
RF	Indoor	0.65144	0.96432	0.982	0.80029	2.03945
	Outdoor	0.89171	1.79257	1.33887	0.92599	3.12289
DT	Indoor	0.65007	0.96055	0.98007	0.80107	2.0354
	Outdoor	0.89182	1.81794	1.34831	0.92494	3.12271
SVM	Indoor	0.41856	0.53633	0.73234	0.88892	1.35239
	Outdoor	0.47891	0.62716	0.79193	0.97411	1.59394
LR	Indoor	0.42409	0.53252	0.72974	0.88971	1.37103
	Outdoor	0.47076	0.62528	0.79075	0.97418	1.56435

The task of tuning machine learning models' hyperparameters is straightforward. On the contrary, the deep learning model architecture selection and hyperparameter is a relatively more sophisticated task. Thus, understanding the effect of parameter tuning on the proposed GRU model is vital. Figure 3 depicts the MEA values against the number of feature lags. Figure 3 can help select the lag value that achieves the highest accuracy rates. The best lag value for the indoor and outdoor temperatures prediction was 2 and 4, respectively. In Fig. 4, the overfitting of the GRU model was examined. As the difference between the training and validation losses is small, the proposed GRU model does not suffer from the overfitting problem. Finally, the variance of the proposed GRU model was examined in Fig. 5 for five runs of each model. The indoor and outdoor prediction models have the same behavior, except the overall performance of the former is better than the latter. The results revealed that predicting the outdoor temperature is less accurate to the indoor temperature. This can be linked to the fact the outdoor temperature is affected by more factors than the indoor temperature.

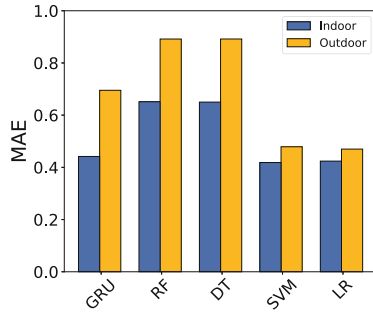


Fig. 2. MAE of the proposed models for indoor and outdoor temperature prediction.

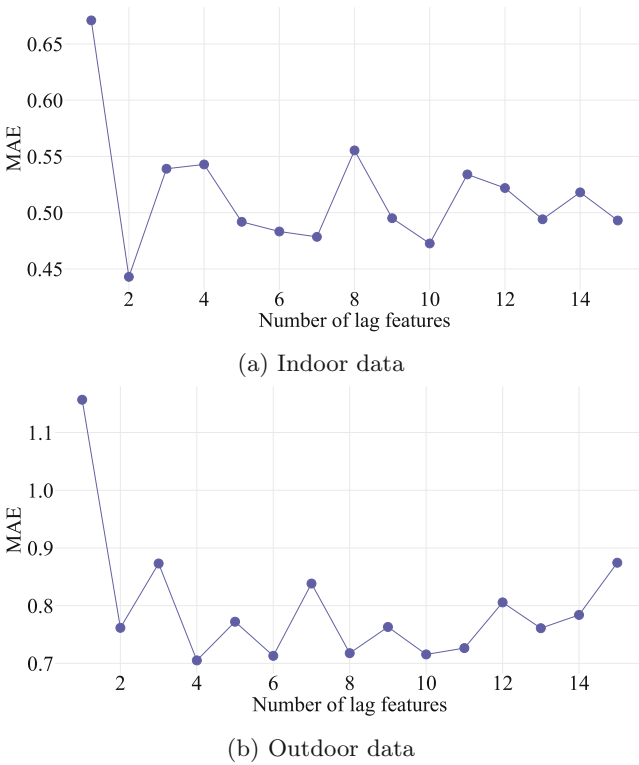


Fig. 3. Grid search results for obtaining optimal number of lags for the GRU model.

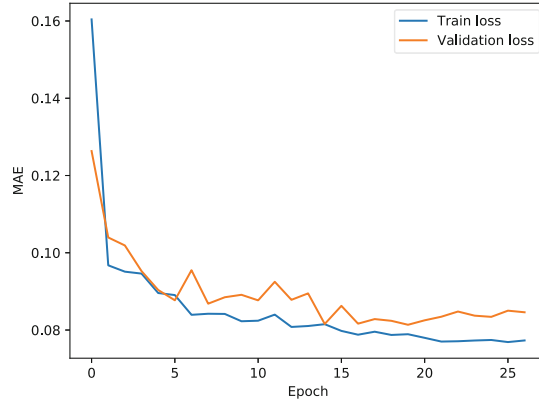


Fig. 4. Training and validation loss for the GRU model.

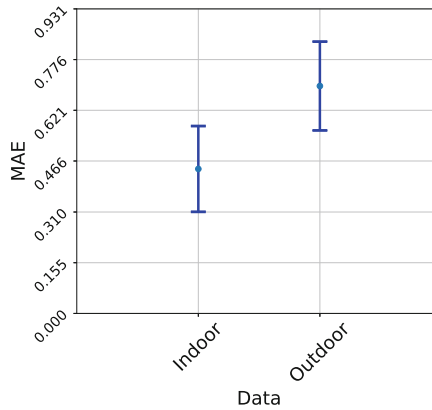


Fig. 5. Error-bar for running GRU models for 5 times.

6 Conclusion

Temperature monitoring through IoT-based systems is commonplace. These systems can help in making decisions that control power consumption. In this work, we utilized four machine learning models and one deep learning model for predicting indoor and outdoor temperature based on the historical temperature data collected by an IoT system. This study aims to know which type of temperature is more predictable and to figure out the performance gap of the five utilized models. Based on a real-life dataset, the utilized models are evaluated on five accuracy metrics: MAE, MSE, RMSE, MAPE, and R^2 . The obtained results revealed that the indoor temperature prediction is more predictable than the outdoor temperature. Moreover, the SVM and LR models achieved the best performance, while the worst performance was obtained from the RF and DT models. The results outlined that the more accurate the model is, the less the dif-

ference of the prediction error between the indoor and outdoor models. Finally, the proposed model can be utilized to predict the future temperature when the sensor goes down temporarily. The future direction includes comparing the machine learning and deep learning models to the statistical models such as ARIMA.

References

1. Alameer, Z., Fathalla, A., Li, K., Ye, H., Jianhua, Z.: Multistep-ahead forecasting of coal prices using a hybrid deep learning model. *Resour. Policy* **65**, 101588 (2020)
2. Alawadi, S., Mera, D., Fernández-Delgado, M., Alkhabbas, F., Olsson, C.M., Davidsson, P.: A comparison of machine learning algorithms for forecasting indoor temperature in smart buildings. *Energy Syst.*, 1–17 (2020)
3. Aldahiri, A., Alrashed, B., Hussain, W.: Trends in using IoT with machine learning in health prediction system. *Forecasting* **3**(1), 181–206 (2021)
4. Anochi, J.A., de Almeida, V.A., de Campos Velho, H.F.: Machine learning for climate precipitation prediction modeling over south America. *Remote Sens.* **13**(13), 2468 (2021)
5. Attoue, N., Shahrour, I., Younes, R.: Smart building: use of the artificial neural network approach for indoor temperature forecasting. *Energies* **11**(2), 395 (2018)
6. Ben-Nakhi, A.E., Mahmoud, M.A.: Cooling load prediction for buildings using general regression neural networks. *Energy Convers. Manage.* **45**(13–14), 2127–2141 (2004)
7. Bojja, P., Prasanna, N.M., Kumari, P.R., Bhuvanendhiran, T., Kumar, P.J.: Development of conventional controller based on image processing for monitoring and controlling burning zone temperature in a cement plant in rotary kiln process through IoT. *Instrum. Mesures Métrologies* **20**(4) (2021)
8. Catalina, T., Virgone, J., Blanco, E.: Development and validation of regression models to predict monthly heating demand for residential buildings. *Energy Buildings* **40**(10), 1825–1832 (2008)
9. Cifuentes, J., Marulanda, G., Bello, A., Reneses, J.: Air temperature forecasting using machine learning techniques: a review. *Energies* **13**(16), 4215 (2020)
10. Dong, B., Cao, C., Lee, S.E.: Applying support vector machines to predict building energy consumption in tropical region. *Energy Buildings* **37**(5), 545–553 (2005)
11. Dounis, A.I., Caraiscos, C.: Advanced control systems engineering for energy and comfort management in a building environment—a review. *Renew. Sustain. Energy Rev.* **13**(6–7), 1246–1261 (2009)
12. Eldesouky, E., Bekhit, M., Fathalla, A., Salah, A., Ali, A.: A robust UWSN handover prediction system using ensemble learning. *Sensors* **21**(17), 5777 (2021)
13. Erickson, V., Cerpa, O.: Occupancy-based system for efficient reduction of HVAC energy. In: *Proceedings of the 10th International Conference on Information Processing in Sensor Networks (IPSN 2011)* (2010)
14. Fathalla, A., Li, K., Salah, A., Mohamed, M.F.: An LSTM-based distributed scheme for data transmission reduction of IoT systems. *Neurocomputing* **485**, 166–180 (2021)
15. Fathalla, A., Salah, A., Li, K., Li, K., Francesco, P.: Deep end-to-end learning for price prediction of second-hand items. *Knowl. Inf. Syst.* **62**(12), 4541–4568 (2020). <https://doi.org/10.1007/s10115-020-01495-8>

16. Foyсал, M.R., Hossain, R.A., Islam, M.M., Sharmin, S., Moon, N.N.: IoT based temperature control system of home by using an android device. In: 2021 1st International Conference on Emerging Smart Technologies and Applications (eSmarTA), pp. 1–8. IEEE (2021)
17. Gamal, M., Abolhasan, M., Lipman, J., Liu, R.P., Ni, W.: Multi objective resource optimisation for network function virtualisation requests. In: 2018 26th International Conference on Systems Engineering (ICSEng), pp. 1–7. IEEE (2018)
18. Gamal, M., Jafarizadeh, S., Abolhasan, M., Lipman, J., Ni, W.: Mapping and scheduling for non-uniform arrival of virtual network function (VNF) requests. In: 2019 IEEE 90th Vehicular Technology Conference (VTC2019-Fall), pp. 1–6. IEEE (2019)
19. Hosny, K.M., Darwish, M.M., Li, K., Salah, A.: Covid-19 diagnosis from CT scans and chest X-ray images using low-cost raspberry PI. PLoS ONE **16**(5), e0250688 (2021)
20. Hussain, W., Merigó, J.M., Raza, M.R.: Predictive intelligence using ANFIS-induced OWAWA for complex stock market prediction. Int. J. Intell. Syst. (2021)
21. Hussain, W., Merigo, J.M., Gao, H., Alkalbani, A.M., Rabhi, F.A.: Integrated AHP-IOWA, POWA framework for ideal cloud provider selection and optimum resource management. IEEE Trans. Serv. Comput. (2021)
22. Hussain, W., Sohaib, O., Naderpour, M., Gao, H.: Cloud marginal resource allocation: a decision support model. Mob. Netw. Appl. **25**(4), 1418–1433 (2020)
23. Jin, W., Ullah, I., Ahmad, S., Kim, D.: Occupant comfort management based on energy optimization using an environment prediction model in smart homes. Sustainability **11**(4), 997 (2019)
24. Krintz, C., Wolski, R., Golubovic, N., Bakir, F.: Estimating outdoor temperature from CPU temperature for IoT applications in agriculture. In: Proceedings of the 8th International Conference on the Internet of Things, pp. 1–8 (2018)
25. Kwok, S.S., Yuen, R.K., Lee, E.W.: An intelligent approach to assessing the effect of building occupancy on building cooling load prediction. Build. Environ. **46**(8), 1681–1690 (2011)
26. Li, Q., Meng, Q., Cai, J., Yoshino, H., Mochida, A.: Applying support vector machine to predict hourly cooling load in the building. Appl. Energy **86**(10), 2249–2256 (2009)
27. Muslim, M.A., Setyawan, R.A., Basuki, A., Razak, A.A., Hario, F.P., Fernando, E.: IoT based climate monitoring system. In: IOP Conference Series: Earth and Environmental Science, vol. 746, p. 012044. IOP Publishing (2021)
28. Nguyen, T.A., Aiello, M.: Energy intelligent buildings based on user activity: a survey. Energy Buildings **56**, 244–257 (2013)
29. Pallavi, S., Mallapur, J.D., Bendigeri, K.Y.: Remote sensing and controlling of greenhouse agriculture parameters based on IoT. In: 2017 International Conference on Big Data, IoT and Data Science (BID), pp. 44–48. IEEE (2017)
30. Priyanka, E., Maheswari, C., Thangavel, S.: IoT based field parameters monitoring and control in press shop assembly. Internet Things **3**, 1–11 (2018)
31. Roque, G., Padilla, V.S.: LPWAN based IoT surveillance system for outdoor fire detection. IEEE Access **8**, 114900–114909 (2020)
32. Shete, R., Agrawal, S.: IoT based urban climate monitoring using raspberry PI. In: 2016 International Conference on Communication and Signal Processing (ICCSP), pp. 2008–2012. IEEE (2016)
33. Ullah, I., Ahmad, R., Kim, D.: A prediction mechanism of energy consumption in residential buildings using hidden Markov model. Energies **11**(2), 358 (2018)