Explainable AI-powered Edge Computing Solution for Smart Building Energy Management in Green IoT

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Abstract

Today, climate change and global warming are among the most serious problems of humanity. In combating these problems, urgent and serious actions are needed especially in energy preferences, utilization, and management. Especially in the building sector, energy consumption has increased rapidly and today it has reached 40% of total global energy consumption. Therefore, the use of low-cost, eco-friendly, and sustainable green technologies is critical to mitigate the negative environmental impacts of carbon emissions and the depletion of the world's energy resources. In this context, emerging technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), and edge computing are both necessary and promising in terms of ensuring energy efficiency in buildings, grid security, and supply-demand balance. In this paper, we propose a low-cost end-to-end IoT system architecture for energy monitoring and management in smart buildings. In this architecture, we develop explainable ML models that predict building energy consumption based on edge computing. We also develop a mobile application with video call and instant messaging features for monitoring and managing energy consumption for expert users. Experimental and test results show that the proposed system can be used in building energy management in a fast, effective and interpretable way with the support of AI and IoT. With the developed prototype architecture, we present a future projection that the energy management of buildings in Green IoT can be low-cost, transparent, and understandable.

Keywords: Green Internet of Things, Building Energy Management, Explainable Artificial Intelligence (XAI), Edge Computing

1 Introduction

In recent years, the effects of climate change have been felt on a global scale. This change has negative impacts on societies, economies, human health, environment, energy, food and water security, causing serious losses and damages [1]. Societies have begun to experience events such as melting polar ice, rising sea levels, extreme natural events (droughts, floods, storms, rain, etc.), and food and water shortages more frequently [2]. It has been determined that changes in the climate system have a human fingerprint and are primarily caused by human-induced emissions [3]. In particular, human-induced climate change is mainly caused by greenhouse gas emissions from improper and inappropriate energy use, land use, lifestyles and consumption patterns. At this point, achieving rapid and deep emission reductions and securing a sustainable future requires a broad transition across all sectors and systems [4]. In this context, critical and decisive action is needed to reduce emissions, generate electricity from low-carbon sources, phase out coal and gas-fired power plants, increase the use of wind, solar and other renewable energy sources, and reduce energy consumption [5]. In addition to these actions, it is predicted that greenhouse gas emissions caused by climate change can be reduced by 44-67% in various sectors by 2050, with demand-side measures and innovative approaches in the provision of services in areas such as food, transportation, building and construction. industry and energy on a global scale [4]. In particular, since buildings are responsible for about 40% of primary energy and 36% of GHG emissions, actions in this sector are of critical importance [6]. The Intergovernmental Panel on Climate Change (IPCC) reports predict that actions in buildings have the potential to reduce greenhouse gase emissions by 66%. In the context of all sectors, it was found that electricity consumption has the potential to be reduced by 73% with demand-side mitigation options based on electricity consumption [4]. Unlocking the projected mitigation potential requires steps to reduce and shift demand through the deployment of low or zero-emission technologies, infrastructure design and access, sociocultural and behavioral changes, and increased technological efficiency and adoption [7,8]. However, the cost of building energy management and savings is challenging and costly due to improper control and operational errors [9]. Therefore, monitoring, predicting and managing building energy consumption requires feasible, effective and cost-efficient solutions in terms of both architecture and data analysis based on innovative technologies and green energy.

In the context of network, architecture and design, Green IoT has emerged as an innovative field that takes a solutions-oriented approach to environmental issues, providing eco-friendly and energy-efficient IoT systems and networks by reducing emissions, pollution, and power consumption [10]. Green IoT aims to realize strategies, techniques, and network architectures that reduce energy consumption, greenhouse gas emissions and IoT device pollution by focusing on green design, green manufacturing, green utilization, and green disposal [11]. In terms of data analysis, decision systems suitable for green energy can be designed using AI and Explainable Artificial Intelligence (XAI) models that guarantee a high accuracy rate. Recent advances in IoT technologies and advanced AI algorithms can provide solutions to mitigate the impacts of climate change by offering data-driven approaches that are compatible with green energy. These solutions can be low-cost energy manage-

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ment systems that provide data-driven predictive analytics. In this regard, there are several studies in the literature based on statistical and ML/AI methods. For instance, Chen and Tan [12] proposed a hybrid Support Vector Regressor (SVR) model with wavelet decomposition for energy monitoring and management of hotel and shopping mall buildings. The authors focus on generalized electricity usage forecasting for all buildings by estimating the hourly electricity demand intensity in the hotel and shopping mall case study. Fan et al. [9] proposed a new methodology based on interpretable machine learning to explain and evaluate building energy performance models. They used techniques such as clustering analysis and Gower's dissimilarity coefficients to evaluate the results of data analysis. Goudarzi et al. [13] developed a hybrid model based on SVR and Particle Swarm Optimisation (PSO) for predicting energy consumption in smart buildings. The proposed model is tested on the energy consumption data of the library building. It is shown that the model outperforms the ARIMA model. Sembroiz et al. [14] present a building management system based on a wireless sensor network that can both efficiently control building elements and reduce building energy consumption according to human behavior. With the proposed system, they aim to ensure the efficiency of building heating, ventilation, and air conditioning (HVAC) systems by guaranteeing adequate thermal comfort. Ke et al. [15] proposed a SCADA-based energy management framework to provide advanced control in buildings. The proposed framework aims to provide flexibility and scalability to different stakeholders based on a four-tier IoT architecture. The authors utilize regression tree (RT) and the least-squares boosting (LSBoost) algorithms to predict energy in both residential and office buildings. Goudarzi et al. [16] proposed a hybrid technique called AIK-EWMA based on ARIMA and the Imperialistic Competitive Algorithm (ICA) algorithm to predict the energy consumption of actuators in green buildings. In study [17], decision tree (DT), random forests (RF) and K-nearest neighbor (KNN) algorithms were used for the same purpose.

Rahman et al. [18] proposed two recurrent neural network (RNN) models to profile electricity consumption in commercial buildings and to predict total electricity consumption in residential buildings in Salt Lake City and Austin, USA. The authors aimed to provide medium and long-term electricity consumption projections for buildings. Li et al. [19] proposed a novel attention-based neural network model for building energy control and management. The proposed model aims to predict the cooling load in buildings based on an interpretable RNN model. The authors demonstrated that the attention mechanism can ensure the explainability of the RNN model and reveal the influence of inputs on model decisions. Gao et al. [6] proposed an AI-supported IoT system for zero energy planning and management in connected buildings. In the proposed system, the HVAC system is controlled by programming building electrical loads, charging cycles and storage systems based on deep reinforcement learning model. Wenninger et al. [20] used the Qlattice algorithm based on the path integral formulation from Feynman's quantum field theory to predict the annual energy consumption of buildings using residential data sets in Germany. They compared the Qlattice algorithm with SVR, ANN, XGBoost and MLR and showed that it is superior to them.

Although there are some studies in the literature that focus on energy consumption, there are no studies that specifically focus on both XAI and low-cost and green IoT architecture design. Therefore, in this paper, we show that we can provide energy management in smart buildings with a low-cost end-to-end IoT infrastructure and that building energy decisions can be more transparent and understandable with XAI techniques. Key novelty and contribution aspects of our paper are as follows:

- We propose an end-to-end four-tier green IoT architecture for energy management in smart buildings.
- We develop XAI-supported ML models for building energy consumption prediction based on edge computing approach.
- We develop a mobile application called GreenIoT for fast and easy monitoring, tracking and management of building energy consumption

The remainder of the paper is organized as follows: Section II presents the proposed XAI-powered smart building energy management system. Section III presents the experimental results and evaluations. Finally, Section IV concludes the paper.

2 Explainable AI-powered Smart Building Energy Management System

In this section, we provide comprehensive information about our proposed Green IoT architecture, the XAI methods used in the architecture, and our GreenIoT application.

2.1 Proposed Green IoT Architecture

In this paper, we propose a four-layer IoT architecture, shown in Figure 1, for real-time monitoring of energy consumption in smart buildings by estimating energy consumption based on edge computing. Our four-layer IoT system architecture consists of a physical device layer, edge layer, fog layer, and cloud layer.

- Physical Layer: This layer includes electronic devices and sensors that cause energy consumption in buildings. Building energy consumption data are collected periodically based on location and device (floor, room, and specific device information) and transferred to edge devices.
- Edge Layer: In this layer, there are edge devices that run the XAI-supported prediction model by collecting electricity consumption data for each building. In this layer, we use a low-cost Raspberry Pi device to run both ML Algorithms and XAI techniques on it. When the electricity consumption data arrives at this layer, the total energy consumption is predicted by the ML model on the Raspberry Pi. This prediction result and the three devices(features) that affect this result are detected by the XAI method and sent to the cloud.
- Fog Layer: This layer includes network components such as a base station responsible for data transfer between the edge and cloud layer.
- Cloud Layer: This layer contains resource-rich components in terms of computation and storage. In this study, we use Firebase cloud database to store building electricity consumption data. This database stores building electricity consumption predictions and the most important three features that affect these predictions in order of feature importance. This information is shared with the subscribers upon request.

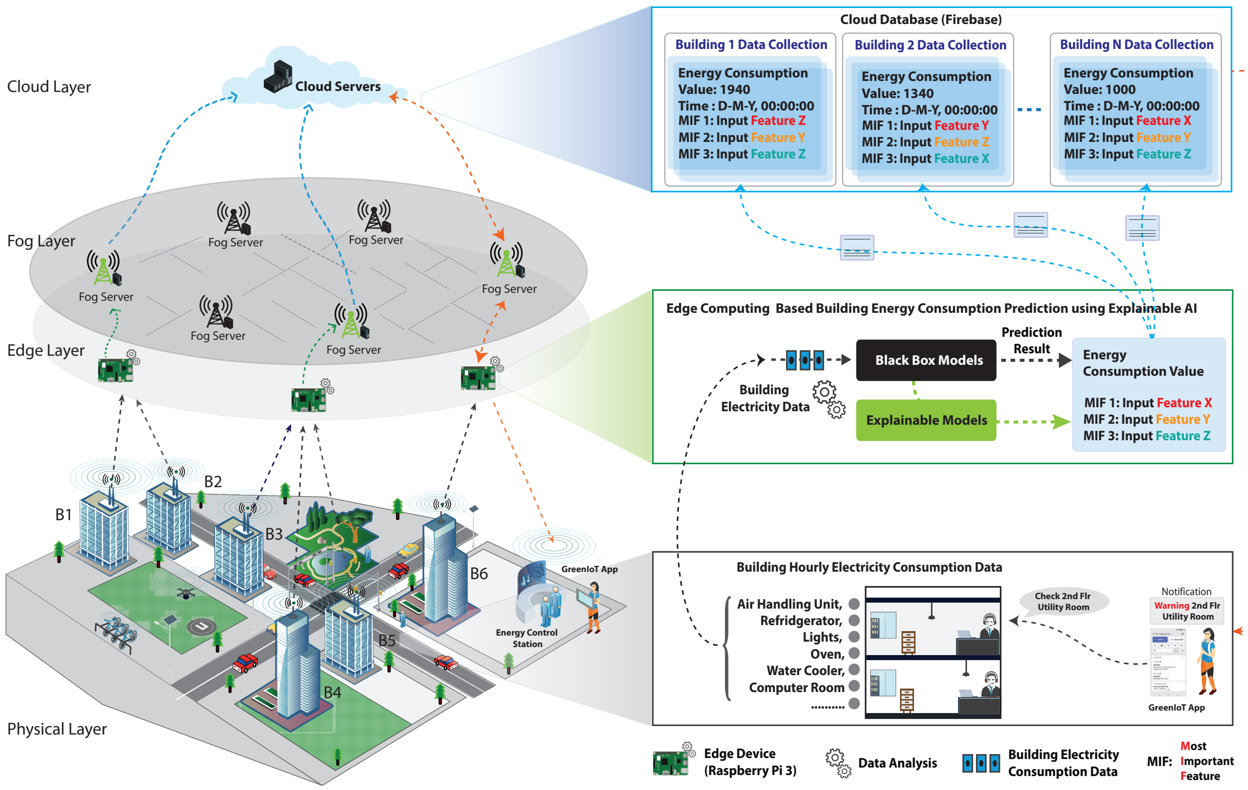

Figure 1: The Proposed end-to-end Green IoT system architecture for building energy management

Data Flow and Processing in the Architecture: In the physical layer, the data collected from the sensors and devices in the buildings are first transferred to the edge devices, which are the closest data collection point. The edge devices predict the total building electricity consumption in specified periods by taking the sensor-based electricity consumption value from each building. At this point, the three most critical devices that affect the prediction result are detected based on location with XAI techniques. The end devices send both the total amount of electricity consumption and the information of the three most important devices to the cloud database through the fog layer via the MQTT protocol. In the cloud layer, data is stored historically. This information is periodically requested via the ground control station or mobile application (GreenIoT). The energy consumption values of the buildings are monitored according to the lower and upper electricity consumption threshold values recorded in the system for each building. In case of exceeding the threshold value or anomalous situations, video chat or messaging can be made with the technical responsible person in the building via mobile application. Thus, the periodic consumption values of the buildings can be monitored and intervened quickly when necessary.

2.2 Explainable Artificial Intelligence (XAI) and Used XAI Methods

In recent years, advanced AI and ML models have been used in many sensitive sectors such as military, banking and healthcare applications. Although these models generate results with high accuracy and precision, they are difficult to understand and trust due to their black-box nature. Therefore, more transparent, interpretable, and understandable models are needed to empower individuals to cope with the negative consequences of automated decision-making, to help individuals make more informed choices, and to reveal and protect vulnerabilities [21]. At this point, XAI offers solutions to the current problems of AI models by providing discovery, enhanced justification, control and improvement regarding the input of AI models, the model itself and its decisions [22]. In terms of explainability, ML/AI models can be explained at two levels: local and global. *Global explainability* focuses on the holistic interpretability of the model architecture and parameters. It tries to characterize the model as a whole by trying to explain the behavior of the model over the whole dataset. *Local explainability*, on the other hand, focuses on each observation in the dataset and provides explanations for the cause of a particular outcome for that observation [9]. In light of the above-mentioned information, the following methods have been used to make local and global explainability of the ML models used in this study.

SHapley Additive exPlanations (SHAP): SHAP allows us to understand the contribution of each feature to the outcome predicted by black-box ML models using the Shapley values from cooperative game theory. The Shapley value is the average marginal contribution of each feature value among all possible values in the feature space. It can be used in both global and local explanations. It is theoretically robust but it is recommended to use it when it is costly to calculate Shapley value in high dimensional data [23].

Local Interpretable Model-agnostic Explanations (LIME): The LIME model is a local explanation technique that attempts to interpret black box models by learning a local model around the predictions. It is very efficient in selecting interpretable data representations that are comprehensible to any non-expert user among the features that affect the result [24].

Explain Like I'm 5 (ELI5): ELI5 is an explanatory framework that finds the order of importance of each feature in the dataset to explain the inner workings of ML and DL models. It can be used

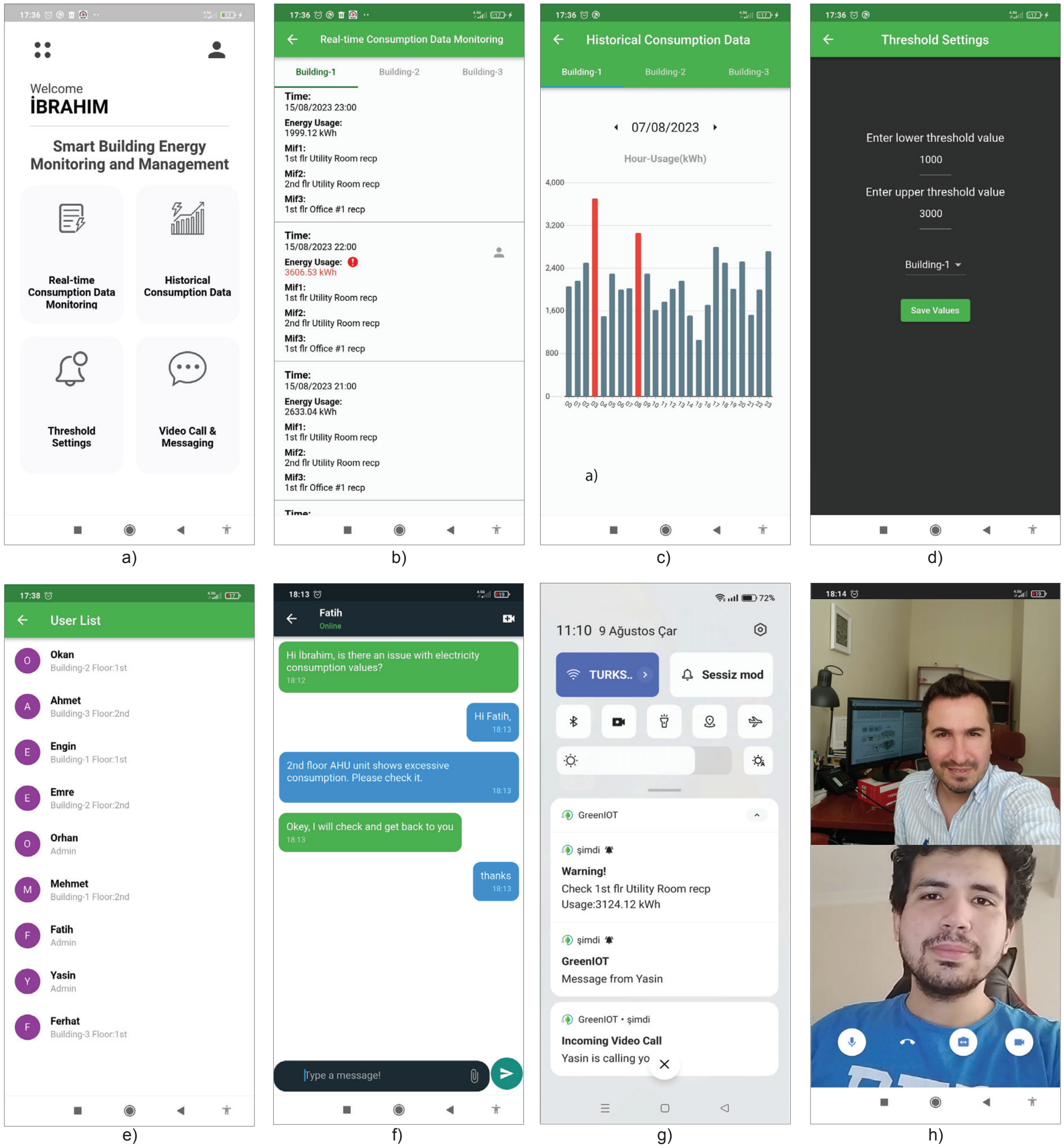

Figure 2: GreenIoT User Interfaces, a) Application home screen and main menus, b) Real-time building electricity consumption data monitoring interface, c) Historical consumption data interface, d) Threshold setting interface, e) User list interface, f) Sample instant messaging interface, g) Video call notification, h) Sample voice and video call

for global and local explainability of parametric linear models and decision tree-based models [24].

2.3 GreenIoT Mobile App: Smart Building Energy Monitoring and Control Application

For this study, we developed a mobile application called GreenIoT for monitoring and management of electricity consumption in smart buildings using the Dart programming language using the Flutter [25] framework. GreenIoT basically has the features of real-time monitoring of electricity consumption in buildings, tracking historical electricity consumption data, defining building-specific threshold values, warning of consumption anomalies, instant video call, and messaging. The user interfaces of the basic features and other additional features of GreenIoT are shown in Figure 2.

- *Real-time electricity consumption monitoring interface:* Periodic (hourly in our application) electricity consumption predictions of the buildings defined in the application can be monitored from this interface. According to the predefined lower and upper consumption threshold values for each building, the administrator is informed on this interface and receives a warning sign for situations exceeding the threshold value.

- *Historical consumption data interface:* From this interface, historical building electricity consumption data saved in the cloud database can be monitored daily on a graphical basis.

Table 1: Dataset Feature Information

Id	Features		Id	Features	
1	Date	Date	18	2nd flr Air Handling Unit (AHU) - Classroom	float64
2	Time	Time	19	2nd flr Air Handling Unit (AHU) - Computer Room	float64
3	1st flr Air Handling Unit (AHU)	float64	20	2nd flr Heat Pump (HP) - Classroom	float64
4	1st flr Heat Pump (HP)	float64	21	2nd flr Heat Pump (HP) - Computer Room	float64
5	1st flr Lights	int64	22	2nd flr Office recp	int64
6	1st flr Lobby recp	int64	23	2nd flr Oven	float64
7	1st flr Office 1 recp	int64	24	2nd flr Lights	int64
8	1st flr Office 2 recp	int64	25	2nd flr Computer Room recp	int64
9	1st flr Office 3 recp	int64	26	2nd flr Classroom 1 recp	int64
10	1st flr Bathroom	int64	27	2nd flr Classroom 2 recp	int64
11	1st flr Kitchen	int64	28	2nd flr Bathoom	int64
12	1st flr Copy Room recp	int64	29	2nd flr Kitchen	int64
13	1st flr Utility Room recp	int64	30	2nd flr Kitchen recp + Dishwasher	int64
14	Refridgerator	int64	31	2nd flr Water Cooler	int64
15	Exterior Lights	int64	32	2nd flr Computer Room + Kitchen recp	int64
16	Energy Recovery Ventilator (ERV)	float64	33	2nd flr Classroom 2 + Copy Room recp	int64
17	Water Heater	float64	34	2nd flr Storage Room + Computer Room recp	int64
			35	Hourly Electricity Use (Wh)	float64

Table 2: Prediction Performance of ML Models

ML Model	Normalized MAE	Normalized RMSE	R-Squared (R^2)
SVR	0.0165	0.0253	0.9409
LR	0.0134	0.0197	0.9641
RFR	0.0265	0.0372	0.8727
MLPR	**0.0126**	**0.0185**	**0.9685**
GBR	**0.0116**	**0.0174**	**0.9720**

- *Threshold settings interface:* Lower and upper limit electricity consumption data can be defined for each building from this interface. According to the threshold values defined here, the real-time consumption monitoring interface provides a warning to the system and intervention to the administrator.

- *Video call and messaging interface:* This interface is used for communication between the administrator and the building floor personnel. In case of anomalies, the administrator can video call or send a message to the personnel he deems necessary. Its main purpose is to communicate with the floor attendant where the three most critical devices (obtained from the results of the XAI method) that cause consumption are located and to intervene in the devices when there is an excessive consumption warning in the system. It can also be used for general communication among other personnel.

3 Experimental Results and Evaluation

3.1 Dataset

In this paper, we used energy usage data from a 328 m2 all-electric, zero-energy commercial building in Virginia, USA. The dataset contains energy usage data collected over two years at 1-hour intervals using circuit-level energy monitors [26]. The dataset consists of electricity consumption data of many electricity-consuming devices such as room-based lighting, ventilation, heating and receptacle of the building with two floors. The dataset contains 35 features and a total of 21823 recorded data. Detailed dataset features are given in Table 1.

3.1.1 Results and Evaluations of ML Models

We used Support Vector Regressor (SVR), RandomForest Regressor (RFR), Lasso Regressor (LR), GradientBoostingRegressor (GBR), and Multi-layer Perceptron Regressor (MLPR) models to predict electricity consumption values in buildings. In order to obtain the best structure for each used model, we performed training with the GridsearchCV method in different parameter spaces. We tested the parameters kernel:[linear, rbf, poly], C:[0.1,1,10] for SVR, alpha:[0.1, 0.5, 1.0], fit_intercept:[True, False], normalize:[True, False] for LR, max_depth: range(4,10), n_estimators: range(10,150), criterion: squared_error, absolute_error, friedman_mse, poisson for RFR, hidden_layer_sizes:(50,),(50,50), (50,100), (100,100), (100,200), max_iter:1000,2000, alpha:[0.1, 0.01] for MLP, and n_estimators:[50,100,200], max_depth:[2,3,4,5], learning_rate:[0.1,0.5], loss: ls, lad, huber for GBR. On this basis, the results given in Table2 show the ML estimation results obtained with the best parameter space for each model.

As seen in Table 2, MLPR and GBR models stand out with the lowest error and the highest R-squared value (96% and 97% respectively) among the models used. The results of these models can be attributed to the fact that these models have more power capabilities than other models. Specifically, MLPR is based on deep learning, its ability to adapt to the data and its flexibility may have caused it to produce better results compared to other simple models. on the other hand, the fact that GBR is an ensemble model, its capacity to create a strong model by combining weak learners together may have contributed to its performance.

3.1.2 XAI Results and Evaluations

In this subsection, we present the global and local explainability of the ML models with the best prediction performance: MLRP and GBR. We use the ELI5 method for global explanations and the

MLP Regressor

Weight	Feature
0.2366 ± 0.0118	2nd_flr_AHU_ComputerRoom
0.1005 ± 0.0012	1st_flr_AHU
0.0950 ± 0.0035	2nd_flr_HP_Classroom
0.0501 ± 0.0023	WaterHeater
0.0391 ± 0.0022	1st_flr_Office_#2recp
0.0266 ± 0.0008	1st_flr_CopyRoom_recp
0.0253 ± 0.0012	1st_flr_HP
0.0182 ± 0.0008	2nd_flr_Office_recp
0.0182 ± 0.0011	1st_flr_Office_#3recp
0.0161 ± 0.0008	1st_flr_Office_#1recp
0.0149 ± 0.0010	2nd_flr_HP_ComputerRoom
0.0141 ± 0.0012	2nd_flr_AHU_Classroom
0.0131 ± 0.0008	2nd_flr_Oven
0.0117 ± 0.0011	2nd_flr_ComputerRoom+Kitchen_recp
0.0088 ± 0.0008	2nd_flr_Classroom_#1recp
0.0083 ± 0.0005	2nd_flr_Classroom_#2recp
0.0071 ± 0.0004	2nd_flr_WaterCooler
0.0069 ± 0.0011	2nd_flr_StorageRoom+ComputerRoom_recp
0.0040 ± 0.0005	ERV
0.0040 ± 0.0006	2nd_flr_Kitchenrecp+Dishwasher
	… 10 more …

GradientBoostingRegressor

Weight	Feature
0.2215 ± 0.1879	1st_flr_Office_#2recp
0.1714 ± 0.2061	2nd_flr_HP_Classroom
0.1282 ± 0.2102	2nd_flr_AHU_ComputerRoom
0.0804 ± 0.1764	1st_flr_AHU
0.0613 ± 0.1467	2nd_flr_Office_recp
0.0593 ± 0.1077	1st_flr_HP
0.0534 ± 0.1523	1st_flr_CopyRoom_recp
0.0460 ± 0.1518	WaterHeater
0.0381 ± 0.1371	1st_flr_Office_#3recp
0.0303 ± 0.1352	2nd_flr_StorageRoom+ComputerRoom_recp
0.0224 ± 0.1480	2nd_flr_AHU_Classroom
0.0205 ± 0.1447	2nd_flr_ComputerRoom+Kitchen_recp
0.0159 ± 0.1144	2nd_flr_Classroom_#1recp
0.0146 ± 0.1234	2nd_flr_Classroom_#2recp
0.0084 ± 0.1033	2nd_flr_WaterCooler
0.0057 ± 0.1292	1st_flr_Office_#1recp
0.0053 ± 0.1482	ExteriorLights
0.0041 ± 0.1113	2nd_flr_Oven
0.0033 ± 0.0980	2nd_flr_Kitchenrecp+Dishwasher
0.0023 ± 0.0931	2nd_flr_ComputerRoom_recp
	… 10 more …

Figure 3: Global explainability of the MLPR and GBR method with ELI5

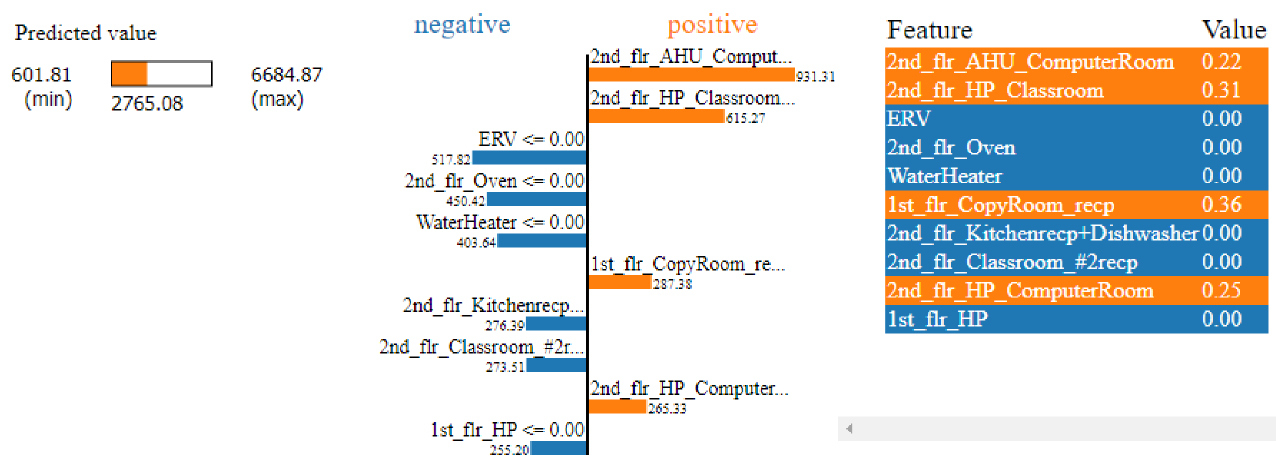

Figure 4: Local explanations of the MLRP model with LIME for an example data (row 5 in the test data)

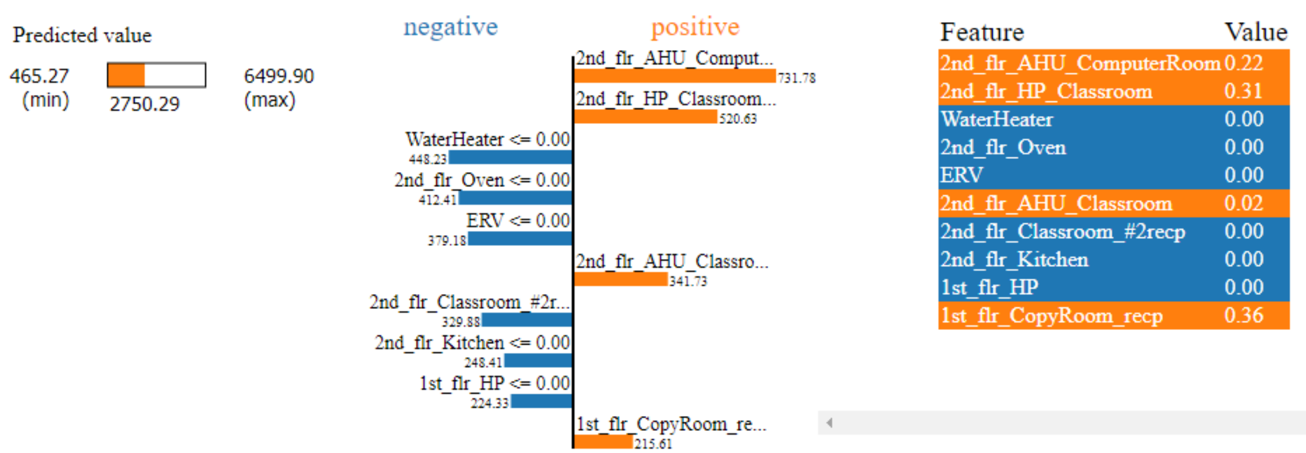

Figure 5: Local explanations of the GBR model with LIME for an example data (row 5 in the test data)

LIME and SHAP methods for local explanations.

ELI5 global explainability extracted by considering the whole dataset is given in Figure 3. In the figure, the devices that cause the most energy consumption for the data collected building are listed in order of importance. Accordingly, both MLPR and GBR models identified four devices (although their ranking is different) in the first five features. These results revealed that the devices that affect the building energy consumption the most are actually 1st

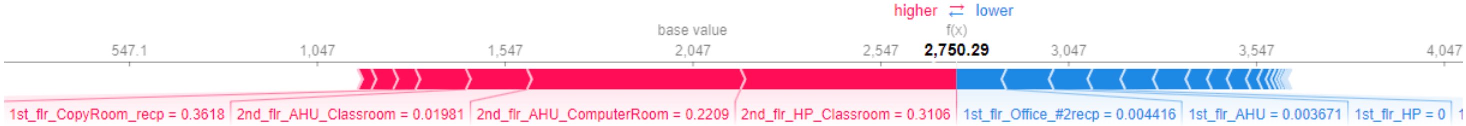

Figure 6: Local explanations of the GBR model with SHAP for an example data (row 5 in the test data)

floor Office 2#recp, 2nd floor AHU Computer Room, 2nd floor HP classroom, and 1st floor AHU. Apart from these, other device rankings that cause electricity consumption are ranked in the same way according to the feature importance.

On the other hand, the explainability of each sample of hourly measured data is also important. The explainability of each sample data during real-time monitoring was critical for instant intervention. Therefore, local descriptions are also needed for each data. For this purpose, we used the LIME to provide local explanations for a sample of data (line 5) in the test set. When the local descriptions in Figures 4 and 5 are examined, the features on the positive (orange-colored) side represent the features that affect the increase in energy consumption for this sample data. According to the LIME local explanation of the GBR model for the sample data, 2nd floor computer room AHU unit, 2nd floor classroom HP and 2nd floor classroom AHU unit are found as the most electricity-consuming devices. According to the MLPR model, 2nd floor computer room AHU unit, 2nd floor class HP and 1st floor CopyRoom recp device were determined as the devices causing the highest electricity consumption, respectively.

In addition, we performed a local explainability analysis with SHAP for the most successful GBR model to test whether different XAI methods would produce different results. When we compared the GBR model with the LIME results (Figure 5), we saw that the first three features are the same (even if their order changes). According to these results, we have seen that although XAI methods vary, the results are similar and consistent.

4 Conclusion

In this study, we aim to develop a system based on eco-friendly, low-cost, interpretable, and innovative technologies in order to reduce human-caused factors in the fight against climate change, which is the most important problem of our time. In this context, we designed an end-to-end Green IoT testbed architecture. We test this architecture with low-cost devices, applications, and AI models. At the same time, we use XAI methods to ensure that the developed system and models are understandable to the end user. Although the developed system offers low-cost and easy solutions for building energy management, it depends on the human factor at the edge. As a future vision, autonomous IoT systems that will eliminate human intervention on the end-user side are promising. As a result, we present a projection on how to make effective efficient energy management in the smart buildings of the future with the developed system, through a prototype application example.

Authorship contribution statement

İbrahim Kök: Conceptualization, Methodology, Software, Visualization, Writing- Reviewing and Editing, Supervision, **Yasin Ergun:** Investigation, Software (Mobile Application) **Nagihan Uğur:** Investigation, Software (Data communication)

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