Antony Francis[1] , Sheema Madhusudhanan[1] , Arun Cyril Jose[1] , Reza Malekian [2,3]

Department of Computer Science & Engineering, Indian Institute of Information Technology Kottayam (IIITK) (1), Department of Computer Science and Media Technology, Malmö University, Sweden(2); Department of Electrical, Electronic and Computer Engineering, University of Pretoria, Pretoria, South Africa (3)

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An Intelligent IoT-based Home Automation for Optimization of Electricity Use

Abstract. *The world is gearing towards renewable energy sources, due to the numerous negative repercussions of fossil fuels. There is a need to increase the efficiency of power generation, transmission, distribution, and use. The proposed work intends to decrease household electricity use and provide an intelligent home automation solution with ensembled machine learning algorithms. It also delivers organized information about the usage of each item while automating the use of electrical appliances in a home. Experimental results show that with XGBoost and Random Forest classifiers, electricity usage can be fully automated at an accuracy of 79%, thereby improving energy utilization efficiency and improving quality of life of the user.*

Streszczenie. *Świat zmierza w kierunku odnawialnych źródeł energii ze względu na liczne negatywne reperkusje paliw kopalnych. Istnieje potrzeba zwiększenia efektywności wytwarzania, przesyłu, dystrybucji i użytkowania energii. Proponowane prace mają na celu zmniejszenie zużycia energii elektrycznej w gospodarstwach domowych i zapewnienie inteligentnego rozwiązania automatyki domowej z połączonymi algorytmami uczenia maszynowego. Dostarcza również zorganizowanych informacji na temat użytkowania każdego elementu, jednocześnie automatyzując korzystanie z urządzeń elektrycznych w domu. Wyniki eksperymentów pokazują, że dzięki klasyfikatorom XGBoost i Random Forest zużycie energii elektrycznej można w pełni zautomatyzować z dokładnością do 79%, poprawiając w ten sposób efektywność wykorzystania energii i poprawiając jakość życia użytkownika.* (***Inteligentna automatyka domowa oparta na IoT do optymalizacji zużycia energii elektrycznej***)

Keywords: Smart home automation, Ensembled Machine learning algorithms, Microcontroller, Proximity Sensors.
Słowa kluczowe:automatyka domowa, .optymalizacja zużycia energii,Mikrokontroler, czujniki zbliżeniowe

I. Introduction

In the coming years, the world's capacity to generate electricity will depend on wind turbines, solar panels, and other renewable sources. There will be a steep acceleration towards a net zero CO2 emission futures using renewable energy sources like solar, hydro, wind, etc [1]. Figure 1 shows world-wide energy consumption and the share of global primary energy from fossil fuels is trending downwards .

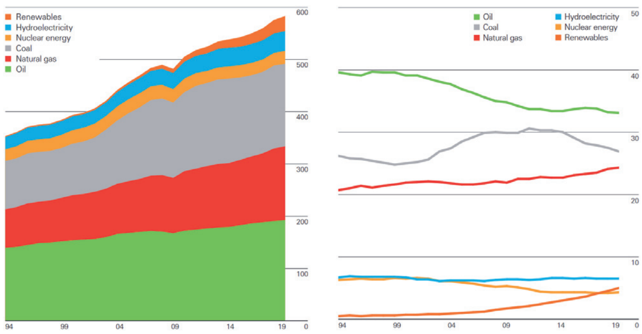

Fig. 1. Primary energy consumption in world wide view (in Exa-Joules), and shares of global primary energy (in percentage) [3]

The International Energy Agency (IEA's) annual Renewables Market Report predicts that by the end of the year 2026, the global renewable electricity capacity will increase by 60% compared to 2020 [2]. Furthermore, 4800 GW of electricity will get generated, equivalent to the current total global power capacity of fossil fuels and nuclear energy.Therefore a drastic shift in the energy sector can be expected, and such renewable sources will reduce the energy intensity of GDP growth [4] To reduce the GDP's dependency on fossil fuel sources, electrification of the economy and renewable sources are the essential elements [4].

Internet of things (IoT) home automation systems are flexible and reliable, and thus communication is achieved between home appliances and the user via the internet [5][6]. Recently the importance and usage of home automation systems like smart home devices have increased due to the dominant use of the internet, the evolution of smartphone technology, and raised mobile communication standards [7]. These IoT systems provide users comfort, convenience, security, and energy consumption efficiency [8]. It involves real-time control and monitoring of multiple electric appliances [9][10].

In this work, we deployed our model with a structure that includes cloud server access from outside the local network and a cloud database system for storing records and usage time for each appliance. A mobile app is designed to give access to the user for manual control and usage information via a local connection or remote login and extended with relays for switching ON/OFF the devices. Likewise, a computation unit (raspberry pi) is used for managing (sending, receiving, and processing) all the requests from the mobile app via the server or directly through a local connection and making the relays workable. Furthermore, some sensors have been used to detect the user's presence, including proximity sensor and motion sensor, and later provide home electric appliance usage data with the help of a Machine Learning (ML) model. The rest of this paper is organized as follows.We summarize the literature review in section II. Section III discusses the proposed architecture, while testing and results are demonstrated in Section IV. Next, we conclude the research work.

II. Related Works

An IoT system consists of a server relaying instructions to and from the microcontroller [11]. This server should also contain a database to store each appliance's usage record. Using a cloud server would enable the mobile app user, only after proper authentication, to connect to the local server, responsible for switching on/off the devices using the cloud server. Then, the sensors are used to gain live

information from the environment, and the microcontroller is used to act on the information coming from the sensors and relay it to and from the server. Finally, the remote connection to the user through the mobile app allows the user to access each appliance and change the layouts of rooms giving high customizability options. It should also be secure and needs a login system to prevent unauthorized access to the user's appliances. The system's structure works on two levels (global and local) [12]. At the global level, it allows remote access via Wi-Fi. It uses the mobile app via a direct local connection at the local level, improving the speed of processing user requests. We can see that the local server is connected to
the global server, hence maintaining synchronized storage of usage records [12].

According to Benjamin K. Sovacool et al. [9], a sobering 267 smart home technology options are available to consumers today, provided by 113 different companies and available from a multitude of direct suppliers, home improvement stores, general department stores, and electronics and appliance retail shops. This array of options ranges from devices that can merely create isolated or bundled smart services at lower levels of the smart spectrum to more automated, intuitive, and sentiment options such as artificial intelligence, robots, and drones. Industrial applications and different scenarios require different IoT platforms and devices[11]. Typically IoT architecture has the features such as hardware and software interface that includes various protocols and devices, user requirement fulfillment with operative IoT applications, and it should be extensible and scalable [10].

Al-Ali et al propose a Home Energy Management System (HEMS) architecture [13] that involves a data acquisition module consisting of System on Chip (SoC) that tracks and collect the energy consumption details from smart home electrical devices and transmit the data to a centralized server and later performs processing and analysis of data. PSO clustering module where the power data will be clustered into two groups according to time and power consumption variables. The two groups are high activity groups and low activity groups. An outlier detection module to find out unusual data and mark them. Furthermore, a linear regression module where all data of each group will be operated through Linear regression. Moreover, we can make further statistical analysis using that regression model. For scheduling, they have assigned different group classes to different appliances based on the electrical appliance characteristics,such as power consumption, frequency of usage, and usage time.

Hepeng Li et al.[14] developed an appliance optimal scheduling algorithm based on deep reinforcement learning considering appliance states, real-time electricity price, and outdoor temperature. In contrast, Can Li et al.[15] have used a Mixed Integer Linear programming (MILP) algorithm to minimize the generation, transmission, and electricity cost. Chun-Te Lee et al. [12] have constructed a scenario where they identify human presence in a room and to satisfy the goal of energy saving with a collaborative system counter and an infrared (IR) human movement sensor. L. Cao et al. [16] have proposed electrical load prediction on health care buildings with ensemble machine learning. The proposed technique finds the presence of a human being and feeds in some information in the neural network in the form of voltage and current. The intermediate hidden layer calculates the function to decide the output. They used a feed-forward neural network for this case as they have selected the presence of the human along with the instantaneous consumption of current and voltage as the contributors to making the final decision on whether to switch on/off the device.

Recent advances in machine learning have produced unique and sophisticated models that are enhancing forecasting outcomes across a variety of industries [21][22]. Yunlong Li et al. proposed a methodology to predict energy consumption on HVAC with fusion of XGBoost and LightGBM models on IoT [17]. A.Lahouar et al. brought forward the concept of Random Forest classifier for short term load fore- cast and they validated the model for regular working days, weekends and holidays [19]. A multivariate logistic regression (MLgR) model was proposed by L. Liu et al. to forecast the occurrence of extremely high and low electricity prices [20].

In this work, we use a Raspberry Pi over Arduino UNO as the microcontroller/compute unit of the system, mainly due to its compatibility with using novel Node-Red architecture and Tensorflow Lite to run ensembled ML algorithms. Furthermore, we have worked on the data in the SQLite database about the usage of each appliance and accord it to the user to give him/her an idea about the total electricity usage in the house.

III. Proposed Architecture

The proposed architecture shown in Figure 2 automates the usage of home electric appliances in a house and provides organized information about the usage of each home electrical appliance.

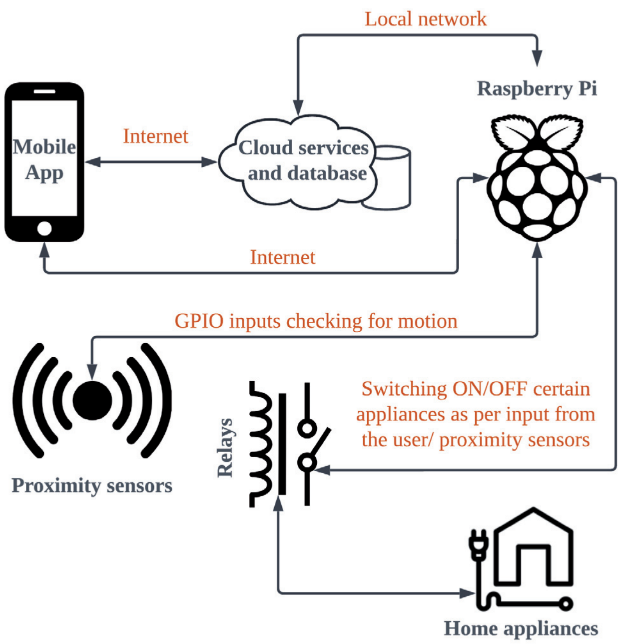

Fig. 2. Automate the usage of home electric appliances

The Proximity sensors are used to detect if someone has entered the room. To check if a person is entering or leaving a room, we use two proximity sensors at a certain distance from each other near the door, one closer to the room and one further. If the one closer to the room gets triggered first, then it means that the person is leaving the room. Otherwise, it shows the person just entered the room.Then the computation unit (raspberry pi) takes action based on the user's behavior. The computation unit sends signals to relays per the user's needs. Similar to the work proposed in [11], upon reception of requests from the user via the mobile app, the computation unit executes the commands by turning ON/OFF the dedicated GPIO (general purpose input- output) pins for the sensors that users requested. Therefore, we control the GPIO pins. So, if the person is leaving the room, the computation unit will send signals to switch OFF all appliances after receiving that information from the proximity sensors. If the person enters the room, the user can select which appliances he wants to turn on automatically and take manual control of the appliances.

The person communicates via the mobile app and in-forms which appliances will be switched on/off. The mobile app will have a login password system for each user. In the mobile app, the user can see the usage of each home electric appliance in the house. The mobile app can run on two levels. When the user is in the same network to which the computation unit is connected, it is a local connection; hence, all the requests go directly to the computation unit (local server) and execute the user-requested commands. The mobile app can be run via Wi-Fi from a global server (AWS IoT) to check on the appliances outside the local network. Once the request is submitted, the user's credentials get verified and forward the requests to the computation unit.

The usage data gets recorded in the cloud server database and periodically provides information about the individual home electric appliances. The data about the usage of each home electric appliance gets analyzed and displayed in a proper format. Furthermore, an estimation is carried out to provide information regarding the usage.

IV. Experimental Setup and Result

The hardware testbed for automating the evaluation of home electric appliances usage is shown in Figure 3.

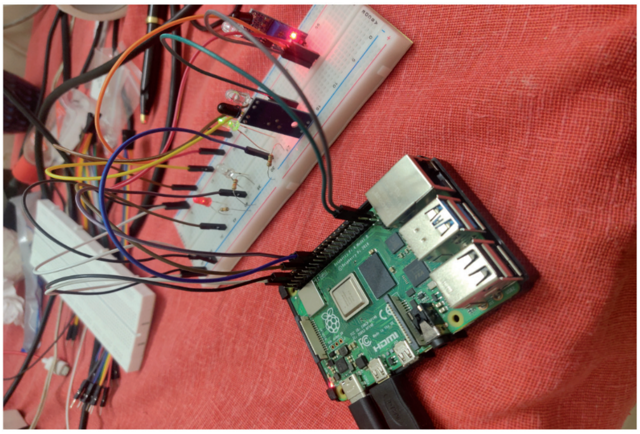

Fig. 3. Testbed for automation of home electric appliances

The data collected are stored in the cloud server database and made available in the mobile app based on the user's request. The app was developed using Android Studio. It has 3 major use-cases, Login, Sign-up and Device Dashboard. The Login and Sign-up features have been implemented(Figure 4) and the users data is stored in SQLite Database.

The Devices control screen(Figure 5) enables the user to connect to the Raspberry Pi Server using a local connection and send inputs ON/OFF for each device connected to the system.

The data collected are pre-processed, and dataset contains three target variables and 24 predictors for each hour in a day.

The data was collected with 10s gap between each input. It was collected in this experimental setup using Google Sheets API over a period of 10 days.

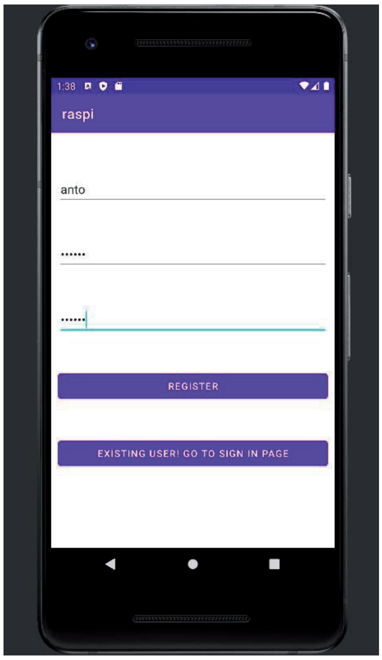

Fig. 4.Registration Screen

Later, it is trained and passed to a Machine Learning (ML) model. This model can then predict if the device is ON/OFF at a particular time. Based on past usage data, we have ensembled three ML classifiers, such as Logistic Regression, XGBoost, and Random Forest Classifier, to compare data classification. Furthermore, we have employed Max-Voting Ensemble as an ML model to predict device status and decide when to turn ON/OFF a home electric appliance.

Fig. 5.Device Control Screen

This model is further improved by giving it access to power usage prediction and minimizing its usage. We have calculated the precision (P), recall (R), f1-score (F1), and

Table 1. Electric Home Appliances Usage Data Performance Metrics Comparison based on the ML Models

ML Models	**Logistic Regression**				**XGBoost**				**Random Forest**				**Max-Voting Ensemble**			
Performance Metrics	**P**	**R**	**F1**	**S**	**P**	**R**	**F1**	**S**	**P**	**R**	**F1**	**S**	**P**	**R**	**F1**	**S**
0.0	0.55	0.60	0.57	231	0.68	0.53	0.60	177	0.69	0.57	0.62	190	0.69	0.56	0.62	190
1.0	0.74	0.69	0.71	376	0.82	0.90	0.86	430	0.82	0.88	0.85	417	0.81	0.88	0.85	417
Accuracy			0.66	607			0.79	607			0.79	607			0.78	607
Macro Average	0.64	0.65	0.64	607	0.75	0.71	0.73	607	0.76	0.73	0.74	607	0.75	0.72	0.73	607
Weighted Average	0.66	0.66	0.66	607	0.78	0.79	0.78	607	0.78	0.79	0.78	607	0.78	0.78	0.78	607

support (S) based on all the classifiers ensembled in our ML model, as shown in Table 1. In the given table, 0.0 signifies that the device is OFF and 1.0 implies that the device is ON. A large number of duplicate values reduces the precision of simple models such as logistic regression. Logistic Regression has a very low accuracy(66%) as compared to the more complex algorithms such as XGBoost(79%), and Random Forest Classifier(79%). These 2 algorithms show very similar results in all the fields (P, R, F1 and S).

V. Conclusion

In this work, we have researched and analyzed different aspects of home automation systems and Home Energy Management Systems (HEMS). Here, we have proposed changes such as using proximity sensors (to detect presence of humans) and raspberry pi (due to accessibility to Node-Red and TensorFlow Lite as compared to an simple Arduino Uno) as the micro-controller of the system. We have ensembled three different classifiers Machine Learning (ML) models, such as Logistic Regression, XGBoost, and Random Forest Classifier, along with an ensemble model (Max-Voting). In this model, users can manually access their home electric appliances connected to the computation unit via the mobile app designed to turn the home electric appliances ON/OFF. Furthermore, they can set it to automated mode to use the ML model to have a completely automated experience. Duplicate values cause different problems to different models. For linear models, weight distribution becomes much more challenging. For tree based models, feature importance is not as significant. For distance based models, those duplicate values add more significance to those certain features in the distance. But using more complex models such as XGBoost and Random Forest Classifiers yield much stronger results. As a future work, we would like to scale this system for higher energy consuming buildings such as hospitals, commercial office complexes etc.

Author: *Antony Francis, Sheema Madhusudhanan, Arun Cyril Jose Department of Computer Science and Engineering, Indian Institute of Information Technology Kottayam (IIITK), Kerala, India, email: tonyfran18bcs@iiitkottayam.ac.in,sheemamadhu.phd2116 @iiitkottayam.ac.in and aruncyril@iiitkottayam.ac.in, Reza Malekian, Department of Computer Science and Media Technology, Malmö University, Malmö, Sweden, email: reza.malekian@ieee.org*

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