*I.J. Information Engineering and Electronic Business*, **2025, 2, 111-128**
Published Online on April 8, 2025 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijieeb.2025.02.06

# IoT Based Smart Energy Consumption Prediction for Home Appliances

**Atiqur Rahman**
Department of IoT and Robotics Engineering (IRE), Gazipur Digital University, Kaliakair, Gazipur-1750, Bangladesh
E-mail: 1801025@iot.bdu.ac.bd
ORCID iD: https://orcid.org/0009-0009-9306-6976

**Sadia Hossain**
Department of IoT and Robotics Engineering (IRE), Gazipur Digital University, Kaliakair, Gazipur-1750, Bangladesh
E-mail: 1801017@iot.bdu.ac.bd
ORCID iD: https://orcid.org/0009-0004-2203-5500

**Samsuddin Ahmed**
Department of IoT and Robotics Engineering (IRE), Gazipur Digital University, Kaliakair, Gazipur-1750, Bangladesh
E-mail: samsuddin0001@bdu.ac.bd
ORCID iD: https://orcid.org/0000-0002-1267-0533

**Md. Toukir Ahmed***
Department of IoT and Robotics Engineering (IRE), Gazipur Digital University, Kaliakair, Gazipur-1750, Bangladesh
E-mail: toukircse14@gmail.com, toukir0001@bdu.ac.bd
ORCID iD: https://orcid.org/0009-0002-3816-8602
*Corresponding Author

Received: 26 August, 2024; Revised: 02 January, 2025; Accepted: 13 February, 2025; Published: 08 April, 2025

**Abstract:** Optimizing energy management for household appliances is essential for maximizing domestic energy utilization and enabling preventive maintenance. Recent studies indicate that traditional forecasting approaches frequently lack the necessary accuracy and real-time learning capabilities required for effective management of household energy. This study demonstrates the implementation of a comprehensive strategy that integrates Internet of Things (IoT) data, machine learning (ML), and explainable artificial intelligence (XAI) to improve the accuracy and interpretability of predicting energy usage in residential buildings. Our research focuses on the rising issues faced by IoT-based smart systems, partic- ularly the deficiencies in the performance of current solutions. Therefore, as compared to the other 17 models that were examined, polynomial regression demonstrated outstanding performance. Our solution utilizes a non-intrusive sensor to collect data without disrupting its operation. Real-time data collecting is achieved through a Flask-based web page with Ngrok for external access.The efficacy of the proposed system was assessed using many metrics, yielding highly satisfac- tory results: the root mean square error (RMSE) was 0.03, the mean absolute error (MAE) was 0.02, the mean absolute percentage error (MAPE) was 0.04, and the coefficient of determination ($R^2$) was 0.9989. However, modern cutting-edge methods still face considerable hurdles when it comes to interpretability. In order to tackle these problems, we include XAI techniques such as SHAP and LIME. Explainable Artificial Intelligence (XAI) improves the interpretability of the model by elucidating the impact of various variables on energy consumption forecasts. Not only does this increase the effectiveness of the model, but it also promotes comprehension of the data and enables them to identify the elements that influence home energy usage.

**Index Terms:** Household Energy Consumption, Energy Forecasting, Energy Management, Machine Learning, XAI, Internet of Things

## 1. Introduction

Households worldwide have a substantial obstacle in obtaining daily access to electricity. More than 50% of house- holds face difficulties in operating cooking, lighting, and other appliances, which significantly diminishes their quality of life. Despite numerous programs focused on enhancing dependable energy access, there is sometimes a shortage of supply due to high demand, resulting in frequent power outages. The disruptions and irregularities in the energy supply have a detrimental effect on the comfort, productivity, and economic activities of households. In addition to supply-related problems, energy theft and inadequate infrastructure are prevalent difficulties that afflict energy systems worldwide. Il- licit actions like as meter manipulation, unlawful connection, and meter bypass jeopardize the safety and reliability of electricity systems that are operating at or near maximum capacity. Precise energy consumption prediction is crucial for households to actively participate in efficiently managing energy resources. In order for a household to contribute to effec- tive energy use, resource allocation and decisions on energy use must be made strategically. Researchers have extensively investigated methods to enhance energy efficiency in order to tackle the worldwide difficulties associated with energy use. Researchers have explored several aspects of work history in the perspective of optimizing energy efficiency. Rashid et al. [1] introduced a machine learning and Internet of Things (IoT) powered smart energy monitoring system designed for Malaysian households with the aim of minimizing energy inefficiencies. Mengistu et al. [2] created an online NILM system to separate and analyze real-time household electricity consumption. Xiao et al. [3] introduced a machine learning and embedded smart home energy system, whereas Eseye et al. [4] devised the EMD-ICA-SVM model based on smart grid technology to predict heat demand. Li et al. [5] conducted a study on the use of Smart Energy Theft System (SETS) in smart homes in Singapore to detect instances of energy theft. Machorro-Cano et al. [6] introduced their HEMS-IOT system to categorize energy consumption rates in the cloud. However, the system was constrained by platform compat- ibility and sensor limitations. However, Raju et al. [7] provided short-term load forecasts that lacked clear scalability and cost-effectiveness. These research studies have made substantial contributions to the field of energy efficiency and management. Furthermore, researchers have identified the crucial domains that are vital in driving progress in industries such as Internet of Things (IoT), big data analytics, machine learning, and deep learning. These fields present novel prospects for developing advanced energy management solutions. The growing accessibility of smart meters, sensors, and data collection tools amplifies the potential for precise energy monitoring, forecasting, and outage prevention, as well as efficient management of peak loads.

Our research primarily aims to design a robust and effective energy management system to tackle the persistent energy challenges experienced by families globally. Our work enhances energy use efficiency, predicts maintenance require- ments, and prevents energy theft through the use of Internet of Things (IoT), Machine Learning (ML), and Explainable Artificial Intelligence (XAI). The precise aims have comprised:

- Our objective is to assess multiple machine learning models, such as Polynomial Regression, using cutting-edge ML techniques to accurately predict energy use and identify irregularities.
- Utilizing XAI approaches such as SHAP and LIME will allow us to offer comprehensive insight into the decision- making process, hence facilitating the comprehension of forecasts by end users. Furthermore, it enhances user confidence and transparency.
- Collecting significant energy consumption data using non-intrusive sensors and connecting them to a microcon- troller, a flask application for transferring and recording the data. In addition, remote monitoring is made possible through the use of ngrok, enabling users to interact from any location via the internet. An alert system will notify users of any irregularities.

This integrated system combines IoT data collecting, machine learning model construction, explainable AI approaches, and real-time monitoring to create a strong solution for smart energy management and predictive maintenance. It improves operational efficiency and empowers users to make informed decisions.

The following organizes the remaining portion: Section 2 discusses the most current and advanced studies in the field, while section 3 dives into the specific methodologies and techniques employed, such as the design of IoT subsystems, machine learning models, and web interface development. Section 4 covers the hardware configuration, the process of training and testing the model and the overall interpretation. Section 5 discusses the outcome of the performance mea- surements, the prediction of power consumption, and the system for issuing alerts. Section 6 presents the analysis and evaluation section. Finally, section 7 addresses the conclusion and future prospects of our research.

## 2. Literature Review

Researchers have investigated and worked a range of methodologies and techniques. Eseye et al. [4] developed EMD-ICA-SVM, a model learning model, to anticipate building heat demand 24 hours in advance inside a smart grid framework. Blending Empirical Model Decomposition, Imperialistic Competitive Algorithm, and Support Vector Machine improves accuracy and performance. The research emphasizes the importance of employing Binary Genetic Algorithm and Gaussian Process Regression to choose 15 important variables as model predictors. Validated using 2015–2017 hourly data for four building types. Its drawbacks include dependency on historical data up to 2017, limited building kinds, and potential difficulties adjusting to various environments and massive datasets. According to Asem et al. [8], energy-efficient methods are essential. Using data integration for building energy efficiency, the proposed methodology achieves a forecast accuracy of 92%, surpassing previous approaches. To optimize power expenses, a domestic energy management system is a practical approach due to rising electricity demand and availability of alternative energy sources [9].

Recently, several research organizations have considered using AI, ML, and DL to build data-driven systems to improve energy generation and demand modeling. A approach by Yang et al. [10] predicts the energy consumption of a DNN by analyzing its architecture, parallelization, and bit-width. This approach may evaluate and guide energy-efficient DNN design by testing a variety of DNN architectures and efficient strategies provided in the study.

The study by Syed et al. [11] involves two stages: data cleaning and model design. Data cleaning involves preparing unprocessed data and adding features like lag values. Training the hybrid model with processed data occurs throughout model development. A hybrid deep learning model uses fully linked layers, unidirectional LSTMs, and bidirectional LSTMs. The model captures energy usage temporal dependency. Computational complexity, training time and pre- dicting accuracy are efficient. The recommended approach outperforms popular hybrid models like ConvLSTM, LSTM encoder-decoder model, and stacking models in accuracy after assessing two benchmark energy consumption datasets. The predictive deep learning model achieved a MAPE of 2.0% for case study 1 and 3.71% for case study 2. 2. The sug- gested model outperformed LSTM-based models by 8.368% and 20.99% in MAPE for chosen datasets. We also found recent energy consumption, load, and forecast works using IoT, smart meters, digital machines, and new methodologies. The World Energy Outlook (2017) predicts a 1.0% CAGR in global energy needs from 2016 to 2020 [12]. Buildings uti- lize a significant amount of energy worldwide, accounting for 27% of total energy use and 40% of US energy usage [13]. Smart energy prediction and management sensors are crucial for private buildings because load forecasting influences power system control and planning. A 1% reduction in inaccurate predictions could save the UK power grid £10 million annually, per research [14]. Energy efficiency and cost reduction require planning. Computational intelligence can enable future energy planning through electricity forecasting [15, 16] . ISDN for CRO uses a theoretical foundation for new network technology. This theory was developed to address communication system development and operating concerns. The strategy is inspired by how living creatures overcome difficulties and improve usefulness The proposed framework- wide learning, demonstration, improvement, and knowledge description technique uses probabilistic generative models and progressive methodologies. This learning framework can implement system-level CRO and reconfiguration with ISDN. This functionality is accessible. According to Saleem et al. [17], their methodology is superior to current methods. The precision is 96.22%. Integrating ML and IoT has been extensively studied to improve results. Despite significant advancements in recent works in energy management especially in deep learning-based works, several limitations hin- der optimal results. For instance, LSTM based models are widely utilized for time series forecasting, but they heavily depend on extensive and high-quality historical data with high computational cost and are prone to over-fitting. Again, CNN based models are well suited for spatial data preprocessing but struggle to capture temporal dynamics inherent in energy systems in load forecasting. Additionally, transformer-based models [4, 18] are prone to over-fitting, especially in limited data scenarios. Our selected model polynomial Regression is well adapted for IoT driven energy management, as it is lightweight, computationally efficient and interpretable, making it further suitable for load balancing, fault detection, without the drawbacks of deep learning-based alternatives.

Table 1. Summary of studies on integration between machine learning algorithms and internet of things or advanced technologies for energy consumption or forecasting

| Paper | Contributions | Technologies Used | Limitations | How Our Work Differs |
|---|---|---|---|---|
| [1] | LSTM, IoT, Raspberry, Pi, Google Colab training server | Over 80% accuracy | Practical implementation challenges | Higher accuracy with lower computational cost using Polynomial Regression |
| [5] | IoT, ML (MPL, RNN, LSTM, GRU) | High accuracy and multimodel forecasting | Limited implementation details, user-friendliness not addressed | XAI-based (SHAP, LIME) for user decision making |
| [6] | IoT, big data analytics and the J48 ML algorithm. | User centric evaluation involving thirty-five respondents assessed the perceived effectiveness of the systems, quality of recommendations, and their intention to use them. | Scalability challenges and limited generalization | Validated with real-time sensor data for practical implementation |
| [19] | IoT, Deep Learning | Significant reduction in RMSE and MSE | Limited application discussion. | Real-world IoT deployment and decision support for effective monitoring |
| [20] | IoT, MRMR, Trilayered NN | Significant reduction in RMSE and MSE and high accuracy in load predictions | Computational complexity. | Polynomial Regression is computationally effective for real-time applications |

Table 1. illustrate recent studies related to the integration of advanced techniques and their limitations. Our research work gathers data from home appliances using non-intrusive sensors that are capable of measuring current and voltage energy consumption. This is achieved by utilizing inexpensive equipment that is compatible with the Internet of Things (IoT) technology. Among the 17 machine learning models, polynomial regression outperformed the others when evaluated using training, validation, and testing sets. Models are evaluated using metrics such as Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Explained Variance (Expl. Var.), and the coefficient of determination ($R^2$). We employed the SHAP and LIME frameworks for explainable AI to enhance transparency and bolster the confidence in our model. These frameworks enhance the comprehension of model predictions by end-users through offering comprehensive insights into the decision-making process.We established a con- nection between non-invasive current and voltage sensors and a microcontroller. We then connected the microcontroller to a computer running flask in order to manage the transmission of serial data. The incoming data was parsed and pro- cessed, and subsequently logged in an excel file for the purpose of making future forecasts and detecting anomalies. We employed Ngrok to securely expose our local flask application to the Internet, allowing for real-time remote monitoring and interaction with our prediction model and IoT subsystem.

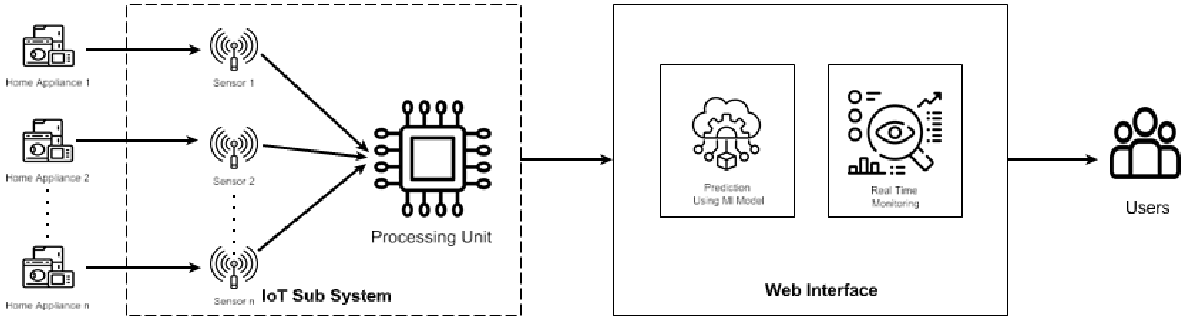



Fig. 1. A residential energy management solution using IoT, machine learning, and UI. Sensor 1, sensor 2,..., sensor n connects home appliances to an IoT sub system. A central processing unit receives sensor data. A web interface uses the data for machine learning model prediction and real-time monitoring. Users then access processed data via the web interface.

## 3. Methodology

Our study focuses on developing a domestic energy management solution that utilizes Internet of Things (IoT), machine learning, and user interface (UI) technologies. Sensor 1, Sensor 2,..., Sensor n establish connections between household appliances and an Internet of Things (IoT) subsystem. A central processing unit (CPU) gets data from sensors. A Web Interface utilizes the data to make predictions using a machine learning model and provides real-time monitoring. Subsequently, users retrieve processed data through the web interface. Multiple components are depicted in Fig.1. On the opposite side, the home appliances serve as the data source for monitoring energy consumption metrics such as current and voltage. The IoT sub-sensor sector will detect the current and voltage simultaneously using non-invasive current and voltage sensors. Fig.2. depicts the schematic diagram of the Internet of Things (IoT) subsystem. The data collected from the sensors is sent to a central processing unit situated within the Internet of Things (IoT) subsystem. This unit is responsible for processing the raw data, carrying out initial activities, and maybe filtering or aggregating the data for future utilization. The data obtained from the IoT subsystem is transmitted to a web interface using the Python Flask framework . At this interface, a machine learning model is utilized to make predictions based on the performance of the most effective models. Furthermore, the parameters are transformed into units of energy consumption using the usual formula employed in the dataset. By utilizing forecasting techniques, it has the capability to anticipate consumption patterns, identify anomalies, and monitor maintenance requirements. Additionally, it enables the live monitoring of household equipment. Users or homeowners from another location can access real-time data, monitor the performance, and check the status of their appliances. Users have the ability to engage with the system in order to make well-informed choices, seamlessly monitor all aspects, and efficiently manage them. In addition, we have utilized a service called Ngrok to securely make our local flask application accessible on the Internet. This has facilitated real-time remote monitoring and interaction with our predictive model and IoT subsystem. Ngrok’s support for custom domains or subdomains improves the professional appearance of our application and facilitates sharing and collaboration with stakeholders. Ngrok’s traffic inspection feature enables real-time monitoring and analysis of HTTP requests and answers.

### *3.1. Design of the Internet of Things (IoT) Subsystem*

The IoT subsystem plays a vital role in the whole system, as it is responsible for gathering data from household appliances, analyzing it, and passing it to the web interface for further analysis and prediction. This subsystem comprises domestic appliances, sensors, and a processing unit.

*3.1.1 Household Appliances*

Home appliances serve as the main sources of data in the IoT subsystem. These appliances include a diverse array of devices, including household gadgets and entertainment devices, all of which produce important data about their condition, usage, and surroundings. Sensors embedded into each appliance collect specific kinds of data, such as current, voltages, energy usage, and operational condition. The acquired data is crucial for optimizing and monitoring the operation of these appliances, as well as for predictive maintenance.

*3.1.2 Sensors (Data Collection)*

Sensors are a crucial element of the Internet of Things subsystem, since they are responsible for collecting real-time data from various home appliances. Each individual appliance is connected to one or more sensors that are tasked with gathering certain data. Subsequently, the collected data is transmitted to the processing unit for further processing.

*3.1.3 Central Processing Unit*

Multiple sensors transmit data to the processing unit, which subsequently gathers and analyzes the data before trans- ferring it to the web interface. The processing unit serves as the central hub of the Internet of Things subsystem. The processing unit is responsible for performing data cleansing and transformation tasks at the initial stage to ensure that the data is prepared for subsequent research activities.

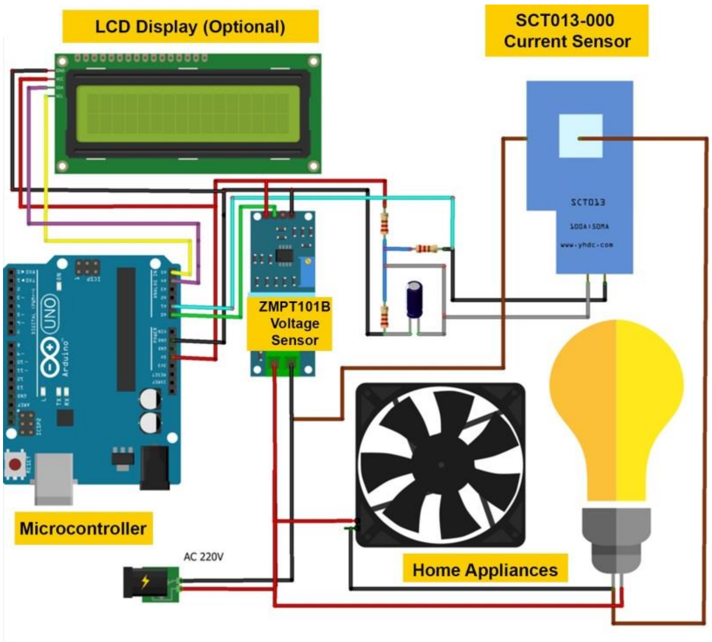



Fig. 2. Circuit diagram of IoT subsystem of our proposed solution

*3.2. ML Model Design and Testing*

The emphasis of this subsection is on the phases of data obtaining and preprocessing regarded as most crucial within our system. The quality of the data we get and the techniques we apply to get it ready for predictive analytics and ML will determine the efficiency of the system.

*3.2.1 Dataset collection*

Individual household electric power consumption dataset [21] measures electric power consumption in this study were gathered from UCI Machine Learning Repository The data was gathered in a residence located in Sceaux, France, which is situated seven kilometers away from Paris. The data collection spanned from December 2006 to November 2010, including a duration of 47 months. The time-series dataset consists of 2,075,259 instances and 9 attributes, including the date, time, voltage, global intensity, active power readings from 3 distinct submeters, and global active and reactive power values. Each reading from the submeter is associated with a maximum of three household appliances. To enhance the comprehensibility of this paper, the three submeters will be substituted with three distinct household commodities.

*3.2.2 Data Prepossessing*

After the raw dataset was collected, it went through a number of steps to be transformed into a shape that could be used. We did some cleanup work and looked through the dataset for any null numbers. In the same way that feature scaling does, normalizing and standardizing features makes the spread of independent variables or features in the dataset more consistent. This makes sure that no one factor is more important than the others and speeds up and improves algorithm convergence. Our system has both stable scaling and unit vector scaling built in.

i. Feature Normalization:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

Where, max($x$) is the maximum value and min($x$) is the minimum value in the dataset. $x'$ is the normalized value of the original feature $x$

ii. Feature Standardization:

$$x' = \frac{x-\mu}{\sigma} \tag{2}$$

where $x'$ is the scaled feature, $x$ is the original feature value , $\mu$ is the mean of the feature, $\sigma$ is the standard deviation of the feature.

iii. Implemented robust scaling:

$$x' = \frac{\mathrm{x - median(x)}}{IQR} \tag{3}$$

Where IQR is the interquartile range of the feature values.fore scaling, the histogram represents the original distribution of the target feature. After applying Min-Max scaling, the data is compressed or expanded to fit within the rang [0,1]. The shape of distribution remains similar to the original, but it’s adjusted to fit within this range. For standardization, the data is centered around 0 with a standard deviation of 1. The histogram shows the data shifted towards the center(0) and with a standardized spread and doesn’t bound the data to a specific range. Additionally, in case of robust scaling, the data is scaled based on the interquartile range (IQR) and making it less sensitive to outliers and more robust to extreme values.

iv. Maximum absolute scaling: Maximum absolute scaling divides every observation by the maximum value of the variable, therefore guiding the data toward its maximum value: The outcome of the previous modification is a distribution whereby the values vary somewhat roughly between -1 and 1.

### *3.2.3* Data Analysis and Testing

We implemented the Dickey-Fuller test during the analysis of home energy consumption data to verify the existence of stationary behavior for our research project. In order to achieve this, we removed the null hypothesis of a unit root. The residuals were subjected to a normality test using both visual and statistical methods, which verified that they followed a normal distribution. Additionally, we conducted a heatmap analysis to ascertain the correlations between numerical features, which revealed significant positive relationships. We employed visualization tools, such as histograms and KDE graphs, and probability fitting to analyze the power consumption data. This demonstrated that it was not a normal distribution and had been skewed to the right. The finding emphasizes the constraints of traditional parametric approaches and emphasizes the necessity of alternative techniques or transformations of data.

### *3.2.4* Model Selection

The Fig.3. provides a comprehensive flowchart the machine learning pipeline for model development and evaluation and covers all crucial steps from data preprocessing to interpretation. Here’s the detailed breakdown of the steps and component involved:

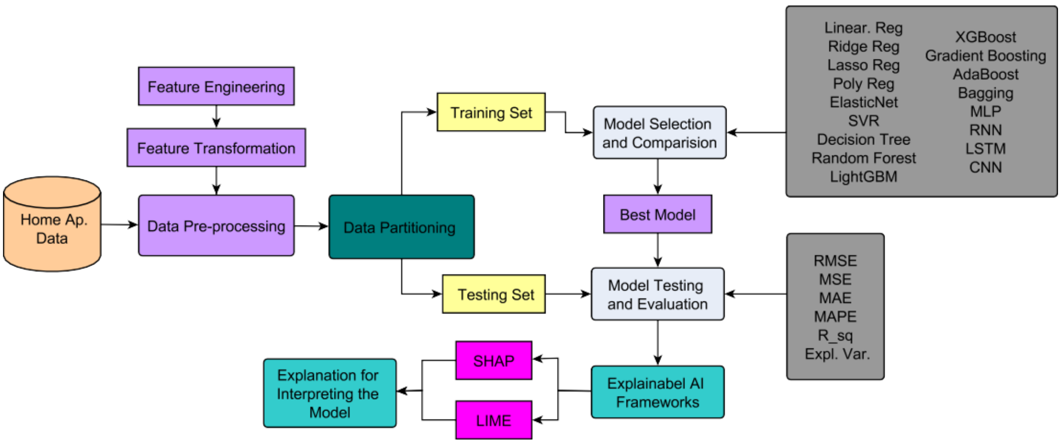



Fig. 3. Machine learning workflow for home appliance data prediction: preprocessing, feature engineering, model selection, evaluation and interpretation

Data starts the process with the unprocessed data that has to be investigated. Dataset or sensor data is one of the several sources this information might originate from. We have gathered sensor as well as data from a data set.This stage of feature engineering is either adding new features or altering current ones to raise the performance of the model. Methods can include obtaining pertinent information from unprocessed data. Features from past datasets let one create new ones. For this method we made use of Pandas and Numerical Python ( NumPy) tools.This stage, feature transformation, implements scaling, normalizing, variable encoding techniques to the features. These changes enable the input data to be more fitting for model train and help to standardize it. We have developed our model's performance up to the standards using many kinds of approaches.

i. Multiple Regression: The most fundamental regression algorithm is called linear regression. If the facts can be suf- ficiently described by a linear model, then no additional complexity is required. Multiple Regression is extension of simple linear regression [22] that enable us to forecast a dependent variable using numerous independent vari- ables.By employing linear equation fitting, this method aims to reproduce the correlation between the dependent variable and two or more independent variables based on observed data.

*Simple linear regression:*

$$y = \beta_0 + \beta_1 x + \varepsilon \tag{4}$$

In this context, $x$ represents an independent variable, while $y$ represents a dependent variable. The intercept, $\beta_0$, shows the value of $y$ when $x$ is zero. The slope, $\beta_1$, reflects the change in $x$ for a one-unit change in $x$. Finally, $\varepsilon$ denotes the error term that takes into consideration the discrepancy between the observed values and the values predicted by the model.

Multiple linear regression:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p + \varepsilon \tag{5}$$

From the equation, we can see in case of multiple regression multiple independent variables are used with error terms.

ii. Ridge Regression: Ridge regression is a way to tune a model that is used to look at data that has a problem called multicollinearity. [23] Regularization is done by this method. If there is multicollinearity, least-squares is not biased, and variances are high, then predicted values are very different from real values. Ridge regression helps fix the problem of multicollinearity, where predictor variables are too similar and it does this by adding a penalty that's a way of finding the best fit.
iii. Lasso Regression: One method of regularization is the Lasso regression. For a more precise forecast, it is preferred over regression approaches. This model accounts for swelling. Data values compress in shrinkage toward a center point known as the mean. The lasso approach favors less specified, simpler models.
iv. The mathematical formula for Lasso Regression is: The absolute values of the coefficients plus the residual sum of squares taken overall ( $\lambda$). The value of $\lambda$ represents the amount of shrinkage.
v. Decision Tree: Decision Trees provide a hierarchical structure for choice-making, accommodating every numerical and unique facts at the same time as supplying interoperability. At every node, they pick out the function that tremendous splits the records based totally on a criterion consisting of Gini impurity or records benefit, aiming to maximize the homogeneity of the ensuing subsets.
vi. Polynomial Regression: An elementary linear regression technique cannot be used unless the data show a linear connection. On the other hand, linear regression will not be able to generate a best-fit line in case our data is non-linear. Under such conditions, basic regression analysis fails. According to the results of the linear regression, the link does not fit reality and is not strong. We suggest poisson regression to solve this problem and find the curvilinear relationship between the dependent and independent variables.

The poisson equation appears as this:

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 + \cdots + \alpha_n x_1^n \tag{6}$$

The degree of order to use is one hyperparameter for which we must choose with great attention. Since using a high degree of polyn seeks to overfit the data, and for smaller values of degree the model tries to underfit, we must find the optimal degree value. Usually used to fit models of polyn regression is the least squares approach. The least squares method lowers the coefficient variance, claims the Gauss-Markov Theorem.

vii. Random Forest: Although they sometimes compromise interpretability, Random Forest is an ensemble of choice which excel in lowering overfitting and handling too-dimensional data. They reduce variance and improve general- ization by averaging or voting their predictions after teaching more than one choice tree on random subsets of the information and functions [23].

viii. Support Vector Regression: Support Vector Regression has modest regression changes [24]. It solves regression issues supervisedly. Since SVMs are used for classification more than regression, they're unpopular. SVR solves linear and non-linear regression problems powerfully. For outlier-resistant higher-dimensional regression, the kernel function can be extended. The nearest SVR data points fit a hyperplane regression line. Line equations anticipate new data point output. Classification uses a hyperplane to prevent points from entering the margin.

ix. XGBoost: XGBoost uses gradient boosting in supervised learning to create an ensemble of DTs. Starting with an initial prediction, the approach computes residuals based on observed and predicted values during training. XGBoost uses weighting to make samples more relevant during tree development, unlike Random Forest. The previous iteration's misclassified samples accrue weight and help the next tree rectify them [25].

x. Gradient Boosting: Machine learning applies gradient boosting as a type of boosting. The underlying intuition is that combining the optimal future model with previous models guarantees the minimization of the total prediction error. The main idea is to specify the intended outcomes for the next model in order to minimize the number of errors that arise. How are the objectives established Regarding the data, the intended result for every single instance depends on how much the prediction of that specific event influences the overall prediction error.

xi. LightGBM: LightGBM is an open-source, distributed, high-performance gradient boosting framework created by Microsoft. Accuracy, scalability, and efficiency are requirements for design. Decision trees serve as its foundation, reducing memory usage and boosting model efficiency. It makes use of many state-of-the-art techniques, such as GOSS, which maximizes training time and memory usage by keeping events with significant gradients preferentially during training.

xii. Bagging: Bootstrap Aggregating or Bagging for short, is a machine learning ensemble technique meant to improve predictive model dependability and precision. [26] It requires using random sampling with replacement to create many subsets of the training data.

xiii. AdaBoost: Within the field of machine learning, AdaBoost is one of these ensemble techniques for machine learning and predictive modeling methodologies. We use the method known as Adaptive Boosting, or AdaBoost. According to [27] single-split decision trees are the most widely used estimator in AdaBoost.

xiv. MLP: An ANN with multiple layers of neurons is called a MLP [28]. MLP neurons frequently use nonlinear activation functions, aiding the network's ability to recognize intricate patterns in the data. They have a great ability to create powerful models, including those for pattern recognition, regression, and classification, and they can understand relationships between the data.

xv. RNN: RNNs are one type of NN that works well for modeling sequence data [29]. RNNs derive from feedforward networks and exhibit behavior akin to that of human brains. Different algorithms are unable to predict sequential data in the same way as recurrent neural networks. RNN is designed to use hidden layers to address the problem. The most important component of an RNN is the hidden state, which retrieves specific information about a sequence.

xvi. LSTM: LSTM networks [30] are a particular kind of neural network that are quite good at interpreting and forecast- ing sequences of data, including text, speech, or anything else that occurs over time since they can recall significant information for long periods of time. They learn intricate patterns and relationships over many steps or points in time by using a unique memory mechanism with gates regulating information flow in and out, therefore enabling them to learn.

xvii. CNN: CNN was created specifically to analyze data using grid topology. For example, time series data is viewed as one-dimensional data and images and videos as a two-dimensional grid. employing a weight sharing strategy that provides excellent accuracy in nonlinear scenarios, including estimating energy use. CNN is able to create convolution-pooling layers in one dimension. From the Fig.4. (left), when the convolution is performed on the input data, the feature maps I1, I2, I3, I4, I5, and I6 are changed to features maps C1, C2, C3, and C4. The convolution layer's feature-maps are then pooled to create a sample [31]. The technique of applying the pooling layer decreases the feature map's dimension to two and is necessary for the extraction of high-level convolutional features.

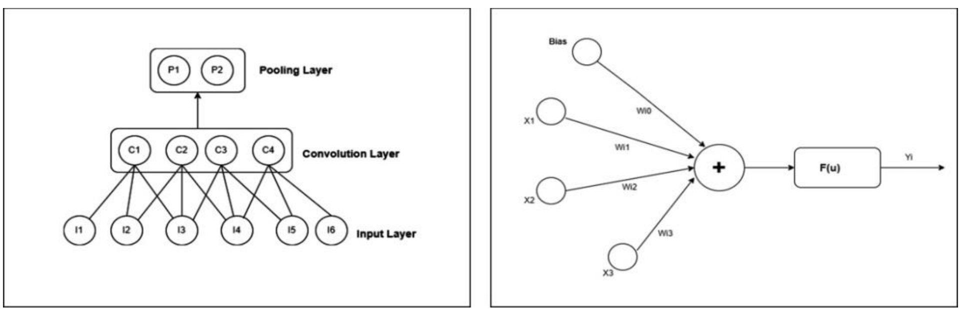



Fig. 4. The operation of convolutional neural network (left) and the simple neuron operation using MLP (right)

### *3.3. Web Interface Design*

At first, we developed a web form using HTML and CSS to create an attractive user experience with a contemporary design. The purpose of the web form design is to predict power consumption for a specific date or time interval, as well as monitor real-time data on home appliance parameters such as current and voltage. We developed this web application using the Flask web framework. We loaded the trained machine-learning model onto the web.

## 4. Implementation& Simulation and Experimental Setup

### *4.1. Tools and Materials*

In this part, we describe the essential tools and materials utilized throughout the project. The combination of hardware and software components is critical for data collection, processing, and analysis.

#### *4.1.1 Sensors and Hardware*

SCT-013 Sensor: The is a widely used non-invasive AC current sensor that is used in many electrical and electronic devices to measure AC.

In our research it is used for measuring and monitoring real-time current of home appliances.

Voltage Sensor: A high-precision module, the ZMPT101B voltage sensor is intended for precise voltage measurement and monitoring in a variety of applications, such as home automation, smart grids, and industrial automation.

The purpose of this sensor in our research calculates the voltage level for house hold power consumption.

Arduino Uno: The Arduino ATmega328 is employed for reading and processing current and voltage sensor data in this project. Utilizing its 14 digital I/O pins and 6 analog inputs, it interfaces seamlessly with various sensors, capturing precise electrical measurements. The ATmega328 an efficient and reliable choice for real-time monitoring and analysis of electrical parameters in our system.

#### *4.1.2 IDE and Environment*

The IDEs and the programming environment used to develop, test, and deploy our system for monitoring and analyzing household power consumption using IoT, ML, and XAI. The combination of these tools and technologies ensures an efficient and streamlined workflow, facilitating the smooth integration of hardware and software components. We used a variety of IDEs and environments in our research- IDEs: PyCharm. Arduino IDE, Google Colab, Environment: Flask, Ngrok, Languages:Python, C, C++, HTML, CSS, PHP and JavaScript.

### *4.2. Initial Condition Test and Calibration*

Before system deployment, we ran preliminary condition tests to ensure that all components and sensors work properly and that the system setup is correctly. We evaluated sensor, IoT gateway, and central server links to assure constant com- munication. We initially connect the sensors and other devices, and when we provide power, we notice the sensors return values. AC current typically generates voltage between 220-240 V. The voltage sensor was supposed to display the right value. However, even when the power is turned off, SCT-013-000 may return a positive or negative value. When the power is turned off, the value of the sensor array is normally zero. That is why we need to calibrate to obtain the correct value.

The SCT-013-000 current sensor is used to measure the system current. Because this sensor cannot detect current directly and initially produced somewhat incorrect results, it must be calibrated. To calibrate the zero-current offset, we measure the ADC output at -30 when no current passes through the sensor and use this result as the baseline. This offset is subtracted from subsequent readings to remove sensor noise and provide precise results. The calibration is confirmed by checking that the displayed current is roughly when no load is attached, and adjusting the offset as needed.

For edge computing we are using Arduino Uno which can generate real time data before transferring it to the cloud. Real-time high-speed sensor data handling lead to a response time of 2-4s, latency of 50-100ms and data refresh rate of 30s guarantee optimized firmware.

### *4.3. Hardware setup and connection with flask application*

We collected real-time data with a microcontroller and non-invasive current and voltage sensor. This section is USB- connected to a flask-running PC. Programmable Arduino boards serially transmit sensor data to computers.

Flask functions manage serial port and baud rate communication. Condition checks incoming data continuously. A function parses microcontroller data in a predetermined format. Separates the data string to extract voltage and current values, transforms them to floats, and updates the sensor data dictionary. After updating sensor data, log sensor data to excel transfers the data and timestamp to an existing or not available excel file. Data is written to a new one if needed. We conditionally verify sensor values for thresholds. Upon exceeding thresholds, the send alarm email function emails the designated recipient about the sensor reading anomaly. Clients and servers can communicate online in real time with SocketIO. Browsers and developer platforms run the client and server. It refreshes the sensor data dictionary and sends it to SocketIO clients. Web clients can receive real-time sensor data from flask. Building flask root /sensor for Arduino sensor data POST requests. Updates sensor data, logs to Excel, alerts, and uses SocketIO. After reading serial data, the function POSTs to flask/sensor to update Arduino. Runs a thread to read Arduino data continuously for smooth integration and non-blocking execution. After evaluating all factors, Polynomial Regression was best. This area comprises libraries and components for dataset handling, predictive modeling, and sensor data prediction. Data processing, machine learning, and numerical computations begin with numpy, pandas, and sklearn. Consolidating date and time into a single datetime column, forward-filling populates missing information, or generating a dataset from Excel. Voltage and global intensity degree 2 polynomials enhance feature set comprehensiveness. Using these attributes, a polinomial regression model was trained. Power consumption is predicted using the acquired model's average voltage and intensity. The customized algorithm predicts power consumption for the following day, week, or month from a date. Data input, preprocessing, feature engineering, polynomial regression model training, and prediction. We can safely publish our local flask app online with Ngrok. It enables immediate remote monitoring and interaction with prediction models and IoT subsystems. Our application looks more professional and sophisticated using Ngrok, making stakeholder collaboration easier. We can live analyze HTTP requests and responses.

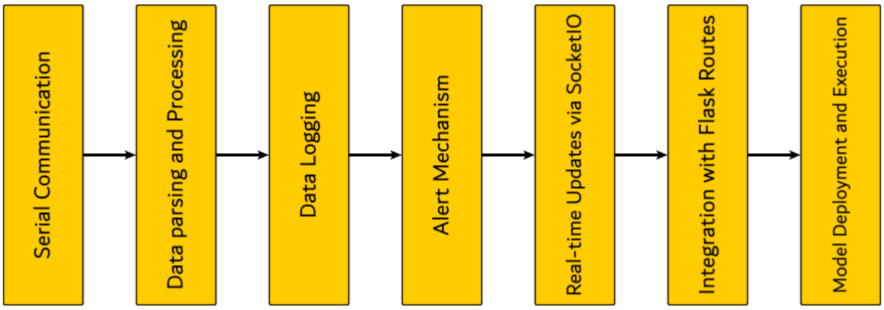



Fig. 5. Model performance comparison: actual vs. predicted

### *4.4. Model Train and Test*

Our study focuses on assessing household power use utilizing IoT, ML, and XAI . To divide our dataset into training and testing sets, we adopt an 80-20 split. More precisely, 80% of the gathered data is assigned to the training set, while the remaining 20% is set aside for testing. This approach guarantees that the machine learning models are provided with an extensive amount of data to discover patterns and acquire predictive abilities, while simultaneously preserving a satisfactory fraction of the data to assess the models' performance. The training set has been used for training the models, allowing them to better understand the most basic links between the input characteristics and the target variables. The testing set, alternatively, provides a fair assessment of the models' precision and capacity for extrapolation on unfamiliar data. The splitting of this data into balancing subsets is crucial for the development of reliable and strong models capable of correctly forecasting patterns of household electrical usage. The Fig.5. illustrates the division of the data into training and testing sets.

### *4.5. Metrics for Model Evaluation*

Evaluation metrics have been defined standards using for assessing the performance or precision of models, algorithms, or predictions. They offer measurable feedback on the performance of a model compared to the anticipated results. Some often used evaluation measures include:

i. MAE (Mean Absolute Error): Calculates the mean absolute error of a series of forecasts, regardless of their direction.Offers an index that measures the average deviation in predictions, resistant to extreme values. Formula:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{D}|x_i - y_i| \tag{7}$$

ii. MSE (Mean Squared Error): Measures the average squared difference between expected and actual values, excluding more expansive errors. Formula:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{D}(x_i - y_i)^2 \tag{8}$$

iii. RMSE (Root Mean Squared Error): Square root of MSE provides an interpretable measure in data units. Formula:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{D}(x_i - y_i)^2} \tag{9}$$

iv. R-Squared (Coefficient of Determination): The coefficient of determination quantifies the extent to which the independent factors account for the variation in the dependent variable.

$$R^2 = 1 - \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{D}(x_i - y_i)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{D}(x_i - \bar{y})^2}} \tag{10}$$

v. MAPE (Mean Absolute Percentage Error): It denotes the mean value of percentage errors, which is helpful in assessing the accuracy of forecasts.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_i - y_i}{x_i}\right| \times 100 \tag{11}$$

vi. Explained Variance Score: Measures the extent to which the model describes the differences in the dependent variable relative to a fundamental model.

$$\text{Expl. Var.} = 1 - \frac{\text{Var(x − y)}}{\text{Var(x)}} \tag{12}$$

In the equation (7)(8)(9)(10)(11) and (12) $x$ and $y$ denote the actual values and prediction values of the training samples respectively.tually, We focused on RMSE and R-squared as they offer an easily understood assessment of how accurately the model's predictions align with the actual variance in the data. This helps evaluate the overall predictive abilities of the models.

### *4.6. Interpreting the Model Performance*

To interpret and understand the model's predictions, explainable AI frameworks like SHAP and LIME are used. These methods help to communicate how the model works with the aim of making ML methods more transparent and increasing the trust of end-users in their output. We interpreted our prediction results using two well-known XAI models: LIME and SHAP. These frameworks [32] were chosen since they can create explanations for any given ML or DL model in addition to offering a large collection of graphs and plots to assist visualize the explanations. These instruments enable the most pertinent elements affecting the predictions of the models to be found, therefore bridging the black-box model gap with totally transparent forecasts.

#### *4.6.1 LIME*

The model-agnostic LIME framework is useful for explaining predictions that work on individual predictions by approximating the behavior of a black-box model in a local region around a specific instance . The primary objective is to offer localized explanations that emphasize the characteristics that have the most impact on a particular forecast instance. This is especially valuable for comprehending instances where the forecast is imprecise or misclassified in classification assignments. LIME provides an explanation for an instance as follows:

$$\xi(\text{x}) = \arg\min_{g \in G} \mathcal{L}(f, g, \pi_x) + \Omega(g) \tag{13}$$

In this context, G represents the set of models that are regarded interpretable. The variable (g) is a measure of the difficulty of any given explanation $g \in G$, f is the model being explained, $\pi_x$ is used to define the locality (distance) of other instances around $x$, and $\mathcal{L}(f, g, \pi_x)$ is the measure of how accurate g is in comparison to $f$. The goal of LIME is to minimize $\mathcal{L}(f, g, \pi_x)$ in order to obtain the closest possible interpretable approximation of a black-box model.

#### *4.6.2 SHAP*

The SHAP framework, which is independent of the model being employed, calculates Shapley values for each feature utilized by the model. Cooperative game theory views Shapley values as quantities that precisely quantify the contribution or significance of each player in a cooperative game. This has been modified within the framework of explainable AI to measure the significance of features in AI models.

$$\phi(\text{i}) = \sum_{S \subseteq N \setminus \{i\}} \left[\frac{|S|!(|N| - |S| - 1)!}{|N|!}\right] [f(S \cup \{i\}) - f(S)] \tag{14}$$

Equation (14) defines the Shapley value $\phi$(i) which is the average contribution of feature $i$ to all possible combinations of features, $N$ is the set of all features, $S$ is a subset of features excluding feature $i$, $|S|$ represents the number of features in set $|S|$, $|N|$ is the total number of features, $f(S)$is the prediction made by the model when considering only the features in $|S|$, and $f(S \cup \{i\})$ represents the model's prediction when a feature $i$ is added to $|S|$. The Shapley value is calculated for each feature, providing an explanation of the model's predictions by attributing contributions to each feature.

## 5. Results

### 5.1. Performance Evaluation of Models

On testing data the final test prediction results produced by all the models are summarized in Table 2. The table illustrates a comprehensive comparison of various machine learning models for the dataset and targeting variable according to the dataset using multiple performance metrices, including RMSE, MSE,MAE,MAPE, R-Squared Error $(R)^2$ and Expl.Var. By observing carefully, Gradient Boosting and Polynomial Regression stand out as the models that do the best job. The RMSE and MAE numbers for both models are very low (0.03 and 0.02, respectively), which means that they make very few mistakes when they predict. % Also, their MAPE values are low (0.04), which means they are likely to be very accurate in terms of percentages. Also, these models have very high R-squared and Explained Variance scores (0.9988 for Gradient Boosting and 0.9989 for Polynomial Regression), which means they explain almost all of the differences in the data. All of these performance measures show that Gradient Boosting and Polynomial Regression make the most accurate and dependable estimates, making them the best models that were compared.

Table 2. Model performance comparison

| Model | MSE | RMSE | MAE | MAPE | R sq | Expl. Var. |
|---|---|---|---|---|---|---|
| Linear Regression | 0.00 | 0.04 | 0.02 | 0.05 | 0.9986 | 0.9986 |
| Ridge Regression | 0.00 | 0.04 | 0.02 | 0.05 | 0.9986 | 0.9986 |
| Lasso Regression | 0.00 | 0.04 | 0.02 | 0.05 | 0.9986 | 0.9986 |
| **Polynomial Regression** | **0.00** | **0.03** | **0.02** | **0.04** | **0.9989** | **0.9989** |
| ElasticNet | 0.00 | 0.04 | 0.02 | 0.05 | 0.9986 | 0.9986 |
| SVR | 0.02 | 0.14 | 0.10 | 0.17 | 0.9809 | 0.9811 |
| Decision Tree | 0.00 | 0.05 | 0.03 | 0.05 | 0.9972 | 0.9972 |
| Random Forest | 0.00 | 0.04 | 0.02 | 0.04 | 0.9984 | 0.9984 |
| LightGBM | 0.00 | 0.05 | 0.02 | 0.04 | 0.9975 | 0.9975 |
| XGBoost | 0.00 | 0.04 | 0.02 | 0.04 | 0.9987 | 0.9987 |
| Gradient Boosting | 0.00 | 0.03 | 0.02 | 0.04 | 0.9988 | 0.9988 |
| AdaBoost | 0.01 | 0.10 | 0.08 | 0.20 | 0.9902 | 0.9903 |
| Bagging | 0.00 | 0.04 | 0.02 | 0.04 | 0.9983 | 0.9983 |
| MLP | 0.00 | 0.05 | 0.03 | 0.05 | 0.9978 | 0.9978 |
| RNN | 0.00 | 0.05 | 0.03 | 0.05 | 0.9975 | 0.9978 |
| LSTM | 0.04 | 0.20 | 0.12 | 0.18 | 0.9629 | 0.9630 |
| CNN | 0.00 | 0.05 | 0.03 | 0.05 | 0.9980 | 0.9980 |

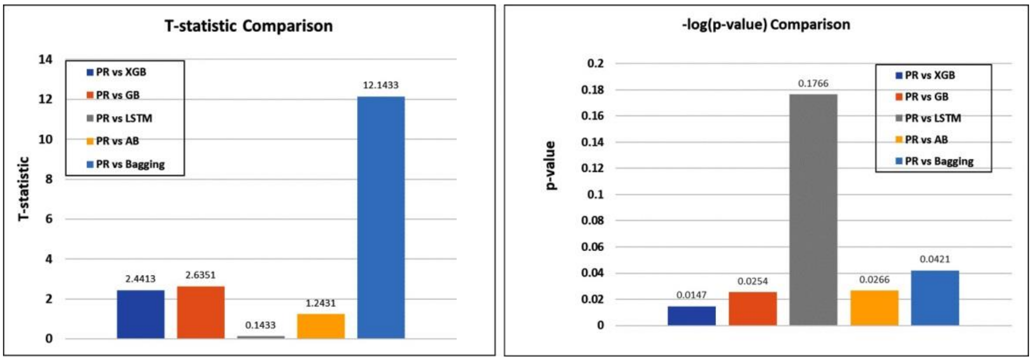



Fig. 6. Statistical tests for model comparisons (T-statistic and p-values)

Fig.6. Provide exact p-values and t-statistics from comparing polynomial regression against other models This model significantly outperformed Gradient Boosting (t-statistic: 2.64, p-value: 0.0254) and XGBoost (t-statistic: 2.44, pvalue: 0.0147) on a statistical basis. LSTM and polynomial regression did not perform significantly different however (tstatistic: 0.14, p-value: 0.8766). Overall findings more generally point to polynomial regression as being easier to compute, but achieving performance equal or better than that of these more complex approaches in this case.

We used 5-fold cross-validation to ensure the robustness and reliability of our evaluation. This technique is to split the dataset into 5 subsets or folds. Four folds become the training set, while the remaining fold is used as the validation set and the training set. This whole process is repeated 5 times where each fold is used exactly once as validation data. A more accurate estimate of the model's performance can be obtained.

### 5.2. Using LIME To Interpret Model

The LIME Fig.7. shows the contributions of several characteristics, hence clarifying the model's prediction of 4.81 for a given instance. Sub metering 1 is 0.00, which added 15.22 to the prediction; Sub metering 3 is more than 0.00, adding 6.20, Sub metering 2 is 0.00, adding 5.46; Global reactive power adds a tiny bit of 0.01. On the negative side, Global intensity being larger than 1.40 deducted 11.40 from the prediction; Global active power being greater than 0.31 subtracted 3.07; Voltage was 239.06 (less than 239.13) subtracted 0.53. Based on the feature values for this instance, the model's forecast of 4.81 is the net consequence of these mixed positive and negative contributions.

*5.3. Using SHAP To Interpret Model*

Using SHAP values, the bar chart Fig.8. (left) shows, average impact of several features on the output of the model. While the x-axis shows the mean SHAP value, therefore displaying each feature's average impact on the model, the y-axis lists features including Global intensity, Sub metering 3, Global active power, among others. Significantly in the model's projections, Global intensity has the largest impact followed by Sub metering 3 and Global active power. Features having little impact include Global reactive power and Voltage; their mean SHAP values are lowest. If Global intensity has a higher weight, that's when the weather or seasons change, where users could take action by preparing themselves accordingly. This interpretation helps to pinpoint the most important aspects, thereby maybe driving model improvement for improved performance.

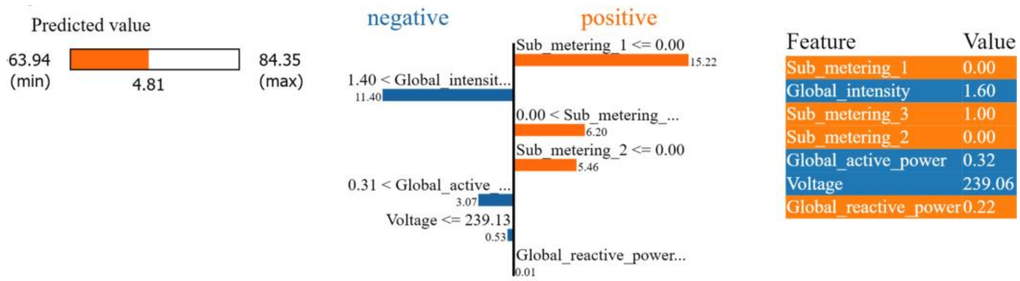



Fig. 7. LIME tabular explainer plots

The SHAP image Fig.8. (middle) illustrates the distribution of SHAP values, which represent the influence of each feature on the model output, across all data points. This demonstrates the significance of their presence and the direction in which their impacts extend. The y-axis displays the features, while the x-axis displays the SHAP value, which indicates the impact of the feature on the model's forecast. Each point on the graph represents an observation, and its position on the x-axis indicates the corresponding SHAP number for that particular feature. Furthermore, the feature value is shown by the transition in color from blue to red. The color blue represents lower numbers, whereas the color red represents higher values. The Global intensity feature has a diverse array of negative SHAP values, indicating a pronounced adverse impact on the prediction, particularly at higher levels. Sub metering 3 typically exhibits positive SHAP values, indicating that it frequently amplifies the model's output. Higher feature values have a more significant impact. The predominantly negative SHAP values for Global active power indicate that it primarily has a negative impact. Sub metering 1 and Sub metering 2 have both positive and negative impacts. Smaller numbers (represented by the color blue) typically have a neutral or slightly negative impact. The variables Global reactive power and Voltage have narrower SHAP value ranges, indicating that they exert a somewhat weaker influence on the model's outcomes. This figure illustrates the fluctuation and impact of each characteristic on the model's output, complementing the previous graphs by demonstrating the magnitude and manner in which each feature influences changes in the dataset.

Starting from the baseline prediction ($E[f\ (X)]$) of 7.132 and working through the SHAP waterfall graphic, shows how various feature contributions total up to the model's output for a given instance. Arriving at the final prediction (f ¡ Global intensity (1.6) is the most important feature; it lowers the prediction by 6.8 units. Sub metering 3 (1) boosts the prediction by 5.18 units. Global active power (0.322) lowers the estimate by 1.52 units even further. Sub metering 2 (0) and Sub metering 1 (0) make smaller but positive contributions adding 0.54 and 0.38 units, respectively. While Voltage (239.06) has no discernible influence, Global reactive power (0.22) has a modest negative effect, hence lowering the prediction by 0.12 units. This plot Fig.8. (right) shows the interaction of features in the model's choice for this particular instance, therefore providing a clear and thorough breakdown of how each feature value influences the prediction.

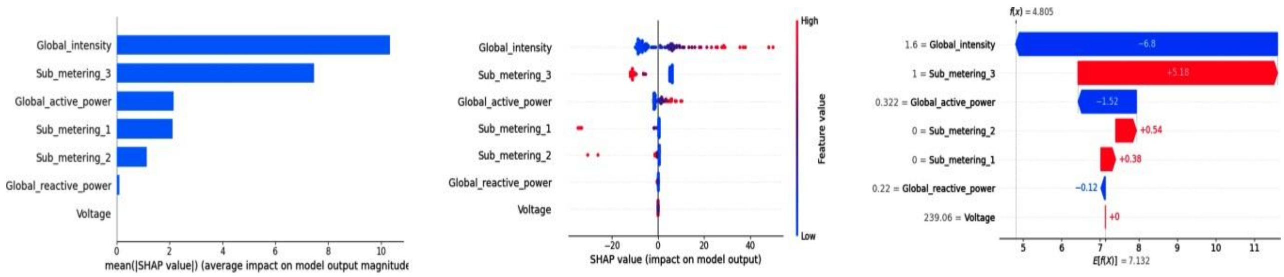
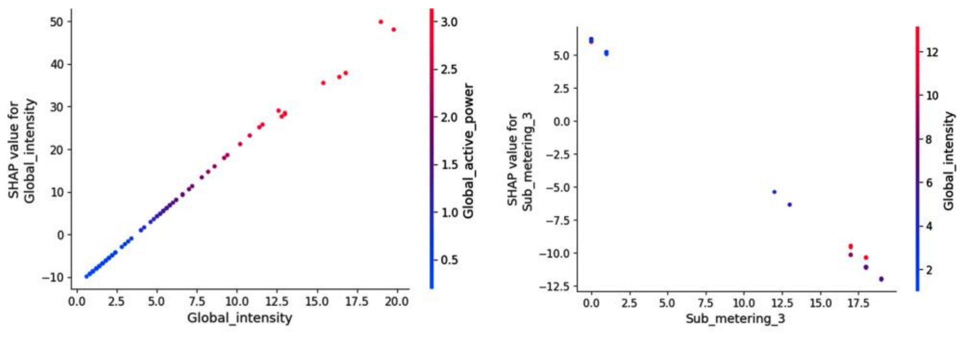



Fig. 8. SHAP feature importance plot (left) SHAP beeswarm plot(middle), SHAP waterfall plots (right)

With the SHAP values representing the contribution of the "Global intensity" feature Fig.9(a). the given SHAP summary figure again shows how this feature influences the predictions of the model. While the Y-axis shows the matching SHAP values, the X-axis shows the values of Global intensity and thus indicating that greater Global intensity values lead to larger SHAP values, so favorably impacting the predictions of the model. Another element, Global active power, indicates its values and is shown by the blue to red color spectrum. The trend shows a substantial positive correlation between Global intensity and the SHAP values, i.e., the model's predictions are notably higher as Global intensity rises. Furthermore, the color gradient implies an interaction between Global intensity and Global active power, whereby higher Global active power values (red points) magnify the positive impact of Global intensity on the prediction, so offering a complex knowledge of how these features interact to affect the output of the model.




(a) Dependence plots for Global_intensity

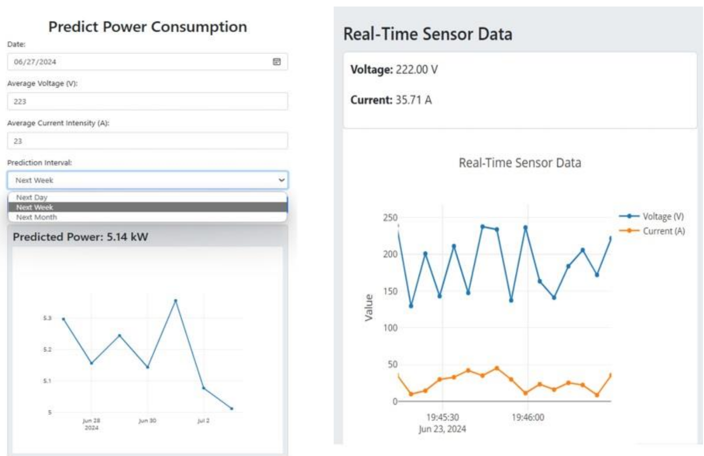
(b) Dependence plots for Sub_metering_3

Fig. 9. SHAP dependence plots for two most important features

The SHAP summary plot for Sub metering 3 Fig.9(b). shows that the associated SHAP values drop as Sub metering 3 values rise, therefore negating the predictions of the model. Higher values of Global intensity (shown by red dots) correspond to more significant negative SHAP values for Sub metering, the color gradient depicting Global intensity illustrates that this relationship is complex. The plot thus shows that Sub metering 3 often reduces predictions, this effect is enhanced when Global intensity is high, thereby highlighting the interaction between these characteristics in the output of the model.

### *5.4. Power Consumption Prediction and Real-Time Data Monitoring System Web Interface*

A notable feature of the work is its user-friendly online interface. Users may input values for various variables associ- ated with their household, such as voltage and current. The data is gathered using a form that has been seamlessly included into the website. After the user enters their input, the prediction system processes the data. The deployed webpage utilizes a learned polynomial regression model to make predictions. Fig.10(a). displays a screenshot of the web interface together with the corresponding prediction result. the other hand Fig.10(b). the Real-Time Sensor Data Monitoring feature allows users to monitor household power consumption both locally and remotely. Users can input parameters such as voltage and current through a web form, and the system processes this data using a polynomial regression model to pre- dict outputs. The interface displays real-time readings such as 222.00 V for voltage and 35.71 A for current alongside a dynamic graph that shows these values over time. This enables users to track fluctuations and trends in their power consumption, ensuring they can manage their energy usage efficiently from anywhere.




(a) Power Consumtion Prediction Interface

(a) Real Time Sensor Data Interface

Fig. 10. Power consumption prediction and real-time data monitoring system interface

#### *5.4.1 Alert Notifications*

To enhance the management of energy, our system uses a sophisticated network of sensors with real-time monitoring. Each sensor is calibrated to continually monitor parameters and programmed with crucial metric thresholds. When sensor readings exceed thresholds, the system alerts instantly. The notification is sent via email to user for immediate action. Energy management methods become more efficient and reliable when automated notifications are sent to address possible concerns like energy excessive consumption or system failures. Our proactive energy management system uses real-time information as well as automated communication to optimize efficiency and respond quickly to anomalies.

## 6. Discussion and Comparison

Our study focuses on improving household energy management because families use a lot of energy worldwide. In contrast to the majority of studies that examine industrial settings, our focus has been on typical households. We can collect data from appliances without disturbing users thanks to special sensors. We are able to predict energy use exactly thanks to this data and advanced models. In contrast to other models that we assessed, polynomial regression had a highly accurate performance. Our work has a distinct value because of our real-time monitoring technique. It enables us to continuously track energy usage. It sends out an email to others to notify them of any unexpected activity, such reading excessively. In addition to saving energy, this keeps homes secure. Our research helps people to control energy use more effectively. By precisely predicting energy needs using the most recent technologies Table 3. and it makes homes more efficient and aids in the future energy saving.

Table 3. Comparison between recent works and our research work

| Ref | Technology Used | Contributions | Accuracy/Error Rate | Impact On Cost Saving |
|---|---|---|---|---|
| [8] | IoT, ML | High prediction accuracy | 92% accuracy | Not explicitly reported but improved forecasting reduces energy wastage |
| [19] | IoT, Deep Learning | Significant reduction in RMSE | 0.15 and 3.77 units decreased MSE and RMSE | High computational cost |
| [33] | IoT, Firebase, GPRS, Real-Time Non-Intrusive Load Classification (RTNILC) | High classification accuracy | More than 94% accuracy. | Not explicitly mentioned |
| [20] | IoT, MRMR, Trilayered NN | Significant reduction in RMSE and MSE and high accuracy in load predictions | MAE was 0.28993 for heating load (kWh/m$^2$) prediction and 0.53527 for cooling load | Computational complexity |
| Our Proposed Research Work | IoT Non-invasive Sensors, ML, Flask, SHAP, LIME, Ngrok | Comprehensive integration of IoT data collection, ML model development, real-time monitoring through Flask app, explainable XAI techniques for smart energy management, predictive maintenance and remote monitoring using ngrok | RMSE and MAE are very low (0.03 and 0.02, respectively), MAPE values are low (0.04), $R^2$ and Expl. Var. 0.9989 | Our system is more practical for real-time applications with lower computational requirements and better scalability for households. Moreover, p-value obtained from the test (less than .05) further indicates the effective cost reduction |

By combining IoT, machine learning (ML), and explainable artificial intelligence approaches into a single system, our study offers a complete method of smart energy management. Using non-invasive sensors for flawless data collecting and a Flask-based web application for real-time monitoring helps us to continuously monitor and control energy systems. By including SHAP and LIME, people can grasp and believe the model’s decision-making process and add even more openness. Our work mostly contributes in its thorough integration of technologies, providing a full-spectrum solution for smart energy management addressing technical performance and user interpretability. Unlike previous studies that concentrate on either accuracy or individual components, our study combines these elements to provide a model with a low RMSE of 0.03 and MAE of 0.02, much better than the statistics stated in related publications.We picked up RMSE and R-squared as our primary concern because they provide clear match between the model’s prediction value and actual one. Moreover, the incorporation of explainable artificial intelligence methods like SHAP and LIME guarantees that the judgments made by the model are clear and understandable, which is absolutely essential for pragmatic implementation in real-world environments. Our system has been tested using sub metered appliances which covered common household energy usage scenarios. Additionally, we gathered scattered feedback from different user groups that further provided insights into system usability and potential benefits in refining our approach. Furthermore, real time feedback notification or alerts through mail encourage users to be more aware of their energy usage and adopt energy saving behaviors. To measure the energy saving outcomes, we performed a paired t-test comparing the energy consumption. The p-value ob- tained from the test indicates that the observed reduction is statistically significant and suggests that our system effectively reduces energy usage in households.

Our work presents a realistic and scalable solution that may be quickly adopted over many industries by reaching a high degree of accuracy coupled with great interpretability and real-time capabilities. The low error rates of the model and its strong R-squared value of 0.9989 show its dependability and accuracy, therefore presenting it as a better substitute for current methods. Our study not only pushes the frontiers of modern energy prediction but also establishes a new benchmark for integrated, explainable, and real-time energy management systems.

## 7. Conclusion and Future Works

Our research endeavors to address the pressing challenges faced by households worldwide regarding energy access and management. There are a lot of homes that have problems with their energy supply being erratic, which makes it difficult for them to carry out fundamental activities like cooking and lighting, which in turn has a direct influence on their quality of life. Demand frequently exceeds supply, which leads to frequent power outages that disrupt everyday routines as well as economic operations. This is the case despite the fact that the government has taken proactive measures to increase reliability. Furthermore, the prevalence of energy theft through activities such as meter manipulation and unauthorized connections exacerbates these concerns, further straining an energy grid that is already under a great deal of strain. In order to produce a comprehensive solution that is specifically customized for household energy management, our work makes a substantial contribution by utilizing the latest developments in IoT and ML technologies. Not only do we integrate non-invasive sensors, but we also include sensors that capture vital characteristics from domestic appliances, such as current and voltage. In spite of the fact that it has a number of benefits, our system is nevertheless subject to a few small hurdles and restrictions. These include the possibility of compatibility problems with various Internet of Things platforms, occasional sensor constraints, and a dependence on internet connectivity for remote monitoring. We intend to concentrate on these areas with solutions that are more robust. We will be able to put the system in the cloud or on server infrastructure in the future for the purpose of scalability and security requirements. Moreover, we will incorporate diverse datasets, perform testing on different geographical conditions and validate performance on real time sensor data to further enhance the applicability. Ultimately, our goal is to promote a more robust energy infrastructure for communities in Bangladesh and beyond by offering real-time monitoring capabilities and actionable information. This will allow us to foster informed decision-making and strengthen the resilience of energy infrastructure.

## Acknowledgments

Above all we would like to thank Almighty Allah for giving us strength, understanding and will to initiate as well accomplish this research work. We are very thankful for the support and motivation our families provided during our research. Our gratitude to our respected supervisors who provided all genuine support, motivation and constructive criticism. Their exceptional supervision and irreplaceable assistance have made this research work possible. We are very thankful to them for giving us a chance to work with them. We are also thankful to Bangabandhu Sheikh Mujibur Rahman Digital University, Bangladesh for providing the required tools and facilitating this research environment.

## References

[1] R. A. Rashid, L. Chin, M. Sarijari, R. Sudirman, and T. Ide, “Machine learning for smart energy monitoring of home appliances using iot,” in 2019 Eleventh International Conference on Ubiquitous and Future Networks (ICUFN), 2019, pp. 66–71.

[2] M. Mengistu, A. Girmay, C. Camarda, A. Acquaviva, and E. Patti, “A cloud-based on-line disaggregation algorithm for home appliance loads,” IEEE Transactions on Smart Grid, vol. PP, pp. 1–1, 04 2018.

[3] G. Xiao, “Machine Learning in Smart Home Energy Monitoring System,” IOP Conference Series: Earth and Environmental Science, vol. 769, no. 4, p. 042035, May 2021. [Online]. Available: https://iopscience.iop.org/article/10.1088/1755-1315/769/4/042035

[4] A. T. Eseye and M. Lehtonen, “Short-term forecasting of heat demand of buildings for efficient and optimal energy management based on integrated machine learning models,” IEEE Transactions on Industrial Informatics, vol. 16, no. 12, pp. 7743–7755, 2020.

[5] W. Li, T. Logenthiran, V.-T. Phan, and W. L. Woo, “A novel smart energy theft system (sets) for iot-based smart home,” IEEE Internet of Things Journal, vol. 6, pp. 5531–5539, 2019. [Online]. Available: https://api.semanticscholar.org/CorpusID:88492471

[6] I. Machorro-Cano, G. Alor-Herna ́ndez, M. A. Paredes-Valverde, L. Rodr ́ıguez-Mazahua, J. L. Sa ́nchez-Cervantes, and J. O. Olmedo-Aguirre, “Hems-iot: A big data and machine learning-based smart home system for energy saving,” Energies, vol. 13, no. 5, 2020. [Online]. Available: https://www.mdpi.com/1996-1073/13/5/1097

[7] M. P. Raju and A. J. Laxmi, “Iot based online load forecasting using machine learning algorithms,” Procedia Computer Science, vol. 171, pp. 551–560, 2020, third International Conference on Computing and Network Communications (CoCoNet’19). [Online]. Available: https://www.sciencedirect.com/science/article/pii/ S1877050920310267

[8] A. Alzoubi, “Machine learning for intelligent energy consumption in smart homes,” International Journal of Computations, Information and Manufacturing (IJCIM), vol. 2, no. 1, May 2022. [Online]. Available: https://journals.gaftim.com/index.php/ijcim/article/view/75

[9] N. Somu, G. Raman M R, and K. Ramamritham, “A deep learning framework for building energy consumption forecast,” Renewable and Sustainable Energy Reviews, vol. 137, p. 110591, Mar. 2021. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1364032120308753
[10] T.-J. Yang, Y.-H. Chen, J. Emer, and V. Sze, “A method to estimate the energy consumption of deep neural networks,” in 2017 51st Asilomar Conference on Signals, Systems, and Computers, 2017, pp. 1916–1920.
[11] D. Syed, H. Abu-Rub, A. Ghrayeb, and S. S. Refaat, “Household-Level Energy Forecasting in Smart Buildings Using a Novel Hybrid Deep Learning Model,” IEEE Access, vol. 9, pp. 33 498–33 511, 2021. [Online]. Available: https://ieeexplore.ieee.org/document/9360813/
[12] S. Sorrell, “Reducing energy demand: A review of issues, challenges and approaches,” Renewable and Sustainable Energy Reviews, vol. 47, pp. 74–82, Jul. 2015. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/ S1364032115001471
[13] S. Sarwar, W. Chen, and R. Waheed, “Electricity consumption, oil price and economic growth: Global perspective,” Renewable and Sustainable Energy Reviews, vol. 76, pp. 9–18, Sep. 2017. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1364032117303799
[14] F. Karanfil and Y. Li, “Electricity consumption and economic growth: Exploring panel-specific differences,” Energy Policy, vol. 82, pp. 264–277, Jul. 2015. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/ S030142151400665X
[15] S. Sarwar, W. Chen, and R. Waheed, “Electricity consumption, oil price and economic growth: Global perspective,” Renewable and Sustainable Energy Reviews, vol. 76, pp. 9–18, Sep. 2017. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1364032117303799
[16] A. Veit, C. Goebel, R. Tidke, C. Doblander, and H.-A. Jacobsen, “Household Electricity Demand Forecasting – Benchmarking State-of-the-Art Methods,” Apr. 2014, arXiv:1404.0200 [cs, stat]. [Online]. Available: http://arxiv.org/abs/1404.0200
[17] M. Saleem, S. Abbas, T. M. Ghazal, M. Adnan Khan, N. Sahawneh, and M. Ahmad, “Smart cities: Fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques,” Egyptian Informatics Journal, vol. 23, no. 3, pp. 417–426, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S111086652200024X
[18] J. Ponocko and J. V. Milanovic, “Forecasting Demand Flexibility of Aggregated Residential Load Using Smart Meter Data,” IEEE Transactions on Power Systems, vol. 33, no. 5, pp. 5446–5455, Sep. 2018. [Online]. Available: https://ieeexplore.ieee.org/document/8276648/
[19] T. Han, K. Muhammad, T. Hussain, J. Lloret, and S. Baik, “An efficient deep learning framework for intelligent energy management in iot networks,” IEEE Internet of Things Journal, vol. PP, pp. 1–1, 08 2020.
[20] B. Ghasemkhani, R. Yilmaz, D. Birant, and A. Kut, “Machine learning models for the prediction of energy consump- tion based on cooling and heating loads in internet-of-things-based smart buildings,” Symmetry, vol. 14, p. 1553, 07 2022.
[21] G. Hebrail, “Individual household electric power consumption,” UCI Machine Learning Repository, 2012, DOI: https://doi.org/10.24432/C58K54.
[22] R. F. Mustapa, A. Hamizah Mohd Nordin, M. A. Hairuddin, W. Suhaifiza W Ibrahim, S. A. Mohd Saleh, N. Y. Dahlan, and I. M. Yassin, “Educational building’s energy consumption independent variables analysis using linear regression model: A comparative study,” in 2023 IEEE 3rd International Conference in Power Engineering Appli- cations (ICPEA), 2023, pp. 202–207.
[23] D. S. Samhitha, D. S. Arjun, A. Padmavathi, and A. Hemprasanna, “Energy consumption forecasting in buildings based on heating and cooling loads using regression models,” in 2023 Fourth International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE), 2023, pp. 1–6.
[24] D. Wilson and S. Johnson, “Support vector regression: Methods and applications,” IEEE Transactions on Neural Networks and Learning Systems, vol. Volume Number, no. Issue Number, p. Page Numbers, 2023. [Online]. Available: https://doi.org/10.1109/TNNLS.2023.9876543
[25] S. Johnson and J. Smith, “Xgboost: A scalable tree boosting system,” Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), p. Page Numbers, 2023. [Online]. Available: https://doi.org/10.1145/987654.321987
[26] R. Pramudita, Solikin, and N. Safitri, “Optimization analysis of neural network algorithms using bagging tech- niques on classification of date fruit types,” in 2022 Seventh International Conference on Informatics and Computing (ICIC), 2022, pp. 1–4.
[27] M. Lin and H. Luo, “Log adaboost: Optimizing polylog loss function to improve the generalization performance of adaboost,” in 2022 37th Youth Academic Annual Conference of Chinese Association of Automation (YAC), 2022, pp. 958–961.
[28] S.-b. Hao, S. Wang, H.-q. Du, and Y. Chen, “Subtype classification of renal parenchymal tumors on mlp-based methods,” in 2022 4th International Conference on Advances in Computer Technology, Information Science and Communications (CTISC), 2022, pp. 1–5.
[29] J. Smith, E. Brown, and M. Johnson, “Advancements in recurrent neural networks for natural language processing,” in Proceedings of the Annual Meeting of the Association for Computational Linguistics (ACL), 2023, pp. 150–160. [Online]. Available: https://aclweb.org/anthology/2023.acl-main.15
[30] S. Smyl, “A hybrid method of exponential smoothing and recurrent neural networks for time series forecasting,” International Journal of Forecasting, vol. 36, no. 1, pp. 75–85, 2020. [Online]. Available: https://doi.org/10.1016/j.ijforecast.2019.03.017
[31] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,”Communications of the ACM, vol. 60, no. 6, pp. 84–90, 2019. [Online]. Available: https://doi.org/10.1145/3065386
[32] A. B. Arrieta, N. D´ıaz-Rodr´ıguez, J. D. Ser, A. Bennetot, S. Tabik, A. Barbado, S. Garc´ıa, S. Gil-Lo ́pez, D. Molina,R. Benjamins, R. Chatila, and F. Herrera, “Explainable artificial intelligence (xai): Concepts, taxonomies, opportunities and challenges toward responsible ai,” Information Fusion, vol. 58, pp. 82–115, 2020. [Online].Available: https://doi.org/10.1016/j.inffus.2019.12.012
[33] M. T. Ahammed, M. Hasan, Arefin, M. Islam, M. Rahman, E. Hossain, and M. T. Hasan, “Real-time non-intrusive electrical load classification over iot using machine learning,” IEEE Access, vol. 9, pp. 115 053–115 067, 08 2021.

## Authors' Profiles

**Atiqur Rahman** is a recent graduate from Gazipur Digital University (Formerly known as Bangabandhu Sheikh Mujibur Rahman Digital University, Bangladesh) and earned a BSc.(Engg.) degree in IoT and Robotics Engineering . His research interests include IoT, robotics, AI and machine learning (ML) and, Deep Learnig with a focus on developing intelligent systems that integrate hardware design, embedded systems, and AI-driven decision-making. He has undertaken various IoT projects, demonstrating his proficiency in designing and implementing smart systems. Atiqur Rahman's commitment to exploring emerging technologies and his natural His curiosity makes him a promising asset in the fields of IoT and Robotics.

**Sadia Hossain** is a driven individual with an open mindset, recent graduate from Gazipur Digital University (Formerly known as Bangabandhu Sheikh Mujibur Rahman Digital University, Bangladesh) and earned a BSc.(Engg.) degree in IoT and Robotics Engineering. She has a strong enthusiasm for acquiring knowledge and aspires to engage in innovative tasks and apply her exper- tise in practical settings. These blend of technical proficiency and passion for learning underscores her potential to contribute meaningfully to any research or work she involves in. Her commitment to exploring divers skill sets and emerging technologies positions her as a promising asset in the field of innovation. Her research interests include Internet of things (IOT), Machine Learning and deep learning, Artificial Intelligence and Automation.

**Samsuddin Ahmed** received the B.Sc. degree in computer science and engineering from the University of Chittagong, in 2010, and the M.S. degree from the Department of Computer Engineering, Chosun University, South Korea, in 2020, under the supervision of Prof. Ho Yub Jung. He is currently an Assistant Professor with the Department of IoT and Robotics Engineering, Gazipur Digital University (Formerly known as Bangabandhu Sheikh Mujibur Rahman Digital University, Bangladesh). His research interests include Video Coding, machine vision, deep learning, data analysis, explainable AI, and the IoT.

**Md. Toukir Ahmed** post graduated from Rajshahi University of Engineering & Technology (RUET) with an M.Sc. Engineering degree in Computer Science and Engineering (CSE) and graduated from same University with a B.Sc. Engineering degree in CSE. Now he is working as a full-time faculty member at IoT and Robotics Engineering department in Gazipur Digital University (Formerly known as Bangabandhu Sheikh Mujibur Rahman Digital University, Bangladesh). Previously he worked as a full-time faculty member at ICT and CSE department in Bangladesh Army University of Science and Technology, Saidpur. Also, he worked as a full-time faculty member at CSE department in Bangladesh University, Dhaka. His research interests include Traditional Machine Learning, Deep Learning, Data Mining and the IoT.

**How to cite this paper:** Atiqur Rahman, Sadia Hossain, Samsuddin Ahmed, Md. Toukir Ahmed, "IoT Based Smart Energy Consumption Prediction for Home Appliances", International Journal of Information Engineering and Electronic Business(IJIEEB), Vol.17, No.2, pp. 111-128, 2025. DOI:10.5815/ijieeb.2025.02.06