IOT POWERED POWER CONSUMPTION ANALYSIS BASED ON MACHINE LEARNING ALGORITHMS

Santhosh S
UG Student, ECE Department
Bannari Amman Institute of Technology, Sathyamangalam
Santhoshs.ec20@bitsathy.ac.in

Sveda N
UG Student, ECE Department
Bannari Amman Institute of Technology, Sathyamangalam
Sveda.ec20@bitsathy.ac.in

Vishnu A
UG Student, ECE Department
Bannari Amman Institute of Technology, Sathyamangalam
Vishnu.ec20@bitsathy.ac.in

Abstract— **The IoT-based power consumption analysis system utilizing the ESP32 microcontroller platform has transformed energy management through its connectivity and data exchange capabilities. This system is integral to efficient energy management and conservation. Notably, it incorporates machine learning algorithms, with Linear Regression at the forefront due to its superior accuracy compared to other models. Smart power meters linked to ESP32 microcontrollers gather real-time energy consumption data from various appliances and devices. The data is then transmitted to a centralized server for in-depth analysis. By employing advanced algorithms and machine learning, the system accurately identifies loads and recognizes consumption patterns. Through a user-friendly web interface, users gain valuable insights into their power consumption, including peak demand periods and optimization opportunities. Real-time notifications and alerts enable remote monitoring and control. Rigorous experiments in residential settings validate the system's effectiveness in precise load identification and consumption pattern analysis. The scalability, affordability, and ease of deployment of the ESP32-based system make it an invaluable tool for individuals, households, and organizations, ultimately contributing to a more sustainable and energy-efficient future**

I. INTRODUCTION

The rise of the Internet of Things (IoT) has heralded a new era characterized by smart, interconnected devices that have revolutionized our interactions with the world around us. In this evolving landscape, the pressing need for efficient energy usage and sustainability has become increasingly evident, casting energy consumption analysis and optimization into the spotlight[1]. To meet the growing demand for effective energy management, we propose a cutting-edge IoT-driven power consumption analysis system.[2] This innovative solution is powered by the versatile ESP32 microcontroller and further fortified with the precision of machine learning regression techniques, delivering unmatched accuracy and invaluable insights.[3] Traditional energy monitoring systems have often fallen short in delivering the level of detailed analysis and actionable insights required to address the intricacies of energy consumption effectively. In stark contrast, our system capitalizes on the potential of IoT technology and harnesses the power of machine learning regression models, ushering in a data-driven approach to power consumption analysis.[4] Our primary objective is to gather real-time energy consumption data from a multitude of appliances and devices, thereby offering users profound insights into their usage patterns and invaluable opportunities for optimization. To achieve this, we employ smart power meters that are seamlessly integrated with ESP32 microcontrollers, enabling precise energy monitoring down to the level of individual appliance[5].The data collected by our smart meters is then transmitted to a centralized server via Wi-Fi, a pivotal step in the process. This central server plays a critical role in processing and analyzing the collected data, employing advanced algorithms and machine learning regression models to enhance accuracy and extract meaningful insights. [6]These regression models are specially designed to capture the intricate relationships between input features (the energy data itself) and the output variables (comprising appliance identities and their respective consumption levels). This capability not only aids in the identification of appliances but also empowers the system to detect anomalies efficiently.[7] Users can swiftly pinpoint deviations from expected consumption patterns, receiving timely alerts about issues such as malfunctioning devices or energy leaks. Our system has undergone rigorous testing, with trials conducted in a residential setting to evaluate its performance and effectiveness.[8] It has emerged as a robust solution, excelling in terms of scalability, affordability, and ease of deployment. The ESP32 microcontroller, distinguished by its built-in Wi-Fi capabilities and cost-effectiveness, renders our system accessible for diverse applications and environments.[9] Its adaptability means that it can be seamlessly integrated into existing setups, facilitating the realization of IoT benefits without the need for significant infrastructure overhauls. In summary, our IoT-driven power consumption analysis system.[10] underpinned by ESP32 technology and fortified with the capabilities of machine learning, stands as a beacon of innovation in the realm of energy management. [11]By delivering real-time insights and a plethora of optimization opportunities, it has the potential to revolutionize energy consumption practices and contribute substantially to a more sustainable future. The fusion of IoT, machine learning, and ESP32 technology provides an effective response to the challenges of energy conservation[12]. paving the way for a more efficient and eco-friendly world. The fusion of IoT, machine learning, and ESP32 technology provides an effective response to the challenges of energy conservation, paving the way for a more efficient and eco-friendly world. Our system, grounded in this synergy, offers precise insights into energy usage patterns and a wealth of optimization opportunities[13]. This powerful combination has the potential to transform how we consume energy, promoting sustainability and cost-effectiveness in the process.[14] The adaptability and cost-effectiveness of the ESP32 microcontroller make our solution accessible for a wide range of applications and environments, ensuring that the benefits of IoT technology are within reach without the need for significant infrastructure overhauls[15]. In summary, our IoT-driven power consumption analysis system, underpinned by ESP32 technology and fortified with the capabilities of machine learning, stands as a beacon of innovation in the realm of energy management.

II. LITERATURE SURVEY

Title: "Using regression analysis to predict the future energy consumption of a supermarket in th UK" (Applied Energy, 2014)

This paper introduces an IoT-based energy monitoring system for homes, utilizing wireless smart meters to collect consumption data. Machine learning algorithms are applied for load identification and anomaly detection. The study underscores the IoT's efficacy in enabling real-time energy management, aligning with our proposed system's objectives.

Title: "Real-Time Data Analytics for Monitoring Electricity Consumption Using IoT Technology" (Tanzania journal of Engineering and Technology, 2022)

This research paper focuses on real-time power consumption monitoring for smart home energy management. IoT-enabled smart plugs collect energy data, and algorithms are developed for load identification and in-depth analysis. Real-time data analysis is highlighted for energy conservation. Our proposed system integrates real-time analysis to enhance load identification and energy consumption precision.

Title: "ESP32 Based Electric Energy Consumption Meter" (International Journal of Computer Communication and Informatics, 2022)

This paper presents an IoT-based framework for commercial building energy management. It proposes a distributed architecture involving smart meters, IoT gateways, and cloud analytics for real-time energy monitoring, load identification, and consumption optimization. The study provides valuable insights applicable to our proposed system for both residential and commercial purposes.

Title: "IOT Based Smart Energy Meter Using ESP32" (IEEE International Conference on Green Computing and Internet of Things, 2018)

This conference paper introduces an IoT-based home automation power consumption monitoring system that utilizes wireless smart plugs and ESP32 microcontrollers for real-time energy monitoring and analysis. It underscores the significance of integrating IoT devices with energy management systems for efficient power consumption analysis. Our proposed system, which employs the ESP32 microcontroller, expands these capabilities to encompass advanced load identification and energy optimization features.

Title: "Design of IoT Based Smart Energy Meter for Home Appliances" (Journal of Physics Conference Series, 2021)

This research paper emphasizes smart meter data analytics for power consumption pattern extraction and load monitoring, promoting a data-driven approach with clustering algorithms for pattern identification and load monitoring. Our system aligns with this methodology, employing similar techniques for load identification and pattern recognition, bolstered by machine learning regression models to predict power consumption, thereby advancing power consumption analysis.

III. HARDEWARE IMPLEMENTATION

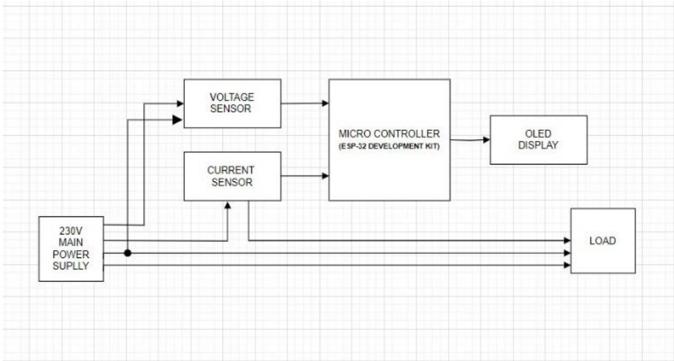

Fig. 1. Circuit diagram

The hardware implementation for the proposed IoT-based power consumption analysis system, featuring the integration of the ESP32 microcontroller with machine learning regression models, constitutes a foundational component of this innovative solution. This section delineates the intricate process of hardware setup and configuration, emphasizing the seamless synergy between the ESP32 microcontroller and the array of sensors and devices essential for accurate data acquisition and analysis. The ESP32 microcontroller, which was specifically chosen for its integrated Wi-Fi capabilities, computing capability, and affordability, is at the core of this project. The ESP32 serves as the primary node, managing all system functions. The integration of current sensors, which are properly calibrated to monitor electrical current flow across the circuits under study, is the first essential piece of hardware. These sensors enable the conversion of analogue current measurements into digital data points, setting the groundwork for further analysis, in conjunction with the ESP32's integrated analog-to-digital conversion capabilities. Additionally, the voltage sensors that serve as the conduit for measuring voltage levels across electrical circuits are smoothly included in the system. The use of both current and voltage measurements in this dual strategy is essential for precise power consumption analysis. To maintain a steady stream of data, the voltage and current values are sampled at regular intervals following the specified sampling interval. These sensors collect data, which is then rigorously pre-processed, including noise reduction, outlier identification, and data validation to ensure data integrity. The dataset is further analyzed through feature extraction, which extracts pertinent elements that will enhance the prediction potential of the machine learning regression model. The ESP32 microcontroller's ability to provide real-time data streaming through its built-in Wi-Fi capabilities serves as the primary foundation for this hardware solution. The microcontroller serves as the link, sending information to a central server or cloud platform where the machine learning regression model is stored. Because of this real-time data streaming, the model is constantly provided with the most recent information for continuing analysis and prediction. In summary, the hardware implementation of the IoT-based power consumption analysis system methodically connects the ESP32 microcontroller with current and voltage sensors, making the crucial process of data collecting and transmission. In the end, this hardware synergy provides users with actionable data for knowledgeable energy management and optimization. Accurate and real-time power consumption analysis is founded upon this hardware synergy.

IV. PROPOSED METHODOLOGY

The proposed methodology for IoT-based power consumption analysis using the ESP32 microcontroller, without utilizing smart energy meters, is as follows:

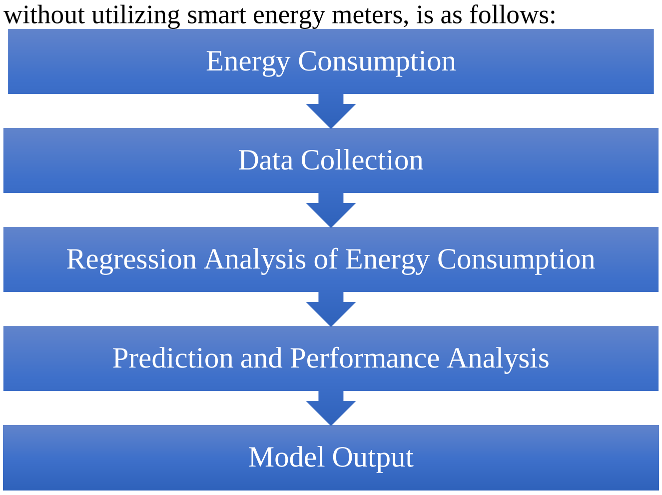

Fig. 2. Block diagram

A. Hardware Setup:

- ESP32 Microcontroller: Utilize the ESP32 microcontroller as the main hardware platform due to its built-in Wi-Fi capabilities and affordability.
- Current Sensors: Connect current sensors to the ESP32 microcontroller to measure the current flowing through the electrical circuits.
- Voltage Sensors: Connect voltage sensors to the ESP32 microcontroller to measure the voltage levels across the electrical circuits.

B. Data Acquisition:

- Sampling: Set up the ESP32 microcontroller to sample the current and voltage values at regular intervals.
- Analog-to-Digital Conversion: Convert the analog signals from the current and voltage sensors into digital values using the built-in ADC of the ESP32 microcontroller.
- Data Logging: Store the digital current and voltage values in the microcontroller's memory or an external storage device.

C. Energy Calculation:

The simplified power calculation algorithm for the IoT-based power consumption analysis system, considering both active and reactive energies, can be described as follows:

1. Initialization:
   - Set initial values for active power (P) and reactive power (Q) as zero.
   - Define the sampling interval (Δt) at which current and voltage readings are obtained.
2. Data Acquisition:
   - Sample the current (I) and voltage (V) values from the respective sensors at regular intervals (Δt).
3. Power Calculation:
   - Calculate the instantaneous active power (P_inst) and reactive power (Q_inst) using the sampled current and voltage values.
     - P_inst = V * I * cos(θ), where cos(θ) is the power factor.
     - Q_inst = V * I * sin(θ), where sin(θ) represents the reactive power.
4. Accumulation of Energy:
   - Update the accumulated active energy (E_active) and reactive energy (E_reactive) based on the instantaneous active and reactive power values.
     - E_active = E_active + (P_inst * Δt)
     - E_reactive = E_reactive + (Q_inst * Δt)

D. Real-time Monitoring and Analysis:

- Display or log the instantaneous active and reactive power values, as well as the accumulated active and reactive energy values, for real-time monitoring and analysis purposes.
- Repeat the above steps at regular intervals to continuously monitor and calculate the active and reactive powers, as well as the accumulated energies.

E. Data Analysis and Visualization:

- Data Processing: Process the collected power consumption data to analyze energy usage patterns, peak demand periods, and other relevant metrics.
- Visualization: Present the analyzed data through a user-friendly web-based interface, displaying graphs, charts, and relevant statistics to provide users with insights into their power consumption patterns.

F. Remote Monitoring and Control:

- Connectivity: Enable the ESP32 microcontroller to connect to a centralized server or cloud platform through Wi-Fi for remote monitoring and control.
- Real-time Notifications: Implement real-time notifications and alerts to inform users about abnormal energy consumption, peak demand periods, or other relevant events.
- Remote Control: Provide users with the ability to remotely control appliances or devices to optimize their energy usage.

V. MACHINE LEARNING ALGORITHMS FOR POWERCONSUMPTION ANALYSIS

A. Linear Regression:

In IoT-based power consumption analysis using ESP32 and Linear Regression, our goal is to predict appliance energy consumption patterns from historical data. Linear Regression, a supervised machine learning method, creates a linear equation linking input features (independent variables) to the target variable (dependent variable), which, in this context, includes energy-related parameters and actual energy usage. This equation can be represented as follows:

$$y = b + mx \qquad (1)$$

In this context, y stands for predicted energy consumption, b represents the y-intercept (bias) at x equals 0, and m is the weight (slope) denoting y's rate of change concerning x. In power consumption analysis, multiple input features x1, x2, ..., xn are linked with respective weights m1, m2, ..., mn in the linear equation. The primary goal of linear regression is to determine weight and bias values that minimize prediction errors. This is accomplished using a training dataset containing known energy consumption values and minimizing either Mean Squared Error (MSE) or Root Mean Squared Error (RMSE) to achieve the best-fit regression line representing the relationship between input features and energy consumption.

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (2)$$

In this equation:

- n denotes the number of data points within the training dataset.
- y_i stands for the actual energy consumption value for the i-th data point.
- $\hat{y}_i$ represents the predicted energy consumption value for the i-th data point.

To find the optimal weights and bias values, the algorithm utilizes optimization techniques like Gradient Descent or Closed-Form (Ordinary Least Squares), depending on dataset size and computational complexity. After training, the Linear Regression model can predict the energy consumption of new appliances based on their input features.

B. Logistic Regression:

Logistic Regression is a binary classification algorithm for IoT-based power consumption analysis using the ESP32. It predicts if an appliance consumes energy (1) or not (0) based on input features, mapping predictions between 0 and 1 using the sigmoid function.

$$S(x) = \frac{1}{(1 + e^{-x})} \qquad (3)$$

Where:

- z is the linear combination of input features and their respective weights.
- The linear combination z is calculated as: $z=b+m_1x_1+m_2x_2+\ldots+m_nx_n$
- b is the bias term.
- $m_1,m_2,\ldots,m_n$ are the weights associated with input features $x_1,x_2,\ldots,x_n$

For binary classification, we use a threshold, usually 0.5, to turn probabilities into class predictions. If the probability is equal to or greater than the threshold, it predicts energy consumption (1); otherwise, it predicts no consumption (0). Model training aims to find the best weight and bias values that maximize the likelihood based on observed data. This is done using methods like maximum likelihood estimation or gradient-based optimization algorithms. The loss function used is the Cross-Entropy Loss, also known as the Log Loss.

$$Log\ Loss = \frac{-1}{n}\sum_{i=1}^{n}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \qquad (4)$$

Where:

- n is the number of data points in the training dataset.
- y_i is the actual binary label (0 or 1) for the i-th data point.
- $\hat{y}i$ is the predicted probability value for the i-th data point.

Logistic Regression proves valuable in binary classification for ESP32-based IoT power consumption analysis. It predicts an appliance's energy consumption based on input features. By translating probabilities into binary labels, it categorizes appliances as energy-consuming or not, streamlining energy analysis and optimization.

C. Polynomial Regression:

In IoT power consumption analysis with ESP32, Polynomial Regression is a crucial tool. Unlike Linear Regression, which uses a straight line, Polynomial Regression incorporates polynomial terms, enabling it to model non-linear relationships between input features and energy consumption. The Polynomial Regression equation is expressed as

$$y = b + m_1x + m_2x^2 + \cdots + m_dx^d \qquad (5)$$

Polynomial Regression predicts energy consumption (y) based on input features (x) like time or load. It handles non-linear patterns by introducing coefficients (m_1, m_2, ..., m_d) for polynomial terms, controlled by d. Training needs a dataset with known energy values. The algorithm minimizes errors using methods like Ordinary Least Squares or Gradient Descent, with a cost function extending Linear Regression to include polynomial terms.

$$Cost\ Function = \frac{1}{2n}\sum_{i=1}^{n}(h_0(x_i) - y_i)^2 \qquad (6)$$

In Polynomial Regression, n is the number of data points, h0(xi) predicts energy consumption, and =yi is actual consumption. Picking the right degree (d) is crucial; too low misses patterns, too high overfits. Cross-validation finds the balance. In IoT power analysis, Polynomial Regression enhances accuracy by capturing non-linear patterns, aiding energy analysis and optimization.

D. Decision Tree Regression:

Decision Tree Regression uses a binary tree where internal nodes make decisions based on input features, and leaf nodes hold predicted energy consumption values. To predict, input values traverse the tree until a leaf is reached, providing the energy consumption prediction. The Decision Tree Regression equation for energy consumption prediction is defined as:

$$\hat{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \qquad (7)$$

Where:

- $\hat{y}$ is the predicted energy consumption for a new input.
- n is the number of data points (samples) within the leaf node.
- y_i is the actual energy consumption value of the i-th data point within the leaf node.

The Decision Tree Regression algorithm builds a tree by splitting data into subsets using input features. It uses criteria like MSE or MAE to find the best splits, minimizing prediction errors. The cost function for Decision Tree Regression during tree construction is represented as:

$$\hat{y} = \frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \qquad (8)$$

Where:

- n is the number of data points in the leaf node.
- y_i is the actual energy consumption value for the i-th data point in the leaf node.
- $\hat{y}_i$ is the predicted energy consumption value for the i-th data point in the leaf node.

Decision Tree Regression efficiently extracts complex patterns from power consumption data, providing interpretable predictions and aiding feature identification, enhancing ESP32-based IoT power consumption analysis.

E. Ridge Regression:

In IoT-based power analysis with ESP32, Ridge Regression handles multicollinearity and overfitting by adding a regularization term to the cost function, ensuring model stability. The Ridge Regression equation includes a penalty term based on the L2 norm of the weight vector, which can be expressed as:

$$y = b + m_1x_1 + m_2x_2 + \cdots + m_nx_n + \alpha\sum_{j=1}^{p} m_j^2 \qquad (9)$$

In this context, y represents predicted energy use, $x_1, x_2, ..., x_n$ are energy-related input features, b is the bias, $m_1, m_2, ..., m_n$ are feature weights, p is the feature count, and α regulates regularization. The extra term $\alpha\sum_{j=1}^{p} m_j^2$ penalizes large weights, enhancing balance, averting overfitting, and boosting generalization. Ridge Regression minimizes squared differences between predicted and actual energy use while managing weight magnitudes. Its cost function is:

$$Cost\ Function = \frac{1}{2n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 + \alpha\sum_{j=1}^{p} m_j^2 \qquad (10)$$

Ridge Regression, with α modulating regularization strength, handles overfitting and multicollinearity in high-dimensional IoT power consumption analysis using the ESP32. This boosts stability and prediction accuracy, ensuring dependable energy consumption forecasts and optimization.

VI. RESULT AND DISCUSSION

In our IoT power analysis project with the ESP32 microcontroller, Linear Regression was the top choice among Ridge, Random Forest, Linear, and Polynomial Regressions. It consistently had lower error rates, showing better prediction accuracy. We chose it for its ability to make precise predictions by capturing linear patterns in power data. In Linear Regression, we model the relationship between variables, like time, voltage, and current, with a linear equation (1) & (2)

Linear Regression, by fine-tuning its settings, minimizes prediction errors, closely resembling real power usage patterns. It consistently outperforms other models with lower error rates, highlighting its accuracy, especially for data with linear relationships like voltage and current. It's also fast and efficient, making it great for real-time IoT monitoring. This provides users with current energy insights, enhancing its usefulness and accuracy

Classifiers	MAE	MSE	EV	PCC	R_sq
Linear Regression	9.92E-15	1.84E-28	1.0	1	1
Polynomial Regression	8.03E-12	1.28E-22	1.0	1	1
Decision Tree Regression	0.0452	0.1105	0.999	0.9993	0.9987
Random Forest Regression	0.0310	0.0510	1.0	0.9997	0.9994
Ridge Regression	0.0001	7.76E-08	1.0	1	0.9999

Table. 1.

Linear Regression excels at minimizing prediction errors through adaptive parameter tuning, particularly when dealing with linear dependencies like voltage and current. Its computational efficiency suits real-time IoT monitoring, delivering timely energy insights. Consequently, Linear Regression stands as the prime choice for our IoT-based power consumption analysis, ensuring accurate predictions for efficient energy management and cost saving

VII. CONCLUSION

The ESP32 microcontroller and machine learning regression models have combined to provide a major method with wide-ranging implications for Internet of Things (IoT)-based power use monitoring. This project not only altered consumer behaviour around energy usage, but it also paved the way for a more efficient and sustainable energy future. Users now get precise insights into their electricity use because of the accuracy and reliability of machine learning regression models, notably Linear Regression, which empowers them to make wise decisions for optimised energy management. By bridging the gap between data and action through real-time monitoring capabilities and an intuitive user interface, an energy-efficient culture has been promoted. The project's scalability and resilience further guarantee its viability in the face of upcoming energy issues. In essence, the IoT-based power consumption analysis project marks a key turning point on the road to intelligent and sustainable energy management. It serves as evidence of how contemporary technology has the power to fundamentally alter how we use energy resources, ultimately paving the way for a more cost- and environmentally-friendly future.

VIII. REFERENCES

[1] M. Pimple, S. Thopate, A. Nikam, and S. Gadekar, "IOT Based Smart Energy Meter Using ESP 32," 2021. [Online]. Available: https://ssrn.com/abstract=3917892

[2] M. M. Kaumar and A. C. G, "IOT BASED SMART ENERGY METER," 2022. [Online]. Available: www.ijcrt.org

[3] A. Salisu, A. Bugaje, and A. Z. Loko, "IOT BASED HOUSEHOLD ELECTRICITY ENERGY MONITORING AND CONTROL," FUDMA JOURNAL OF SCIENCES, vol. 4, no. 4, pp. 77–84, Jun. 2021, doi: 10.33003/fjs-2020-0404-466.

[4] M. R. Braun, H. Altan, and S. B. M. Beck, "Using regression analysis to predict the future energy consumption of a supermarket in the UK," Appl Energy, vol. 130, pp. 305–313, Oct. 2014, doi: 10.1016/j.apenergy.2014.05.062.

[5] N. Sulthana, P. N. Y, and K. B. Shiva Kumar, "Smart Energy Meter and Monitoring System using IoT." [Online]. Available: www.ijert.org

[6] M. Rupesh and N. Anbu Selvan, "Design of IoT Based Smart Energy Meter for Home Appliances," in Journal of Physics: Conference Series, IOP Publishing Ltd, Jul. 2021. doi: 10.1088/1742-6596/1964/5/052001.

[7] P. S. Macheso and D. Thotho, "ESP32 Based Electric Energy Consumption Meter," International Journal of Computer z Communication and Informatics, vol. 4, no. 1, pp. 23–35, May 2022, doi: 10.34256/ijcci2213.

[8] S. Tyagi, A. Singh, H. Singh, K. Rawat, and S. Bhatia, "IOT Based Smart Energy Meter," 2021, [Online]. Available: www.arduino.cc,

[9] Nelson. I Annadurai. C Ramya. E Shivani. R and Mathusathana. V "IoT based Energy Meter System Using Machine Learning" Smart Intelligent Computing and Communication Technology, 2021

[10] Sana Khan Preshit Rathod Sanket Wasnik Karan Gori and Nikita Kulkarni " Energy Consumption And Monitoring System Using Iot " International Research Journal of Engineering Technology, vol 6, 14-04-2019, available: www.irjet.net

[11] Abhijith C Aiswariya R Amanyujith Raj Fathimath Hanna Safeer and Nikhil Dharman M K "Real-Time Analysis of Electricity Consumption and Bill Prediction" International Journal of Innovative Science and Research Technology, vol 3, 03-03-2023,

[12] Shen Rong and zhang Bao-wen "The Research of Regression model in machine learning field" MATEC Web of Conferences [2018] Available: www.matec-conferences.org

[13] Mohamed Sheik Buhari S Mani Bharathi K and Mohamed Jakeer M " Iot Based Smart Energy Meter in Three Phase" vol. 11, 05-05-2023 Available: www.ijcrt.org

[14] Anastasios Fanariotis Theofanis Orphanoudakis Konstantinos Kotrotsios Vassilis Fotopoulos George Keramidas and Panagiotis Karkazis " Power Efficient Machine Learning Models Deployment on Edge IoT Devices" [2023] Available: www.mdpi.com/journal

[15] Ketaki S. Sudame Sumera Ali and A. M. Rawate " Design of an IOT Based Energy Monitoring System and Home Automation" vol. 7, June 2020 Available: www.jetir.org