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ELECTRIC DEVICE CLASSIFICATION BY POWER CONSUMPTION FOR OPTIMAL POWER MANAGEMENT IN IOT NETWORK

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Abstract

The technological revolution that is leading the world today has given the Internet of Things the supremacy, living in a smart environment, rapid development and control over most daily life matters. The Internet of Things, which is called the abbreviation IoT, consists of sensors or devices, communication, data processing and user interface. By connecting these devices with the Internet and automated systems, we can collect and analyze information logically and quickly, as data is analyzed and processed in cloud systems or in the device itself. The Internet of Things can also connect all devices to the Internet and allow them to communicate with others, creating a world covered by a complex network of technology. Which allows communication between things and people with ease. These devices usually do their work without any human intervention. When we look at this matter, we find how truly amazing it is. Since iot has the advantage of dealing with artificial intelligence (AI) systems, learning and benefiting from them, this helps make the process of data collection and analysis easier and faster. This article focuses specifically on the system of classification and prediction of electrical appliances based on the losses of electrical loads in order to reach the best consumption.

Keywords: Internet of Things (IoT), Machine learning, Sensors, Cloud, Home appliance, Device failure.

1. INTRODUCTION

Electric energy today is one of the most important elements and needs of daily life that are indispensable. Therefore, it has become necessary to find ways to reduce its consumption [1].

And since any decrease in electrical energy leads to major problems worldwide in several respects, the most important of which are economic and commercial, most life facilities depend heavily on electrical energy, so it is very necessary that we have an effective management of electrical energy to prevent energy loss as well as reduce consumption [2]. We must not forget that electricity today has become one of the contributors to raising the standard of living of any society, and this in itself is a very important issue [3].

Technology today and the great development in it led to a great change in many fields. After information technology was at the forefront in terms of its clear large consumption of electrical energy for a long time [4][5], today it has proven to the whole world its ability to give positively in all fields, especially in the field of electric energy. It is considered one of the positive contributors in this field by using several methods and technologies to control and control energy consumption [6][7], and the most important of these technologies is the Internet of Things [8] This technology allowed devices to communicate

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with each other and work with high efficiency. This technology has entered many fields and many applications such as health, agriculture and electricity, and among its most important applications are smart homes, smart buildings, smart networks, etc. Recent years The Internet of Things is seen as an important factor in the development of technologies to support access to the 5G ecosystem [9].

It is also possible to define IoT as a group of devices connected to each other by smart networks through platforms and interfaces used for a number of transmission protocols such as TCP/IP protocol, etc. [10], and recent years have witnessed the connection of a wide range of different devices estimated at billions of devices, whether they are electronic devices or sense if it supports smart buildings.

The Internet of Things consists of sensors, communication devices, and systems that process data [8].

One of the most important applications of the Internet of Things technology is smart grids. Smart grids did not appear in vain, but appeared to provide unparalleled assistance in the field of energy, i.e. electrical grids. These grids have great independence and the ability to connect with high efficiency [11] This technology is fundamentally different from regular grids, as it It has the advantage of remote control as well as it has the feature of automation through two-way communication and it also enjoys higher reliability and very high efficiency as it has the ability to answer many requests by integrating distribution and generation sources at the same time [12].

Machine learning will have an important role in this thesis, as machine learning is a type of artificial intelligence that helps machines learn and simulate human intelligence. Machine learning has its entry into multiple fields, as it has a large number of fields. The most important characteristic of machine learning is that it has two types of models: supervised machine learning and unsupervised machine learning [11]. For the convenience of the user, it is important to provide the best solution to the issue of load problems, reduce bill payment, as well as support and provide convenience for the user [13]. In our proposed system, we will classify the electrical load losses, the type of electrical loads, and predict the type of electrical load using machine learning, especially the reinforcement of the decision tree and the mlp algorithm, in addition to our use of plc.

2. LITERAL REVIEW

In 2016 Muralitharan, et.al, discusses the implementation of a system and reduces the cost in relation to the electricity bill by balancing the loads through a mechanism that reduces the delay in the implementation of electrical appliances by using the Load Balancing Algorithm for Electrical Appliances, where the proposed algorithm will give an idea about the load management control mechanism in the house, as it also makes a proposal to the service provider To manage all pregnancy needs during peak hours. The researcher obtained a cost result using this improvement method estimated at 28.67 compared to the normal average cost without improvement. The cost was estimated at 33.09. As for the waiting time delay (Davg), it will decrease by approximately 10 to 15 Using MOEA. If you help the user to use energy within the specified limit to avoid paying

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additional costs, this will also help in using more energy at a lower cost. If this method is good for reducing costs, besides reducing the delay time for implementing devices [14].

In 2017 Wasoontarajaroen.et.al., presented an advanced device for IOT. This device measures power, current, voltage, and the energy of a four-phase line inside a laboratory building. The device is damaged from the control unit, the sensor unit, and the Wi-Fi unit. The device is originally one of the low-cost devices. This device was chosen through the data that was He collected it for a week and found the result that the device works well in energy management through that data [15].

In 2017 Chen, et.al, dealt with a new study of cloud load balancing by comparing it with previous studies. This proposal provided the possibility of implementing the CLB model with a physical and virtual web load balancing architecture and algorithms. Experiments conducted on physical and virtual servers that support cloud load balancing (CLB). The results have proven that the cloud server of any form depends on the proposed architecture. The study balances when users log in at the same time [16].

In 2018 Motlagh.et.al., presented a study on a control system for modern and old buildings and providing comfort to the residents, based on the Internet of Things, where he presented a test platform for the Internet of Things in which he used sensors to monitor lighting and compared a traditional energy system with a smart energy system, and the smart system proved its effectiveness in old buildings in terms of reducing consumption and providing comfort to its residents [17].

In 2019 Mylonas.et.al., discussed a way to save energy using specific methods and steps to be followed systematically based on data taken from the infrastructure of schools, i.e. using a strategy directed towards the energies saved, and the tangible results were that these strategies help in saving energies and environmental friendliness. One of the results of the examples was approximately 15-20% of thrift [18].

In 2020 Muralidhara, et.al, introduced a smart energy meter to reduce the problem of consumption and measurement, in which he used Arduino UNO. This meter made us get a lower cost of energy and control of the meter, as it helped in classifying energy and reducing consumption, as it gives the ability to monitor and record consumed energy data [19].

In 2020 Cao, et.al., Discuss a study comparing 8 trained machine learning models with daily and weekly data from a hospital in Shanghai. It was found that the daily electrical load predictions of XGBoost, SVR, RF are the most accurate and individual models. In the MAPE run of the data test 9.64%, 9.81% and 10.67% sequence of These can be considered reliable intelligent forecasting models for energy managers/management to perform daily forecasting of future electrical load. By making a comparison between daily and weekly forecasting it is found that performance will improve by using more granular or detailed energy usage data. One possible explanation is that a detailed load profile can reduce com-mode uncertainty. In terms of feature significance, the outside temperature, air pressure and operating status of the central air conditioning system were found to be the top 3 contributing factors [20].

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In 2021 Awan.et.al., used the machine learning algorithm in the management of smart buildings for smart cities, where he suggested the use of CDBR based on improving the particle swarm that enjoys its effectiveness by using smart cities, as this algorithm granted a smooth method and a specific pattern using energy, and the result was to reduce the peak to moderate [21]

In 2021 Xiaoyi,et.al., discussed the integration of energy with artificial intelligence with electricity networks through the use of the modda algorithm intended to send a multi-purpose distributor [22].

In 2022 Jasim, et.al, discussed a smart system that measures and monitors energy consumption based on the Internet of Things, where the system gives users the ability to monitor their energy consumption through smart phone applications, all by relying on the Internet of Things. In the end, the system has proven effective in reducing energy consumption and saving it, and thus this leads to saving money as well [23].

3. MACHINE LEARNING ALGORITHMS

3.1 Decision Tree Classifiers

The need for big data that is not scattered and organized called for finding a way to infer, extract and manage that data. One of the most important of these methods is the decision tree of supervised learning. The decision tree is one of the great techniques that has proven its effectiveness over the years. The decision tree is similar to hierarchical models. The decision tree is very similar to the ordinary tree, as it consists of leaves, nodes, and roots. The root nodes are considered the basis of all nodes. As for the leaves, they represent the results of the idea, and the branches represent specific decisions. [24] The structure of the tree is as follows:

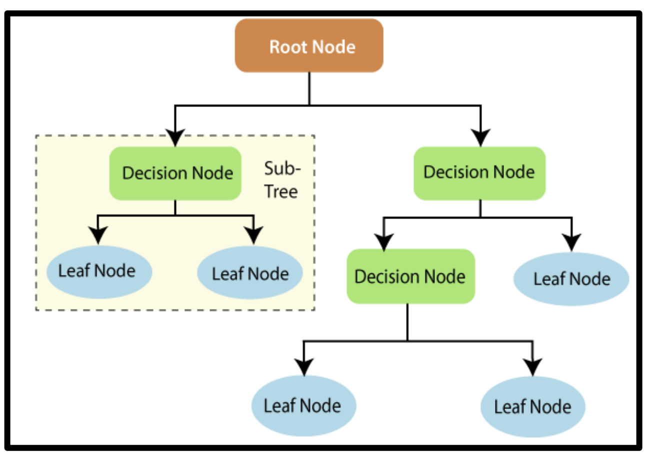

Figure 1: decision tree structure

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The working mechanism of Decision Tree Classifier is as follows.

- Data Preparation: The first step is to prepare the data by dividing it into training and testing sets. The training set is used to build the decision tree, while the testing set is used to evaluate its performance.
- Tree Creation: The algorithm starts by selecting a feature from the dataset that will be used as the root node of the tree. The feature is selected based on its ability to split the data into groups that are as homogeneous as possible with respect to the target variable. This process is repeated recursively for each subgroup of the data until a stopping criterion is met.
- Splitting Criteria: The decision tree algorithm uses various metrics, such as Gini Index or Entropy, to determine the best split for each node. The goal is to minimize the impurity of the resulting subsets, which means that the subsets should contain data points that are as similar as possible to each other with respect to the target variable.
- Pruning: Decision trees can be prone to over fitting, which means that the tree becomes too complex and captures noise in the data rather than the underlying patterns. To prevent over fitting, decision trees can be pruned by removing branches that do not improve the performance of the tree on the testing data.
- Prediction: Once the decision tree is built, it can be used to make predictions on new data points. The algorithm follows the branches of the tree based on the values of the features of the new data point, until it reaches a leaf node, which represents a predicted value for the target variable.

3.1.1 Boosting

Reinforcement is one of the basic and very important examples of a decision tree [25]. In our system, we have used two algorithms for reinforcement, namely:

3.1.2 LightGBM

An ensemble algorithm based on Decision Trees is called LightGBM (DT). The forward distribution algorithm is used. To learn a decision tree, the residual is fitted by a negative gradient in each iteration. As $D = \{(x_i, y_i)\}_{i=1}^{n}, x_i \in\ R^{m\times 1}, y_i \in R.n$, where n is the number of samples, $x_i(i = 1, 2, \dots\dots, n)$ is first constructed. $m = N_{tw} \times N_{ft} + N_{age}$, where N_{tw} is the size of the time window, N_{tw} is the number of features that will be selected, and Nage is the duration of the turbofan engine. Target RUL value in one dimension is $y_i = (i = 1, 2, \dots\dots, n)$. Figure (2) shows the LightGBM structure for RUL prediction [26]. The RUL estimation is obtained by adding the forecasts of all the trees in an ensemble of trees:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in F \quad \dots\dots\dots (1)$$

Where *K* is the number of trees, *F* denotes a space containing every potential tree structure, and f_k denotes one of the trees with the highest leaf scores. By lowering the objective, f_k is obtained:

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$$f_k = \arg\min_{f_k} \sum_{i=1}^{n} L\left(y_i, \hat{y}_i^{(k)}\right) + \Omega(f_k) \quad \text{............ (2)}$$

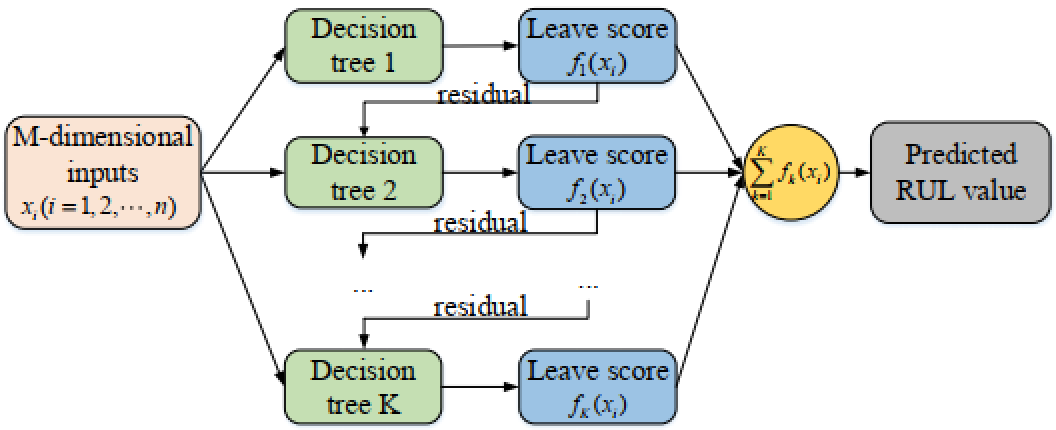

Figure 2: The structure of LightGBM [26]

Where the regularization (Ω) function and L is the training loss function. Typically using Equation (3).

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^{\,2} \quad \text{........ (3)}$$

Where γ is a punishment boundary for the quantity of leaves T and w is the loads of leaves. At the point when L purposes a squared mistake misfortune capability, its misfortune becomes:

$$L\left(y, \hat{y}^{(k-1)} + f_k(x)\right) = \left[y - \hat{y}^{(k-1)} - f_k(x)\right]^2 = [r - f_k(x)]^2 \quad \text{.. (4)}$$

f_k is gotten by fitting the lingering r.

A quadratic estimate permits us to characterize the capability to limit at round *k* as:

$$f_k = \arg\min_{f_k} \sum_{i=1}^{n} \left[g_i f_k(x_i) + \frac{1}{2} h_i f_k^{\,2}(x_i)\right] + \Omega(f_k) \quad \text{.......... (5)}$$

Where,

$$g_i = \partial_{\hat{y}(k-1)} L\left(y_i, \hat{y}^{(k-1)}\right), h_i = \hat{y}^2_{\hat{y}(k-1)} L\left(y_i, \hat{y}^{(k-1)}\right). \quad \text{......... (6)}$$

Thusly, another tree is acquired by limiting this goal capability. Also, the choice tree parts every hub with the most elevated data gain. The change gain of parting highlight j at point d for a hub is characterized as Equation (7).

$$V_{j|O}(d) = \frac{1}{n_O}\left\{\frac{\left(\sum_{\{x_i \in O,\ x_{i,j} \le d\}} g_i\right)^2}{n^j_{l|O}(d)} + \frac{\left(\sum_{\{x_i \in O,\ x_{i,j} > d\}} g_i\right)^2}{n^j_{r|O}(d)}\right\} \quad \text{......... (7)}$$

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Where O is the examples on a proper hub of the choice tree, $n_O = \sum I[x_i \in O]$, $n_{l|O}^j(d) = \sum I\left[x_i \in O: x_{i,j} \leq d\right]$, $n_{r|O}^j(d) = \sum I\left[x_i \in O: x_{i,j} > d\right]$ .. (8)

Registering the information gain requires analyzing all guides to find the ideal section point. When stood up to with tests with enormous aggregates and high perspectives from sensor indications of turbofan engine, their adequacy and versatility are difficult to satisfy. LightGBM uses Incline based One-Side Sampling(GOSS) computation to lessen the size of the planning data when center point plits [16], as Equation (9):

$$V_j(d) = \frac{1}{n}\left\{\frac{\left(\sum_{x_i \in A_l} gi + \frac{1-a}{b}\sum_{x_i \in B_l} g_i\right)^2}{n_l^j(d)} + \frac{\left(\sum_{x_i \in A_r} gi + \frac{1-a}{b}\sum_{x_i \in B_r} g_i\right)^2}{n_r^j(d)}\right\} \quad \text{.... (9)}$$

where *A* is an occurrence subset of top *a*×*100%* occasions with the bigger slopes, and *B* is an example subset haphazardly examined from the excess set comprising (*1−a)*×*100%* percent cases with more modest inclinations.

$A_l = \left\{x_i \in A: x_{ij} \leq d\right\}$

$A_r = \left\{x_i \in A: x_{ij} > d\right\}$

$B_l = \left\{x_i \in B: x_{ij} \leq d\right\}$

$B_r = \left\{x_i \in B: x_{ij} > d\right\}$

The GOSS calculation works out the $V_j(d)$with a more modest occasion subset rather than every one of the occurrences to decide the split point, in this manner the processing load is decreased and the overt repetitiveness of commotion signals is expanded.

3.1.3 CatBoost

This algorithm is very important in slope support, which was proposed by the scientist Prokhorenkova CatBoost This algorithm was distinguished in its ability to make a neutral measurement and reduce overfitting. One of the most important improvements in the path of changing the absolute highlights to digital. This algorithm has proven to achieve the goals and its effectiveness in machine learning [27]. Here's how it works [28]:

- Data Preparation: The first step is to prepare the data by splitting it into training and validation sets. The training set is used to train the CatBoost model, while the validation set is used to evaluate its performance.
- Gradient Boosting: CatBoost is a variant of gradient boosting algorithm, which builds an ensemble of weak learners such as decision trees. The algorithm starts by creating a single decision tree, which is usually small and shallow. This tree is used to make predictions on the training data, and the errors are calculated as the difference between the predicted values and the actual values.
- Boosting: The next step is to create a new tree that focuses on the errors of the previous tree. This new tree is designed to correct the errors of the previous tree by predicting the residuals. The residual is the difference between the actual value and

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the predicted value of the previous tree. This process is repeated iteratively to create a series of trees that each corrects the errors of the previous tree.

- Categorical Features: CatBoost is particularly useful for datasets with categorical features. It can handle categorical features directly, without the need for one-hot encoding or label encoding. It uses an algorithm called ordered boosting, which sorts the categories based on their target statistics and assigns each category a numerical value.
- Regularization: CatBoost includes several regularization techniques to prevent overfitting. It uses L1 and L2 regularization, as well as a novel technique called "feature importance calculation using Shapley values". This technique helps to identify the most important features and avoid overfitting by reducing the impact of less important features.
- Prediction: Once the CatBoost model is trained, it can be used to make predictions on new data points. The model follows the same process as during training, by combining the predictions of a series of weak learners to make a final prediction.

Overall, CatBoost is a powerful and flexible algorithm that can handle a wide range of data types and prediction tasks, and can achieve state-of-the-art performance on many benchmarks [29].

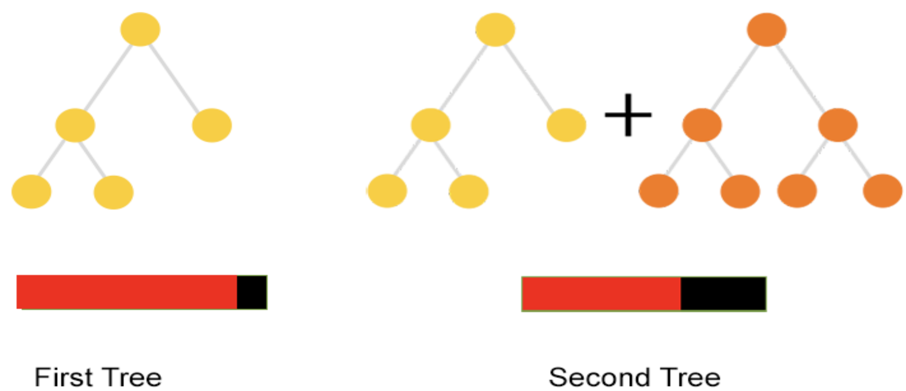

Figure 3: Cat Boosting Mechanism

3.2 Neural Networks

Difficult neural networks usually consist of multiple layers, the input layer, and two, three, or one hidden layers that will connect the cells to each other, including digital communication, or what is called weight. The following figure will show us how the layers relate to each other and how they represent [30]. (See Figure 4)

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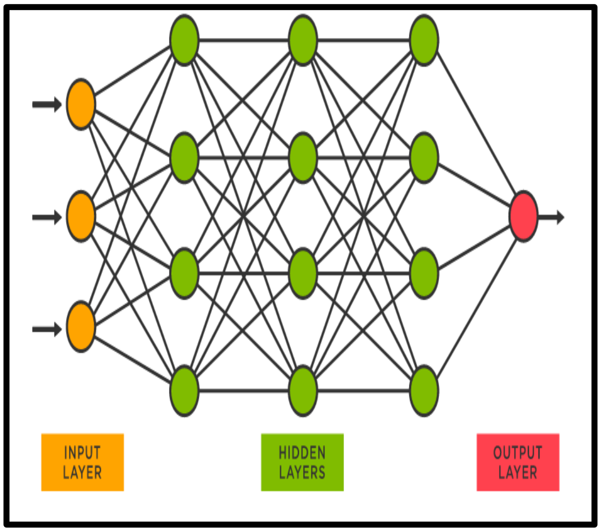

Figure 4: Neural Networks structure

3.2.1 Multi-Layer Perceptron (MLP)

Sensory perception consists of multiple layers because it represents a non-linear neural network, as it consists of an input and output layer and a hidden layer. It can be more than one hidden cell. The hidden cell will represent a non-linear sigmoid. All cells will be connected to each other [30].

4. METHODOLOGY

4.1 Dataset collection

To find out how much energy each device consumes, measure it, and know the performance of the device, whether capacitive or inductive. We connected the Arduino circuit with both the CT sensor and the ACS712 sensor, where the CT measures the current and the ACS712 measures the voltage for each device. After that, we took the Wi-Fi ESP 8266 and connected it to the network in order to connect after that, we saved the data in an Excel file and uploaded it to Google Drive.

The collected data collection consists of power readings for approximately 12,000 homes, each house of which 128 devices were selected, including inductive devices and capacitive ones, as the power readings for inductive devices have been programmed so that they contain a positive value, as the phase difference angle between voltage and current is positive. As for the capacitive devices, they contained a power value with a negative sign, depending on the negative angle between the voltage and current vectors in the capacitive load.

Figure (5) represents a circle showing how to collect data at the level of one device. This data included readings for about 12,000 homes, each containing 128 devices distributed between a capacitive or inductive device

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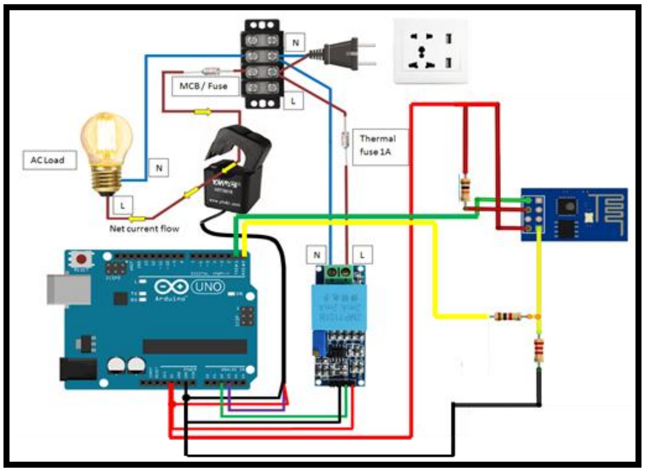

Figure 5: Dataset collecting circuit

4.2 Proposed method

The designed system consisted of two stages. The first stage is related to the machine learning algorithms used in this work, where two systems were built in this stage, the first distinguishes whether the load is inductive or capacitive, while the second distinguishes the classification category, where the data was divided into five categories according to the difference between inductive and capacitive loads, as follows:

- 05% difference between capacitive and inductive loads lead to (Class 1).
- 10% difference between capacitive and inductive loads lead to (Class 2).
- 20% difference between capacitive and inductive loads lead to (Class 3).
- 30% difference between capacitive and inductive loads lead to (Class 4).
- 40% difference between capacitive and inductive loads lead to (Class 5).

The Block Diagram of First Stage shown in Figure (6) below.

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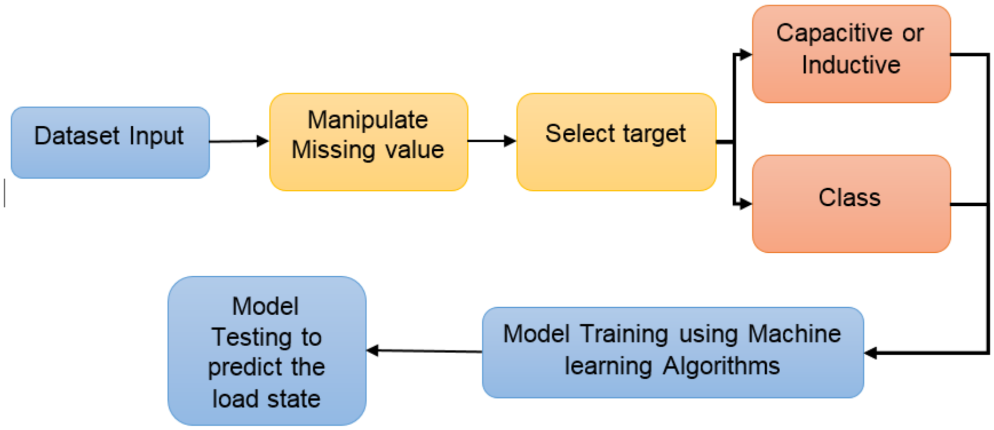

Figure 6: Machine Learning System mechanism

From the block diagram shown in Figure (6) above, the proposed system plan can be described, as its work began by entering the collected data set into the machine learning program, and then the missing values were processed in the data processing stage, where the rows containing the missing values were neglected due to the large number of rows The data set is approximately 12,000 entries. After that, the target were chosen according to the proposed function of the program, where the first goal was to divide between inductive and capacitive, and the second goal was to divide according to categories.

The second stage is related to the programming of the Programmable Logic Control (PLC) device, where three external switches were identified that are connected to the PLC to give commands to the device to deal with turning on and off according to the category obtained by the machine learning system. In the PLC device, 12 ports were approved to which loads are connected for the purpose of operating it, and since the power factor of electrical appliances ranges Between 98% and 99%, two devices were turned off alternately from a total of 12 non-main (secondary) devices in the house for the purpose of matching the loads, as this programming was for the first category. As for the second category, it chose four devices between switching on and off alternately, as well as the third category, six devices. As for the fourth and fifth categories, they were considered one category due to the scarcity of the fourth category in the data collected. . Figure (7) below shows the working mechanism of PLC.

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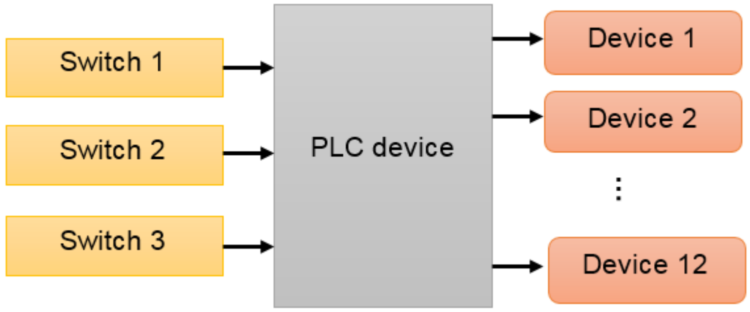

Figure 7: PLC device connections

3.5 Evaluation metrics

Confusion matrix for a binary classifier. Actual values are marked true (1) and False (0), and are predicted as Positive (1) and Negative (0). Estimates of the possibilities of classification models are derived from the expressions TP, TN, FP, FN, which exist in the confusion matrix [31].

TP (True Positive) - The data of interest in the disarray framework is the genuine positive point (TP) when a positive result is normal and exactly the same thing occurs.

FP (False positive) - The data of interest in the disarray lattice is a bogus positive when a positive outcome was normal, and what happened is an adverse outcome. This situation is known as a sort 1 mistake. It resembles the gift of awful premonition.

FN (False Negative) - The data of interest in the disarray lattice is bogus negative when an adverse result was normal, and what happened is a positive result. This situation is notable as a kind 2 blunder and is considered as perilous as a sort 1 mistake.

TN (True Negative) - The data of interest in the disarray framework is Valid Negative (TN) when an adverse result is normal and the equivalent occurs.

Accuracy: the percentage of accurately anticipated data from tests is easily determined by dividing all accurate forecasts by all predictions [32].

$$Accuracy = \frac{Tp+TN}{TP+TN+FP+FN} \qquad \text{.................. (10)}$$

Precision: The proportion of outstanding instances among all anticipated ones from a specific class [32].

$$Precision = \frac{TP}{TP+FP} \qquad \text{...................... (11)}$$

Recall: The ratio of the total number of occurrences to the proportion of instances that were supposed to be members of a class [33]

$$Recall = \frac{TP}{TP+FN} \qquad \text{..................... (12)}$$

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F1-Score: The phrase is used to describe a test's accuracy. The maximum F1-score is 1, which denotes outstanding recall and precision, while the lowest F1-score is 0 [33].

$$F1 - Score = 2 \times \frac{percision \times recall}{Percison + recall} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

5. RESULT of Machine Learning System Prediction

The system evaluation use three ML algorithms, they are (LightBoost, CatBoost, and MLP), the confusion matrix of each one shown in Figures (14, 15, and 16), where the results summary shown in Table (1).

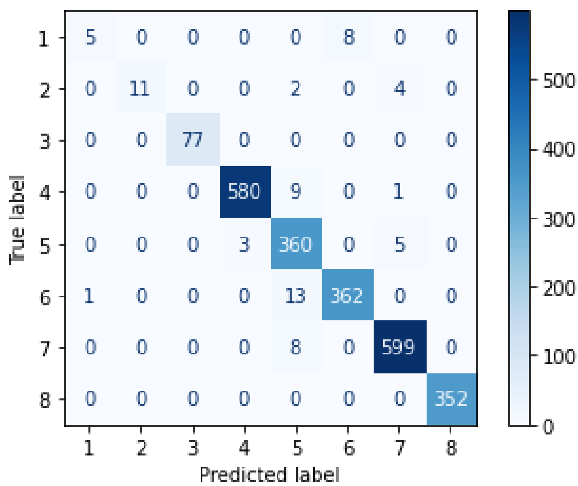

Figure (14) LightBoosting Classifier results

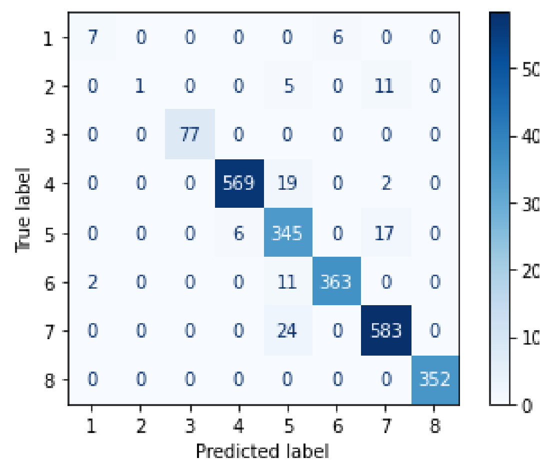

Figure (15) CatBoosting Classifier results

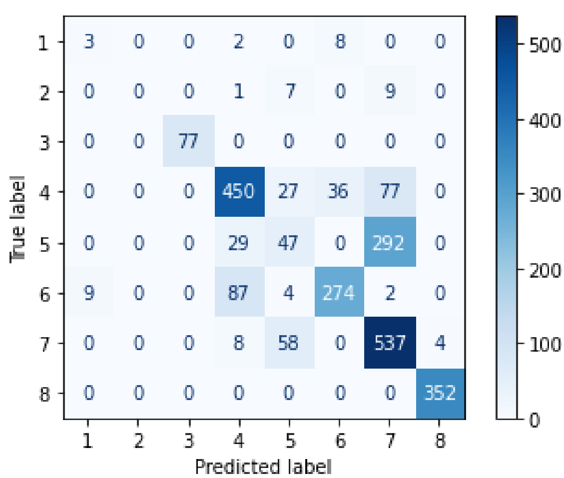

Figure (16) MLP Classifier results

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Table 1: Results Summary

Algorithm	Accuracy	Precision	Recall	F1-score
LightBoost	98%	0.96	0.87	0.90
CatBoost	96%	0.94	0.80	0.82
MLP	73%	0.94	0.80	0.82

After classifying the load of the house according to the aforementioned algorithms, a PLC device is used as it was programmed in the Lader language. Four classes have been identified for the diffraction of the load according to the inductive or capacitive tendency, assuming that the first class has a difference of 5% of the total load, while the second class has a difference of 10% of the total load. As for the third class it is a difference of 20% of the total pregnancy and the fourth class or more. In the PLC system, 12 household electrical appliances of little importance were selected for the purpose of operating them alternately according to the aforementioned classes, as the process of turning off or temporarily disabling these devices works to balance the load. With regard to programming, several timers were set with a phase difference of half an hour between one timer and another for the purpose of regulating the operation of the loads, and from it a balanced load was obtained very close to the pure ohmic load, and this in turn reduced the power losses.

6. DISCUSSION

The study methods and results compare to relative work and displayed in Table (2).

Table 2: Relative Work comparison

Citation	Method		Results
Muralitharan, et.al, 2016	Smart meter load Balancing using MOEA	-	They decreases both the expense of power and the defer time in executing electrical apparatuses for the buyer.
Wasoontarajaroen.et.al., 2017	Use smart power meter monitors	-	Track consumption by mobile phone
ALRikabi.et.al.,2017	Use GSM to alert devices to start working at 7:00 AM	-	Send an alert to the manager about the negligence of employees by leaving the devices on when they are not needed
Chen, et.al, 2017	Dynamic attachment scale method		Decrease the likelihood that the server cannot

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			deal with unreasonable computational necessities
Zheng, et.al.2017	Use a weighted averages algorithm based on extreme gradient augmentation to evaluate the similarity between forecast and historical days. The EMD method is used to analyze the SD load into several internal and residual mode functions (IMFs).	LSTM	Accuracy 82%
Li,et.al., 2017	The periodic similarity of the power load fluctuations characteristics at different time scales has been given.	XGBoost	RMSE 373.22
		KNN	RMSE 1451.57
Sicchar et. al., 2018	Switching between devices using Fuzzy Logic Control	Microgrid Cluster Based	Fuzzy Logic Balancing
Present Study	Machine Learning and PLC controlling	CatBoost	accuracy 98.52%
		LGBM	accuracy 96.81%
		MLP	accuracy 73.23%

From the comparison to relative works we can said that our proposed system has maximum accuracy to relative works, and our dataset is more effective.

7. CONCLUSION

The Internet of Things This frightening term with its great capacity includes several meanings, including everything connected to the Internet. It also describes devices and things that communicate with each other. This term has proven its high ability in the development of technology. The electrical loads are of great importance in the consumption of electrical energy, as they played a very important role in reducing and increasing consumption. The machine learning, especially the reinforcement of the decision tree and the multi-layered algorithm of the Neural Network, have the property of prediction, classification, and others. Our proposed system classified the electrical loads according to the losses occurring in them at the city level, as well as according to the type of loads, and it predicted at the level of one house according to the type of load, Where we got excellent results, after that we used plc to balance the loads. This system is based on many important technologies, as it is a very useful system in the field of electrical consumption.

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