

Prediction of renewable energy consumption for future world by using artificial neural networks.

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Abstract

Artificial intelligence has proven itself in many areas in combating complex and challenging problems. In this study, the estimation of the use of artificial neural networks in long term renewable energy consumption was undertaken. The study proposes an artificial intelligence predicting energy consumption and energy needs of houses and buildings in the future by using feedback artificial neural networks. In this study, "Google Project Sunroof-Solar Panel Power Consumption Offset Estimate" data set is used. With the database, artificial intelligence has been obtained by using artificial neural networks with feedback. The training of the artificial intelligence obtained was completed with 7999 samples with 25 different categories. This database, which Google collects, is obtained at high costs, so it is not possible for everyone to access such and its bases. Our artificial intelligence with feedback artificial neural network obtained a high percentage for training success. Validation success was high and test success was high too.

Keywords: Artificial Neural Networks; Energy Consumption; Energy; Renewable Energy.

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1. Introduction

Supportable power sources are obtained essentially from the force of the sun's radiation. There is similarly non-sun arranged renewables, specifically, tidal imperativeness and geothermal essentialness. Sun based power, both as immediate daylight-based radiation and indirect structures, for instance, wind, water, and bioenergy was the essential source that early human social needs are relied upon. Going before the cutting-edge change, these sources were basically the primary kinds of essentialness used by man. During the past 150 years, present-day human advancement has ended up being logically liable to non-sustainable power sources, for instance, coal, oil, and vaporous petroleum. These are constrained resources which by their disposition are limited in their openness into the more expanded term. Their start discharges carbon dioxide into the earth which is a vital supporter of unnatural climate change. The various sorts of practical power sources unequivocally have lower natural impact than oil subsidiaries, and they are regularly re-established, allowing them to give imperativeness uncertainly. They add to overall fundamental imperativeness demands in three essential regions: control creation, warmth and cooling, and transport [1].

The sustainable power source is the vitality gotten from characteristic assets recharged, which are not actualized. It is in a general sense not quite the same as non-renewable energy sources from oil, coal, flammable gas, or nuclear fuel utilized in nuclear reactors. Sustainable power source commonly does not create build-ups, for example, carbon dioxide (CO₂) or unsafe gases or increment ozone-depleting substances, for example, when consuming non-renewable energy sources or dangerous nuclear waste from nuclear reactors [1].

The sustainable power source created from wind, water, and sun can be delivered from waves and tides or geothermal vitality, just as from rural harvests and oil-creating trees. In any case, the last have deposits that expand a dangerous atmospheric deviation. The most sustainable power source creation is delivered in hydroelectric power plants by the Great Dams any place suitable places are built on rivers and watersheds. Wind and solar-based methods are widely used in developed and some developing countries. Recently, many countries have made plans to increase their production of renewable energy to cover their energy needs by 20% of their consumption in 2020. At the Kyoto Conference in Japan, most heads of state agreed to hide CO₂ production in the coming years to avoid major threats to climate change due to pollution and depletion of fossil fuels, as well as the social and political risks of fossil fuels and nuclear energy [2].

The so-called renewable energy trade, a type of business that interferes with the promotion of renewable energies into sources of income, has recently increased, despite many non-technical barriers that prevent the widespread of renewable energies such as the cost of high initial investments and others. However, approximately 65 countries plan to invest in renewable energies and have worked out policies to develop and encourage investment in renewable energies. Interest in renewable energy has increased in recent years in the Middle East, especially Saudi Arabia, where the Saudi private sector has begun to inject large sums of investment into the renewable energy sector [2].

A large portion of the supportable power sources starts from the force of the sun's radiation, in either quick or underhanded structure, while there are in like manner alluded to sun situated manageable power sources, for instance, geothermal and tidal. The manageable power source is perpetual in its reserve and is a sensible wellspring of imperativeness. Going before the cutting-edge change which started in the late eighteenth century, economic power hotspot (generally as wood essentialness) controlled society's imperativeness supply [1,2]. The usage of oil subsidiaries, for

instance, coal and oil, has empowered individuals to create economies at a definitely more important rate than as of late experienced, yet there are as of now two noteworthy issues in association with non-sustainable power source use which are of fantastic concern. The first is the constrained thought of oil-based commodities and the path that at some stage, they will run out. The toxic gas wastes dispersed into the atmosphere due to the combustion of petroleum products disrupt the oxygen and nitrogen balance in the air and cause many diseases in this context.

The world has been using reliably extending proportions of imperativeness and this example is set to continue with masses advancement and the improvement of rising present-day economies. The potential for the maintainable power sources to supply all foreseen essential requirements for an overall reason is most likely not going to even out in the medium term. There will be a need to decrease [3]. As a rule, imperativeness is essential in the running of our economies and the use of essentialness is even more beneficial. In Europe, there is a drive to increase both imperativeness adequacy and the dedication starting from a maintainable power source, to indicate fundamental essentialness' necessity. It has been seen as a critical test and there is an affirmation from the European Commission that European freedom will be hard to achieve.

Utilization of sustainable power source offers a scope of outstanding advantages, including a lessening in outside vitality reliance, a lift to the neighbourhood and provincial part fabricating ventures. It also affects the advancement of territorial designing and consultancy administrations' time spent in the use of sustainable power source, expanded R&D, decline in effect of power generation and change, increment in the degree of administration for the rustic populace, work, and so forth [3]. Intriguing results can be acquired from the examination of the pattern of primary world vitality markers somewhere in the range of 1973 and 2004 [4]: (1) the pace of populace improvement was well underneath the GDP, there was an essential move of per capita, very close pay and by and large riches, (2) central vitality use are made at higher rates than the majority, inciting the advancement of its per capita, propelling power on 15.7%, all through the most recent 30 years. (3) CO₂ floods were at lower rates than vitality use, showing a 5% improvement during this period. (4) Electrical criticalness' uses irrefutably rose, prompting a rate increment in final vitality use (18% in 2004).

[5] noted that maintainable power source improvement has various excellent benefits. The requirement for complex headway methodology is central in this field in view of the current age, and this came to fruition as a result of climate changes. By then, they gave an expansive review on the single and multi-target streamlining procedures that use watchful perfect models. For instance, innate counts, Artificial neural networks, differential advancement similarly as logical showing. Also included are number direct programming methodologies, which are applied in different bits of maintainable power source, for instance, wind control, sun-based imperativeness, hydropower, bioenergy, geothermal essentialness, and cream systems. Similarly, their review covers the strategy applied in the structure, orchestrating, and control of feasible power source systems. Another entrancing review covering the models using upgrade methods in the essentialness division is made by [6]. Sadowsky presented a test model of supportable power source used for the G7 countries and applied Panel cointegration for desire. The actual result of this assessment was that eventually, augments in veritable GDP per capita and CO₂ per capita are viewed as noteworthy drivers behind per capita feasible power source usage. We have considered these parts in our assessment similarly as other most huge factors affecting maintainable power source use.

The author [7] used an artificial neural framework technique to estimate warming stores of structures similarly concerning the figure of essentialness using a segregated daylight-based structure. Distinctive hid layer designing has been used in showing. The paper [8] showed an intensive review of the productive usage of ANNs in maintainable power source structures. This work considers different sections of supportable power source systems including exhibiting the daylight-based steam generator, sun-based radiation estimate, and wind speed desire. [9] executed an efficient ANN model for envisioning sun-based resources in Turkey. The back-causing learning count is used in feed-forward single covered layers. They uncovered the efficiency of applied ANN with respect to conventional backslide models to evaluate daylight-based resources.

From the above concentrated relevant works in supportable power source, the centrality of utilizing a viable power source, its significant benefits and its fundamental occupation in decreasing ozone hurting substance transmission and key orchestrating appears. Therefore, the precise estimation and decoding of practical power sources are fundamental for technique and essential initiative structures in the essentialness portion.

1.1. Purpose of study

This paper develops an efficient ANN model prepared to measure and figure manageable power source use in a perfect way considering convincing data factors depicted in the past fragment. Therefore, this article aims to estimate the consumption of renewable energy for the future world using artificial neural networks. A feedback ANN is used in education and learning processes, considering data from previous years. In this article, environmental aspects of energy and fossil fuels are evaluated in detail. The ANN approach seems to be an appropriate method for estimating energy consumption data and should be used to model world energy consumption.

2. Methods

2.1. Data Collection procedure

2.1.1. Artificial Neural Networks

The logic of artificial neural networks is similar to biological neural cells. Artificial neurons, like biological neurons, create artificial neural networks by forming bonds between them. Artificial neurons, like biological neurons, receive input signals, collect, and process these signals, and draw conclusions. Artificial neural networks consist of five layers [10]. Inputs: At this stage, we can use the data collected from the outside world as information input for the system to learn.

Weights: All information on artificial nerve cell has weights. We can call these weights the value of that information. It also represents the effect of the information coming to the artificial neural network on the system. Whether weight values are large or small does not represent the importance of information. Addition Function: Addition function is a mathematical function. This function allows us to find the net input to the cell. A lot of functions are used in artificial neural networks, the most important of which is the sum of weights function. At this stage, each information entered into the system is multiplied by its own weight.

Activation Function: Activation function is the function that initiates the learning process in artificial neural networks. Like all functions, the activation function is a mathematical function. This function provides the net output to be obtained by processing the net input. Activation functions are nonlinear functions. There are many types of activation functions, and these are mathematical functions. The activation function must be selected by the designer. It is preferable that the derivative can be taken easily when selecting the activation function. Derivation of activation function is used in feedback neural networks [11].

Output of the Cell: The output value of the activation function is the output value of the cell. This value can be given to the outside world as the output of the artificial neural network or can be used inside the network again. Although each cell has more than one input, it has only one output. The output can be connected to any number of cells [12].

2.1.2. Back Propagated Artificial Neural Networks

Artificial neural networks with back propagation consist of 2 main stages: forward feed and back propagation. Feed forward is the stage where the network input data is provided. The outputs obtained at the end of this stage are entered into the error function and the weights are updated by spreading the errors back. The gradient descent method is used to bring the error function and thus the total error closer to the minimum [13].

The back propagation neural network used in this article is a subclass of artificial neural networks. The main purpose is to assign value to the information remaining between the inputs and outputs, and continuously update the assigned value. $E(t)$ represents the error. The aim is to determine the difference between the output $t(t)$ and the output $y(t)$.

$$e(t) = t(t) - y(k); t = 1, m \quad (2)$$

The basic structure of the backpropagation learning algorithm is to propagate the effects of the E error function to all weights on the network using the chain rule. Thus, it minimizes the total error value.

$$E_{Top} = \lim_{t \rightarrow \infty} ((\sum_{t=1}^m tE^t) / t) \quad (3)$$

It can be easily observed in Equation 3 that if the E_t value can be reduced in any 't' trial, the system's error will decrease. There are several methods for defining weights in artificial neural networks. The actual weight values are obtained at the end of the training and testing process. x_i presents the inputs. In the assignment of values between the elements i and j used for input, it is tried to calculate the change of $w_{ji}(t)$. This equation

$$\Delta w_{ji}(t) = \eta \delta_j x_i + \alpha \Delta w_{ji}(t-1) \quad (4)$$

In equation 4, η always represents the learning coefficient and α represents the momentum coefficient. δ_j is the mathematical factor of any j neuron in the hidden layer or output layer stage. For the output stage, this factor is given as follows.

$$\delta_j = \frac{\partial f}{\partial net_j} (y_j^{(t)} - y_j) \quad (5)$$

The target output of the processor element is represented by $Y_j(t)$. The processor element is always defined by j . The factors in the intermediate layers are represented by IE. This factor is

$$\delta_j = \left(\frac{\partial f}{\partial net_j} \right) \sum w_{qi} \delta_q \quad (6)$$

given. Since there is no target output for the EEs in the intermediate floors, Use equation 6 instead of equation 5. Accordingly, the factor δ_j starting from the output floor is calculated for the IEs on all floors. Then, by formula 4, weights are updated for all connections. The activation function to be used in the back propagation algorithm must have several important characteristics. The activation function should be a continuous, derivative-derived, and non-uniformly decreasing function. It is preferable that the derivative of this function is easily retrieved. Generally, the function is expected to extend between the minimum and maximum asymptotes.

2.1.3. Gradient Descent

This method must be understood before the back propagation algorithm can be understood. Because this method is the basis of the training phase in back propagation artificial neural networks. The name of the method is also referred to as the steepest descent in the welds.

When a point P on a function with a variable of one variable is written in its derivative instead, the value to be obtained is the slope of the line tangent to the function curve at point P. The slope of this line indicates the speed and direction of the increase in function. The direction of the local minimum point can be determined by looking at the slope. If the slope is greater than zero, the minimum value remains in the negative direction, and if less than zero, it remains in the positive direction. As the minimum value of the function approaches, the slope of the tangents decreases. Using this situation, it is aimed to approach the minimum values by reducing the slope step by step [14].

2.1.4. Derivative of Error Function

The error function is basically based on weights. To calculate the weight values that will ensure the function to be minimum according to the gradient descent method, the gradient must be taken, and a vector must be obtained by replacing the weights in the obtained vector function. This vector is then subtracted from the vector generated by the weights multiplied by the learning coefficient. Thus, the weights are updated at each step to reduce the result of the error function further.

2.1.5. Training Sets and Training Process

The training process is not random. It must be planned. The input data should not be randomly transmitted to the artificial neural network. Preparing the data to be trained in the network in advance and entering the network in sequential order provides better results. The regular data set for training the network is called the training set, containing as much data as possible that the network may encounter later [15] After the network has been trained, acceptable answers can be received from the network when a series of data is entered in the network that is not included in the training set. This capability of the network increases in direct proportion to the diversity of data in the training set.

2.2.Database

In this paper, we used "Solar Project Power Consumption Offset Estimates" for this Project. Since introducing sunlight-based vitality is increasingly costly, more and more mortgages are going to a potential alternative to reducing living bills. We need to make solar panels reasonable and straightforward for everyone. This data set, which consists of the energy needs of previous years, has been used to estimate our energy needs in the future accurately. In the database created by Google, table 1 and table 2 indicate our input and output values. All values used as input to the system are explained in detail in table1, together with their descriptions. 7999 samples from 25 different values are presented as an introduction to the system. Inputs and output used for training artificial neural networks in the system.

We have 25 inputs.

lat_max,	Maximum latitude for that region
lat_min,	Minimum latitude for that region
lng_max,	lng_max,maximum longitude for that region
lng_min,	lng_min,minimum longitude for that region
lat_avg,	lat_avg,average latitude for that region
lng_avg,	lng_avg,average longitude for that region
yearly_sunlight_kwh_kw_threshold_avg	yearly_sunlight_kwh_kw_threshold_avg,75% of the optimum sunlight in the county containing that zip code
count qualified	count qualified,# of buildings in Google Maps that are suitable for solar
percent covered	percent covered,% of buildings in Google Maps covered by Project Sunroof
percent qualified	percent qualified,% of buildings covered by Project Sunroof that are suitable for solar
number_of_panels_n	number_of_panels_n,"# of solar panels potential for north-facing roof space in that region, assuming 1.650m x 0.992m panels"
number_of_panels_s	number_of_panels_s,"# of solar panels potential for south-facing roof space in that region, assuming 1.650m x 0.992m panels"
number_of_panels_e	number_of_panels_e,"# of solar panels potential for east-facing roof space in that region, assuming 1.650m x 0.992m panels"
number_of_panels_w	number_of_panels_w,"# of solar panels potential for west-facing roof space in that region, assuming 1.650m x 0.992m panels"
number_of_panels_f	number_of_panels_f,"# of solar panels potential for flat roof space in that region, assuming 1.650m x 0.992m panels"
number_of_panels_median	number_of_panels_median,# of panels that fit on the median roof

number_of_panels_total	number_of_panels_total,"# of solar panels potential for all roof space in that region, assuming 1.650m x 0.992m panels"
kw_median	kw_median,kW of solar potential for the median building in that region (assuming 250 watts per panel)
kw_total	kw_total,# of kW of solar potential for all roof types in that region (assuming 250 watts per panel)
yearly_sunlight_kwh_n	yearly_sunlight_kwh_n,total solar energy generation potential for north-facing roof space in that region
yearly_sunlight_kwh_s	yearly_sunlight_kwh_s, total solar energy generation potential for south-facing roof space in that region
yearly_sunlight_kwh_e	yearly_sunlight_kwh_e,total solar energy generation potential for east-facing roof space in that region
yearly_sunlight_kwh_w	yearly_sunlight_kwh_w,total solar energy generation potential for west-facing roof space in that region
yearly_sunlight_kwh_f	yearly_sunlight_kwh_f,total solar energy generation potential for flat roof space in that region
yearly_sunlight_kwh_total	yearly_sunlight_kwh_total,total solar energy generation potential for all roof space in that region

Table1. Description of information presented as input to the system.

1 output

Existing installs count	Existing installs count,"# of buildings estimated to have a solar installation, at time of data collection"
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Table2. Description of our output.

2.3.Data analysis

2.3.1. Scaling of Input and Output Data

In a neural network that uses a sigmoid function, the network can be given numbers between 0 and 1 or only between these two values. However, the network may be required to use large numbers. To achieve this, the input and output data between any 2 values are multiplied by two coefficients and drawn to the range 0 and 1. Thus, as the network continues to operate with values between 0 and 1, the input-outputs can be exchanged at the desired intervals [16].

2.3.2. Neural Network Application

In this system we used a data table of 25 rows of 7999 columns as input. We used a feedback neural network consisting of 1 hidden layer and 10 neurons.

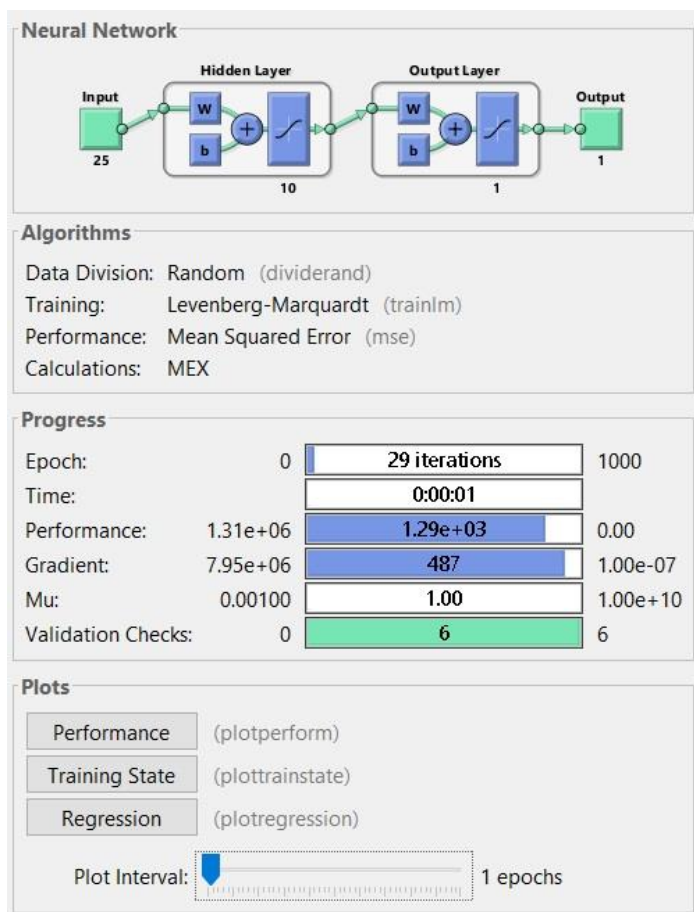


Figure1. Neural Network Applications

As shown in Figure 1, our epoch value ended in 29. The Epoch value is a stop criterion that stands for the intended success. Our gradients descent value was terminated at 487. Our validation check value is 6 as targeted.

3. Results

In this study, open-source data set "Google Project Sunroof-Solar Panel Power Consumption Offset Estimate" database was used. The data set consists of 7999 records and 25 properties. All features used as databases are explained in detail in the database section of the article. With the obtained database, feedback artificial neural network method is used for the estimation of renewable energy in the future. Feedback artificial neural networks are composed of 3 layers. The data obtained in the input layer was used as input. In the hidden layer, the learning process of the artificial intelligence is realized. From the output layer, the results of the trained artificial intelligence were obtained. As a result, our artificial intelligence with feedback artificial neural network obtained 92,344% training

success, validation success 84,041% and test success 79,546%. Our overall success is 90,222%. In Figure 2, all results are presented visually.

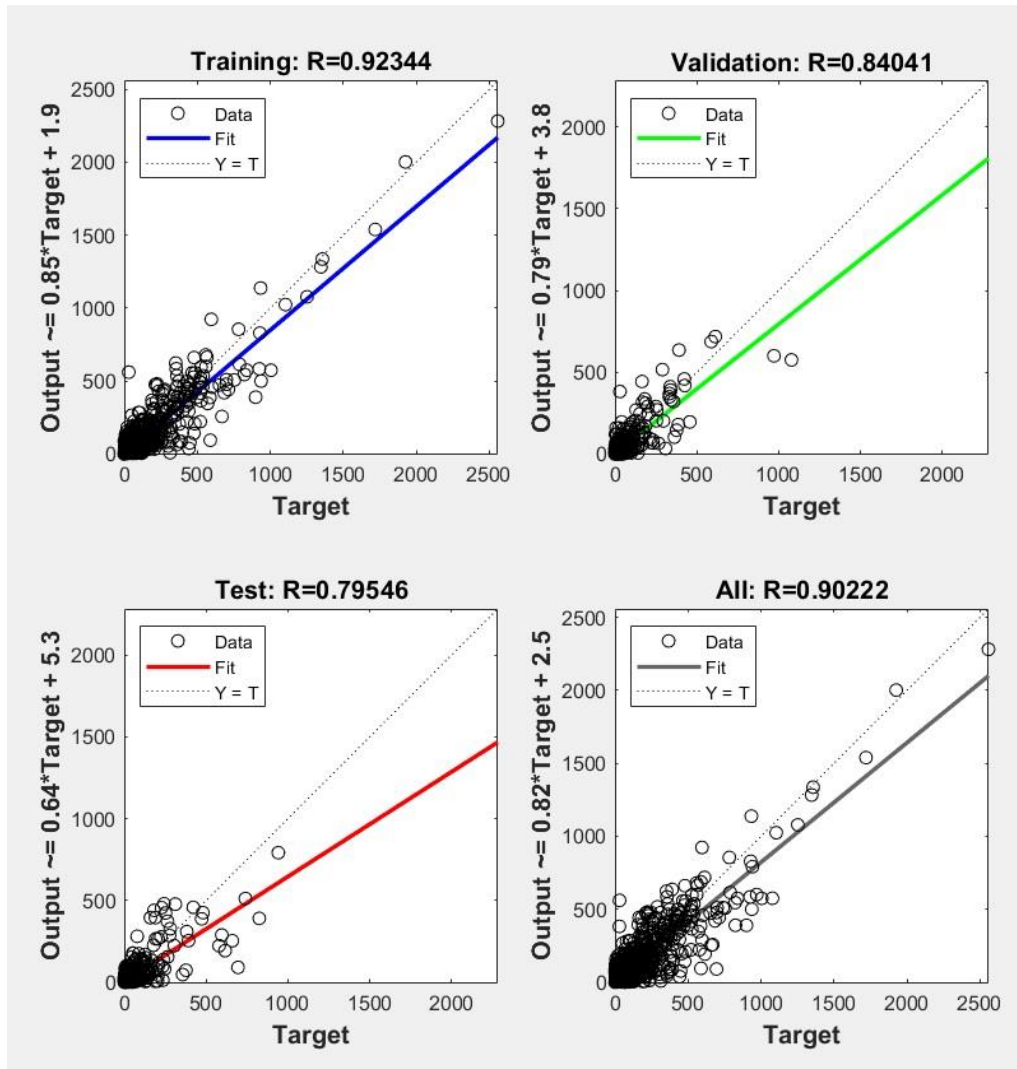


Figure2. Results

4. Discussion

In this study, artificial intelligence predicting energy consumption and energy needs of houses and buildings in the future by using feedback artificial neural networks is proposed. Predicting energy consumption is one of the tasks of countries and governments. As the energy needs increase day by day, the costs of meeting the energy needs are also increasing. It is necessary to anticipate this situation and avoid any bad scenarios. Not only governments but also people need to be prepared to meet their future energy needs [3,5,6].

Humans and many living species need electrical energy for the survival of their lives. Electrical energy is one of the most important sources of life. In this study, "Google Project Sunroof-Solar Panel Power

Consumption Offset Estimate" data set is used. With the database, an artificial intelligence has been obtained by using artificial neural networks with feedback.

5. Conclusion

The training of the artificial intelligence obtained was completed with 7999 samples with 25 different categories. This database, which is collected by Google, is obtained at high costs, so it is not possible for everyone to access such data bases. In this way, the fact that large databases are open-source benefits science and humanity. The success of the artificial intelligence trained with 7999 samples is due to the quality and sufficient samples. When the results are examined, it is understood that the data is sufficient.

In this study, the highest success was achieved by using 10 neurons in the feedback neural network. Since the number of neurons used is often related to the architecture of the artificial neural network, using 10 neurons cannot always be expected to work best. In this study, estimation of future energy consumption is presented with 90.22% success using historical data. This success can be increased and updated with more data.

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