Machine Learning in Smart Home Energy Monitoring System

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Abstract. In order to solve the insufficiency of the existing smart home energy monitoring system in autonomous adaptability, a smart home energy monitoring system based on machine learning and embedded technology is proposed. The system uses a gateway to collect sensor data, and then uses a cloud computing platform running Hadoop and machine learning algorithms to learn and identify user behaviours to achieve autonomous decision-making capabilities. Through the analysis of examples, it can be seen that the solution greatly improves the humanization of the smart home system.

1. Introduction
In order to integrate smart home resources and provide integrated smart home services, multitasking, intelligence and phantomizations have gradually become the development direction of the smart home industry. The intelligent automatic control of home equipment is the core capability of the smart home platform. The ideal smart home The automatic control system needs to have three basic characteristics: (1) It can automatically control the home environment without disturbing the user, freeing the user from the tedious operation of equipment, that is, "service without influence"; (2) Ability Accurately predict and adjust the working status of smart devices in a complex home environment to avoid equipment maloperation, that is "service precision"; (3) Being able to fully explore user habits, understand user needs, and optimize user experience, that is, "service intelligence" In the field of artificial intelligence, machine learning, especially deep learning methods, have achieved remarkable results in recent years. Compared with traditional technologies, deep learning methods have greatly improved the performance of speech recognition, image recognition, and natural language processing. Development and application prospects [1]. Based on the deep learning method, this paper proposes a home intelligent perception control model Deep home. This model is based on the smart home environment data for deep neural network model training, and perceptual analysis of smart home users' behaviour and habits to realize the smart home environment Centralized control of automation.

2. Machine Learning System

2.1. Principle analysis
The smart home machine learning system based on the LSTM network proposed in this paper is mainly composed of two parts, namely a predictive model and a business logic module [2]. Forecasting models are divided into benchmark forecasting models and household forecasting models. The benchmark prediction model is the improved recurrent neural network model based on LSTM proposed in this paper. It is generated based on a large amount of sample data training. The sample data refers to the

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environmental data inside and outside the home and the corresponding equipment status. The machine learning system needs to be customized for each family on the basis of the benchmark model, that is, to update the benchmark model according to the existing family environment data to become a family-specific predictive model. Therefore, the machine learning system in this article establishes a prediction model for each family connected to the system. At the beginning of the establishment of the family prediction model, it is based on the benchmark prediction model. After that, the machine learning system predicts the corresponding family based on the new sample data. The model is updated to adapt the predictive model to the environmental characteristics of the family, thereby improving the accuracy of predicting the state of the equipment. Figure 1 shows the equipment state prediction and prediction model update process of the machine learning system [3]. Before entering the machine learning system, the environmental data or sample data is normalized, and the family_id attribute is added, where the family_id attribute is used to distinguish which household the data is collected from. When the machine learning system judges that the received data is environmental data, the prediction execution module parses the data and judges its integrity, and then calls the prediction model of the corresponding household according to the family_id attribute carried in the environmental data, and takes the environmental data as input. Generate predictive data about equipment status information.

![Figure 1. Machine learning system equipment state prediction and prediction model update process.](image_url)

### 2.2. Machine learning model settings

The predictive model in the smart home machine learning system proposed in this paper is essentially a recurrent neural network model based on the improved LSTM. Recursive neural networks have shown strong learning ability in many natural speech processing tasks, especially the ability to model sequence data well and fully dig out the hidden information in the sequence [4]. In the LSTM variant proposed in this paper, the input of the "forgotten gate" layer consists of three vectors, they are the state $C_{t-1}$ of the "memory cell" at the previous time, the output $H_{t-1}$ of the "memory cell" at the previous time, and the input $X_t$ of the "memory cell" at the current time. Using $W_f, b_f, f$ to denote the weight, offset, and output vector of the "forgotten gate" sigmod neural network layer. The sigmod activation function is shown in equation (1):
Then the output vector of the "forgotten gate" neural network layer is shown in formula (2):

\[ f_i = \sigma(W_f [C_{i-1}, H_{t-1}, X_t] + b_f) \]  \hspace{1cm} (2)

Let \( C'_i \) denote the vector into which new information will be injected into the "memory cell", which is the output of the Tanh neural network layer, and \( w_c, b_c \) respectively denote the weight and offset of the Tanh neural network layer. Tanh activation function is shown in equation (3):

\[ \tanh(x) = \frac{1 - e^{-2x}}{1 + e^{-2x}} \]  \hspace{1cm} (3)

Then the expression of \( C'_i \) is as shown in formula (4):

\[ C'_i = \tanh(W_c [H_{t-1}, X_t] + b_c) \]  \hspace{1cm} (4)

Use \( C_i \) to represent the vector of the state of the "memory cell" at the current moment, then \( C_i \) is as shown in formula (5):

\[ C_i = f_i C_{i-1} + (1 - f_i) C'_i \]  \hspace{1cm} (5)

The "output gate" layer adds a "peephole". The input vector of this "peephole" is the state \( C_i \) after the update of the "memory cell". Therefore, the input of the "output gate" layer consists of three components, which are the current moment. State \( C_i \) of the "memory cell", output \( H_{t-1} \) of the "memory cell" at the previous moment and input \( X_t \) of the "memory cell" at the current moment. Use \( w_o, b_o \) to represent the weight and offset of the “output gate” sigmoid neural network layer, then the current “The expression of the output vector \( H_t \) of "memory cell" is shown in formula (6):

\[ H_t = \sigma(W_o [C_i, H_{t-1}, X_t] + b_o) \]  \hspace{1cm} (6)

In addition to the cross-entropy function, this article also uses the prediction accuracy of the prediction model on the test set as an evaluation indicator of the model's prediction performance.

3. Smart home energy monitoring system design

3.1. Hardware design

The local end of the system builds the home internal control network through WIFI and wireless router, and uses the gateway as the master control end. At the same time, the gateway communicates with the cloud via the Internet, and performs operations such as storage and machine learning on the cloud. Users can monitor the home environment and control equipment through smart terminals such as mobile phones and the cloud. The overall structure of the system is shown in Figure 2.
3.1.1. Gateway hardware design. The gateway functions as a hub and control. The outside is connected to the cloud through the Internet, and the inside communicates with the point through the WIFI module working in AP mode. Secondly, the gateway saves some configuration information and data information through the Flash memory.

3.1.2. Node hardware design. Since the node needs to communicate with the gateway, a WIFI wireless communication module working in STA mode is adopted. In addition, nodes are divided into two types: control nodes and sensor nodes [5]. Among them, the control node provides driving electrical equipment through signals such as PWM and SPI, and the sensor node obtains sensor data through the corresponding communication protocol. At the same time, the LCD display screen is used to display some device-related information, and the configuration information is stored through the EEPROM memory.

3.2. Software design

In terms of mobile clients, considering the wide distribution and ease of use of the Android platform, this system uses the Android platform as the development platform of the mobile client, and controls the home appliances and outdoor video capture through the Android platform, which is convenient for users to control anytime and anywhere. Home appliances and view outdoor video conditions.

3.2.1. The software of the central control subsystem. The central control subsystem is the core of the entire green building intelligent control system. It is divided into two parts, the intelligent system central controller and the mobile client. The software workflow is shown in Figure 3:

**Figure 2.** The overall structure of the intelligent and energy monitoring system.

**Figure 3.** Software flow chart of the central control subsystem.
In the intelligent central controller, the system must first initialize the two communication serial ports through the System Net Init () function, set the corresponding port number, baud rate, data bit, stop bit and parity bit and other parameters, and open the serial port, if it cannot be opened, an exception needs to be thrown. If it can be opened successfully, read the sensor information from one serial port and read from another serial port. Secondly, the system initializes the network port that needs to be monitored through the System Net Init () function the intelligent central controller acts as a server, accepts the connection of the mobile client and the data of the relevant intelligent node and records it. In addition, the central controller itself can also be operated by the user [6]. Through the operation of the display screen, the corresponding subsystem can be turned on to meet the requirements of the system.

3.2.2. **The software of the home appliance control subsystem.** The control of household appliances also adopts the method controlled by the 0x05 command in the Modbus-RTU standard protocol to force the relay to turn on or off. The 0x01 command is used to read the status of the output coil and keep it synchronized with the central control subsystem. The workflow of the home appliance control subsystem is shown in Figure 4:

![Figure 4. Software flow chart of home appliance control subsystem.](image)

3.2.3. **Software design of home security subsystem.** In the home security subsystem, it is necessary to monitor the video situation and possible fire occurrence, and feed this news back to the user in time. For fire warning, when the home security subsystem judges that the indoor smoke concentration is too high, it will first output an alarm sound higher than 85dB. If it is not handled in time, it will feed back the abnormal situation to the central control subsystem, and then the central control subsystem informs users to deal with possible fire situations [7]. For video surveillance, the home security subsystem needs to implement video surveillance access and monitoring functions on the embedded PC and Android clients respectively. Since the encoding format of the video is MJPEG format, it needs to be decoded when playing the video. Considering the large video capacity of the MJPEG format, it needs to be compressed. In order to ensure the indoor warning of fire at all times, a query method is used to check the fire situation. Once a fire is found, an audible alarm will be issued immediately. If the format of the obtained data frame conforms to the standard Modbus-RTU, and the CRC check code is passed at the same time, the system bus will return the data frame to the central control subsystem, and at the same time, the central control subsystem will notify the user and issue an alarm.
4. System Inspection
In order to study the performance of the Deep home model, 4 sets of related experiments were designed and carried out in this paper to test the accuracy of the model, the convergence speed of the model, the influence of the model parameters on the algorithm results, and the predictive ability of the model on real data samples. After data collation after that, 80% of the data of users S1 and S2 were randomly selected to form training sets T1 and T2, and the remaining 20% of data were used to form test sets A1 and A2. In order to fully evaluate the response speed of the model to user needs, T1 and T2 were intercepted respectively. Records that are different from the device status at the previous moment constitute test sets B1 and B2. Generally, users change the device status at home to meet their own needs. Therefore, when the model predicts the device status and the user’s device status at the next moment If the result of the operation (or do nothing, keep the device status unchanged) is consistent, it can be considered that the decision of Deep home meets the needs of the user. The prediction accuracy obtained by the test represents the user's control ability of Dephome to a certain extent Use training set T1 to perform 50 rounds of iterative training on the Dephome model, and use A1 and B1 for testing; similarly, use training set T2 for 50 rounds of iterative training, and use A2 and B2 for testing. The predictions of each test set are accurate the rate is shown in Figure 5.

![Model accuracy](image)

**Figure 5.** Deep home model prediction accuracy rate under the real data set.

From the experimental results, it can be seen that for users S1 and S2, the decision of the deep home model meets the user's needs in 98.9% and 97.3% of the time. The accuracy of the prediction of the user's change of the device status reaches 71.3%, 65.8%. On the one hand, the data submitted by user S1 is more abundant than that of user S2, but the number of devices is less, so the prediction of user S1 is more accurate. On the other hand, in the face of actual home environment data, the Dephome model is about Under 80 days of recorded data training, its prediction accuracy reached an acceptable 98.9%, which proved that the model can provide users with reliable smart home automatic control services in the actual environment.

5. Conclusion
This article innovatively introduces cloud computing and machine learning into the smart home system to realize the function of independent learning and control. According to the case analysis, this scheme can achieve a relatively high accuracy rate, which makes up for the shortcomings of traditional smart home in terms of humanization. However, the conditions achieved in this article are relatively simple, and do not fully reflect the advantages of this scheme, so in the future, we still need to study some realistic home environments.
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