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Intelligent Home Control System Leveraging IoT and Deep Learning Technologies

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Abstract. *Smart home technologies are slowly altering how people live as a result of the "Internet of Things' (IoT)" rapid development. By using sensors and cameras to gather environmental data in real time and allowing remote management of household appliances via a network, these systems enhance life's ease, security, and energy efficiency. But as the number of IoT devices rises, managing the massive volume of data these devices produce has emerged as a crucial problem for smart home systems. Deep learning technology has emerged as a key instrument to address this issue because of its potent data processing and pattern recognition capabilities. In this research, we propose an IoT and deep learning-based smart home system control scheme that uses deep learning algorithms to evaluate and comprehend the multimodal data in the home environment and make intelligent decisions. The perception, network, and application layers of the system architecture gather data using a laser sensor module, send it to a cloud recognition module using a ZigBee wireless data transmission module, and then use an STM32 control board to operate the household appliances. According to experimental results, the system exhibits a good intelligent control effect with a high recognition rate and control accuracy for voice control in smart homes. This paper's research offers a fresh viewpoint and technical assistance for the advancement of smart home systems.*
Keywords: IoT; deep learning; smart home

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1. **Introduction.** Smart home technologies are transforming people's lives as a result of the Internet of Things' (IoT) quick development. With the rapid development of IoT technology, smart home system is becoming a key factor to improve living comfort, security and energy efficiency. Smart home systems can gather environmental data in real time and remotely operate house gadgets via the network by utilising a range of sensors, cameras, and other IoT devices [1]. In addition to making life more convenient at home, these systems have a lot of promise for increasing security and reducing energy consumption [2]. But as the number of IoT devices rises, managing the massive amounts of data these gadgets produce has become a major concern for smart home systems.

Deep Learning Technologies, with their powerful data-processing and pattern-recognition capabilities, have become key tools for addressing these challenges, particularly in improving the adaptability of systems to environmental changes and their predictive accuracy. With its strong data processing and pattern recognition skills, deep learning technology has emerged as a crucial problem-solving tool in this situation. The system can better assess and comprehend the multimodal data in the home environment and make wise decisions by using deep learning algorithms [3]. There are still a lot of issues with combining multi-source data, system real-time, and restricted equipment resources, which require more study and investigation even if the combination of IoT and deep learning offers fresh concepts for the intelligent control of smart homes [4].

1.1. **Related work.** Over the past decade, smart home systems have evolved from basic device connectivity to complex systems that integrate advanced data analysis and machine learning techniques. Over the past several years, there has been a significant amount of focus placed on the investigation of smart home systems. The combination of IoT and deep learning technologies is often regarded as the most effective means of attaining advances in this niche. Suciu et al. suggested an end-to-end Internet of Things architecture that handles a huge volume of sensor data through cloud computing in order to accomplish interconnection and effective administration of smart home devices [5]. This architecture was developed in relation to Internet of Things applications. The findings of this study provide a theoretical basis for the implementation of Internet of Things technology in smart homes, particularly in the areas of cloud computing and data processing.

As the number of IoT devices continues to rise, an increasing number of researchers are concentrating their efforts on figuring out how to incorporate deep learning into smart home systems. Bianchi et al. developed a smart surveillance system that is based on a convolutional neural network (CNN). This system makes use of the picture data that is taken by Internet of Things devices for the purpose of anomaly detection [6]. Additionally, the system is able to recognise and respond to anomalous events in home security situations automatically. This research not only provides technological support for security monitoring in smart homes, but it also highlights the benefits of using deep learning in image processing.

Not only does the Internet of Things generate a great amount of image data, but it also generates a significant amount of time-series data, which is the focus of deep learning applications. Zhang et al. created a system that is based on recurrent neural networks (RNN) [7]. This system analyses and predicts the user's daily behavioural data, which allows the smart home system to automatically adapt the home equipment according to the user's habits. For example, the system can adjust the indoor temperature, light brightness, and other aspects of the home. The purpose of this study is to give technical support for smart home security monitoring and to demonstrate the benefits of supporting neural networks in image processing. This research not only highlights the effectiveness of RNN in the processing of time series data, but it also enhances the level of personalised service that smart home systems provide.

Although IoT technology and deep learning provide strong support for automation and intelligence in smart home systems, the combination of the two still faces some technical challenges [8]. Firstly, the multimodal data generated by IoT devices (e.g., temperature, humidity, images, and sound) are highly heterogeneous, which puts higher requirements on data fusion and processing. How to achieve efficient and accurate fusion between different types of data and ensure the real-time response of the system is one of the current challenges to be solved [9]. In addition, deep learning models, although excellent in processing complex data, are computationally intensive and require high hardware resources, how to lighten these models so that they can run on resource-constrained IoT devices is also an important challenge in system design.

Overall, existing research shows that significant progress has been made in the application of IoT and deep learning techniques to smart home systems, especially in home device control, security monitoring and personalised services. However, as the complexity of the system increases, how to efficiently process multi-source data and guarantee the security and real-time performance of the system remains one of the major challenges in the field.

1.2. Contribution.

The key innovations and contributions of this work are highlighted in the following areas, which mainly focused on the following three points:

(1) Innovation of system architecture: a smart home system control architecture based on IoT and deep learning is proposed, which collects home environment data through a laser sensor module, transmits the data to a cloud recognition module using a ZigBee wireless data transmission module, and finally realises precise control of home devices through an STM32 control board.
(2) Innovation in data processing: deep learning algorithms are used to analyse and understand the multimodal data in the home environment, which improves the system's ability to identify the user's intention and control accuracy.
(3) Innovation in experimental design: by constructing a dataset containing a variety of smart home scenarios, the system was subjected to comprehensive experimental tests, including key performance indicators such as speech recognition accuracy, control command execution accuracy, and system response time.

2. Theoretical analysis.

2.1. IoT in smart home systems.

A smart home system is built on the IoT, which uses a network of sensors and actuators to enable intelligence and automation in the house. Three layers typically make up an IoT architecture in a smart home system: the application layer, network layer, and sensing layer.

The sensing layer is in charge of continuously monitoring a number of home environment characteristics [10]. For instance, the following equation can be used to represent the data gathered by the temperature and humidity sensors:

$$T(t) = T_s + n(t) \tag{1}$$

where $T(t)$ denotes the real-time temperature at time t, T_s is the standard temperature value measured by the sensor, and $n(t)$ is the error caused by sensor noise.

The network layer is responsible for data transmission and processing [11]. The data is transmitted to the central processing unit through wireless communication protocols such as Wi-Fi and ZigBee. The effectiveness of data transmission can be evaluated by the channel capacity equation:

$$C = B \log_2 \left(1 + \frac{P}{N}\right) \tag{2}$$

where C is the channel capacity, B is the channel bandwidth, P is the signal power and N is the noise power.

The application layer, on the other hand, executes a specific control strategy based on the processed data [12]. For example, a smart home system may automatically adjust the air conditioning system according to the ambient temperature, and its control strategy can be described by a PID controller:

$$u(t) = K_p e(t) + K_i \int e(t)dt + K_d \frac{de(t)}{dt} \tag{3}$$

where $u(t)$ is the control input, $e(t)$ is the difference between the desired temperature and the real-time temperature, K_p, K_i and K_d are the proportional, integral and differential gains, respectively.

2.2. **Deep learning algorithms in smart home control.** The application of deep learning algorithms in smart home control systems mainly focuses on speech recognition, image recognition and natural language processing [13]. These algorithms improve the intelligence of the system by learning a large number of data features.

CNNs are particularly well suited for processing image data, where they extract image features through multiple layers of convolution and pooling operations. In smart home systems, CNNs can be used to identify security threats in the home, such as intruders or fires [14]. The heart of a CNN lies in its convolutional layer, which captures local features in an image through filters and integrates these features through deep network structures to recognise complex patterns.

$$(W * x)(i, j) = \sum_m \sum_n W(m, n)x(i + m, j + n) \tag{4}$$

where W is the convolution kernel weight, x is the input image, and $*$ denotes the convolution operation.

Pooling Layer is used to reduce the spatial size of the feature map and reduce the number of parameters [15], which can be represented by Max Pooling:

$$P(i, j) = \max_{m,n}(H_{i+m,j+n}) \tag{5}$$

where P is the pooled feature map and H is the output feature map of the convolutional layer.

LSTM is a special kind of RNN that can learn long-term dependencies. In smart home systems, LSTMs can be used to analyse users' behavioural patterns [16]. For example, to predict and automatically adjust lighting and temperature settings in the home by learning users' daily activity habits [17]. The core unit of an LSTM can be represented as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{6}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{7}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{8}$$

$$h_t = o_t * \tanh(C_t) \tag{9}$$

where f_t, i_t, o_t are the activation vectors of the forgetting gate, input gate and output gate respectively, C_t is the state of the memory cell and h_t is the hidden state.

NLP technology enables smart home systems to understand and respond to users' natural language commands [18]. By using deep learning models, such as recurrent neural networks or Transformer models, the system can extract key features in speech signals and convert them into executable commands. The feature extraction of the speech signal can be represented by the Mel Frequency Cepstrum Coefficient (MFCC):

$$MFCC = \log\left(\frac{1}{T}\int_{f_{min}}^{f_{max}} Mel(f) \cdot S(f)df\right) \tag{10}$$

where T is the integration time, f_{min} and f_{max} are the minimum and maximum frequencies of the filter, respectively, $Mel(f)$ is the Mel filter, and $S(f)$ is the spectral envelope.

3. IoT and deep learning based control of smart home systems: IoT-DL SHSC.

3.1. System hardware design. The control of smart home system based on IoT and deep learning is divided into a three-layer structure, the perception layer is designed with laser sensor module and language input, the laser sensor module collects home indoor temperature, humidity and other perceptual information, the user analyses the indoor data perceived by the sensor module, and then inputs voice control commands in the language input, and the speech input is transmitted to the cloud recognition module in the network layer for command recognition by ZigBee wireless data transmission module, and finally gives commands to the application layer STM32 control board to implement home equipment control response commands to achieve the overall control of the smart home [19]. After voice input, the voice input is transmitted to the cloud recognition module in the network layer for command recognition. Finally, the command is given to the STM32 control board in the application layer to implement home equipment control response commands [20]. This process achieves the overall control of the smart home. In this paper, the overall structure of the system is depicted in Figure 1.

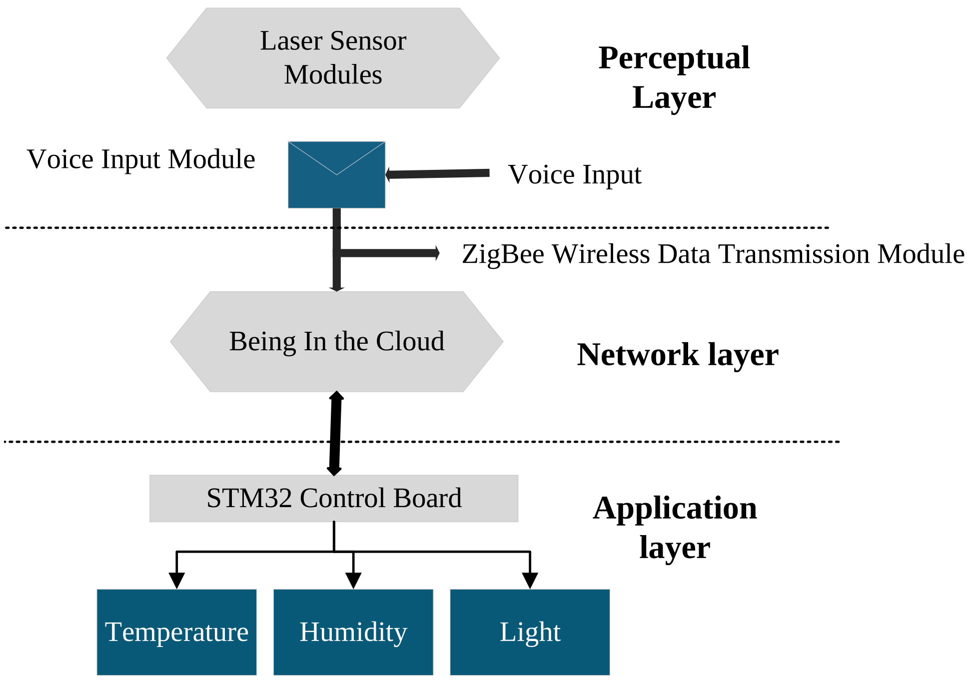

Figure 1. IoT-based control system for smart home language inputs

(1) Laser Sensor Module: The system user obtains home site sensing data through the laser sensor module in the sensing layer, and the laser sensor module collects data through the laser sensor nodes deployed in the site. The setup of laser sensor nodes in the smart home must follow the requirements of minimum energy consumption and minimum loss of communication data, so a cluster structure is used.

A common two-room, two-bathroom home construction is used as an example to set up the laser sensor nodes, and the structure diagram of the laser sensor node setup is described in Figure 2.

System perception layer in the smart home on the basis of the Internet of things system, through the Internet and the laser sensor to establish a wireless sensor network, the laser sensor is set in the approximate centre of the home environment, the node is set in the four edges of the laser sensor, the number of nodes that each edge has is three, the edge

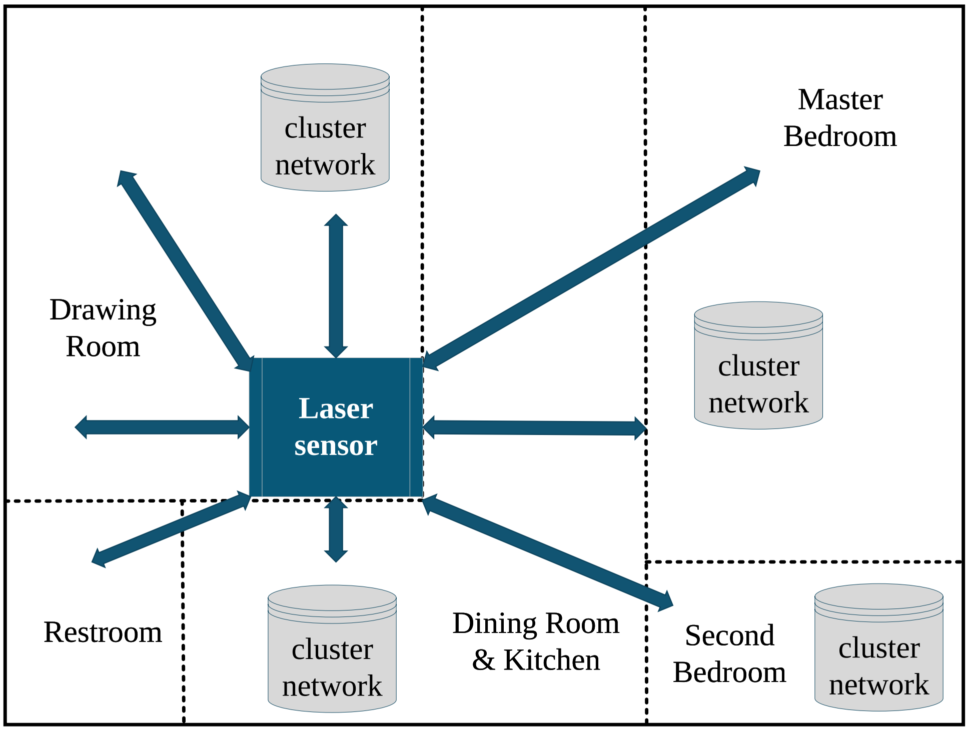

Figure 2. Structure of laser sensor node setup

of the intersection point to use the same node, the overall number of nodes in the home environment is eight, the node in the form of clusters of sensory The overall number of nodes in the home environment is 8. The nodes sense external data in the form of clusters, and the user can control the home temperature, humidity, and other conditions based on the known indoor sensing data by giving home control commands through the language input. Home indoor temperature, humidity and light data collectively referred to as the smart home environment data, the laser sensor is a symmetric device, with a laser transmitting element and laser receiving element, the two types of components installed in a symmetric form, the user is not stationary will block the laser signal, so the laser sensor will detect the user's human body data, when the user sends a command to automatically adjust the indoor temperature, the laser sensor will automatically adjust the human body temperature based on the collected data. When the user sends a command to adjust the room temperature automatically, the laser sensor will automatically adjust the home environment temperature according to the collected human body temperature.

(2) Language input terminal: the language input terminal in the system perception layer inputs the corresponding control language commands based on the home site data collected by the laser sensor module. The functions of the language input terminal are mainly reflected in the following four aspects: account login and cancellation, voice wake-up, voice recognition, and key control.

The main functional structure of the language input terminal is described in Figure 3, which sets up an account on the cloud server to obtain access privileges to log in and obtain control privileges, i.e. account login; waking up the system according to a specified word becomes the voice wake-up function, which does not require key touch, and the voice recognition function requires key control to be turned on.

(3) Cloud recognition module: the function of the cloud recognition module is to control the Baidu voice cloud recognition permissions as well as to set the relevant parameters of voice recognition and give commands to be transmitted to the application layer, and

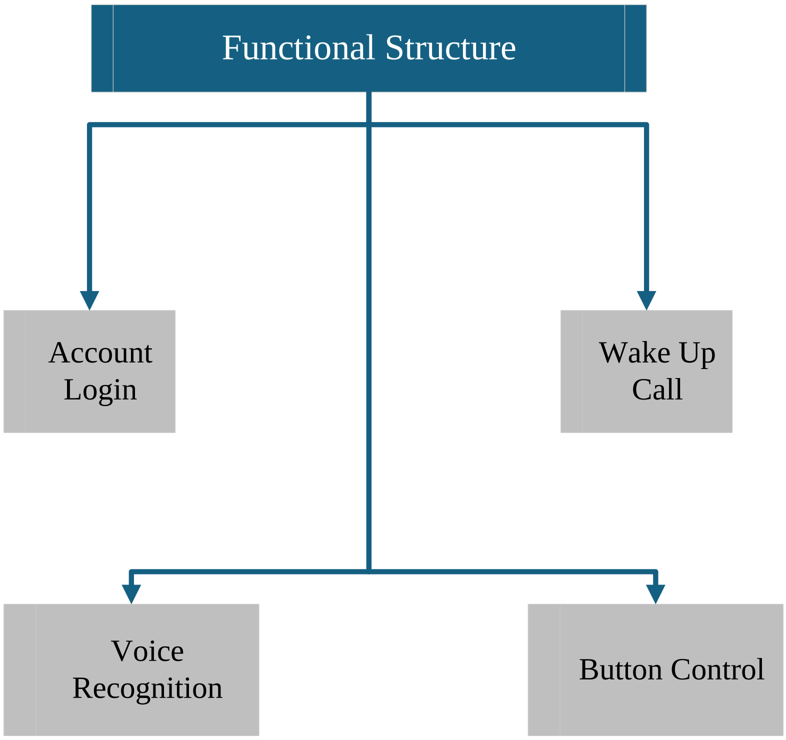

Figure 3. Functional structure of language input

at the same time, it needs to control the http request of NodeJS. The overall structure is described in Figure 4:

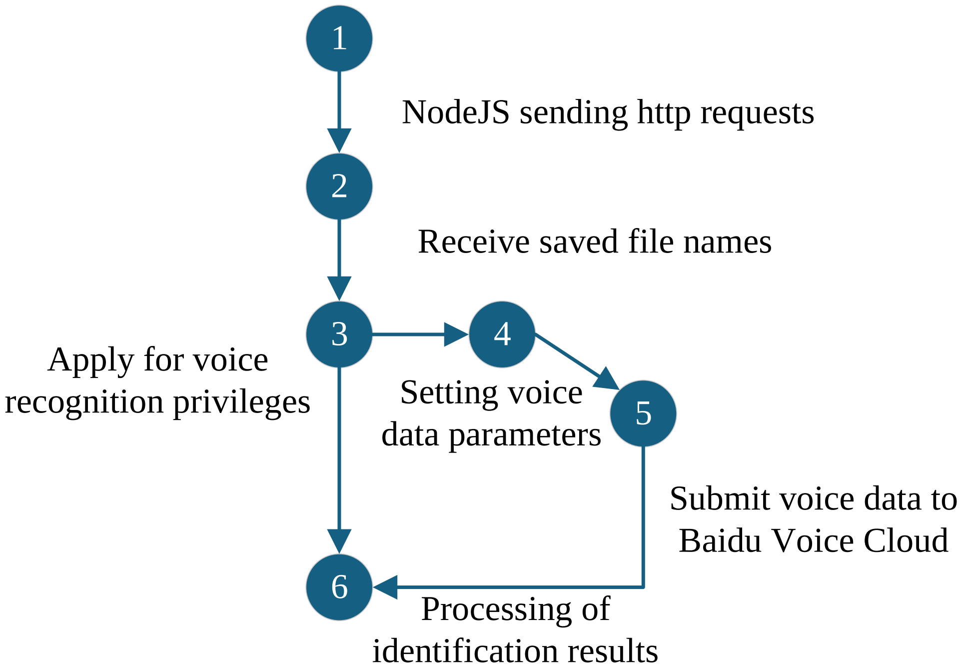

Figure 4. Structure of cloud recognition module

NodeJS is used to apply for the php file which is used to set the voice recognition parameters and turn on the voice recognition privileges, and this php uses ytf-8 no BOM encoding [21, 22]. When identifying Baidu voice, you must provide the product's apokey and secretKey, and the cloud returns the result after the audit. Only after the cloud audit meets the requirements, the voice file can be recognised. In addition addition, the encoding of the voice data must be provided.

3.2. **System software design.** (1) Smart home speech signal feature parameter extraction

In smart home systems, feature parameter extraction of speech signals is the basis for achieving accurate speech recognition. MFCC is a widely used technique that can effectively extract features of speech signals that are essential for distinguishing different speech commands [23]. The process of extracting MFCC parameters involves several key steps:

First, the actual physical frequency $R(n)$ of the smart home speech signal is transformed into the Mel frequency, where f is the physical frequency in Hertz (Hz) and M is the Mel frequency.

$$M = 2595 \log_{10}\left(1 + \frac{f}{700}\right) \tag{11}$$

$$f = 700\left(10^{\frac{M}{2595}} - 1\right) \tag{12}$$

Next, the time domain signal is converted into a frequency domain signal by Fast Fourier Transform (FFT), a step that reveals the spectral content of the speech signal [24]. The FFT formula is:

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi kn/N} \tag{13}$$

$x(n)$ denotes the time domain signal, $X(k)$ represents its frequency domain counterpart, and N signifies the number of points in the FFT.

The spectrum post-FFT is further processed with bandpass filters to replicate the aural characteristics of the human ear. Each filter is associated with a particular Mel frequency range, and its output represents the energy distribution within that range.

The outputs of the filters are logarithmically transformed, followed by the application of the Discrete Cosine Transform (DCT) to derive the MFCC feature vectors. DCT is defined as follows:

$$C_k = \sum_{n=0}^{N-1} x(n) \cos\left[\frac{\pi}{N}\left(n + \frac{1}{2}\right) k\right] \tag{14}$$

where C_k is the kth coefficient of the DCT, while $x(n)$ represents the logarithmically transformed filter output.

By following these procedures, we can extract essential features from the speech signals recorded in the smart home environment, which can then be utilised to train deep learning models for precise recognition and response to user voice requests. This method not only augments the naturalness of interactions within the smart home system but also amplifies its capacity to comprehend the user's intentions.

(2) DTW based keyword extraction technique for smart home linguistic inputs

Recognition of linguistic syllables: According to the preceding subsection, the parameters of the smart home language signal features are acquired and converted into a collection of smart home language signal feature vectors [25]. Language recognition necessitates the comparison of the tested language feature vectors with the stored language feature vectors in the cloud. When employing the DTW algorithm to discern and evaluate the keywords in smart home language inputs, the variability in the lengths of the test and reference languages necessitates the dynamic computation of proximity, referred to as distortion distance, between the two. Specifically, if we possess a set A of test speech feature vectors and a set B of reference speech feature vectors, the DTW method will identify the optimal matching path by minimising the cost function:

$$D(A,B)=\min_{\omega}\sum_{i=1}^{A}d(a_i,b_{\omega(i)}) \tag{15}$$

where d is a distance metric, usually Euclidean distance, and ω is a time regularisation function which maps the feature vector a_i of the test speech to the feature vector $b_{\omega(i)}$ of the reference speech. With this approach, we are able to accurately assess the similarity between the test speech and the reference speech even if they differ in length.

Linguistic Keyword Recognition: After the language syllable recognition, we need to identify the language keywords, separate the test language according to the syllables, and match the feature vector parameter W_1 in the acquired smart home language signal syllable with the syllable W_2 in the cloud, if the proximity between the detected syllable and the syllable in the cloud is $W_1 > W_2$, then we can preliminarily determine that it is likely to be the first syllable of the keyword, and the next syllable can be examined: if $W_1 < W_2$, then the next syllable can be examined, until the monitored syllable is the first syllable of the keyword, and then the next syllable can be examined. If $W_1 < W_2$, the next syllable will be examined until $W_1 > W_2$, and then we will return to the cloud and match the keywords with the keyword parameters, and if there is a similarity of $W_1 > W_2$, then we can decide that the 'possible keyword' is a keyword. If there is a similarity of $W_1 > W_2$, it can be decided that the 'possible keyword' is the keyword, and at the same time, it can determine the meaning of the keyword and implement the matching home control command.

(3) Integration and improvement of deep learning models

In smart home systems, the integration and optimisation of deep learning models are essential for attaining effective intelligent control. We utilise diverse deep learning architectures, such as CNNs for image recognition, LSTMs for time series analysis, and NLP models for spoken command interpretation. We utilise model compression approaches, including weight pruning and quantisation, to facilitate the operation of these models on resource-constrained IoT devices by minimising their storage and computational demands.

The weight pruning technique diminishes model complexity by eliminating insignificant links in the weights, whereas quantisation transforms model parameters from floating-point numbers to low-precision formats, such as int8, to decrease storage and computational demands of the model. The utilisation of these strategies can be expressed by the subsequent equation:

$$W_{\text{pruned}} = W \odot M \tag{16}$$

Let W represent the original weight matrix, M denote a mask matrix indicating which weights are to be preserved, and W_{pruned} signify the pruned weight matrix.

Furthermore, we utilise edge computing methodologies to implement deep learning models on edge devices within smart homes, such as smart speakers or gateways, to minimise data transfer latency and enhance system responsiveness. This distributed computing design enables devices to process data locally and interact with the cloud only when required, thereby enhancing system efficiency and safeguarding privacy.

(4) Design and Implementation of Control Strategies

The results of deep learning models are utilised to build control strategies for smart home devices. For instance, the NLP model discerns the user's intent from voice instructions and produces the appropriate control signals. The STM32 control board implements these control signals on the application layer to ensure precise management of home devices. The control strategy design include the analysis of model outputs, the execution of decision logic, and the integration with physical devices.

In the design of the control system, we employed an adaptive control method grounded in reinforcement learning. This method enables the system to autonomously modify its behaviour based on external feedback to attain optimal control. The essence of reinforcement learning is that the Agent acquires the optimal Policy through interaction with the Environment as follows:

$$\pi_\theta(s_t, a_t) = \frac{\exp(\theta^T f(s_t, a_t))}{\sum_{a' \in A} \exp(\theta^T f(s_t, a'))} \tag{17}$$

where π_θ is the policy defined by the parameter θ, s_t is the state at time t, a_t is the action at time t, A is the set of all possible actions, and $f(s_t, a_t)$ is the eigenvector of the state-action pair.

5. Conclusion. The smart home system control scheme based on IoT and deep learning proposed in this paper achieves intelligent decision-making and control by analysing and understanding multimodal data in the home environment through deep learning algorithms. The experimental results demonstrate the high recognition rate and control accuracy of the system for smart home voice control, providing a new technical solution for the development of smart home systems. This study was mostly conducted in controlled simulated situations throughout the experimental phase, perhaps constraining our comprehension of the system's applicability in varied real household settings. The intricacy of actual home settings, encompassing ambient noise, voice commands in various dialects and accents, together with the variability of human behaviours, may affect the system's accuracy and response time. Furthermore, the system's security and privacy protocols, while acknowledged, may encounter more intricate data protection issues in actual implementations. Consequently, the system's resilience, security, and privacy protection mechanisms require further testing and enhancement across a broader spectrum of user demographics and environmental conditions. Future research may investigate the following avenues in further depth. The system must be implemented and tested in actual household contexts to assess its performance and user experience across various environmental conditions. Secondly, to enhance the system's generality, the speech recognition skills should be expanded to accommodate various dialects and accents, hence allowing the system to cater to a broader spectrum of user demographics. Furthermore, the system's security and privacy protection features require augmentation to safeguard user data effectively. Ultimately, adaptive learning techniques informed by user behaviour may be investigated to enable the system to autonomously modify the control strategies of home devices in accordance with user habits and preferences, thereby delivering a more personalised and intelligent domestic experience. By exploring these research avenues, the sophistication of smart home systems can be significantly improved, providing consumers with a more convenient, pleasant, and secure living environment.

4. **Conclusion.** The smart home system control scheme based on IoT and deep learning proposed in this paper achieves intelligent decision-making and control by analysing and understanding multimodal data in the home environment through deep learning algorithms. The experimental results demonstrate the high recognition rate and control accuracy of the system for smart home voice control, providing a new technical solution for the development of smart home systems.

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