Smart Memory Storage Solution and Elderly-oriented Smart Equipment Design under Deep Learning

Abstract: This study is to explore the memory characteristics of the elderly to design effective smart devices, so as to improve the learning efficiency of the elderly. The different stages of memory formation in the existing human brain are analyzed. A smart memory storage solution based on memory-enhanced embedded learning is constructed using the deep learning. Based on meta-learning, the constructed solution learns the universal meta-knowledge of different learning tasks by establishing the identically distributed meta-learning tasks, thus reducing the cost of learning new tasks to the greatest extent. Finally, to the performance of proposed solution is verified using different data sets. The results reveal that the solution based on deep learning has obvious effects on different data sets, with an average accuracy rate of 99.7%. The solution reduces the learning by synthesizing a large number of target sample features, which greatly reduces the difficulty of learning and improves the learning effect. The elderly-oriented smart device proposed effectively reduces the problems in the current market and lowers the difficulty of learning, which provides an important reference for further enriching the devices in the aging market.

Keywords: deep learning; smart memory; storage solution; elderly-oriented; smart device

1. Introduction

With the rapid development of Chinese society, the social aging has gradually become prominent. According to statistics from relevant departments, the population over 65 years old in China will account for 14% of the total population by about 2022, realizing the transition to an aging society [1]. Among the population with chronic diseases, the elderly account for a larger proportion. The accelerated aging and the increasing number of people infected with chronic diseases in China have caused serious social development problems [2]. Especially for the elderly, the demand for chronic disease management is gradually increasing. This disease generally has a short onset period and a more rapid onset, which also seriously endangers the health of the elderly [3]. The development of traditional medical treatment is restricted by region and technology. However, with the development of Internet of Things (IoT), deep learning, and global positioning system (GPS) technology, smart medical methods are gradually emerging. Compared with traditional medical methods, the core of smart medical care is healthy management and testing of the elderly, which can provide more convenient and efficient services for the elderly [4]. With the help of IoT technology and corresponding human sensors, smart medical care can realize the collection and analysis of patient-related body data. Smart medical care can effectively shorten the connection among patients, doctors, and hospitals, and strengthen the mutual relationship of the three, ultimately achieving the timely prevention and timely treatment [5]. Although the home smart health management equipment has been greatly improved in technology, there are still some problems in practical applications, which brings great difficulties to the adaptation of the elderly [6]. Therefore, designing a corresponding elderly-oriented smart device according to the physical function of the elderly has very important practical value for protecting the health of the elderly.

The new medical service model developed by smart medical care helps the win-win cooperation for medical institutions, Internet companies, and smart medical product design companies, and provides patients with home smart health management products with better user experience [7]. The research and development of home medical equipment for the elderly in China is still in its infancy stage, and the operation difficulties encountered by the elderly in interacting with products in their daily lives. Some scholars have deeply analyzed the advantages and disadvantages of the current smart device, and proposed that the design has to ensure the ease of use based on the user characteristics of the elderly, and the intermediate operation process has to be reduced to make it more convenient, which helps to effectively monitor the health of the elderly [8]. Smart medical and health equipment can effectively prevent the deterioration of diseases to a certain extent and protect the physical safety of the elderly [9]. Deep learning is a branch of machine learning. It is an algorithm that uses artificial neural network (ANN) as the architecture to perform characterization learning on data. It is an algorithm in machine learning based on characterization learning of data [10]. This method can update the device data according to the way the human body learns, which can effectively simulate the learning process of the elderly to a certain extent, and it is more convenient to implement. Therefore, some scholars have applied it to the elderly-oriented smart device and obtained good experimental effects [11]. From the background of aging, the domestic aging is intensifying, and the development speed of chronic diseases is accelerating among the elderly [12]. From the perspective of the industry background, the current more common smart health management terminal products are mainly designed for young people, ignoring the memory and learning of the elderly, and reducing the utilization rate of product among elderly users [13]. Therefore, on the basis of studying the memory and learning of the elderly, it is very necessary to adopt a deep learning method to establish a design system for the ease of use of the smart health management terminal based on the memory and learning rules of the elderly.

In this study, deep learning methods are introduced from the perspective of memory storage to establish and design corresponding elderly-oriented smart device solutions based on the learning efficiency and memory research theories. In addition, a smart memory storage solution based on the memory-enhanced embedded learning is proposed, the effectiveness of which is verified further through performance analysis of the specific data set. The core of this study is to improve the learning efficiency of elderly users when using smart health management terminals, which can provide reliable ideas for the research and development of related smart devices.

2. Recent related works

2.1 Learning rate

Learning efficiency is the amount of knowledge that can be accepted and absorbed in an effective time. The research on learning efficiency is mostly concentrated in the field of teaching. The core is to study the memory characteristics of the human body and adopt different strategies to effectively improve people's learning efficiency [14]. Fattinger et al. (2017) introduced a new deep sleep method used to locally disturb the motor cortex, and found that when slow waves are selectively disturbed in the motor cortex, this recovery process can be greatly weakened, showing that deep sleep is a necessary condition to maintain sustainable learning efficiency [15]. Katona and Kovari (2018) developed a brain-computer interface (BCI) system and applied it to the learning efficiency test of cognitive neuroscience to evaluate the output results by observing the vigilance level calculated by Think Gear-ASIC module technology, and found that there is an obvious difference between this method and the conventional cognitive neuroscience test [16]. Pu et al. (2019) believed that the learner's internal motivation is the most critical determinant that affects the nature of the results, and critical thinking is essential to improve learning efficiency, which were proved through specific experiments [17]. Ma et al. (2020) used a clustering strategy to divide the population into multiple clusters, and proposed an orthogonal learning framework to improve its learning mechanism; the experiment proved that this method is very effective in optimizing complex functions and improving learning efficiency [18]. These studies analyzed the relationship between different types of memory materials in educational disciplines on the working memory and learning of different types of subjects, confirmed the important position of memory in high-level cognitive activities, and reflected that memory has a great influence on learning efficiency. The psychological and physiological effects of the elderly on some specific factors will be correspondingly reduced, so this study focuses on how to improve the learning efficiency of the elderly using smart health management terminal products so as to reduce their learning costs from the perspective of memory.

2.2 Memory theory

Memory theory is a cognitive psychology theory that studies the occurrence, development, and laws of human memory. The earliest method is proposed by the psychologist Ebbinghaus for various memorization materials, which need to adopt different methods of checking the storage capacity to improve the memory ability of the human body [19]. Subsequent, American scientists further refined the above theory and proposed that primary memory involves direct conscious experience, and its reappearance does not require effort but is a true reappearance of things that have just been noticed, so it is inseparable from the current consciousness and has a temporary nature [20]. Later, related scholars put forward a corresponding forgetting curve, which proposed that the secondary memory is a retelling of primary memory, in which only part of primary memory can form the secondary memory, and the rest is forgotten by the human brain [21]. For the study of memory theory, Weger et al. (2018) used a systematic method to develop a taxonomy of mental processes involving recall, and found that this method can provide support for human memory and mental activities involving various types of recall are greatly different [22]. Sweller et al. (2019) introduced emotional memory from memory psychology into the field of product interaction design, and established a basic emotional memory system architecture, proving the value of emotional memory in design innovation [23]. Kvavilashvili and Rummel (2020) pointed out that when people naturally engage in forward thinking without clear instructions, they are mainly considering upcoming tasks and planned activities, rather than simulating specious but novel hypothetical scene [24]. Although memory characteristics belong to the field of psychology that is difficult to carry out quantitative research, the current research basically focuses on how to make the learning plans reasonably and effectively based on the human memory characteristics, and scholars who combine memory theory and design theory for research are relatively rare.

3. Methods

3.1 Memory process of human

Learning and memory can be considered as a process of combination, and the ability of the human brain to remember information will affect the learning efficiency of the human body to a certain extent. As shown in Figure 1, the main memory process in human brain includes (1) attention and selection (the core of which is to form a certain cognitive ability through the perception of the surrounding environment), (2) information coding (the core of which is to realize effect combination and management of the obtained information), and (3) information storage (the core of which is to permanently record the sorted information and knowledge). The attention and selection is the first process of memory. At any moment, there will be a lot of information in everyone's environment. In many cases, the human sensory system can't process all the information, so it has to make selection, which can be conscious or unconscious [25].

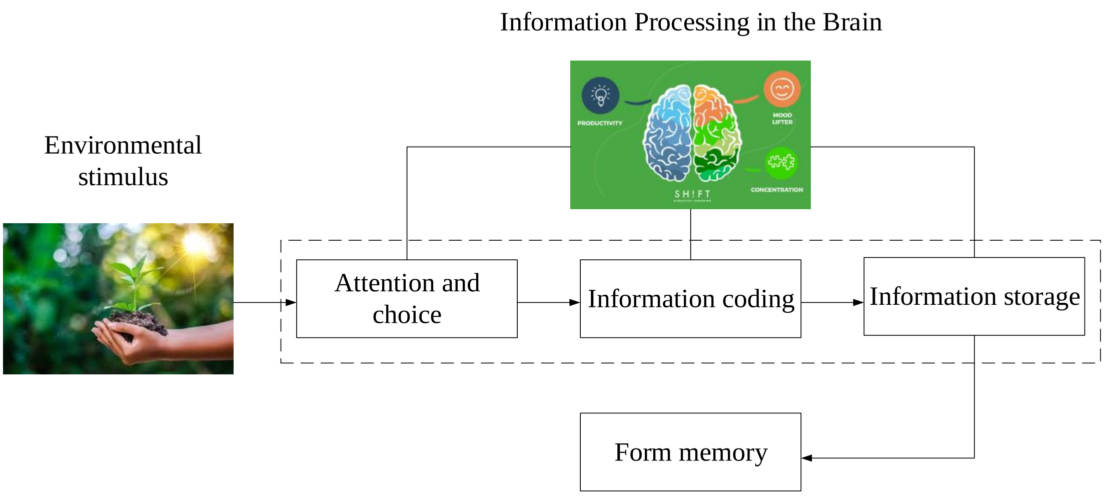

Figure 1. The main memory process in human brain.

If there is a large amount of information, the things that are interested by the human brain are perceived by the sensory system and stored as clear sensory memories, which are processed into long-term memories and stored. Things that are not interested by the human brain are not perceived by the sensory system, forming a vague sensory memory, and finally are forgotten. The specific process can be obtained in Figure 2. The information that the human brain consciously selects to remember is the information that people deliberately wants to remember. Therefore, the key information that users need to perceive are required when a product is designed. Increasing the amount of information stimulus to the human senses can help body to better perceive and remember this information [26].

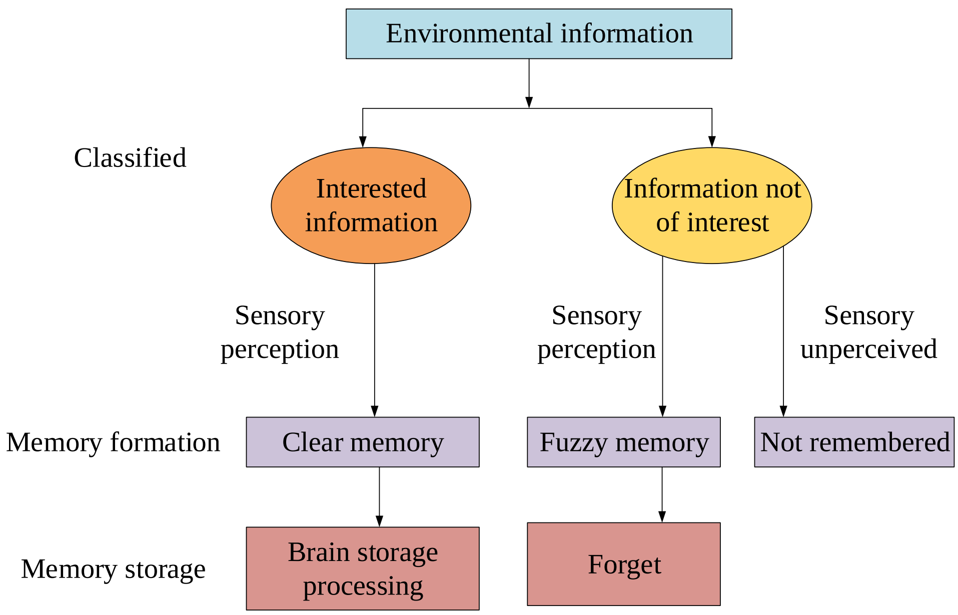

Figure 2. Information processing in the human brain.

Coding is to process the information that has attracted the attention of the human brain. It is a complex and changeable process in the brain. Encoded information varies from person to person. For different information received by the sensory organs, the human brain has a different encoding process. For a single piece of information, humans will always use multiple sensory organs to receive information, so they will remember the information more deeply and the information content of the memory will be more accurate. The main reason for the decline in memory of the elderly with age is that the process of encoding information is weakened, especially those involving complex logical relationships are difficult for the elderly to remember. Storage is to store the information in memory. The stored information will form short-term memory and long-term memory according to the length of time. Short-term memory refers to brief and short-term memory. Simple repetition or practice can help to convert short-term memory into long-term memory to a certain extent, and another strategy for conversion is the deep thinking [27].

3.2 Smart and memory solution under deep learning

Based on the above-mentioned memory process and the memory characteristics of the elderly, it is found that the deep learning method is more suitable for the memory analysis of the elderly, so the smart memory and storage solution of deep learning is introduced. As shown in Figure 3, the mechanism of spatial attention is adopted to help the elderly distinguish different environments, establish corresponding feature aggregation images in space, and then use two activation functions with ReLU and Softmax to convolute, and output a corresponding soft attention weight result. At the position with smaller weight, the feature representation method of spatial attention enhancement [28] is obtained by calculating the initialized characterization weight value. The specific calculation method is as follows:

$$S_p = \sum_{m,n} \alpha_{m,n} e_{m,n,p} \tag{1}$$

In the above equation, S_P refers to any element in the feature vector S; $a_{m,n}$ represents any element and information; and $e_{m,n,\ p}$ represents any element in any initial character E.

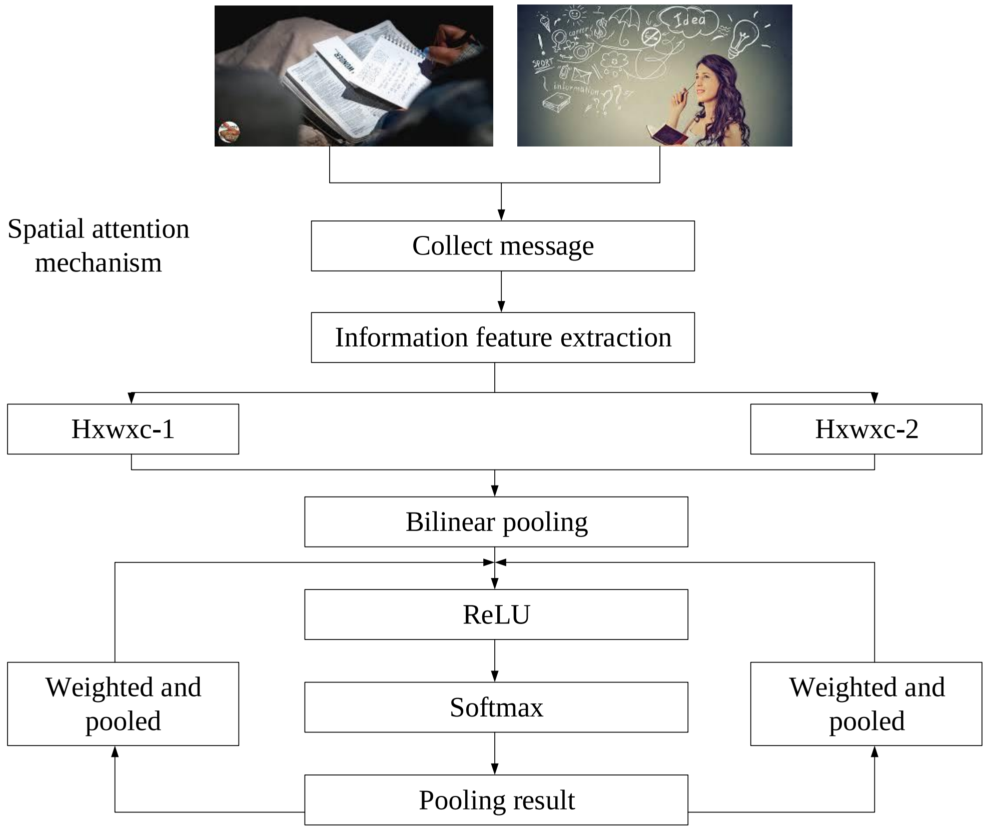

Figure 3. The mechanism of task-related spatial attention.

Different from those methods that rely entirely on memory block to generate feature representations, memory block is undertaken as an auxiliary part in this study. For the categories in the meta-training set, a memory module M is trained, and the memory block is adopted in the meta-testing stage to enhance task-related representations. In the meta-training stage, the feature representation of the support set samples will be continuously used to update the memory slots of their corresponding categories. A mechanism is designed in this study to avoid forgetting the previous memory when the memory is updated. Specifically, the sample features of a support set enhanced by spatial attention are updated according to the following equation:

$$m_{cls} \leftarrow \frac{m_{cls} + \gamma^{tcls} S_s^{(i,j)}}{\left\| m_{cls} + \gamma^{tcls} S_s^{(i,j)} \right\|_2}, t_{cls} = 1 \tag{2}$$

In the above equation (2), γ^{tcls} is the attenuation rate; cls represents the category in the meta-training set; m_{cls} represents the representation of the category in the memory module; t_{cls} refers to the number of times the memory of the category is updated, and is $S_s^{(i,j)}$ represents the support set sample feature enhanced by spatial attention. As memories about categories accumulate, the importance of newly added representations will decrease. The amount of data in the meta-training set is fixed, and as the number of training rounds increases, the probability of encountering repeated data becomes greater. In the early stage of training, the memory relies to a large extent on newly added representations to update. With the accumulation of memory, the memory in the memory slot is more robust than the newly added representation, so the weight of the new representation needs to decrease with the increase of time. The weight vector w_{cls} can be obtained by calculating the cosine similarity of each:

$$w_{cls} = Soft\max\left(\frac{v \cdot m_{cls}}{\|v\| \cdot \|m_{cls}\|}\right) \tag{3}$$

In the equation above, v represents the function of obtaining the auxiliary vector of memory enhancement. The memory update is performed only in the meta-training stage. In the meta-test, only the read value of the memory is performed to support the data set. The average value of the sample features of the supporting data set can be calculated with equation (4) below:

$$C_{cls}^{mean} = \frac{1}{k}\sum_{i} S_S^{(i,j)} I(y_S^i = cls) \tag{4}$$

In equation (4) above, $I(y_S^i = cls)$ is the designated symbol, the value is 1 or 0; and k is the correlation coefficient. Next, the category representation can be calculated using the auxiliary vector:

$$C_{cls} = \sigma(\alpha) C_{cls}^{mean} + (1-\sigma(\alpha)\xi(C_{cls}^{mean})) \tag{5}$$

In above equation, σ is a Sigmoid function, which is used to weigh the weight between the representation of spatial attention enhancement and the memory auxiliary vector. The characterization of the query sample set *cls* of the K vector can be calculated, as follows:

$$Q_{j,cls} = \frac{1}{k}\sum_{i} S_q^{(j,i)} I(y_s^i = cls) \tag{6}$$

Finally, the related tasks can be embedded and the output can be regarded as a two-tuple. These two-tuples will be input to the metric learning calibration block to learn the similarity metric between the respective elements. In the metric learning part, the compact bilinear pooling is adopted, so that all elements in the category feature can interact, so as to obtain a comprehensive and compact fusion feature representation [29]. The specific structure is shown in Figure 4.

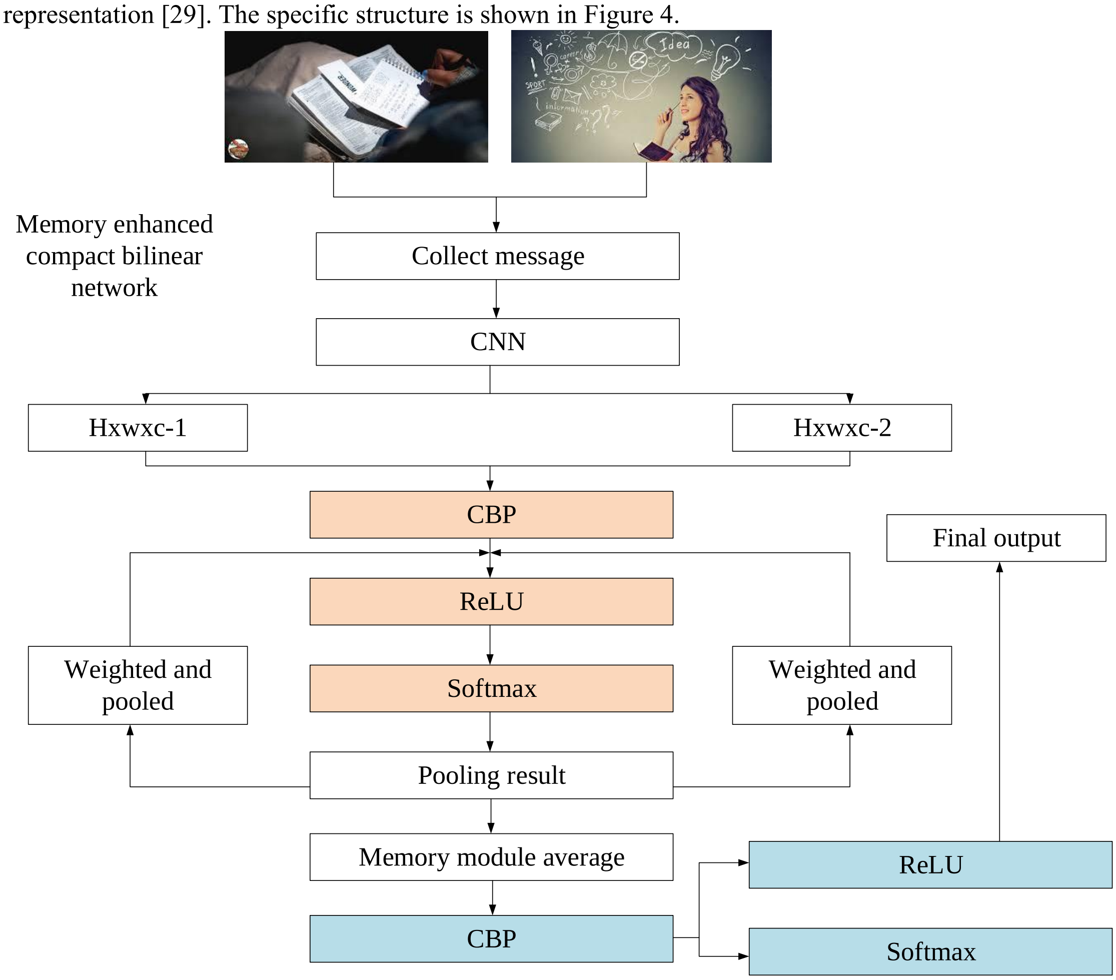

Figure 4. Memory enhanced compact bilinear network.

3.3 Elderly-oriented smart device

Based on the above-mentioned core memory process, the corresponding elderly-oriented smart device is designed, which is mainly divided into information perception layer, information coding layer, and information storage layer. The core is the easy-to-use design of the home smart health management terminal for elderly users, which is to make the product easy to learn and use for elderly users, with less memory burden and high user satisfaction. Improving product usability can be achieved by reducing product functions, streamlining interface information, or reducing user cognitive costs. Reducing the burden of memory in the process of using the product is also the embodiment of the ease of use design of the product. Therefore, a hierarchical model is constructed in this study for the three stages of the information memory process in the human brain and the connection with the smart health management terminal products. The specific details of the model are shown in Figure 5. The information perception layer helps the human brain draw attention to the surrounding environment and make a certain selection of information, which is also the basic condition for the user to complete the task. After obtaining the information, the information coding layer processes and combines the information. The information storage layer is to permanently record the information after assembly and sorting. First of all, the human brain acts on the information perception layer for the huge amount of information in the surrounding environment. Secondly, the information further enters the deeper information coding layer. Finally, the information can be stored by the human brain only after the coding process. Therefore, the three layers of the constructed model can be deemed as a process in which information generates memory in the brain, which is continuous and gradually increasing from the shallower to the deeper.

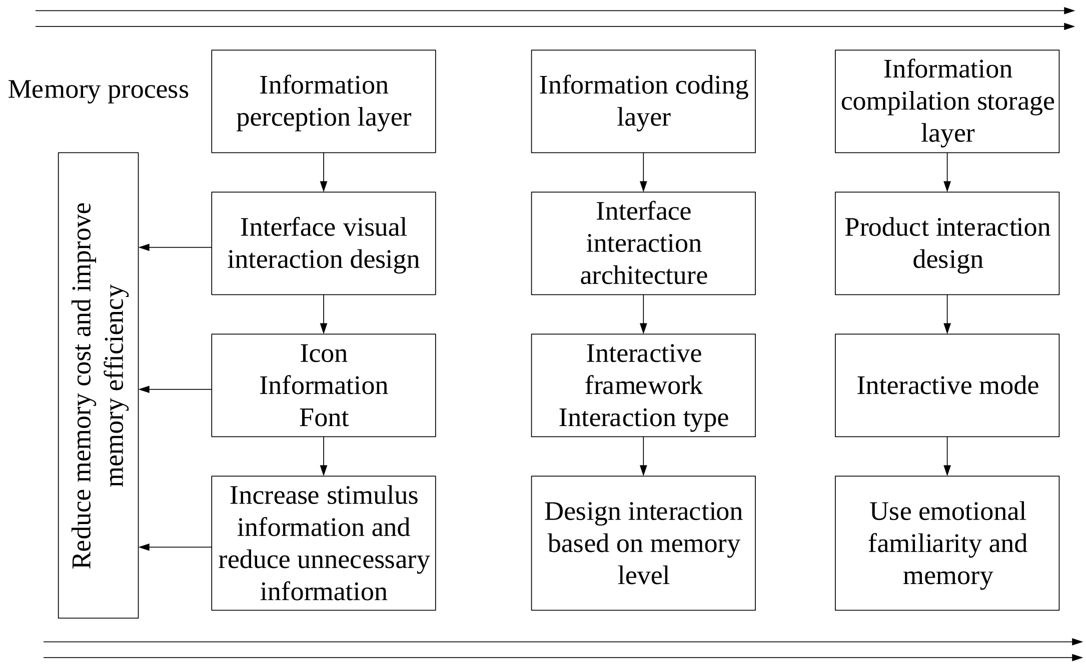

Figure 5. The specific details of hierarchical model with easy-to-use design.

3.4 Parameters setting and data sources of the model

The proposed model is verified on different data sets, including image data sets and the video data sets. The image data sets include Omniglot (the first image data set for small-sample classification), minilmageNet (containing 60,000 color images in 100 categories) [30], and tieredlmageNet (containing 779,165 images in 34 higher-level categories, which are subdivided into 20 training categories, 6 verification categories, and 8 test categories). The video data sets include UCF11 (a very challenging action recognition data set, containing 1,600 videos in 11 action categories), UCF101 (an action recognition data set, covering 101 different types of actions and a total of 13,320 videos), and HMDB51 (covering indistinguishable fine-grained categories such as smile, laughter, diet, and drinking) [31].

The task-based training is adopted in this study, and the meta-testing process is simulated by sampling the N-way K-shot task of the meta-training set. In the Omniglot data set, the size of the image is 28×28; and the image in the minilmageNet and tieredlmageNet data sets is scaled to a size of 84×84. For all experiments in this section, the Adam optimizer is adopted, the initial learning rate is set to 0.001, and the learning rate is halved after 20,000 episodes. The training is stopped when there is no lift on the validation set. The memory calibration block is updated and extracted during the meta-training process, and the updated decay rate y is set to 0.995. In the meta-test, the update process of the memory calibration block is frozen, and only auxiliary vectors are extracted to enhance the representation of the category level. The bilinear pooling rate is set to 0.7% ~ 3%.

4. Results and discussion

4.1 Classification of image data

Figure 6 shows the sample classification results on the Omniglot dataset. Figure 6A illustrates the classification results on the 5-way, and Figure B shows the classification results on the 20-way. Except for the earlier Siamese Network, other models can achieve more than 90% accuracy rate on all tasks. On the simpler 5-way 1-shot and 5-way 5-shot tasks, many models including the proposed solution have reached the accuracy rate of 99%. When the supporting samples of categories increase, the classification effect of all models is improved; and when the number of categories in the task increases from 5 to 20, the accuracy of all methods is lower than that of other tasks. In the most difficult 20-way 1-shot task, the solution proposed can achieve an accuracy rate of about 98%, which is about 0.6% higher than the best results in other methods.

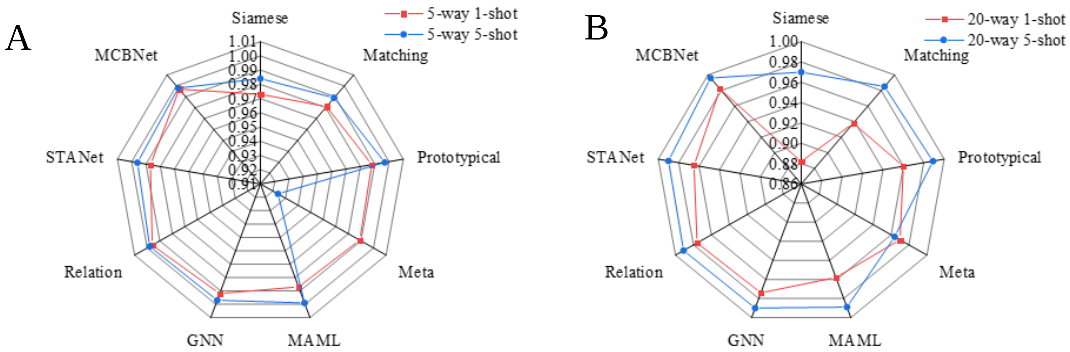

Figure 6. The sample classification results on the Omniglot dataset.

Figure 7 illustrates the sample classification result on the minilmageNet data set. Figure 7A shows the classification result on G64F-4, and Figure 7B shows the classification result on Resnet-12. Three types of feature extraction networks are used. When the C64F-4 is adopted, the accuracy rate of TPN solution is increased by about 1.4% and 2.4% on the 5-way 1-shot and 5-way 5-shot, respectively, which is good before. When the Resnet-12 is adopted, the accuracy rate on the 5-way 1-shot task is improved by about 2.1%, and that on the 5-way 5-shot task is about 0.8% lower than that of TADAM. However, the WRN-28 is adopted, the accuracy rate of LEO is improved by 0.4% and 1% on 5-way 1-shot and 5-way 5-shot tasks, respectively, in contrast to the previous models with good performance.

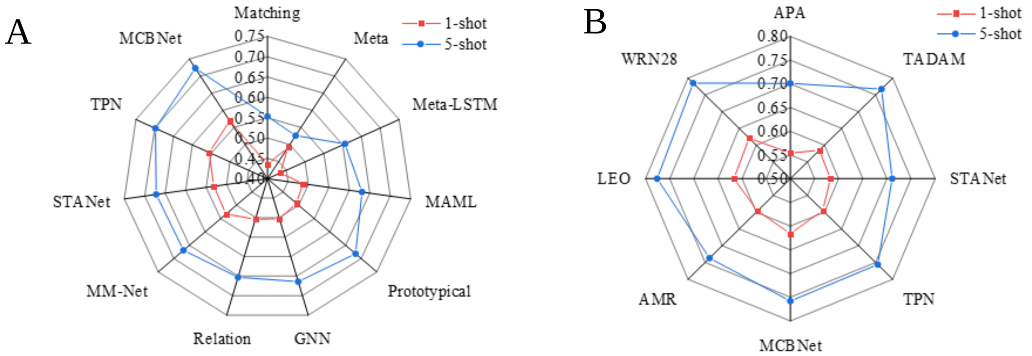

Figure 7. The sample classification results on the minilmageNet data set.

The sample classification results on the tieredlmageNet data set are illustrated in Figure 8 below. As the feature extraction network deepens, the gap among the models becomes smaller and smaller. The design of the proposed solution proposed can obtain more discriminative features through a deeper feature extraction network, and these features will be more linearly separable, which makes the advantages of the solution proposed in this paper gradually become insignificant.

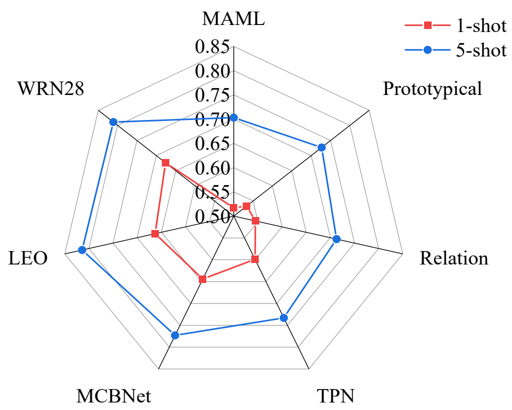

Figure 8. The sample classification results on the tieredlmageNet data set.

4.2 Classification of video data sets

As shown in Figure 9, Figures 9A ~ 9C show the classification results on the UCF11, UCF101, and HMDB51 data sets, respectively. The number of categories in the data set has a more obvious impact on the results. There are only 11 categories of UCF11 meta-training set and meta-test, and its category division ratio is 6:5, which means that 5 categories are sampled in 6 categories during the training, so there are 6 possible combinations for the category space of the task. Therefore, compared to UCF101 with 101 categories, each model performs poorly on UCF11. Secondly, the differences among the categories of the data sets also have some impacts on the results. In contrary to UCF101, the categories of HMDB51 are more fine-grained, and the quality of videos is uneven, so the performance of each calibration type on HMDB51 is relatively poor. The MCBNet solution using deep learning still has a big improvement over the relational network. Figure 9D shows the results of ablation experiments of different experimental solutions. It is found that the accuracy rate of solution proposed is improved by about 1.8% on the 1-shot task and nearly 3% on the 5-shot task.

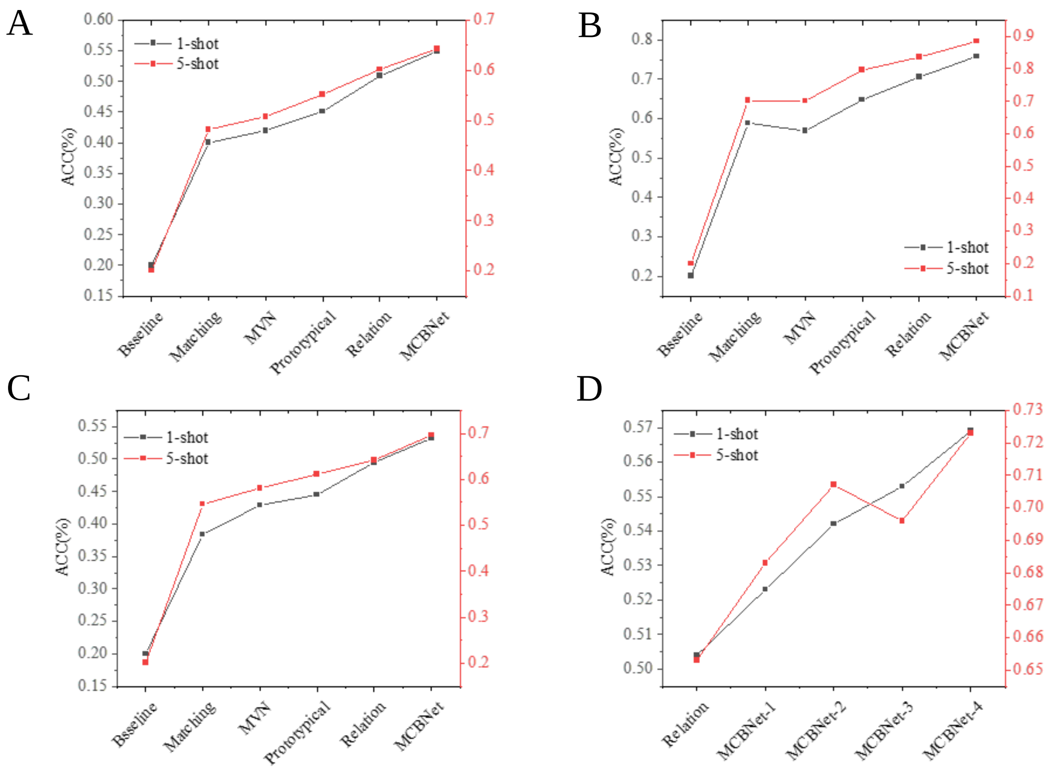

Figure 9. Classification results on different video data sets.

4.3 Comparison of different extraction networks

Figure 10 illustrates the comparison results of different extraction networks. Figures 10A and 10B are the results under 1-shot and 5-shot, respectively. Under different deep neural networks (DNNs), the advantage of the solution proposed is that the feature extraction network shrinks gradually during the deepening. This is essentially because the linear separability of the feature will increase with the deepening of the feature extraction network, so even a fixed distance metric can show the similarity well in this case.

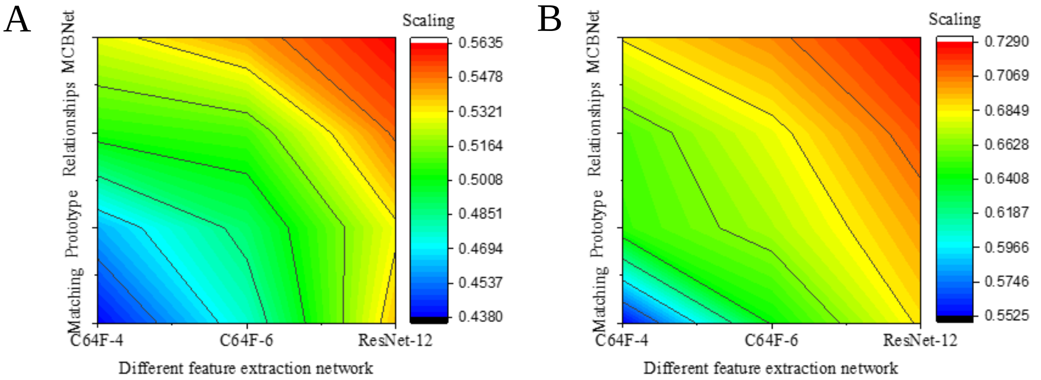

Figure 10. Comparison of different extraction networks on the data sets.

4.4 Learning ability

Figure 11 shows the comparison results of different learning methods. Figures 11A and 11B illustrate the comparisons of learning difficulty and learning efficiency, respectively. It is found that as the amount of information increases, the learning difficulty and learning efficiency of the elderly show volatility changes. Compared with other models, the smart learning and memory model based on the deep learning can synthesize a large number of target sample features, greatly lowering the difficulty of learning and improving the learning efficiency.

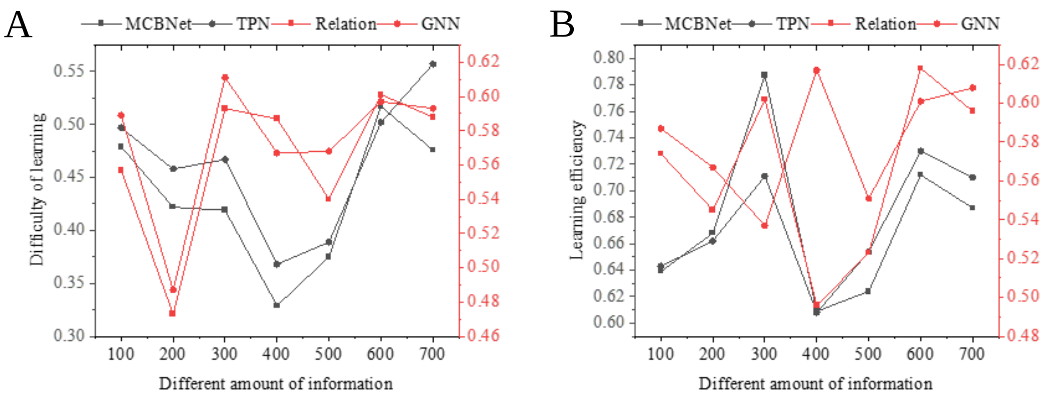

Figure 11. Comparison of learning capabilities of different models.

5. Conclusion

The learning efficiency and memory theory is analyzed, and a framework for elderly-oriented smart device is designed using the deep learning based on the learning characteristics of the elderly and the smart memory storage. In addition, a home smart health management terminal product suitable for the elderly is constructed in this study. The effectiveness of the proposed solution is verified by comparison and analysis on different image data sets and video data sets. The smart memory storage solution based on deep learning has obvious effects on different data sets. The solution greatly reduces the difficulty of learning by synthesizing a large number of target sample features, and the learning effect is further improved. This study provides corresponding research ideas for the design of elderly-oriented smart device. However, there are still some limitations in the article: Firstly, the product is designed from the perspective of technical algorithms, and it needs continuous testing and optimization in the actual use process. Secondly, the product designed can effectively collect the health data, but how to interconnect these smart devices in series to form a complete health analysis index system for the elderly is crucial to the establishment of the system. In the follow-up, in-depth research will be developed on these two aspects to continuously improve the effectiveness of the solution.

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