Using Deep Learning Recognition to Aid Early Diagnosis and Rehabilitation of Senior Aphasia Care

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Abstract. Aphasia, caused by brain damage, affects comprehension, expression, reading, and writing. Early intervention improves outcomes. This study developed a system to help senior aphasia patients practice writing by comparing their writing to correct forms and providing corrections. Using Information and Communication Technology (ICT) and Artificial Intelligence (AI), the system aims to improve rehabilitation efficiency. It uses mobile devices like smartphones and tablets to deliver personalized handwriting training modules designed for seniors, with terms selected by speech therapists. To enhance text recognition accuracy, the study optimizes the training model using loss functions, focusing on minimizing Cross-Entropy loss. Lower Cross-Entropy values indicate more accurate classification, while values near 1 suggest prediction errors. By averaging these values, the study assesses overfitting and training effectiveness, guiding adjustments in datasets. Cross-validation is used to prevent overfitting and enhance model robust-ness by splitting data into multiple subsets and validating each iteratively. This process refines model parameters and improves accuracy. Experimental results showed that the Inception Net model demonstrated high efficiency and stability, while the Inception Net model had superior accuracy. These enhancements effectively aid in patients' language recovery.

Keywords: Deep Learning · Aphasia · Image Recognition · Handwriting Therapy

1 Introduction

Aphasia is a language disorder caused by brain damage, affecting comprehension, expression, reading, and writing abilities. Common causes include stroke, dementia, head injury, brain tumors, or infections [1]. The symptoms and severity of aphasia depend on the location and extent of the damage, with common symptoms including (1) inability to correctly name objects, (2) difficulty using proper grammar to form complete

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sentences, (3) inability to repeat others' speech, and (4) grammatical errors in writing or inability to write correctly [2]. Patients with aphasia can recover gradually without treatment, but potential language impairments often remain. Recovery varies based on treatment duration, age, and physical condition [3]. Early detection and intervention with appropriate speech therapy for elderly aphasia patients can significantly aid in restoring language abilities, boosting confidence, and improving social interaction and daily living skills.

Recent literature highlights the growing importance of writing therapy for aphasia patients. Most studies focus on grammatical and spelling errors but are not tailored to traditional Chinese. This study developed a new system to compare patients' writing with correct forms, displaying errors and correction suggestions. The system accurately indicates the correctness of each character, facilitating efficient writing practice. This development fills a gap in existing research. With advances in Information and Communication Technology (ICT) and Artificial Intelligence (AI), using such technology to address healthcare challenges shows promising results. This system aims to enhance rehabilitation services for elderly aphasia patients, improving their recovery efficiency.

2 Literature Review

2.1 Aphasia

Aphasia generally refers to speech disorders that occur after losing language abilities, including difficulties in reading and writing, which lead to communication barriers [4]. These barriers primarily result from damage to the brain's language areas, often caused by stroke. A stroke occurs when a blood clot leaks or a ruptured blood vessel flows to parts of the brain, leading to brain cell death due to a lack of normal blood supply. This damage to the brain's language areas results in aphasia, which can be categorized into two main types: (1) fluent aphasia and (2) non-fluent aphasia:

(1) The most common type of fluent aphasia is Wernicke's aphasia. Patients with this condition may produce long, complete but meaningless sentences, sometimes using invented words, making it difficult for listeners to understand the intended meaning.
(2) The most common type of non-fluent aphasia is Broca's aphasia. This condition often accompanies right-side limb paralysis and weakness. Patients can understand what others are saying but struggle to respond, only managing to speak in short, effortful phrases rather than complete sentences. Regardless of the type of aphasia, it significantly hampers communication and causes inconvenience for patients [2].

2.2 Handwriting Therapy for Patients with Aphasia

Aphasia is a long-term language disorder that significantly impacts a patient's social abilities and severely hinders social interactions. Over time, this leads to increasing isolation from interpersonal relationships, ultimately reducing the quality of life. Therefore, with the help of speech therapy, these patients can restore their daily spoken and written language skills as early as possible. Common speech therapies, depending on the training tasks, can improve various language symptoms, such as language practice, writing phone numbers, writing digits, composing letters, and spelling words. These compensatory strategies use everyday items and habits for text training, encouraging aphasia patients to continuously engage with a large volume of text, thereby stimulating the brain's language processing and recovery capabilities and improving the accuracy of daily spoken and written language use.

These text-based training sessions are conducted with the assistance of speech therapists (STs) to support patients in their verbal training. Consequently, the burden on therapists increases over time. If ICT compensatory technology-assisted training mechanisms can be integrated, it would enable patients to complete training tasks at home or within institutions independently. The results of their handwriting processes could be presented to the users to help them understand their deficiencies in writing skills. Therapists can then provide accurate guidance based on these results to enhance the text processing abilities of aphasia patients.

2.3 Speech Therapy-Related Training Mechanisms for Handwriting Disorders

This study focuses on compiling research related to speech therapy training courses, specifically those that use handwritten text exercises, to provide a systematic process for establishing appropriate training programs. Various scholars have proposed relevant training courses to meet the needs of aphasia patients in text processing training. In 2011, Anne Marie Piper et al. [5] implemented a training method called Write-N-Speak, which used a self-developed digital paper toolkit over a 12-week period. They placed interactive stickers in the home environment to help identify objects and used a digital pen for simultaneous speech and language activities, offering an innovative training program. In 2010, the same Anne Marie Piper et al. [6] developed a system using a multi-modal digital pen combined with a paper interface prototype. This system was designed for elderly users, utilizing the interactive capabilities of cards and a digital pen for writing and verbal conversation. Apart from structured therapy activities, individuals could carry a book to support daily activities and paper-pen print content, providing therapists with different therapeutic prescriptions and environmental interactions. Also in 2010, Khalyle Hagood et al. [7] used Bangaten and HTML5 technologies to assist therapists in helping patients find the correct images described by words. By integrating cross-platform information technology, they displayed audio prompts on mobile phones, providing aphasia patients with images for naming objects. This compensatory tool on mobile phones stimulated patients and recorded their therapeutic progress.

Many scholars have developed models for text image recognition using deep learning techniques, achieving high accuracy in text recognition. This section will compile literature on text recognition to adjust suitable model parameters for the deep learning model framework of this project. In 2007, M. Hanmandlu et al. [8] used a fuzzy model to recognize handwritten Hindi and English digits. By modifying the membership functions in the fitting fuzzy model, they improved recognition accuracy, achieving a 95% recognition rate for Hindi digits and a 98.4% rate for English digits. In 2019, Haiqing Ren et al. [9] proposed a novel Recurrent Neural Network (RNN)-based endpoint recognizer for online handwritten Chinese. They introduced two new computational architectures within the traditional RNN system—variance constraints and attention weight vectors—achieving higher recognition accuracy with fewer parameters and obtaining a recognition rate of 97.6%. In 2021, Amirreza Fateh et al. [10] proposed a Convolutional Neural Network (CNN)-based language-independent model to address different handwriting styles. They used transfer learning to enhance image quality and improve model recognition performance. The results showed that the recognition accuracy for handwritten Chinese and English reached 99.26% and 97.33%, respectively.

3 Methodology

This study combines smartphones, tablets, and other mobile devices to develop a personalized handwriting training module specifically designed for the elderly. The course content is based on common nouns from daily life, such as names, addresses, and everyday tools, selected by speech therapists based on their professional knowledge to suit individual cases. These materials are built into a course database and provided through a visual interface on mobile devices, allowing the elderly to complete writing exercises using a stylus or hand gestures. Additionally, this study has developed a text recognition system that incorporates deep learning models to improve the accuracy of handwriting recognition. Users log into the app through identity authentication, where they can view past training records and evaluations from speech therapists and perform writing tasks based on text prompts provided by the system. Each writing result is immediately recognized by the system, which points out errors and offers suggestions for improvement, helping to assess whether the individual's writing skills have significantly improved. All writing records are stored in a back-end database for subsequent analysis and case evaluation. This system not only effectively enhances the writing abilities of the elderly but also reduces the workload of speech therapists. Through data analysis, it optimizes training plans, ultimately improving the language communication skills of aphasia patients.

The process of this study is shown in Fig. 1. First, the dataset is divided into a training set and a test set, followed by data preprocessing for both. Data preprocessing includes grayscale conversion, resizing, and normalization of the images, providing a consistent data format for subsequent model training and testing. Next, three different models, including VGG16, ResNet, and Inception, are trained, and their performance is evaluated using the test set. The model with the best performance is selected as the final model and integrated into the system. During the testing phase, handwritten content is input into the system, and after undergoing the same preprocessing steps as the training data, the image is fed into the optimal model for recognition. The results are displayed in real time and automatically saved in a database for therapists to review and analyze.

3.1 DL Technology and Image Recognition System Development

To compare the structural differences of various deep learning models, as shown in the Table 1, this study aims to evaluate the most suitable model for application in a handwriting recognition system. This is to enhance the system's recognition performance and provide a basis for therapists to assess individual cases. The study considers the following three models for training text accuracy: VGG [11], ResNet [12], and Inception [13]. The comparison of these models is shown in Table 1. To identify the most suitable training model for constructing high-accuracy text recognition technology, these three

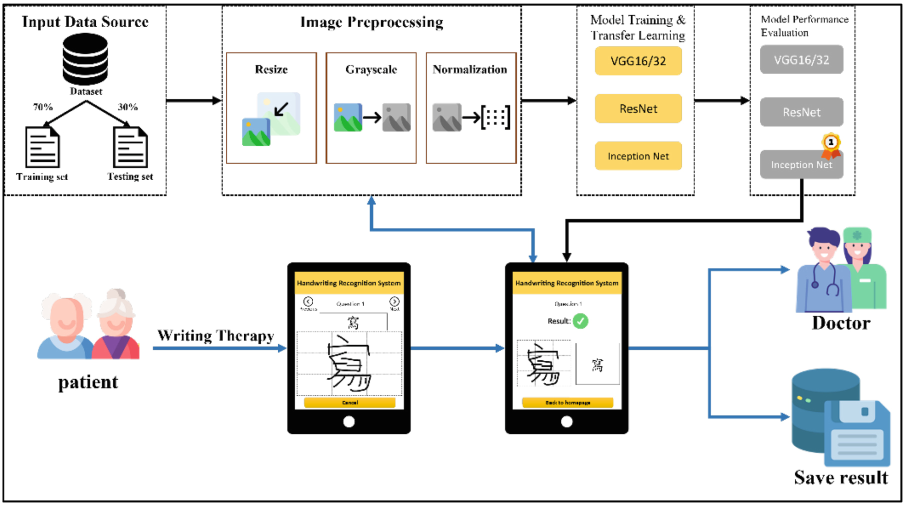

Fig. 1. System Architecture Diagram

models will undergo individualized training. This process involves creating a training dataset and a test dataset and inputting the handwritten text content of aphasia patients into the model parameters to generate the training model's recognition accuracy. By transmitting the handwritten text images of patients with writing disabilities to the training models, the study compares the text recognition accuracy to determine the most appropriate model architecture.

Table 1. Comparison Table of Various Deep Learning Models

Models	Concept	Structure	Advantage
VGG16	Use many 3 × 3 convolution kernels and combine them into a convolution sequence	16 layers (13 convolutional layers and 3 fully connected layers)	Improve network depth by replacing larger convolution kernels with smaller convolution kernels
ResNet	Provides the output of two consecutive convolutional layers and shunts the input into the next layer	Use residual learning to solve the problem of decreased accuracy of network deepening without using fully connected layers	To reduce the difficulty of training ultra-deep neural networks
Inception	Extract different information from the image through multiple convolutions and fuse them to obtain more image features	1 × 1 convolution > 3 × 3 convolution > 5 × 5 convolution > 3 × 3 max pooling	Solve the problem of improving the accuracy of deep learning networks while preventing over-fitting

Transfer learning is a method that transfers knowledge from a source domain to a target domain, thereby achieving better learning outcomes in the target domain. Since the source domain typically has a larger amount of data, the learning and recognition performance is generally more stable. However, when the target domain has limited data, the recognition results of deep learning models can often be biased. By using transfer learning, it is possible to learn from a smaller dataset and achieve recognition results that are comparable to those obtained with larger datasets, thus improving the performance and accuracy of the system model. Based on the feature values marked on the text images, transfer learning can be used to improve model learning effectiveness through hierarchical transfer. The initial layers of a CNN network handle basic shapes such as points, lines, and horizontal lines. As the layers become more complex, they eventually interpret the entire image.

The earlier layers do not significantly affect the final target object, so they can be retained, while the later layers are replaced and retrained to update the model's parameters, resulting in a newer model recognition outcome. Since the retrained layers have fewer parameters, this approach helps avoid overfitting. By applying transfer learning to text images, it is possible to obtain test data of handwritten text from the elderly, providing optimized recognition results from the original dataset. This approach addresses the issue of poor recognition performance due to insufficient test data and enhances the performance and accuracy of the model parameters.

This study uses an open database as the source for the training dataset. The dataset is a publicly available Traditional Chinese Handwriting Dataset [14]. The dataset was split into 70% for training and 30% for testing to evaluate the model at different stages. Due to the large size of the dataset, direct training would lead to excessively lengthy processing times. Therefore, we selected commonly used vocabulary from the dataset as the basis for the experimental training. In the end, we filtered out 8 commonly used words, comprising 16 different characters, including: telephone, tissue, television, Wang Xiaoming (example name), water bottle, mobile phone, book, and desk. The selection criterion for these words was their high frequency of use in daily life.

The input text is transmitted to the trained AI model framework through the frontend text recognition system app for identification. Each training session involves selecting and averaging different types of handwriting. For example, if the training session focuses on words, users are asked to write three characters: "人" (person), "由" (cause), and "自" (self). Using the text recognition feature for multiple questions, this set of characters undergoes the model recognition process in sequence, producing three distinct recognition accuracies. Then, the accuracy of handwriting for this set is calculated using a weighted average to assess any potential handwriting difficulties. The output result is displayed on the frontend to inform users of the training outcome as a percentage, providing language therapists with guidance and assessment suggestions for individual cases. This training record is also stored in the patient's database, facilitating the review of previous training results, comparing sequential data differences, and assessing whether there is improvement in handwriting. Ultimately, it helps elderly individuals with aphasia improve their language processing abilities.

The training records will be stored in a case database, allowing for easy review of previous training results and comparison of sequential data to assess whether there has been improvement in the patient's handwriting abilities. This helps aphasia patients, particularly the elderly, to enhance their language processing capabilities.

3.2 DL Model Parameter Correction and Testing

In the testing phase of the system model's text recognition accuracy, this study aims to correct errors in the text recognition application and improve model parameters to address the issues arising from recognition errors. If the AI model performs poorly during training and testing, it could lead to significant inaccuracies. Therefore, this study focuses on correcting and improving the model based on two common types of erroneous learning features.

1. Incorrect Feature Selection Leading to Misclassification:

When extracting features for two different target objects, using similar data characteristics can lead to misclassification. For example, if an AI model is trained to distinguish between dogs and cats, it should use features with significant differences such as body size and facial features. If features like fur color and weight, which are less distinct, are used, the system will struggle to differentiate between a black cat and a black dog.

2. Inconsistent Labeling Leading to Model Confusion:

When the same object feature is labeled differently, it can confuse the machine learning model. For instance, if training a self-driving car model, and two sedans are inputted where one is correctly labeled as a sedan and the other is incorrectly labeled as a bus, the model will learn incorrectly and be unclear about which label is correct.

To improve these issues, it is essential to accurately collect and process data and discuss handwriting features with speech therapists when labeling text features for patients with writing disabilities. This will enhance the model's recognition accuracy during subsequent training. However, poor performance in handwriting test data can also lead to overfitting, where the model memorizes the training data and fails to generalize to new data, resulting in misclassification. To address overfitting, this study uses loss functions to examine model parameters and appropriately reduce model complexity for better test results. Common loss functions include regression loss functions, binary classification loss functions, and multi-class classification loss functions. Regression loss functions are primarily used for continuous values such as salary and price predictions, adjusted based on distance errors, and are less suitable for text images, which are non-continuous values.

Binary classification and multi-class classification loss functions, on the other hand, are suitable for adjusting appropriate data for classification problems, categorizing various objects into correct prediction outcomes. These functions are also appropriate for classifying different texts during the recognition process. The multi-class classification loss function assumes a probability distribution of the input data D, as shown in Eq. (1). The actual or target probability distribution of data D is shown in formula (2). Then calculate the cross-entropy (Cross-Entropy) of the specific data D, such as formulas (3) and (4). Finally, the cross entropy of each category is averaged as in formula (5).

$$P(D) = \begin{bmatrix} p1 \\ p2 \\ pn \end{bmatrix} \tag{1}$$

$$Y(D) = \begin{bmatrix} y1 \\ y2 \\ yn \end{bmatrix} \tag{2}$$

$$\begin{aligned} L_{CE} &= \sum_{i=1}^{n} t_i \log(P_i), \quad \textit{for n classes}, \\ (y, p) &= -y^T \log(p) = -(y_1 \log(p_1) + y_2 \log(p_2) + \ldots y_n \log(p_n)) \end{aligned} \tag{3}$$

$$\therefore \mathrm{Cross-entropy\ \ loss(y, p)} = -\begin{bmatrix} \mathrm{y1\ y2\ yn} \end{bmatrix} \begin{bmatrix} \log(p1) \\ \log(p2) \\ \log(pn) \end{bmatrix} \tag{4}$$

$$\mathrm{Cross-entropy} = \frac{\sum \mathrm{(Cross-Entropy)}}{\mathrm{N}} \tag{5}$$

This study utilizes loss functions to adjust the error parameters of the training model to enhance the system's text recognition accuracy. The goal is to minimize the Cross-Entropy loss, as a smaller value indicates that the classification results are closer to the true data. Conversely, a Cross-Entropy value approaching 1 suggests that the model is unable to correctly predict the data. By averaging the Cross-Entropy values, we can determine if the model suffers from overfitting or if it has poor training effectiveness, leading to classification errors. This insight allows us to adjust the training and testing datasets to improve recognition accuracy.

To understand the optimization of test data when model performance declines due to high loss function values, this study employs cross-validation to repeatedly compare the test data and evaluate the effectiveness of model training improvements. The purpose of cross-validation is to prevent issues of overfitting that can arise from relying on a single test dataset. By splitting the data into multiple test sets, the model's data optimization is enhanced, and its parameters can be adjusted to build a more robust model architecture. After splitting the data, each subset undergoes validation according to the model's set number of iterations. The average of the iteration results is then calculated to estimate recognition accuracy. This method allows for individualized validation stages for different datasets, preventing overfitting caused by a limited amount of test data. Simultaneously, it strengthens the model parameter optimization process, thereby increasing the overall accuracy of the model.

4 Simulation Result

4.1 Experimental Parameter Setting

This experiment utilizes the Traditional Chinese Handwriting Dataset to train and test three models: VGG16, ResNet, and Inception Net. To ensure the rigor and reliability of the experiment, each model underwent 2000 epochs of training, with key metrics such as accuracy and loss values recorded for each run. Detailed training and testing data for each model are presented in Sect. 4.2, followed by a comprehensive comparative analysis.

The experiment was conducted under a standardized hardware and software environment, running on Ubuntu 22.04 LTS (WSL). The hardware specifications include an AMD Ryzen 7 5800X processor, an NVIDIA RTX 4070Ti Super graphics card, and 48 GB of RAM.

4.2 Data Preprocessing

In the data preprocessing, we first divided the data set into a training set and a test set, with a ratio of 7:3. To simplify image processing, we convert the input image into a grayscale image by setting the RGB channel to 1 to reduce the computational burden. The image size is set to 224 × 224 pixels, and the image is normalized to scale the pixel value to between [0,1] to prevent the gradient from exploding or disappearing, thereby improving the convergence efficiency and accuracy of the model.

4.3 Analysis and Presentation of Experimental Results

Based on the experimental results, Inception achieved the lowest loss during training, indicating high efficiency and stability in its learning process. In terms of test accuracy, Inception performed the best, achieving the highest accuracy, demonstrating its superior feature learning ability and robust model architecture. In contrast, VGG16 performed worse than Inception and ResNet in both training loss and test accuracy, showing the weakest performance, as summarized in Tables 2, 3, 4 and 5.

According to the data in Table 2, VGG16 still maintained a loss rate of 0.6723 at the 200th epoch, suggesting that the model may not have fully converged, which could negatively affect the final prediction results and prevent the model from reaching optimal performance. In contrast, the loss rates of ResNet and Inception at the 200th epoch were 0.0000 and 0.0001, respectively, clearly indicating that these two models had already converged earlier in the training process, meaning they had learned stable and accurate features. Thus, the rapid convergence of ResNet and Inception allows them to achieve optimal performance in a relatively shorter time and make more accurate predictions, showing their superiority over VGG16.

According to the data in Fig. 2, ResNet achieved the lowest training loss around the 60th epoch, while Inception reached its lowest training loss around the 50th epoch. This indicates that the Inception model converges faster compared to ResNet. Figure 3 further confirms that Inception had higher test accuracy than ResNet at each epoch, showing that Inception not only excelled during training but also exhibited higher accuracy during the testing phase (Table 6).

4.4 Image Recognition Results

Based on the experimental results from the previous section, the Inception model demonstrated the highest accuracy in all tests. Therefore, this study chose Inception as the final

Table 2. Training Loss of Each Model at Different Epochs

Models Epoch	VGG16	ResNet	Inception Net
10	2.7727	2.9104	1.6737
50	2.7726	0.9090	0.4883
100	2.7725	0.2400	0.0721
150	0.9843	0.0001	0.0004
200	0.6723	0.0000	0.0001

Table 3. Performance of VGG16 on various metrics at Different Epochs

Metrics Epoch	Train Accuracy	Test Accuracy	Precision	Recall	F1
10	0.062	0.051	0.952	0.051	0.005
50	0.062	0.051	0.952	0.051	0.005
100	0.062	0.051	0.952	0.051	0.005
150	0.636	0.573	0.598	0.573	0.572
200	0.777	0.669	0.681	0.669	0.663

Table 4. Performance of Resnet on various metrics at Different Epochs

Metrics Epoch	Train Accuracy	Test Accuracy	Precision	Recall	F1
10	0.058	0.056	0.947	0.056	0.006
50	0.671	0.489	0.602	0.489	0.473
100	0.919	0.691	0.739	0.691	0.678
150	1.000	0.764	0.780	0.764	0.764
200	1.000	0.764	0.780	0.764	0.764

text recognition model. When patients write answers to specific questions on the tablet, the Inception model recognizes the text and displays whether the input is correct in real time. If recognition errors occur, the system will automatically mark the incorrect text using a nine-grid frame and highlight missing or incorrect strokes in red, allowing patients to see and understand the errors immediately. Figure 4 simulates a scenario where a patient answers questions, and after pressing the submit button, the written text is recognized using Inception. Figure 5 shows the recognition results, with the error marking method illustrated in the figure.

Table 5. Performance of Inception on various metrics at Different Epochs

Metrics Epoch	Train Accuracy	Test Accuracy	Precision	Recall	F1
10	0.343	0.303	0.537	0.303	0.251
50	0.816	0.798	0.798	0.798	0.785
100	0.980	0.927	0.934	0.927	0.925
150	1.000	0.910	0.926	0.910	0.903
200	1.000	0.904	0.922	0.904	0.898

Table 6. Performance of Three Different Models on various metrics

Metrics Model	Test Accuracy	Precision	Recall	F1
VGG16	0.669	0.681	0.669	0.663
Resnet	0.764	0.780	0.764	0.764
Inception	**0.904**	**0.922**	**0.904**	**0.898**

Fig. 2. Training Loss Comparison

In the initial experimental setup, each model was trained for 6000 iterations. However, it was observed that the VGG16 model failed to converge during training, in stark contrast to the performance of the other two models. After multiple attempts and adjustments, it was eventually found that when the learning rate was gradually reduced from 0.01 to 0.000001, the VGG16 model began to show signs of convergence after 2000 epochs. In contrast, ResNet and Inception started converging after approximately 150 epochs, indicating a more stable and efficient training process. This phenomenon may

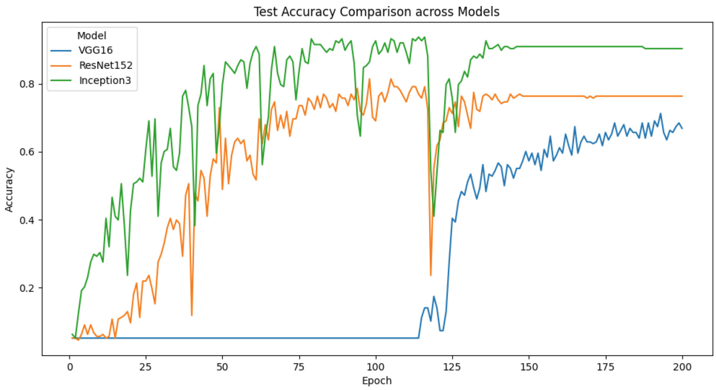

Fig. 3. Test Accuracy Comparison

Fig. 4. Simulation of Patient Response Scenario

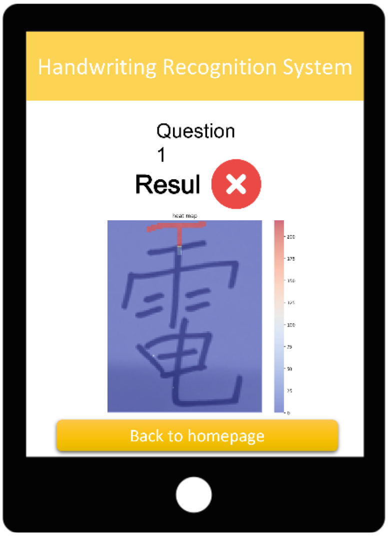

Fig. 5. Recognition Result Screen

be due to the characteristics of the VGG16 model, which make it prone to gradient vanishing or exploding problems at high learning rates, leading to difficulties in effectively updating model parameters.

5 Conclusion

This study developed a handwriting recognition system designed to improve communication efficiency for elderly patients with aphasia during rehabilitation therapy. Among many candidate models, we ultimately chose Inception Net for text recognition due to its outstanding performance during training and evaluation phases, achieving the highest F1 score, Recall, Accuracy, and Precision. This system not only accurately recognizes the content written by patients but also clearly displays errors using red markings, helping patients quickly and effectively correct themselves. In future work, we plan to further optimize this system to enhance the model's accuracy in judgment.

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