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Design of a Wheelchair Control System Based on Hand Gesture Recognition Using ResNet18

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ABSTRACT

The development of wheelchairs utilizing advanced technology at low costs is gaining attention to improve the quality of life for approximately 800 million people with disabilities worldwide. These individuals often face challenges in mobility, access to education, and social integration. Among various wheelchair control methods, hand gesture control is considered optimal due to its efficiency and health safety. However, in Vietnam, research in this field remains limited. This project focuses on designing a smart wheelchair system using computer vision to recognize hand gestures and convert them into control commands, combining hardware and software solutions. The study employs deep learning models such as ResNet-18 for image processing, integrated on a Jetson Nano device, and hardware optimization to achieve the highest efficiency. Although challenges remain, such as ensuring accuracy in diverse environments and maintaining stable control under real-world conditions, this research promises not only to enhance user independence but also to open new opportunities in biomedical engineering. It contributes to improving the quality of life and fostering social inclusion for people with disabilities.

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1. Introduction

A report from WHO shows that about 16 percent of the world's population, equivalent to 1.3 billlion people, are suffering from significant disability [1]. The inability or limited ability to move not only severely impacts the quality of life of individuals but also hinders their ability to study, work, and integrate into society. In a context where society places a strong emphasis on improving the quality of life, developing effective and independent mobility solutions for people with disabilities has become essential.

With the rapid development of artificial intelligence and computer vision, these technologies offer solutions for gesture and human behavior recognition, which can be translated into control commands. Applying such technologies to the design of smart wheelchair systems not only enables users to move easily but also enhances their autonomy and confidence while embodying profound humanitarian significance. This research aims to design an integrated hardware and software system that uses hand gesture recognition to control a wheelchair. This system is aimed at meeting the needs of people with disabilities and providing support for the elderly in the context of an aging population. This research aligns with current trends, emphasizing the role of technology in addressing practical issues, improving quality of life, and promoting social inclusion.

The main concern is to manufacture a wheelchair that uses good technology but at low cost. Recent researches is dedicated to applying artificial intelligence technology to modify electric wheelchairs to improve the quality of life of disabled people or patients who cannot move by themselves. In recent years, many university laboratories abroad have conducted research on wheelchair control methods, including hand gesture control [2], [3], [4], [5], [6], voice control [7], [8], [9], [10], eye gesture control

[10], [11], [12], [13], [14], and EEG signal control [15], [16], [17], [18]. These methods basically recognize the user's desired movement directions and send control commands to the electric wheelchair. Using brain waves to control, if used for a long time, will have a negative impact on the patient's health. previous study by the authors proposed controlling a wheelchair using eye gestures. However, the system still has some drawbacks, such as difficulty in real-world installation or eye movements being distracted by external factors [19]. Therefore, the control method through hand gestures is the optimal choice.

The hand-gesture-controlled wheelchair system must meet several key requirements: rapid and accurate gesture recognition in real-time with minimal latency to ensure timely response, particularly in emergency situations. The system must operate reliably in diverse environments, from indoor to outdoor settings, and resist interference from external factors. Safety is the top priority, with mechanisms for emergency stops, operational status checks, and manual mode switching when necessary. The interface should be user-friendly and easy to operate, accompanied by high-performance hardware that is energy-efficient and compact in design. Additionally, the system needs to be flexible, allowing for the integration of supplementary technologies such as GPS or facial recognition to expand its future applications, thereby providing maximum convenience and safety for users.

2. Materials and Methods

1.1. Overview of CNNs

Convolutional Neural Networks (CNNs) are a specialized type of deep learning model designed specifically for processing grid-like data such as images, videos, and audio. Inspired by the human visual system, CNNs are based on three key principles: local connectivity, spatial invariance, and robustness to local variations [20].

The primary layers of CNNs include Convolutional layers, Pooling layers, and Fully Connected layers. Unlike traditional Artificial Neural Networks (ANNs), CNNs are more efficient due to their convolutional and pooling layers, which organize data in a three-dimensional space consisting of width, height, and depth. This structure enables CNNs to effectively learn spatial features and reduces the risk of overfitting.

CNNs have demonstrated exceptional performance in image processing and recognition tasks such as classification, face recognition, object detection, and image segmentation. The advancement of CNNs has not only significantly improved performance in image-related fields but also driven deep learning applications in industries such as healthcare, transportation, and entertainment, cementing its role in the modern technological revolution.

1.2. Residual Network (ResNet)

1.2.1. Overview of ResNet

In recent years, deep learning models have achieved remarkable milestones in computer vision, particularly in image recognition and classification tasks. One significant breakthrough is the ResNet (Residual Network) architecture, which was introduced by Kaiming He and colleagues in 2015 [21]. ResNet effectively addresses the issues of accuracy degradation and vanishing gradients that arise as network depth increases, as shown in Figure 1. In deep neural networks, the vanishing gradient problem occurs when gradient values become extremely small during backpropagation, slowing or even halting the weight update process and hindering the network's ability to learn.

The ResNet architecture overcomes this limitation by employing residual connections (skip connections), which allow the input of a layer to be directly passed to the output of a subsequent layer. This approach preserves information and gradients during propagation, significantly enhancing the training efficiency of deep networks. ResNet not only marked a turning point in deep neural network design but also became the foundation for numerous advanced models in computer vision and other domains.

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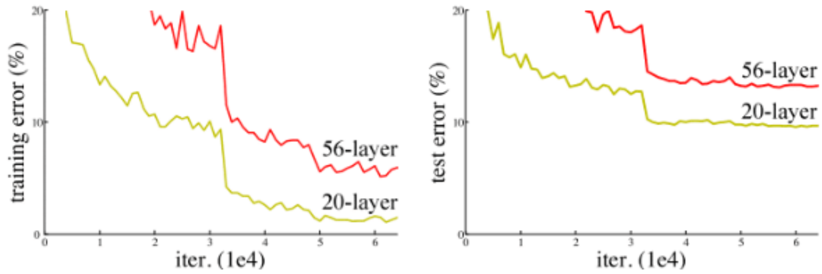

Figure 1. *Correlation between network depth and performance [22].*

According to the diagram in Figure 2, let the input be denoted as x. The ideal mapping to be learned is $f(x)$,, which is passed through an activation function. The portion within the dashed box on the left must exactly match the mapping $f(x)$,. However, this may not be straightforward if we aim to keep the basic structure unchanged and retain the input x. In this case, the portion within the dashed box on the right only needs to learn the residual x, as the final output will be $x + f(x)$. In practice, learning the residual mapping is often easier because it can start from $f(x) = 0$.

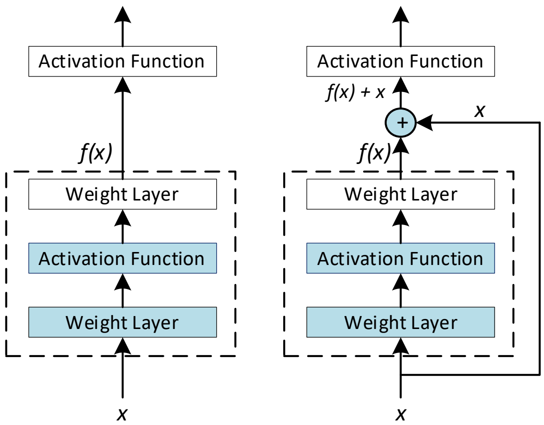

Figure 2. *The difference between a standard block (left) and a residual block (right) [23].*

1.2.2. ResNet18 Network

In this research, the ResNet18 version will be used for the application of controlling a wheelchair through computer vision. ResNet18 is one of the lightest and simplest versions of the ResNet architecture series, consisting of 18 layers (16 convolutional layers and 2 fully connected layers), with the main layers designed to optimize learning efficiency and reduce computational complexity. The architecture of ResNet was shown in Table 1.

Table 1. *Detailed architecture of ResNet [22]*

Layer name	Output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2.x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times 3, 64 \\ 3\times 3, 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times 3, 64 \\ 3\times 3, 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times 1, 64 \\ 3\times 3, 64 \\ 1\times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times 1, 64 \\ 3\times 3, 64 \\ 1\times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times 1, 64 \\ 3\times 3, 64 \\ 1\times 1, 256 \end{bmatrix} \times 3$
Conv3.x	28×28	$\begin{bmatrix} 3\times 3, 128 \\ 3\times 3, 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times 3, 128 \\ 3\times 3, 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times 1, 128 \\ 3\times 3, 128 \\ 1\times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times 1, 128 \\ 3\times 3, 128 \\ 1\times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times 1, 128 \\ 3\times 3, 128 \\ 1\times 1, 512 \end{bmatrix} \times 8$

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Conv4.x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 36$
Conv5.x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Specifically, the structure of ResNet18 consists of the components shown in Figure 3 below:

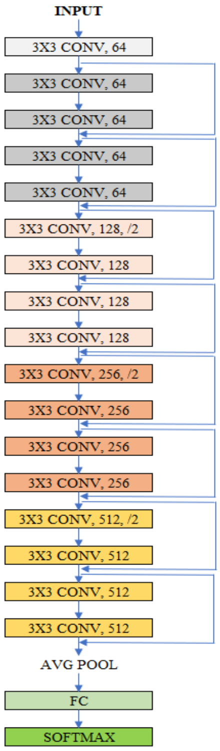
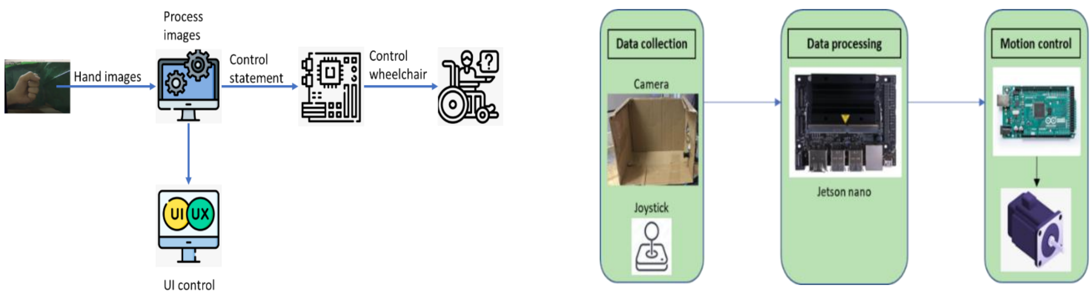


Figure 3. *ResNet18 structure [22].*

2.2. Wheelchair system overall

The general structure of the system is shown in Figure 4, which includes a camera used to capture the user's hand gestures, the model that analyzes the hand gestures, MCU for controlling the wheelchair, and user interface (UI/UX) used to display and interact with the end user.



a) General system structure *b) System connection diagram*

Figure 4. *The structure of the wheelchair system.*

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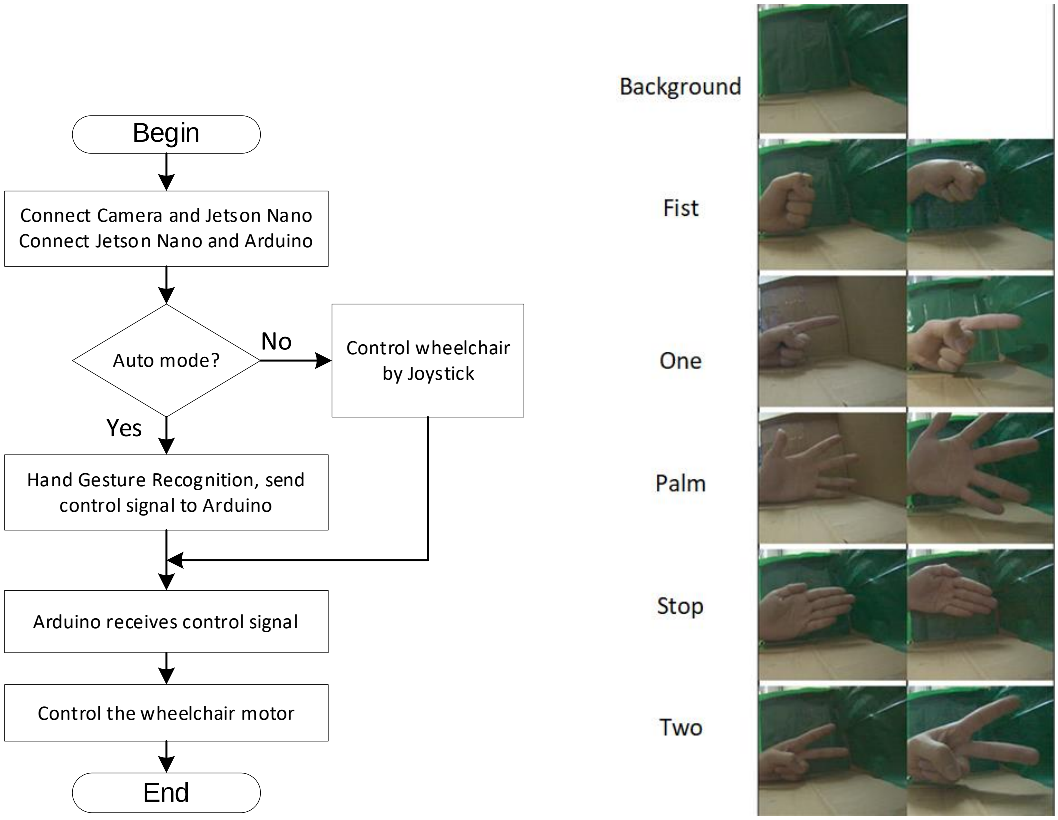
The data collection and processing system includes a high-resolution camera (720p) to capture clear images and a joystick, providing direct control signals from the user. The image data from the camera is processed on the Jetson Nano, a powerful embedded device from NVIDIA, designed for real-time AI applications, while also sending control commands to subsequent components. The motion control system uses Arduino as the microcontroller, receiving signals from the Jetson Nano and converting them into electrical commands to control the motors. The motors perform mechanical movements such as rotating wheels or moving the device according to commands, ensuring accurate and smooth feedback.

2.3. Control system design

The control sequence of the wheelchair system is presented in Figure 5. The dataset used in this study is a specialized image dataset for hand gesture recognition, consisting of three distinct subsets: the training set, the validation set, and the test set. Each subset contains images from 6 different hand gesture classes, including: background, fist, one, palm, stop, two, which are classified and organized into separate folders. The dataset includes a total of 32,400 images, collected from 4 different individuals and divided in a 70-20-10 ratio for the training, test, and validation sets, respectively. In particular:

- Training set: Number of images: 22,680 (70%). Average distribution: 3,780 images per class.
- Validation set: Number of images: 6,480 (20%). Average distribution: 1,080 images per class.
- Test set: Number of images: 3,240 (10%). Average distribution: 540 images per class.



(a) *(b)*

Figure 5. *Sequence and control set a) Control sequence flowchart b) Control data file.*

Using Docker with the PyTorch image offers several benefits in setting up the development environment and training deep learning models. Specifically, Docker ensures environment consistency, minimizes version conflicts between libraries, and makes it easier to reproduce experiments. PyTorch is a powerful deep learning library, and the official Docker image for PyTorch has been optimized to leverage GPUs, accelerating model training. The server used for training is a desktop computer with 32GB of RAM and a 6GB 2060 GPU.

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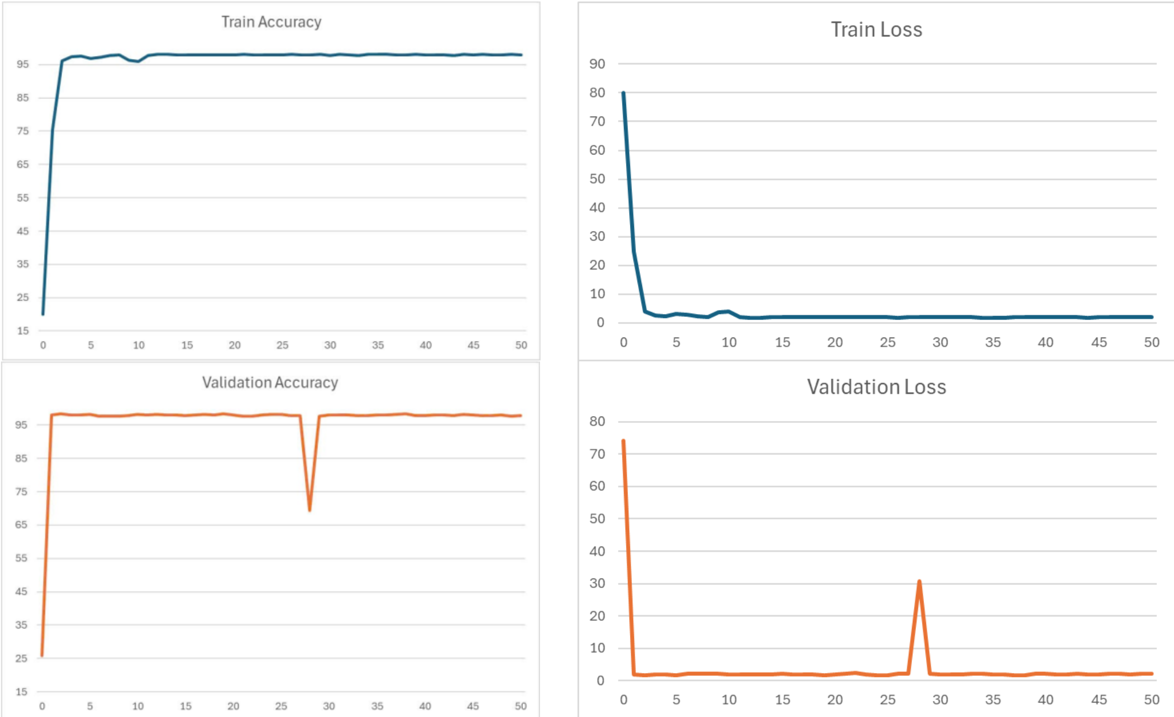
3. Results and Discussion

3.1. Model training results

The training accuracy reached approximately 99.36%, while the accuracy on the validation set achieved 100%. This is a very high result, consistent with the strict control conditions of the experimental environment. The Loss values during both training and validation decreased smoothly throughout the training process. The training loss stabilized at 0.0169, while the loss on the validation set reached a very low value of 0.0001. This indicates that the model learned effectively without experiencing fluctuations or instability during the training process.



(a) Accuracy graph *(b) Loss graph*

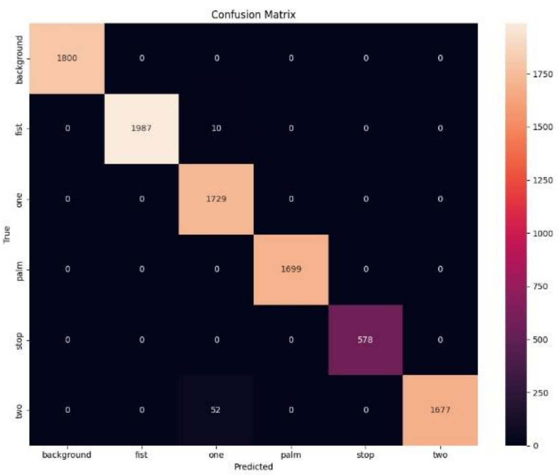
Figure 6. *Training results.*

From the accuracy and loss graphs shown in Figure 6, the model converges very well with smooth curves. The training accuracy gradually increases and reaches its highest point after about 20 iterations. Meanwhile, the validation accuracy achieves 100% early on, after only about 3-5 iterations. There are no signs of unstable training or significant overfitting, which is reasonable given the tightly controlled experimental environment. These factors demonstrate that the model is well-designed for the experimental conditions and has achieved optimal learning performance.

3.2. The confusion matrix

After training the model, a test was conducted to evaluate its performance on a different dataset in classifying various classes, including background (1800 samples), fist (1997 samples), one (1781 samples), palm (1699 samples), stop (578 samples), and two (1729 samples).

The confusion matrix results in Figure 7 show that the model achieves very high classification performance, with near-perfect accuracy in the *background*, *palm*, and *stop* classes. The fist and two classes only have minor confusion with the one class (10 and 52 samples), while the one class also achieves high accuracy with 1,729 correct samples. The confusion between the one and two classes is attributed to the similarity in the data, but the confusion rate is very small and does not significantly affect overall performance. Overall, the model demonstrates excellent classification ability and shows great potential for effective real-world applications.



(a) *Confusion matrix results*

(b) *Hand gestures identified by the model*

Figure 7. *Simulation results on a different dataset.*

3.3. The experiment system

The hardware system includes a wheelchair designed with two control modes: automatic mode (controlled by hand gestures) and manual mode (controlled by a joystick). The experimental wheelchair system was shown in Figure 8 below.

(a) The experimental system

(b) Inside the camera box

Figure 8. *The experimental powered wheelchair system.*

In automatic control mode, the user performs hand gestures according to the commands listed in Figure 5, and the wheelchair moves according to the user's intention. For the stop command, the camera recognizes two cases to issue a stop instruction. The user can use either: removing the hand from the camera box, meaning no interaction with the automatic mode; or showing an open palm with fingers closed, facing the camera. In both cases, the wheelchair will stop. In manual control mode, the user rotates the joystick to navigate.

The test operation of the system shows that the wheelchair can function correctly according to the hand gesture, meeting the system requirements at an acceptable level.

4. Conclusions

This research has designed and built the control system for the wheelchair that ensures safety and aesthetics, trained a hand gesture recognition model with 6 layers, and controlled the wheelchair to move through automatic and manual modes. However, there are still some limitations that need to be addressed. The system has not integrated a user interface, making it difficult to visually inspect and adjust. The model is not stable due to limited training data, only from 4 individuals, which reduces its generalizability in practical applications. Additionally, the lack of an operational status monitoring system and PID controller poses a risk of undetected technical errors, along with the accuracy and smoothness of movement not being guaranteed.

This research offers some future developments such as creating a more intuitive user interface that allows for better monitoring of the system's status, hand gesture calibration, and more efficient system oversight, while also providing error notifications and emergency control options. Collecting more hand gesture data from a wider range of users and applying data augmentation techniques will improve the stability and generalization of the model. An automatic status monitoring system will be integrated, including monitoring sensors and fault detection algorithms, along with an emergency stop mechanism to ensure safety. A PID controller will also be implemented to enhance the accuracy and smoothness of movement. Additionally, facial expression recognition technology and GPS or SLAM positioning systems will be incorporated, not only to enhance safety but also to reduce the burden on users, moving towards a more complete and optimized solution in practice.

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Conflict of Interest

The authors declare no conflict of interest.

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