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Original Research Paper

Intelligent Identification and Sorting of Chinese Herbs Recommend a String-Level Predictive Electromechanical System

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Abstract: Based on the analysis of a large number of Chinese medicinal materials, a mobile robot visual function research and development experimental domestic chips electromechanical arm-controller, which was constructed using a typical kernel algorithm recommended by Chinese medicinal materials visual recognition, which the cascade Electromechanical Control System was based on iterative learning electromechanical control for multi-joint manipulators. The original and improved YOLOV5 algorithm models were compared to detect and recommend targets in the color recognition and shape recognition vision scene of mobile robots in human-computer interaction. The experimental results show that, on the self-made data set, the improved system can obtain a better average accuracy score and detection speed and meet the requirements of real-time and accuracy, it provides a new reference design scheme for the experimental platform of mobile robot vision recognition.

Keywords: Domestic Chips, Electromechanical Controller, Mobile Robot Vision, Target Recognition Recommendation, YOLOv5, Distance-IOU, CSPNet, FocalLoss

Introduction

The development of Traditional Chinese Medicine, to ensure authenticity, efficiency, standardization, conservation, and scientific exploration within the field of traditional Chinese medicine. The intelligent recognition and recommendation of Chinese medicinal materials played a very important role. The system of paper had many advantages, such as accurate information identification, a combination of recommended references, and so on (Tang *et al*., 2023). The necessity of intelligent identification and recommendation of Chinese herbal medicines (Liang *et al*., 2023), has been demonstrated by several studies: The necessity of intelligent identification and recommendation of Chinese herbal medicines from the perspective of automatic Chinese herbal prescriptions, which was discussed in the article of "Automatic calculation system of Chinese herbal prescriptions" (2017); and which was introduced on the possibility of using rule-based method and machine learning method to realize the intelligent recognition and recommendation of Chinese medicinal materials. The method of intelligent recognition of Chinese material medicine based on image recognition technology was discussed in "Research and application of Chinese material medical image recognition technology (2020). The article, to be pointed out that the method could be well applied in practice and improve the accuracy rate. By adopting modern techniques such as machine learning and deep learning, the system could process a large amount of information and accurately identify and recommend the correct combination of materials (Xia *et al*., 2022; 2023a); which makes it more efficient and accurate compared to traditional manual methods (Ahmadyar *et al*., 2024).

Therefore, while inheriting the culture of traditional Chinese medicine, the intelligent identification and recommendation of traditional Chinese medicine would play a very important role in the development of modern Chinese medicine (Abdurahman *et al*., 2021) with the development of intelligent control technology, big data operation and the progress of computer, the mobile robot involved in many technical fields develops rapidly and it was put into the intelligent production of all social industries. To improve the practical application effect and improve the recommendation and recognition of the mobile robot to the target in the complex environment, the

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deep learning algorithm was one of the research hotspots and it was one of the main research directions and problems to realize the method of rapid detection of a given target in a complex running environment so ask the question (Ajlouni *et al*., 2023).

The method of quickly detecting designated targets in complex environments was an important issue in the field of computer vision (Tang *et al*., 2022; Xia *et al*., 2023b). Deep learning algorithms could achieve high efficiency and accuracy in object detection and recognition by using techniques such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) (Magana-Salgado *et al*., 2023). The following was some relevant literature on conventional methods and their shortcomings to address The issue: 'Faster R-CNN: Towards Real-Time Object Detection with region proposal networks' (2015) reduced the number of processing by introducing candidate boxes, thereby improving detection speed. The disadvantage of the method was that it may experience performance degradation when there were a large number of targets (Tang *et al*., 2022; Xia *et al*., 2023b). The article "R-FCN: Object detection via region-based fully convolutional networks" (2016) introduced a fully convolutional network, which would make all pixels an effective region for the detection network, thereby improving the detection speed. The disadvantage of the method was that it was relatively insensitive to detecting small targets (Zhuang *et al*., 2022; Xia *et al*., 2023c). Overall, conventional methods included Faster R-CNN and R-FCN, both of which had certain advantages and disadvantages (Momen *et al*., 2021). For example, Faster R-CNN had high accuracy but slow speed, while R-FCN had relatively fast speed but was not sensitive to small targets. Visual object detection and recognition recommendation was one of the research hotspots in machine vision. In recent years, the rapid development of deep learning has provided a new approach to visual recognition recommendation. Compared to traditional feature extraction methods such as Open CV, deep learning would extract features with better robustness and detection ability in various complex environments. Therefore, the article would select a deep learning-based object detection algorithm to identify and recommend target feature images within the image (Badgujar *et al*., 2023). By inheriting the detected target feature images, information in the target feature images would be obtained. Currently, among deep learning-based object detection algorithms, the SSD algorithm is sensitive to image resolution and has poor detection performance. The YOLO (Magana-Salgado *et al*., 2023; Momen *et al*., 2021; Pun *et al*., 2023; Choutri *et al*., 2023; Kim *et al*., 2023) series algorithms directly would be obtained from the category and bounding box of the target by utilizing the information contained in the input image (Neupane *et al*., 2024). Their detection speed would be fast, especially for the YOLOv5 series, which could achieve a detection speed of up to 0.007 sec on the GPU (Agramelal *et al*., 2023). Considering the characteristics of simple target feature images and easy recognition and recommendation (Neupane *et al*., 2024; Agramelal *et al*., 2023; Vohra *et al*., 2023; Sheela *et al*., 2023), the article would be selected to improve the YOLOv5 model for research on target feature image detection, recognition, and recommendation (Quiñones-Espín *et al*., 2023).

Overall, the results of the study show the solution to improve the YOLOv5 network to further enhance detection performance; the experimental results show that the system had achieved practical results in real-time and balanced performance in complex environments in practical scenarios. The deep learning model is at the core of establishing an effective decision support system for Chinese herbs recommend inspection and the overall application framework lays the foundation for practical application. The present approach also indicates when insufficient information has been provided as input to the model at the level of accuracy (reliability) needed by the user to make subsequent decisions based on the model predictions.

Materials and Methods

General Framework of the System

The design of the recommendation system for mobile robot vision recognition based on improved Yolov5 was presented in a paper (Sheela *et al*., 2023). The general frame is shown in Fig. 1, the field images collected by the image acquisition equipment in real-time, through the corresponding data line transmission and image preprocessing, are used as the input of the improved YOLOV5 algorithm on the Muenster data set for target detection and recognition recommendation, after Gauss blurring, morphological manipulation, and perspective transformation, the coding information of the target image is extracted by genetic algorithm to obtain information such as target class, pixel, physical coordinates, etc., (Quiñones-Espín *et al*., 2023). Wireless communication was used in mobile robot control terminals.

Iterative Learning Cascade Electromechanical Controller for Multi-Joint Manipulators

The dynamic equation of the moment arm of the multi-joint robot is:

$$M(q_{k(t)})\ddot{q}_{k(t)} + C(q_{k(t)}, \dot{q}_{k(t)}), \dot{q}_{k(t)} + G(q_{k(t)}) = \tau_{k(t)} + d_{k(t)} \qquad (1)$$

where, $q_k \in R^n, q_k \in R^n, \ddot{q}_k \in R_n$ is the joint angular displacement, angular velocity, and angular acceleration metrics and $M(q_k) \in R^{n*m}$ is the inertia matrix of the robot. $C(q_{k,}\dot{q}_k)\dot{q}_k \in R^n$ represents the centrifugal force and Coriolis force, $G(q_k) \in R^n$ is the gravity term and $\tau \in R^n$ is the control moment. $d_k \in R^n$ for various unmolded dynamics and perturbations.

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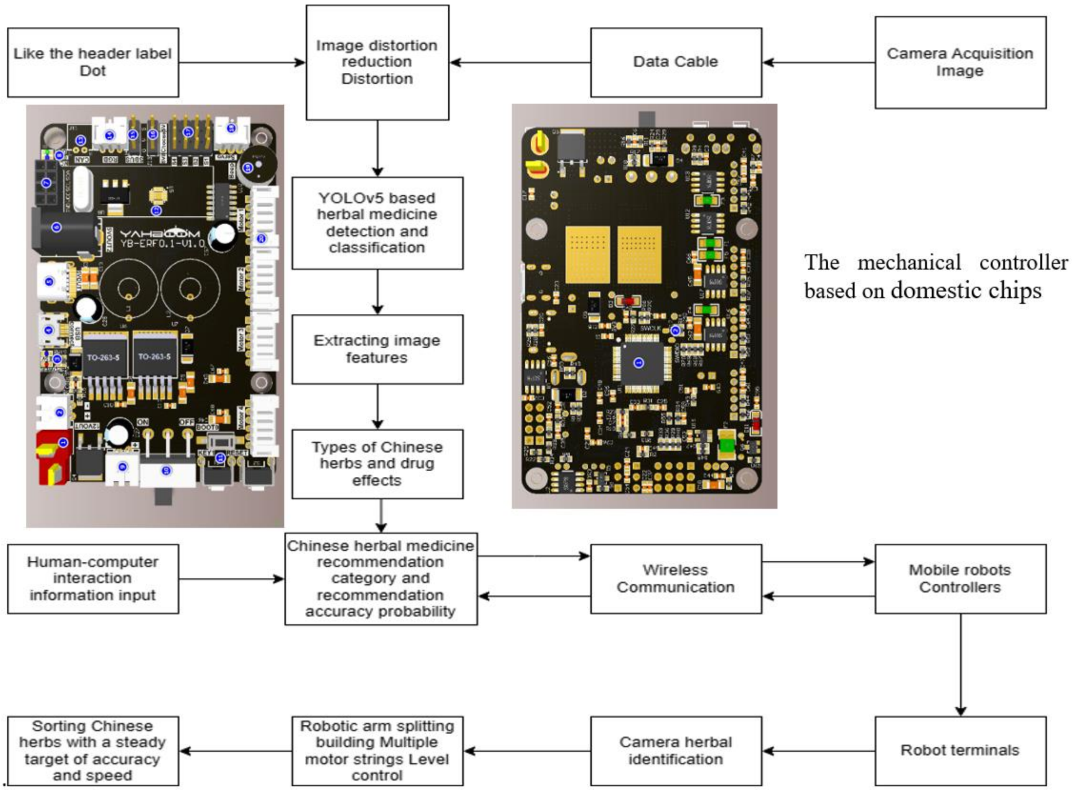

Fig. 1: Overall system framework design

Suppose that the system parameters are unknown and the system satisfies the following assumptions:

1. For $\forall_t \in [0,T]$, instruction trace $q_{d(t)}, \dot{q}_{d(t)}, \ddot{q}_{d(t)}$ and interference $q_{d(t)}$ are bounded
2. The initial value satisfies $\dot{q}_{d(0)} - \dot{q}_{k(0)} = q_{d(0)} - q_{k(0)} = 0$

And meet the general robot model has the following four characteristics:

1. $M(q_k) \in R^{n*m}$ is a symmetric positive definite and bounded matrix
2. $\dot{M}_{(qk)} - 2C(q_k, \dot{q}_k)$ is a symmetric matrix and $\dot{M}_{(qk)} - 2C(q_k, \dot{q}_k)x = 0, x \in R^n$
3. $G(q_k) + C(q_k, \dot{q}_k)\dot{q}_{d(t)} = \psi(q_k, \dot{q}_k)\xi^T(t), \psi(q_k, \dot{q}_k) \in R^{n*(m-1)}$ is the known matrix, $\xi_t \in R^{m-1}$ is the unknown vector; (P4)$\|C(q_k, \dot{q}_k)\| \leq k_c\|\dot{q}_k\|$,$\|G(q_k)\| < k_{g,} t \in [0,T], k_c$ andk_g as the positive real numbers

The proof was divided into three steps:

(1) Proof of boundedness of $\Delta W_{k(t)}$: We first define the Lyapunov energy function and then prove that $\Delta W_{k(t)}$is a no-increasing sequence by proving that $\Delta W_{k(t)} \leq 0$
(2) Proof of continuity and boundedness of $\Delta W_{0(t)}$: Firstly, the boundedness of $\Delta \dot{W}_{0(t)}$was proved, and then according to the uniform continuity decision theorem, it was proved that $\Delta W_{0(t)}$ is uniformly continuous on [0, *T*] and then according to the boundedness theorem of a continuous function on a closed interval. Proof $\Delta W_{0(t)}$ is bounded on [0, *T*]
(3) Convergence proof of error: Since $\Delta W_{0(t)}$ is bounded on [0, *T*] and is bounded on $\Delta W_{k(t)}$, it can be proved that $\tilde{q}_{k(t)}$, $\dot{\tilde{q}}_{k(t)}$ are bounded and $\lim_{k\to\infty} \tilde{q}_{k(t)} == \lim_{k\to\infty} \dot{\tilde{q}}_{k(t)} = 0, t \in [0,T]$. Based on the above controller, there were controller designs and two methods were given as follows:

Theorem 1:

$$\tau_k(t) = K_p\tilde{q}_k(t) + K_D\dot{\tilde{q}}_k(t) + \eta(\dot{\tilde{q}}_k)\hat{\theta}_k(t) \tag{2}$$

Theorem 2:

$$\tau_k(t) = K_p\tilde{q}_k(t) + K_D\dot{\tilde{q}}_k(t) + \hat{\delta}_k(t)\mathrm{sgn}(\dot{\tilde{q}}_k(t)) \tag{3}$$

$$\hat{\delta}_k(t) = \hat{\delta}_{k-1}(t) + \gamma\dot{\tilde{q}}_k^{\mathrm{T}}\mathrm{sgn}(\dot{\tilde{q}}_k(t)) \tag{4}$$

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According to the above formula, the following conclusion was obtained for system (1), if the control law is used:

$$\tau_k(t) = K_p\tilde{q}_k(t) + K_D\dot{\tilde{q}}_k(t) + \varphi(q_k, \dot{q}_k, \dot{\tilde{q}}_k)\hat{\theta}_k(t) \tag{5}$$

$$\hat{\theta}_k(t) = \hat{\theta}_{k-1}(t) + \Gamma\phi^{\mathrm{T}}(q_k, \dot{q}_k, \dot{\tilde{q}}_k)\dot{\tilde{q}}_k(t) \tag{6}$$

Here, $\hat{\theta}_{k-1}(t)_{k(t)=}q_{d(t)} - q_{k(t)}, \dot{\tilde{q}}_{k(t)} = \dot{q}_{d(t)} - \dot{q}_{k(t)}, \varphi(q_k, \dot{q}_k, \dot{\tilde{q}}_k) \in R^{n*n}$ and $\varphi(q_k, \dot{q}_k, \dot{\tilde{q}}_k) \triangleq [\psi(q_k, \dot{q}_k)sgn\tilde{q}_k 0)]$, matrices $K_P \in R^{n*m}, K_D \in R^{n*m}$ and$\Gamma \in [0, T]$ are positive definite symmetric matrices. Then $\tilde{q}_{k(t)}\dot{\tilde{q}}_{k(t)}$ are bounded and $\lim_{k\to\infty} \dot{q}_{k(t)} = \lim_{k\to\infty} \dot{\tilde{q}}_{k(t)}, t \in [0, T]$.

Mechanical Controller Experiment

The controlled object is a two-joint robot arm and the dynamic parameter in Eq. (1) is as follows: where the terms of the upper form are expressed $M = [m_{ij}]_{2*2}$as: $m_{12} = m_{21} = m_2(l_{c1}^2 + l_1 l_{c2}cosq_2) + l_2$, $C_{21} = -h\dot{q}_1$, $C_{22} = 0$ $h = -m_2 l_1 l_{c2} sinq_2$ $G = [G_1 G_2]^T G_1 = (m_1 l_{c1} + m_2 l_1)gcosq_1 + m_2 l_{c2} gcos(q_1 + q_2), G_2 = m_2 l_{c2} gcos(q_1 + q_2)$; The Interference is $d_{k(t)} = [d_m \sin(t) d_m \sin(t)]^T d_m$, of them are random signals with an amplitude of 1. The parameters of the robot system are $m_1 = m_2 = 1\ kg$, $l_1 = l_2 =$ 0.5 m, $l_{c1} = l_{c2} =$ 0.25 m, $I_1 = I_2 = 0.1 \times \mathrm{m}^2 =$ 9.81 m/s^2. Sin (2πt) and cos (2πt) were used as the position command signals of the two joints. To ensure that the initial output of the controlled object is consistent with the initial value of the instruction, take the initial state of the controlled object as $x(0) = [0\ \ 2\pi\ \ 1\ \ 0]^T$. The controller parameter is selected as $K_P = K_D = \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix}$ and the parameters of the adaptive law are selected as:

$$\Gamma = \begin{bmatrix} 10 & 0 & 0 & 0 & 0 \\ 0 & 10 & 0 & 0 & 0 \\ 0 & 0 & 10 & 0 & 0 \\ 0 & 0 & 0 & 10 & 0 \\ 0 & 0 & 0 & 0 & 10 \end{bmatrix} \tag{7}$$

Here, there showed the total number of iterations was 5 and the simulation time was 1 per iteration. Using the Control Law (2) and the Adaptive Law (3), the simulation results are shown in Figs. 2-5, which was the position tracking of the position command signal of a two-joint robot arm after 10 iterations.

Here, there showed the convergence process of the absolute value of position tracking error during ten iterations of a two-joint robot arm in Fig. 3.

Here, there showed the process of number tracking after 10 iterations by tuning the algorithm in research in Fig. 4.

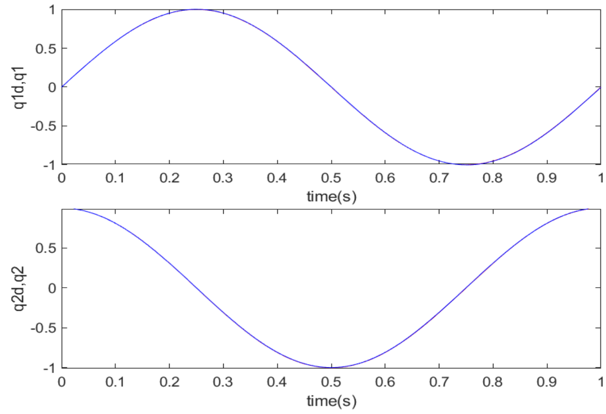

Fig. 2: Position tracking after 10 iterations

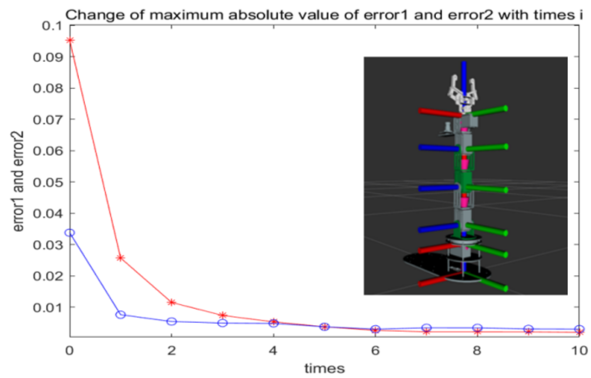

Fig. 3: Convergence process of the absolute value of position track during or during 10 iterations

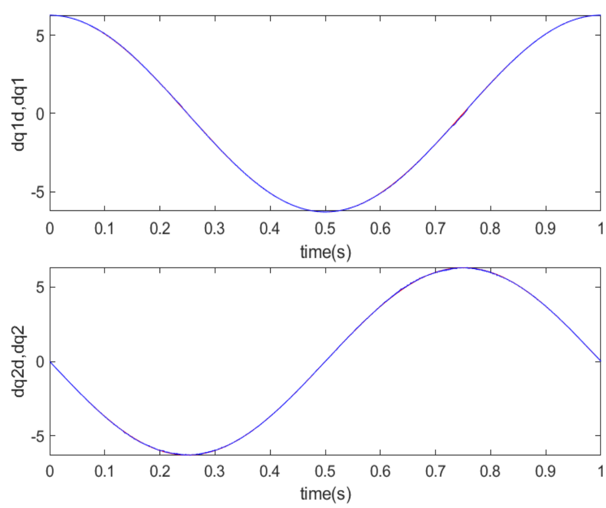

Fig. 4: Speed tracked after 10 iterations

Here, there specifically showed the convergence of the absolute value of the number tracking error of the two-joint robot arm during 10 iterations in Fig. 5.

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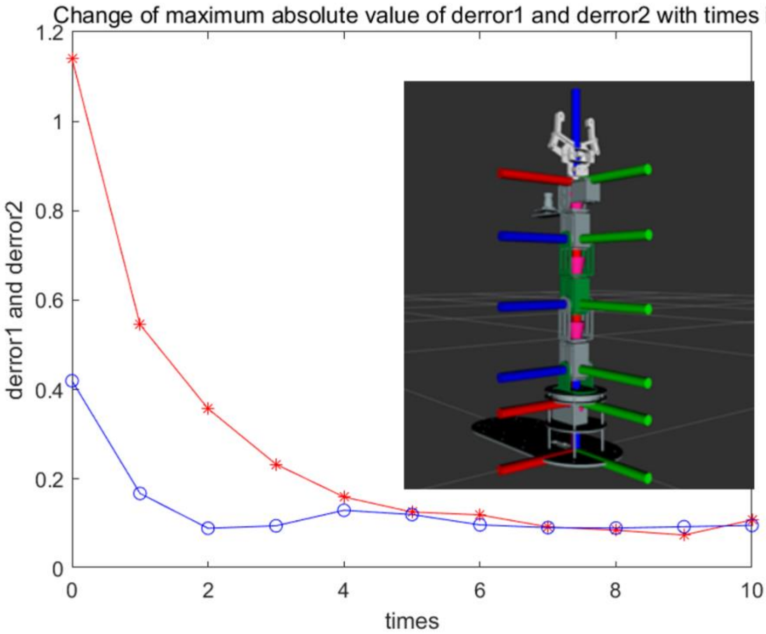

Fig. 5: Convergence process of the absolute value of speed-tracked error during 10 iterations

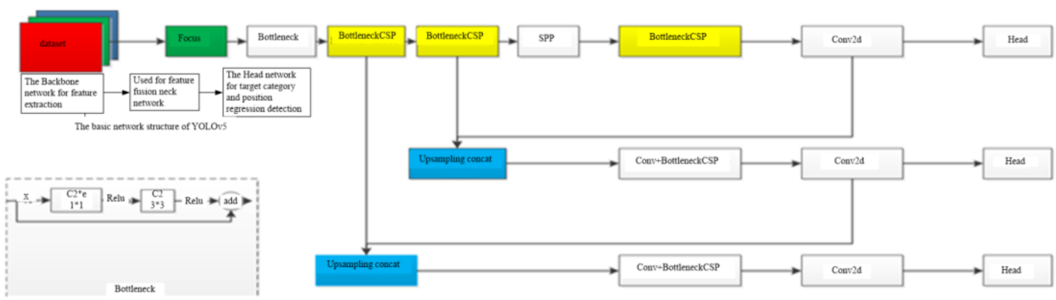

Fig. 6: Improved YOLOv5s basic network structure

Improved Yolov5 Network and Extracting Image Features of Traditional Chinese Medicine

As shown in Fig. 6, the YOLOv5 object detection framework has a relatively simple network structure, which can be roughly divided into three parts: The backbone network for feature extraction (Backbone), the neck network for feature fusion (Neck), and the head network for target category and position regression detection. The article selects the YOLOv5 network model as the training model, dividing the image into cells and determining candidate boxes in each cell. If the center of the target falls in the cell, which is responsible for predicting the target:

(1) The article aims to improve the backbone network by introducing the V-CSPNet module

Replace the CSPNet module in the YOLOv5 backbone network with the V-CSPNet module. The approach is to integrate a Cross-Stage Local Network (CSPNet) and residual structure based on the OSA module. By dividing the feature map of the base layer into two parts and then merging them through the proposed cross-stage hierarchy structure, the improved framework can form a richer combination of gradients, propagate gradient flows in different network paths, further enhance the model's ability to extract features while reducing computational complexity; The residual network structure can enable deeper and finer model training (Pun *et al*., 2023; Xu *et al*., 2018):

(2) Optimize loss function

The training dataset contains a large number of simple negative samples (background), which account for a large proportion of the total loss. This will lead to the optimization direction of the model leaning more towards negative samples, which is also the main reason why the accuracy of the first-stage algorithm lags behind the

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second-stage algorithm. Therefore, to alleviate the problem of imbalanced sample categories, the article uses focal loss to evaluate the confidence of the target.

The optimization loss function contains a large number of simple negative samples (background) in the training data set, which accounts for a large proportion of the total loss, The is also the main reason why the precision of the first-stage algorithm lags behind that of the second-stage algorithm.

After improving the YOLOv5's object detection algorithm, the extracted target image may have interference factors such as lighting, occlusion, and tilt, which require image processing to ensure the subsequent input of the genetic algorithm path planning controller (Sayyad *et al*., 2023).

The software part of the platform: To recommend system operation configuration and to write recommendation system programs in the latest Python environment; Write a facial recognition program in Python 2.7, Anaconda 2, opencv 2.4.13.4 of environments, using convolutional neural network algorithms to collect 106863 datasets of 530 male and female facial images for training. The test achieved a recognition rate of 98.1%; The application of the SVM classifier model, as well as the fusion of the LBP algorithm and SVM classifier algorithm, has proven a model with high accuracy in facial detection and recognition of gender and age; Applying facial recognition to recommendation systems can quickly obtain user information, classify users and improve recommendation speed. By collecting user facial information and mining data to identify user age and gender, a user-based recommendation system is used for making recommendations.

Hardware part of the platform: The hardware architecture for building a user facial information recommendation system can be divided into four functional modules, mobile robotic arm, visual, collaborative filtering recommendation, and recommended logistics (using components such as motors, conveyor belts, and microcontrollers to build sorting systems). After power management, the system can be independently demonstrated or demonstrated in series as a whole, as shown in Figs. 7-8.

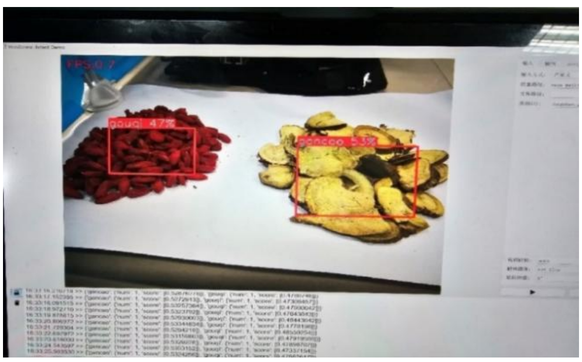

Fig. 7: Physical image of collaborative filtering recommendation system

Fig. 8: Robot arm grabbing Goqi berries and recognition confidence rate

Results and Analysis

Experimental Environment and Process Analysis

The target detection algorithm, YOLOv5 was used, which YOLOv5 was a single-stage object detection algorithm. YOLOv5 provided four models, namely Yolov5s, Yolov5m, Yolov5l and Yolov5x. The network depths of the four models were deepened in sequence and the network widths were widened in sequence. In the YOLOv4 network structure, the design concept of CSP-Net was borrowed, and the CSP structure was designed in the backbone network (Norinder and Lowry, 2023; Choutri *et al*., 2023; Kim *et al*., 2023; Quach *et al*., 2023; Stark *et al*., 2023; Vijayan *et al*., 2023; Betti Sorbelli *et al*., 2023). The difference between YOLOv5 and YOLOv4 was that only the backbone network of the 1st CSP structure and the 2nd CSP structure.

YOLOv5 adopts the Mosaic data augmentation method, which references the CutMix method. Mosaic data augmentation uses 4 images, which are randomly scaled, cropped, and arranged from composition. However, the method can directly calculate the data of 4 images, so that the Mini batch size does not need to be very large and a GPU can achieve good results. In addition, using 4 images, randomly scaling, and then randomly distributing them for stitching greatly, enriches the detection dataset, especially by adding many small targets to the random scaling, making the network more robust. The experimental collection of medicinal herb images mainly comes from internet searches, collecting approximately 2000 images related to traditional Chinese medicine, including 210 images of licorice, 200 images of honeysuckle, 200 images of Codonopsispilosula, 190 images of wolfberry berries, 182 images of sophora japonica and the composition of the Chinese medicine dataset. In addition, there are 500 pictures of Chinese herbal medicines affected by pests and diseases and 400 pictures of normal growing Chinese herbal medicines. The Chinese medicinal herbs in the picture have clear pixels and are suitable for use as training objects. The shapes of the same type of medicinal herbs can be sliced, blocky, or striped. By training different shapes, the model can be consolidated and trained.

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Experimental Result and Analysis

Following experimental training and testing on data images from each category to determine recommended objects (in thousands), the result illustrated the accuracy of visual target detection and target recognition recommendations for martial arts circular mobile robots in Fig. 9.

Here, there are the experimental results for the training part in Fig. 10, which iteration step size and loss under yolov5 and yolov4, as well as details of the experimental results for the accuracy curves.

Here, there showed the confidence results and the confidence experiment results are good, in the range of 0.635-0.97 and the model performs well in Fig. 11.

For instance, within the context of mobile robot vision for herbal target detection and target category recognition recommendations, a camera designed and developed for real-time acquisition of surrounding space Comprehensive processing of facial information in the environment, including direct backend storage, has been achieved fast and effective construction of data sets; Equipped with the latest Python ring Jing has developed a functional software for a facial recommendation system, which uses a volume integrated neural network algorithm, collecting 106 863 faces of 530 men and women with using traditional Chinese medicine face to face diagnosis, in the color category testing, the baseline YOLOv5 model exhibited an average accuracy of 37% on the test dataset, which improved to 45% after optimization. In the shape testing, the initial YOLOv5 model achieved an average accuracy of 46% on the test dataset, whereas the optimized YOLOv5 model demonstrated an average accuracy of 56% on the data (Choutri *et al*., 2023). Regarding dataset-wide detection, the optimized YOLOv5 model achieved an average accuracy of 56%. In the case of face testing, the unimproved YOLOv5 model achieved an average accuracy of 71% on the test dataset, while the optimized YOLOv5 model achieved an average accuracy of 82% on the dataset for detection. Among these scenarios, a comparison of identified recommended objects across various categories is presented in Table 1 and Fig. 12.

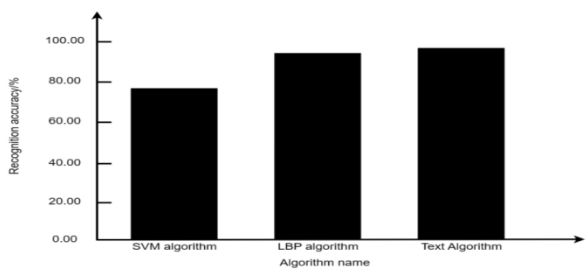

Fig. 9: Deep learning training of herbal recognition algorithm

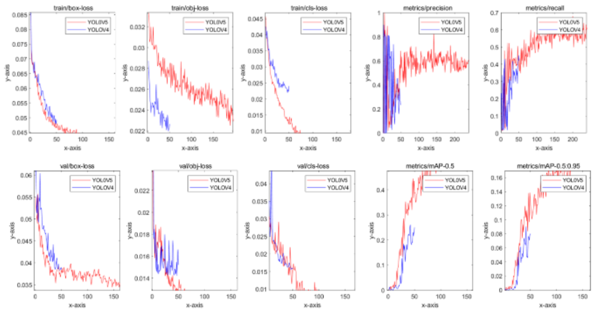

Fig. 10: The results of the training part of the experiment

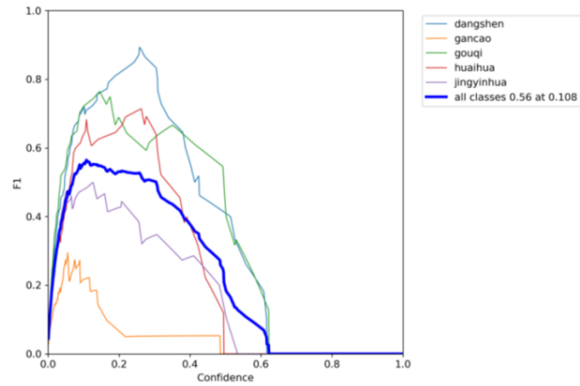

Fig. 11: Confidence curve

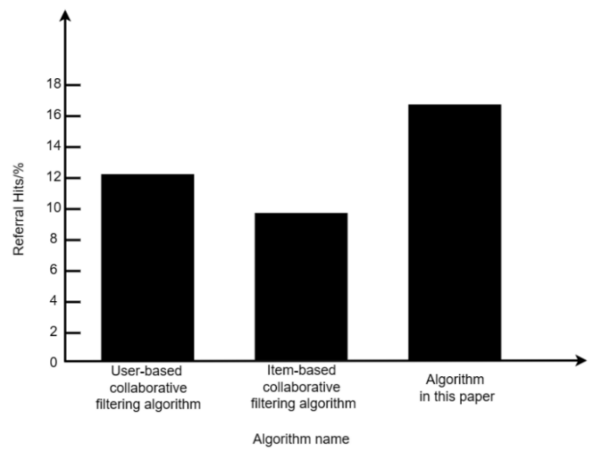

Fig. 12: Comparison of recommended click rates of several recommendation algorithms

Table 1: Comparison of accuracy in identifying recommended categories

Identification category	Original model	Improvements model	Increase (%)
Sophora	0.37	0.45	21.6
Codonopsis root	0.46	0.56	21.7
Wolfberry	0.71	0.82	15.5

Discussion

After the introduction of the background and need for intelligent identification and recommendation of Chinese herbal medicines and the reference of the previous research in the field, the system in paper of visual robotic arm control was used for the sorting of Chinese herbs recommend string-level predictive control, which the system of detecting was accurate,stable,and testing with high recognition efficiency; The paper provided mathematical formulations and controller design methods, to be enhancing the accuracy of the robot's motion control, to strengthen the field of Traditional Chinese Medicine (TCM) and the potential for modern technology to enhance TCM practices.

This paper combines deep learning with a large amount of data to achieve the recognition of traditional Chinese medicine by ordinary users with the help of intelligent mobile devices. Firstly, the performance of the model is greatly affected by hardware, and it can be deployed to the server to recognize the high-performance resources of the server, and then the results can be sent back to the local area to sort the traditional Chinese medicine. Secondly, there is still room for improvement in the model's performance, which can be achieved through methods such as increasing the dataset and training frequency. However, from an overall and future development perspective, there are still some shortcomings in this system that can be improved and optimized to a certain extent.This system realizes the design of an intelligent traditional Chinese medicinal materials recognition and sorting system. In practical applications, it can reduce the risk of people accidentally ingesting incorrect medicinal materials or alleviate the labor intensity of workers. By enhancing people's cognitive abilities regarding traditional Chinese medicinal materials and broadening their knowledge of health preservation, it allows for a deeper understanding of one's physical health status. In short, it can improve people's quality of life. Additionally, it promotes the development of traditional Chinese medicine and modern computer technology, serving as both an inheritance and innovation of traditional Chinese medicine. This system holds significant importance in advancing the modernization of traditional Chinese medicine in future.

Conclusion

Starting with the target recognition technology of Traditional Chinese Medicine (TCM), the paper has proposed to ensure authenticity, efficiency, standardization, conservation, and scientific exploration within the field of Traditional Chinese Medicine. The main conclusions were as follows:

(1) The paper proposed a new Chinese herbal medicine recognition and mobile robot visual robotic arm control system, which was constructed a mobile robot visual function research and development experimental domestic chips electromechanical arm-controller using typical kernel algorithm recommended by Chinese medicinal materials visual recognition, which the cascade electromechanical control system was based on iterative learning electromechanical control for multi-joint manipulators. So the system was aimed to combine the capabilities of deep learning and computer vision to identify and accurately grasp Chinese herbal medicines in real time
(2) The paper proved the advantages of using machine learning and deep learning techniques for accurate and efficient identification and recommendation of herbs, which could be proposed as a crucial innovation aspect of TCM. The proposed system employed the YOLOv5 model, a state-of-the-art object detection algorithm, and an improved version of the model. The paper discussed the system's architecture, which included image acquisition, pre-processing, target detection, and recommendation. The system incorporated image augmentation techniques, which played a significant role in improving model performance. The use of mosaic data augmentation was highlighted as a method to improve dataset diversity and robustness. The YOLOv5 model has undergone an improvement process which included optimizing the backbone network by introducing the V-CSPNet module, to enhance feature extraction and reduce computational complexity. The paper also focused on optimizing the loss function to address issues of imbalanced sample categories, further improving the model's performance
(3) The paper conducted a series of experiments and analyzed the results to collect an extensive dataset of Chinese herbal images and test the target detection and recognition capabilities of the YOLOv5 model, providing detailed accuracy data for different Chinese herbal categories and recommended objects. The results were summarized in tables and graphs, demonstrating the effectiveness of the proposed system. The paper concluded by summarizing its contributions, highlighting the improved accuracy and real-time capabilities of the intelligent recommendation system

In summary, the paper presented a comprehensive study on intelligent herbal identification and recommendation in the field of Traditional Chinese Medicine (TCM) using a combination of advanced computer vision techniques and deep learning algorithms. The proposed system showed promising results and had the potential to revolutionize the field of herbal medicine identification and recommendation. The paper's detailed description of the system's architecture and its extensive experimental analysis made it a valuable reference to the field of computer vision in traditional Chinese Medicine.

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Author's Contributions

Wenyi Zhang, Gang Wang, Xiaofei Xu and Junjie Zhu: Designed and performed the experiments, analyzed the data and prepared the paper.

Keping Mao,Tao Ma and Zixuan Li: Designed the experiments and revised the manuscript.

Ethics

The authors declare their responsibility for any ethical issues that may arise after the publication of this manuscript.

Conflict of Interest

The authors declare that they have no competing interests. The corresponding author affirms that all of the authors have read and approved the manuscript.

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