



HONG KONG
ASIAWORLD-EXPO
亞洲國際博覽館

3RD TO 6TH
DECEMBER
2025



Application Effect of Artificial Intelligence Visual Recognition System on the Receiving and Inventory Process of Loaner Instruments

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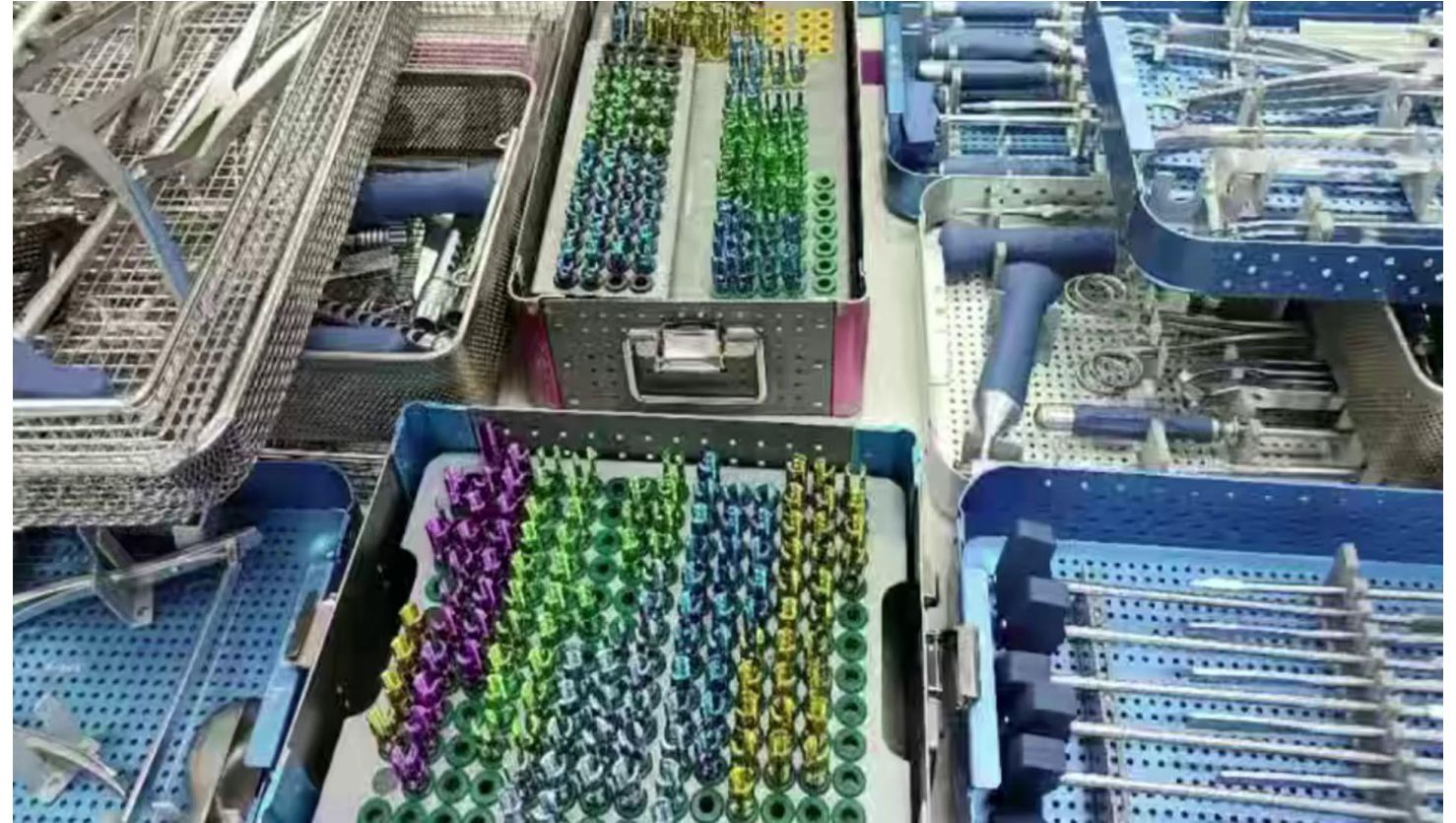
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A. Background and Objective

Research Background



On loan instruments : Reprocessing process is complex, challenging, but related to patient safety



A. Background and Objective Clinical Background Analysis

Growth in operations and instrument usage



With the continuous advancement of medical technology and the increase in patient demand, the number of surgeries has shown an increasing trend year by year; in order to adapt to diverse surgical needs, the use of on loan instruments has become more and more frequent.

Challenges and limitations of manual counting



The traditional manual inventory model has many challenges and limitations, such as low efficiency and accuracy greatly affected by human factors, which makes it difficult to meet the dual pressures of medical quality and safety requirements and efficiency improvement.

Manual handover mode: cumbersome process, manual counting, easy to get confused, incomplete traceability



A. Background and Objective Clinical Background Analysis

Current bottlenecks and pain points during receipt of loan instruments

Operation

- **Inefficiency: time Consuming**
- Manpower requirement
- Low turnover rate;
- **Information not shared**

Quality Control

- **High risk of error**
- **Difficulty in tracing**
- Risk of foreign body left behind;
- Equipment management costs

Staff Safety

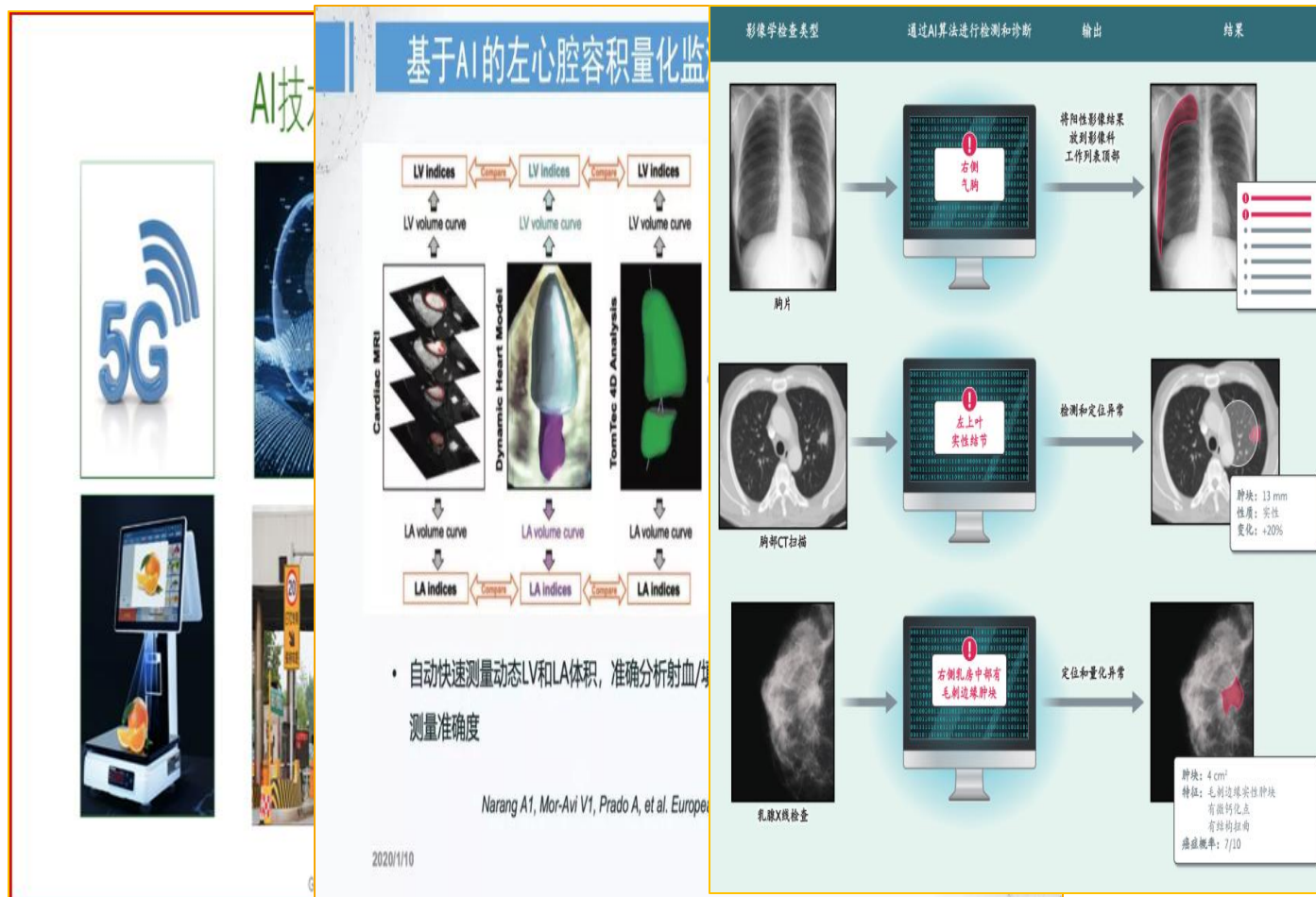
- Visual fatigue: wrong sight and missed sight
- Human fatigue leading to mis recording and omission
- **High staff pressure**
- Low satisfaction

Low operational efficiency, increased safety risks, and difficulty in quality control



A. Background and Objective

Technology Development



Current Status of Computer Vision Technology

Computer vision technology is increasingly used in the medical field, and it has shown great potential in medical image recognition and diagnosis.

Progress in Deep Learning Object Recognition

Deep learning algorithms have made recent progress in object recognition, providing strong technical support for artificial intelligence visual recognition systems.

From Assisted Tools to Transformative Cores -- The AI Era





A. Background and Objective Literature review

中华医院感染杂志 2023 年第 23 卷第 2 期 Chin J Nosocomiol Vol. 23 No. 2 2023

• 291 •

doi:10.11816/cn.ni.2023.221399



开放科学(资源服务)标识码(OSID):

人工智能系统在外来医疗器械交接中应用效果的多中心研究

护士进修杂志 2024 年 1 月第 39 卷第 2 期

• 161 •

人工智能视觉识别系统在外来医疗器械检查中的应用效果

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摘要 目的 探讨人工智能视觉识别系统在外来医疗器械供应中心(CSSD)外来骨科医疗器械包装质量的应用效果。方法 我院于 2022 年 1 月将采集在 CSSD 处置的骨科外来器械信息,包括(图像、名称规格、数量)等传至人工智能视觉识别系统中存档,实现图像数据分析和识别,并同步提示。即选取 2021 年 2~12 月系统应用前我院消毒供应中心接收处理的 9 400 包骨科外来器械为对照组。2022 年 1 月~11 月系统应用后约 9 400 包为观察组,比较 2 组医疗器械包装质量及管理工作情况(包装质量、平均耗时、使用满意度)。结果 观察组医疗器械包装质量优于对照组,差异有统计学意义($P<0.05$)。包装质量提高,平均耗时及使用满意度优于对照组,差异有统计学意义($P<0.05$)。结论 人工智能视觉识别系统在外来骨科医疗器械包装环节,检查应用中效果较好。提升包装质量的同时,也优化了外来骨科医疗器械管理流程,提高了手术室满意度和工作效率。

关键词 消毒供应中心; 人工智能; 视觉识别; 外来骨科医疗器械; 包装质量

Research and application of artificial intelligence visual recognition system in inspection package quality of external medical instruments in disinfection supply center

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Abstract Objective To explore the application effect of artificial intelligence visual recognition system on the packaging quality of external orthopedic medical devices in the Central Sterile Supply Department (CSSD). Method In January 2022, information on external orthopedic instruments disposed by CSSD were collected in our hospital, including images, names, specifications, and quantities and were archived in the artificial intelligence visual recognition system; so as to realize the image data analysis and backtracking and archive warning prompts. A total of 9,400 packages of orthopedic external instruments received and processed by CSSD of our hospital before the system application from February to December 2021 were selected as the control group, and a total of 9,400 packages after system application were selected as the observation group. The quality and management of medical device packaging (average packaging inspection time, user satisfaction) were compared between the two groups. Results The quality of medical device packaging and satisfaction with use in the observation group were better than those in the control group, and the difference was statistically significant ($P<0.05$). The average packaging time was lower than that of the control group, and the difference was statistically significant ($P<0.05$). Conclusion The artificial intelligence visual recognition system has shown good effectiveness in the packaging process of CSSD external orthopedic medical devices. While improving packaging quality, it has also optimized the management process of external orthopedic medical devices, and improved operating room satisfaction and work efficiency.

Keywords central sterile supply department; artificial intelligence; visual identity; foreign orthopedic medical devices; packaging quality

中文分类号: R172 文献标识码: C DOI: 10.11821/cn.ni.2023.02.010

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scientific reports

OPEN An efficient annotation method for image recognition of dental instruments

Shintaro Oka^{1,2*}, Kazumori Nozaki^{2,3} & Mikako Hayashi^{2,3}

To prevent needlestick injury and leftover instruments, and to perform efficient dental treatment, it is important to know the instruments remained during dental treatment. Therefore, we will obtain a

RESEARCH

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Artificial intelligence model for automated surgical instrument detection and counting: an experimental proof-of-concept study

Elamir S. Deol¹, Grant Henning¹, Spondon Basuakal¹, Ravneet A. S. Vardol¹, Vidit Sharma¹, Nicholas L. Kawar¹, R. Jeffrey Kames¹, Bradley C. Leinbach¹, Stephen A. Boorjian¹ and Abhinav Khanna^{1*}

Abstract

Background Retained surgical items (RSIs) are preventable events that pose a significant risk to patient safety. Current strategies for preventing RSI rely heavily on manual instrument counting methods, which are prone to human error. This study evaluates the feasibility and performance of a deep learning-based computer vision model for automated surgical tool detection and counting.

Methods A novel dataset of 1,004 images containing 13,213 surgical tools across 11 categories was developed. The dataset was split into training, validation, and test sets at a 60:20:20 ratio. An artificial intelligence (AI) model was trained on the dataset, and the model's performance was evaluated using standard object detection metrics, including precision and recall. To simulate a real-world surgical setting, model performance was also evaluated in a dynamic surgical video of instruments being moved in real time.

Results The model demonstrated high precision (98.5%) and recall (99.9%) in distinguishing surgical tools from the background. It also exhibited excellent performance in differentiating between various surgical tools, with precision ranging from 94.0% to 100% and recall ranging from 97.1% to 100% across 11 tool categories. The model maintained strong performance on a subset of test images containing overlapping tools (precision range: 89%–100%, and recall range: 97.2%–98.2%). In a real-time surgical video analysis, the model maintained a correct surgical tool count in all non-transition frames, with a median inference speed of 40.4 frames per second (interquartile range: 4–5).

Conclusion This study demonstrates that using a deep learning-based computer vision model for automated surgical tool detection and counting is feasible. The model's high precision and real-time inference capabilities highlight its potential to serve as an AI safeguard to potentially improve patient safety and reduce manual burden on surgical staff. Further validation in clinical settings is warranted.

Keywords Retained surgical items; Computer vision; Artificial intelligence; Surgical tool detection; Surgical safety

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Background

Retained surgical items (RSIs) are surgical instruments or materials unintentionally left inside a patient's body after surgery [1]. RSIs are considered "never events," which are defined as serious, preventable incidents that should ideally never occur in healthcare settings [2]. Despite increased efforts to prevent RSIs, they remain a significant problem, with an estimated incidence of 1 in every 3000 surgeries [3]. The impact of RSIs on patients, healthcare providers, and the healthcare system is substantial, including physical and psychological harm to patients, emotional distress for surgeons, and increased healthcare costs [4].

Traditional programs for preventing RSIs center around manual counting of surgical items, commonly conducted by nursing staff [5, 6]. However, such programs often require specialized personnel training, and can increase surgical duration [7]. Furthermore, manual counting is subject to human error due to communication breakdowns, time pressure, competing demands, and environmental distractions [8, 9–10]. Current programs recognize the limitations of individual manual surgical counts and seek to use several layers of security to prevent RSIs [6]. Depending on institutional policies, these can include the use of technologies such as radio-

frequency identification (RFID) technology, bar codes, or computer vision to accurately detect and track surgical tools throughout a procedure, serving as a potential AI safeguard against RSIs.

Methods

Study design and setting We hypothesized that a deep learning-based computer vision model for automated surgical tool detection and counting. The study was performed at the Department of Urology, Mayo Clinic, Rochester, Minnesota, USA, between January 2024 and May 2024.

Hypothesis

We hypothesized that a deep learning-based computer vision model could accurately detect and classify surgical instruments in real-time from a standard surgical table, potentially serving as an AI safeguard against RSIs.

Primary and secondary outcomes

The primary outcome was the model's performance in detecting and classifying surgical tools, as measured by precision, recall, and mean average precision, standard measures to benchmark the performance of computer vision models. The secondary outcome was the model's inference speed (frames per second) and its ability to maintain a correct surgical tool count in real-time.

Scientific Reports | (2024) 14:1824 |

<https://doi.org/10.1038/s41598-024-26372-y>

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the model could keep pace with the dynamic nature of a surgical procedure, correctly identifying tools as they are being used in real-time. All data analysis was conducted in Python using the PyTorch and Ultralytics packages [23].

Results

The overall dataset consisted of 1004 images, of which 603 (7891) tool instances/images were used for model training, 201 (2667 tool instances) for internal validation, and 200 (2655 tool instances) for testing model performance. For detecting the presence or absence of surgical tools in the test dataset the model made 2,693 surgical tool predictions, of which there were 41 instances in which the model falsely identified the background as a surgical tool (false positive). Thus, the overall precision for distinguishing surgical tools from the background was 98.5%. Conversely, the model failed to identify a surgical tool in only three instances, incorrectly labeling a tool as background in all three instances (false negative). This translates to an overall recall (sensitivity) of 99.9%. The model's mean average precision (50–95) was 88.4%, and mean average precision 50 was 99.4%.

Model performance was also explored for differentiating between the 11 types of surgical instruments. The basin class exhibited a precision and recall of 100%, indicating that the model perfectly predicted all basin instances without any false positives or false negatives. Syringes also achieved a precision of 99.6% and a recall of 100%, demonstrating nearly perfect performance in identifying all syringe instances. The surgical scissors class attained a precision of 99.2% and a recall of 99.5%. In contrast, the scalpel class had the lowest precision at 94.0% and a recall of 97.1%. The precision and recall values for the remaining instrument classes can be found in Table 1, and a confusion matrix illustrating these results is presented in Fig. 2A.

Similar model performance was observed on the subset of test images containing overlapping tools. For

identifying surgical tools, the model achieved a precision of 100%. Precision remained constant between surgical tool scalps to 100% for basins, forceps to 98.2% for retractors, the overlapping tool subset shows examples of predicted surgical tools in a real-time surgical video analysis, maintained a correct surgical tool count during all non-transition times with an inference speed suitable for real-time use. These results highlight the potential for computer vision models to maintain an automated tool count during surgery which has the potential to reduce errors and thereby help improve surgical safety.

Discussion

This study demonstrates the feasibility and effectiveness of employing a deep learning-based computer vision model for the automated detection and enumeration of surgical instruments. The model achieved high precision and recall in distinguishing surgical tools from the background and in differentiating between various surgical instruments, even in challenging scenarios involving overlapping tools. In a real-time surgical video analysis, the model maintained a correct tool count during all non-transition times with an inference speed suitable for real-time use. These results highlight the potential for computer vision models to maintain an automated tool count during surgery which has the potential to reduce errors and thereby help improve surgical safety.

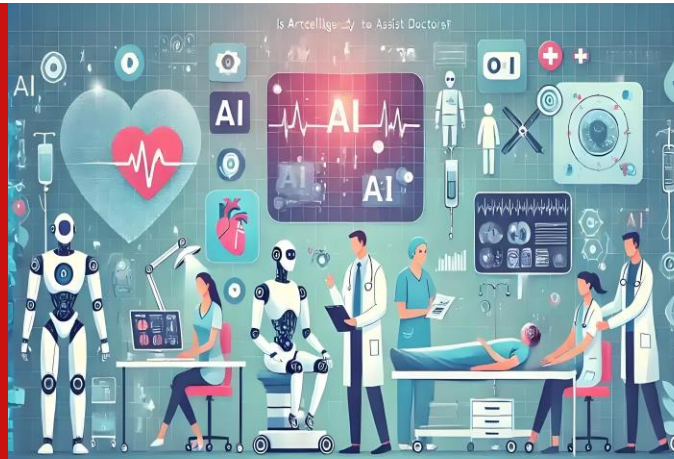
Our study's high precision and recall in detecting a broad array of surgical tools, even in challenging conditions with overlapping items, address some of the critical gaps in previous research, such as the need for robust detection across a diverse range of surgical objects and the demonstration of an inference speed suitable for practical real-world applications. Lavado et al. previously developed a computer vision model based on YOLOv3 for detecting surgical tools in cluttered trays and performed occlusion reasoning to determine which tool should be removed first following sterilization [24]. Their model was trained on only four different surgical tool classes and performed moderately well (mean average precision at 0.50 of 92.0%). In contrast, our model was trained on 11 different classes and achieved a mean average precision at 0.50 of 99.4%. Also, of note, Lavado et al. photographed surgical tools in a metallic background, whereas our models were trained on tools in a blue surgical cloth background, which is similar to most real-world surgical tray setups [24]. Jiang et al. examined automated



A. Background and Objective Research Objective Setting

AIM : The application effect and value of artificial intelligence visual recognition system in the CSSD loaned instruments receiving and inventory process

improvements of AI visual recognition systems in counting loaned instrument to ensure efficient and accurate medical processes.



Long Term Goal

Establish standardized processes and quality control systems for intelligent equipment inventory to promote intelligent development in the medical field.

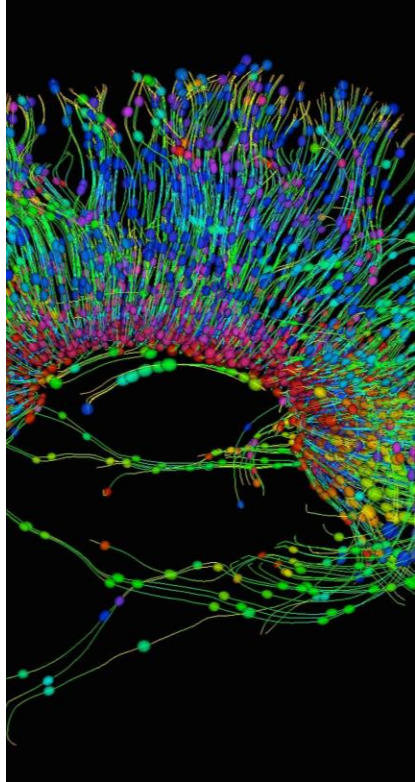


Analyze the cost-benefit ratio and personnel acceptance of system implementation, providing strong data support for decision-making .



B. Research Details

System Technical Principles



Convolutional Neural Networks

In device image recognition, convolutional neural networks* automatically extract image features to achieve high-precision classification, providing technical support for foreign device recognition.



Deep Learning Algorithms

The algorithm module adopts advanced deep learning algorithms to continuously optimize the recognition model and improve the accurate recognition rate of instrument images under complex backgrounds.

Note*: A convolutional neural network is a type of artificial neural network specifically designed to process data with a grid-like structure, most notably images. Through a unique operation called convolution, it can efficiently identify spatial patterns in images, such as edges, corners, object parts, and even entire objects.



B. Research Details

System Structure

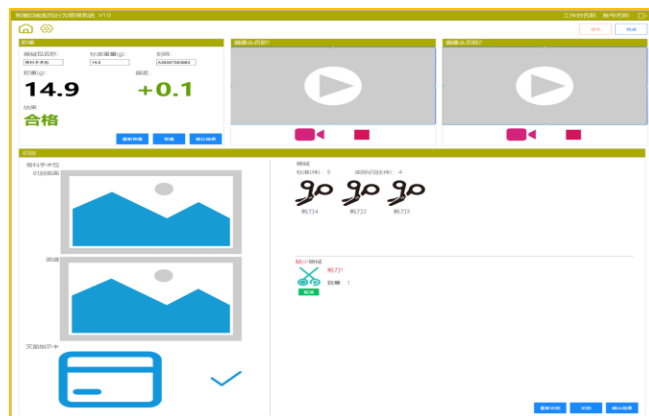
Hardware composition

The system is equipped with high-definition cameras to capture clear images; the computing unit quickly processes recognition tasks; and the display terminal intuitively displays the results to ensure convenient operation.



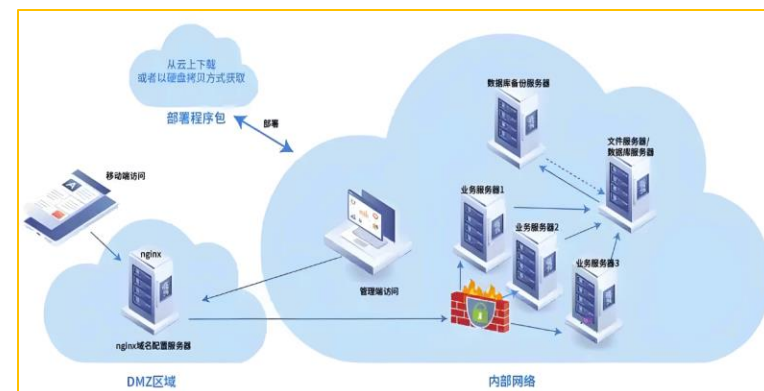
Software System

The image acquisition module enables efficient capture; the core of the recognition algorithm module is responsible for deep learning and model reasoning; the data management module ensures data integrity and security.



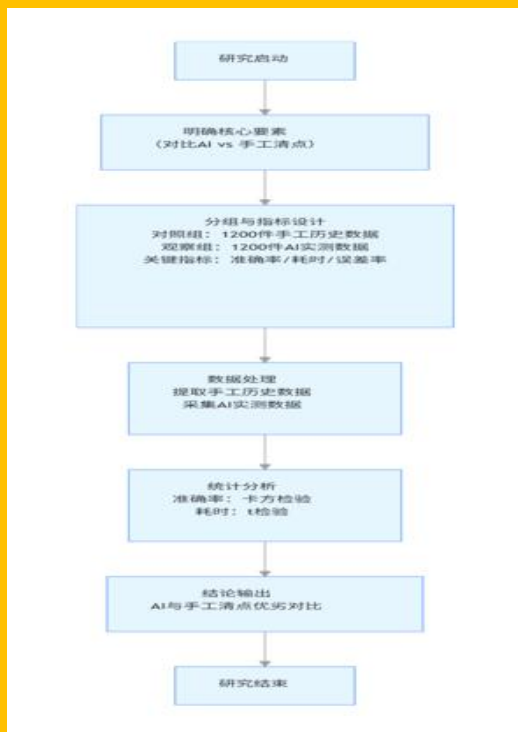
Network Architecture

Adopting a local deployment solution, data and processing equipment are stored locally to ensure data security and privacy, reduce network dependence, and improve system stability and response speed.



B. Research Details

Workflow Design



Standardized collection process

Establish detailed instrument image acquisition standards, including lighting, angle, resolution, etc., to ensure consistent image quality and lay a solid foundation for identification.

Collaborative identification mechanism

The system identifies the device in real time and quickly feeds back the results; at the same time, a manual review channel is established to conduct a second confirmation of suspected errors or complex devices..

Exception handling process

Clarify the responsibilities and processes for exception handling, such as the response measures for blurred images, recognition failures, etc., to ensure that errors are corrected and handled in a timely manner .



B. Research Details

Study Design



Controlled trial plan

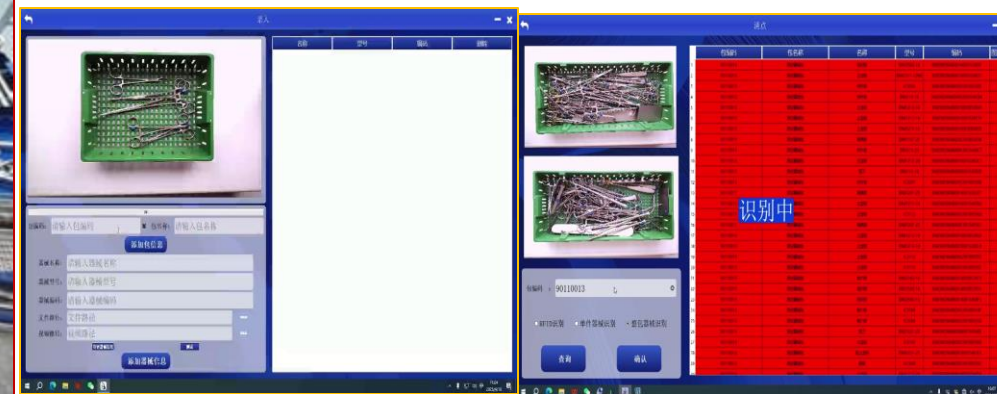
A control group and an experimental group were set up. The control group adopted the traditional manual counting mode, and the experimental group adopted the AI visual recognition system. The counting efficiency and accuracy of the two groups were compared.

Limited scope

The study is limited to a specific time period and specific device type to ensure the representativeness of the research sample and the reliability of the results, avoiding interference from irrelevant variables. .



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	91:00	㊿ 10	✓					10	11/15	18:30	唐浩	
	92:00	㊿ 10	✓					10	11/15	18:30	唐浩	
	93:00	㊿ 10	✓					10	11/15	18:30	唐浩	
	94:00	㊿ 10	✓					10	11/15	18:30	唐浩	
	95:00	㊿ 10	✓					10	11/15	18:30	唐浩	
	96:00	㊿ 10	✓					10	11/15	18:30	唐浩	
	97:00	㊿ 10	✓					10	11/15	18:30	唐浩	
	98:00	㊿ 10	✓					10	11/15	18:30	唐浩	
	99:00	㊿ 10	✓					10	11/15	18:30	唐浩	
	100:00	㊿ 10	✓					10	11/15	18:30	唐浩	



B. Research Details

Research Subject

Inclusion criteria for on loan instrument

The study was limited to devices of specific types, materials, and complexity to ensure the effectiveness and accuracy of the identification process and avoid interference from non-target devices.

&

Personnel training and operating procedures

Researchers need to receive unified training to ensure standardized operations, reduce human errors, and ensure the accuracy and reliability of research data.

Set up inclusion criteria



C. Research Method and Data Collection

Research Method

Comparison between traditional methods and artificial intelligence recognition

Traditional Method



VS

Artificial intelligence recognition



C. Research Method and Data Collection

Method of Data collection

Main evaluation indicators

Recognition accuracy, inventory time, and error rate are used to comprehensively evaluate the performance of the AI visual recognition system to ensure that the data is accurate and effective.

Data collection time and frequency

Collect data in real time and record key indicators at high frequencies to ensure the timeliness and integrity of data and provide a basis for system optimization.

Quality control and data review

Establish a strict quality control system, conduct multiple audits on the data to ensure its accuracy and reliability and eliminate outliers.

AI识别系统使用前员工满意度调查量表

1. 基本信息:
姓名: _____
科室: _____
联系方式: _____

2. 准确识别复杂外来器械的结构与功能让我感到满意。
非常不满意 非常满意
① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

3. 发生器械缺失或损坏时,能快速追溯定位让我感到满意。
非常不满意 非常满意
① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

4. 我对工作操作步骤的便捷程度感到满意。
非常不满意 非常满意
① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

5. 单个器械包平均处理时间让我感到满意。
非常不满意 非常满意
① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

6. 清点/核对一次通过率让我感到满意。
非常不满意 非常满意
① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

7. 器械包内容标准化程度让我感到满意。
非常不满意 非常满意
① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

8. 科室质量缺陷(错包、漏包)事件发生率让我感到满意。
非常不满意 非常满意
① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

9. 针刺伤发生率让我感到满意。
非常不满意 非常满意
① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

10. 我对工作节奏带来的心理压力负担感到满意。
非常不满意 非常满意
① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

11. 整体上,我对目前工作体验感到满意。
非常不满意 非常满意
① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩

提交

隐私政策 问卷来源 提供技术支持 举报

植入物与外来医疗器械接收清点环节检查表									
班组 (人工) 清点外来器械记录					观察组 (人工智能识别系统) 清点				
序号	清点错误 (多件、少件、型号不匹配、其他)	清点人	复核人	备注	器械包名称	件数	清点用时 (秒)	清点正确	清点错误 (多件)
1									
2									
3									
4									
5									
6									
7									
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100									

2025年消毒供应中心护理质量管理监控指标									
1. 护理质量目标:									
序号	指标名称	目标值	评价标准	评价方法	数据来源	评价周期	评价人	评价结果	备注
1	临床护理质量指标	100%	严格执行消毒隔离制度, 规范操作流程, 确保患者安全。	现场检查、病历审查、患者访谈。	临床科室、消毒供应中心。	每月	护士长	达标	
2	不良事件发生率	≤ 0.5%	严格执行不良事件报告制度, 及时上报, 及时处理。	不良事件报告系统、科室记录。	消毒供应中心、临床科室。	每月	护士长	达标	
3	器械清洗合格率	100%	严格执行清洗消毒流程, 确保器械清洁、无菌。	现场检查、水质检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
4	器械包装合格率	100%	严格执行包装规范, 确保包装完整、密封。	现场检查、包装检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
5	从进入消毒柜 (柜) 率	100%	严格执行消毒柜使用规范, 确保器械彻底消毒。	现场检查、消毒柜使用记录、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
6	器械使用合格率	100%	严格执行器械使用规范, 确保器械使用安全、有效。	现场检查、器械使用记录、患者反馈。	消毒供应中心、临床科室。	每月	护士长	达标	
7	器械清洗合格率	100%	严格执行清洗消毒流程, 确保器械清洁、无菌。	现场检查、水质检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
8	器械包装合格率	100%	严格执行包装规范, 确保包装完整、密封。	现场检查、包装检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
9	从进入消毒柜 (柜) 率	100%	严格执行消毒柜使用规范, 确保器械彻底消毒。	现场检查、消毒柜使用记录、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
10	器械使用合格率	100%	严格执行器械使用规范, 确保器械使用安全、有效。	现场检查、器械使用记录、患者反馈。	消毒供应中心、临床科室。	每月	护士长	达标	
11	临床护理质量指标	100%	严格执行消毒隔离制度, 规范操作流程, 确保患者安全。	现场检查、病历审查、患者访谈。	临床科室、消毒供应中心。	每月	护士长	达标	
12	不良事件发生率	≤ 0.5%	严格执行不良事件报告制度, 及时上报, 及时处理。	不良事件报告系统、科室记录。	消毒供应中心、临床科室。	每月	护士长	达标	
13	器械清洗合格率	100%	严格执行清洗消毒流程, 确保器械清洁、无菌。	现场检查、水质检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
14	器械包装合格率	100%	严格执行包装规范, 确保包装完整、密封。	现场检查、包装检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
15	从进入消毒柜 (柜) 率	100%	严格执行消毒柜使用规范, 确保器械彻底消毒。	现场检查、消毒柜使用记录、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
16	器械使用合格率	100%	严格执行器械使用规范, 确保器械使用安全、有效。	现场检查、器械使用记录、患者反馈。	消毒供应中心、临床科室。	每月	护士长	达标	
17	临床护理质量指标	100%	严格执行消毒隔离制度, 规范操作流程, 确保患者安全。	现场检查、病历审查、患者访谈。	临床科室、消毒供应中心。	每月	护士长	达标	
18	不良事件发生率	≤ 0.5%	严格执行不良事件报告制度, 及时上报, 及时处理。	不良事件报告系统、科室记录。	消毒供应中心、临床科室。	每月	护士长	达标	
19	器械清洗合格率	100%	严格执行清洗消毒流程, 确保器械清洁、无菌。	现场检查、水质检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
20	器械包装合格率	100%	严格执行包装规范, 确保包装完整、密封。	现场检查、包装检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
21	从进入消毒柜 (柜) 率	100%	严格执行消毒柜使用规范, 确保器械彻底消毒。	现场检查、消毒柜使用记录、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
22	器械使用合格率	100%	严格执行器械使用规范, 确保器械使用安全、有效。	现场检查、器械使用记录、患者反馈。	消毒供应中心、临床科室。	每月	护士长	达标	
23	临床护理质量指标	100%	严格执行消毒隔离制度, 规范操作流程, 确保患者安全。	现场检查、病历审查、患者访谈。	临床科室、消毒供应中心。	每月	护士长	达标	
24	不良事件发生率	≤ 0.5%	严格执行不良事件报告制度, 及时上报, 及时处理。	不良事件报告系统、科室记录。	消毒供应中心、临床科室。	每月	护士长	达标	
25	器械清洗合格率	100%	严格执行清洗消毒流程, 确保器械清洁、无菌。	现场检查、水质检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
26	器械包装合格率	100%	严格执行包装规范, 确保包装完整、密封。	现场检查、包装检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
27	从进入消毒柜 (柜) 率	100%	严格执行消毒柜使用规范, 确保器械彻底消毒。	现场检查、消毒柜使用记录、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
28	器械使用合格率	100%	严格执行器械使用规范, 确保器械使用安全、有效。	现场检查、器械使用记录、患者反馈。	消毒供应中心、临床科室。	每月	护士长	达标	
29	临床护理质量指标	100%	严格执行消毒隔离制度, 规范操作流程, 确保患者安全。	现场检查、病历审查、患者访谈。	临床科室、消毒供应中心。	每月	护士长	达标	
30	不良事件发生率	≤ 0.5%	严格执行不良事件报告制度, 及时上报, 及时处理。	不良事件报告系统、科室记录。	消毒供应中心、临床科室。	每月	护士长	达标	
31	器械清洗合格率	100%	严格执行清洗消毒流程, 确保器械清洁、无菌。	现场检查、水质检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
32	器械包装合格率	100%	严格执行包装规范, 确保包装完整、密封。	现场检查、包装检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
33	从进入消毒柜 (柜) 率	100%	严格执行消毒柜使用规范, 确保器械彻底消毒。	现场检查、消毒柜使用记录、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
34	器械使用合格率	100%	严格执行器械使用规范, 确保器械使用安全、有效。	现场检查、器械使用记录、患者反馈。	消毒供应中心、临床科室。	每月	护士长	达标	
35	临床护理质量指标	100%	严格执行消毒隔离制度, 规范操作流程, 确保患者安全。	现场检查、病历审查、患者访谈。	临床科室、消毒供应中心。	每月	护士长	达标	
36	不良事件发生率	≤ 0.5%	严格执行不良事件报告制度, 及时上报, 及时处理。	不良事件报告系统、科室记录。	消毒供应中心、临床科室。	每月	护士长	达标	
37	器械清洗合格率	100%	严格执行清洗消毒流程, 确保器械清洁、无菌。	现场检查、水质检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
38	器械包装合格率	100%	严格执行包装规范, 确保包装完整、密封。	现场检查、包装检测、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
39	从进入消毒柜 (柜) 率	100%	严格执行消毒柜使用规范, 确保器械彻底消毒。	现场检查、消毒柜使用记录、器械检测。	消毒供应中心、临床科室。	每月	护士长	达标	
40	器械使用合格率	100%	严格执行器械使用规范, 确保器械使用安全、有效。	现场检查、器械使用记录、患者反馈。	消毒供应中心、临床科室。	每月	护士长	达标	

C. Research Method and Data Collection

Statistical Case Study



Sample size calculation and efficiency evaluation

Based on previous data and expected effect size, accurately calculate the required sample size and evaluate the power of statistical tests to ensure reliable results.

Descriptive statistical analysis

Descriptive statistical analysis is conducted on the main indicators to reveal the data characteristics and lay the foundation for subsequent in-depth analysis.



Statistical methods for intergroup comparisons

Appropriate inferential statistical methods were used to compare the differences in main indicators between different groups and reveal the advantages of the AI visual recognition system.

Paired Samples Statistics

	Mean value (E)	Number	Standard deviation	Mean standard Error
Pair 1 - Control group	85	47	5.473	.798
Research group	98	47	2.126	.310

Paired Samples correlation

	Number	correlation coefficient	Significance
Pair 1. Control group & research group	47	-.015	.921

Normality test

	Kolmogorov-Smirnov(K)a			Shapiro-Wilk		
	statistics	df	significance	statistics	df	significance
difference	.077	47	.200*	.979	47	.553

*. The lower limit of true significance

a. Lilliefors significance correction



D. Result Analysis

Major Results Analysis

AI system recognition accuracy

The AI system's recognition accuracy is as high as 99.2%, significantly better than the 88% of traditional methods.

Improved inventory efficiency

The AI system improves inventory efficiency, effectively shortens working time and improves overall efficiency.

Differences in device recognition performance

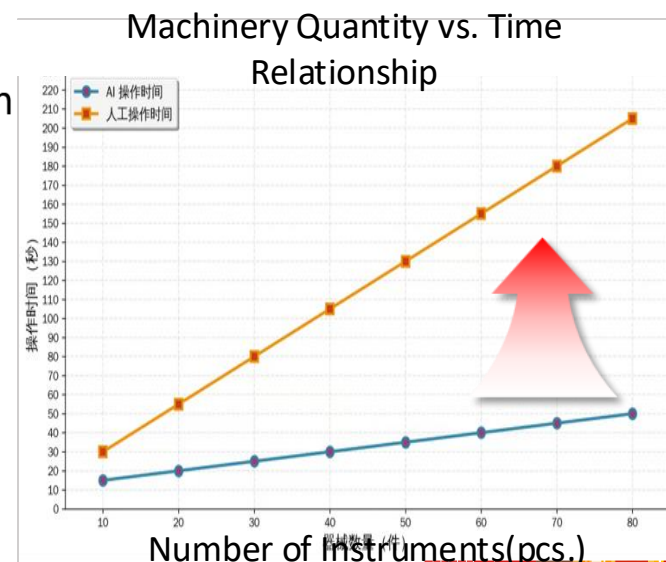
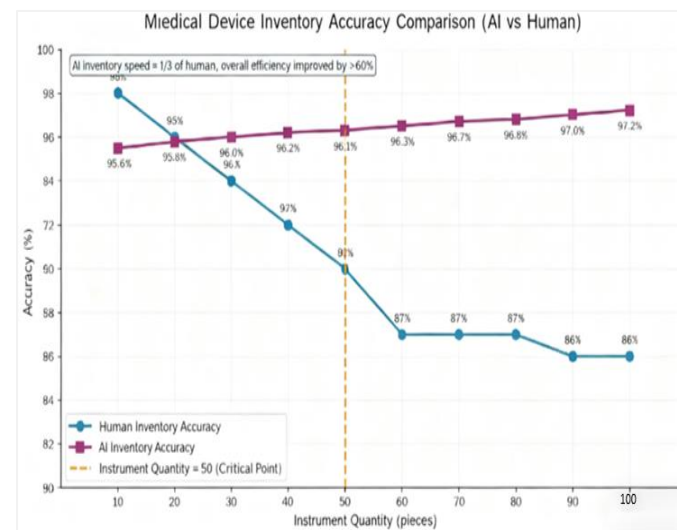
There was a significant difference in recognition performance between simple and complex instruments, but the impact on overall accuracy was minimal.

Average time/package for counting instrument before and after using the AI recognition system

packages	Experimet group (AI) (n=1200)	Control group (manual) (n=1200)	Z-score	P-score
<20	10.70 (9.80, 11.70)	22.40 (20.90, 23.62)	-13.598 ^a	<0.001
pcs/package (n=246)				
20-50	36.25 (33.20, 40.30)	92.40 (89.20, 95.30)	-25.434 ^a	<0.001
pcs/package (n=862)				
>50	56.75 (54.32, 59.17)	146.50 (142.22, 150.47)	-8.331 ^a	<0.001
pcs/package (n=92)				

The accuracy of counting instrument packages before and after using the AI recognition system

Classification	Indicator	Experimet group (AI) (n=1200)	Control group (manual) (n=1200)	X ² value	P-score
<20	Accuracy rate	244 (99.2%)	237 (96.3%)		0.039 ^a
pcs/package (n=246)	of Instrument inventory (%)				
20-50	Accuracy rate	835 (96.9%)	803 (93.2%)	22.881	<0.001
pcs/package (n=862)	of Instrument inventory (%)				
>50	Accuracy rate	88 (95.7%)	80 (87.0%)		0.021 ^a
pcs/package (n=92)	of Instrument inventory (%)				



D. Result Analysis

Secondary Outcome Analysis

Costs and benefits
of System
Utilization

Staff acceptance
and satisfaction

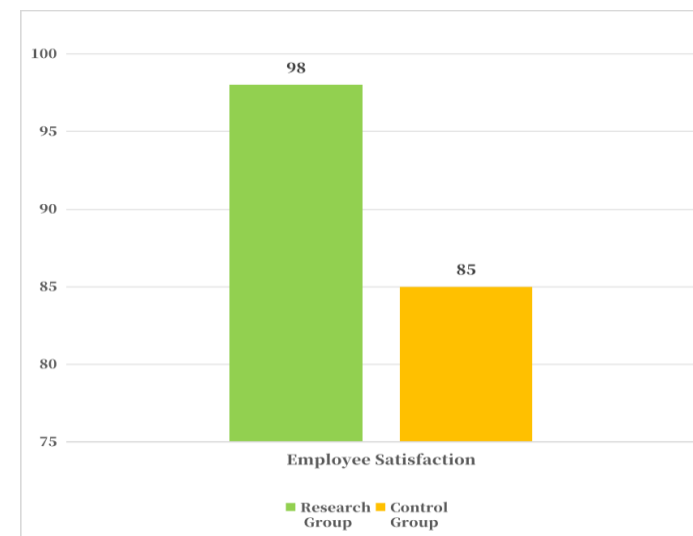
System stability
and reliability

Traceability system management quality

indicator	Experiment group(AI)	Control group (manual)
The completion of instrument inventory work can be ensured to be recorded	Y	N
The information on the type and quantity of instruments can be ensured to be recorded	Y	N
It can facilitate the implementation of full-process quality traceability	Y	N
Can it reduce the operational difficulty for staff?	Y	N
Can it display the usage information in real time?	Y	N

Employee satisfaction before and after using the AI recognition system

indicator	Experiment group(AI) (n=47)	Control group (manual) (n=47)	t-score	P-score
Staff Satisfaction	98.00±2.126	85.00±5.473	-15.102	<0.001



D. Result Analysis

Abnormal situation analysis

Case study on Identification failure

Conduct in-depth analysis of cases of recognition failure to identify reasons including poor instrument image quality and difficulty in recognizing special materials.

Systematic Errors and Human Factors

By comparing recognition failure cases caused by system errors and human factors, the difference between the two and their respective proportions can be clarified.

Verification of the effectiveness of improvement measures

Based on the analysis of the causes of recognition failure cases, improvement measures are proposed and implemented, such as optimizing the image acquisition process and enhancing the ability to recognize special materials.

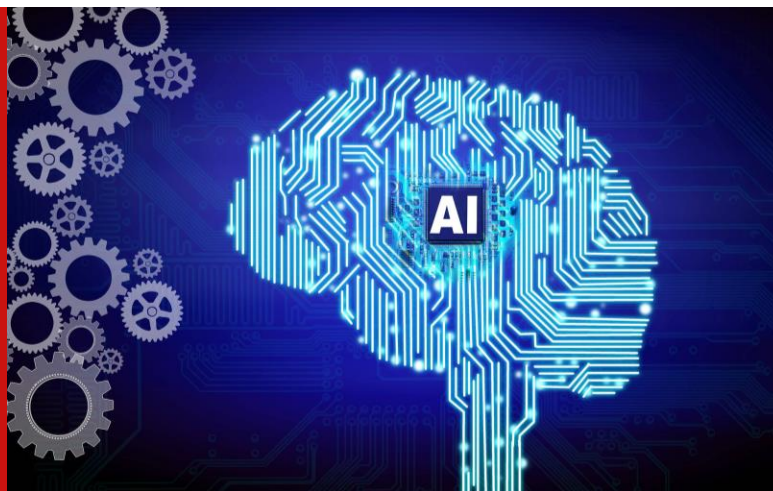


E. Recommendation

Technical optimization suggestions

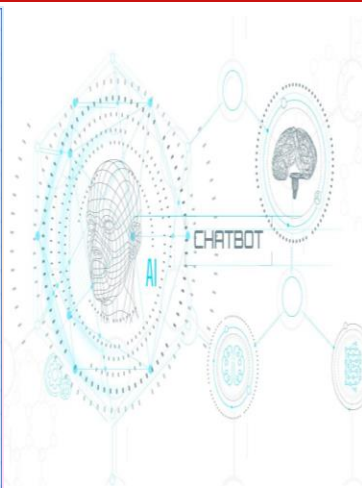
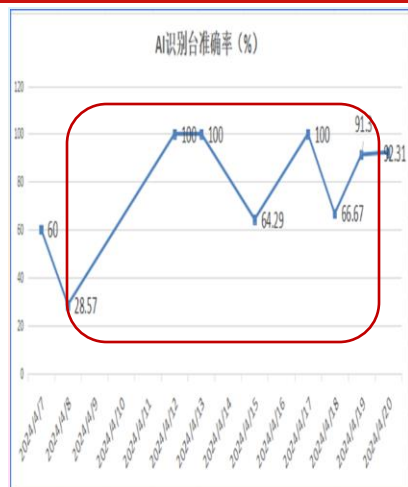
Algorithm model optimization

Continuously collect data, optimize algorithm models, improve recognition accuracy and efficiency, and ensure the ongoing enhancement of AI system performance.



System integration and compatibility

Strengthen system integration capabilities, improve compatibility with other medical systems, and realize data sharing and process collaboration.



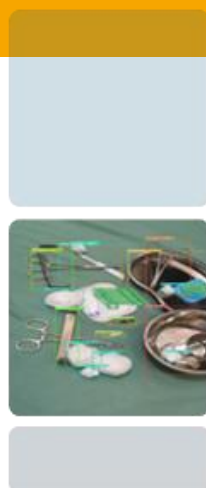
Hardware equipment upgrade

As technology develops, timely upgrades to high-definition camera equipment, computing units and other hardware to ensure system speed and stability .



Image acquisition specifications

Develop detailed standardized image acquisition specifications to ensure image quality and reduce recognition errors caused by unclear images.



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Human-machine collaborative optimization

Optimize the human-machine collaborative working mechanism, clarify the responsibilities and interaction methods between AI systems and personnel, and improve overall work efficiency.



E. Recommendation



Training and promotion

Operator training

Design training courses for operators, covering basic operation, maintenance and troubleshooting of AI systems to improve personnel skills.

Industry promotion

Formulate a multi-center promotion and application strategy, pilot it in some hospitals first, and then gradually expand it to a wider area after summarizing the experience.



F. Conclusion and Implication Main Research Conclusions

AI Vision Advantages

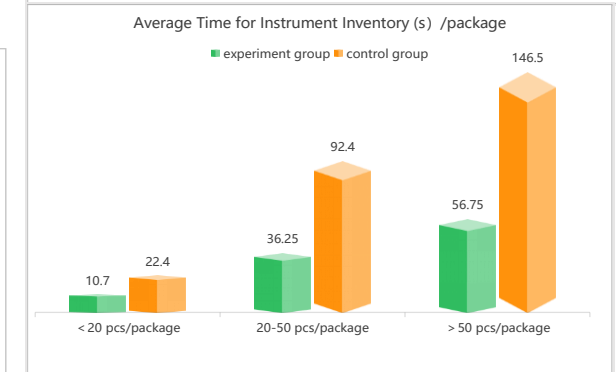
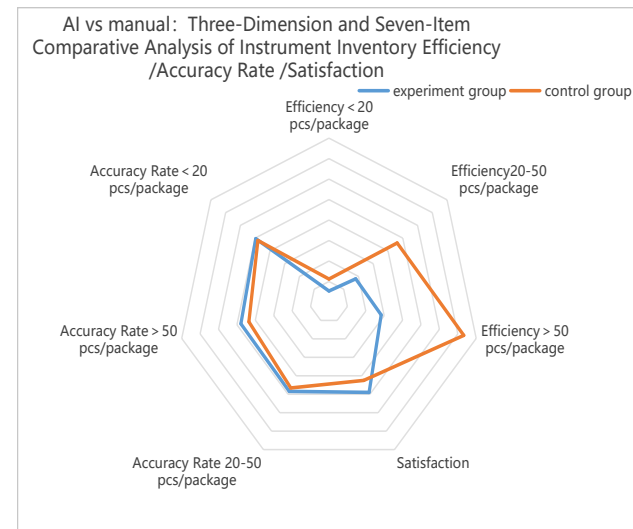
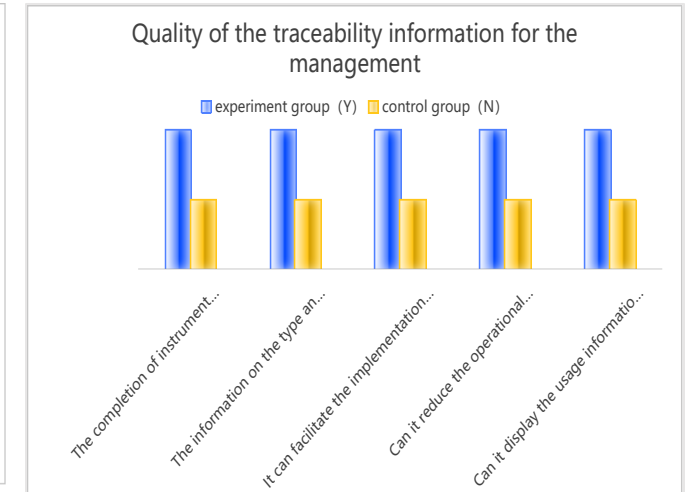
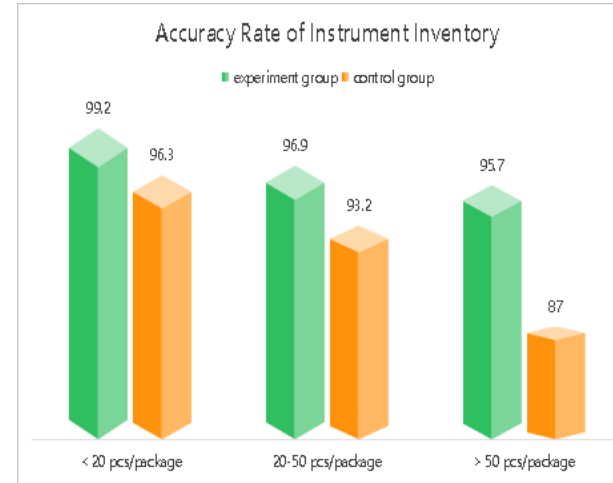
Accurate identification, efficient inventory, reduced labor costs, and improved CSSD efficiency and quality .

Limitation Factor

The technical threshold is high, the equipment cost is high, customization is required, and it is greatly affected by environmental factors.

Technology Outlook

As technology matures and costs decrease, the application prospects of AI visual recognition systems are broad and will lead to innovation and upgrading of CSSD management.



F. Conclusion and Implication

Practical Significance



Management Implications

The AI visual recognition system helps the disinfection supply center achieve process optimization and intelligent management, improving work efficiency and quality.

Contribution to medical safety

Through accurate identification and efficient inventory, we can reduce medical risks, strengthen the medical quality and safety line, and protect patient safety.



F. Conclusion and Implication

Research Limitations and Prospects

Limitation Analysis

The sample size of this study is limited and does not cover all types of devices; the scope of research needs to be expanded in the future to consider more influencing factors.

Research Direction

Explore the application effects of AI visual recognition systems in different medical institutions and design more efficient algorithms and processes .

Follow-up Evaluation

Continuously monitor system performance and results, adjust optimization plans in a timely manner, and ensure the timeliness and practicality of research results.





Thank you for your attention

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