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RESEARCH ARTICLE

Nursing Intervention of Children's Lower Limb Chronic Wound Healing Under Artificial Intelligence

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ABSTRACT This work aimed to compare the effect of family-centered nursing and routine nursing on the treatment of children with chronic lower limb wounds. A total of 112 children with chronic wounds of the lower limbs were divided into a test group (56 cases) and a control group (56 cases). The children in the test group were given a family-centered nursing intervention, while those in the control group were given a routine nursing intervention. Additionally, an image segmentation algorithm based on a deep convolutional neural network was proposed to segment chronic wound images. The results showed that there were no significant differences in sex, injury site (left or right limb), age, height, weight, and cause of disease (scald, blow, fall) between the test group and the control group ($P > 0.05$). The wound pain score of the test group was 3.38 ± 0.75 and that of the control group was 6.24 ± 1.48. Compared with the control group, the wound pain score of the test group was lower ($P < 0.05$). The total effective rate of the test group (92.86%) was significantly higher than that of the control group (78.57%) ($P < 0.05$). The accuracy of the DCNN model in both the training and test datasets was significantly higher than that of the FCM model ($P < 0.05$). The results showed that, compared with routine nursing, family-centered nursing intervention had a more significant effect on children with chronic wounds of the lower extremities and had clinical promotion value.

INDEX TERMS Deep convolutional neural networks, family-centered nursing, chronic wounds in children's lower limbs, image segmentation, wound pain.

I. INTRODUCTION

Chronic wounds usually refer to refractory wounds that heal slowly, fail to heal for more than a month, or have no tendency to heal [1], [2], [3]. Common chronic wounds include the burn scald with a large area, brush touch injury, cut scratch, bedsore, old sodden leg, and diabetic foot. Generally, measures such as cleaning wound surfaces, antibacterial and anti-inflammatory activity, and active control of primary disease are adopted [4]. Many factors cause chronic wounds, such as the presence of rotting flesh and necrosis of wound ulcers and serious infection and inflammation of the wounds. In addition, there is inadequate drainage of cysts, abscesses, and sinuses in wounds. The wound is deep with cavities and subcutaneous cavities, and it even touches the tendon sheath and bone joint soft tissue [5], [6], [7]. Chronic wounds are characterized by high incidence and high risk. If they can't be dealt with in time, the best time for treatment of patients will be delayed, which results in amputation and other consequences that damage patients' physical and mental health and seriously affect patients' quality of life. Consequently, it has become an urgent problem to be solved in the field of medical nursing [8], [9]. Chronic wound treatment involves the mechanistic study of wound damage and the adoption of wound repair materials, new technologies, and new instruments and equipment, which is a highly professional field and is always a topic of focus [10]. Compared with adults, children are more likely to experience chronic wounds due to their imperfect body functions and poor ability to deal with and resist sudden risks. Hence, chronic wounds in children were explored in this work.

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In addition to the basic dressing change, binding, and disinfection, the treatment of chronic wounds also requires real-time, careful, and thorough nursing for children [11]. Family refers to the marriage relationship, blood relationship, or adoptive relationship based on the social life unit formed among relatives by one or more individuals. Family refers to the place where people with a marriage relationship, blood relationship, or adoptive relationship based on the social life units among relatives formed by one or more individuals live together, with permanent relationships of blood, marriage, sustenance, and emotional commitment. Family members work together to achieve life goals and needs [12], [13]. The family-centered nursing model has always been a new nursing model advocated by developed countries. Its core concept is respecting children and families, transmitting health information, respecting family members' choices, emphasizing collaboration among children, families, and caregivers, and giving them strength and support [14], [15]. Family-centered nursing can make clinical nursing staff realize that only by involving family members in the nursing process can children receive good nursing, and a friendly relationship of mutual respect and support between the medical staff and children's families is established [16], [18]. In recent years, the adoption of this nursing model in pediatric emergencies, newborns, asthma, diabetes, and children's health education has played a very substantial effect. Additionally, family-centered nursing can obviously improve the satisfaction of inpatients and their families and reduce the cost of treatment. Convolutional Neural Networks (CNN) have found widespread applications in medical image segmentation, owing to their efficient and accurate feature extraction capabilities, making them an ideal choice for medical image segmentation in the field of medicine [19]. CNNs are applied in the preprocessing of medical images, as medical images often exhibit noise, low contrast, and other interfering factors. CNNs can be used to denoise, enhance contrast, and perform edge detection on medical images, thereby clearly extracting regions of interest. In some studies, CNNs have been utilized for medical image segmentation, precisely delineating the contours and boundaries of tissues, organs, or lesions. By training on a large dataset of medical images, CNNs can learn features of different tissues or pathologies, and classify and segment different regions within an image accordingly [20]. In lung CT image segmentation, for example, CNNs can accurately extract structures such as lung tissue, lesions, and blood vessels, aiding in disease diagnosis and treatment decisions [21]. Additionally, CNNs have been applied to target detection and localization in medical image analysis. In-depth research on early breast cancer screening has demonstrated that CNNs can automatically identify and locate breast masses, providing quantitative analysis and tracking of suspicious lesions [22]. This automated target detection and localization technology not only improves the accuracy of early breast cancer diagnosis but also reduces the workload of medical professionals and shortens the diagnosis time. The accurate measurement of wound area and the assessment of recovery status are very important in the clinical treatment of chronic wounds. However, due to the irregular shape and great difference in color distribution of chronic wounds, it is impossible to accurately evaluate them by relying solely on the experience and knowledge of physicians [23], [24]. Therefore, it is vital to select an efficient segmentation method for the automatic segmentation of chronic wound images. As a very popular image analysis method in recent years, deep learning technology can use machines to automatically extract relevant image features, which has good adoption prospects in medical image processing, with strong learning ability, good adaptability, and good portability [25].

To sum up, an artificial intelligence image processing model was constructed using deep learning technology at first, and then 112 children with chronic lower limb trauma were randomly divided into test group (home center nursing combined dressing change) and control group (routine nursing combined dressing change), with 56 cases in each group. Finally, wound healing time, hospital stay, treatment efficiency, and wound pain were compared between the two groups. The purpose of this study was to deeply explore the effect of family-centered nursing program combined with dressing change on the healing of children's lower limb chronic wounds under the background of artificial intelligence.

II. RELATED WORKS

Clinical nursing intervention research for chronic wound healing has been very common, and scholars have discussed the application value of many methods in promoting chronic wound healing. Himes [26] proposed that protein-calorie malnutrition and involuntary weight loss in the hospital and long-term care were common in patients with chronic wounds still and emphasized the protein-calorie malnutrition and involuntary weight loss in the block effect in the process of wound healing and to establish the best anabolic environment to increase the weight and the necessity of improving wound healing. Bellingeri et al. [27] applied propyl betaine and polygonite (PP) solution in the clinical treatment of patients with chronic wounds and compared it with normal saline. The results showed that PP solution was significantly more effective than saline in reducing signs of inflammation and accelerating healing of vascular leg ulcers and pressure sores, a finding that supports updating chronic wound care protocols. Bullough et al. [28] proposed that active healthy foam contact dressings can effectively manage the exudate and can also help autonolysis and support the improvement of the periwound state. It is crucial to select the appropriate dressing to care for patients with chronic wounds.

The use of artificial intelligence technology to evaluate patients' wounds for more effective nursing intervention is also the focus of clinical research. Hsieh et al. [29] proposed a virtual algorithm for chronic wound care based on telemedicine assistance, which was applied to the nursing treatment of patients with chronic wounds during COVID-19. This comprehensive algorithm for chronic wound care through telemedicine assistance can protect the safety and health of patients and medical service providers. Li et al. [30] argued that although standard imaging methods such as computed tomography, single photon emission computed tomography, magnetic resonance imaging, terahertz imaging, and ultrasonic imaging have been widely used in wound diagnosis, they are unable to explain the dynamic changes of wound environment and lack the ability to predict healing results. Therefore, there is still an urgent need for more effective methods in the future that can not only indicate the current state of the wound, but also help determine whether the wound is healing properly. Hsu et al. [31] proposed a wound infection evaluation algorithm based on machine learning. Wound pictures confirmed by three doctors were used to evaluate the four symptoms of swelling, granulation, infection, and tissue necrosis. The results showed that the algorithm achieved 83.58% of accuracy. Wang et al. [32] used support vector machine (SVM) to determine the wound boundary of foot ulcer images captured by image capture box, and applied conditional random field method to narrow the detected wound boundary. The results showed that this method provided a high global energy rate (mean sensitivity = 73.3%, specificity = 94.6%), and it has enough efficiency for image analysis. In addition to SVM, deep convolutional neural networks (CNNs) also find extensive applications in wound classification. In the study conducted by Malihi et al., a deep CNN was employed to classify wound types. They trained a CNN algorithm model on 863 cropped wound images and evaluated its performance using a test set. The study reported an F1-score of 0.85 for cropped test images and an F1-score of 0.70 for complete images in the trained deep CNN model [33]. Furthermore, CNNs have demonstrated utility in segmenting wounds in microscopic imaging. Using unlabeled multiphoton microscopy (MPM) images of patient wounds for training, the overall accuracy of the MPM wound slice CNN was reported as 92.83%, and for in vivo wound z-stack CNN, it was 89.66% [34]. The application prospects of convolutional neural networks in medical image segmentation are extremely promising. By continuously optimizing network architectures and training algorithms, we can further enhance the performance and accuracy of CNNs in medical image segmentation tasks, providing robust support and assistance for medical diagnosis and treatment.

III. MATERIALS AND METHODS

A. RESEARCH OBJECTS

A total of 112 children with chronic wounds in the lower limbs who were admitted to and treated in the outpatient department of the hospital from January 2020 to January 2021 were selected as the research subjects. The medical ethics committee of Baotou Fourth Hospital approved this experiment. All patients signed informed consent forms.

The inclusion criteria were as follows. I. Patients aged between 3 and 12 years old; II. Patients with no tendency to heal after more than one month of wound formation; III. Patients with complete relevant data; IV. Patients with chronic wound disease of the lower limbs confirmed by pathology.

The exclusion criteria were as follows. I. Patients with heart, liver, and kidney damage; II. Patients with a history of mental disease; III. Patients who dropped out of the experiment for personal reasons.

B. GROUPING AND NURSING MEASURES

According to different nursing measures, 112 children with chronic wounds in the lower limbs were randomly divided into the test group (56 cases) and the control group (56 cases). The test group was treated with family-centered nursing combined with dressing change, and the control group was treated with conventional nursing combined with dressing change.

For the dressing change, all the children were treated with Rikanel iodine type III skin disinfectant for wound disinfection and cleaned with 0.9% normal saline, and the wet wound dressing was used for dressing change, with a frequency of 1-2 times/day.

Children in the control group received conventional nursing. During dressing change, the children's family members were told the common nursing methods and precautions for chronic wounds as well as the purpose of dressing to strengthen their cognition of chronic wound nursing treatment.

The test group was treated with family-centered nursing. First, the whole operation process of chronic wound treatment was elaborated on to the family members of the children. The treatment compliance of the children was improved through interactive communication so that the family members could cooperate to divert the attention of the children, such as by watching cartoons and playing with toys. Second, the psychological status of the children and their families was assessed, and targeted emotional counselling was performed. For example, many parents of school-age children were concerned that the treatment cycle was long, which delayed their children's education. Regular psychological nursing helped correct parents' misconceptions and reduce their negative emotions. Then, a health propaganda and education team with professionals of wound ostomy and nursing staff was set up. The health propaganda and education programs were developed, propaganda and education for patients with video materials and health manuals were performed, and the degree of chronic wound cognition of family members was regularly assessed. Finally, the family members were guided to take care of the children together, such as teaching the family members the emergency treatment operation of wounds and dietary knowledge. The cognitive errors of the family members were corrected at any time. If they could still not master it, the teaching needed to be repeated.

Using the 112 patients included in this work as the training dataset and the 76 patients admitted during the same period with chronic lower limb injuries as the test dataset.

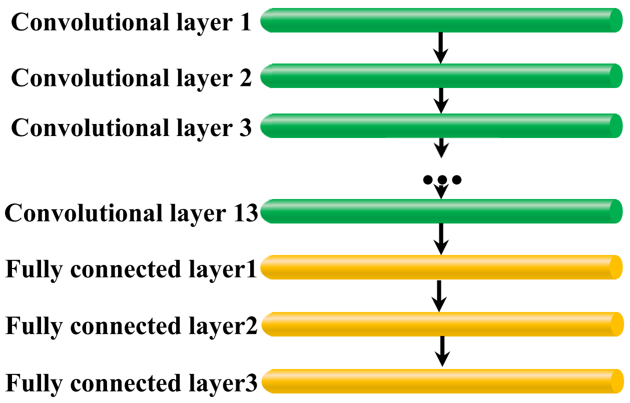

FIGURE 1. Schematic diagram of the structure of VGG-16.

C. IMAGE SEGMENTATION ALGORITHM BASED ON DEEP CONVOLUTIONAL NEURAL NETWORKS

It was difficult to collect and label wound images, and its dataset size was smaller than common image data. Consequently, the scale of the DCNN model greatly exceeded the requirements of the wound image segmentation task, and it was difficult to obtain a good segmentation model through network training. Fig. 1 showed the network structure of the visual geometry group network (VGG-16), including 13 convolutional layers and 3 fully linked layers, which greatly increased the computational complexity of the model.

After consideration, the convolution layer of the DCNNs was optimized. For a standard convolution layer, the feature diagram was input to the convolution layer and mapped to the output feature diagram through the convolution kernel. If the convolution step was 1, the relationship between the input and output could be expressed as shown in Equation (1).

$$Con(L, H) = \sum_{i,j,v}^{AL,AL,V} L_{i,j,v,w} * H_{l+i-1,l+j-1,v} \quad (1)$$

In Equation (1), L represented the convolution kernel, H represented the feature diagram, and W represented the size of the output feature diagram. $V \cdot W$ represented the number of convolution kernels, and $AL * AL$ represented the size of the convolution kernel. Then, Equation (2) showed how the computational complexity of the standard convolution layer (D) was expressed.

$$D = A_H * B_H * AL * AL * V * W \quad (2)$$

In Equation (2), $A_H * B_H$ expressed the size of the feature diagram. According to the above equations, feature extraction and feature combination could be divided into two processes. Equations (3) and (4) showed the relationship between the input and output of these two processes.

$$Con(L, H)* = \sum_{i,j}^{AL,AL} L_{i,j,w} * H_{l+i-1,l+j-1,w} \quad (3)$$

$$Con(L, H) ** = \sum_{v}^{V} L_{v,w} * H_{l,w} \quad (4)$$

In Equations (3) and (4), $Con(L, H)*$ represented the feature extraction, and $Con(L, H) **$ represented the feature combination. Equation (5) showed the expression of the total computational complexity.

$$D_{total} = A_H * B_H * AL * AL * V + A_H * B_H * V * W \quad (5)$$

In Equation (5), D_{total} represented the total computational complexity. According to Equations (2) and (5), Equation (6) could be obtained.

$$\frac{A_H * B_H * AL * AL * V + A_H * B_H * V * W}{A_H * B_H * AL * AL * V * W} = \frac{1}{W} + \frac{1}{AL * AL} \quad (6)$$

The computational cost of the improved convolutional layer was approximately 1/9 of that of the standard convolutional layer, which greatly improved the computational efficiency.

D. PERFORMANCE EVALUATION INDEXES OF WOUND SEGMENTATION

To evaluate the performance of the wound segmentation model, the sensitivity (Sen), precision (Pre), overlap rate (IOU), and Dice similarity coefficient (DSC) were used as the evaluation indexes of the segmentation results of the model. Meanwhile, the fuzzy c-means (FCM) model and region convolutional neural network (R-CNN) model were introduced as controls.

$$Sen = \frac{TP}{(TP + F)} \quad (7)$$

$$Pre = \frac{TP}{(TP + FP)} \quad (8)$$

$$IOU = \frac{TP}{(TP + FP + FN)} \quad (9)$$

$$DSC = \frac{2 * TP}{(2 * TP + FP + FN)} \quad (10)$$

In Equations (7)-(10), TP expressed the true positive, TN expressed the true negative, FP expressed the false positive, and FN expressed the false negative.

E. OBSERVATION INDEXES

General information was recorded, including sex, age, location of injury (left or right limb), cause of the disease (traffic accident, heavy blow, or fall), and course of the disease.

Wound healing time and hospitalization time were recorded. A wound surface rating scale was adopted to evaluate wound healing (wound edema, exudate amount, wound depth, degree of redness, and swelling around the wound), with a total score of 15 points. The higher the score was, the better the wound recovery effect. A total of 0-8 points was judged as invalidation, 9-12 points was judged as marked effectiveness, and 13-15 points was judged as effectiveness, and the total effective rate was calculated based on this. The visual analog scale (VAS) was adopted to evaluate the degree of wound pain in children, with a total score of 10 points. The higher the score was, the higher the pain degree was. The hospital knowledge questionnaire was adopted to evaluate the family members' knowledge of health, with a total score of 10 points. A higher score indicated a higher degree of knowledge mastery. The satisfaction of the children's family members with hospital nursing services was recorded during follow-up visits, and it was classified into very satisfied, satisfied, and dissatisfied cases. Then, the satisfaction rate was calculated.

$$\text{Total efficiency} = \frac{\text{Show effect}+E_{\text{ffective}}}{\text{Total sample size}} \times 100\% \quad (11)$$

$$\text{Satisfaction rate} = \frac{\text{Very satisfied}+S_{\text{atisfying}}}{\text{Total sample size}} \times 100\% \quad (12)$$

F. STATISTICAL METHODS

SPSS 19.0 was employed for data statistics and analysis. Mean ± standard deviation ($\bar{x}\pm s$) was how measurement data were expressed, and percentage (%) was how count data were expressed. Pairwise comparison was performed by one-way analysis of variance. The difference was statistically significant at $P < 0.05$.

IV. RESULTS

A. COMPARISON OF THE NOISE REDUCTION PERFORMANCE OF THE ALGORITHMS

In Fig. 2, the Sen, Pre, IOU, and DSC of the proposed model for image segmentation were 92.32%, 95.54%, 88.72%, and 91.87%, respectively. The Sen, Pre, IOU, and DSC of the FCM model were 82.55%, 83.55%, 68.83%, and 81.03%, respectively. The Sen of the R-CNN model for image segmentation was 85.01%, Pre was 84.72%, IOU was 75.05%, and DSC was 82.97%. Hence, the Sen, Pre, IOU, and DSC of the DCNN model for image segmentation were remarkably higher than those of FCM and R-CNN, with a considerable difference ($P < 0.05$).

Fig. 3 showed the noise reduction effect of the three algorithms on echocardiography. Compared with the original image, the three algorithms had obvious effects on echocardiography noise reduction. After denoising by the non-local means (NLM) algorithm, the image had a certain improvement in brightness and clarity, but the overall background was dim, and the difference in detail contrast was not obvious. Through the Bayes shrink denoising algorithm, the sharpness and brightness of the images were also improved, but there was the problem of overexposure, which affected the display of tissue details. After denoising by the original nonlocal means (ONLM) algorithm, the overall quality was the highest, and the noise and artifacts were greatly reduced, with good clarity and brightness.

Fig. 3 showed the segmentation effect of the algorithm on children's chronic wound images. The edge matching degree of the segmentation results of the model in this work was closest to the real wound image. The segmentation results of the FCM model and R-CNN model deviated greatly from the real wound image, and the area contaminated by blood and tissue fluid was easily misjudged as the wound area.

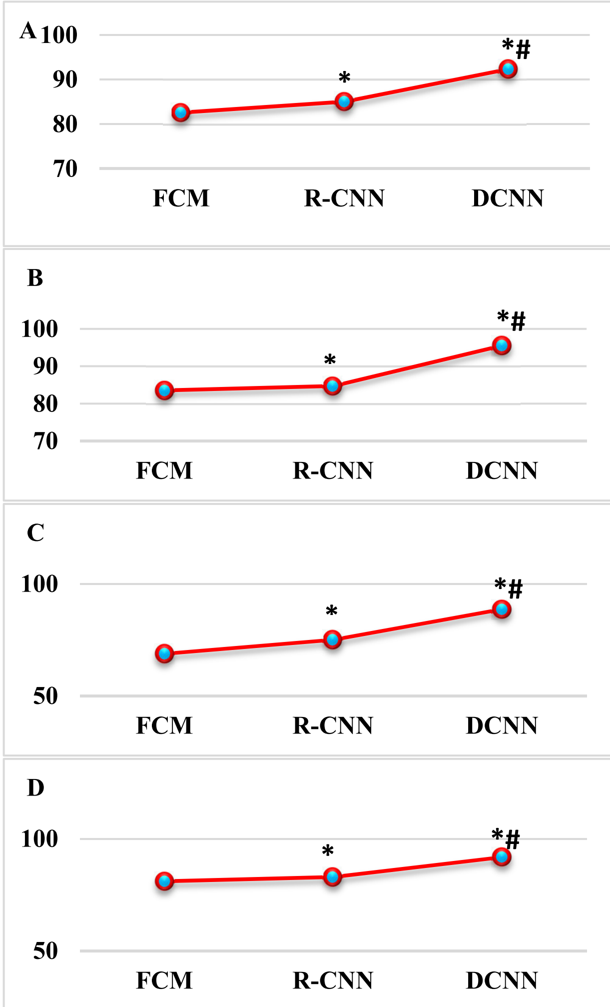

FIGURE 2. Comparison of the noise reduction index among the three algorithms. (A: signal-noise ratio; B: figure of merit; C: structural similarity index measure). Note: *$P < 0.05$ indicated a significant difference compared to FCM; #$P < 0.05$ indicated a significant difference compared to R-CNN.

FIGURE 3. Segmentation effect of the algorithm on children's chronic wound images. (A: Image of a child scald wound; B: segmentation results of the FCM model; C: segmentation results of the R-CNN model; D: segmentation results of the model in this work).

B. IMAGES OF PARTIAL CHRONIC WOUNDS IN CHILDREN

Fig. 4 showed an image of partial chronic wounds in children. The common chronic wounds were mainly caused by falls and scalds.

FIGURE 4. Some images of partial chronic wounds in children.

C. COMPARISON OF GENERAL DATA BETWEEN THE TWO GROUPS

The pairwise comparison between the test group and the control group showed no considerable differences in sex, injury location (left limb or right limb), age, height, weight, or pathogenic causes (scald, heavy blow, and fall) ($P > 0.05$) (Fig. 5).

D. COMPARISON OF WOUND HEALING TIME AND HOSPITALIZATION TIME BETWEEN THE TWO GROUPS

In Fig. 6, the wound healing time in the test group was 15.73±4.28 days, and the hospitalization time was 9.44±3.05 days. In the control group, the wound healing time was 33.94±6.81 days, and the hospitalization time was 16.07±3.51 days. The wound healing time and hospital stay time of the test group were observably shorter than those of the control group, with a considerable difference ($P < 0.05$).

E. COMPARISON OF THE DEGREE OF WOUND PAIN BETWEEN THE TWO GROUPS

The wound pain score in the test group was 3.38±0.75 and that in the control group was 6.24±1.48 (Fig. 8). The wound pain score in the test group was significantly lower than that in the control group ($P < 0.05$).

F. COMPARISON OF FAMILY MEMBERS' HEALTH KNOWLEDGE BETWEEN THE TWO GROUPS

In Fig. 9, the score of family members' health knowledge in the test group was 8.16±2.13 and that in the control group was 5.33±1.14. Compared with the control group, the score of family members' health knowledge in the test group was markedly higher, with a statistically considerable difference ($P < 0.05$).

G. COMPARISON OF TREATMENT EFFICACY BETWEEN THE TWO GROUPS

In the test group, 30 cases were effective, 22 cases were markedly effective, and 4 cases were invalid after treatment. In the control group, 22 cases were effective, 22 cases were markedly effective, and 12 cases were invalid (Fig. 10). The total effective rate of the test group (92.86%) was higher than that of the control group (78.57%), with statistically considerable differences ($P < 0.05$).

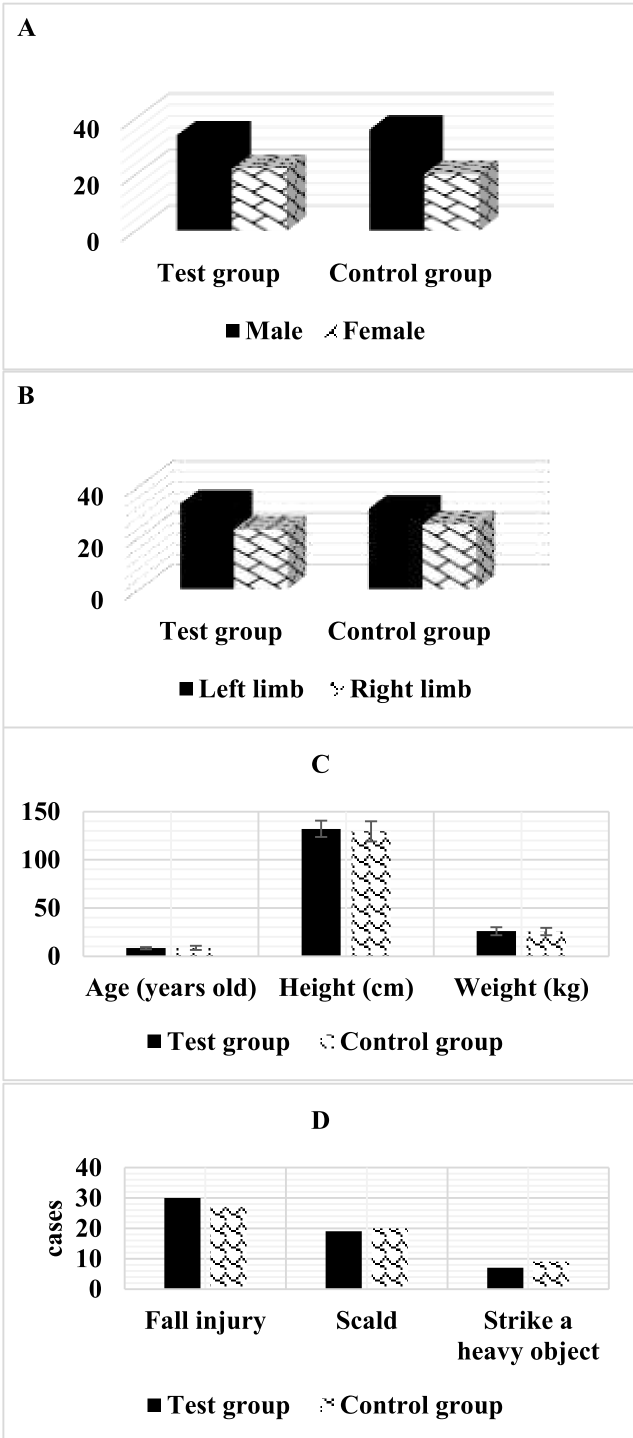

FIGURE 5. Comparison of general information between the two groups. Note: A: sex; B: injury location (left limb or right limb); C: age, height, and weight; D: pathogenic causes (scald, struck by a heavy object, and fall).

H. COMPARISON OF SATISFACTION DEGREE BETWEEN THE TWO GROUPS OF CHILDREN'S FAMILY MEMBERS WITH HOSPITAL NURSING SERVICES

In the test group, families of children in 29 cases were very satisfied with hospital nursing services, those in 21 cases

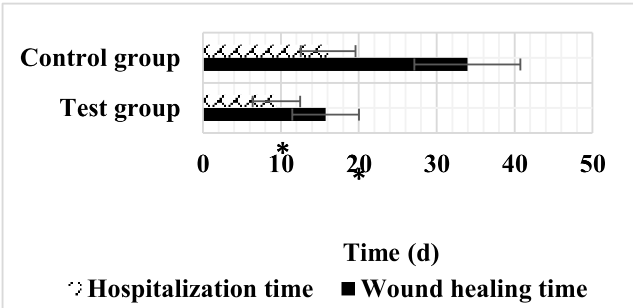

FIGURE 6. Comparison of wound healing time and hospitalization time between the two groups. Note: * indicated that compared with the control group, P < 0.05.

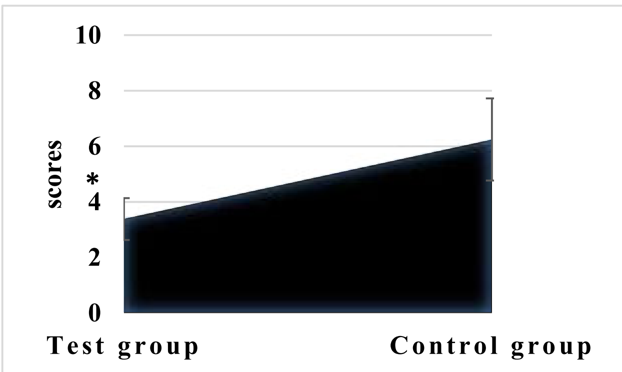

FIGURE 7. Comparison of the degree of wound pain between the two groups. Note: * indicated that compared with the control group, P < 0.05.

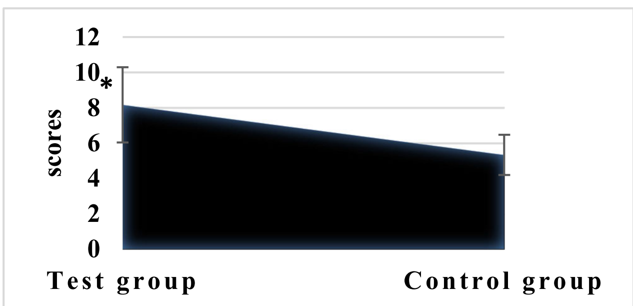

FIGURE 8. Comparison of family members' health knowledge between the two groups. Note: * indicated that compared with the control group, P < 0.05.

were satisfied, and those in 6 cases were dissatisfied (Fig. 7). In the control group, family members of the children in 18 cases were very satisfied with hospital nursing services, those in 25 cases were satisfied, and those in 13 cases were dissatisfied. In contrast to the control group (76.79%), the satisfaction rate of family members of children with hospital nursing services in the test group (89.29%) was significantly higher, with a statistically considerable difference ($P < 0.05$).

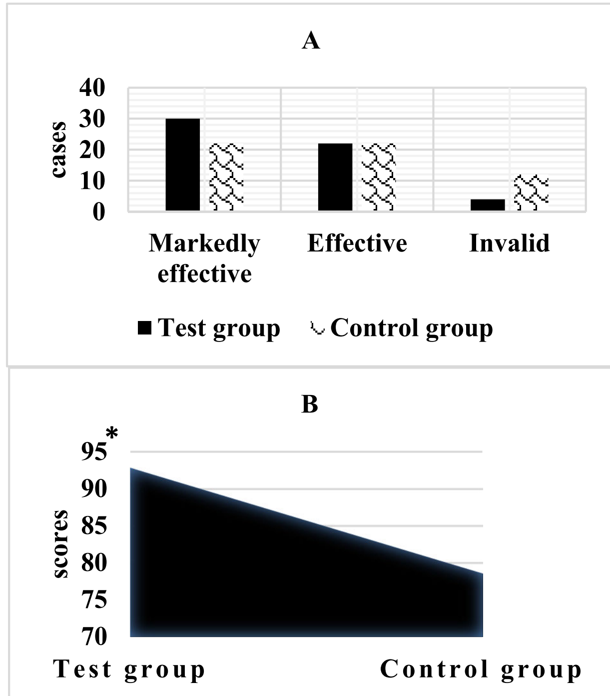

FIGURE 9. Comparison of treatment efficacy between the two groups. (A: the number of effective, markedly effective, and invalid cases; B: the total effective rate). Note: * indicated that compared with the control group, P < 0.05.

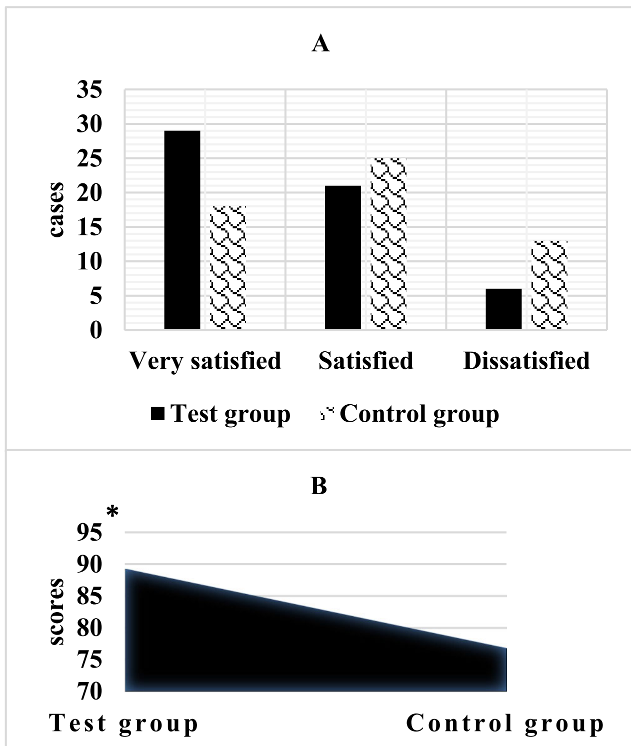

FIGURE 10. Comparison of satisfaction degree between the two groups of children's family members with hospital nursing services. (A: the number of very satisfied, satisfied, and dissatisfied cases; B: the satisfaction rate). Note: * indicated that compared with the control group, P < 0.05.

I. PERFORMANCE OF THE DCNN MODEL

In the DCNN model, the accuracy of patient wound segmentation images in the training set was 0.962, while in the testing set, it was 0.894. In the FCM model, the accuracy of patient wound segmentation images in the training set was 0.853, and

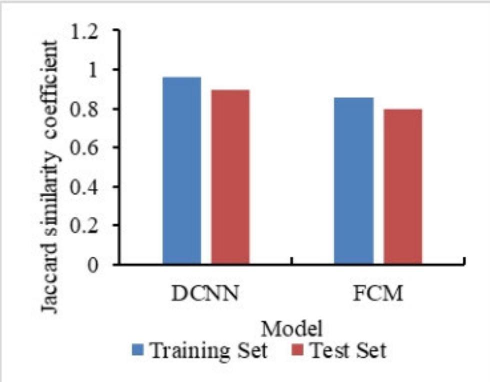

FIGURE 11. Comparison of accuracy between DCNN model and FCM model Note: *P < 0.05, the difference was statistically significant compared to the FCM model.

in the testing set, it was 0.795. The accuracy of image segmentation in the DCNN model is significantly higher than that in the FCM model ($P < 0.05$), and this difference is statistically significant. These results were detailed in Figure 11.

J. DISCUSSION

As children are naturally active, they inevitably suffer from bumps and bruises. In addition, their body is not fully developed, so acute wounds easily develop into chronic wounds [35], [36]. Currently, the clinical treatment efficacy of chronic wounds in children is not ideal, and the related cost is high. It can not only increase the pain of children but also place great economic and psychological pressure on their parents. Hence, seeking efficient and consistent nursing treatment is a very important research direction [37], [38]. Medical image segmentation has always been a hot topic in clinical research. Chronic wound images are difficult to segment due to their irregular features. The traditional method uses machine learning technology to divide the image into different regions to identify the features in the region. Nevertheless, feature extraction of machine learning mainly relies on manual extraction, which is simple and effective for specific simple tasks, but it is not universal [39], [40]. Therefore, the convolutional layer of DCNNs was first optimized, and a new image segmentation model based on DCNNs was proposed, which was compared with the FCM model and R-CNN model. The results reflected that the Sen, Pre, IOU, and DSC of the proposed model for image segmentation were obviously higher than those of the FCM and R-CNN models ($P < 0.05$). Furthermore, in terms of the accuracy of image segmentation between the DCNN model and the FCM model, the DCNN model exhibited significantly higher accuracy in both the training and testing datasets ($P < 0.05$) compared to the FCM model. This result indicated that the new image segmentation model proposed in this work had better segmentation performance than the traditional algorithms for chronic wound images, and the segmentation accuracy was improved. According to the qualitative analysis, the edge matching degree of the segmentation results of the model in this work was closest to the real wound image. The segmentation results of the FCM model and R-CNN model had a large deviation from the real wound image, and the area contaminated by blood and tissue fluid was easily misjudged as the wound area. The results were consistent with the above quantitative data.

Furthermore, this work suggested that the wound healing time and hospitalization time of the test group were significantly shorter than those of the control group ($P < 0.05$). Children face a strange environment and crowd in past treatment, which leads to emotional tension and anxiety in children. Family-centered nursing could enable family members to cooperate with doctors for treatment, improve the treatment compliance of children, facilitate wound healing as soon as possible, and shorten the length of hospital stay [41], [42]. This demonstrated that family-centered nursing combined with dressing change therapy could improve the efficiency of wound healing and help children leave the hospital as soon as possible. The wound pain score in the test group was 3.38 ± 0.75 and that in the control group was 6.24 ± 1.48. In contrast to the control group, the wound pain score in the test group was lower ($P < 0.05$). This finding indicated that family-centered nursing combined with dressing change therapy helped reduce the pain of children and improve their tolerance [43]. In the test group, 30 cases were effective, 22 cases were markedly effective, and 4 cases were invalid after treatment. In the control group, 22 cases were effective, 22 cases were markedly effective, and 12 cases were invalid. The total effective rate of the test group (92.86%) was higher than that of the control group (78.57%) ($P < 0.05$). It demonstrated that family-centered nursing combined with dressing change therapy could improve the cure of children [44]. The satisfaction rate of family members with hospital nursing services in the test group (89.29%) was remarkably higher than that in the control group (76.79%) ($P < 0.05$). This result indicated that family-centered nursing combined with dressing change therapy was helpful to improve the satisfaction of family members with the hospital and improve the doctor-patient relationship.

V. CONCLUSION

A. RESEARCH CONTRIBUTION

First, the convolutional layer of DCNNs was optimized, and a new image segmentation model based on DCNNs was proposed, which was compared with the FCM model and R-CNN model. Then, 112 children with chronic wounds of the lower limbs who were admitted to and treated in the hospital from January 2020 to January 2021 were selected as the research subjects. According to different nursing measures, they were randomly divided into the test group (family-centered nursing combined with dressing change) and the control group (conventional nursing combined with dressing change), with 56 patients in each group. Furthermore, the DCNN model was trained using wound images from the included patients and subsequently tested on patients with the same condition during the same period. The results revealed that the DCNN model exhibited a high level of accuracy in image segmentation, indicating its potential for clinical use in wound assessment. In addition, according to the results, the new image segmentation model proposed in this work had better performance than the traditional algorithm for chronic wound image segmentation, and the segmentation accuracy was improved. Furthermore, family-centered nursing combined with dressing change therapy could improve the treatment compliance and wound healing efficiency of children, reduce wound pain, and shorten hospitalization time, thereby improving the treatment efficacy of children. In conclusion, the results of this experiment provided a data reference for the clinical nursing treatment of chronic wounds in children's lower limbs.

B. RESEARCH LIMITATIONS AND FUTURE WORK

In this study, only 112 cases of chronic wounds in children's lower limbs were included, with a small sample size, all from the same hospital. In addition, there were no long-term follow-up visits, and the long-term prognosis that possibly occurs after treatment for all children was not obtained. A large sample size of chronic wound cases in children will be included in the future, and the popularity of the family-centered care model in a multicenter will be explored.

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