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Application of Deep Learning in Lower Limb Joint Images

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Abstract: *Deep learning provides favorable conditions for the application of artificial intelligence in the medical field, which has been widely used in medical images and has great application potential in the diagnosis and treatment of lower limb joint diseases. Deep learning techniques used to train and analyze images of the lower limb joints can be used in the clinical auxiliary diagnosis and offer a fresh approach to the study of joint diseases. For many tasks involving imaging of joint diseases, significant results have currently been attained. This paper reviews the development history of deep learning, describes the application progress of deep learning in lower limb joint images, expounds on the existing problems in the application of deep learning in the diagnosis and treatment of lower limb joint diseases, and looks forward to the future development direction.*

Keywords: *Artificial Intelligence, Deep Learning, Convolutional Neural Network, Fracture, Osteoarthritis, Joint Replacement*

1. Introduction

Artificial intelligence (AI) is a new technical discipline that investigates, develops, mimics, and expands the theoretical methodologies, technologies, and application systems of human intelligence [1], with studies in this topic encompassing robots, language recognition, image recognition, natural language processing, and expert systems [2]. Deep learning (DL), a concept proposed by G. E. Hinton [3] and other scholars at the University of Toronto, is an important branch of the field of artificial intelligence [4], which is a method for prediction and classification by establishing deep-seated neural network models, training a large number of data, and learning the main characteristics [5]. Deep learning technology is being researched further in the medical industry to be applied to medical images and to detect diseases in their early stages. Deep learning, in contrast to the original algorithm, doesn't need human input and is capable of processing a lot of data while figuring out the key aspects of image data without outside assistance. The most effective deep learning model for image identification is the convolutional neural network (CNN), which is a deep learning model akin to the multi-layer perceptron of an artificial neural network. It can automatically extract features from images and then carry out various analysis tasks on medical images, such as image detection, classification, segmentation, and disease prediction. The AlexNet convolutional neural network model created by Krizhevsky [6] and others took first place in the 2012 ImageNet competition, establishing convolutional neural networks as the primary algorithmic model in the disciplines of image identification and detection. Subsequently, a huge number of superior models have been developed. The rapid growth of deep learning has aided in the advancement of the AI sector; particularly in the field of medical image processing, deep learning has demonstrated excellent application potential. The majority of medical picture interpretation is done by doctors, but since every doctor interprets images differently due to subjectivity and knowledge base disparities, deep learning techniques may be applied to this task. At present, the application of computer vision technology derived from deep learning to the processing of medical images is becoming a cutting-edge research method. This method's test results in research have a high degree of accuracy. Furthermore, deep learning has high robustness in image size resolution; in illness diagnosis, its performance has reached or even surpassed that of expert doctors, such as in predicting the severity of diabetic retinopathy from retinal fundus images [7], classifying skin disorders [8], and detecting and classifying masses in X-ray films [9].

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This paper introduces the deep learning model frequently used in the diagnosis and treatment of lower limb joint disorders, emphatically discusses the application of existing lower limb joint images from the perspective of model accuracy and test efficacy, evaluates the benefits of this model and future application prospects based on its detection results, elaborates on the current issues of deep learning in the diagnosis and treatment of lower limb joint diseases, and looks forward to the future development of this model.

2. The Current State of Deep Learning Application in Lower Limb Joint Image

Medical image analysis data is frequently required to support clinical diagnoses and scientific research, making medical images vital in this field. Numerous joint illnesses, such as rheumatoid arthritis, joint congenital dysplasia, fractures, and bone and joint degeneration, among others, require the assistance of medical imaging for diagnosis in the majority of cases. It is a common procedure to employ X-rays, computed tomography (CT), and magnetic resonance imaging (MRI) for the acquisition of medical pictures (MRI). X-ray is the preferred examination, which has the advantages of convenience, speed, and low price, and can provide strong information for disease diagnosis, surgical planning, etc.; MRI is clearer in soft tissues and uses no ionizing radiation, but it is time-consuming. CT has a higher resolution on tissues with a higher density, however, it is conceivable that some areas of the scan will be missed, and the radiation dose is significant.

With the emergence of deep learning technology in various clinical applications, deep learning has been successfully applied in the ophthalmology, dermatology, and cardiology fields. The study of deep learning in medicine has grown steadily over the last five years. Deep learning has been successfully utilized in orthopedic joint imaging and has achieved excellent accuracy in three primary categories, including image detection, image classification, and image segmentation. It presently involves the fields of medical disciplines including ophthalmology, dermatology, oncology, orthopedics, and pathology; however, there is still a lack of review reports on the application of deep learning in lower limb joint images to identify the classification of the knee, hip, and hip fracture types, detect the presence of implanted prostheses, stage knee osteoarthritis (OA), and review the progress in the application of deep learning in lower limb joint images to provide new ideas and references for future related research.

2.1 Application in hip fracture

Hip fractures and the resulting consequences are major public health problems throughout the world [10]. Fractures are the main cause of death and disability in the elderly, and radiographic diagnosis is a frequently utilized fracture diagnostic method. Epidemiological surveys have shown that the age of occurrence of femoral neck fractures is mainly concentrated between 65 to 69 years, with an average of 65.4 years, more common in women, with a male-to-female ratio of 1:3.70; intertrochanteric fractures are mainly concentrated in the age class of 70 to 74 years, with an average age of 70.7, mostly in men, with a male to female ratio of 1:0.77, and subtrochanteric fractures are relatively rare [11]. The primary method of detecting fractures is routine radiography, although the relative sensitivity of X-rays to identify hip fractures is unsatisfactory [12] According to reports, 2.7% of hip fractures are difficult to detect on standard radiography and urge further investigation with magnetic resonance imaging[13]. Additional radiography, nuclear medicine bone scans, CT, and MRI scans are advised as regular diagnostics to prevent sequelae and medical expenditures related to delayed diagnosis [14]. Reports have shown that the misdiagnosis rate of hip fractures varies between 7% and 14% [15]. Failure to receive timely diagnosis and treatment may lead to fracture malunion, arthritis, and osteonecrosis, ultimately resulting in a poor prognosis [16]. Early and timely detection and treatment are essential to protect the patient's hip joint and even their survival.

Convolutional neural networks in deep learning are most suitable for image recognition and have gradually been developed to detect fractures of the extremities in recent years. In order to improve the accuracy of the model, the researchers trained AlexNet [6] and GoogLeNet [17] two deep convolutional neural networks, using hip X-ray datasets with different numbers of samples [18] to achieve the purpose of detecting femoral neck fractures, respectively. The test results showed that the datasets with more diverse samples increased the overall accuracy of these two deep convolutional neural networks to 90.9% and 85.5% in the detection of femoral neck fractures. It shows that the accuracy of the model increases with the number of samples in the training dataset when the convolutional neural network model is used to perform the target task. A deep learning model with more radiographs has been studied to conduct a classification task for fractures, and the accuracy of the findings exhibited in images of the validation set

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has also been done well [19], which also verifies this hypothesis. Additionally, the DCNN model is enhanced by the addition of the training data, which lowers the false-negative rate for the intended task and demonstrates the algorithm's superior performance. Deep learning improves the accuracy with which physicians can locate more subtle fractures, and in some cases, it may be better than the clinician. The performance of the model and the surgeon for detecting intertrochanteric fractures were compared based on hip images at the same time as the model and the surgeon for detecting intertrochanteric fractures using hip images, and the results showed that the CNN was slightly superior to the surgeon in accuracy [20]. The performance of this CNN model in detecting intertrochanteric fractures was found to be superior to that of surgeons, leading to the hypothesis that the CNN model may have significant potential in detecting intertrochanteric fractures. Nevertheless, due to the model's limited range of target detection tasks and the drawbacks of requiring manual cropping of plain radiography images when used, this model algorithm will be restricted to a certain extent in clinical settings. The researchers' findings showed that they could identify femoral neck fractures, trochanteric fractures, and non-fractures with up to 98% accuracy when a lateral view of the pelvis was combined with an anteroposterior view of the pelvis [12]. As can be shown, the method that uses both lateral and anteroposterior views to detect the relative position of the fracture site has higher accuracy than either anteroposterior or lateral views alone. It can also reduce the number of photos in the training set. Deep learning with CNN was used in studies involving the detection of acetabular fractures, and it was able to accurately detect the presence of femoral neck fractures as well as learn to differentiate between undisplaced Garden I/II fractures and displaced Garden III/IV fractures [21].

In conclusion, expanding the training set and getting image data from various perspectives can significantly improve the model's accuracy. The performance of combining this image data with fracture features into multimodality prediction models can be improved, even though there aren't many available medical images that are acceptable for model training and that deep learning accuracy still largely depends on data acquisition. Furthermore, preprocessing the image lowers its resolution, which may result in the loss of some of the fracture's unique characteristics. Deep learning may not be able to distinguish effectively based entirely on images labeled with fractures since physicians incorporate several radiographic and non-radiographic data at the time of diagnosis. However, these models are highly accurate at recognizing fractures, which lowers the missed diagnostic rate of fractures and the degree of reliance on MRI imaging techniques to some extent. It also shortens the time needed for surgical intervention, which helps patients have a better prognosis. Deep learning has considerable potential for fracture screening while also offering a solid foundation and suggestions for further research and model refinement.

2.2 Application in osteoarthritis

Osteoarthritis, a degenerative disease of the joint, is one of the most common causes of knee pain. Currently, it is thought to be the most common chronic joint inflammation [22]. The cause of OA is still unclear and incurable, and the only treatments for individuals with OA at this time are behavioral interventions, which include weight loss, adequate exercise, and joint muscle strengthening. These treatments temporarily relieve pain and slow the advancement of OA, but they ultimately result in total knee replacement. In previous studies utilizing deep learning to diagnose knee OA [23] [24], a multitask detection learning model of deep learning was utilized to examine numerous pathological aspects of hip osteoarthritis. These studies divided knee radiographs into five KL classes. Applying the previously validated CNN model VGG-16, the researchers trained and tested hip radiographs in groups and compared them between various physician groups. By using the model for automatic detection and diagnosis of hip radiographs, the model's sensitivity, accuracy, and other performance could be considerably improved [25], and it had a high level of consistency compared to the diagnoses provided by doctors. Many data studies on image segmentation are in the study of brain and brain tissue malignancies, and some studies also involve the prostate, liver, articular cartilage, and meniscus. As a result, these studies may offer ideas for future research. It has been discovered that the combined use of 2D CNN, 3D SSM, and 3D CNN models can be used to segment the knee meniscus [26]. In order to develop an automatic cartilage lesion detection method based on deep learning [27], the knee joint was first automatically divided into the femur, tibia, femur cartilage, and tibia cartilage in MRI images of 175 patients by using CNN, and then the lesions of articular cartilage tissue after segmentation were detected by using the second CNN model. It can detect cartilage degeneration and acute cartilage injury, and this deep learning method has high accuracy in detecting cartilage lesions in the knee joint. The purpose of this study is to more accurately predict the feasibility of using a deep learning method to detect cartilage injury in the knee joint on MRI images. The knee image is optimized based on the extraction of morphological characteristics and 2D U-Net CNN [28]. The results of the previous step can be greatly

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improved through SSM, thus making the final cartilage segmentation effect more accurate.

Accuracy can be improved by stacking the CNN model. Numerous studies have demonstrated that 2D U-Net CNN works better in terms of segmentation accuracy and that following this improvement, both its accuracy and picture segmentation time are greatly enhanced. The current task is capable of quickly and accurately segmenting an image of the knee, but due to the model's superior accuracy, it can be used in clinical settings for the identification and diagnosis of degenerative joint disease of the knee. As powerful algorithms in deep learning models continue to improve, the results of segmentation tasks for cartilage, bone, and meniscus in the entire knee become more precise and efficient.

2.3 Application in joint replacement

The most common applications of deep learning in orthopedics are the detection of fractures, the detection and prediction of osteoarthritis, and cartilage image segmentation. At the moment, it is also being used in joint replacement. A recently developed deep learning model is used to predict which osteoarthritis patients should undergo joint replacement surgery. Failure to accurately determine the design of the implant before arthroplasty leads to increased operative time, greater surgical complexity, increased intraoperative blood loss, bone loss, longer recovery times, and higher overall medical costs.

It has been found that the trained CNN model can be used before Total Hip Replacement (THR), and unmatched implants can be identified within a few seconds [29]. In order to visualize the model's attention, gradient-weighted class activation mapping is also used. The guided model focused on the area of interest and finally achieved 100% accuracy in the identification of three commonly used THR implants, thereby saving time, improving recognition accuracy, and effectively improving the surgical efficiency of joint surgeons. Using a deep learning model that reliably predicts the Kellgren-Lawrence score and the risk of OA patients most likely to progress requiring TKR by matching radiographs between patients who underwent total knee replacement (TKR) and patients who did not undergo TKR, the DL-based prediction model had an AUC of 0.87, which predicts the progression outcome of OA directly from radiographs while additionally performing the KL grading task, which enables multi-task simultaneous performance compared with previous methods, improving accuracy and reducing error in KL grading prediction. Although this model only applies to radiographs, it does not immediately predict the risk of TKA in OA patients on other forms of radiographic images. Future solutions to this problem can be developed by expanding the model's applicability to all sorts of radiographic images.

In summary, automatic image processing through deep learning can be applied to distinguish specific prosthesis implants in assisted joint replacement. The model obtains the output parameter index directly in the test set, without using the verification set to alter additional hyperparameters. If the verification set is used for training, its performance can be further improved, and then it can assist clinicians to make corresponding clinical decisions. At the same time, due to its quick and time-saving benefits for target task identification, it may be able to potentially enhance the effectiveness of patient care, free up surgeons' time, and lower medical expenses. Additionally, it can be utilized to complete this activity in the future at different locations, using the same or a better model after optimization, but the effectiveness of this technology still has to be increased.

3 Summary and outlook

In this study, the application of deep learning to lower limb joint images, including lesion detection, segmentation, and prediction, is described, and the application status of deep learning in the field of lower limb joints is reviewed. The present study suggests that deep learning may be superior to clinicians in some tasks and to some extent in lower limb joint images and has considerable potential application value, but there are still many problems and difficulties in this field that remain to be solved and still need to be further improved in methods and applications.

First, there is the issue of labeling images of lower limb joints, which necessitates experienced clinical surgeons to spend a lot of time labeling, but also hopes that more joint surgeons will actively participate in this study. At the same time, in order to avoid unnecessary errors in the labeling of images, a consensus may need to be achieved. Moreover, with the development of medical imaging machines, high-resolution image data may lose part of the information when performing image preprocessing, and better models are required to overcome this potential difficulty in the future. Additionally, target images that yield false negative results in target detection tasks, such as the identification of lower limb joint fractures, should be frequently learned to minimize the false negative rate and improve the accuracy and dependability of

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the results.

In summary, the application of deep learning to various tasks of lower limb joint images has achieved remarkable results, and future model optimization and improvement are inextricably linked to the active involvement of numerous clinical joint surgeons. It is believed that with the continuous improvement, progress, and improvement of deep learning technology, landing applications will be realized in the near future and will serve as a useful auxiliary tool for joint surgeons.

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