Advancements in Pancreatic Cancer Detection: A Comprehensive Investigation of Convolutional Neural Network Applications

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Abstract: Pancreatic cancer is one of the leading causes of cancer death and poses a major challenge to the current health care system due to its early concealment and high mortality. At the same time, the excellent performance of machine learning technology, especially convolutional neural network technology in the fields of medical image target detection and semantic segmentation provides a new solution for the recognition and early prevention of pancreatic cancer. This review introduces the application of Convolutional Neural Networks (CNNs) in the field of pancreatic cancer detection in recent years, introduces the basic structure and function of CNN model, and further introduces the characteristics of classical CNN models such as ResNet and DenseNet and their applications in the field of pancreatic cancer detection. Three complex CNN models, PANDA, YCNN and DACTransNet, are emphasized, and their structures, characteristics and applications in pancreatic cancer detection are introduced. These models leverage CNN's ability to extract complex features from medical images, facilitating precise tumor identification. Then, the user-friendliness and interpretability of different models are discussed, and the lack of clinical evaluation in current studies is pointed out. Future research may focus on improving the CNN architecture, enhancing model generalization, and addressing interpretability issues to optimize clinical applications. This review provides insight into the current state and prospects of CNN-based pancreatic cancer detection and outlines possible directions for future exploration.

1 INTRODUCTION

In the US, pancreatic cancer has a about 13% 5-year survival rate, making it an extremely deadly illness. (Siegel, 2024). By 2040, pancreatic cancer is expected to overtake colorectal cancer becoming the second-leading cause of cancer-related deaths in the United States, where it presently ranks third. (Halbrook, 2023). Smoking, obesity, type 2 diabetes, and family history are associated with risk for pancreatic cancer. Patients with locally located tumours are frequently disregarded since they do not exhibit any symptoms or have nebulous symptoms until they become signs of advanced disease. (Mizrahi, 2020). Computerized Tomography (CT) is the primary imaging method used to detect and evaluate pancreatic cancer, but the diagnostic performance of this method depends on the experience of the radiologist. In addition, in pancreatic cancer detection, about 40% of tumors smaller than 2cm evade CT detection (Kang, 2021), and new methods are urgently needed to supplement the judgment of radiologists to improve the sensitivity and accuracy of pancreatic cancer detection.

In recent years, the use of computer-aided detection with Artificial Intelligence (AI) has demonstrated great potential in the medical field (Qiu, 2022; Shen, 2017). Medical imaging is considered an important source of information needed to diagnose diseases. Using a variety of ways to detect disease at its earliest stages is one of the most important factors in reducing cancer and tumor mortality. AI has produced encouraging outcomes in categorization and decision support. A kind of AI called machine learning, or ML, has sped up a lot of medical research. A kind of machine learning called "deep learning" (DL) uses layers of neural networks to identify the precise characteristics required for illness identification (Plis, 2014; Tajbakhsh, 2016). Neural networks are built using a collection of neurons consisting of activation functions and parameters. These neurons harvest and integrate information from

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pictures to create a model that accurately represents the complex connection that exists between diagnosis and images.

One possible solution is to apply Convolutional Neural Networks (CNNs) to the recognition of pancreatic cancer as well. CNN is one of the main algorithms of deep learning (DL) and is a type of feedforward neural network with depth structure and convolutional computation, which can effectively extract features from image data and learn complex data patterns, and is specially used for processing and analyzing data with grid structure, especially image and video data. In the identification of pancreatic cancer, CT images of patients can be used as different CNN models and the specific use of models can get better detection results, but it is still difficult to determine the best use of CNN and the future development direction.

On the one hand, classical CNN models, such as ResNet and DenseNet, have achieved certain effects in the recognition of pancreatic cancer (Zavalsız, 2023; Huy, 2023). On the other hand, in order to improve the recognition effect and reduce the amount of computation, more complex models have been applied (Kou, 2023; Cao, 2023; Dinesh, 2023). For example, by stacking different models to create a hybrid network architecture, or introducing other algorithms outside the CNN model, these methods have improved the recognition effect of pancreatic cancer to a certain extent.

This review will briefly introduce the application of CNN model in pancreatic cancer recognition, and then provide the details of their implementation. Then, the advantages and existing problems of these recognition methods will be discussed. Finally, last section will summarize this review and give the conclusions drawn from the discussion.

2 METHOD

2.1 Framework of AI-Based Pancreatic Cancer Detection

The construction process of AI-assisted pancreatic cancer recognition system generally includes data set establishment, data preprocessing, feature extraction, model training, model evaluation, model testing and other steps. Some relatively complete research studies will carry out real-world deployment and clinical testing.

In terms of the establishment of data sets, some researchers choose to use existing public medical image data sets, such as TCGA or TCIA, which are large-scale public databases whose image modes include MRI, CT, etc., for research use, while others choose to cooperate with local medical institutions to obtain de-identified patient data sets.

CNN extracts features from images by stacking multiple convolution layers and pooling layers. The pooling layer is utilised to shrink the feature map's size, while the convolution layer is in charge of collecting local features from the input. By stacking multiple convolution layers and pooling layers, CNN can gradually extract the abstract features of images. The specific feature extraction is highly related to the CNN structure selected by the fusion method, and the feature extraction processes of different types of model structures are very different. After feature extraction, CNNs typically include one or more fully connected layers that map features to the final category score. Every neuron in the fully connected layer is connected to every other neuron in the preceding layer, and the activation function uses all of the inputs from the previous layer to weight each neuron's output.

Through the above operations, CNN will obtain the expected output of the model, calculate the loss, optimize the parameters, and conduct continuous iterative training until the stopping condition is reached. In general, the maximum number of iterations and the loss threshold are used as stopping conditions, but some models also use the results evaluated by the validation set directly as criteria. Validation sets are the subset of the data set dedicated to evaluating the performance of the model, and in addition to validation sets, there are test sets that evaluate the generalization ability of the model by identifying data that the model has not seen before.

2.2 Classical CNN Model for Pancreatic Cancer Detection

Hoang Quang Huy et al. used DenseNet for cancer detection. Multiple densely connected convolutional layers make up a dense block, which is the fundamental building block of DenseNet. Within the dense block, the output of each layer is associated with the output of all previous layers, and the feature transfer is carried out by a dense connection, which allows the model to better capture the details in the pancreatic cancer image. In order to decrease the dimension of the feature map, DenseNet further adds a transition layer. This densely connected structure enables the network to make full use of features, thus improving the expressiveness of features and the accuracy of the model (Huy, 2023).

Muhammed Talha Zavalsız et al. used ResNet for cancer detection. The basic unit of ResNet is the residual block, which contains two branches: the main branch and the residual branch. The main branch contains a series of convolutional layers, while the residual branch adds the input to the output by connecting across layers. This design allows the network to learn residual mapping, helping to better capture complex features in pancreatic cancer images. At the same time, ResNet was pre-trained on a large dataset, requiring only further training using pancreatic cancer images (Zavalsız, 2023).

2.3 CNN Model with Hybrid Network Architecture

2.3.1 PANDA

The deep learning model consists of a cascade of three network phases, which increases the complexity of the model and allows the model to accomplish more complex and rich recognition tasks. The first phase of the network used the nnU-Net model for pancreas localization. In the second stage, CNNS were constructed, and the classification heads were used for lesion detection. The third stage is the differential diagnosis of pancreatic lesions when abnormal pancreatic lesions are found in the second stage, and the characteristic prototype of pancreatic lesions is automatically encoded by the auxiliary memory transformer branch for more accurate fine-grained classification (Cao, 2023).

2.3.2 YCNN

The deep learning model consists of a cascade of three network phases, which increases the complexity of the model and allows the model to accomplish more complex and rich recognition tasks. The first phase of the network used the nnU-Net model for pancreas localization. In the second stage, CNNS were constructed, and the classification heads were used for lesion detection. The third stage is the differential diagnosis of pancreatic lesions when abnormal pancreatic lesions are found in the second stage, and the characteristic prototype of pancreatic lesions is automatically encoded by the auxiliary memory transformer branch for more accurate fine-grained classification (Cao, 2023).

2.3.3 DACTransNet

The two primary modules of DACTransNet comprise: By combining the local features of CNN with the global features of the VIT-based model—which consists of alternating superimposed convolution blocks and converter blocks—the hybrid CNN-Transformer network, which serves as the model's backbone, and the ASPP module with deformable convolution improve the model's capacity to derive distinctive features from medical images of pancreatic cancer. With multiple expansions and in multiple sensing fields, multiple filters and pooling are used, the innovative deformable Porous Space Pyramid (DC-ASPP) module used in this model detects the characteristics of pancreatic cancer photos, acquiring information on multi-scale irregular objects (Kou, 2023).

3 DISCUSSION

First of all, the models based on CNN mentioned in this paper have good performance in the task of pancreatic cancer recognition and detection. However, compared with the CNN model with complex architecture, there is a certain gap in the generalization of classical CNN model. In addition, the recognition tasks of some models focus on the binary classification of the presence or absence of pancreatic cancer (Zavalsız, 2023; Huy, 2023), which is not user-friendly and applicable, which is not conducive to doctors to use the models for further diagnosis, and does not fit the use scenario in the real world, which brings great difficulties to clinical use. On the contrary, the PANDA and DACTransNet models can identify specific areas of pancreatic lesions and generate visual results with good interpretability. The PANDA model can directly output the segmentation mask of detected masses and the patient-level probability, providing more direct interpretability (Kou, 2023; Cao, 2023).

In terms of the selection of data sets, some studies chose public medical image data sets, such as TCGA or TCIA, etc. (Zavalsız, 2023; Huy, 2023; Kou, 2023), in which data bias, labeling standard deviation, data potential bias and other problems will affect the generalization performance of the model and make the model obtain worse evaluation and test results.

Instead, some researchers have worked with medical institutions to build custom datasets and even conduct real-world clinical evaluations (Cao, 2023; Dinesh, 2023). Among the model studies mentioned in this paper, only Kai Cao et al. 's PANDA model study conducted clinical validation and evaluation in the real world, and verified the model through a large number of tests (Cao, 2023). Through the diagnosis of the same CT image with the clinician, the reliability of the model decision-making can be strongly proved, and clinical use will accelerate the process of its application in addition to verifying the applicability of the model.

A large number of studies have proved the superior performance of CNN-based models in the identification of pancreatic cancer (Zavalsız, 2023; Huy, 2023; Dinesh, 2023). Future studies should pay more attention to the generalization ability of models by building complex architecture CNN models, and at the same time focus on the interpretability of models. Studies of algorithms and models have yielded excellent results in terms of performance, but more research should be done to prove the applicability and reliability of the models through real-world clinical testing.

At the same time, considering the invisibility of early pancreatic cancer and the high lethality of late pancreatic cancer, binary classification of obvious pancreatic cancer images cannot bring significant improvement in the real world, and some models should focus on more difficult to identify tasks, such as pancreatic cancer classification and screening of early pancreatic cancer, to provide AI assistance for the prevention of pancreatic cancer. Some advanced deep learning models widely used in other domains (Sun, 2020; Wu, 2024) may be considered in the future to improve the prediction performance for pancreatic cancer.

4 CONCLUSIONS

This paper introduced the construction process of CNN-based pancreatic cancer recognition system. In addition, it also introduces the structure of some classical CNN models, such as ResNet and DenseNet, and briefly describe their applications in pancreatic cancer recognition. In the same way, three complex CNN models PANDA, YCNN and DACTransNet are also mentioned, and how to design the structure of these complex CNN models for pancreatic cancer recognition is introduced. In the future, this kind of research should pay more attention to how to identify more subtle early pancreatic cancer images, enhance the generalization ability of the model, especially in the real-world clinical test, and improve the real-world situation through research.

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