ISSN 2959-6157

Application of Convolutional Neural Networks in Thyroid Cancer Diagnosis and Analysis

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Abstract:

Due to the difficult and expensive diagnosis of thyroid cancer, this paper would like to discuss the possibility of using Convolutional Neural Network (CNN) model to assist doctors to classify and recognize medical images. Consequently, this article focuses on the three types of CNNs: Xception, VGG, and Inception. For the traditional models like VGG and basic Inception, they are trained for the basic image classification and recognition. Although they are only basic model in CNNs, they can also achieve a great success rate. For example, VGG-19 could deal with the four main types of thyroid cancer and the accuracy of the classification both over 98%. For the advanced model like Xception and Inception-ResNet-v2, they are combined with various kinds of basic model and improved the parameters and structures. They are extensions and innovations based on the traditional models which also attained a successful result. For example, Xception could classify two kinds of medical images, the accuracy of ultrasound images is 0.98 and the accuracy of CT images is 0.96. According to analysis of the result, it is obviously found that the accuracy of each model could achieve a high rate. It proves that CNNs plays a significant role in diagnosis of the thyroid cancer. However, there are also some challenges and difficulties that need to be improved, including the selection of datasets and more comprehensive system coverage.

Keywords: Thyroid Cancer; CNNs; image classification and recognition.

1. Introduction

The thyroid, an endocrine gland, plays a significant role in the human body to control heart rate, maintain blood pressure balance and body temperature [1]. According to research by Cabanillas reported that there have been over 62,000 cases of thyroid cancer since 2015, and this number also continues to rise around the world [2]. Chen also reported in GLOBOCAN 2020 published by the World Health Organization's for Research on Cancer, that thyroid cancer's incidence rate is the ninth cancer in the world [3]. It indicates that there are many people suffering from this disease and the number of patients is also rising. These studies highlight the importance of diagnosing and treating thyroid cancer. However, the process of thyroid cancer diagnosis which also has a lot of challenges including difficulties in diagnosis, high costs and accurately identifying the ultrasound images [4]. Consequently, it is an emergency to find an effective way to improve the situation.

The standardized detection procedure in thyroid cancer diagnosis relies on medical images tools such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), radio-iodine scintigraphy, Positron Emission Tomography (PET) scanning, and ultrasound image [5]. However, medical images cannot full support the thyroid cancer diagnosis when the doctors cannot distinguish the benign and malignant thyroid nodules, and it will be necessary to use the Fine-needle Aspiration Cytology (FNAC) to test and diagnose [5]. It indicates that the process of diagnosis will lead to unnecessary operation and the results will fully depend on the skill and experience of the doctor. Chen also mentioned that overdiagnosis of thyroid cancer may result in medical overspending, increasing the patients' psychological stress [3]. And Chan supported the idea that there is risk of infection during the operation [6]. Fortunately, with the development of Artificial Intelligence (AI) technology, using Deep learning Convolutional Neural Network (CNN) as an assist tool in image classification and recognition has achieved a great success. Therefore, this method can be considered as an effective method in the medical field to help the doctor complete the image diagnosis.

Deep learning CNN is an AI model that can be combined with Computer-aided Diagnosis (CAD) techniques in medical field to avoid unnecessary biopsies [7]. Fortunately, in recent years many studies have successfully utilized the CNN technique to assist in the diagnosis of thyroid cancer. For example, as the Zhang reported that their study used the Xception neural network as the basic structure which the diagnostic accuracy of ultrasound image was 0.989, and that of computed tomography was 0.975 [5]. Similarly, Chan and Guan employed InceptionV3, ResNet10 and VGG19 [6, 8], while Zhu used VGG – 16T [9], and Park utilized US CAD [10], all of which have made significant progress in aiding the diagnosis of thyroid cancer.

The remainder of the paper is organized as follows. First, this paper will analyze the various methods of CNN models in thyroid cancer diagnosis in Section 2. Then the advantages and disadvantages of each model will be discussed and the possibility of combining the advantages of each model is analyzed. This paper will also discuss the future development of CNN in the medical field. Finally, the last section summarizes the paper and draws a conclusion based on the contents discussed before.

2. Method

2.1 The Introduction of CNN

CNN is a significant part of deep learning which has achieved great accomplishments in computer vision and natural language processing [11]. As O'Shea reported, CNNs are comprised of three types of layers, including convolutional layers, pooling layers and fully connected layers [12]. CNN can optimize itself each iteration and the users can build the CNN architecture in different ways such as changing the number of layers, choosing various optimizers, and adjusting the size of parameters. With the development of CNNs, there are many applications in face recognition, self-driving cars, smart healthcare [11]. Consequently, based on these great achievements by CNNs, this paper aims to investigate the application of CNN in thyroid cancer detection.

2.2 CNNs Model

2.2.1 Xception neural network

Xception neural network is a depth-separable convolutional neural network based on Inception [13]. Xception could reduce the model complexity and keep the excellent performance, making it an important tool in image classification due to its great feature extraction capability. According to Zhang, researchers used the multi-channel Xception model to test image classification and compare the results with the traditional models [5]. The process was divided into two parts. First, they trained the Xception model using real CT images and ultrasound images, analyzing the accuracy rates, f1 score, precision, recall, negative predictive value (npv), and running time. Typical thyroid disease includes functional and neoplastic disease, and the clinicians divide the thyroid nodules into benign nodules and malignant kinds (cancerous cells) [5]. In the thyroid cancer, it mainly includes Papillary Thyroid Carcinoma (PTC), Follicular Thyroid Carcinoma (FTC), Medullary Thyroid Carcinoma (MTC), Anaplastic Thyroid Carcinoma (ATC) four types. Second, based on the clinicians' needs, they applied the Xception architectures for binary and multi-class classification tasks. The experiment included three types: the Single Input Dual-channel (SIDC), the Double Inputs Dual-channel (DIDC), and the four-channel architectures. The different channels processed the same input image in different ways [5]. For example, the image was divided into two parts and each part was further divided. The four parts of the image will be input into the four-channel models. The model classified each part then combines the result together to generate the final accuracy. In Xception, Zhang set the Amada as the optimizer and 0.001 as the learning rate [5]. The results of this model were as follows: Accuracy:0.980, Precision: 0.990 in the DDTI sets for ultrasound image and Accuracy: 0.966, Precision: 0.961 in the hospital sets for CT images.

2.2.2 VGG models

VGG model is one of the most classical models in CNNs which was invented by the University of Oxford in 2014 [8]. This model is mainly composed of the VGG-16 and VGG-19. The difference between the two architectures is the number of depths. According to a report by Guan, they built a VGG-16 model, which has a total of 25,088 (7×7×512) vector channels, to test the performance of the architecture [8]. In this experiment, they tried to use 279 images of thyroid nodules as input and divided the image into a 6:1 for training and testing. During the data pre-processing, each image was manually segmented into several 224×224 fragments. Zhu also used the VGG-16 model to classify benign and malignant Thyroid Nodules (TNs) using thyroid US images [9]. In total, there were 592 patients with 600 TNs as the datasets, including training, testing, and validation, whose parameters and data setting were similar to Guan's research. The difference between the two studies is that Zhu's research added Batch Normalization (BN) and dropout layers in addition to the fully connected layers. Fortunately, both experiments achieved great success in image classification. For Guan (2019), they had an accuracy of 97.66% and a specificity of 94.91%. For Zhu, they had an 86.43% accuracy and an 85.43% specificity [9]. On the other hand, Wang also used the VGG-19 model to classify thyroid images [4]. In this study, the total 11,715 fragmented images were divided into a training dataset and a test dataset for each pathology type at a ratio of 5:1. Each image was labeled with one of 7 classes: 0: normal tissue, 1: adenoma, 2: nodular goiter, 3: PTC, 4: follicular thyroid carcinoma (FTC), 5: medullary thyroid carcinoma (MTC), and 6: anaplastic thyroid carcinoma (ATC). But the size of images and the number of the vector channel are the same as the VGG-16 setting. The difference between the two architectures is that VGG-19 has three more convolutional layers than VGG-16. And the result from Wang was also encouraging. This model has an accuracy of 88.33% for normal tissue, 98.57% for ATC, 98.89% for FTC, 100% for MTC, 97.77% for PTC, 100% for nodular goiter, and 92.44% for adenoma [4].

2.2.3 Inception models

Inception is also a classical pre-training model in CNNs. The most important feature of this model is its inception module, which applies convolution cores of different sizes and a pooling operation on the same input in parallel. This design could maintain great performance while reducing the calculation and complexity. As reported by Guan, they also use the same datasets and image pre-processing which this paper has mentioned in the VGG part of this paper [8]. They built the Inception V3 models, which included three modules called Inception A, Inception B, and Inception C. This architecture stacks 3 Inception A, 5 Inception B, and 2 Inception C modules in series and totally has 8×8 with 2,048 channels. The dropout layer was also used to avoid overfitting. The result of InceptionV3 was great, achieving the 92.75% accuracy, 98.55% sensitivity, and 86.44% specificity. And in the research by Wang, they combined the characteristics of Inception and ResNet, then used the Inception-ResNet-v2 model to classify the image [4]. The default image input size is 299×299, the learning rate was set to 0.001, and the dropout rate was set to 0.4. Finally, the Inception-ResNet-v2 model achieved a fragmentation accuracy of 82.22% for normal tissue, 94.76% for ATC, 95% for FTC, 98.43% for MTC, 93.31% for PTC, 98.43% for nodular goiter, and 91.56% for adenoma.

3. Discussion

On the one hand, according to the results of the method section for the three different kinds of CNN models, it can be obvious that the CNN module achieves a great success rate in thyroid cancer image classification and recognition. For the basic architecture in CNN, such as VGG, it is gratifying that this module can classify the four main types of thyroid cancer with great accuracy and sensitivity. As the Guan found, they used VGG module, which achieved an average accuracy of over 95% for images of four main types of thyroid cancer [8]. The basic pre-training model in CNNs, it has already performed perfectly in the test. For the advanced architecture in CNN, such as Xception and Inception-ResNet-v2, which both had excellent results in thyroid cancer assistance. Xception model could successfully attain the 0.980 accuracy for the ultrasound image and 0.966 accuracy for the CT image [5]. At the same time, Inception-ResNet-v2 also performed better than the basic Inception model, especially in the MTC and nodule goiter part [4]. These studies prove the possibility of using CNN module to assist doctors. Additionally, this technology could cover almost all situations in thyroid cancer, including different kinds of thyroid cancer symptoms and diagnostic images like CT image and ultrasound image. Park had also compared AI classification results to the experienced radiologist, the difference in accuracy between the two was less than 7% but the former had 90.7% sensitivity [10]. As Anari stated, with the AI technology joining in the traditional medical diagnosis which reduces the unnecessary biopsies and improves the accuracy of the image diagnosis [7]. The combination of AI and medical images reduces the subjectivity of diagnosis [14].

On the other hand, there are also many challenges during the application. For the moment, most training and testing only used images from the same datasets. It means that if the hospital wants to apply the model which has already been trained for one dataset to the new images or another dataset, the performance could not be predicted exactly. This suggests that the application of cross-datasets needs to be further strengthened, which ensures users could apply the module directly. For the datasets, it will also be considered whether the thyroid feature is different in different ethnic groups. For example, Zhu only tested and compared the classification result in the US [9]. And for some studies, the number of images in their datasets may not be enough to train a module. In Guan, they only used 279 images to train and validate the architecture [8]. Consequently, it will be difficult to verify the module's performance when the size of the data is enough. At the same time, during the diagnosis, the doctors will use various kinds of medical images like CT and ultrasound images. This shows that the CNN module should also need to be added a function to automatically recognize and process different types of medical images. Certainly, the security and privacy of users and medical images used for training are also important during the application. The hospitals and doctors should also protect the patient's privacy during the application process.

In order to improve and solve the problem mentioned above, there are two suggestions. First, both studies only use one kind of medical images as the dataset. Single type data will be difficult to apply the result to the real world. Therefore, it is recommended to use a various and larger number of images to train and test. The richer data is used, the more reliable result will be attained. Second, it could also be combined with the new AI module, such as transfer learning to improve the intelligence in its application process. It is crucial to learn from more advanced architectures, which could promote the implementation of the item. In the future, it will also require the support of experienced doctors to provide the relevant suggestions and experience to improve the performance of the algorithm. In the end, although there are some challenges and difficulties in the application process, the great performance of the attempt is also showing the possibility of applying CNN in thyroid cancer. With the development of AI technology and the emergence of new architecture, these problems could be solved.

4. Conclusion

This article provides a comprehensive review related to discussion of the possibility of using CNNs in the diagnosis of thyroid cancer. Through the analysis of the above research results, it can obviously be found in existing studies that both basic and advanced CNN architecture could have a great result in medical image classification. Its high accuracy and wide coverage show the potential and prospect in this field. However, there are many challenges and difficulties during the application. It will be important to consider its security and privacy. And it will also need to be improved to adapt to a more complex and comprehensive situation. In the future, CNN will be combined with more advanced models to improve its performance and application. In summary, this paper provides a strong support to apply CNN in the diagnosis of thyroid cancer and expects it to perform better in the future.

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