Renal CT Image Classification Based on Densely Connected Convolutional Networks

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Abstract: In response to the current situation of the increasing incidence of kidney diseases worldwide, the efficiency of traditional clinical diagnosis may not be enough to cope with future needs. Compared with traditional methods of clinical diagnosis, the automatic classification of renal computed tomography (CT) images based on convolutional neural networks (CNN) in this study has the potential to significantly improve the efficiency and accuracy of clinical diagnosis. In the paper, the Densely Connected Convolutional Networks 121 (DenseNet121) model is selected for training on 12,446 CT images, which include categories such as kidney cysts, kidney stones, tumors, and normal tissues. The model training was performed using an early stopping strategy and multi-cycle validation loss assessment. Subsequently, the model was tested on an independent test set to achieve an impressive accuracy of 0.9351 and a precision of 0.9393. The experiments conducted in this study have garnered a good response, and their high accuracy could potentially enhance the efficiency of clinical diagnosis and provide better safety for patients.

1 INTRODUCTION

Nowadays, the incidence of renal diseases has become higher due to factors such aspersonal life habits and deterioration of the external environment (Zhang et al., 2019). Kidneys are one of the very important organs in the human body, which are responsible for maintaining various functions of the body. Such as metabolism, fluid balance, and endocrine functions. Therefore, kidney disease may have a serious impact on health. Therefore, the ability to accurately and quickly determine kidney health is crucial for the timely detection, prevention, and treatment of kidney diseases.

Currently, most of the clinical diagnosis of kidney health is done manually by testing of CT (Zhang et al., 2019). CT, as a medical imaging technique, utilizes X-rays and computer technology to produce detailed cross-sectional images of the internal structures of the body (Goldman, 2007). These scans offer clearer and more detailed images than ordinary X-rays, enabling doctors to accurately view organs, blood vessels, and more within the body. Kidney diseases, including kidney cysts and kidney stones, are likely to grow in the patient base with the effects of frequent diseases and an aging population. Therefore, the efficiency of traditional manual CT diagnosis may need some image recognition algorithms to improve in the future.

At the present time, deep learning has been applied to the problem of kidney CT image classification, and CNNs are widely used in several tasks of image processing (Alzu'bi et al., 2022; Mehedi et al., 2022). Such as VGG16, ResNet, MobileNetV2, they all play an important role in this problem.

The dataset is made up of 12,446 distinct entries, encompassing 3,709 instances of cysts, 5,077 normal samples, 1,377 cases of stones, and 2,283 occurrences of tumors (Islam et al., 2022). The study uses deep learning model DenseNet121, Adam optimization, and other methods. The main research process is as follows: firstly, data preprocessing and data enhancement are carried out on the original data, and a model is constructed to classify and analyze renal CT images using the DenseNet121 deep learning framework. Then the loss rate, accuracy, precision, recall, and other indexes of the model are tested on an independent validation set to evaluate the model (Arulananth et al., 2024; Magboo & Magboo, 2024), and the classification result graphs of the test are output at the same time.

This paper is divided into several parts: the first and current part is the introduction; the second part outlines the main methodology used in the study,

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including specific methods such as data processing and model construction; the third part describes the results of the study, including the performance and evaluation of the model; and the last part summarizes the whole paper.

2 METHOD

The main approaches of this research include data preprocessing and enhancement, and model architecture.

2.1 Data Preprocessing and Augmentation

In this study, data preprocessing and enhancement of images prior to model construction aim to enhance the model's generalization capability and ensure its robustness in real-world applications. (Shorten & Khoshgoftaar, 2019).

All renal CT image data were normalized using the 'ImageDataGenerator' method, a technique that involves scaling the raw pixel values of the images from the range 0-255 to between 0-1. This step helps to optimize the stability of the algorithm during model training and speeds up model convergence.

Data enhancement techniques are also introduced. These transitions include stochastic rotation (up to 40 degrees), horizontal and vertical translation (up to 20%). These steps increase the dataset's diversity while enabling the model to learn the image variations due to operational differences in real clinical settings. For example, rotation and translation simulate the different poses of the patient during scanning, while zooming and shearing allow the model to recognize kidney structures in images of different sizes and scales. Horizontal flipping can further enhance the model's adaptability to changes in image orientation.

2.2 Modeling

The DenseNet model can effectively mitigate the problem of vanishing gradients and enhance feature propagation and reuse by connecting each layer to all previous layers, drastically reducing parameter requirements. Its structural design not only improves the model's training efficiency but also has superior performance on multiple image recognition tasks. Figure 1 below illustrates the structure of the DenseNet model. (Huang et al., 2017).

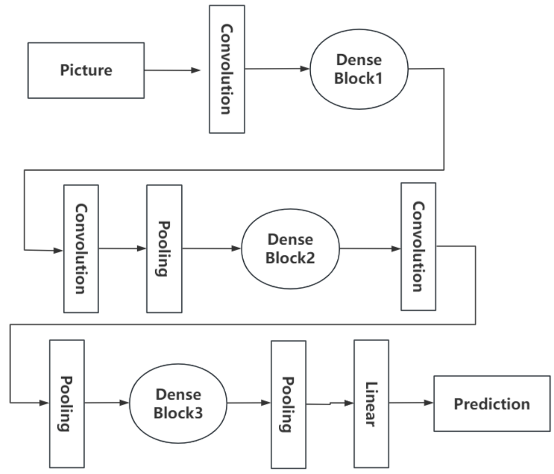

Figure 1: DenseNet model structure.(Picture credit :Huang et al., 2017)

Figure 1 shows the initial image processed by one convolutional layer through three densely connected blocks. The layers within each densely connected block receive the outputs of all previous layers as inputs, which enhances the transfer of features. The dense blocks are connected through a transition layer consisting of a convolutional and pooling layer, and finally the result is output after the features are varied through a linear layer (Huang et al., 2017).

Therefore, the DenseNet121 model is selected for CT image classification in the study.

A global average pooling layer is introduced to reduce the parameters and mitigate overfitting when constructing the model. To enhance the stability of model training, a batch normalization layer is added, and a fully connected layer with the ReLU activation function is introduced to improve the model's nonlinear processing capability. Overfitting of the model is prevented by culling the layer with the scale set to 0.5. Finally, the output layer contains four neurons, each corresponding to a kidney CT image category, and the probability of each category is produced using the softmax activation function.

During the training process, the Adam optimizer is used in the study, which has the property of adaptive learning rate to converge quickly in the early stage of model training and remain stable in the later stage (Hospodarskyy et al., 2024; Reyad et al., 2023). Meanwhile, the classified cross entropy is applied as a loss function to optimize the probability distribution of the model output.

To address the category imbalance in the dataset, weights were calculated and applied for each category during model training. The weights of different categories are set before training to prevent the possibility of biasing back to the category with more samples during training, which improves the prediction accuracy of the model for the category with fewer samples. In addition, to prevent overfitting in model iterations, optimize model performance, and save resources. Training was performed using the early discontinue method. When training was discontinued when the validation loss did not improve for three consecutive cycles, the model with the highest validation accuracy was saved using ModelCheckpoint.

3 RESULT

The data of this study contains four types of kidney CT images. The study splits the raw data into a training set and a test set with a 7:3 ratio. Figure 2 illustrates the training process.

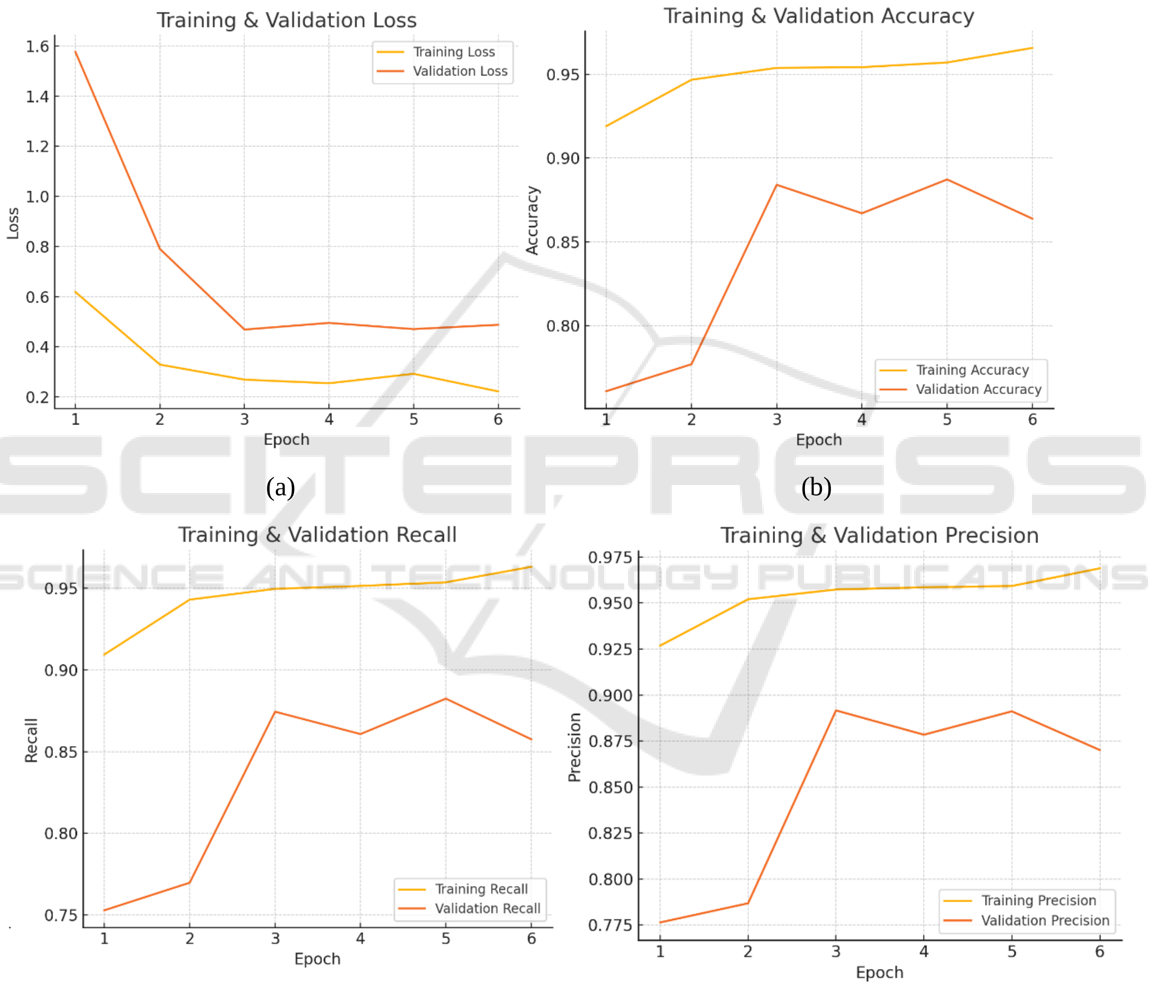

Figure 2: (a) Loss image, (b) Accuracy image, (c) Recall image, (d) Precision image.(Picture credit : Original)

Figure 2 shows the trends of the model's loss, accuracy, precision, and recall over six training rounds. Overall, the loss decreases significantly during model training, the other three values improve, and the validation loss gradually decreases.

The DenseNet121 model training process evaluates the performance of the model at each iteration with four key metrics: loss value, accuracy, precision, and recall. These metrics are used to fully reflect the model capability and save the optimal model at each iteration. The test results are presented in Table 1.

Table 1: Model Evaluation Training Set.

Metric	Value
Evaluation Loss	0.2218
Model Accuracy	0.9658
Prediction Precision	0.9688
Recall Rate	0.9631

Table 1 exhibits the model training results at the optimal iteration period. It can be seen that the model training loss is 0.2218. The low loss shows that the model fits properly on the training data. The model's three metrics on the training set are about 0.96%, reflecting that the model accurately performs the classification task.

The study conducted a comprehensive evaluation of the model using an independent validation set with the same metrics as Table 1 to fully reflect the model's ability to perform on an unknown dataset. The test results are shown in Table 2.

Table 2: Model Evaluation Test Set.

Metric	Value
Evaluation Loss	0.3163
Model Accuracy	0.9351
Prediction Precision	0.9393
Recall Rate	0.9325

In evaluating the performance of the renal CT image classification model, the validation set contains about 5,000 images covering four categories. The following results were obtained from the test study: loss value 0.3163, accuracy 0.9351, precision 0.9393, and recall 0.9325. These results indicate that the model demonstrates high classification accuracy and reliability, effectively recognizing and classifying CT images related to renal diseases in most cases.

In order to demonstrate the model effect in practical applications more intuitively, the study also tested the actual classification prediction on renal CT images, and the results were visualized and graphically presented. The test images and labels were extracted from the validation set, and the categories were tested on randomly selected images. The tested images and the predicted and actual values are finally shown for comparison. Figure 3 shows one of the results of the above presentation.

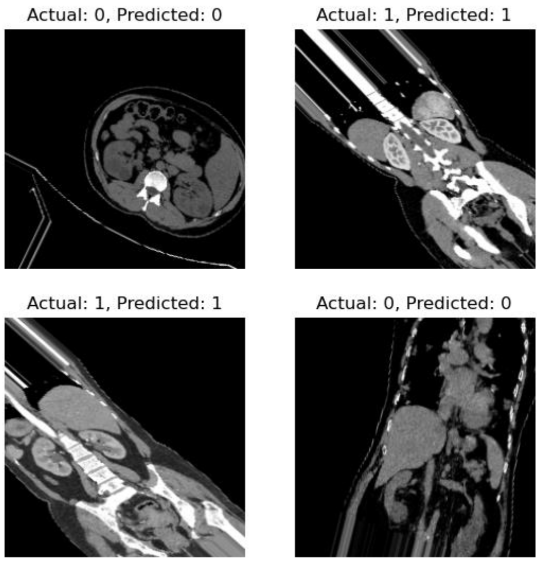

Figure 3: Model effect test.(Picture credit : Original)

Figure 3 shows four CT images and predicted results with four categories: normal kidney, cyst, stone, and tumor. The predicted results are summarized as follows: The first picture shows the normal kidney image and predicted result with the actual label. The label content (Actual: 0, Predicted: 0) indicates that the predicted and actual values are identical. The results of others also show that the predicted values are also in perfect agreement with the actual values, all of which can indicate that the model is very objective in practical applications.

4 CONCLUSIONS

In this paper, it is investigated how deep learning can be combined with renal CT image processing with the aim of improving diagnostic accuracy and efficiency. In this study, the DenseNet121 model was finally trained on 12446 CT images containing different kidney conditions, which performed well on the training set, with evaluation metrics such as accuracy and precision above 0.95. The saved optimal model achieved an accuracy of 93.51% on the independent test set. In order to better visualize the model's effectiveness in real life, samples were extracted from the study to compare the actual and predicted results, and the predictions were all correct as can be seen in the results visualization. All these show that the DenseNet 121 model has a better ability to recognize kidney CT images. However, to enhance diagnostic reliability for patients, this technology requires further refinement and practical application. After all, there are many complex problems encountered in medical image recognition, and the accuracy should constantly strive for 100% while avoiding possible errors such as overfitting.

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