DIAGNOSIS OF KIDNEY MRI IMAGES USING DEEP LEARNING

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Abstract. *Ultrasound images can be used to diagnose kidney disease: identify systemic abnormalities such as cysts, stones, and infections, and provide information about kidney function. This article focuses on the selection of appropriate features for efficient classification of normal and abnormal kidney images. In diagnosing cardiac images, grayscale transformation has been used to classify abnormal images in the kidneys. A data set formed by a convolutional neural network was trained. 2 classes were created and on their basis a recognition result of 89% was achieved.The prevalence of chronic kidney disease (CKD) increases annually in the present scenario of research. One of the sources for further therapy is the CKD prediction where the Machine learning techniques become more important in medical diagnosis due to their high accuracy classification ability. In the recent past, the accuracy of classification algorithms depends on the proper use of algorithms for feature selection to reduce the data size. In this paper, Heterogeneous Modified Artifical Neural Network (HMANN) has been proposed for the early detection, segmentation, and diagnosis of chronic renal failure on the Internet of Medical Things (IoMT) platform. Furthermore, the proposed HMANN is classified as a Support Vector Machine and Multilayer Perceptron (MLP) with a Backpropagation (BP) algorithm. The proposed algorithm works based on an ultrasound image which is denoted as a preprocessing step and the region of kidney interest is segmented in the ultrasound image.*

Keywords: *image contrast, histogram, image classification, convolutional neural network, CNN (convolutional neural network), neural network.*

Introduction

The kidneys are one of the most important organs for a person. Early detection of the disease is important. In humans, the kidneys in a certain sense act as a filter. In addition, its failure leads to changes in a number of human activities. It affects the blood system and other organs as well. Therefore, a number of diseases can be prevented by pre-diagnosing the symptoms of kidney disease [1].

Gunasundari et al. [2] explained the importance of a computer diagnostic system in cancer detection. The stage of image processing in the classification of signs is one of the main stages of diagnostics. Feature selection used to be a difficult task for complete tasks, but now we can solve it with image processing and parallel computing algorithms.

Ode et al. [3] proposed the use of early imaging markers to predict future renal failure, allowing the diagnosis of the disease in infants with posterior urethral valves. Imaging, sponsored by the National Institutes of Health, analyzed serial early postnatal images of cases. At the last follow-up, baseline study results and renal function were dichotomously separated based on glomerular tissue. They determined the importance of circulatory rate and the need for renal replacement therapy. Evaluation of the quantity and quality of the kidney parenchyma allows timely diagnosis of the disease, and early elimination can save a person's life.

Subramanya et al. [4] described a computer-aided classification system for three classes of kidneys, i.e., normal, benign kidney disease (MRD) and cyst detection using B-mode imaging. Thirty-five B-mode kidney images were used, consisting of 11 normal images, eight MRD images, and 16 cystic images. Regions of interest (ROI) were determined by a parenchymal renal radiologist in normal and MRD patients. For the classification task of assessing the contribution of textural features, a good diagnostic result was achieved using the eight-speckle decontamination method, which was pre-processed with original images from images without defects.

Based on this, we found out that the choice of neural network architecture for imaging, pre-processing and diagnostics is important.

When diagnosing kidney imaging:

1) Extracting the main features of images in machine learning;

2) Choice of CNN architecture for image training.

METHODOLOGY

Kidney disease is important to human health and can affect other organs as well. In addition, it affects the blood system, spinal cord and nervous system. It is important to predict the pathological condition of the kidney in advance. Deep learning technology is a CNN, and the main thing is to form a correct and complete data set.

Insufficient data set does not lead to an accurate diagnosis. We also use artificial data collection methods.

Histogram equation

We used the well-known Adaptive Histogram Equalization technique with contrast limiting to equalize the histograms in the image. This prevents other values from appearing in our calculations of excessively high numerical values. The same method was used for the contrast histogram of the image, which led to the possibility of correctly assigning hidden or exaggerated values to the average state.

Images are enhancements to the edges of local objects.

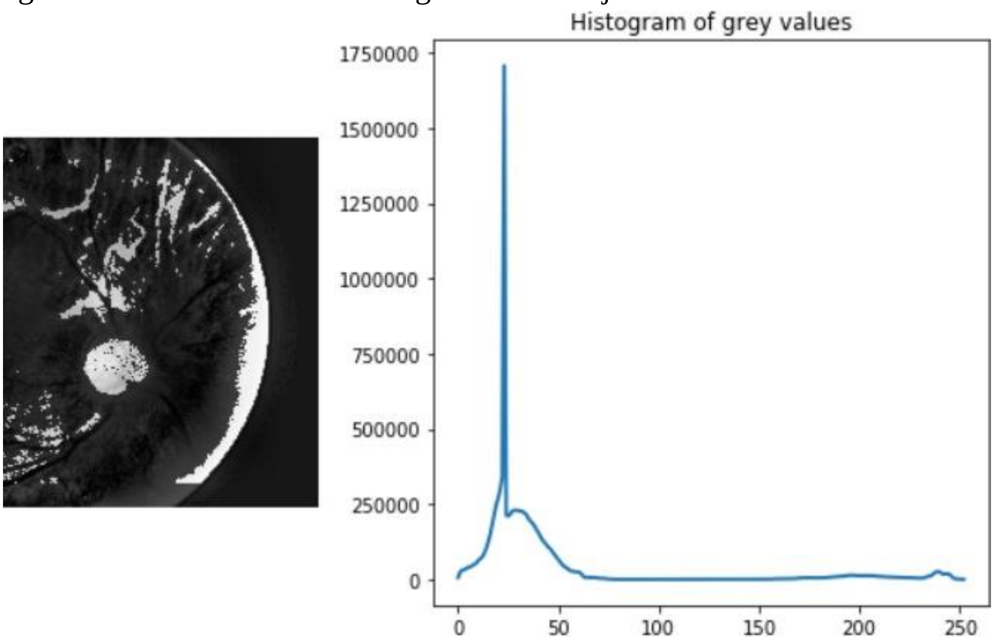

Figure 1. Histogram of pixel distribution of grayscale images

After pre-processing the image, the dataset is divided into training and test sets, each containing 80% and 20% of the data.

Based on the generated data set, a functional learning structure with a convolutional neural network was developed.

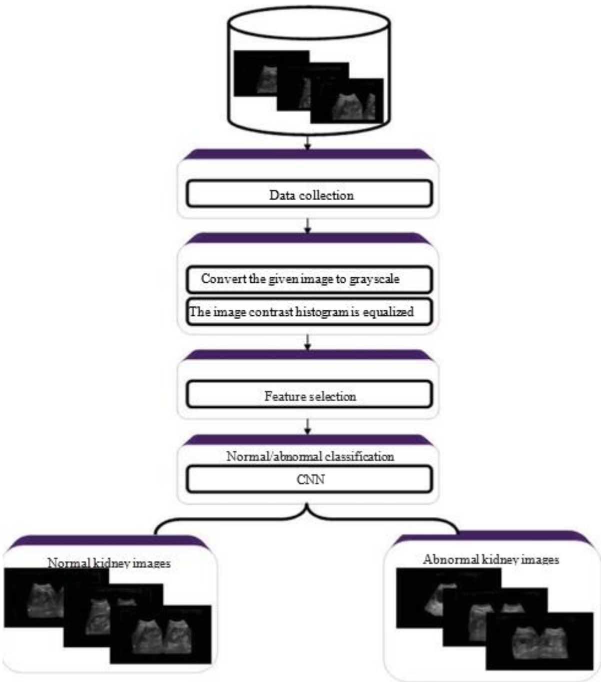

Figure 2. Functional diagram of the software

Classification accuracy obtained for training:

80% of the training data set was trained to train the neural network.

Whereas the test data contained a 20% data set and achieved 88% accuracy.

In recent years, great progress has been made in the field of automated systems for the detection of kidney diseases. Ultrasound systems have made it possible to obtain more volumetric and qualitative data when imaging patients. The use of feature extraction, image analysis, and image recognition methods for classification increases the efficiency of neural networks.

The graph shown in Figure 3 shows the result obtained from training with validation enabled, which displays the accuracy of the model.

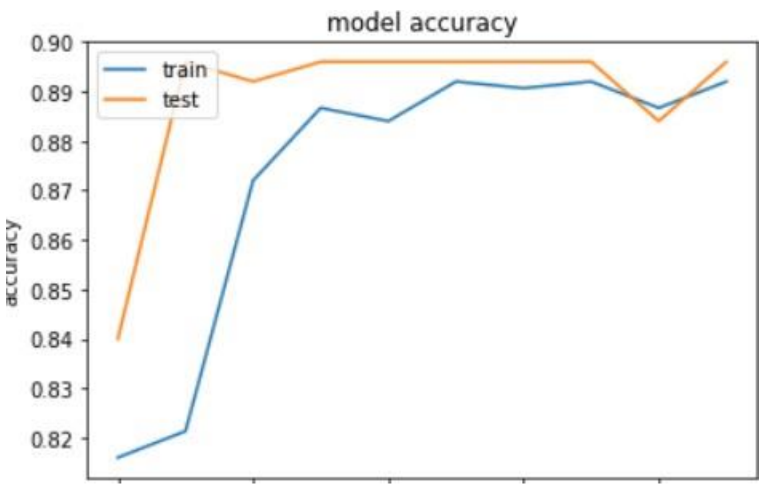

Figure 3. Graph of model accuracy

On the other hand, for the first iteration of the test data, the loss is about 0.67, which includes 0.35 periods for downsizing.

On fig. Figure 4 shows an iterative loss learning graph that provides a visual explanation of the model.

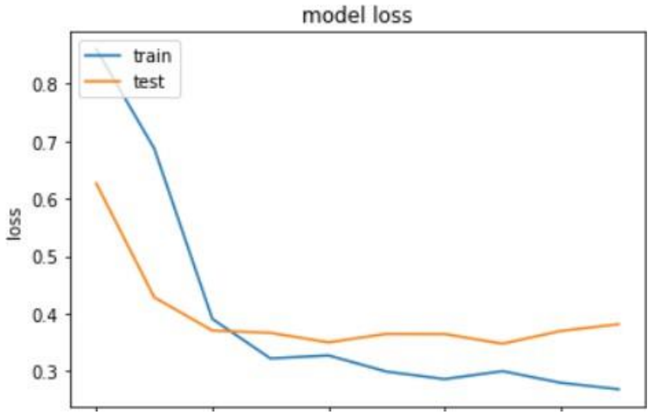

Figure 4. Graph of the loss function

The Adam optimizer played an important role in optimization. This model attempts to adjust the weights by generally observing losses that decrease as the number of training iterations increases.

CONCLUSION

By diagnosing with CNN, we will be able to detect and treat kidney diseases in advance. The choice of image is important. Pre-processing techniques such as limited adaptive histogram equalization were used after data augmentation to create the dataset. For convolutional neural networks, 89 percent diagnostic accuracy was achieved by using transfer learning for VGG16. We can also notice that the minimal log loss significantly improved the classification accuracy of the model. From the results, we can conclude that the model achieved an accuracy of 89% with fewer rules.

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