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DETECTION OF LIVER CANCER FROM CT IMAGES USING CAPSNET

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Abstract

Primary adult liver cancer is currently classified into two main diagnostic categories: cholangiocarcinoma and hepatocellular carcinoma. Hepatocellular carcinoma is the most common kind of liver cancer in adults. These are extremely heterogeneous tumours with a wide range of morphological and clinical characteristics, which reflects the wide range of oncological drugs available and the intricate pathways that lead to carcinogenesis. Because of the large quantity of data acquired from phenotypic and molecular research, the classification of liver cancer is shifting away from the old method, which is based on morphological aspects, and toward a more functional approach based on functional characteristics. In this paper, we develop a Capsule Network (CapsNet) classifier to classify the liver regions from computerized tomography (CT) images. The CapsNet helps in classification of instances using pre-processing and feature extraction stages. The training of the classifier is conducted using various liver images from the input datasets and the classifier is validated using the test images. The simulation is conducted to test the effectiveness of CapsNet and the results of simulation shows that the proposed method achieves higher degree of classification than other methods.

Keywords:

Medical Images, Deep Learning, CapsNet, Image Processing

1. INTRODUCTION

. Lung is one of the largest organs under the right ribcage. Digestive enzymes use it to break down food [1–2]. Some of the nutrients it processes and stores are converted into energy; it also breaks down harmful chemicals [3,4]. It is also in charge of filtering blood cells. The liver has two major lobes, the left and right hepatic lobes, respectively. When the liver is viewed from the underside, two more lobes are visible, namely the quadrate and caudate lobes.

It is possible that HCC [6], a cancer of the liver cells develops when the liver cells begin to multiply uncontrollably and then spread to other parts of the body. Cell abnormalities can cause primary hepatic cancers [7].

In men, liver cancer is the second most common cause of death from cancer, while in women it is the sixth most common. Diagnosed with liver cancer, 696,000 people died from the disease in 2008. Males are twice as likely as females to become infected worldwide. Viral hepatitis can lead to liver cancer, which is far more dangerous. According to the WHO [9], about 1.45 million people die each year as a result of this virus. Hepatitis C (HCV) is the leading cause of liver disease worldwide, afflicting an estimated 7% of Egyptian adults.

Approximately 35 million people have been tested for HCV as of the end of March 2019 [10]. Compared to the United States, Southeast Asia and Africa have a higher incidence of primary hepatic cancer [11] [12]. According to several sources, only 17% of patients make it out alive. To some extent, survival rates are tied to a patient stage of illness when they are first diagnosed.

There are numerous diagnostic tests for primary hepatic malignancy, including ultrasounds, magnetic resonance imaging (MRI) scans, and CT scans. Sagittal, coronal, and axial views are all possible with a CT scan, which uses radiation to produce extremely fine images of the entire body. A CT format is used to make images of organs, bones, and soft tissues, which are then processed by the computer. In many cases, an intravenous injection of contrast material is required for the examination. With the aid of MRI images, it is possible to distinguish malignant lesions from acute infections, chronic inflammation, fibrosis, and cirrhosis with the aid of MRI images.

Hepatic malignancies are classified according to their size and location [8]. As a result, it critical to create an automated method for detecting and extracting the cancerous zone from a CT scan. Image classification is the process of dividing the liver region in a CT scan into distinct regions, each of which represents a distinct component of the liver. This is a critical milestone in the development of computer-aided diagnostic (CAD) systems to assist radiologists in their diagnosis [9]. These manual or semi-manual techniques are expensive, time-consuming, and error-prone, although CT scans of the liver are typically interpreted by these methods.

The liver and spleen are too similar in their grey level intensities to be discernible by the naked eye. Multiple computer-aided methods have been developed to overcome these difficulties and increase the quality of liver tumour diagnosis. This is because of a number of challenges, including low contrast between the liver and other organs and between the liver and tumours, different contrast levels in tumours, variations in number, size, and irregular tumour growth as a response to medical treatment, as well as a variety of abnormalities in the tissues surrounding the tumours. As a result, a new strategy is required to solve these challenges [10].

An overview of recent articles on image analysis for liver malignancy classification is presented in this article. Research has increasingly relied on supervised learning approaches in recent years. The supervised technique uses labelled inputs to train a model for a given goal, such as liver or tumour classification. The deep learning approaches are on top of these methods. Stacked Auto-Encoder (SAE), deep belief nets, convolutional neural networks, and Deep Boltzmann Machines (DBM) are some of the models of deep learning that have been introduced. Research shows the superiority of deep learning models in terms of accuracy. However, finding a large and well-prepared dataset for training is still a challenge.

In terms of deep learning, CNNs are considered the finest. By using two trained deep CNN models [13], minimisation of the computation time for a large number of slices. In order to avoid

image resampling and to avoid missing minor lesions, the second model was used instead of the first.

Image patches were used to train a convolutional neural network (CNN) [12]. Image patches are created for each pixel, with the pixel of interest at the centre. The liver tissue is either classified as normal or tumorigenic based on the colour of the patches. To qualify as a positive sample, the patch must contain at least 50% or more of tumour tissue. The accuracy was reported to be 80.6% of the time [13] with a 94% accuracy rate for classifying images of a liver with tumour areas as normal or abnormal.

In this paper, we present a unique classification technique for liver cross-sectional CT scans based on CapsNet, a deep learning network that has been shown successful in image classification for scene understanding. Two-class classification tasks have been added to the model.

2. BACKGROUND

Traditional neural networks and convolutional neural networks share many characteristics. One or more layers of convolutional, fully connected, pooling, or fully connected and rectified linear unit (ReLU) layers make up a convolutional neural network (CNN). It is generally true that as the network gets deeper and more complex, the accuracy of the results improves, but the computational complexity grows as well.

In recent years, convolutional neural networks (CNNs) have become an increasingly popular tool for analysing and classifying images for a variety of purposes. Image classification and pixel-level categorization cannot be done with the designs mentioned. The CNN model type is the CapsNet network architecture. There are 41 layers in the network. Thirteen convolutional layers and three fully linked layers have weights that can be learned. The architecture of the CapsNet is shown in Fig.1.

Pixel-wise classification networks are typically encoder–decode systems with a CapsNet model as their primary encoder component. While the encoder gradually reduces the spatial dimension of the images, the decoder retrieves the object and spatial dimensions for rapid and exact classification. For image classification, U-Net is a convolutional encoder-decoder network. A completely convolutional network architecture is applied to medical images, making it intriguing. There are certain drawbacks, however.

The predefined weights of the underlying CapsNet network are used in the semantic image classification approach. For pixel-wise classification, the decoding network uses low-to high-resolution feature maps to map the encoder features. For upsampling, the indices of the selected pixel are saved and synchronised with the decoder instead of the pixel values being transferred. In CapsNet, there are more shortcut connections. By replicating the indices from max pooling rather than the encoder features, as is the case with FCN, CapsNet utilises less memory and performs better than FCN or U-Net.

3. PROPOSED METHOD

Step-by-step instructions on how to implement the classification approach presented in this section are provided. Conventional pattern recognition techniques are used in the proposed method: preprocessing, feature extraction, classification, and postprocessing.

3.1 DATASET

Among the 20 patients in the 3D-IRCADb-01 database are 10 females and 10 males, all of whom had hepatic tumours in at least one of the cases. The dimensions of each image are 512×512. Between 74 and 260 slices are taken from each patient. CT images of patients are provided along with labels and masks that can be used for classification purposes.

3.2 IMAGE PREPROCESSING

The CT CT scans were converted to network graphics in the preprocessing processes. It was decided to use the PNG file format because it is a lossless format. The pixel values in CT format are in the range [1000–4000] and are expressed in Hounsfield. It is impossible to view the image in this format, and a great deal of image processing will fail as a result. Color depth conversion and hence the mapping of pixel values to the positive 1-byte integer is required because of this.

The next step is to convert the images into a form that the CapsNet model can use. A simple method of creating a three-channel RGB colour space from the images is to simply copy and resize each slice to 360×480×3. Affinity transformations, including flipping, rotating, and mirroring are applied to the training images in order to improve the system performance.

3.3 TRAINING AND CLASSIFICATION

Traditional feature extraction methods, including LBP, GLCM, Wavelet, and Spectral, were compared to see how good CNN features were. A CNN is one of the texture extractors features that consistently outperforms the others. Training a convolutional network takes longer than other textural methods, but features can be retrieved from the trained network. In classification tasks, CNNs have proven to be effective. The augmented data is sent to the training algorithm together with the training data, which is then merged with the training data and augmented. Training images, pixel labels, and their augmentation forms are taken from the data source before the training begins.

4. EXPERIMENTAL RESULTS

The classification outputs were compared to the dataset ground truth.

4.1 DATA SET AND PREPROCESSING

Earlier, we indicated that 3D-IRCADb was the dataset used to evaluate the algorithm. It is available from the French Research Institute against the Digestive Tract, or IRCAD, which provides the 3D-IRACDb dataset. The first group, 3DIRACDb-01, is appropriate for segmenting liver tumours. As previously mentioned, preprocessing was applied to all of the image slices. Using the same preprocessing steps as the unlabeled images in the dataset, except for the step of range mapping, we may create the labelled images in the range [0,255].

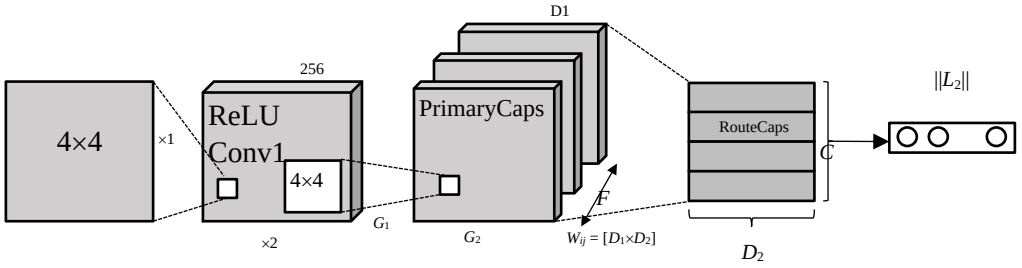

Fig.1. CapsNet network architecture

4.2 TRAINING AND CLASSIFICATION

In the training and testing trials, the U-Net model was used for the first time. Medical images are segmented using the U-Net model, which has been taught to do so. It based on CapsNet, which we have already explored. For extracting the liver, the results were nearly perfect. Despite this, when it was tested to extract tumour locations from an image, it failed to work at all. As in earlier cases, the tumor location was nearly overlooked or forecast incorrectly here.

The encoder and decoder network linked to a 2D multi-classification layer for pixel-based semantic classification are the foundations of the proposed architecture, which is based on the CapsNet model. Binary classification was instead used for the final classification layer. For the encoder, the CapsNet trained model was loaded. Segmentation of input images was supplied with classification scores for each categorical label, so that one image from the test set could be used to run the network for testing purposes.

4.3 TESTING AND EVALUATION

A 9:1 split was made between the training and testing images of the tested cases. In most cases, training yields better results than testing does. At this point, a near-perfect classification has been achieved. The evaluation measures for the three situations are shown in Fig.2-Fig.5. A total of 0.001 epochs of network training on a single GPU with 1000 iterations per epoch for 100 epochs was achieved. For example, in case 3, it is obvious from Fig.2-Fig.5 that, as training images grow, the classification quality improves until it reaches ideal results.

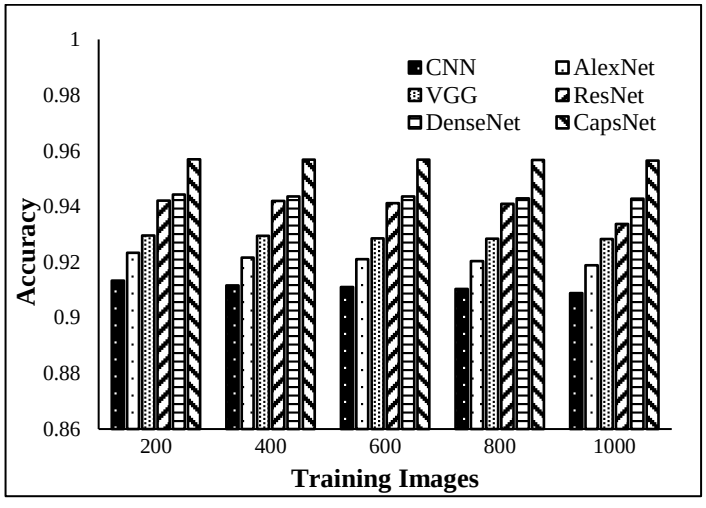

Fig.2. Accuracy

For testing purposes, a semantic classification of the input image is returned, along with the classification scores for each categorical label. True positive tumour pixels, or those that have been correctly classified, are coloured white. It is obvious from this image that results from the first example are less accurate than results from the third, yet the tumour appears larger than it actually is in case 3.

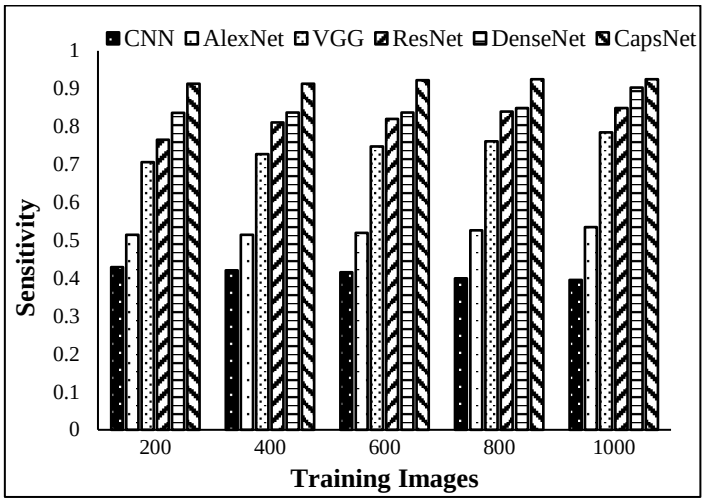

Fig.3. Sensitivity

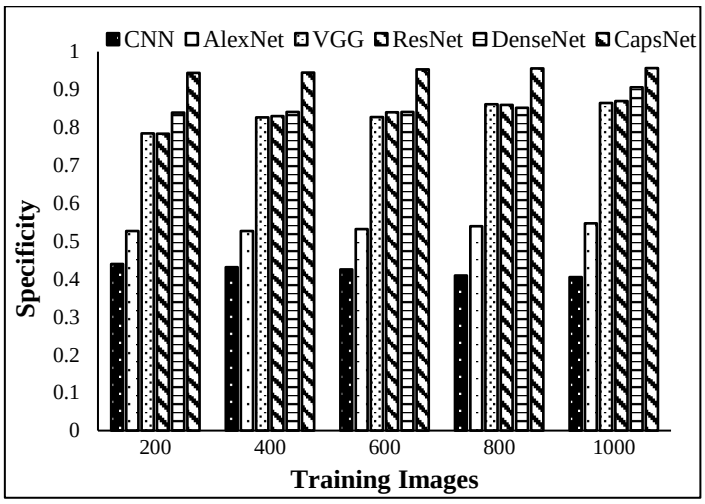

Fig.3. Specificity

True positive (TP) tumour pixels are shown in white on the image. There are a few missing tumour pixels that are coloured purple. The pixels projected to correspond to the tumour but which in fact represent normal tissue or the backdrop, are

coloured green. Normal or background pixels are represented by the black colour.

A comparison of the suggested method accuracy to that of other works in the literature is offered in Fig.2-Fig.5 in order to provide a better understanding of the presented results. As a result of this research, we were able to attain a higher level of precision than in the previous study.

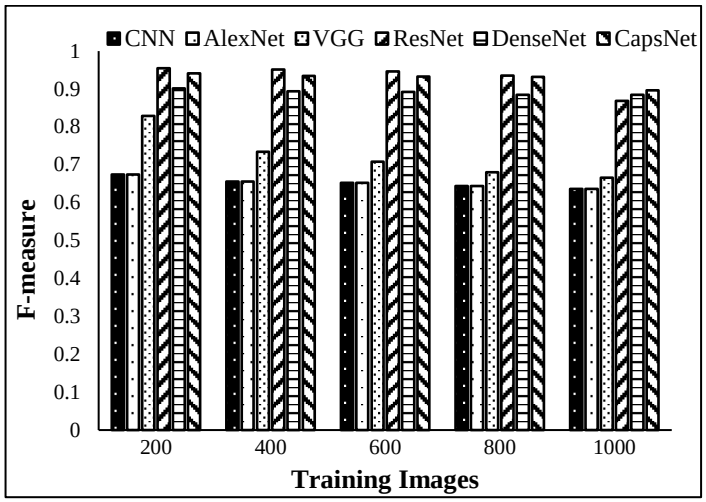

Fig.3. F-measure

5. CONCLUSIONS

A deep learning model was used for the semantic classification of road scenes in CT format and was tested using a deep learning model. A CAPSNET trained image classification network is used as an encoder in CapsNet, and a corresponding decoder architecture is used to translate the features back into the image domain in order to achieve pixel-wise classification at the end of the algorithm. Rather than preserving the entire feature map, CapsNet saves the max-pooling indices instead, giving it an edge over typical auto-encoder design. As a result, the architecture is significantly more efficient in terms of training time, memory consumption, and accuracy.

In medical imaging, binary pixel classification was used as a replacement for the classification layer. The standard 3D-IRCADb-01 dataset was used for both training and testing. The suggested technique correctly identifies most of the tumours, with a classification accuracy of more than 86%. Examining the results, it became clear that there were few false positives that could be reduced by the use of false positive filters or through training the model on a bigger dataset.

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