Classifying magnetic resonance image modalities with convolutional neural networks

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ABSTRACT

Magnetic Resonance (MR) imaging allows the acquisition of images with different contrast properties depending on the acquisition protocol and the magnetic properties of tissues. Many MR brain image processing techniques, such as tissue segmentation, require multiple MR contrasts as inputs, and each contrast is treated differently. Thus it is advantageous to automate the identification of image contrasts for various purposes, such as facilitating image processing pipelines, and managing and maintaining large databases via content-based image retrieval (CBIR). Most automated CBIR techniques focus on a two-step process: extracting features from data and classifying the image based on these features. We present a novel 3D deep convolutional neural network (CNN)-based method for MR image contrast classification. The proposed CNN automatically identifies the MR contrast of an input brain image volume. Specifically, we explored three classification problems: (1) identify $T_1$-weighted ($T_1$-w), $T_2$-weighted ($T_2$-w), and fluid-attenuated inversion recovery (FLAIR) contrasts, (2) identify pre vs post-contrast $T_1$, (3) identify pre vs post-contrast FLAIR. A total of 3418 image volumes acquired from multiple sites and multiple scanners were used. To evaluate each task, the proposed model was trained on 2137 images and tested on the remaining 1281 images. Results showed that image volumes were correctly classified with 97.57\% accuracy.

Keywords: magnetic resonance imaging, MRI, TBI, content-based image retrieval, deep learning, convolutional neural network

1. INTRODUCTION

As biomedical imaging increasingly intersects with “big data”, there is a growing need for automated image processing and archive management. Image databases can store thousands of images, and assigning humans to annotate, sort, organize, and maintain every image is laborious and error-prone. Additionally, different hospitals and medical scanners have their own file naming conventions, resulting in ambiguity and heterogeneity among medical images. Therefore it is advantageous to automatically identify or semantically categorize images in a large database to facilitate searching and sorting purposes. This problem is generally central to image retrieval (CBIR),\footnote{CBIR involves the use of image features (or contents), such as histograms, edges, corners, blobs, ridges, etc., in order to categorize the desired image. This opposes text-based image retrieval (TBIR), which utilizes text entries such as patient reports or human-entered meta-data. The main disadvantage of TBIR is that acquiring and entering these text entries can be time-consuming, laborious, inconsistent between sites, and prone to human error. In contrast, most CBIR techniques involve extraction of image features followed by their classification via machine learning, which is done automatically. As mentioned previously, commonly used features include histograms, edges, corners, blobs, ridges, etc.} which describes automatic retrieval of images from some database based on the content of the image data rather than associated meta-data. For Magnetic Resonance (MR) images in particular, differing acquisition protocols during a scan result in different image contrast properties. Common MR image contrasts are $T_1$-w, $T_2$-w, $PD$-w, FLAIR, etc. The ability to automatically distinguish between these contrasts allows large image archives from multiple sites and scanners to be organized into broad categories for efficient retrieval, especially when image meta-data can be widely inconsistent between sites and scanners. Furthermore, proper contrast identification is often a requirement in multi-contrast image processing pipelines for defining parameters and associating the appropriate training data.

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edges and textures,\textsuperscript{2} which can be estimated and classified using k-nearest neighbors to obtain a semantic classification. Similarly, for multiple modalities such as computed tomography (CT), ultrasound, and MR, edges and local intensity distributions within a patch in the images can be used to generate a sparse feature dictionary\textsuperscript{3} of modalities. Features from a new unobserved image are sparsely matched to the dictionary to find most likely modality. Support vector machine (SVM)-based classification on wavelet features\textsuperscript{4,5} and probabilistic neural networks\textsuperscript{6} have also been previously applied to medical image CBIR and used to distinguish between normal and pathological MR brain images.

In recent years, deep learning\textsuperscript{7} and convolutional neural networks (CNN) have become more prevalent as a means to address image classification. Compared to the traditional machine learning classification methods such as SVM or k-nearest neighbors, CNNs do not need hand-crafted features. Instead, they learn and generate the necessary customized features based on the labeled training data provided in order to correctly classify images. CNNs have been previously used to classify various body parts\textsuperscript{8} in x-ray images. Recently, another approach used CNNs to classify between CT and MR images of various organs.\textsuperscript{9}

The efficacy of a CNN’s performance with regards to its respective task is heavily determined by its architecture, or the underlying structure through which the image signal passes. The prevention of overfitting\textsuperscript{10} and the
Table 1. Distribution of number of images for the three proposed tasks.

| Classification Task       | Image classes | # Training Images | # Testing Images |
|---------------------------|---------------|------------------|------------------|
| $T_1$ vs $T_2$ vs FLAIR  | $T_1$         | 186              | 227              |
|                           | $T_2$         | 189              | 119              |
|                           | FLAIR         | 162              | 63               |
|                           | **Total**     | **537**          | **409**          |
| $T_1$ pre vs post         | $T_1$ pre     | 400              | 204              |
|                           | $T_1$ post    | 400              | 374              |
|                           | **Total**     | **800**          | **578**          |
| FLAIR pre vs post         | FLAIR pre     | 400              | 143              |
|                           | FLAIR post    | 400              | 151              |
|                           | **Total**     | **800**          | **294**          |

need for regularization are commonly considered when designing a model with many parameters. Much work has been done to explore effective CNN architectures for image classification tasks in computer vision, involving state-of-the-art architectures such as AlexNet\textsuperscript{11} in 2012, the Inception Module\textsuperscript{12} in 2014, and ResNet\textsuperscript{13} in 2015. Each of these architectures achieved state of the art performance the year of their release.

In this paper, we propose a new CNN architecture called PhiNet (Φ-Net), which borrows the powerful skip connection concept from the deep residual network ResNet.\textsuperscript{13} Φ-Net was designed with the specific purpose of classifying different contrasts of MR images while being robust to different types of pathologies, such as Alzheimer’s disease, multiple sclerosis, and traumatic brain injury. Example images from our training and test dataset are shown in Fig. 1. Although there are numerous other MR contrasts, we chose these broad categories because these image types are the ones most widely used in various clinical image processing algorithms such as tissue segmentation and registration.

Automated categorization of MR images into these broad categories helps in the homogenization of a “big data” imaging archive, which may contain image data from multiple sites and scanners, with or without visible pathologies, and where even pulse sequence names can be inconsistent. More specifically, we propose three tasks:

1. classifying a brain MR image volume as one of $T_1$-w, $T_2$-w, or FLAIR,
2. classifying a $T_1$-w image as either pre-contrast or post-contrast,
3. classifying a FLAIR image as pre-contrast or post-contrast.

2. METHOD

2.1 Data

In total, 3418 image volumes with various resolutions were obtained from 4 different sites and 5 different scanners: GE 3T, GE 1.5T, Philips 3T, Siemens 3T, and Siemens 1.5T. The distribution of training and test data across these three tasks is shown in Table 1. Images were acquired for both healthy volunteers as well as patients with traumatic brain injury, hypertension, multiple sclerosis, and Alzheimer’s disease. For training, 2137 images were used, while the remaining 1281 images were set aside and classified into the three tasks as described above.

For the first task, we used 537 and 409 images for training and testing, respectively, with numbers of $T_1$, $T_2$, and FLAIR images being 186, 189, and 162 for training and 227, 119, and 63 for testing. The second task involved 800 (400 pre-$T_1$, 400 post-$T_1$) training and 578 (204 pre-$T_1$, 374 post-$T_1$) testing images. For the third task, we also used 800 (400 pre-FLAIR, 400 post-FLAIR) training and 294 (143 pre-FLAIR, 151 post-FLAIR) test images. To preprocess the images, the neck regions were first removed from each image volume using FSL\texttt{robustfov}. Then the images were re-sampled to $2 \times 2 \times 2$ mm\textsuperscript{3} to improve the processing speed for the neural network. Finally, each image was linearly scaled so that their respective 99\textsuperscript{th} percentile of all intensities became unity.
2.2 Φ-Net 3D CNN Architecture

Convolutional neural networks for classification purposes are usually constructed as alternating stacks of convolutional layers, activation layers, and pooling layers. At the end of all of the layers, a softmax layer is appended, producing a probabilistic prediction of the class. Fig. 2 shows the proposed Φ-Net architecture. The design of this 3D CNN is to give three perspectives to contribute to the model’s output. The convolutional branch serves as a type of skip connection to preserve the original image volume signal. The residual module running down the center of the network allows for many high-level features to be learned, where a "high-level feature" is defined as a complex image feature such as the appearance of ventricles or cortical folds, and is composed of many low-level features such as edges, lines, and curves. A residual module is shown in Fig. 2. Instead of using the full 152 residual modules as proposed in the original ResNet paper, we employed a smaller version of ResNet with 7 residual modules. The filters used in the proposed model are the same as the first 7 layers of the original ResNet paper; this was done to fit our model and 3D image data into the 4GB of GPU memory available on an NVIDIA GTX 970 GPU. The pooling branch preserves the overall shape but reduces the level of detail from the original image, allowing the model to be more robust to pathologies or other heterogeneities which could occur across an image population. These three stacks are then concatenated and their output is passed to a global average pooling layer. The output of the pooling layer is finally passed through the traditional softmax layer to produce the probabilities that the image belongs to each class.

The goal with this architecture was to use these three perspectives of an incoming image in parallel to allow the model to learn its class, without requiring hand-crafted features such as wavelets or edges. The Φ-Net architecture was employed with a dynamic learning rate to aid convergence. Categorical cross-entropy was used as the loss function for the multi-class classification task, i.e., $T_1$ vs $T_2$ vs FLAIR. For the binary pre vs post task, i.e. 2$^{nd}$ and the 3$^{rd}$ tasks, binary cross-entropy was chosen as the loss. For each task, the model was trained to convergence, defined as no decrease in validation accuracy after 100 epochs.
Table 2. Classification accuracy of Φ-Net compared with ResNet and registration-based method.

|                     | $T_1$ vs $T_2$ vs FLAIR | pre-$T_1$ vs post-$T_1$ | pre-FLAIR vs post-FLAIR |
|---------------------|--------------------------|-------------------------|-------------------------|
| **Accuracy**        | ResNet– | Φ-Net | ResNet– | Φ-Net | ResNet– | Φ-Net |
| # Correct Predictions | 403/409 | 406/409 | 563/578 | 576/578 | 266/294 | 276/294 |
| # Errors            | 6/409   | 3/409   | 15/578  | 2/578   | 28/294  | 18/294 |

As a competing method, we used a smaller version of ResNet with 11 residual modules (called ResNet–) in contrast to 152 modules in the full version. This was done for speed and memory purposes. Both neural networks were implemented in Keras\textsuperscript{14} with the Tensorflow back-end on Ubuntu 16.04 and trained with an NVIDIA GTX 970 graphics card. Note that the ResNet– architecture lacked the convolution and the pooling branches as shown in Fig. 2. As an additional means of comparison to more traditional machine learning methods, we also classified the test set for the first task ($T_1$-$T_2$-FLAIR comparison) via a registration-based method, where each test image is deform-ably registered\textsuperscript{15} to a template $T_1$, $T_2$, and FLAIR image. Then Pearson correlation coefficients (PCC) were computed between each registered test image and the three templates; the template having the highest correlation was used as the contrast of the test image.

3. RESULTS

Table 2 shows classification accuracy of Φ-Net comparing with ResNet–. Φ-Net outperforms ResNet– in all three classification tasks. Φ-Net has a mean accuracy of 97.57% over all three tasks, while ResNet– has 95.47%. Although accuracies are high for both models, Φ-Net produces more than a 3% improvement for the pre-FLAIR vs post-FLAIR classification, which is usually the most challenging task, even for a visual comparison. To compare the test performances between ResNet– and Φ-Net, we performed McNemar’s test\textsuperscript{16} over each of the three tasks, obtaining the p-values of 0.45, 0.002, and 0.052 for $T_1$ vs $T_2$ vs FLAIR, $T_1$ pre vs post, and FLAIR pre vs post classifications, respectively. Therefore, Φ-Net produces a significantly more accurate classification between pre and post-contrast images than ResNet–, while being similar in the case of the $T_1$-$T_2$-FLAIR classification task. Note that while the first task is comparatively easier, pre- vs post-contrast FLAIR identification can sometimes be difficult for a human observer, and Φ-Net misclassified only 18 of 294 images in this category.

Fig. 3 shows some classification examples from the test set, with the first row corresponding to correct classifications made by Φ-Net and the second row showing the incorrect ones. Of the handful of classification errors that occurred, the majority suffered from imaging artifacts (Fig. 3 yellow arrow) or pathologies (Fig. 3 red arrow).
red arrow), which confounded the model’s ability to make accurate predictions. No post-contrast \( T_1 \) images were misclassified. Although both of the CNN-based methods achieved more than 90\% accuracy, the registration and correlation based method achieved only an average of 81.19\% accuracy on the \( T_1-T_2 \)-FLAIR classification task. It classified 98\% of \( T_2 \) images correctly and 72\% of both \( T_1 \) and FLAIR images correctly. However, its 15\% average lower accuracy compared to the deep learning approaches indicates that the template-based classification is not as robust.

4. DISCUSSION

We have presented \( \Phi \)-Net, a novel 3D convolutional neural network architecture for the classification of MR brain images. Training on an Nvidia 970 GTX took approximately 20 hours and its ability to converge on differing tasks shows that \( \Phi \)-Net is generalizable and can be applied to a variety of classification problems, achieving 97.57\% mean accuracy across 3 tasks. Future work includes expanding the number of classes to categorize, one-step classification of pre vs post \( T_1 \) and FLAIR images rather than separate tasks (or alternatively, cascading the classification first as \( T_1-T_2 \)-FLAIR, then as pre vs post-contrast), comparison with other CBIR techniques, and possible integration with a time-series model to automatically text-annotate MR images with human-searchable features for a smoother CBIR pipeline.

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