Paper I read: ***Nonlinear registration as an effective preprocessing technique for Deep learning-based classification of disease***

In recent years, deep learning (DL) approaches for the automatic classification of diseases have made so many signs of progress. To gain a better understanding of a disease, a doctor requires some image results from patients. In the data science field, they collect a large number of image datasets to analyze, so that they can come up with a machine learning model/algorithm to analyze the disease detailly. The difficulty of analyzing AD by using the DL model is limited datasets. Small datasets often time perform badly on test datasets or new datasets, due to the occurrence of overfitting. Overfitting is a condition that occurs when a machine learning model performs significantly better for training data than it does for new data. According to the article I've read, "Nonlinear registration as an effective preprocessing technique for Deep learning-based classification of disease", they applied different preprocessing approaches such as affine registration and nonlinear diffeomorphic anatomical registration using exponentiated Lie algebra (DARTEL) to prevent overfitting for obtaining a better result for the model. Their approaches have been proposed for the automatic classification of Alzheimer's disease (AD) using brain structural magnetic resonance imaging (MRI) data. Likewise, their experimental results show that nonlinear transformation is a preferable preprocessing step for training DL-based AD classification models on limited datasets.

The dataset they used obtain from "In Proceedings of the 25th International Conference on Neural Information Processing Systems - Volume 1 (NIPS'12)." It's a small dataset of 1.2M images was used for DL based classification of two-dimension (2D) images. Since this dataset is not a large dataset, it is possible to have an overfitting problem. The reason is that the image dataset contains so many features, so it increases the variances in the dataset. If the dataset size is small, overfitting will likely occur. Therefore, it is important to reduce the features that are not necessary for classification while leaving the features that are useful. To reduce features size, we often time use a dimensionality reduction preprocessing method. In their study, they show that the traditional nonlinear transformation can reduce overfitting by reducing the spatial variation of the input data. To evaluate this effectiveness, they compare two different preprocessing methods for DL-based AD classification tasks: affine registration and nonlinear diffeomorphic anatomical registration using exponentiated Lie algebra (DARTEL). One is a linear transformation method; DARTEL is nonlinear.

Image registration is the way of bringing two or more images into spatial correspondence. As figure 1 shown, if two images are similar but are different types of images, we can use image registration to find the similarities and combine them into one image that contains their information.

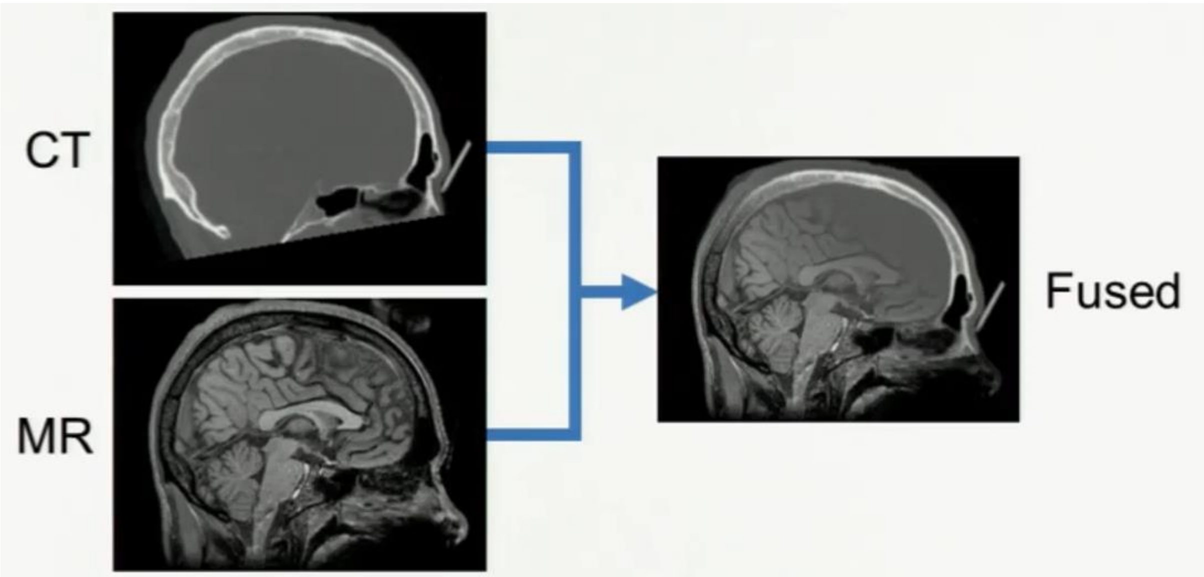

Figure 1. Image registration

Affine registration is an image transformation technique. Affine transformation is an important class of linear 2-D geometric transformations, which maps variables into new variables (e.g., from x1, y1 to x2, y2) in an output image by applying a linear combination of translation, and rotation, scaling and/or shearing operations. (As figure 2 shown below)

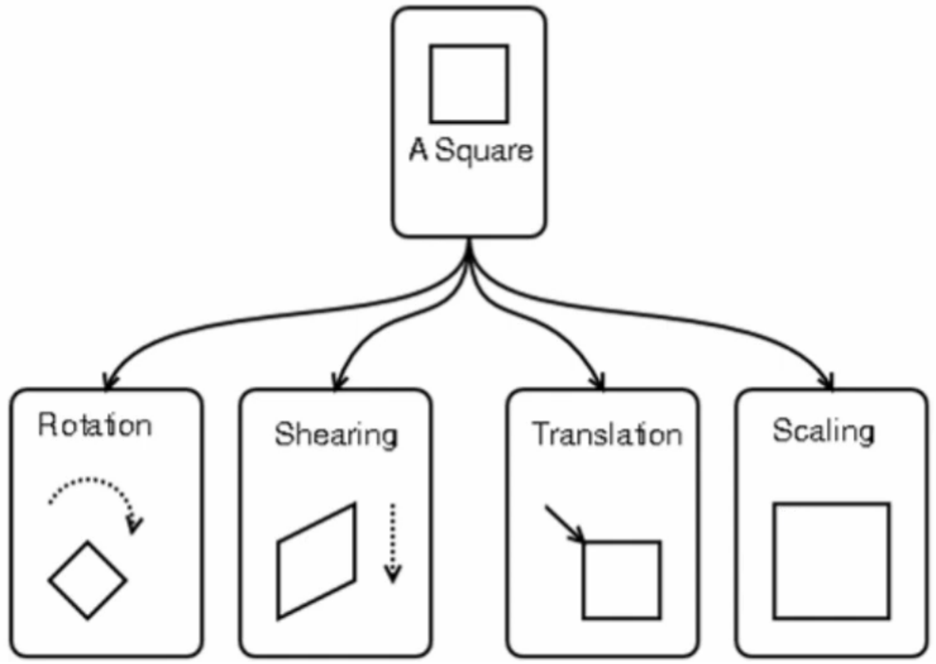

Figure 2. Affine transformation

DARTEL stands for diffeomorphic anatomical registration through exponential lie algebra. It is also an image transformation method. DARTEL provides more accurate inter-subject registration of images. We need to perform transformation for images so that we can find the correlation of images. To evaluate the effectiveness of the preprocessing for each linear transformation and non-linear transformation, they performed the AD classification tasks and assessed based on the impact of two criteria: overfitting owing to the dependency of the number of samples and model robustness to noise. These two criteria are the factors that could reduce model accuracy.

They applied convolution neural networks (CNN) to the DL model. CNN is very similar to normal neural networks in that they both consist of neurons with learnable weights and bias constants (biases). Each neuron receives some input and does some dot product computation, and the output is a score for each classification. CNN often use in images classification, which allows us to encode specific properties into the network structure, making is our feedforward function more efficient and reducing a large number of parameters. In the paper, they used Residual Network (ResNet) model. It's like an advanced version of CNN. Residual Network (ResNet) is a Convolutional Neural Network (CNN) architecture that overcame the "vanishing gradient" problem, making it possible to construct networks with up to thousands of convolutional layers, which outperform shallower networks. ResNet helps to reduce the complexity of computation in layers. As figure 3 shown, if we go to the path from x to F(x) directly, we could potentially create more computation, which can make the model accuracy lower. By using ResNet, we will go the path from x to F(x) without passing through the layers, so it prevents accuracy dropping.

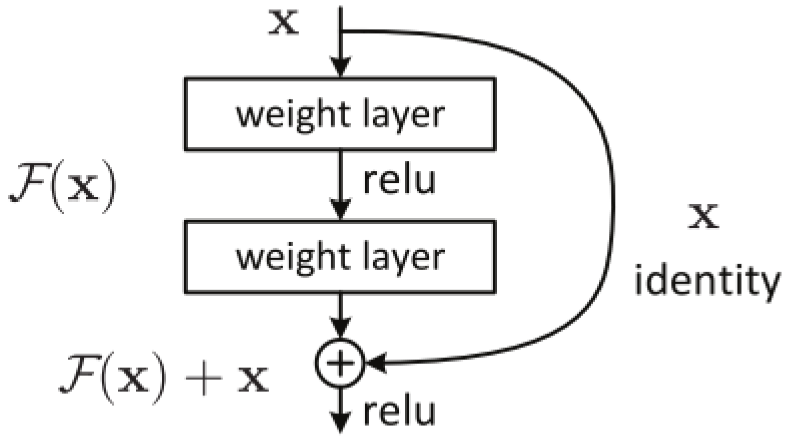

Figure 3. ResNet

As results, they showed that using DARTEL method in preprocessing reduced overfitting and improved the classification accuracy by up to 18%. (As Figure shown below)

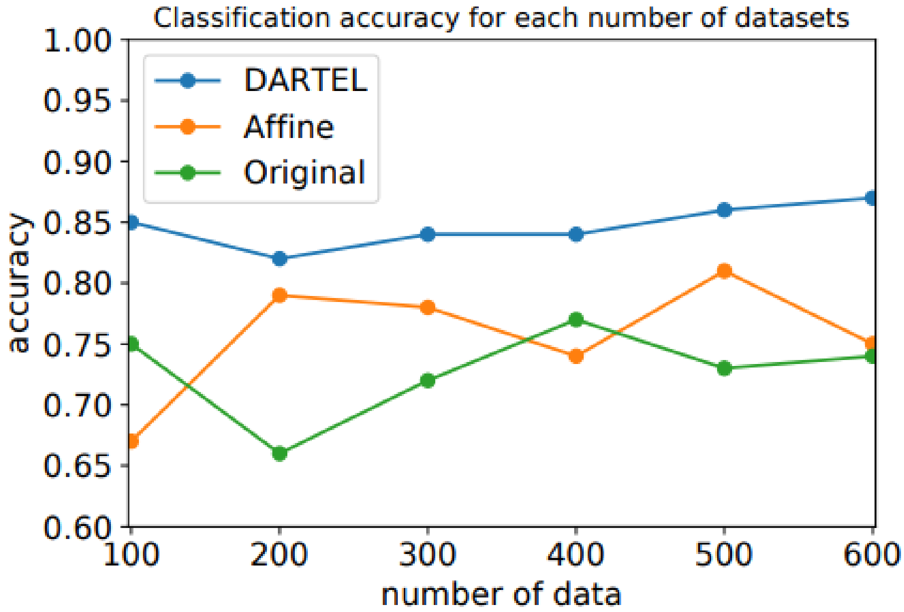

Figure 4. Classification accuracy on different perprocssing methods