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## CNN Based Landmark Detection and Alzheimer's Diagnosis using Landmark Features

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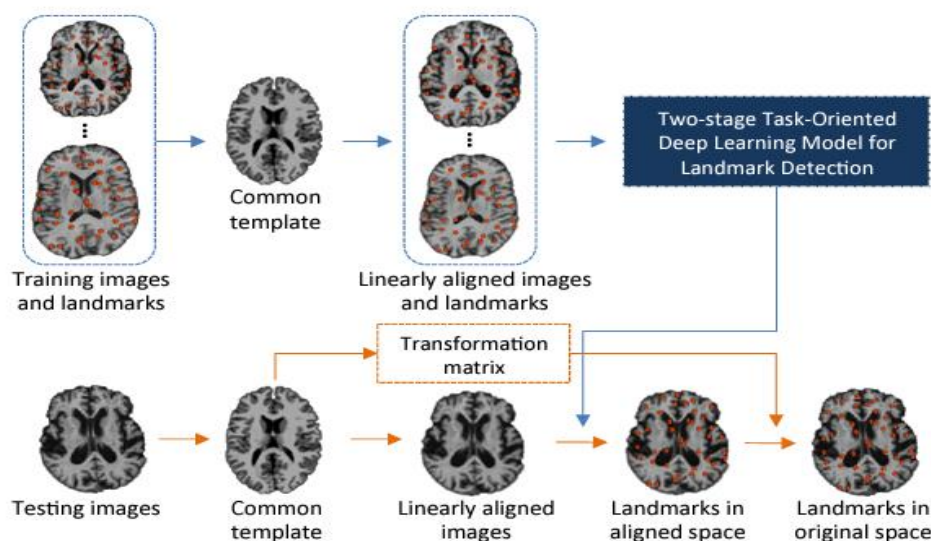
### ABSTRACT

*One of the fundamental challenges in anatomical landmark detection, based on deep neural networks, is the constrained availability of medical imaging data for network mastering. To address this trouble, we present a two-stage task-oriented deep learning method to detect big-scale anatomical landmarks simultaneously in actual time using restrained education statistics. Especially, our technique includes deep convolutional neural networks (CNN), with every specializing in one particular project. In particular, to alleviate the trouble of limited training statistics, within the first stage, we endorse a CNN primarily based regression model the use of millions of image patches as input, aiming to examine inherent associations between nearby photo patches and target anatomical landmarks. to similarly version the correlations amongst image patches, in the second stage, we expand some other CNN model, which includes a) a fully convolutional networks (FCN) that shares the same architecture and community weights as the CNN used within the first stage and additionally b) numerous more layers to at the same time predict coordinates of a couple of anatomical landmarks. Importantly, our technique can jointly locate big-scale (e.g. hundreds of) landmarks in actual time. Using these landmark points we extract HOG and longitudinal features and using SVM to diagnose the Alzheimer's disease.*

**Keywords:** Anatomical Landmark Detection, Deep Convolutional Neural Networks, Task-Oriented, Actual Time, Medical Imaging Data.

### 1. INTRODUCTION

Recent fulfilment of deep studying approaches for landmark detection in natural image analysis is commonly supported by large data sets, i.e., with millions of images. One of the important problems on medical land marking is the availability of medical data's. We don't have enough data to compare, only a small number of MRI scan of patients are available in hospitals. But for another type of land marking, there is a lot of availability of data, for example for marking an area of land or some other things like flowers, trees etc., we should large amount of data from the internet. Here for medical data, MRI data are not available of datasets. This paper is to make an effective landmark detection and Alzheimer's diagnosis.



**Fig.1. Illustration of Landmark Detection Method.**

Figure 1 shows our landmark detection method. particularly, all training and testing images are first linearly aligned into a common template space mutual information- based 2d linear registration, through which transformation matrices may be acquired. Then a two-stage task-orientated deep learning (T2DL) model for landmark detection is trained, with the linearly-aligned training images landmarks. In the testing phase, given a testing image, we first stumble on its landmarks through our T2DL method using its corresponding linearly-aligned image. The usage of the inverse of its corresponding transformation matrix envisioned all through the linear registration method, we can without difficulty obtain the very last landmark locations inside the original space of the testing image. Our technique calls for best about 1 second to locate heaps of landmarks concurrently.

## 2. METHOD

In this study, we try to address two challenging issues in detecting anatomical landmarks with medical imaging data, i.e., 1) limited training data and 2) large-scale landmarks. As shown in Fig. 2, a two-stage task-orientated deep learning (T2DL) method is proposed, where every community has its unique task. Especially, the challenge of the first-stage CNN model is to describe the inherent association between local image patches and their 2D displacements to the target landmarks, with millions of image patches as the input. The task of the second stage CNN model is to estimate the landmark coordinates by way of considering correlations amongst image patches, with the whole image because the input. The following sub-sections describe the architecture of the proposed T2DL method in detail.

### A. First Stage CNN

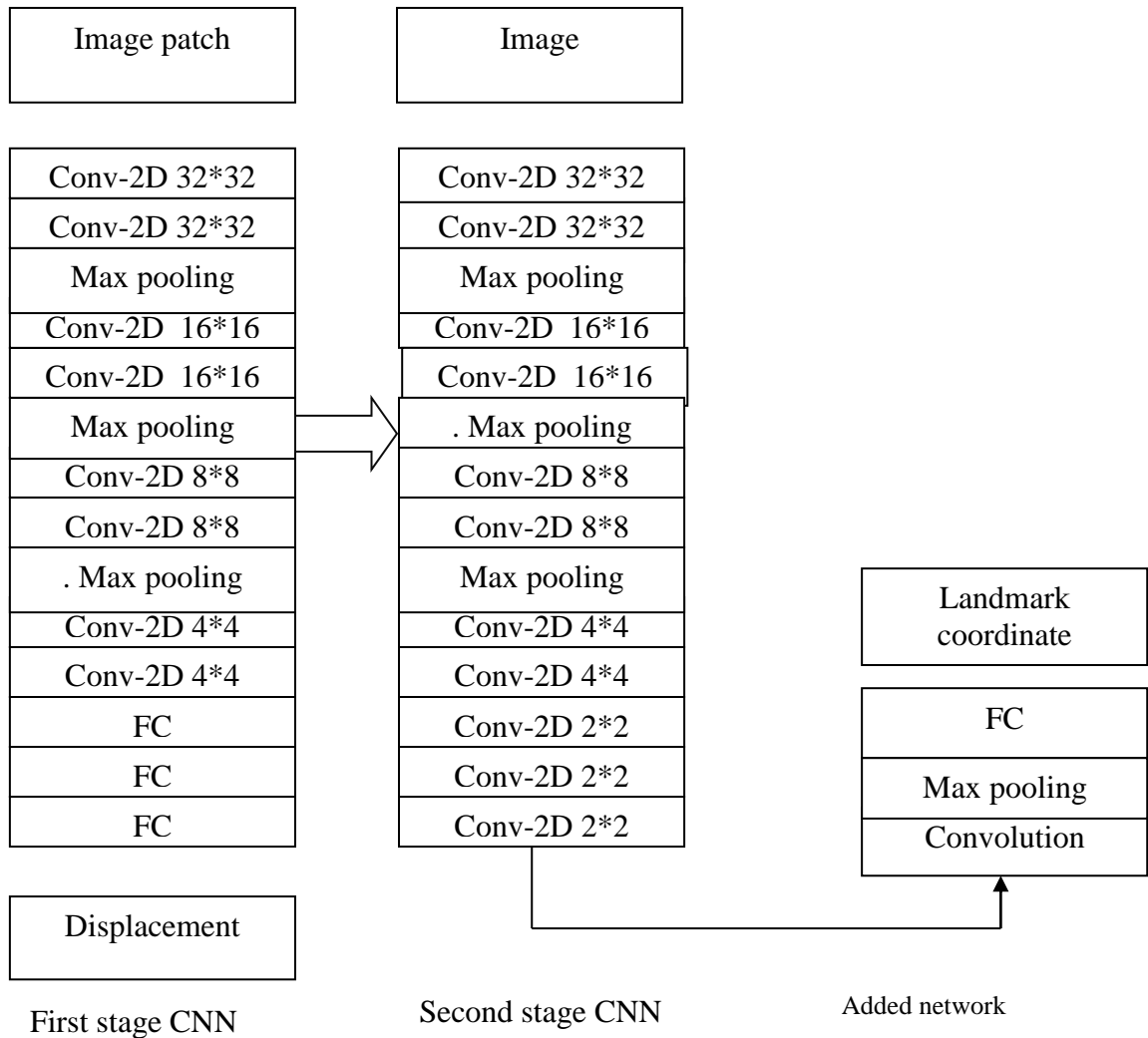
We first develop a patch primarily based CNN regression version by using local image patches instead of the complete snap shots, because the training samples. But, the conventional patch based methods normally without delay estimate the elegance label (i.e., a positive landmark) of a voxel from local patches, where the context records of the image patches is not considered. On this study, we endorse to estimate the displacements of an image patch to multiple landmarks for implicitly modelling the context facts. Given a 2D image patch, our goal is to learn a non-linear mapping to are expecting its 2D displacements to multiple landmarks. The traditional patch based landmark detection strategies construct the mapping using random forest regression models and commonly require pre-defined appearance functions to represent image patches. Without the use of any pre-defined functions, we adopt a patch based totally regression version using CNN.

As shown in Figure 2 the first stage CNN consist of 8 convolutional layers, 3 max-pooling layer and 3 fully connected layer. First we pass the image patch through two convolutional layer that mean the patch is passed through filter to smoothen the image. After convolution pooling process is performed, different types of pooling are present; here max-pooling is used. In this step we can reduce the image size (select large values only). Again convolution and pooling is performed, so it is called deep learning method. Then finally the output of convolution is given to a fully connected layer, in this step we find the loss function. This process continued till the loss function become small.

$$Loss = 1/Nl \sum_{i=1}^{Ni} wi || dig - dip ||_2$$

Where,

$$w_i = e^{-||dig||/\alpha}, \alpha \text{ is the scaling coefficient, and } Nl \text{ is the total number of landmarks.}$$

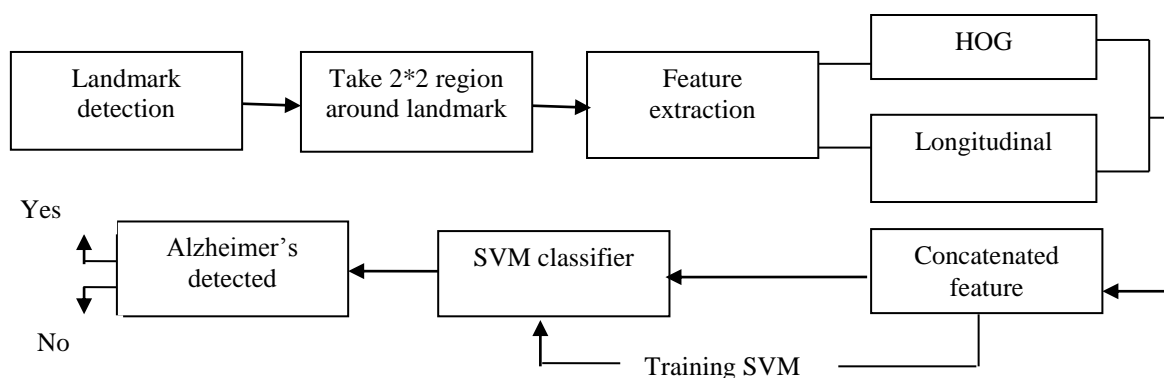


**Fig. 2. Proposed CNN Model**

Then the land mark points are compared in the template image and training image, then find out the displacement.

### B. Second Stage CNN

Second stage consist of FCN and added network. Here we provide the full image in to the neural network, here also the same operations are carried out. Finally we find out the land mark locations. Then it is given to added network, added net work is used to combine first stage land mark point and second stage land mark points. Finally we get landmark coordinates.



**Fig. 3. Proposed Method**

On theoretically explaining the proposed method, the initial section is landmark point detection once the landmark points are extracted. Two type of features are considered namely,

- HOG features
- Longitudinal features

These two features are analysed on a certain region of the obtained landmark point. Histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image. This method is similar to that of edge orientation histograms, scale-invariant feature. Longitudinal features are the root difference between actual landmark points and obtained landmark points.

The features are concatenated, so called concatenated features. Using these features both original image features and detected image features SVM is trained. Support Vector Machine (SVM) is primarily a classifier method that performs classification tasks by constructing hyperplanes in a multidimensional space that separates cases of different class labels. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables. For categorical variables a dummy variable is created with case values as either 0 or 1. Thus, a categorical dependent variable consisting of three levels, say (A, B, C), is represented by a set of three dummy variables:

$$A: \{1\ 0\ 0\}, B: \{0\ 1\ 0\}, C: \{0\ 0\ 1\}$$

To construct an optimal hyperplane, SVM employs an iterative training algorithm, which is used to minimize an error function. According to the form of the error function, SVM models can be classified into four distinct groups:

- Classification SVM Type 1 (also known as C-SVM classification)
- Classification SVM Type 2 (also known as nu-SVM classification)
- Regression SVM Type 1 (also known as epsilon-SVM regression)

Regression SVM Type 2 (also known as nu-SVM regression)

Using the above mentioned logic the detection of Alzheimer's disease is possible.

### III. RESULT

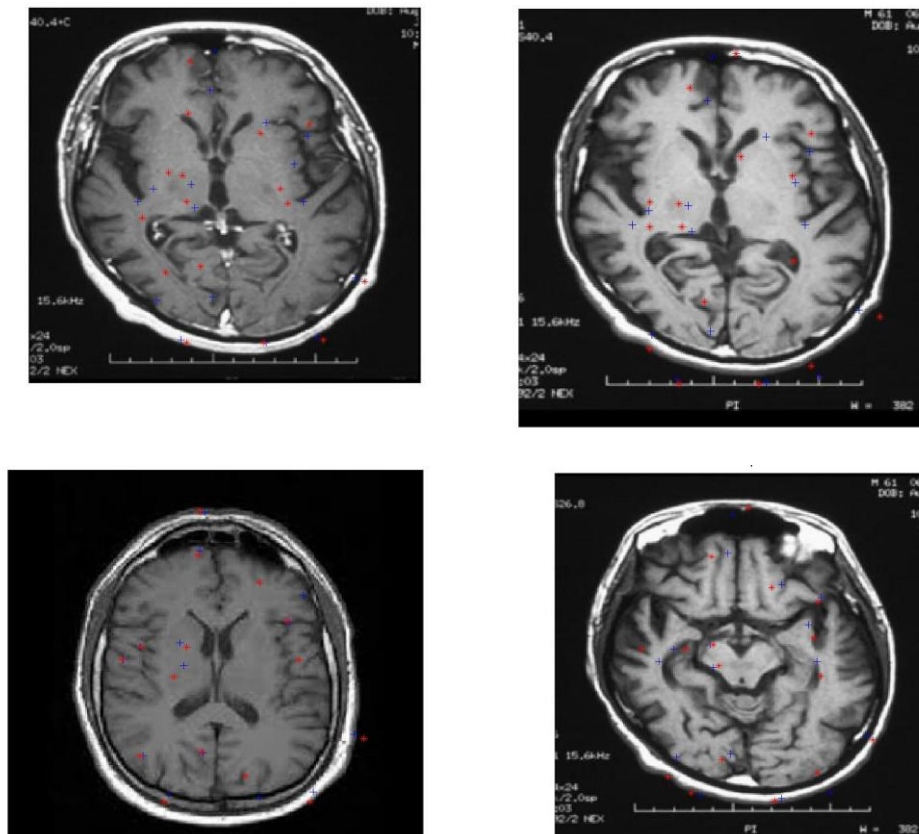


Fig.4. Illustration of Landmark Detection Results, Red Mark Shows Detected Land Marks and Blue Mark Shows Actual Land Mark.

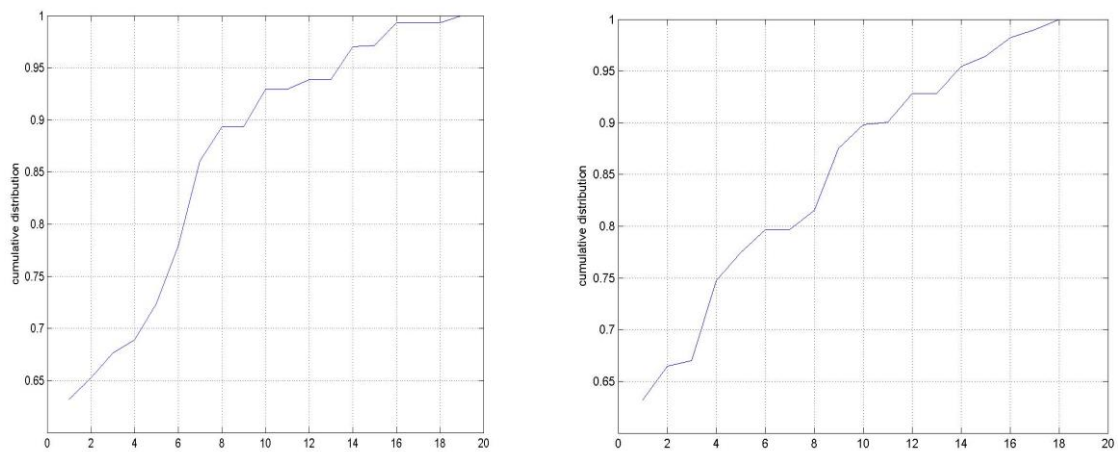
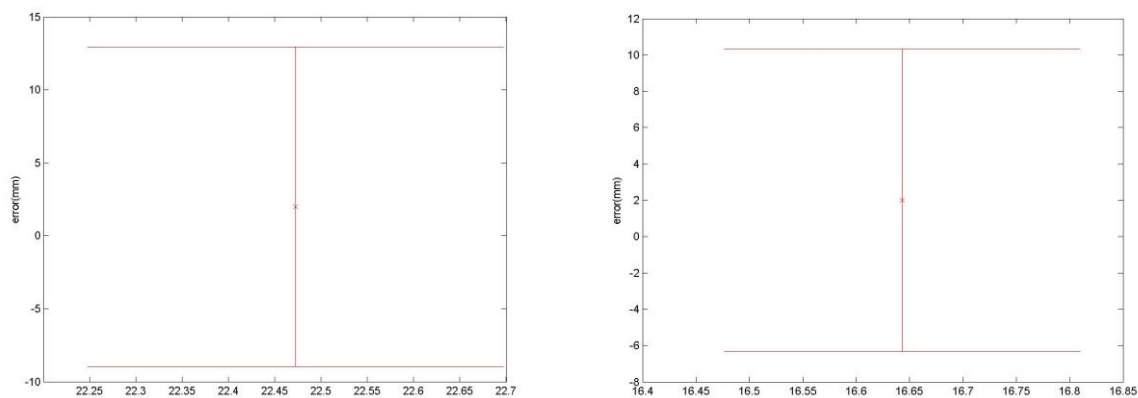
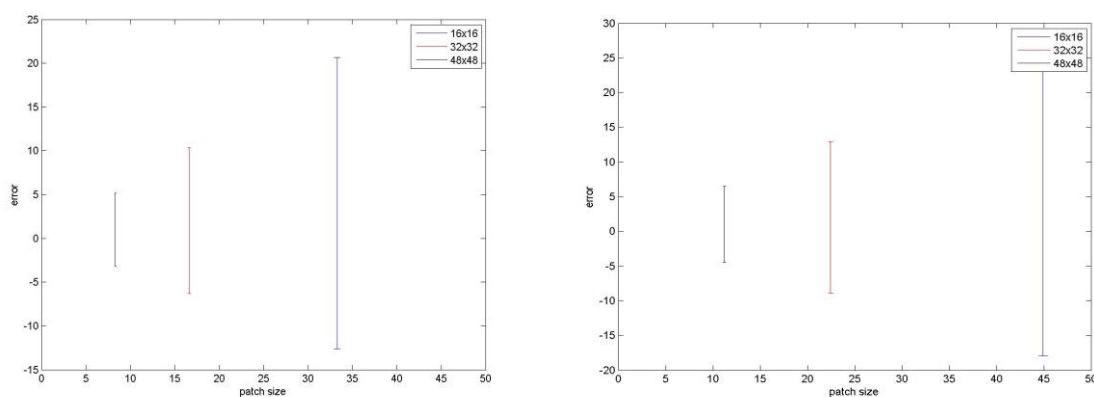


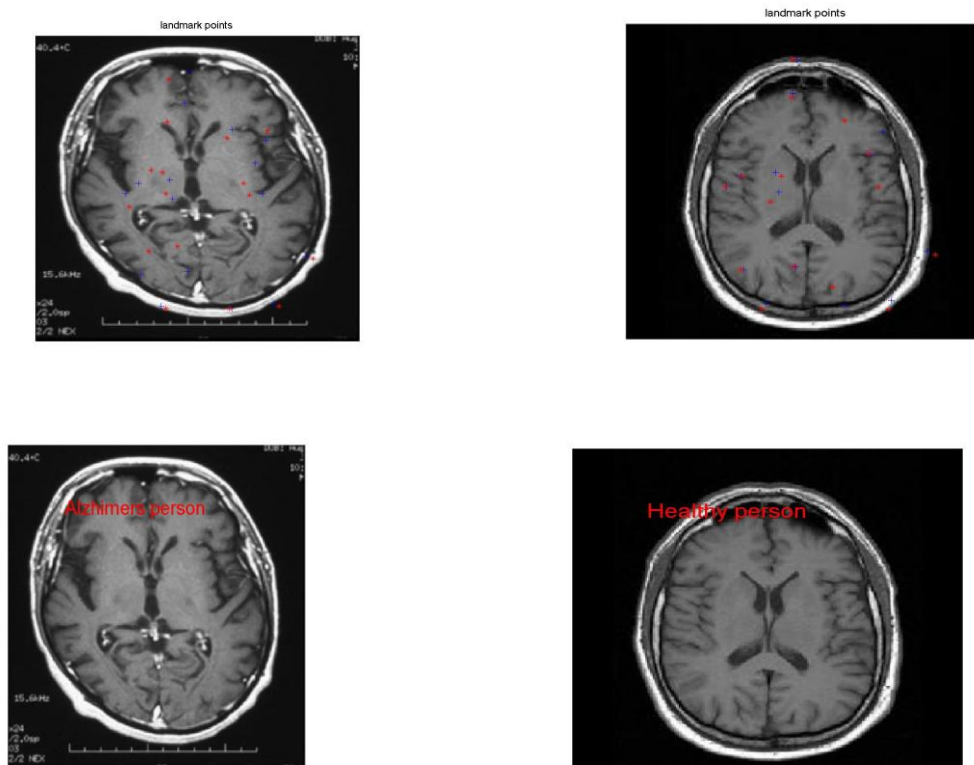
Fig.5. Cumulative Distribution of Land Mark Detection Errors.



**Fig.6. Landmark Detection Errors., it Means the Difference Between Original Points and Detected Points.**



**Fig.7. Landmark Detection Error with Respect to Patch Size. When Patch Size Increases the Error will be Decreases.**



**Fig.8. Landmark Detection and Alzheimers Disease Diagnosis**



#### **4. CONCLUSIONS**

We propose a two-stage task-oriented deep learning method for anatomical land mark detection with limited medical imaging data. Using these land mark points also detect Alzheimer's disease diagnosis. Here two neural networks comes back to back, that's why we call it is a deep neural networks. The first neural network is called local operations and the second neural network is called global operations. After the second stage the landmark points are obtained, then extract HOG and longitudinal features and using SVM to diagnose the Alzheimer's disease.

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