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Utilizing Convolutional Neural Networks for Early Detection of Ataxia

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ABSTRACT: Cerebellar ataxia is a disease that affects movement and coordination, caused by degeneration in specific parts of the brain. There are different genetic forms of this disease, each showing unique patterns of brain damage, which result in distinct movement and thinking problems. Understanding these patterns can help doctors diagnose the type of ataxia, determine how advanced the disease is, and plan treatments. In this study, researchers developed a method using MRI brain scans to identify different types of cerebellar ataxia and predict a score related to the patient's functional abilities. They tackled the challenge of analyzing complex image data with few patient samples by:

1.Training simple models on different parts of the brain images separately, and then combining their results.
2. Making slight changes to the image parts to increase the number of training samples.
3. Using a deep learning technique called stacked auto-encoder to create detailed feature representations of the brain images.

I. INTRODUCTION

Cerebellar ataxia is a rare disease that affects the cerebellum, a part of the brain that controls movement and coordination. There are different genetic types of this disease, each causing unique patterns of brain damage. These patterns result in specific movement and cognitive issues. Currently, diagnosing and treating cerebellar ataxia is challenging because doctors mainly rely on physical and cognitive tests, which aren't very precise. There's no accurate way to predict how the disease will progress Cerebellar or how it will affect a patient's abilities. MRI scans can help improve the evaluation of cerebellar ataxia by showing detailed images of the brain's structure. For example, the images can reveal areas of the brain that have shrunk, known as atrophy. Different types of cerebellar ataxia show distinct patterns of atrophy. For instance, one type (SCA2) shows significant shrinkage in the central part of the cerebellum, while another type (SCA6) shows more atrophy in the back-lower part. Researchers have proposed various methods to study the relationship between these structural changes in the brain and clinical symptoms. Some methods use simple, manually measured features, while others use complex, high-dimensional features that capture detailed changes in brain shape. The latter approach is more effective but also more challenging because it involves analyzing a large amount of data with only a small number of patient samples. In this study, researchers developed a new method to classify different types of cerebellar ataxia and predict how the disease will progress using MRI images. They tackled the challenge of analyzing high-dimensional data with limited samples by:

1.Training simple models on different parts of the brain images separately and then combining their results.
2.Generating more training samples by slightly altering the image parts.
3.Using a deep learning technique called stacked auto-encoder to create detailed feature representations of the brain images.

II. METHOD

2.1. Pre-processing

We have data from 168 people who underwent brain scans called T1-weighted MPRAGE images. Among them, 61 are healthy individuals (HCs), and 107 have different types of ataxia, a neurological condition affecting coordination. Out of these, 120 people completed a series of tests focused on mobility. Based on these tests, they received a Functional Staging Score for Ataxia (FSFA), ranging from 0 to 6. A higher FSFA score indicates more severe mobility issues. This score is part of a larger scale used to assess ataxia (UADRS).To analyze the brain scans, we used software called Freesurfer. This software processed the images to focus only on the cerebellum, a part of the brain crucial for movement. It created images where the cerebellum stands out clearly and adjusted their brightness for consistency. Next, these processed images were aligned (registered) to a standard template using rigid and scale adjustments. This alignment ensures that all images are in the same orientation and size relative to the template. Finally, the images were

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cropped to remove any unnecessary surrounding areas, ensuring that only the cerebellum is included in the analysis. We refer to these processed images as 'I'. In essence, the researchers used advanced software to prepare and standardize brain scans, focusing specifically on the cerebellum, to study differences between healthy individuals and those with ataxia.

Fig. 1. Example coronal sections of the cerebellum from HC and three ataxia type

2.2.Method outline

The method involves breaking down a large, complex task into smaller, more manageable parts. Here's a simplified explanation:

1.Divide the Image: The brain MRI image is divided into 9 smaller regions, called subdomains. These subdomains are square sections of the image, and they're evenly spread out across the whole brain. There are six sections in the coronal plane (three on each side of the brain) and three sections in the sagittal plane.

2.Train Weak Classifiers: For each of these 9 subdomains, a simple classifier (or regressor) is trained separately. These are called "weak" classifiers because they only look at a small part of the image and make simple decisions based on that part.

3.Combine Decisions: After training the weak classifiers, their outputs are combined using another classifier (or regressor). This final classifier takes into account the decisions from all the weak classifiers to make a more accurate overall decision.

Here we use six coronal planes (three on each hemisphere), and three sagittal planes, so K = 9. Let π_k (u, v), u ∈ [0, 1], v ∈ [0, 1] be the parametric equation of the square plane at the k^{th} image subdomain, k = 1, 2,…, K.

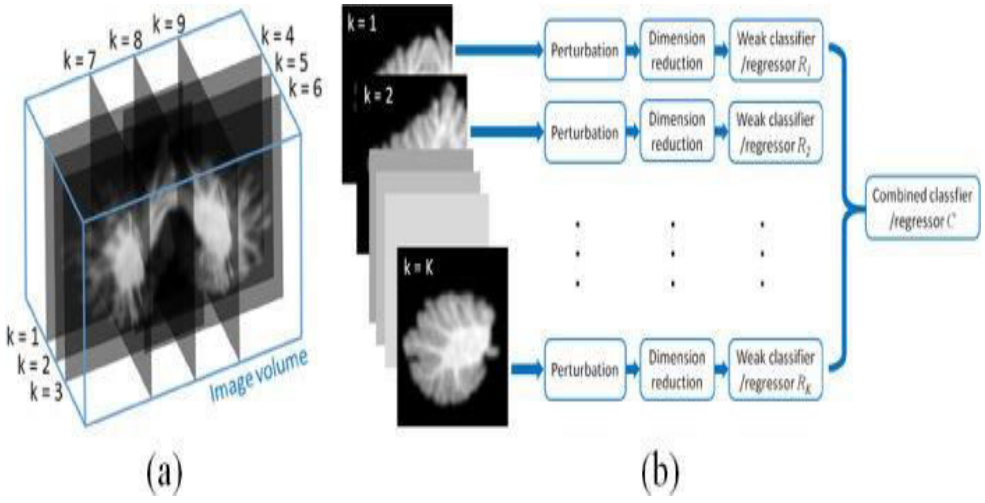

Fig. 2. (a) Image subdomains. (b) Method Diagram.

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Training weak classifier/regressor

1.Generate Image Patches: For each training subject's preprocessed brain MRI image, small 2D sections (patches) of the image are created. These patches are 32x32 pixels and are taken from specific areas of the brain.

2.Increase Training Samples: To get more training samples, the positions and orientations of these patches are slightly altered. This means each subject's image can generate multiple patches by slightly changing the center and angle of the patches.

3.Train a Stacked Autoencoder (SAE): A deep learning model called a stacked autoencoder (SAE) is trained on these patches. The SAE learns to create compact, meaningful representations (feature vectors) of the image patches.

4.Train Weak Classifiers: Using these feature vectors from all the patches, a simple classifier (or regressor) is trained for each subdomain. This classifier can then predict the class (type of ataxia) or a functional score based on the input patch.

5. Get Outputs: The trained classifier (Rk) for each subdomain produces outputs. If it's a classifier, it gives the probabilities of each class (type of ataxia). If it's a regressor, it gives a predicted functional score.

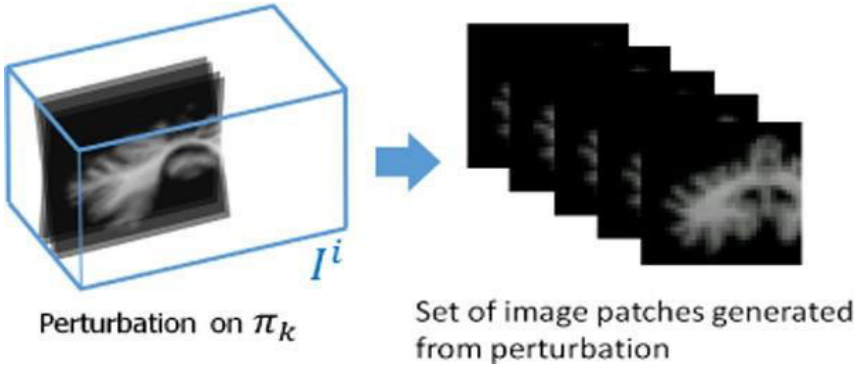

Fig. 3. Image patches.

Now each subject can generate multiple image patches by evaluating I^i on the set of perturbed planes, resulting in a set of image patches $\Omega_k^i = \{S_{k,m}^i\}, m = 1, 2, \ldots, M$. A stacked autoencoder (SAE) is trained on the image patches thus generated from all subjects, i.e. $\{S_{k,m}^i\}, m = 1, 2, \ldots, \mathrm{M}$, i = 1, 2,…, N, and outputs a low dimensional feature vector S_{k,m_j}^i for each input image patch S_{k,m_j}^i. Finally, the set of feature vectors $\{S_{k,m}^i\}$, i = 1, 2,…, M, is used to train the weak classifier R_k. Let $\mathbf{f}_k(\cdot)$ be the outputs from R_k, which is a vector specifying the class probabilities in the case of classification and the predicted functional score in the case of regression.

2.3.Dimensionality Reduction based on Stacked Autoencoder

1.Autoencoder Basics:

- An autoencoder is a type of neural network used to learn efficient representations of data.
- It takes an input vector (a list of numbers, in this case, pixel values of an image patch) and maps it to a hidden representation through a function. This function uses weights and biases to transform the input.
- The hidden representation is then transformed back to try to reconstruct the original input. The goal is to make the reconstructed output as close as possible to the original input.
- The network is trained to minimize the difference between the original input and its reconstruction.

2. Building a Stacked Autoencoder (SAE):

An SAE is created by stacking multiple autoencoders on top of each other. This allows the network to learn more complex and abstract representations.

In this study, two autoencoders are stacked. The first hidden layer has 500 nodes, and the second hidden layer has 100 nodes.

The input layer has 1024 nodes, corresponding to the 32x32 pixels in the image patches.

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3. Training the SAE:
The SAE is trained layer by layer. Each layer learns to transform the data into a more compact and useful representation.

After training the autoencoders, a final classification or regression layer is added on top to use the learned features for predicting the type of ataxia or a functional score.

4. Using the SAE:
When a new image patch is given, it is processed through the SAE to generate a feature vector. This feature vector is a simplified representation of the image patch, capturing the most important information.
This feature vector is then used by the classifier or regressor to make predictions.

The parameter space is optimized to minimize the average reconstruction error:

$$\min_{\theta,\theta'} \frac{1}{n}\sum_{i=1}^{n} L\left(\mathrm{x}^{(i)}, \mathbf{z}^{(i)}\right) = \min_{\theta,\theta'} \frac{1}{n}\sum_{i=1}^{n} L\left(\mathrm{x}^{(i)}, g'_{\theta}\left(f_{\theta}(\mathrm{x}^{(i)})\right)\right),$$

Where

$$L(\mathrm{x}, \mathbf{z}) = -\sum_{k=1}^{d}[\mathrm{x}_k \log \mathbf{z}_k + (1-\mathrm{x}_k)\log(1-\mathbf{z}_k)],$$

is a loss function based on the reconstruction cross-entropy.

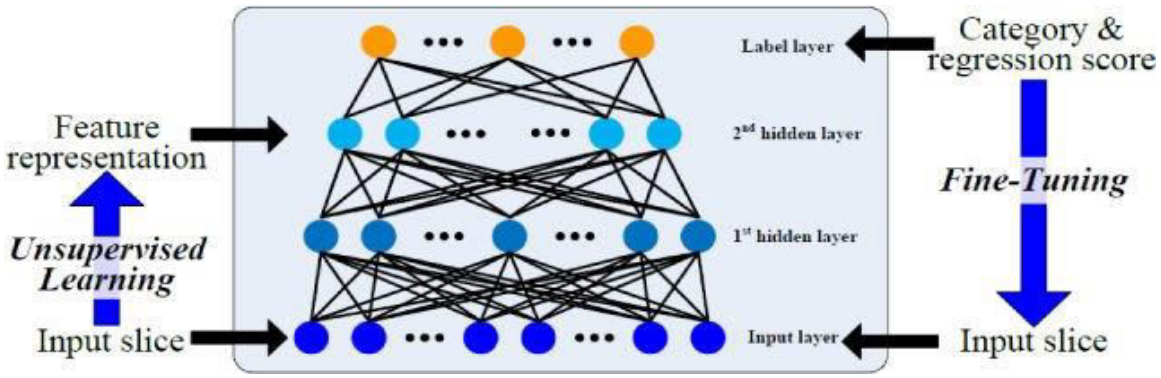

Fig. 4. Stacked auto-encoder.

III. EXPERIMENTS

3.1Cerebellar ataxia classification

1.Classification Task: The goal is to classify MRI images into four groups: Healthy Controls (HC), Spinocerebellar Ataxia type 2 (SCA2), Spinocerebellar Ataxia type 6 (SCA6), and Ataxia-Telangiectasia (AT).

2.Dataset and Validation:
The dataset has 80 subjects: 31 HC, 4 SCA2, 27 SCA6, and 18 AT.
The dataset is split into 10 subsets, each with a similar proportion of the four groups.A 10-fold cross-validation is used: In each trial, one subset is used for testing and the other nine for training.

3.Methods Compared:
ROI Volume PCA: Uses regional brain volumes, reduces dimensions with PCA, and classifies with a random forest.
Image PCA: Uses the whole MRI image, reduces dimensions with PCA, and classifies with a random forest

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Log-Jacobian PCA: Uses deformation features from the MRI image, reduces dimensions with PCA, and classifies with a random forest.

Proposed Method with PCA: Uses the proposed method, reducing dimensions with PCA.
Proposed Method with SAE: Uses the proposed method, reducing dimensions with a stacked autoencoder (SAE).

Results:
The proposed method with SAE had the best performance, with an error rate of 13.75%.
This method was better than using simple volume measurements, whole image data, or deformation features alone.
The stacked autoencoder (SAE) was more effective for dimensionality reduction than PCA within the proposed method.

True \ Pred	HC	SCA2	SCA6	AT
HC	0.97	0.00	0.03	0.00
SCA2	0.25	0.00	0.50	0.25
SCA6	0.11	0.00	0.89	0.00
AT	0.06	0.00	0.11	0.83

Fig. 5. Average confusion matrix for the proposed method using SAE for dimensionality reduction

Method	Error rate (%)
ROI volume PCA	16.25 ± 8.44
Image PCA	16.25 ± 11.86
Log-Jacobian PCA	22.50 ± 15.37
Proposed method with PCA	15.00 ± 11.49
Proposed method with SAE	13.75 ± 12.43

Table 1 Classification error rate.

Method	RMSE	Pearson
Lobule volume PCA	1.187±0.217	0.693± 0.110
Image PCA	1.191±0.274	0.669± 0.153
Log-Jacobian PCA	1.250±0.181	0.635± 0.091
Proposed method with PCA	1.154±0.209	0.687± 0.144
Proposed method with SAE	1.148±0.211	0.685± 0.133

Table 2 Root mean square error (RMSE) and Pearson correlation coefficient between the measured functional score and predicted functional score.

3.2.Functional score regression
In this study, we tried to predict a functional score for ataxia (FSFA) using data from 120 people. We tested our method using a technique called 10-fold cross-validation, which helps to check how well our model works.

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We compared five different methods. Our new method, called SAE, did the best in terms of predicting the score accurately, as shown by the lowest root mean square error (RMSE). It also showed a good correlation with another method that uses lobule volume PCA.Figure 6 in our study shows a comparison between the predicted and actual FSFA scores for the test subjects. We also included brain scan images that match these scores, showing that as the predicted score worsens, the brain scans indicate more severe atrophy. This suggests our method effectively captures the relationship between brain atrophy and functional loss.

However, there are several reasons why predictions might not be perfect. For example, certain types of ataxia, like AT and SCA3, involve more severe sensory changes, leading to worse FSFA scores than what brain changes alone would suggest. Other factors such as height, weight, job, and physical activity level also influence functional performance. Additionally, as mentioned earlier, there is still potential to improve our method by finding more features that relate to FSFA.

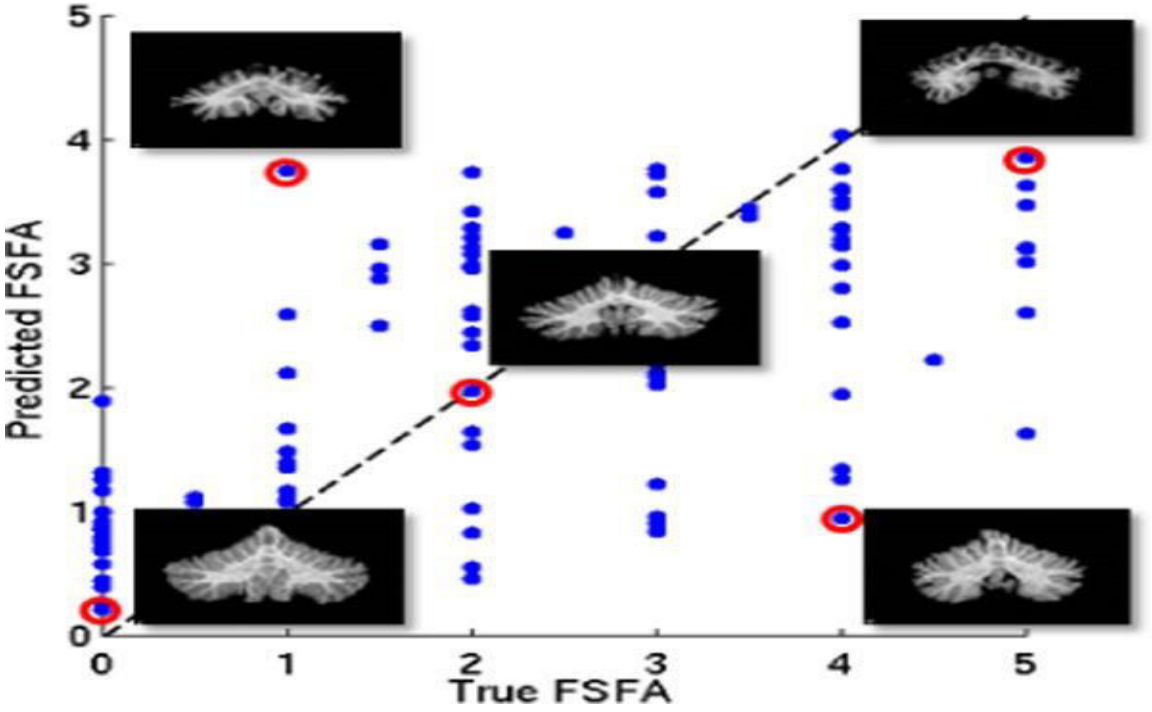

Fig. 6.

Predicted FSFA vs. true FSFA, using the proposed method. Typical MR images of the cerebellum are shown.

IV. CONCLUSION

In our study, we developed a method to classify different types of cerebellar ataxia from MR images and predict a related functional score. To handle the challenge of analyzing detailed image data with only a few training examples, we did three things: We trained small, simple models on different parts of the images separately and then combined their results to make a final decision.

We slightly altered the image parts to create more training examples.

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