Auto-Encoders with MRI Images

Problem: Prediction

Objective: predict an early diagnosis of AD using MRI data

Methods: autoencoder, logistic regression, SVM

Dataset: ADNI

Result: autoencoder (AUC=0.916),

logistic regression(AUC=0.76), SVM(AUC=0.789)

Drawback: CNNs and other machine learning algorithms, such as random forests, were not used for comparison.

Advantages: was the first to exploit the concept of auto-encoders to predict an early diagnosis of AD using MRI data.

Summary:

For instance, Ju et al. [45] used a deep learning-based approach to predict an early diagnosis of AD using MRI data. Their deep learning approach was established on a softmax regression layer and auto-encoders (see Section 3.2.4). Basically, an auto-encoder is an artificial neural network for the encoding purpose, where the input layer serves the original MRI data, layers, and the previousmultiple hidden layers provide nonlinear transformations from the output layer reconstructs MRI samples. In their study, various widely used machine learning methods, such as linear discriminant analysis, logistic regression, and support vector machines, were utilized for benchmarking. Ju et al. [45] reported that the proposed auto-encoder method (AUC = 0.916) surpassed various benchmarking models such as linear discriminant analysis (AUC = 0.710), and logistic Int. J. Mol. Sci. 2021, 22, 7911 10 of 20 regression (AUC = 0.765), and support vector machines (AUC = 0.789) to predict an early stage of AD using MRI images. The main disadvantage of the study by Ju et al. [45] is that only single-modal brain imaging data, namely MRI images, was examined, and thereby other likely morphological changes from multimodal brain image data may be disregarded. Moreover, other deep learning algorithms such as CNNs, and other machine learning algorithms such as random forests were not utilized for comparison. On the other hand, the main advantage of their study is that their approach was the first to exploit the concept of auto-encoders to predict an early diagnosis of AD using MRI data

Deep Belief Networks with PET Images

Problem: Classification

Objective: distinguish AD From mild cognitive impairment using PET data

Methods: DBN

Dataset: ADNI

Result: DBN (AUC=0.866)

Drawback: CNNs and other machine learning algorithms, such as random forests, were not used for comparison.

Advantages: the main benefit of their study is that their approach was the first to apply the concept of DBNs to distinguish AD from mild cognitive impairment using PET data.

Summary:

Shen et al. [46] employed a deep learning-based approach to distinguish AD from mild cognitive impairment using PET data. Their deep learning approach was based on DBNs (see Section 3.2.5.), which serves as feature selection to identify key features from the regions of interest (ROIs). The support vector machine model, which is a popular machine learning method for detecting AD with structural MRI data, was utilized to distinguish AD from mild cognitive impairment. Shen et al. [46] discovered that the proposed DBN-based method obtained good performances for differentiating subjects between AD and mild cognitive impairment (AUC = 0.908). In addition, the DBN model (accuracy = 0.866) excelled PCA (accuracy = 0.795) and anatomical automatic labeling (accuracy = 0.631) [46]. The main limitation of the study by Shen et al. [46] is that only single-modal brain imaging data, namely PET images, was examined and thereby other likely morphological changes from multimodal brain image data may be disregarded. Moreover, other deep learning algorithms such as CNNs and other machine learning algorithms such as random forests were not utilized for comparison. Their study also did not always use AUC, a standard evaluation metric, for comparison. On the other hand, the main benefit of their study is that their approach was the first to apply the concept of DBNs to distinguish AD from mild cognitive impairment using PET data.

Sparse-Response Deep Belief Networks with PET and MRI Images

Problem: Classification

Objective: to predict AD using PET and MRI images.

Methods: the extreme learning machine model, CNN and SVM

Dataset: ADNI

Result: Sparse-response DBNs model (AUC=0.87)

Drawback: GANS and other machine learning algorithms, such as random forests, were not used for comparison.

Advantages: the first to leverage the concept of sparse-response DBNs to predict AD using multimodal brain image data such as PET and MRI images distinguish AD from mild cognitive impairment using PET data.

Summary:

Zhou, P. et al. [47] utilized a deep learning-based approach to predict AD using PET and MRI images. Their deep learning approach was characterized by sparse-response DBNs [39] (see Section 3.2.5), which was used for extracting features from the images. Then, the extreme learning machine model was utilized to distinguish AD, mild cognitive impairment, and normal controls. In their study, support vector machines and CNNs were utilized for benchmarking. Zhou, P. et al. [47] indicated that the proposed approach (AUC = 0.87) outperformed the benchmarking models, such as CNNs (AUC = 0.77) and DBNs (AUC = 0.83) for distinguishing AD and normal controls. In addition, the proposed approach (AUC = 0.79) exceeded CNNs (AUC = 0.60) and DBNs (AUC = 0.73) for distinguishing mild cognitive impairment and normal controls [47]. Moreover, the proposed approach (AUC = 0.71) surpassed CNNs (AUC = 0.60) and DBNs (AUC = 0.68) for distinguishing AD and mild cognitive impairment [47]. The main weakness of the study by Zhou, P. et al. [47] is that other deep learning algorithms such as GANs and other machine learning algorithms such as random forests were not utilized for comparison. On the other hand, the main strength of their study is that their approach was the first to leverage the concept of sparse-response DBNs to predict AD using multimodal brain image data such as PET and MRI images

Study	Model	Data	Tasks
Ju et al	Autoencoders	MRI	Predict early diagnosis of AD
Shen et al	DBNs	PET	Distinguish AD from MCI
Zhou, P. et al	Sparse-response DBNs	PET, MRI	Predict AD risk

Stduy	Datasets	Sample Size	Performance
Ju et al.	ADNI	170 (91 MCI/79 NC)	The auto-encoder model outperformed linear discriminant analysis, logistic regression, and support vector machines (AUC = 0.916, 0.710, 0.765, and 0.789, respectively).
Shen et al.	ADNI	109 (47 AD/62 MCI)	DBNs surpassed PCA and anatomical auto-matic labeling (accuracy = 0.866, 0.795, and 0.631, respectively; no specific AUC values)
Zhou, P. et al	ADNI	340 (116 AD/82 MCI/142 NC)	The sparse-response DBN-based model exceeded CNNs and DBNs for differentiating AD and normal controls (AUC = 0.87, 0.77, 0.83), MCI and normal controls (AUC = 0.79, 0.60, 0.73), and AD and MCI (AUC = 0.71, 0.60, 0.68)