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Clinical Decision Support for Alzheimer's: Challenges in Generalizable Data-Driven Approach

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Abstract. This paper reviews the current research on Alzheimer's disease and the use of deep learning, particularly 3D-convolutional neural networks (3D-CNN), in analyzing brain images. It presents a predictive model based on MRI and clinical data from the ADNI dataset, showing that deep learning can improve diagnosis accuracy and sensitivity. We also discuss potential applications in biomarker discovery, disease progression prediction, and personalised treatment planning, highlighting the ability to identify sensitive features for early diagnosis.

Keywords. Digital health, Deep Learning, 3D-CNN, Neurodegenerative Diseases

1. Introduction and Algorithm Design

Alzheimer's disease (AD) is a neurodegenerative disorder affecting memory and cognition [1]. Early and accurate diagnosis is crucial for effective intervention and patient care, but traditional methods often lack precision. Deep learning (DL) technologies enhance medical image analysis and diagnostic accuracy for neurological disorders, though challenges remain due to AD's complexity and data integration.

We developed a tensor-distribution-regression (TDR) model based on a 3D-CNN [2] to predict clinical scores from MRI images. 3D-TDR is a prediction model which utilises a 3D-CNN backbone [3], a tensor regression layer, label distribution learning, and a total training loss. A multimodal classification method utilising the ADNI dataset [4] integrates MRI images and numerical data related to AD. We proposed a multi-class classification algorithm for normal cognition (CN), early mild cognitive impairment (EMCI), mild cognitive impairment (MCI), late mild cognitive impairment (LMCI), and AD. This approach addresses the continuous nature of disease progression. Key components of the method include a hierarchical feature extraction mechanism, robust cross-validation for generalizability, and consideration of temporal aspects of disease progression, with an emphasis on understanding factors that affect model generalisation.

We used a custom 3D-CNN framework for spatial feature extraction, with batch normalization, pooling, and dropout to mitigate overfitting [5]. The pooling layer was used to reduce feature dimensions, and dropout was employed to mitigate overfitting [5].

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K-fold cross-validation [6] was used as the validation set for each iteration. The model, loss function (cross-entropy), and optimizer (Adam) were initialized at each iteration, performing forward propagation, loss calculation, backpropagation, and parameter updates over epochs. Model performance was assessed using the validation set to monitor validation loss and accuracy. We employed an optimization strategy to set and tune hyperparameters, such as learning rate, batch size, and Dropout rate, for specific tasks and datasets. The Adam optimizer's [9] adaptive learning rate supported model convergence.

2. Results and Discussion

We tested the model by setting up two folders, one for training and one for testing, each with five subfolders corresponding to AD, CN, MCI, EMCI, and LMCI. In each epoch, model parameters were updated to minimize the loss function (Table 1).

Table 1. Loss and cross-validation accuracy for model training

Epoch	1	2	3	4	5	6	7	8	9	10	A
1	13.44	1.618	1.597	1.588	1.579	1.571	1.565	1.559	1.554	1.551	0.295
2	12.73	1.595	1.589	1.583	1.578	1.574	1.570	1.567	1.564	1.562	0.409
3	8.331	1.604	1.595	1.586	1.578	1.572	1.566	1.561	1.557	1.554	0.284
4	11.34	1.605	1.591	1.582	1.580	1.567	1.571	1.570	1.560	1.553	0.352
5	9.911	1.598	1.589	1.582	1.575	1.570	1.565	1.560	1.557	1.554	0.341

The cross-validation results in Table 1 indicate a consistent decrease in loss values across epochs, suggesting that the model successfully learns from the training data. However, the relatively low average accuracy of 0.336 and test accuracy of 0.204 highlight several important considerations for our approach and the broader field of deep learning in AD classification. One notable observation is the significant gap between training and test accuracy, which suggests potential overfitting despite the implementation of preventive measures, such as dropout layers and batch normalization. When comparing our results with existing literature, the performance metrics fall below those reported in some similar studies. However, it's essential to note that our model addresses a more complex five-class classification problem (AD, CN, MCI, EMCI, and LMCI) than many binary classification approaches in the field. This expanded classification scope naturally increases the complexity of the learning task, which in turn affects accuracy metrics.

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