ARMARecon: An ARMA Convolutional Filter Based Graph Neural Network for Neurodegenerative Dementias Classification

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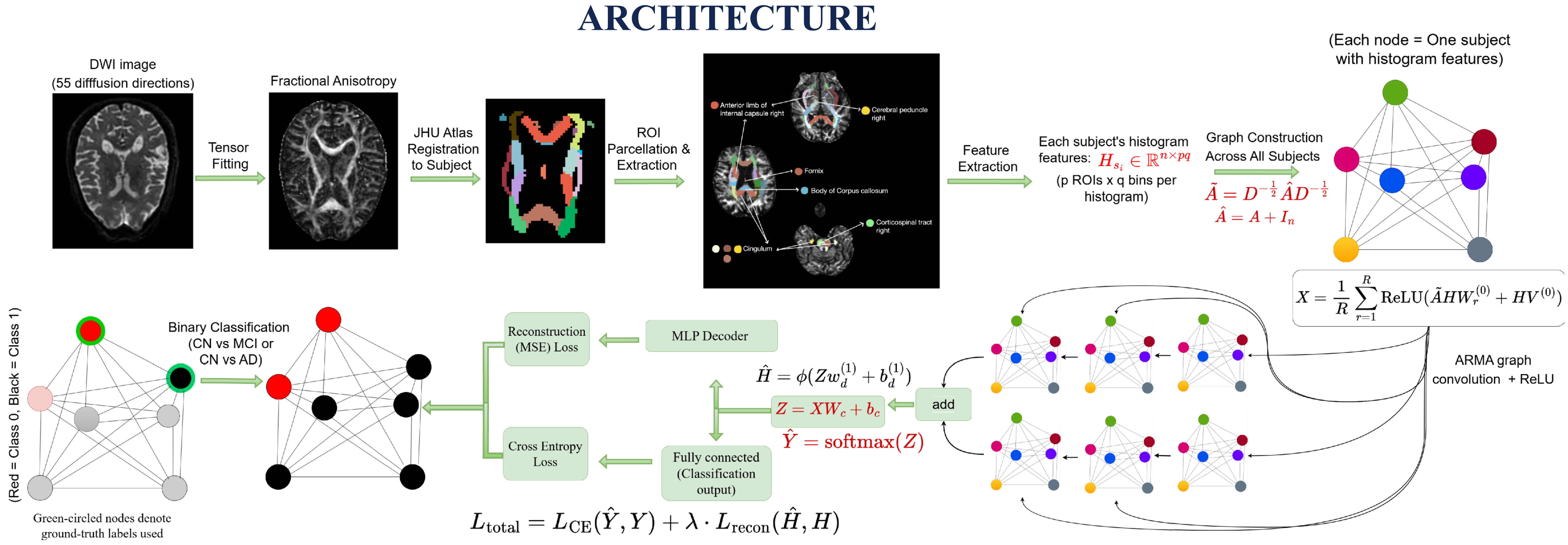
INTRODUCTION

- Early detection of **Alzheimer's Disease (AD)** and **Frontotemporal Dementia (FTD)** is crucial for effective treatment and disease management.
- **Diffusion MRI** provides valuable insights into **white-matter microstructural changes**.
- Traditional methods struggle to capture **complex brain connectivity patterns**.
- We propose **ARMARecon**, a graph neural network framework integrating **ARMA graph convolution and reconstruction regularization**.
- The proposed method learns **robust connectivity representations** and improves **dementia classification across multi-site datasets**.

ARCHITECTURE



$$L_{\text{total}} = L_{\text{CE}}(\hat{Y}, Y) + \lambda \cdot L_{\text{recon}}(\hat{H}, H)$$

RESULTS

(A) Methods	ADNI (CN vs MCI)					ADNI (CN vs AD)					NIFD				
	Acc	Prec	Rec	F1	AUC	Acc	Prec	Rec	F1	AUC	Acc	Prec	Rec	F1	AUC
SVC [1]	0.807 ± 0.06	0.855 ± 0.07	0.803 ± 0.09	0.824 ± 0.06	0.877 ± 0.05	0.863 ± 0.06	0.838 ± 0.10	0.822 ± 0.11	0.823 ± 0.08	0.895 ± 0.06	0.720 ± 0.11	0.785 ± 0.09	0.810 ± 0.09	0.794 ± 0.08	0.789 ± 0.10
MLPClassifier [2]	0.813 ± 0.07	0.836 ± 0.08	0.844 ± 0.08	0.837 ± 0.06	0.889 ± 0.06	0.859 ± 0.07	0.829 ± 0.11	0.822 ± 0.12	0.819 ± 0.09	0.898 ± 0.07	0.717 ± 0.10	0.819 ± 0.09	0.803 ± 0.31	0.776 ± 0.09	0.803 ± 0.09
Random Forest [3]	0.815 ± 0.05	0.858 ± 0.08	0.821 ± 0.10	0.833 ± 0.05	0.913 ± 0.04	0.820 ± 0.09	0.798 ± 0.14	0.744 ± 0.15	0.761 ± 0.12	0.870 ± 0.08	0.770 ± 0.08	0.778 ± 0.06	0.925 ± 0.07	0.843 ± 0.05	0.820 ± 0.10
AE-GCN [4]	0.808 ± 0.06	0.848 ± 0.06	0.815 ± 0.10	0.826 ± 0.06	0.886 ± 0.05	0.808 ± 0.06	0.826 ± 0.06	0.815 ± 0.10	0.826 ± 0.06	0.885 ± 0.05	0.730 ± 0.08	0.692 ± 0.36	0.290 ± 0.17	0.394 ± 0.22	0.808 ± 0.09
GCN (Recon)	0.975 ± 0.03	0.975 ± 0.03	0.982 ± 0.03	0.978 ± 0.02	0.993 ± 0.01	0.863 ± 0.09	0.879 ± 0.13	0.783 ± 0.18	0.812 ± 0.13	0.926 ± 0.07	0.840 ± 0.10	0.918 ± 0.07	0.846 ± 0.16	0.869 ± 0.09	0.929 ± 0.07
GAT [5]	0.777 ± 0.02	0.787 ± 0.03	0.826 ± 0.05	0.804 ± 0.02	0.849 ± 0.02	0.757 ± 0.07	0.700 ± 0.12	0.728 ± 0.13	0.699 ± 0.08	0.839 ± 0.08	0.697 ± 0.09	0.793 ± 0.09	0.750 ± 0.12	0.765 ± 0.07	0.759 ± 0.10
GAT (Recon)	0.955 ± 0.07	0.976 ± 0.04	0.944 ± 0.10	0.957 ± 0.07	0.984 ± 0.02	0.983 ± 0.03	0.976 ± 0.05	0.983 ± 0.04	0.978 ± 0.03	0.993 ± 0.02	**0.983 ± 0.04**	**0.990 ± 0.04**	**0.960 ± 0.08**	**0.973 ± 0.06**	**0.992 ± 0.03**
ChebNet (Recon)	0.978 ± 0.02	0.984 ± 0.03	0.979 ± 0.03	0.981 ± 0.02	0.995 ± 0.01	0.994 ± 0.02	0.990 ± 0.03	0.995 ± 0.02	0.992 ± 0.02	0.996 ± 0.02	0.980 ± 0.03	0.982 ± 0.04	0.990 ± 0.03	0.985 ± 0.02	1.000 ± 0.00
ARMA [6]	0.793 ± 0.08	0.827 ± 0.08	0.812 ± 0.12	0.814 ± 0.08	0.861 ± 0.09	0.822 ± 0.08	0.783 ± 0.13	0.789 ± 0.09	0.779 ± 0.08	0.884 ± 0.07	0.623 ± 0.10	0.815 ± 0.11	0.570 ± 0.14	0.660 ± 0.11	0.743 ± 0.11
ARMA (Recon)	**0.983 ± 0.02**	**0.989 ± 0.03**	**0.982 ± 0.03**	**0.985 ± 0.02**	**0.997 ± 0.01**	**0.997 ± 0.01**	**1.000 ± 0.00**	**0.993 ± 0.03**	**0.997 ± 0.01**	**0.999 ± 0.00**	0.977 ± 0.04	0.978 ± 0.05	0.990 ± 0.03	0.983 ± 0.03	1.000 ± 0.00

(B) Methods	ADNI (CN vs MCI)					ADNI (CN vs AD)					NIFD				
	Acc	Prec	Rec	F1	AUC	Acc	Prec	Rec	F1	AUC	Acc	Prec	Rec	F1	AUC
SVC [1]	0.801 ± 0.02	0.824 ± 0.03	0.818 ± 0.04	0.820 ± 0.02	0.864 ± 0.02	0.795 ± 0.02	0.782 ± 0.02	0.678 ± 0.06	0.725 ± 0.04	0.854 ± 0.02	0.727 ± 0.04	0.783 ± 0.03	0.833 ± 0.06	0.806 ± 0.03	0.803 ± 0.05
MLPClassifier [2]	0.803 ± 0.03	0.816 ± 0.04	0.838 ± 0.03	0.826 ± 0.02	0.868 ± 0.02	0.796 ± 0.03	0.748 ± 0.04	0.742 ± 0.05	0.744 ± 0.04	0.857 ± 0.02	0.747 ± 0.05	0.835 ± 0.04	0.787 ± 0.07	0.808 ± 0.04	0.817 ± 0.05
Random Forest [3]	0.815 ± 0.03	0.834 ± 0.03	0.835 ± 0.04	0.834 ± 0.03	0.893 ± 0.02	0.786 ± 0.02	0.790 ± 0.03	0.637 ± 0.06	0.704 ± 0.04	0.854 ± 0.02	0.744 ± 0.04	0.770 ± 0.03	0.895 ± 0.06	0.826 ± 0.03	0.809 ± 0.06
AE-GCN [4]	0.793 ± 0.03	0.835 ± 0.04	0.787 ± 0.05	0.809 ± 0.03	0.866 ± 0.02	0.732 ± 0.04	0.801 ± 0.08	0.448 ± 0.08	0.572 ± 0.07	0.831 ± 0.04	0.724 ± 0.05	0.705 ± 0.26	0.243 ± 0.13	0.344 ± 0.15	0.756 ± 0.07
GCN (Recon)	0.932 ± 0.04	0.953 ± 0.04	0.927 ± 0.05	0.939 ± 0.03	0.965 ± 0.04	0.831 ± 0.05	0.859 ± 0.10	0.720 ± 0.13	0.770 ± 0.08	0.895 ± 0.03	0.828 ± 0.05	0.771 ± 0.11	0.689 ± 0.17	0.710 ± 0.11	0.900 ± 0.04
GAT [5]	0.773 ± 0.04	0.792 ± 0.04	0.804 ± 0.06	0.797 ± 0.04	0.848 ± 0.03	0.769 ± 0.04	0.703 ± 0.06	0.756 ± 0.08	0.725 ± 0.04	0.841 ± 0.03	0.708 ± 0.04	0.796 ± 0.05	0.778 ± 0.09	0.783 ± 0.04	0.770 ± 0.05
GAT (Recon)	0.920 ± 0.03	0.931 ± 0.03	0.926 ± 0.06	0.927 ± 0.03	0.959 ± 0.02	0.935 ± 0.03	0.917 ± 0.04	0.924 ± 0.05	0.920 ± 0.03	0.962 ± 0.02	0.906 ± 0.04	0.864 ± 0.08	0.843 ± 0.07	0.851 ± 0.06	0.946 ± 0.03
ChebNet (Recon)	0.931 ± 0.02	0.937 ± 0.03	0.940 ± 0.04	0.938 ± 0.02	0.978 ± 0.01	0.943 ± 0.02	0.920 ± 0.04	0.944 ± 0.04	0.931 ± 0.03	0.983 ± 0.01	0.913 ± 0.04	0.862 ± 0.07	0.868 ± 0.07	0.863 ± 0.06	0.973 ± 0.02
ARMA [6]	0.803 ± 0.03	0.824 ± 0.04	0.824 ± 0.05	0.823 ± 0.03	0.875 ± 0.03	0.802 ± 0.05	0.747 ± 0.07	0.774 ± 0.09	0.758 ± 0.06	0.870 ± 0.04	0.663 ± 0.07	0.830 ± 0.07	0.638 ± 0.09	0.718 ± 0.07	0.771 ± 0.06
ARMA (Recon)	**0.939 ± 0.02**	**0.946 ± 0.02**	**0.945 ± 0.03**	**0.945 ± 0.02**	**0.983 ± 0.01**	**0.952 ± 0.02**	**0.935 ± 0.04**	**0.950 ± 0.04**	**0.942 ± 0.03**	**0.987 ± 0.01**	**0.918 ± 0.03**	**0.891 ± 0.06**	**0.850 ± 0.08**	**0.868 ± 0.05**	**0.979 ± 0.01**

(C) Methods	ADNI (CN vs MCI)					ADNI (CN vs AD)					NIFD				
	Acc	Prec	Rec	F1	AUC	Acc	Prec	Rec	F1	AUC	Acc	Prec	Rec	F1	AUC
SVC [1]	0.796 ± 0.02	0.819 ± 0.03	0.816 ± 0.05	0.816 ± 0.02	0.862 ± 0.02	0.796 ± 0.03	0.779 ± 0.05	0.690 ± 0.07	0.729 ± 0.04	0.863 ± 0.02	0.717 ± 0.03	0.760 ± 0.03	0.851 ± 0.05	0.801 ± 0.02	0.767 ± 0.04
MLPClassifier [2]	0.795 ± 0.02	0.808 ± 0.03	0.831 ± 0.04	0.818 ± 0.02	0.862 ± 0.02	0.802 ± 0.03	0.767 ± 0.04	0.732 ± 0.07	0.747 ± 0.05	0.861 ± 0.02	0.721 ± 0.03	0.806 ± 0.05	0.775 ± 0.04	0.788 ± 0.02	0.779 ± 0.04
Random Forest [3]	0.804 ± 0.02	0.823 ± 0.04	0.830 ± 0.05	0.825 ± 0.02	0.885 ± 0.02	0.782 ± 0.03	0.788 ± 0.05	0.629 ± 0.07	0.697 ± 0.05	0.863 ± 0.03	0.724 ± 0.04	0.739 ± 0.03	0.912 ± 0.05	0.816 ± 0.03	0.793 ± 0.06
AE-GCN [4]	0.793 ± 0.07	0.839 ± 0.09	0.803 ± 0.10	0.814 ± 0.07	0.870 ± 0.05	0.726 ± 0.03	0.785 ± 0.05	0.439 ± 0.06	0.561 ± 0.06	0.826 ± 0.03	0.730 ± 0.07	0.580 ± 0.42	0.280 ± 0.21	0.365 ± 0.27	0.791 ± 0.08
GCN (Recon)	0.887 ± 0.03	0.903 ± 0.04	0.895 ± 0.04	0.898 ± 0.03	0.935 ± 0.02	0.804 ± 0.07	0.802 ± 0.12	0.741 ± 0.11	0.756 ± 0.05	0.872 ± 0.04	0.770 ± 0.04	0.838 ± 0.06	0.827 ± 0.10	0.826 ± 0.04	0.825 ± 0.04
GAT [5]	0.730 ± 0.04	0.753 ± 0.06	0.787 ± 0.12	0.760 ± 0.05	0.807 ± 0.04	0.775 ± 0.04	0.714 ± 0.06	0.744 ± 0.07	0.726 ± 0.05	0.849 ± 0.03	0.686 ± 0.05	0.773 ± 0.05	0.760 ± 0.08	0.764 ± 0.04	0.738 ± 0.06
GAT (Recon)	0.886 ± 0.02	0.905 ± 0.03	0.890 ± 0.04	0.896 ± 0.02	0.934 ± 0.02	0.896 ± 0.03	0.861 ± 0.04	0.886 ± 0.05	0.872 ± 0.04	0.941 ± 0.02	0.851 ± 0.05	0.783 ± 0.08	0.769 ± 0.08	0.773 ± 0.07	0.895 ± 0.04
ChebNet (Recon)	0.899 ± 0.01	0.912 ± 0.02	0.907 ± 0.03	0.909 ± 0.01	0.954 ± 0.01	0.903 ± 0.03	0.869 ± 0.04	0.893 ± 0.05	0.880 ± 0.04	0.958 ± 0.02	0.853 ± 0.02	0.905 ± 0.03	0.877 ± 0.05	0.889 ± 0.02	0.934 ± 0.02
ARMA [6]	0.800 ± 0.03	0.819 ± 0.02	0.822 ± 0.04	0.820 ± 0.03	0.868 ± 0.02	0.793 ± 0.04	0.731 ± 0.05	0.771 ± 0.06	0.749 ± 0.04	0.869 ± 0.03	0.649 ± 0.05	0.818 ± 0.06	0.618 ± 0.06	0.702 ± 0.04	0.743 ± 0.04
ARMA (Recon)	**0.904 ± 0.02**	**0.911 ± 0.02**	**0.919 ± 0.03**	**0.914 ± 0.02**	**0.959 ± 0.01**	**0.909 ± 0.02**	**0.888 ± 0.03**	**0.887 ± 0.03**	**0.887 ± 0.02**	**0.967 ± 0.01**	**0.860 ± 0.03**	**0.887 ± 0.04**	**0.910 ± 0.04**	**0.897 ± 0.02**	**0.939 ± 0.02**

Performance comparison (mean ± standard deviation) for (A) 90–10, (B) 70–30, and (C) 50–50 train–test splits with 20-fold cross-validation. The selected ADNI cohorts acquired using Siemens scanners include 133 CN, 167 MCI, and 88 AD subjects, while the NIFD dataset includes 98 FTD patients and 48 healthy controls. The highest values are shown in bold.

CONTRIBUTIONS

1. Compact histogram-based FA features are used to represent diffusion MRI data, reducing dimensionality while preserving important white-matter microstructural information.
2. Subject-level graphs are constructed using 20-bin FA histogram features from 9 clinically relevant white-matter regions.
3. We propose ARMARecon, which combines ARMA graph filtering with reconstruction regularization to improve feature learning and connectivity modeling.
4. Extensive experiments on ADNI and NIFD datasets demonstrate that ARMARecon outperforms traditional machine learning and existing GNN methods across multiple train–test splits.

LOSS FUNCTION

$$L_{\text{total}} = L_{\text{CE}}(\hat{Y}, Y) + \lambda \cdot L_{\text{recon}}(\hat{H}, H)$$

1. Cross-Entropy Loss: supervises dementia classification.
2. Reconstruction Loss (MSE): reconstructs the original FA histogram features from the decoder.
3. λ: balances classification accuracy and reconstruction regularization.

REFERENCES

[1] C. Cortes and V. Vapnik, *Support-vector networks*, Machine Learning, 1995.

[2] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, *Learning representations by back-propagating errors*, Nature, 1986.

[3] L. Breiman, *Random forests*, Machine Learning, 2001.

[4] M. Ma, S. Na, and H. Wang, *AE-GCN: An autoencoder-constrained graph convolutional network*, Neurocomputing, 2021.

[5] P. Veličković et al., *Graph Attention Networks*, 2018.

[6] F. M. Bianchi et al., *Graph neural networks with convolutional ARMA filters*, IEEE TPAMI, 2021.

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