Implicit Neural Representation-based Binary Classification on BRATS Subset

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***Abstract*—This paper investigates the effectiveness of Implicit Neural Representations (INRs) for medical image classification. We extract a subset from the BRATS2021 dataset, where each patient contributes one tumor and one no-tumor slice. Two INR models — SmallMLP_INR and TinySIREN — are trained to reconstruct each image slice. The resulting network parameters (flattened weight vectors) are then used as input features to a simple binary classifier. Our results show that TinySIREN with weight transfer learns more expressive representations and achieves perfect classification accuracy, whereas the SmallMLP_INR shows signs of local minima and lower generalization.**

I. Introduction

Implicit Neural Representations (INRs) have emerged as powerful tools for encoding high-resolution signals in continuous domains, such as images and 3D shapes. Unlike traditional discrete representations, INRs model signals as functions parameterized by neural networks. In this work, we apply INR techniques to a binary classification problem using a subset of the BRATS2021 dataset. The central idea is to train an INR for each image slice, then use its learned weights as a high-dimensional feature vector for classification. We compare a standard ReLU-based MLP (SmallMLP_INR) with a sinusoidal network (TinySIREN) enhanced with weight transfer.

II. Dataset

We use a reduced version of the BRATS2021 dataset:

- **SmallMLP_INR**: 74 tumor and 75 no-tumor slices.
- **TinySIREN + WT**: 50 tumor and 50 no-tumor slices.

Slices were selected from clear brain regions, with each patient contributing one tumor and one no-tumor slice. Images were normalized to $[0, 1]$ and converted into (x, y) coordinates and corresponding pixel intensities.

III. Methodology

A. INR Architectures

Both models take 2D coordinates (x, y) and output a single intensity value.

SIREN (Sinusoidal Representation Networks) is a class of implicit neural representations that employs sine functions as activation layers. Unlike ReLU or `tanh`-based networks, SIRENs are particularly well-suited for modeling signals with high-frequency details and smooth derivatives, which is critical in tasks such as image and wavefield reconstruction. A key property of SIRENs is that both the function and its derivatives remain smooth and expressive due to the periodic nature of the sine activation [1].

1) SmallMLP_INR:

- 4 hidden layers, 256 nodes each
- Activation: ReLU
- Parameters: 264,193

2) TinySIREN + Weight Transfer:

- 4 hidden layers, 256 nodes each
- Activation: Sinusoidal (SIREN-style), defined as $\phi(x) = \sin(\omega_0 x)$ with $\omega_0 = 30$
- This periodic activation enables high-frequency signal modeling and preserves smooth derivatives, which is especially beneficial in image reconstruction tasks.
- Weight transfer: model weights from previous slice of the same class are reused as initialization

B. Training Settings

Model	LR	Epochs	Loss
SmallMLP_INR	10^{-3}	1000	BCEWithLogitsLoss
TinySIREN + WT	10^{-4}	1000	BCEWithLogitsLoss

TABLE I
INR Training Hyperparameters

Average INR Reconstruction Loss:

- SmallMLP_INR: 9.03×10^{-5}
- TinySIREN + WT: 1.44×10^{-3}

C. Theta-Space Classification

The flattened INR parameters (denoted as θ) are used as input features to a fully connected binary classifier:

- Input: 264,193-dimensional θ
- Output: Binary label (tumor vs no-tumor)
- Loss: BCEWithLogitsLoss
- Optimizer: Adam
- Epochs: 100
- Split: 80% Train, 10% Validation, 10% Test

IV. Results and Discussion

Classifier Test Accuracy:

- SmallMLP_INR: 73.9%
- TinySIREN + WT: 100%

A. Qualitative Insights

- **TinySIREN with weight transfer** was significantly more stable and expressive than the ReLU-based model. It reconstructed slices nearly perfectly and exhibited lower reconstruction loss across the board.
- **SmallMLP_INR** suffered from artifacts and occasionally failed to converge due to poor initialization or local minima.
- Weight transfer improved convergence by initializing each new slice's model with the previously trained parameters from the same class.

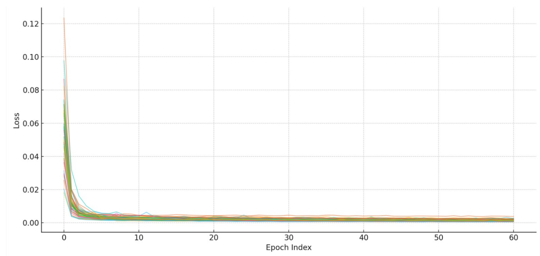

Fig. 1. Training loss curve for SmallMLP_INR

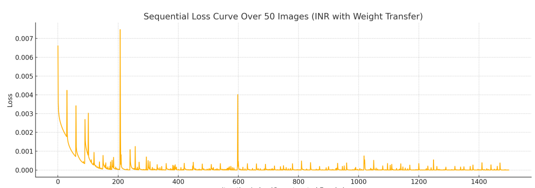

Fig. 2. Training loss curve for TinySIREN + WT

V. Conclusion

This study demonstrates that INRs can serve as effective latent representations for image classification. TinySIREN, with sinusoidal activation and weight transfer, not only achieved better reconstruction loss but also led to perfect classification accuracy on BRATS subset. In contrast, the SmallMLP_INR showed higher reconstruction error and lower classifier performance.

VI. Future Work

- Extend the setup to multi-class datasets (e.g., ACDC)
- Apply PCA or GNN-based techniques for θ feature compression
- Explore Natural Gradient Descent (e.g., K-FAC) to improve optimization dynamics
- Use k-fold cross-validation

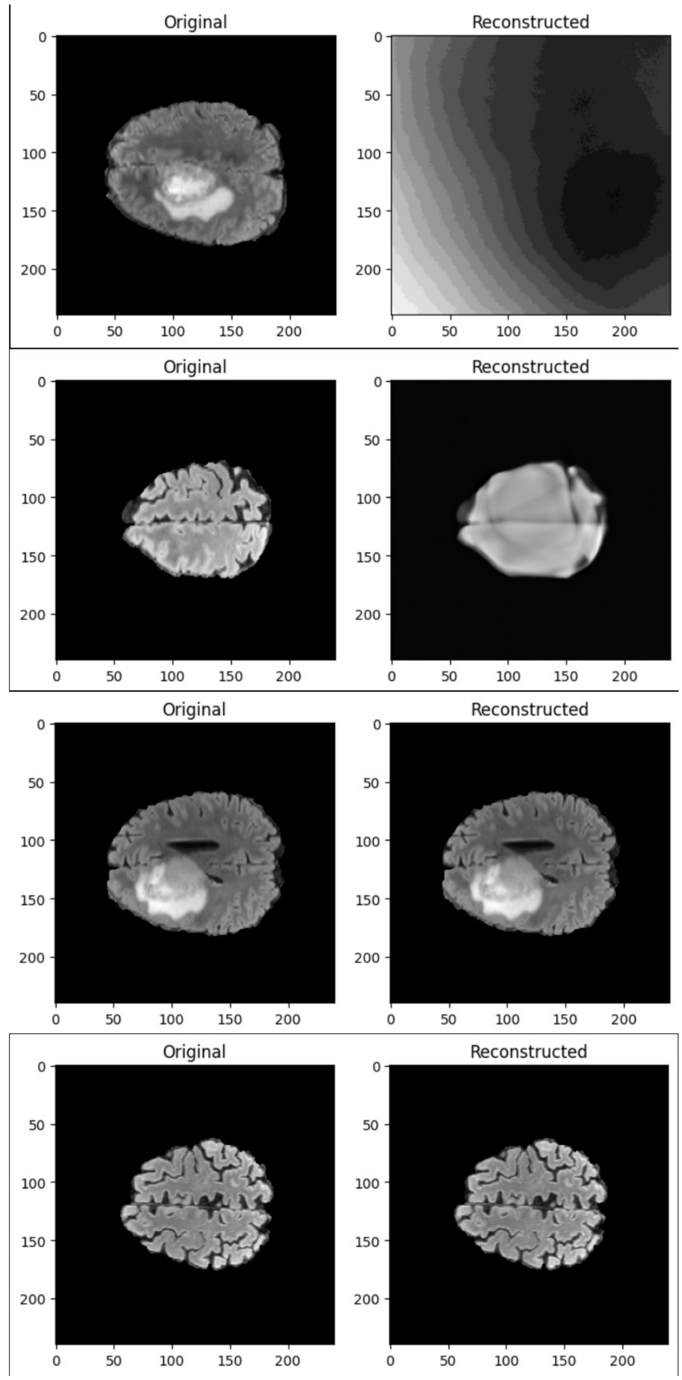

Fig. 3. Reconstruction examples: MLP and SIREN for tumor and no-tumor

References

[1] V. Sitzmann, J. N. Martel, A. W. Bergman, D. B. Lindell, and G. Wetzstein, "Implicit neural representations with periodic activation functions," *arXiv preprint arXiv:2006.09661*, 2020.