Brain MR Image Segmentation using RBF Neural Network

Under the Supervision of

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Overview

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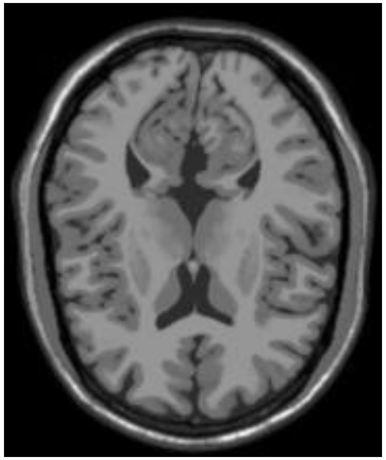
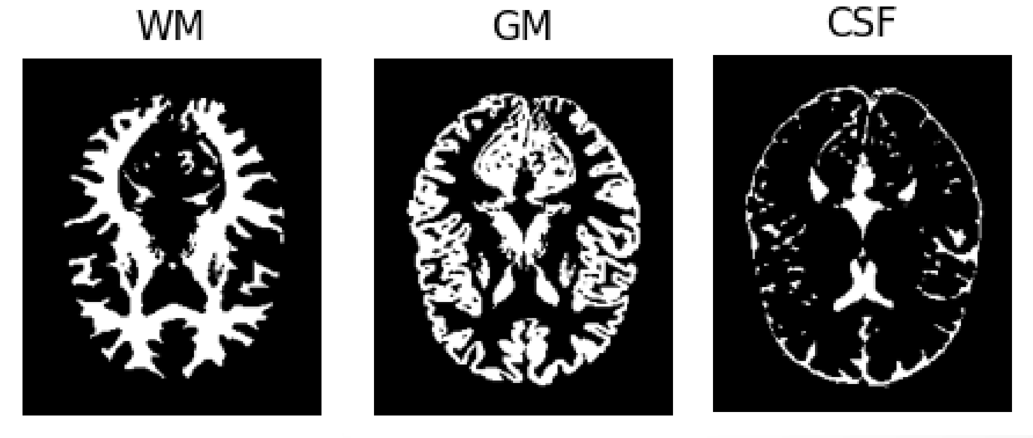
Introduction

- The **brain**, as the central nervous system controlling speech, memory, cognition, and movement, faces increasing threats from diseases due to stress, lifestyle, injuries, and aging.
- **Magnetic Resonance Imaging** (**MRI**) is a cutting-edge, non-invasive technique for precisely visualizing the shape and function of brain tissues to diagnose brain illnesses.
- **Image segmentation** in brain MRIs is crucial for applications such as surgical planning, brain tissue classification, and tumor detection.
- Brain MRI segmentation involves dividing an MRI scan into distinct structures like **white matter**, **gray matter**, **CSF** (cerebrospinal fluid), and regions such as the cortex, ventricles, or tumors.
- To make brain MRI segmentation more accurate when the structure varies, researchers use different methods. These range from basic image processing to more advanced machine learning and deep learning techniques.

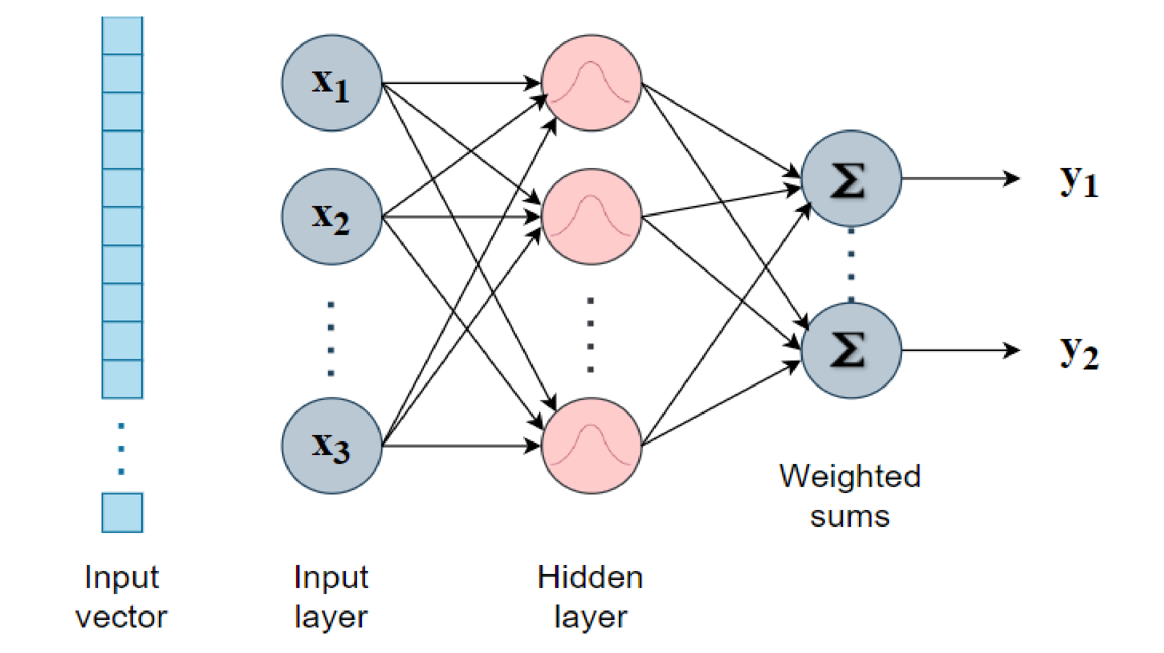
Introduction





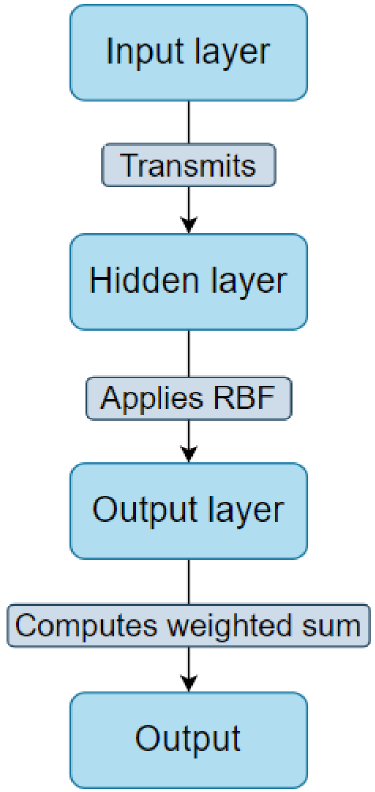
Proposed Method

- In this project, a **Radial Basis Function Neural Network (RBFNN)** is employed specifically for the segmentation of brain MR images into WM, GM, and CSF regions.
- A radial basis function (RBF) neural network is a type of artificial neural network that uses radial basis functions as activation functions.



Proposed Method

- The network consists of **three layers**: an input layer, a hidden layer with radial basis functions, and an output layer.



Proposed Method

The RBF network is a fully interconnected feed- forward network with **one hidden layer**. It can be mathematically described as follows:

$$Z_j = \frac{1}{M} \sum_{m=1}^{M} W_{mj}\,\Phi_m + b_j$$

Where,

$\boldsymbol{Z_j}$ is the activation of the j-th output neuron,

$\boldsymbol{M}$ is the number of hidden neurons,

$\boldsymbol{W_{mj}}$ is the weight between m-th hidden and j-th output neuron and

$\boldsymbol{b_j}$ is the bias term.

Proposed Method

The output of hidden layer neuron is usually generated by a **Gaussian function** as follows:

$$\Phi_m = \exp\left[\frac{-\ ||x-\mu||^2}{2\sigma_m^2}\right]$$

Here,

$\boldsymbol{x}$ represents the input vector,

μ is the fixed center position and

$\boldsymbol{\sigma_m}$ represents the fixed width of the m-th hidden layer neuron.

Proposed Method

Radial basis function networks (RBFNs) work by comparing the input to known examples from the training data to classify it.

Here's a simplified explanation of how it works:

- RBFNs process input vectors through an input layer.
- RBF neurons in the hidden layer assess input proximity using Gaussian functions based on neuron centers.
- Hidden layer outputs are integrated in the output layer.
- Classification is achieved by computing weighted sums of hidden layer outputs.
- The final output represents the input's classification.

Experiments

Database:

The dataset of this study is downloaded from **BrainWeb**, which is acquired from the McConnell Brain Imaging Center of the Montreal Neurological Institute, McGill University .

This database contains a collection of realistic MRI data generated by an MRI simulator. It encompasses various parameters such as variations in slice thickness, noise levels, and intensity non-uniformity (INU).

As the **“Ground Truth”** , I utilize the discrete anatomical model, which assigns class labels (0=Background, 1=CSF, 2=Grey Matter, 3=White Matter etc..) to each voxel.

Experiments

The dataset in my work consists of 11 T1-weighted MRI volumes on normal brain, each yielding 51 images of dimensions 181 pixels by 217 pixels, intentionally manipulated with varying noise and intensity non-uniformity (INU) levels , as meticulously delineated in the table below -

	Volume 1 (%)	Volume 2 (%)	Volume 3 (%)	Volume 4 (%)	Volume 5(%)	Volume 6 (%)	Volume 7 (%)	Volume 8 (%)	Volume 9 (%)	Volume 10 (%)	Volume 11 (%)
Noise	0	1	1	3	3	5	5	7	7	9	9
INU	0	20	40	20	40	20	40	20	40	20	40

Experiments

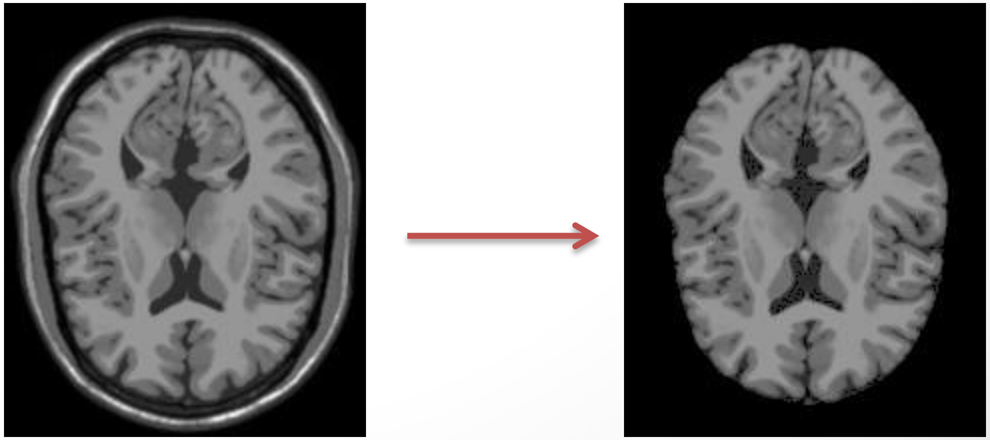
- **Data Extraction:**

  At first, I extracted the data from RAWB files into PGM files, and further transformed them into JPEG format for visualization and analysis.

- **Pre-Processing:**

  Pre-processing brain MR images is fundamental for quality assurance in quantitative analysis, involving operations to enhance quality and remove non-brain tissues, laying the foundation for accurate segmentation.

  - ❑ **Skull- stripping**
  - ❑ **Normalization**

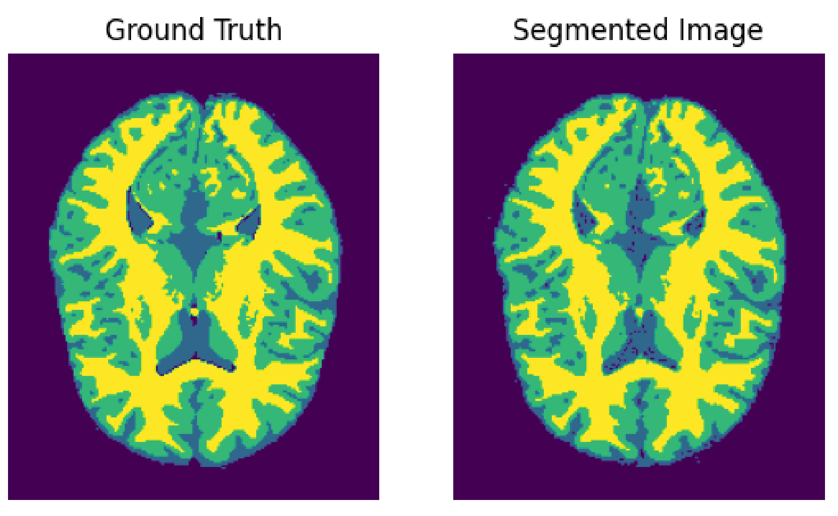


Experiments

- **Segmentation:**

Then I use RBFNN for segmenting brain MRI volumes into white matter, grey matter, and cerebrospinal fluid (CSF), accommodating variations in noise and intensity non-uniformity (INU) percentages across multiple volumes, ensuring comprehensive analysis and reliable segmentation results across diverse imaging conditions.

- ❑ **Split the datasets**
- ❑ **Standardization**
- ❑ **Training**
- ❑ **Evaluation**



Experiments

- **Evaluation Metrics:**

In this experiment, I utilized **Accuracy** , **F_1 Score** and **MSE** (Mean Squared Error) as **'loss'** for evaluation. To calculate accuracy and F_1 score, **Precision** and **Recall** must be computed first. Precision and Recall can be determined using the equations mentioned below:

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

Here,

TP- True Positive (Model has predicted Positive class whether it is actually positive)

FP- False Positive (Model has predicted Positive class whether it is actually negative) and

FN- False Negative (Model has predicted Negative class whether it is actually positive)

Experiments

Accuracy and F_1 Score can be computed using the equation mentioned below –

$$Accuracy = \frac{TP}{Total\ Number\ of\ Actual\ Positives}$$

$$F_1\,Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Accuracy and F_1 Score both lie between [0,1], **higher the values** better Recognition has been done.

Experiments

During model training, **Mean Squared Error** (MSE) served as the **loss function**. MSE calculates the average squared difference between predicted and actual values. Its range is [0.0, 1.0], with values **closer to 0** indicating better performance.

The formula for calculating MSE is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Where:
$\boldsymbol{n}$ is the number of samples
$\boldsymbol{y_i}$ is the true label for sample i
$\boldsymbol{\hat{y}_i}$ is the predicted label for sample i

Results

Experiment Results with Different Data Partitioning Ratios –

Dataset- 70% Train, 15% Validation, 15% Test :-

Volume (Noise, IIH)	Region	Precision	Recall	F1 score	Accuracy (Total)	Loss – 'MSE' (Total)
Volume 1 (0,0)	WM GM CSF	0.9877 0.9204 0.8804	0.9461 0.9696 0.8818	0.9665 0.9444 0.8811	0.9650	0.0396
Volume 2 (1,20)	WM GM CSF	0.9654 0.9244 0.8469	0.9507 0.9385 0.8035	0.9580 0.9314 0.8246	0.9539	0.04901
Volume 3 (1,40)	WM GM CSF	0.9549 0.8816 0.8386	0.9069 0.9308 0.7067	0.9303 0.9055 0.7670	0.9362	0.0626
Volume 4 (3,20)	WM GM CSF	0.9747 0.8958 0.8212	0.9181 0.9433 0.7184	0.9455 0.9189 0.7664	0.9420	0.0584
Volume 5 (3,40)	WM GM CSF	0.9551 0.8753 0.8343	0.9046 0.9339 0.6664	0.9292 0.9037 0.7410	0.9330	0.0658
Volume 6 (5,20)	WM GM CSF	0.9312 0.9162 0.8327	0.9538 0.9060 0.6510	0.9424 0.9111 0.7307	0.9367	0.0638
Volume 7 (5,40)	WM GM CSF	0.9327 0.8759 0.8076	0.9118 0.9090 0.6234	0.9221 0.8921 0.7037	0.9252	0.0728
Volume 8 (7,20)	WM GM CSF	0.9093 0.8689 0.8034	0.9116 0.8785 0.6417	0.9104 0.8736 0.7135	0.9207	0.0764
Volume 9 (7,40)	WM GM CSF	0.8968 0.8570 0.8090	0.9114 0.8766 0.5571	0.9040 0.8667 0.6598	0.9133	0.0823
Volume 10 (9,20)	WM GM CSF	0.8751 0.8081 0.7494	0.8581 0.8458 0.5964	0.8665 0.8265 0.6642	0.8962	0.0933
Volume 11 (9,40)	WM GM CSF	0.8607 0.8090 0.7566	0.8679 0.8341 0.5273	0.8643 0.8214 0.6215	0.8915	0.0975

Results

Dataset- 60% Train, 20% Validation, 20% Test :-

Volume (Noise, IIH)	Region	Precision	Recall	F1 score	Accuracy (Total)	Loss – 'MSE' (Total)
Volume 1 (0,0)	WM GM CSF	0.9822 0.9343 0.8539	0.9541 0.9561 0.8934	0.9680 0.9451 0.8732	0.9654	0.0458
Volume 2 (1,20)	WM GM CSF	0.9614 0.9226 0.8585	0.9492 0.9422 0.7986	0.9552 0.9323 0.8275	0.9547	0.0472
Volume 3 (1,40)	WM GM CSF	0.9496 0.8940 0.8247	0.9167 0.9257 0.7188	0.9329 0.9096 0.7681	0.9387	0.0595
Volume 4 (3,20)	WM GM CSF	0.9737 0.9023 0.8130	0.9202 0.9419 0.7320	0.9462 0.9216 0.7704	0.9443	0.0552
Volume 5 (3,40)	WM GM CSF	0.9420 0.8996 0.8107	0.9254 0.9144 0.6864	0.9336 0.9070 0.7434	0.9360	0.0619
Volume 6 (5,20)	WM GM CSF	0.9341 0.9154 0.8239	0.9514 0.9135 0.6661	0.9426 0.9145 0.7367	0.9391	0.0602
Volume 7 (5,40)	WM GM CSF	0.9267 0.8833 0.7990	0.9152 0.9044 0.6415	0.9209 0.8937 0.7116	0.9272	0.0694
Volume 8 (7,20)	WM GM CSF	0.9010 0.8830 0.7836	0.9221 0.8688 0.6708	0.9114 0.8759 0.7228	0.9232	0.0718
Volume 9 (7,40)	WM GM CSF	0.9026 0.8634 0.7775	0.9031 0.8768 0.5940	0.9028 0.8700 0.6735	0.9157	0.0779
Volume 10 (9,20)	WM GM CSF	0.8760 0.8168 0.7436	0.8567 0.8453 0.6007	0.8662 0.8308 0.6646	0.8988	0.0894
Volume 11 (9,40)	WM GM CSF	0.8626 0.8186 0.7361	0.8632 0.8291 0.5466	0.8629 0.8239 0.6274	0.8938	0.0936

Results

Dataset- 50% Train, 25% Validation, 25% Test :-

Volume (Noise, IIH)	Region	Precision	Recall	F1 score	Accuracy (Total)	Loss – 'MSE' (Total)
Volume 1 (0,0)	WM GM CSF	0.9814 0.9338 0.8663	0.9565 0.9569 0.8686	0.9688 0.9452 0.8675	0.9659	0.0363
Volume 2 (1,20)	WM GM CSF	0.9654 0.9212 0.8526	0.9489 0.9426 0.8034	0.9571 0.9318 0.8273	0.9561	0.0445
Volume 3 (1,40)	WM GM CSF	0.9497 0.8979 0.8280	0.9239 0.9223 0.7188	0.9367 0.9099 0.7696	0.9414	0.0574
Volume 4 (3,20)	WM GM CSF	0.9708 0.9061 0.8349	0.9327 0.9466 0.7220	0.9514 0.9259 0.7744	0.9482	0.0518
Volume 5 (3,40)	WM GM CSF	0.9428 0.8979 0.8256	0.9312 0.9198 0.6834	0.9370 0.9087 0.7478	0.9392	0.0605
Volume 6 (5,20)	WM GM CSF	0.9491 0.9141 0.7926	0.9419 0.9123 0.6882	0.9455 0.9132 0.7367	0.9408	0.0587
Volume 7 (5,40)	WM GM CSF	0.9227 0.8923 0.7974	0.9283 0.8938 0.6444	0.9255 0.8930 0.7127	0.9300	0.0667
Volume 8 (7,20)	WM GM CSF	0.8971 0.8859 0.7925	0.9323 0.8641 0.6661	0.9144 0.8749 0.7238	0.9256	0.0697
Volume 9 (7,40)	WM GM CSF	0.9020 0.8708 0.7682	0.9132 0.8670 0.6102	0.9075 0.8689 0.6802	0.9189	0.0749
Volume 10 (9,20)	WM GM CSF	0.8553 0.8420 0.7487	0.9001 0.8106 0.5998	0.8771 0.8260 0.6661	0.9030	0.0864
Volume 11 (9,40)	WM GM CSF	0.8546 0.8268 0.7575	0.8872 0.8182 0.5328	0.8706 0.8225 0.6256	0.8980	0.0909

Results

Dataset- 40% Train, 30% Validation, 30% Test :-

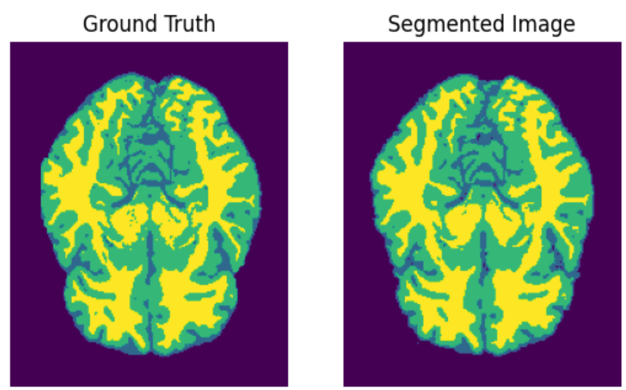
Volume (Noise, IIH)	Region	Precision	Recall	F1 score	Accuracy (Total)	Loss – 'MSE' (Total)
Volume 1 (0,0)	WM GM CSF	0.9907 0.9179 0.8348	0.9375 0.9554 0.8974	0.9633 0.9363 0.8650	0.9636	0.0427
Volume 2 (1,20)	WM GM CSF	0.9570 0.9334 0.8515	0.9625 0.9297 0.8075	0.9597 0.9315 0.8289	0.9581	0.0426
Volume 3 (1,40)	WM GM CSF	0.9504 0.8995 0.8353	0.9299 0.9224 0.7197	0.9400 0.9108 0.7732	0.9442	0.0545
Volume 4 (3,20)	WM GM CSF	0.9718 0.9109 0.8128	0.9357 0.9363 0.7381	0.9534 0.9234 0.7737	0.9494	0.0509
Volume 5 (3,40)	WM GM CSF	0.9467 0.8961 0.8514	0.9339 0.9247 0.6616	0.9402 0.9102 0.7446	0.9420	0.0568
Volume 6 (5,20)	WM GM CSF	0.9498 0.9135 0.8250	0.9488 0.9217 0.6702	0.9493 0.9176 0.7396	0.9446	0.0553
Volume 7 (5,40)	WM GM CSF	0.9077 0.9011 0.8199	0.9467 0.8773 0.6271	0.9268 0.8890 0.7107	0.9317	0.0655
Volume 8 (7,20)	WM GM CSF	0.8981 0.8875 0.7999	0.9390 0.8626 0.6616	0.9181 0.8748 0.7242	0.9284	0.0718
Volume 9 (7,40)	WM GM CSF	0.9030 0.8706 0.7841	0.9202 0.8681 0.5987	0.9115 0.8693 0.6789	0.9221	0.0719
Volume 10 (9,20)	WM GM CSF	0.8786 0.8297 0.7465	0.8856 0.8350 0.6041	0.8821 0.8323 0.6678	0.9074	0.0834
Volume 11 (9,40)	WM GM CSF	0.8714 0.8237 0.7525	0.8822 0.8302 0.5454	0.8768 0.8269 0.6325	0.9028	0.0862

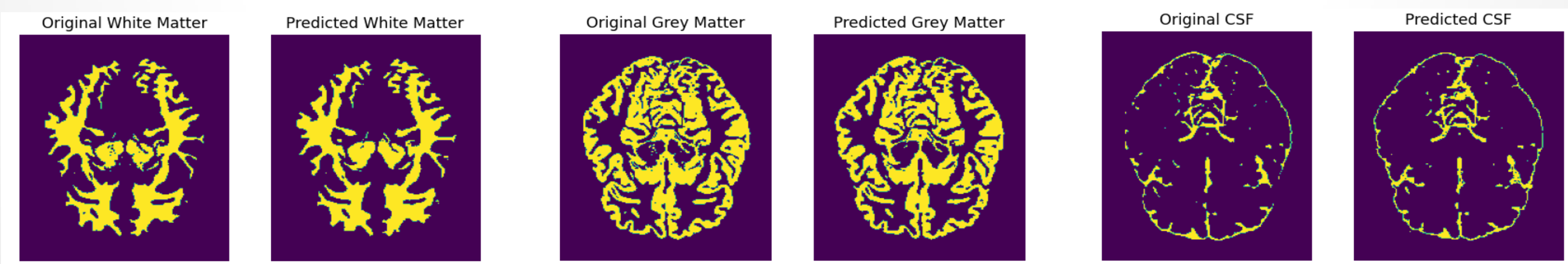
Results

Dataset- 30% Train, 35% Validation, 35% Test :-

Volume (Noise, IIH)	Region	Precision	Recall	F1 score	Accuracy (Total)	Loss – 'MSE' (Total)
Volume 1 (0,0)	WM GM CSF	0.9784 0.9357 0.8785	0.9633 0.9575 0.8714	0.9708 0.9465 0.8749	0.9679	0.0363
Volume 2 (1,20)	WM GM CSF	0.9680 0.9204 0.8619	0.9495 0.9445 0.7975	0.9587 0.9323 0.8284	0.9575	0.0443
Volume 3 (1,40)	WM GM CSF	0.9491 0.8926 0.8341	0.9235 0.9234 0.7240	0.9361 0.9077 0.7752	0.9421	0.0573
Volume 4 (3,20)	WM GM CSF	0.9738 0.9042 0.8490	0.9334 0.9511 0.7203	0.9532 0.9270 0.7794	0.9502	0.0501
Volume 5 (3,40)	WM GM CSF	0.9390 0.9030 0.8441	0.9412 0.9159 0.6777	0.9401 0.9094 0.7518	0.9416	0.0577
Volume 6 (5,20)	WM GM CSF	0.9440 0.9171 0.8098	0.9520 0.9140 0.6886	0.9479 0.9155 0.7443	0.9432	0.0571
Volume 7 (5,40)	WM GM CSF	0.9255 0.8930 0.7933	0.9306 0.8934 0.6576	0.9280 0.8932 0.7191	0.9320	0.0652
Volume 8 (7,20)	WM GM CSF	0.8847 0.8997 0.7680	0.9448 0.8326 0.6901	0.9138 0.8649 0.7270	0.9247	0.0728
Volume 9 (7,40)	WM GM CSF	0.9230 0.8535 0.7507	0.8897 0.8811 0.6273	0.9061 0.8671 0.6835	0.9192	0.0784
Volume 10 (9,20)	WM GM CSF	0.8608 0.8389 0.7607	0.9022 0.8165 0.5944	0.8810 0.8276 0.6674	0.9058	0.0846
Volume 11 (9,40)	WM GM CSF	0.8761 0.8207 0.7271	0.8719 0.8303 0.5776	0.8740 0.8254 0.6438	0.9010	0.0884

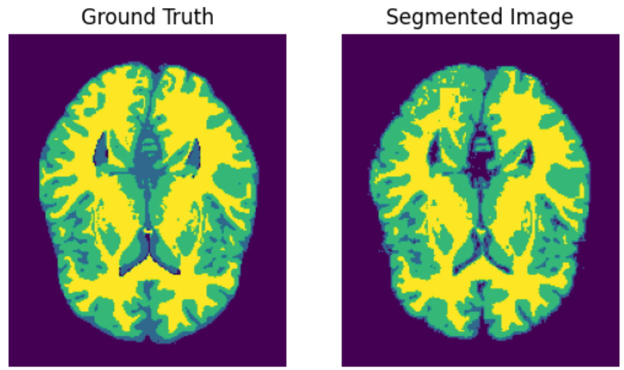
Results

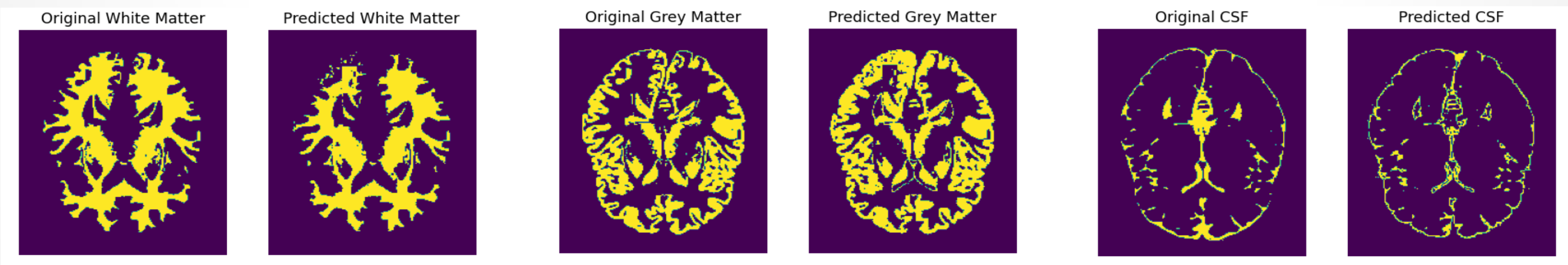




The original and the predicted masks of a random slice (slice- 62) from volume – 1(0,0)

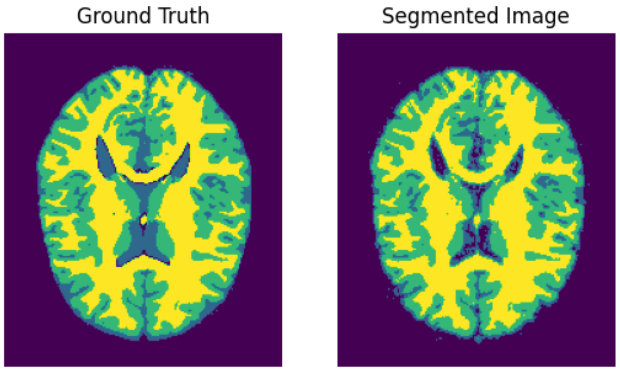
Results

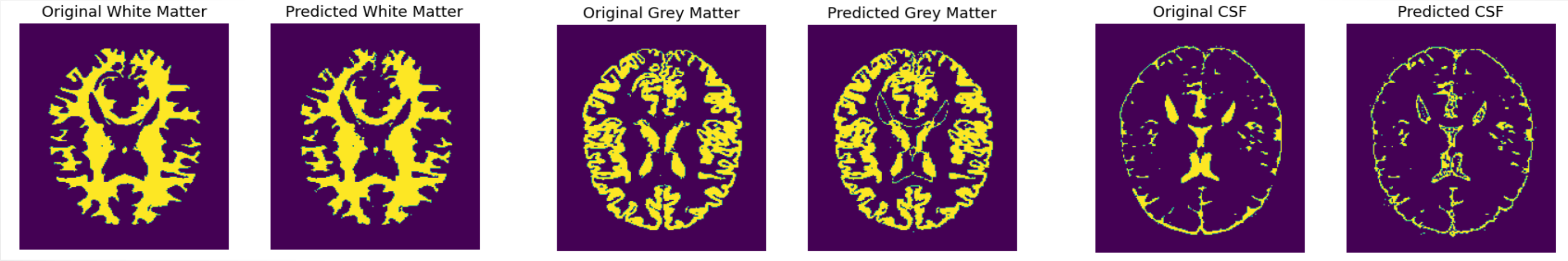




The original and the predicted masks of a random slice (slice- 73) from volume – 3(1,40)

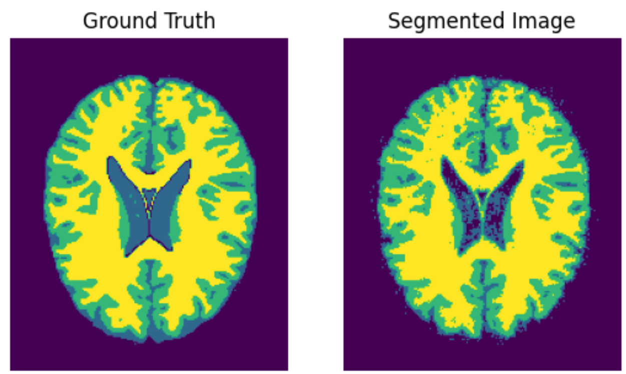
Results

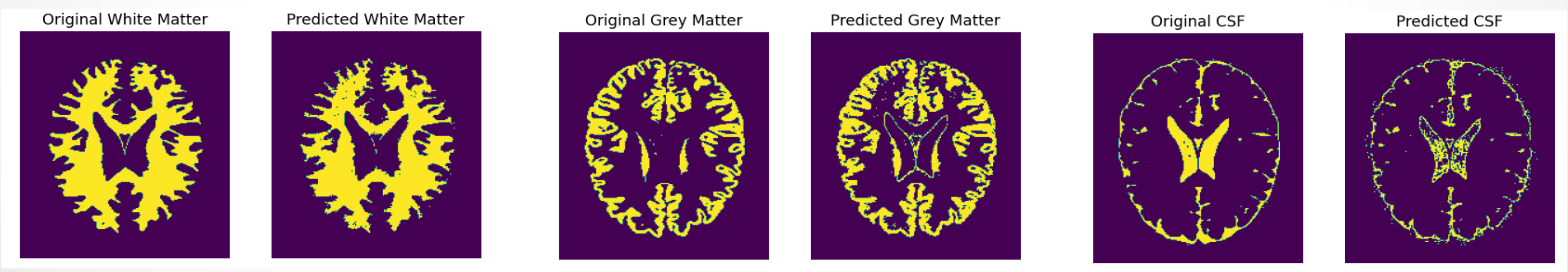




The original and the predicted masks of a random slice (slice- 85) from volume – 4(3,20)

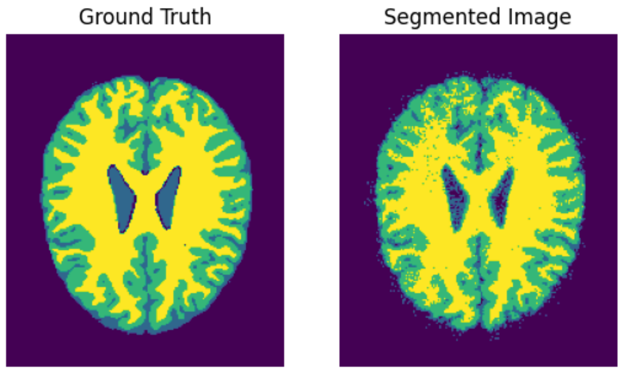
Results

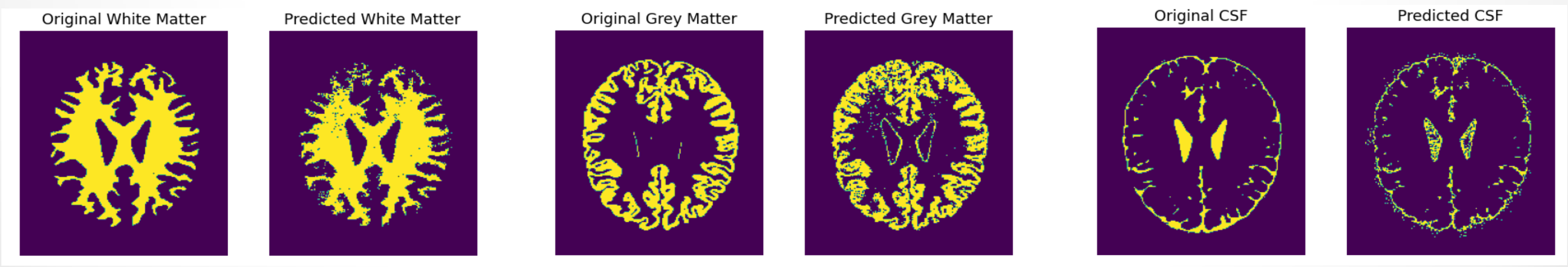




The original and the predicted masks of a random slice (slice- 92) from volume – 6(5,20)

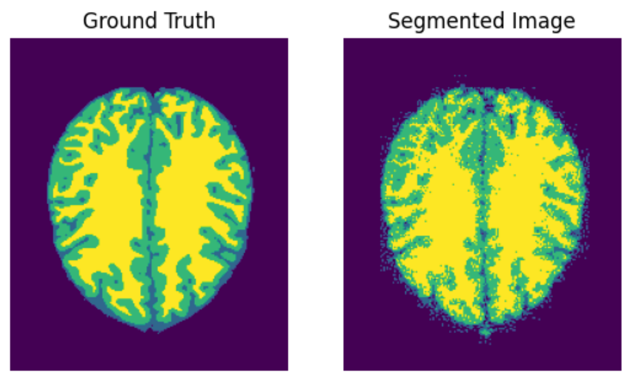
Results

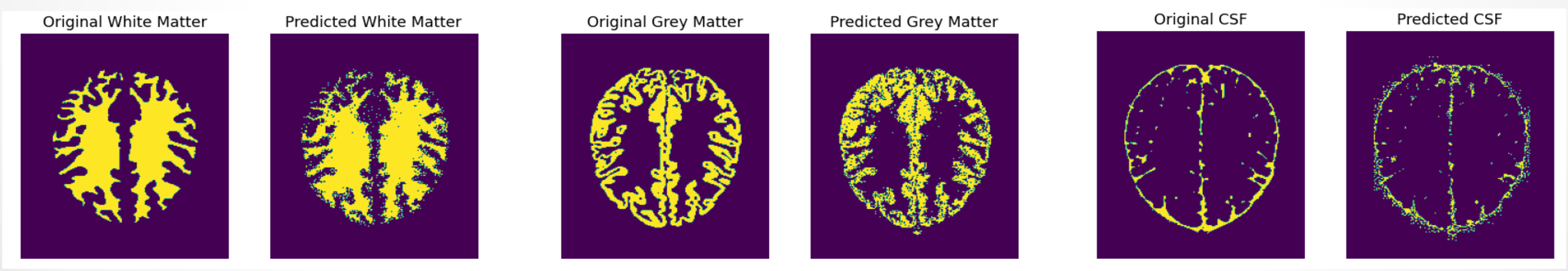




The original and the predicted masks of a random slice (slice- 98) from volume – 9(7,40)

Results





The original and the predicted masks of a random slice (slice- 108) from volume – 11(9,40)

Conclusion

- Medical image segmentation is vital for visualization, diagnosis, and treatment planning in clinical settings.
- Ongoing advancements in medical models lead to new segmentation challenges and the need for new techniques.
- This project highlights the effectiveness of Radial Basis Function Neural Network (RBFNN) for accurate brain MRI segmentation, delineating structures like CSF, grey matter, and white matter with promising outcomes.
- RBFNN's ability to identify patterns enables precise segmentation, while future research may explore other ML and Deep Learning methods like CNNs.
- It is important to acknowledge that the proposed algorithm is not without challenges. The increased complexity and computational requirements may lead to longer processing times. Despite computational challenges, RBFNN advancements offer hope for improved efficiency.
- Ultimately, this study demonstrates the effectiveness of RBFNN in brain MRI segmentation, contributing to the understanding of neuroanatomy and supporting clinical diagnosis and therapy planning for neurological illnesses.

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Thank You