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# **Classification of Alzheimer's and Dementia Subtypes Using R-STDP Driven Spiking Neural Networks**

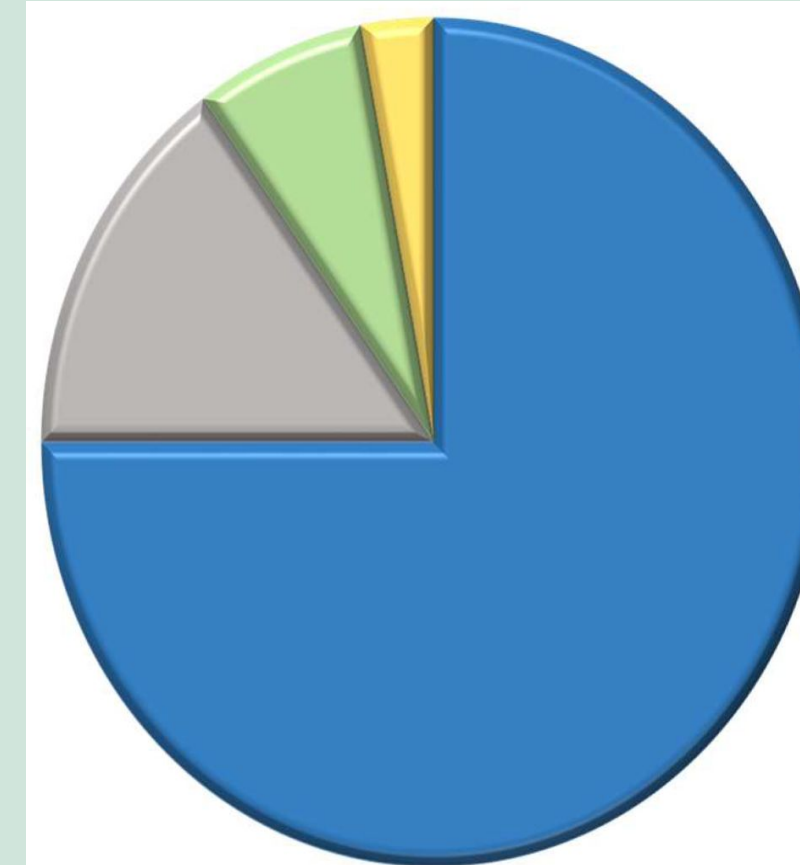


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# Significance of our research

## Current research gaps that we addressed

- Current diagnostic methods — slow, subjective, and resource-intensive
- Traditional deep learning models — computationally expensive and energy-inefficient
- Biologically implausible



■ Alzheimer's disease (AD) 75%

■ Vascular dementia (VD) 15%

■ Lewy body dementia (LBD) and frontotemporal dementia (FTD) 7%

■ Other 3%

# Literature Review

## ❖ Classification of Alzheimer's Disease Using Deep Convolutional Spiking Neural Network

### **Main contributions:**

- Integrating SNN with CNN for Alzheimer's detection.
- Using unsupervised spike pre-training to extract Alzheimer's features before supervised learning.
- Application of time-to-first-spike temporal encoding, enabling biologically inspired spike-based feature learning.
- Accuracy up to 90.15%

R. E. Turkson et al., "Classification of alzheimer's disease using deep convolutional spiking neural network," *Neural Processing Letters*, 2021.

## ❖ Spiking Neural Networks for Multimodal Neuroimaging: A Comprehensive Review of Current Trends and the NeuCube Brain-Inspired Architecture

### **Main contributions:**

- Introduced NeuCube as a 3D brain-inspired SNN framework
- comparative evaluation of SNN software and hardware platforms
- 97% accuracy in epilepsy and cognitive state classification

Garcia-Palencia et al., Spiking Neural Networks for Multimodal Neuroimaging: A Comprehensive Review of Current Trends and the NeuCube Brain-Inspired Architecture. *Bioengineering*, 2025

# Existing Research shortcomings:

- High training complexity
- **High computational complexity**
- Poor performance of SNNs on static MRI data compared to CNNs

## Problem Statement

**Designing a model to address the challenges of early detection of subtle neurostructural alterations caused by dementia and Alzheimer's disease using a neuromorphic feature extraction framework integrating temporal spike encoding with Forward-Forward learning to enable efficient and accurate classification.**

# Novelty

**Biologically inspired  
neuromorphic design**

**R-STDP – driven  
Spiking Autoencoder**

**Temporal spike encoding  
of MRI images**

**Energy-efficient and  
event-driven computation**

# Data Collection

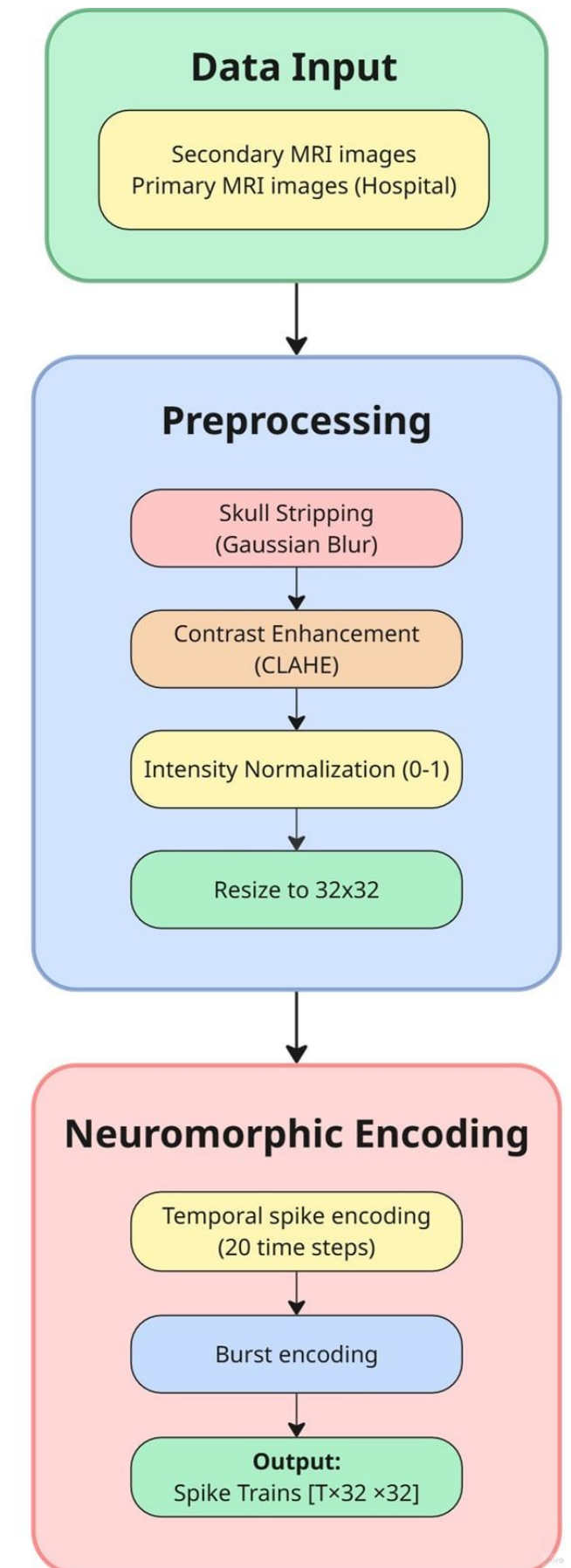
**Our research utilized two main sources of MRI data.**

- Publicly available MRI scans (secondary data) were used for the majority of model development and training.
- Includes pre-labeled grayscale images categorized by disease states.
- In addition to the secondary data, a primary dataset of MRI scans were collected from a collaborating hospital.
- This data was collected by following full institutional approval and ethical guidelines.

# Data Processing

## Robust Data processing pipeline to prepare MRI scans for analysis:

- Grayscale of primary data
- Skull stripping for removing non brain tissues from the MRI scans and isolating the brain region
- Denoising using Gaussian filtering, Otsu thresholding for brain segmentation, morphological operations to remove small and unnecessary artifacts from images.
- Noise reduction and contrast enhancement using CLAHE
- Normalization to standardize the range of pixel intensity values across all images



# Data Processing

Preprocessed images converted to spike trains using Temporal Encoding. Implements an intensity-to-timing mapping where higher pixel intensities generate earlier spike times.

$$t_{\text{spike}} = \text{int}((1 - I_{\text{norm}})(T - 1))$$

Each image resized to a standard 32x32 pixel format.

Random weighted sampling used to overcome class imbalance in datasets and ensure each class was represented adequately during training.

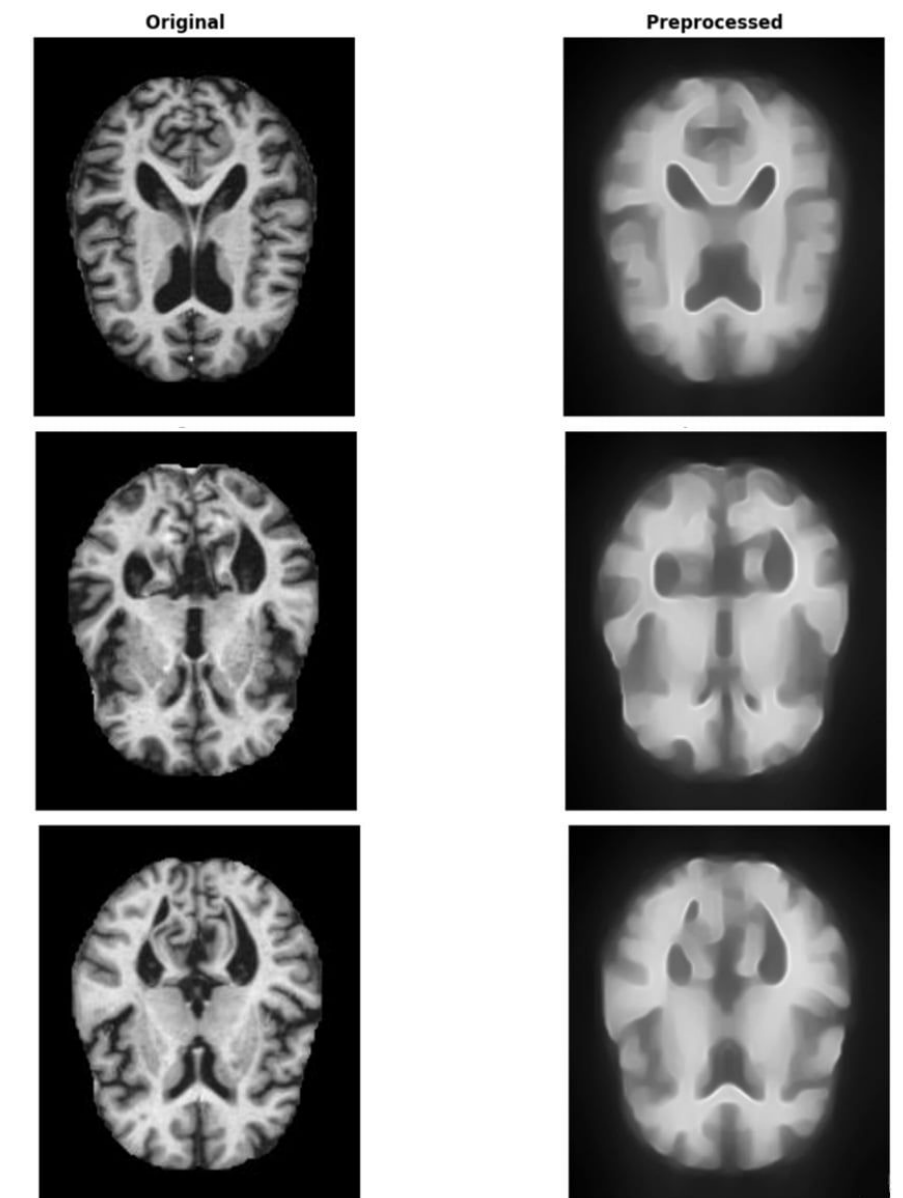
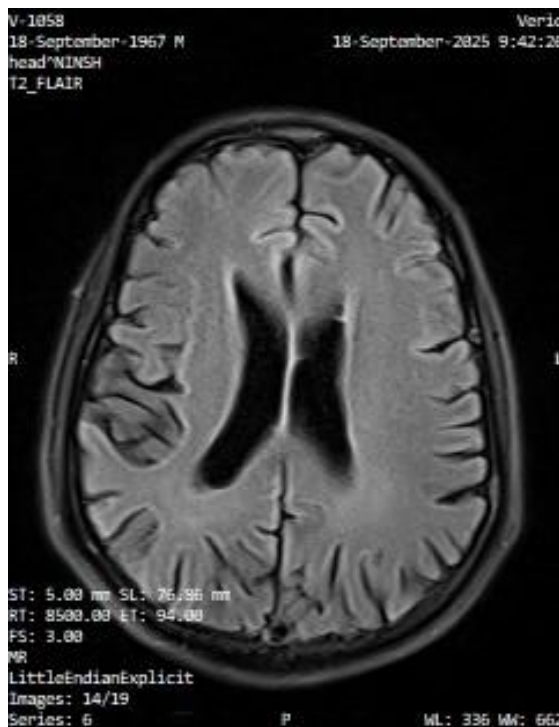


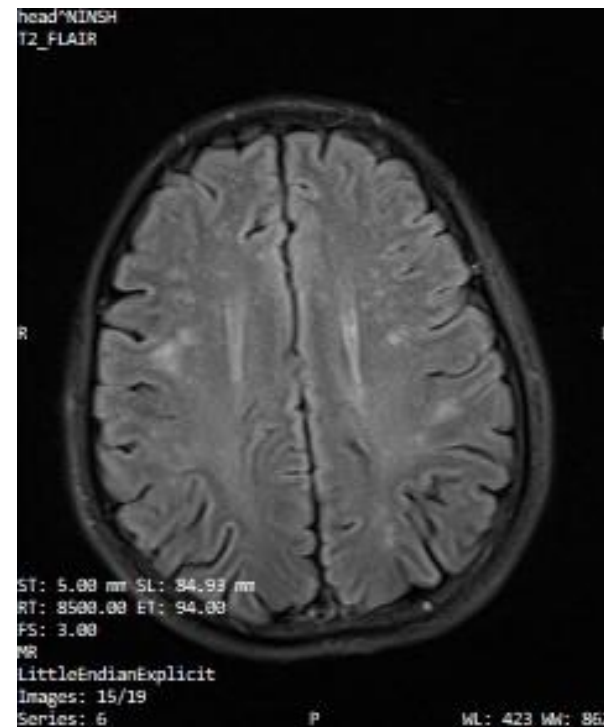
Fig: Original scans vs Preprocessed scans

# Primary Dataset

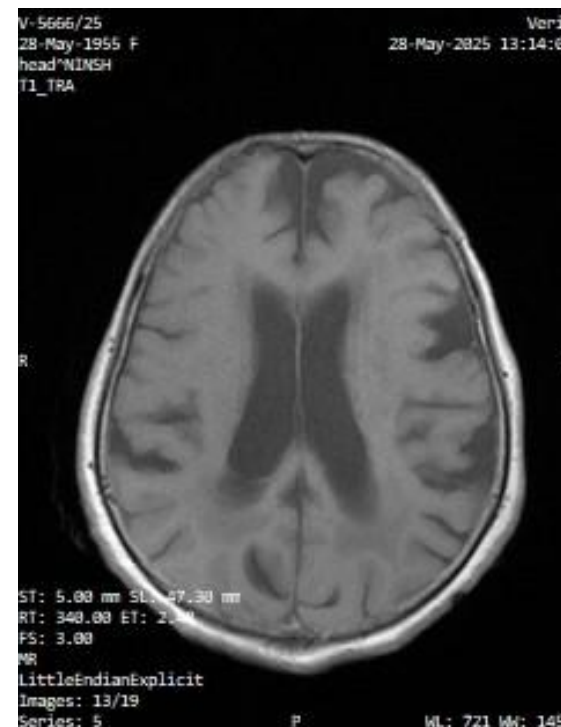
- Brain MRI scans collected in CDs (DICOM format)
- Collaborating hospital: National Institute of Neurosciences and Health, Agargaon
- **Data validation** by neurologist



Enlarged  
ventricle



Tissue  
discoloration

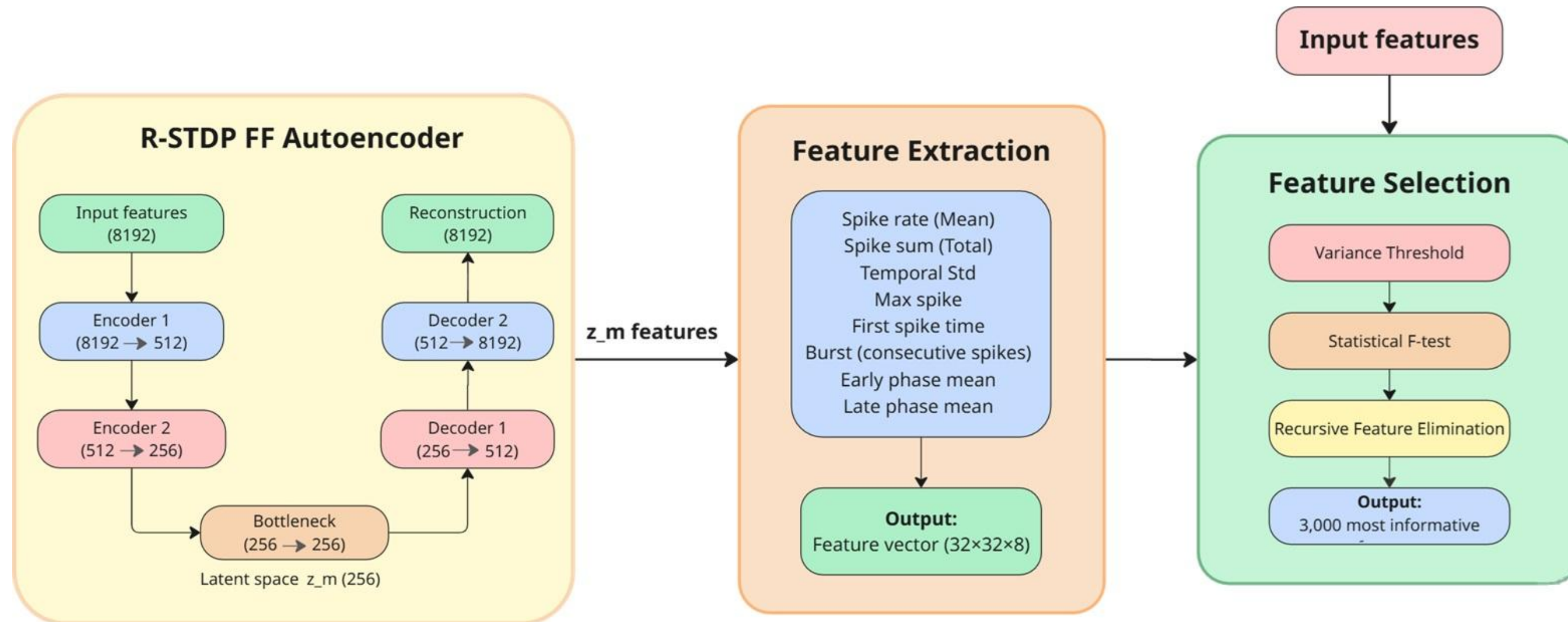


Atrophy(brain tissue shrinkage)



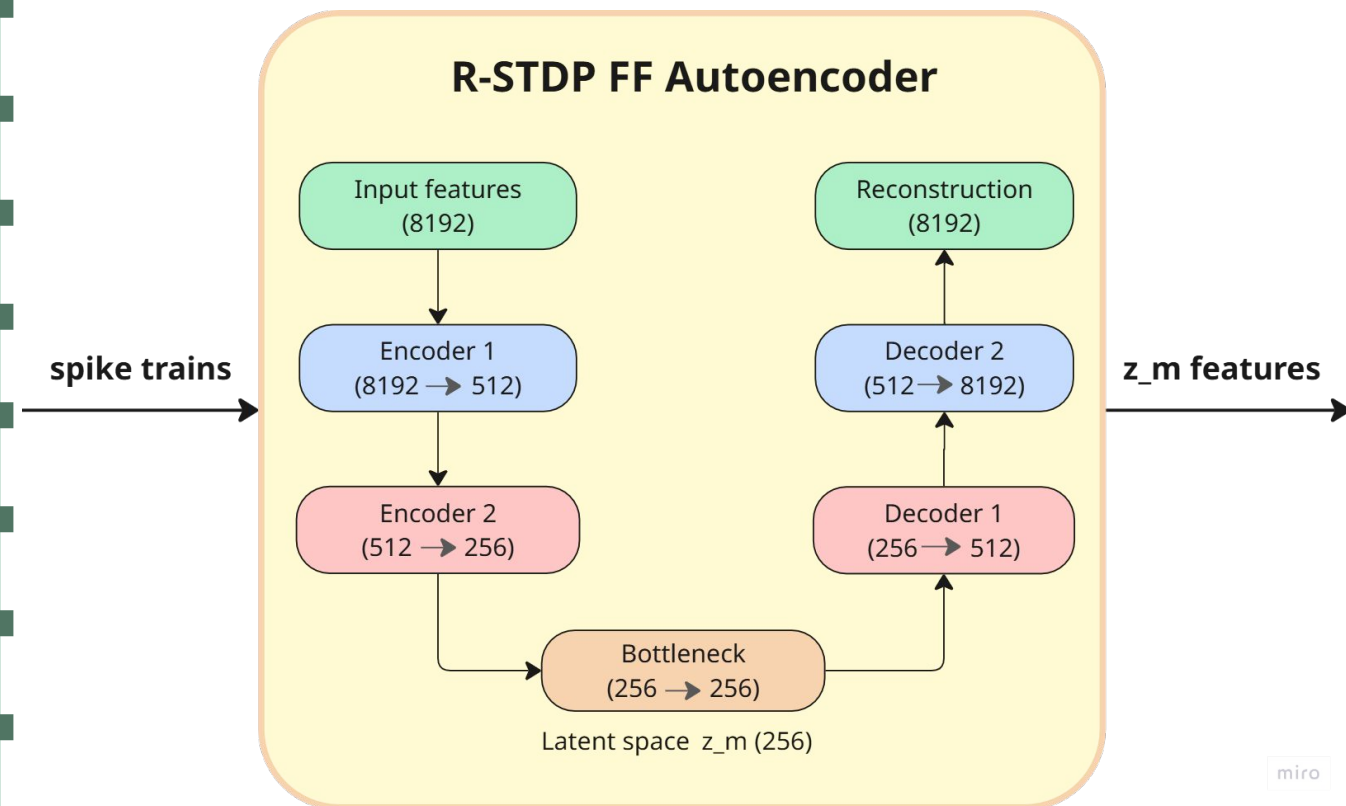
Normal Brain scan

# FF + RSTDP SNN Autoencoder Model Architecture



- classification of demented vs non demented from structural MRI
- no backpropagation

# R-STDP FF Autoencoder



R-STDP weight update:

$$W_{\text{STDP}}(\Delta t) = \begin{cases} A_+ e^{-\frac{\Delta t}{\tau_+}}, & \Delta t > 0 \\ -A_- e^{\frac{\Delta t}{\tau_-}}, & \Delta t < 0 \end{cases}$$

$$\Delta w(t) = \eta \cdot r(t) \cdot e(t)$$

Goodness score:

$$G = \sum_i h_i^2$$

## Reward-modulated STDP

- Synaptic changes depend on spike timing and task performance
- Positive reward for good output (accuracy of reconstruction)

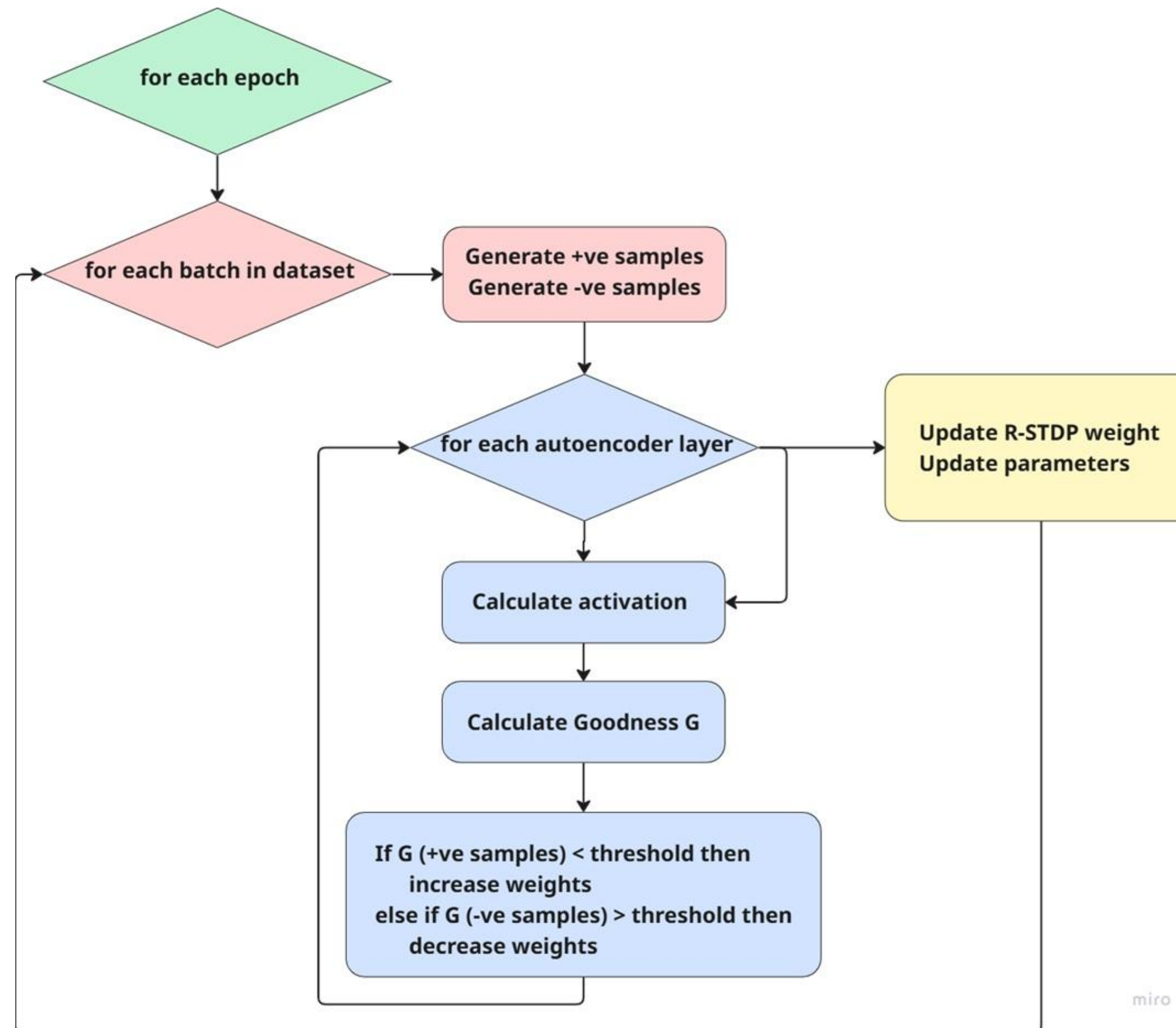
## Forward-Forward Learning (FF)

- Positive data: if goodness  $\ll$  threshold, increase weight
- Negative data: if goodness  $\gg$  threshold, decrease weight
- Each layer maximizes goodness for +ve data, minimizes for -ve
- No backpropagation or global error signals

## Autoencoder

- Compresses high-dimensional input to a bottleneck
- Latent space (bottleneck) captures most informative features

# Training algorithm



# Result Analysis of Proposed Model

- **Ensemble Classifier** for better performance.
- **Random Forest Classifier** with a 78.77% Accuracy and OOB score of 77.69%.
- **Gradient boosting** achieves an accuracy of 76.93%.
- Overall Accuracy of 77.92%

| Ensemble Components | Accuracy |
|---------------------|----------|
| Random Forest       | 0.7877   |
| Gradient Boosting   | 0.7693   |
| Ensemble            | 0.7792   |

Table 2 : Overall System Summary

| Metrics             | Overall |
|---------------------|---------|
| Accuracy            | 0.7792  |
| Precision(weighted) | 0.7947  |
| Precision(macro)    | 0.7449  |
| Recall(weighted)    | 0.7792  |
| F1-Score(weighted)  | 0.7841  |
| OOB Score           | 0.7769  |

Table 1 : Overall Performance Evaluation

# Result Analysis of Proposed Model

- Graphs show Reconstruction Loss **Decreased**, while the Reward Signal **Increased**

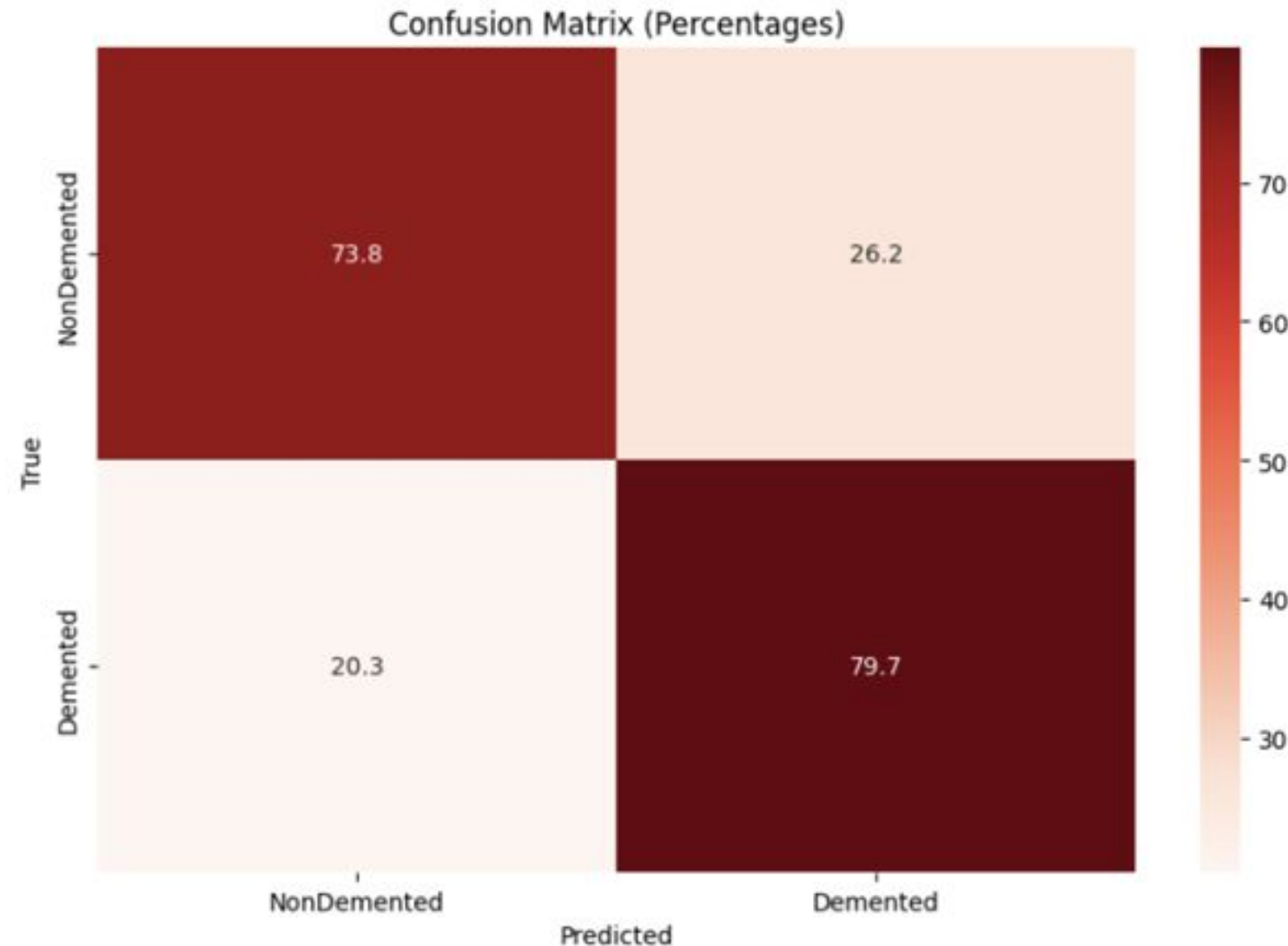


Figure: Confusion matrix of Model

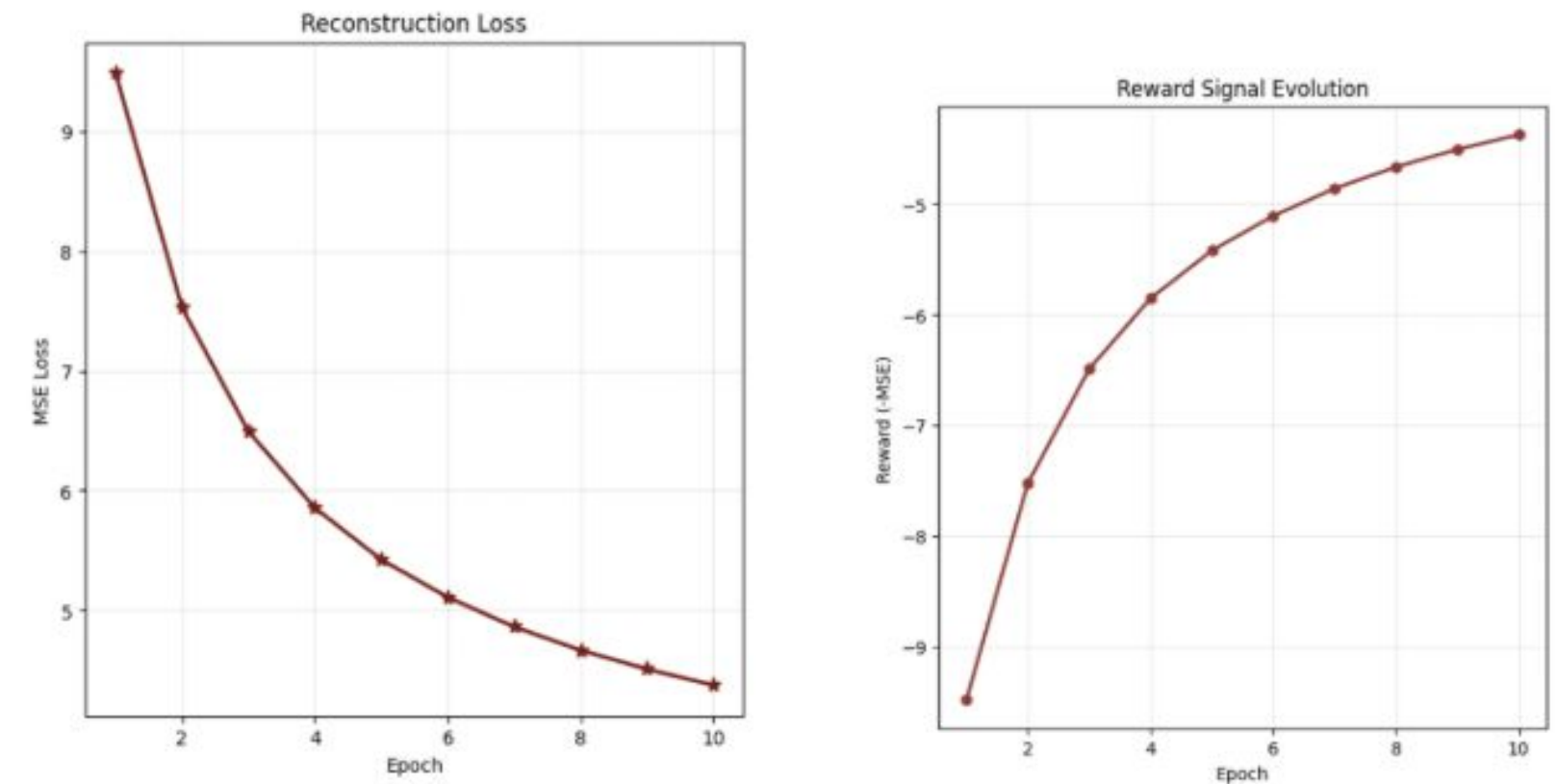


Figure: MSE Loss & Rewards per epochs

# Final Design Adjustments

- To improve Feature Extraction, we implemented **Transfer Learning**
- **ResNet-50 CNN** spatial features obtained and projected to a latent space ( $z_t$ )
- Fusion with latent space from **R-STDP Autoencoder** ( $z_m$ )

| Metrics             | Overall |
|---------------------|---------|
| Accuracy            | 0.8709  |
| Precision(weighted) | 0.8698  |
| Precision(macro)    | 0.8509  |
| Recall(weighted)    | 0.8709  |
| F1-Score(weighted)  | 0.8702  |
| AUC score           | 0.9361  |

Figure: Performance Evaluation of Fusion Model

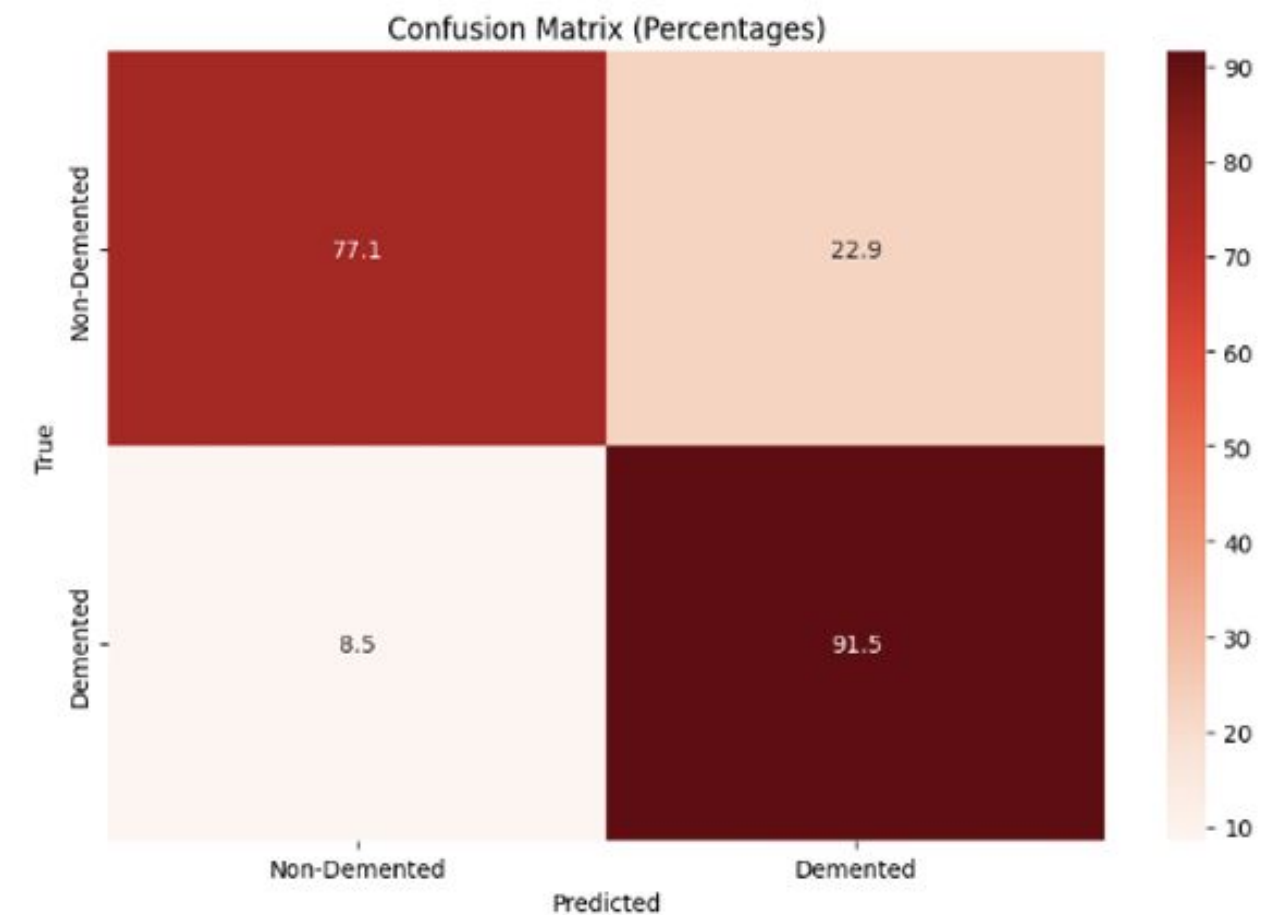
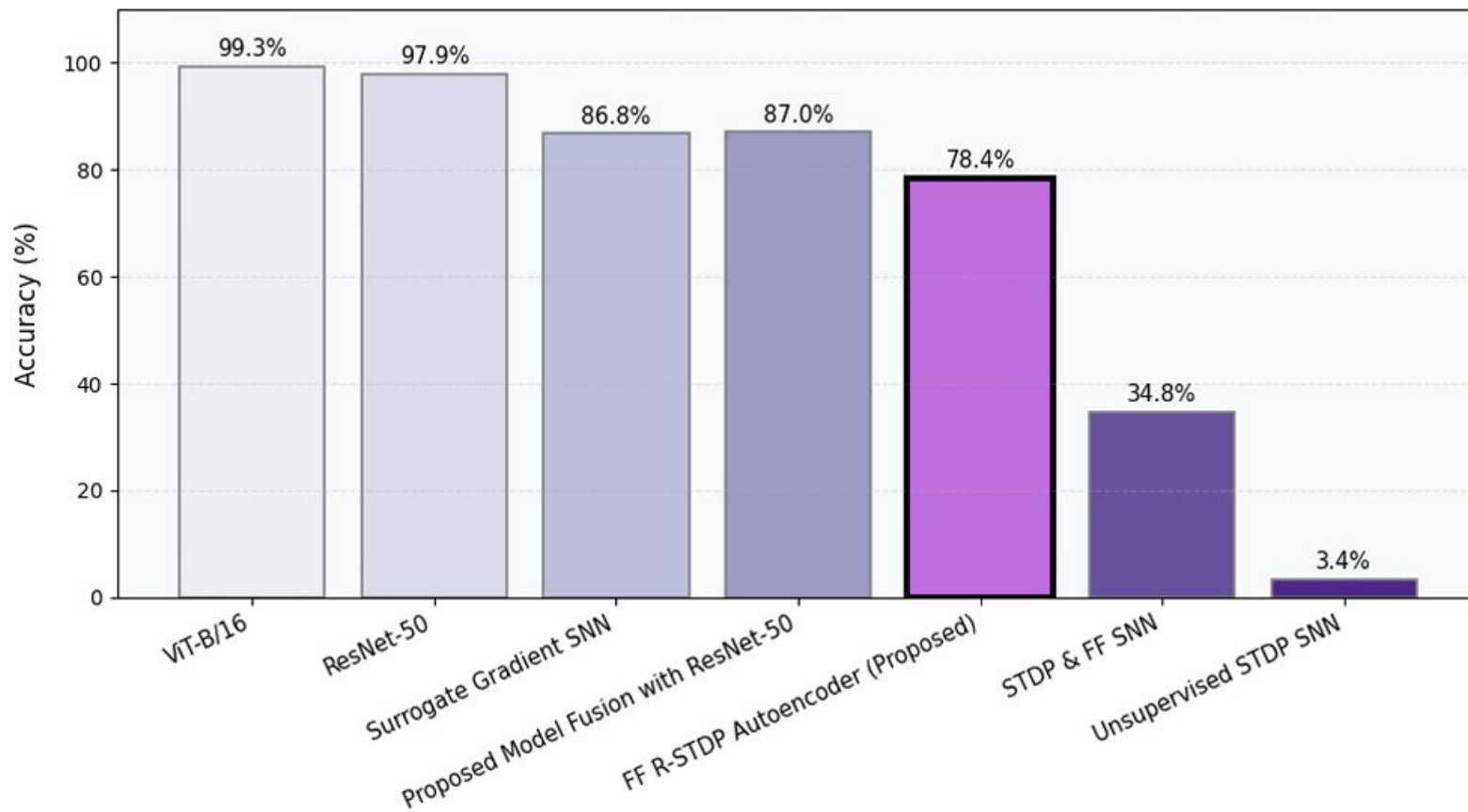


Figure: Confusion Matrix of Fusion Model

# Comparisons



| Model                                | Precision | Recall | F1 Score |
|--------------------------------------|-----------|--------|----------|
| ViT-B/16 (Vision Transformer)        | 0.9928    | 0.9928 | 0.9928   |
| ResNet-50 (CNN)                      | 0.9783    | 0.9821 | 0.9788   |
| SNN with Surrogate Gradient          | 0.8677    | 0.8703 | 0.8678   |
| Proposed Model Fusion with ResNet-50 | 0.8698    | 0.8709 | 0.8702   |
| FF R-STDP Autoencoder (Proposed)     | 0.7947    | 0.7792 | 0.7841   |
| SNN with STDP & FF                   | 0.3475    | 0.3646 | 0.3475   |
| Unsupervised STDP SNN                | 0.0196    | 0.1398 | 0.0343   |

# Contributions, Limitations & Future Work

## **Fundamental improvements:**

- Energy-efficient R-STDP SNN Autoencoder
- Forward-Forward learning combined with R-STDP can replace Backpropagation for feature learning.

## **Limitations:**

- Study focused on Binary Classification
- Lack of intensive pre-processing used to preprocess MRI scans
- Small size of primary dataset

## **Future work:**

- Multiclass Classification
- Multimodal Classification using synchronous datasets from MRI-EEG patients to detect neurodegenerative diseases such as Parkinson's.



**THANK YOU**