



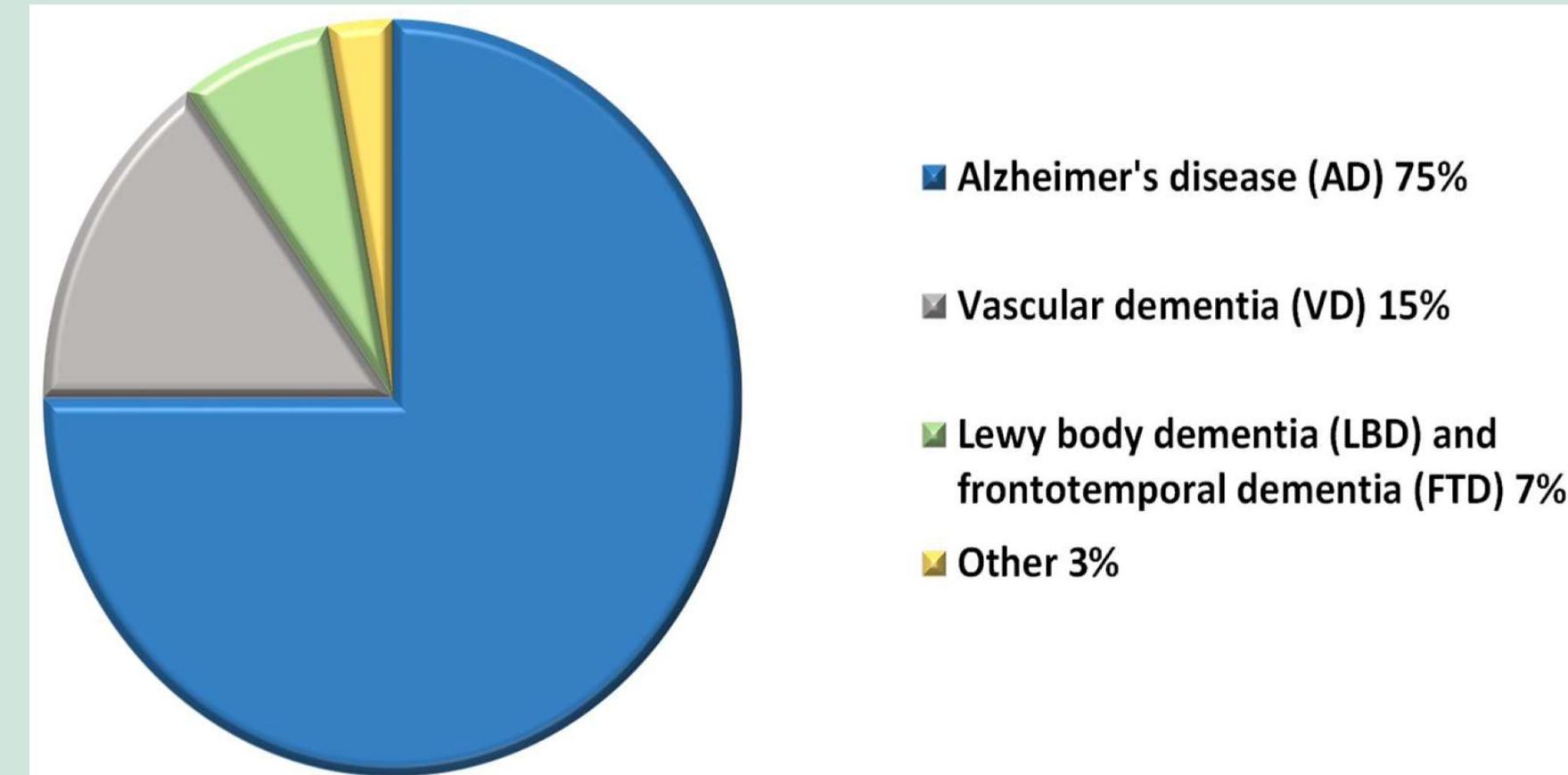
Classification of Alzheimer's and Dementia Subtypes Using R-STDP Driven Spiking Neural Networks



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



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

Problem Statement

Existing Research shortcomings:

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

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

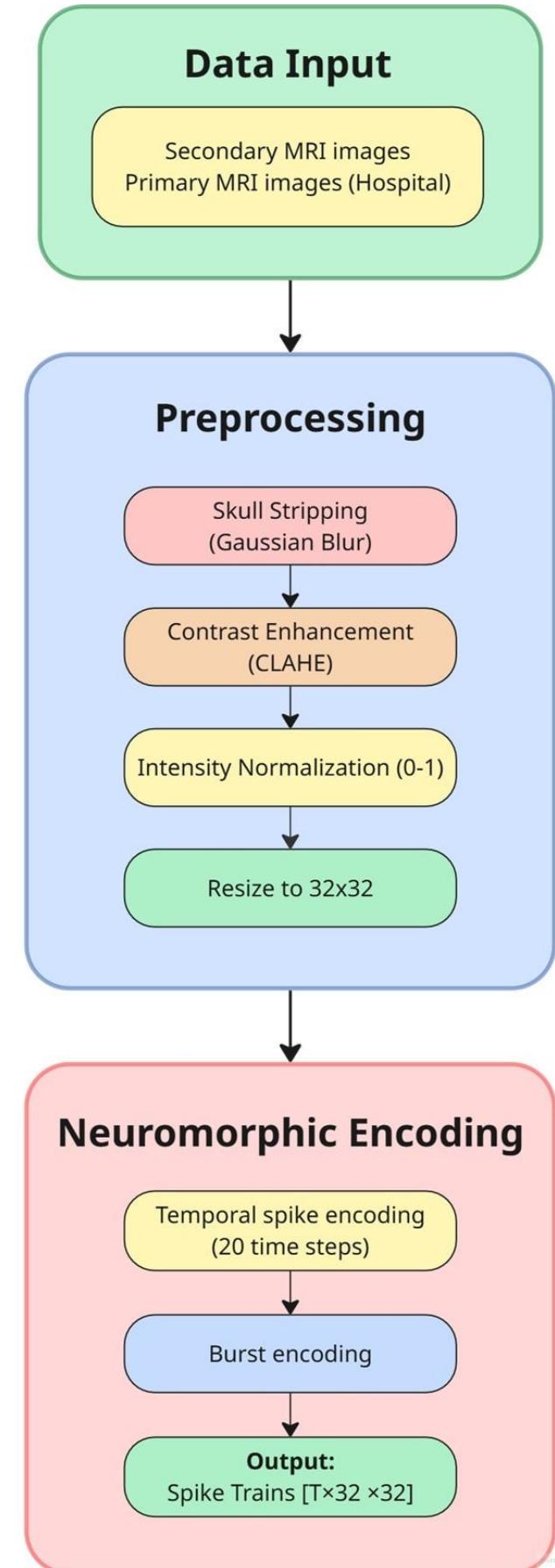
Our research utilized two main sources of MRI data.

- 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:

- Grayscaleing 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.

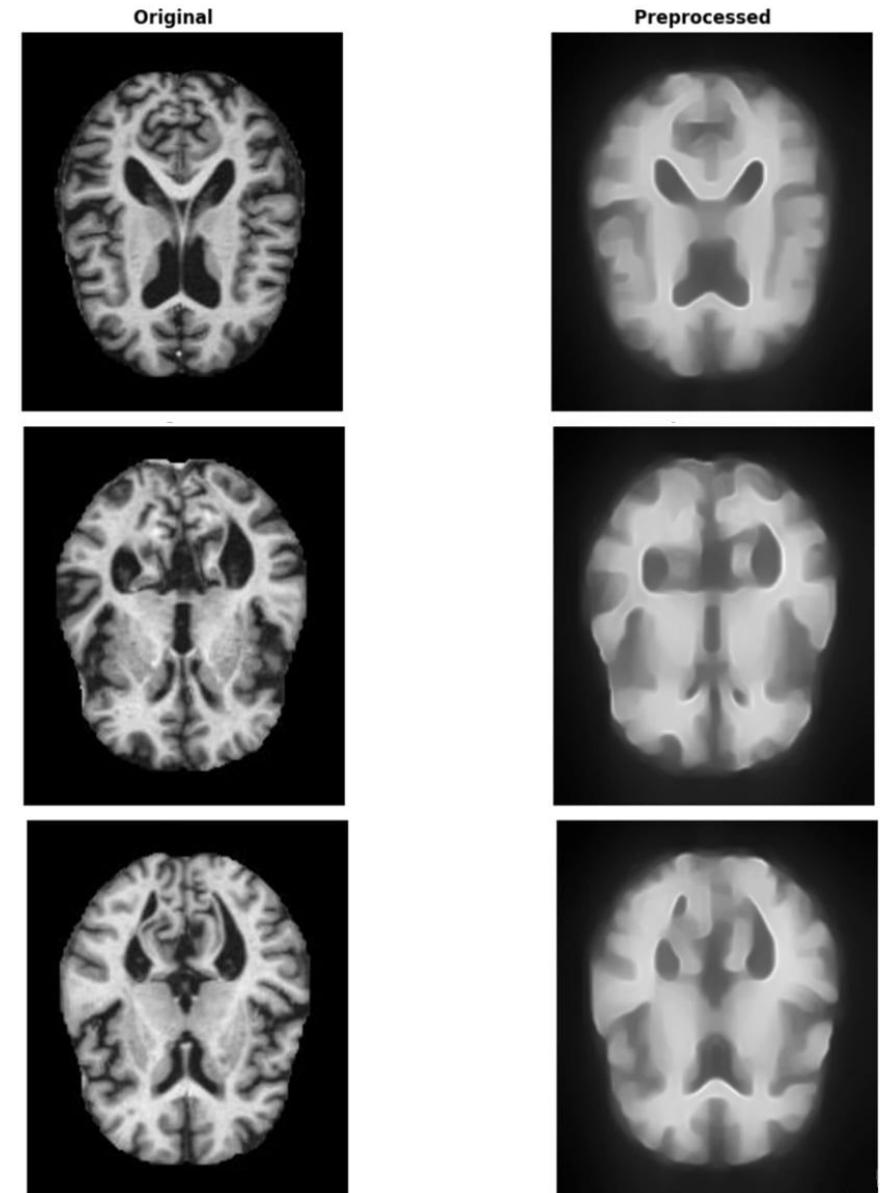


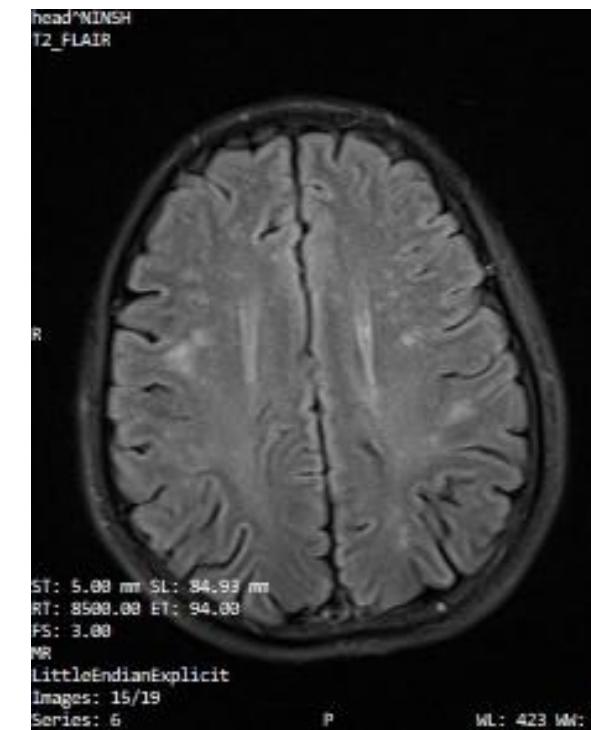
Fig: Original scans vs Preprocessed scans

Primary Dataset

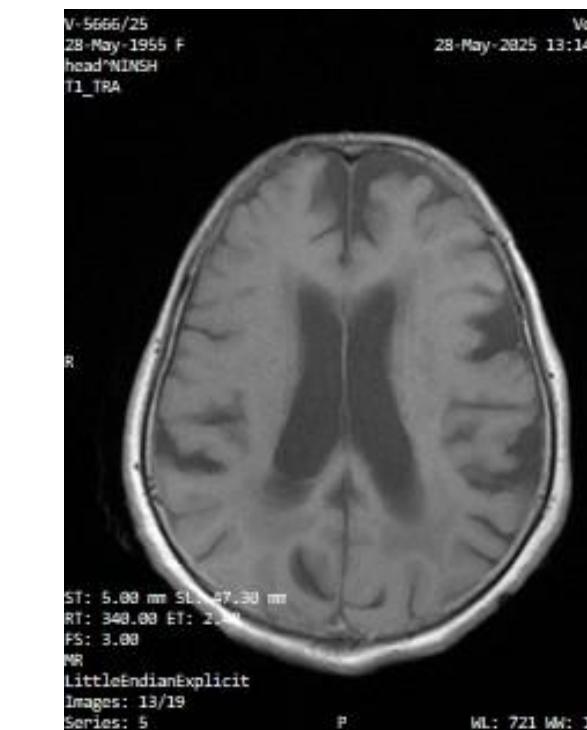
- Brain MRI scans collected in CDs (DICOM format)
- Collaborating hospital: National Institute of Neurosciences and Health, Agargaon
- **Data validation** by neurologist



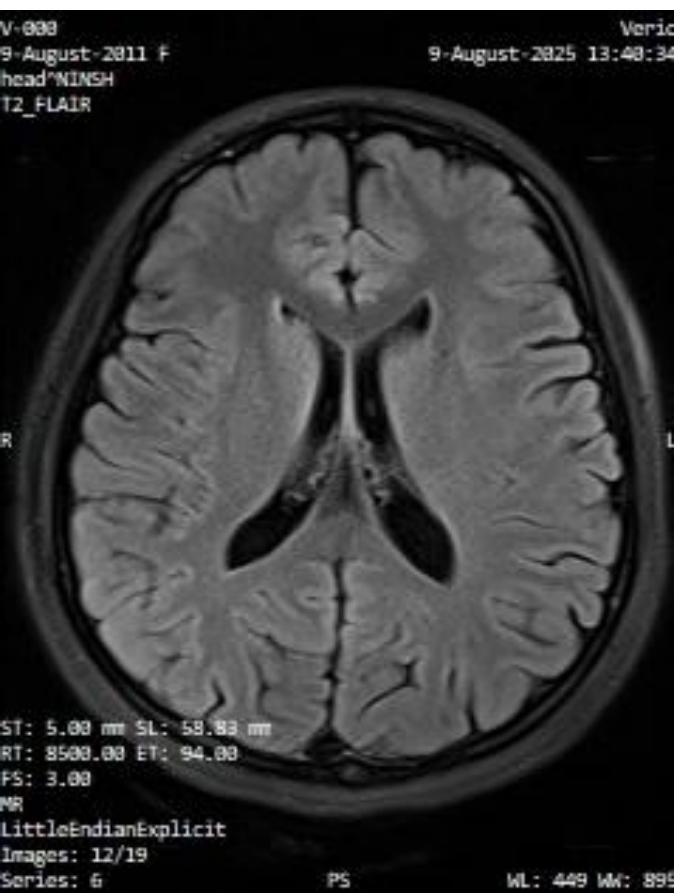
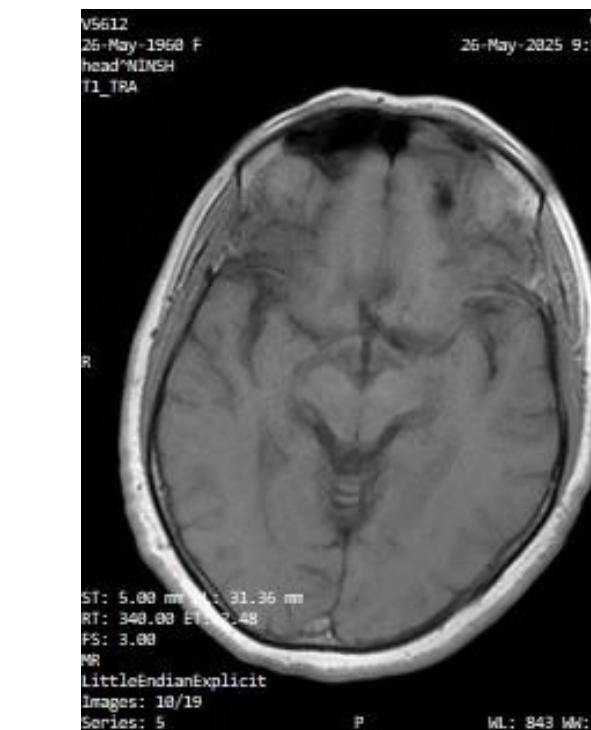
Enlarged ventricle



Tissue discoloration

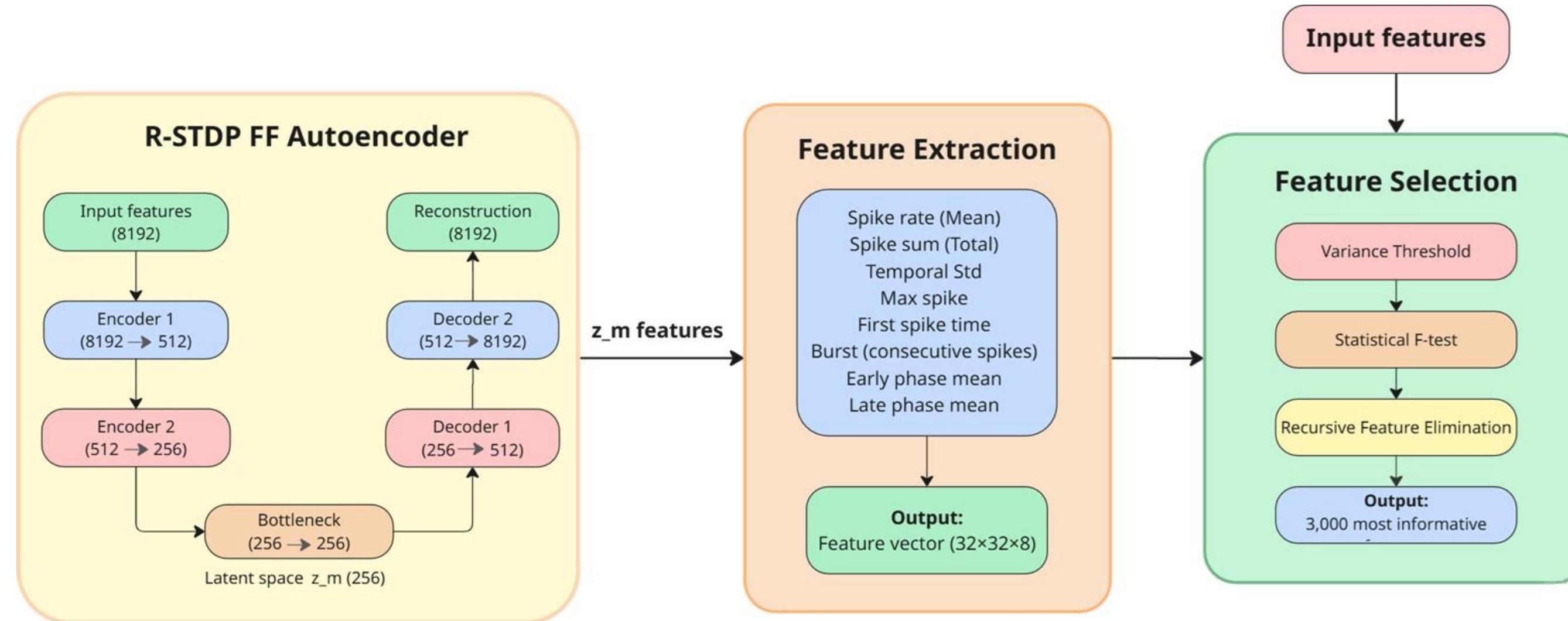


Atrophy(brain tissue shrinkage)



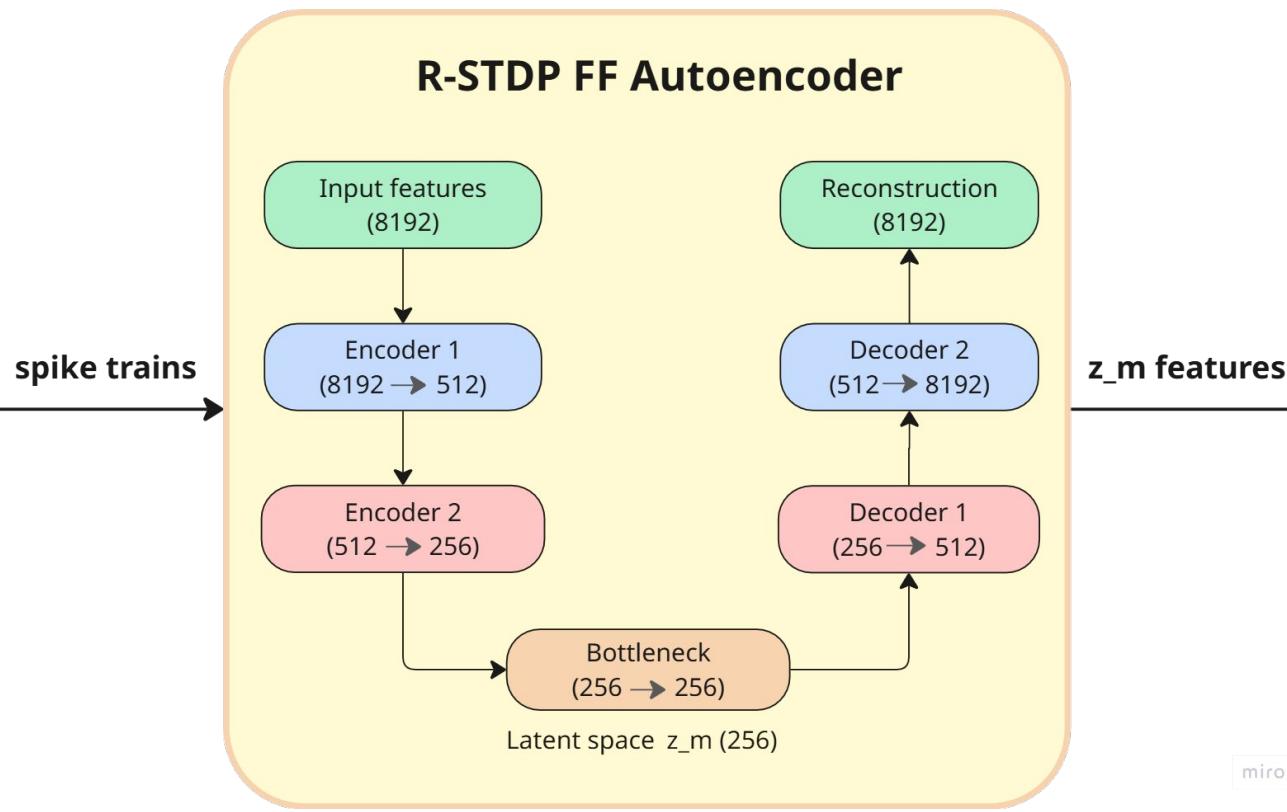
Normal Brain scan

FF + R-STDP 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)

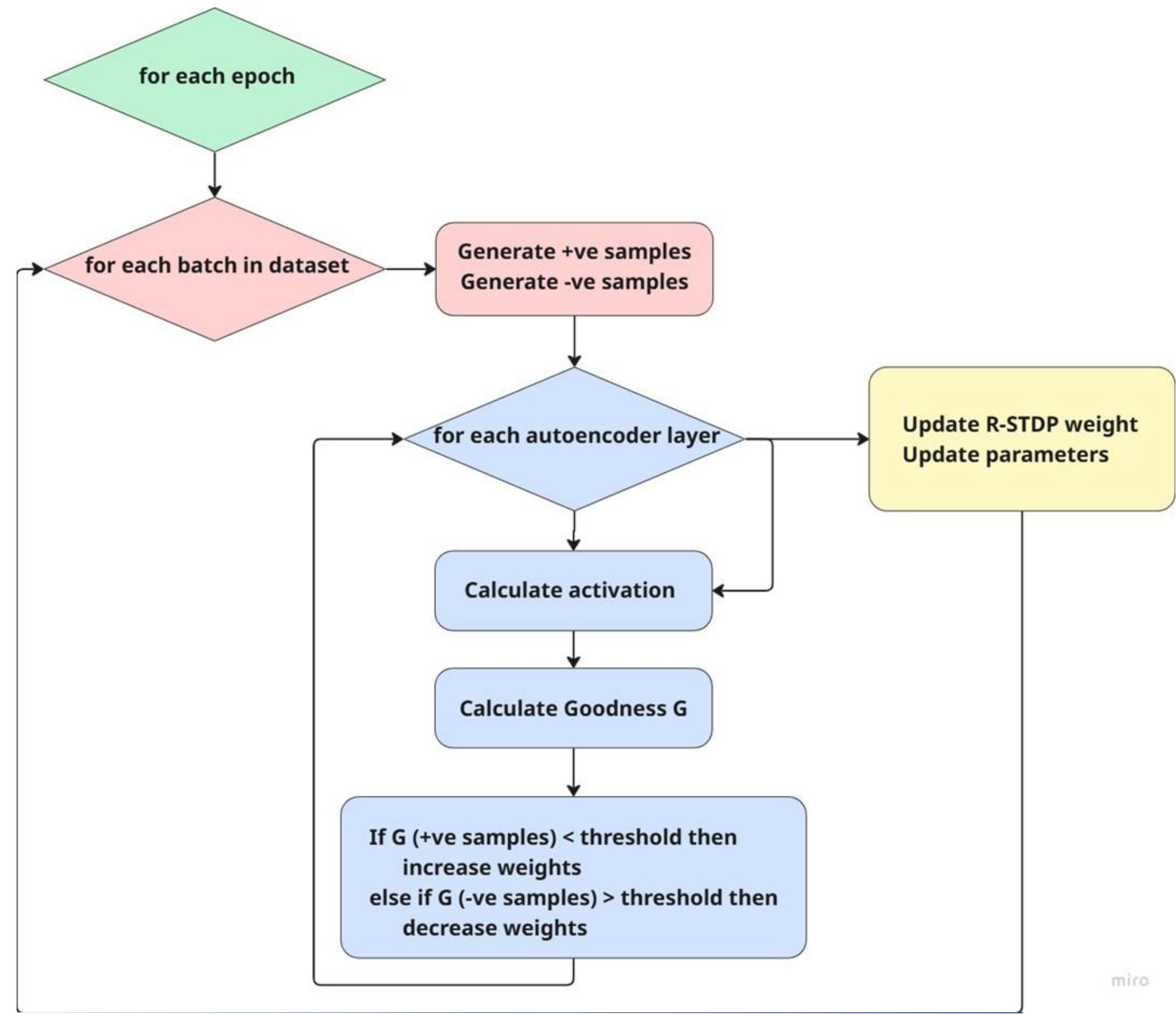
Forward-Forward Learning (FF)

- Positive data: if goodness < threshold, increase weight
- Negative data: if goodness > 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**

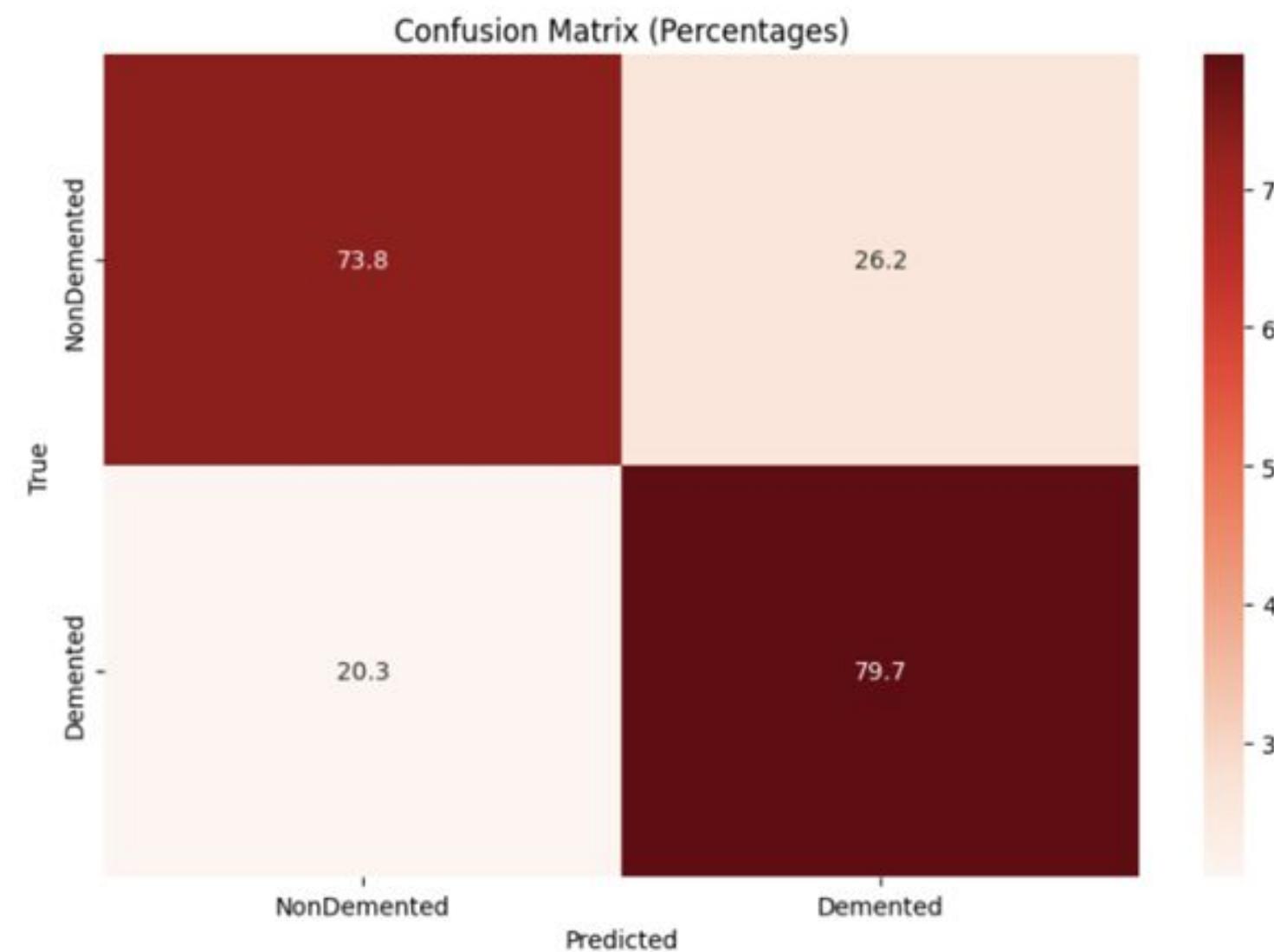


Figure: Confusion matrix of Model

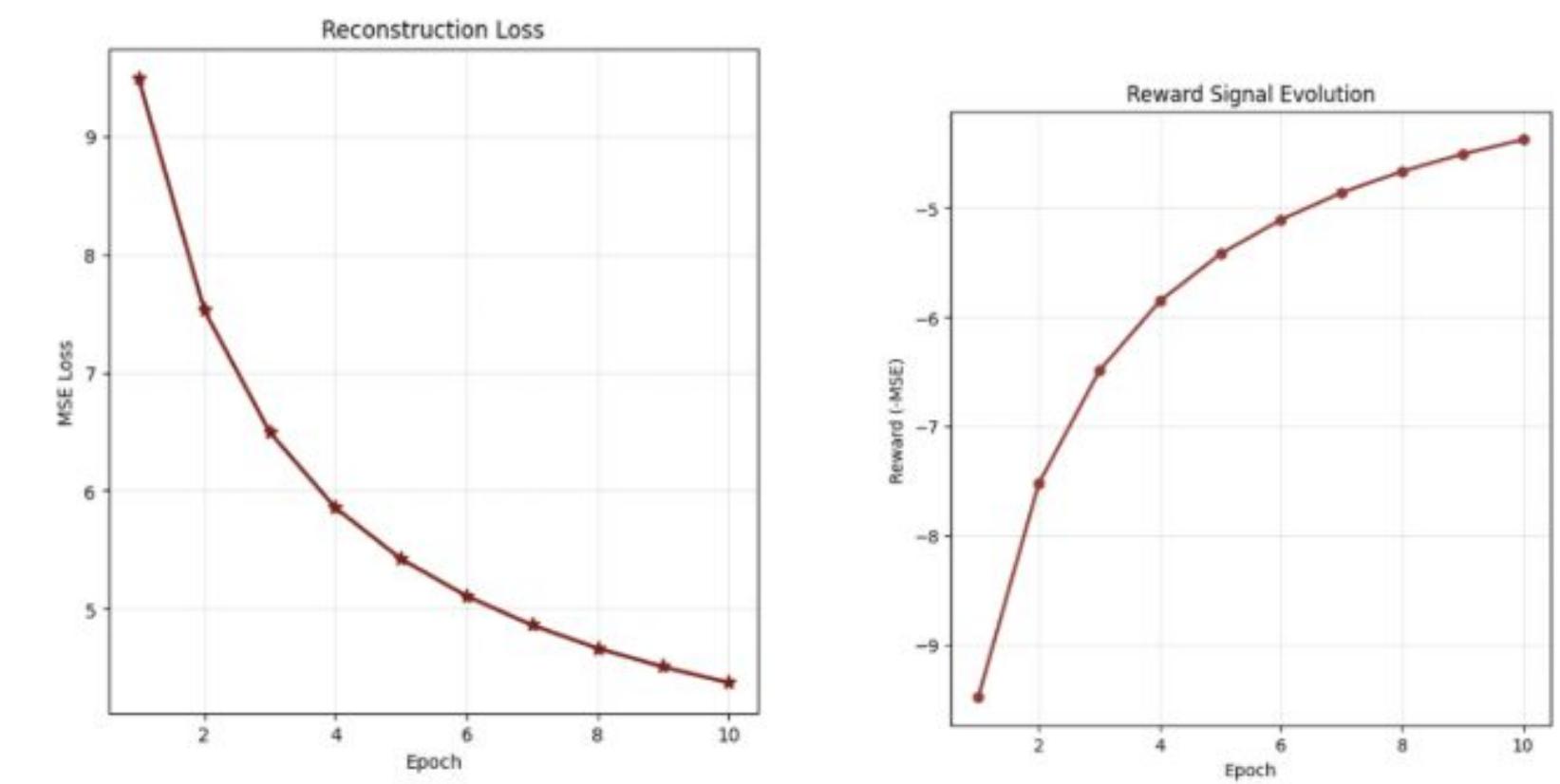


Figure: MSE Loss & Rewards per epochs

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

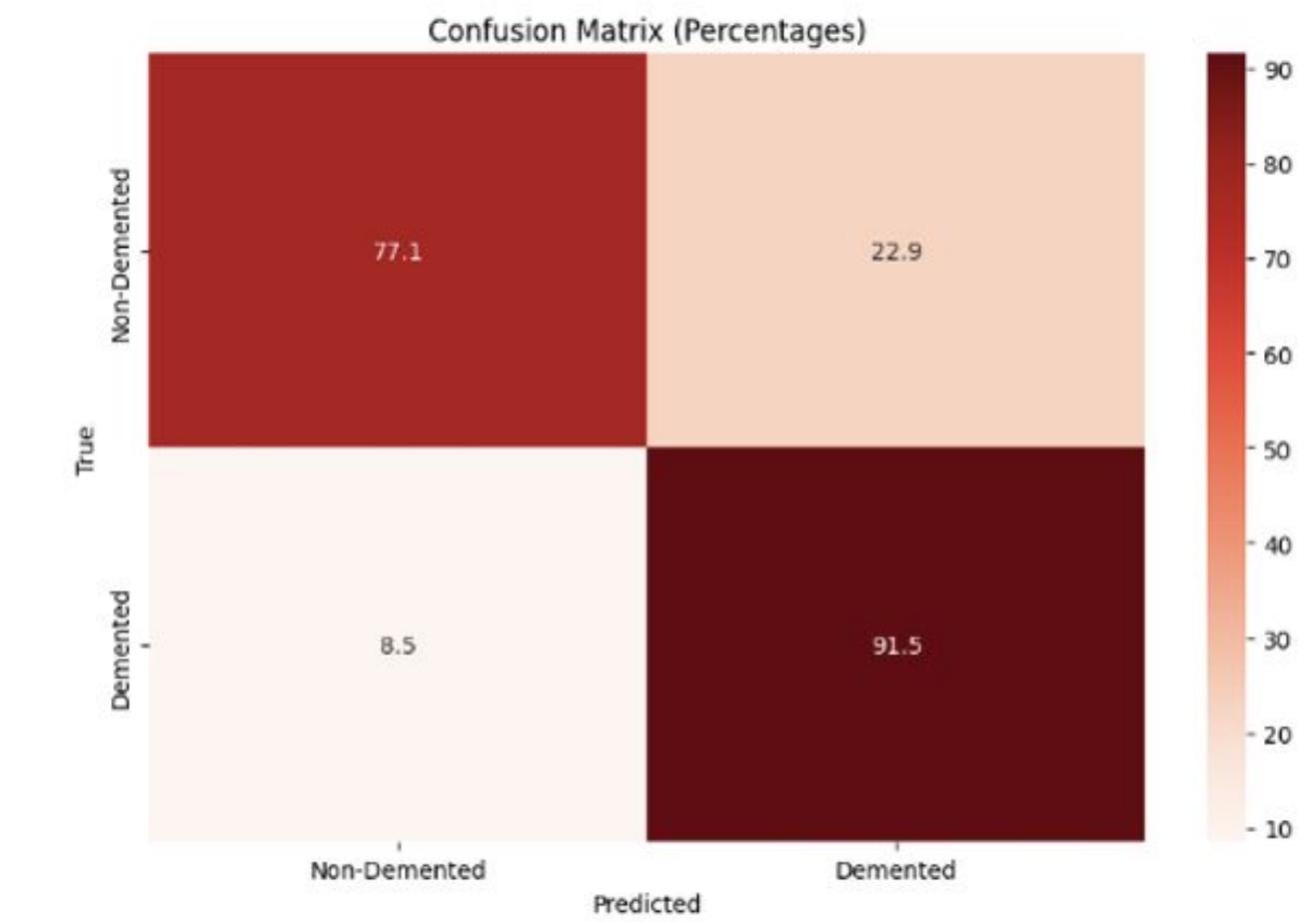
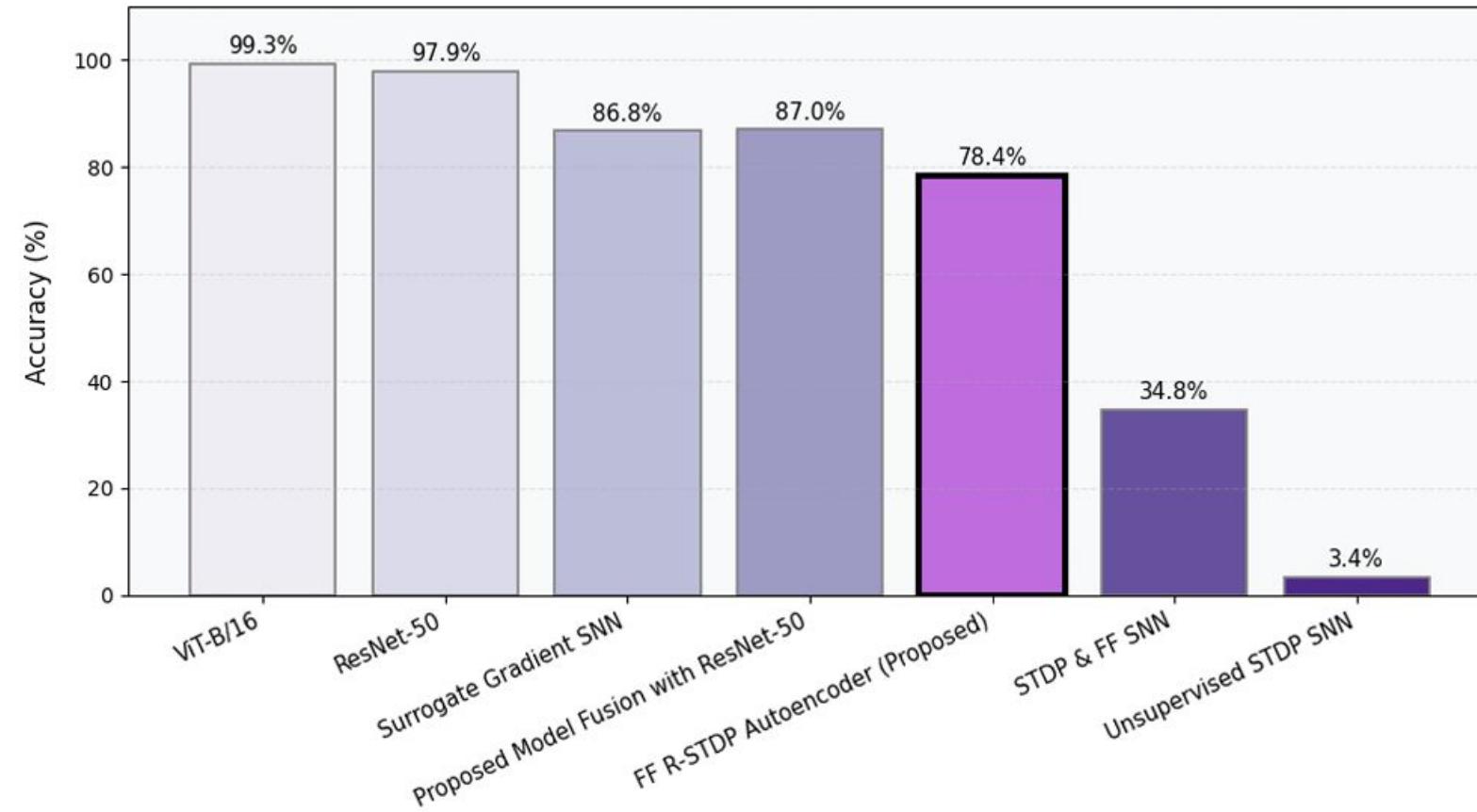


Figure: Confusion Matrix of Fusion Model

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

