Brain-Inspired Neuromorphic Computing for Breast Cancer Classification

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Introduction and Motivation

Enabling Energy Efficiency and Fault Tolerance through neuromorphic approach

- Neuromorphic Computing: Low latency, Fault Tolerance, Cognitive flexibility
- Features:
  - Reduced power consumption
  - Parallel processing capabilities
  - Hardware failures/noise resilience

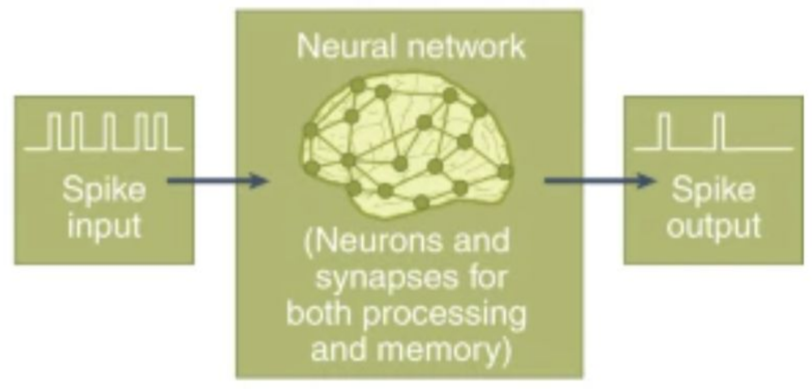


Image Source: https://www.nature.com/articles/s43588-021-00184-y

Problem Statement: Binary Classification for Mammography Breast Cancer Dataset

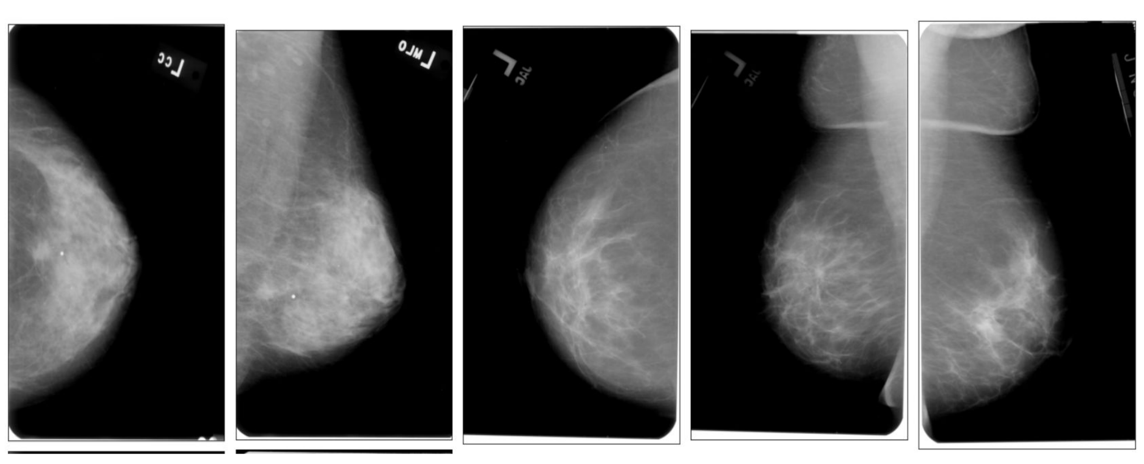


Image Source: https://www.kaggle.com/datasets/awsaf49/cbis-ddsm-breast-cancer-image-dataset

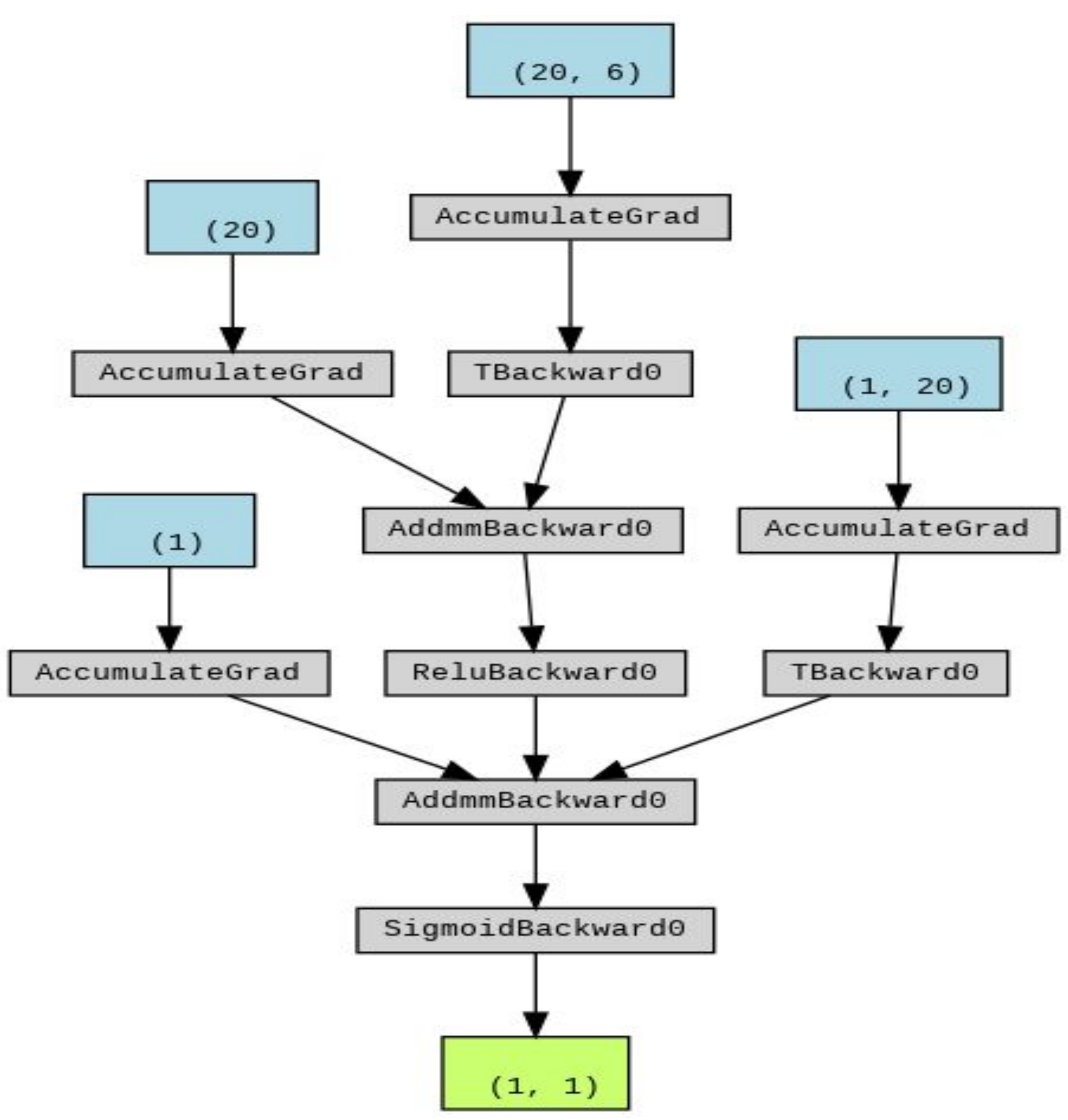
Applying Neuromorphic features enables:

- Enhanced Image Processing
- Adaptability capabilities
- Real time pattern recognition
- Real-Time analysis and Decision Support

Neural Network Model Architecture

GOAL: **Efficient** and **accurate** breast cancer tumor classification into benign or malignant class through **neuromorphic computing principles**: spiking neurons, event-driven processing, adaptive learning

Network Architecture:



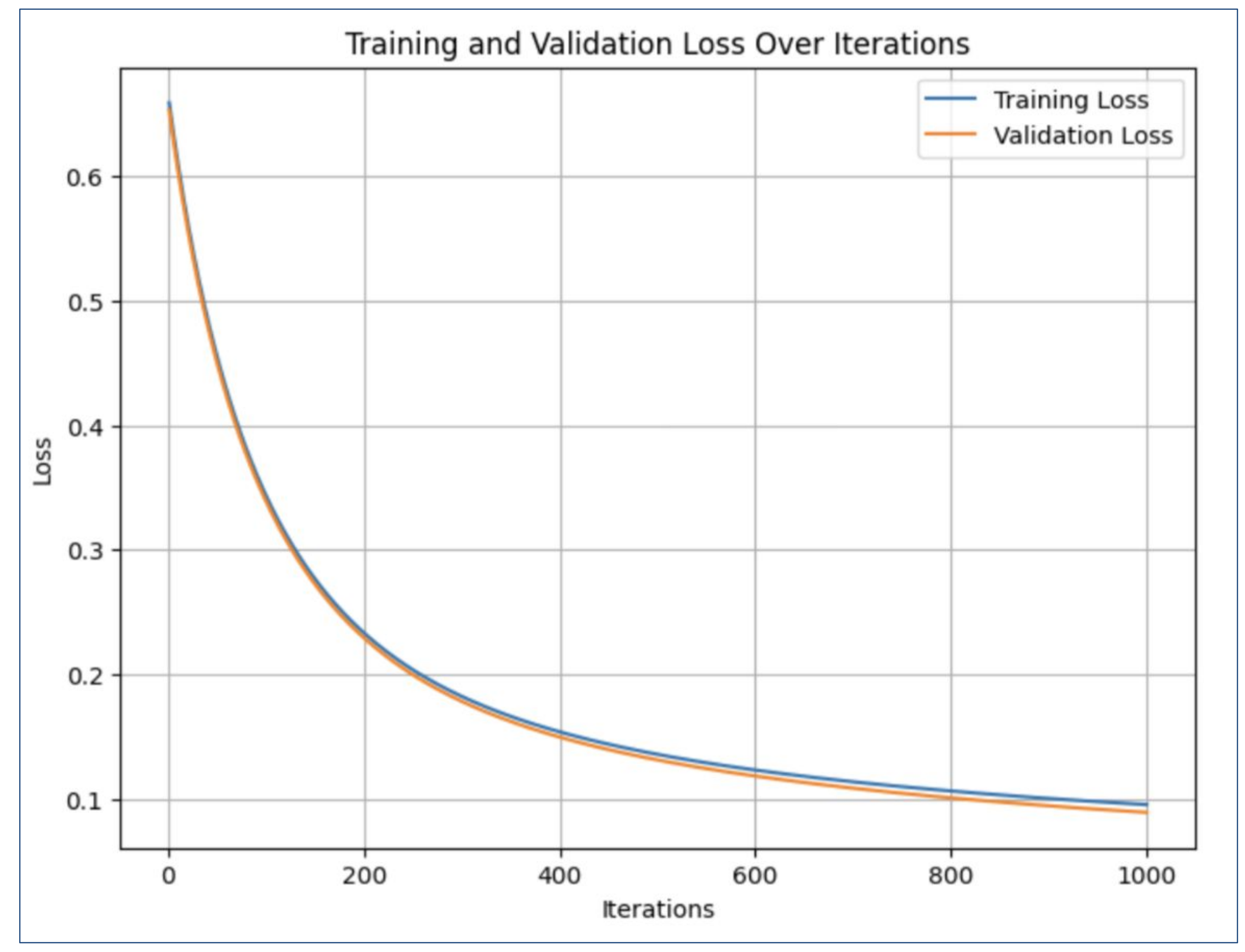
Input Layer: **5** input features extracted from mammography images:

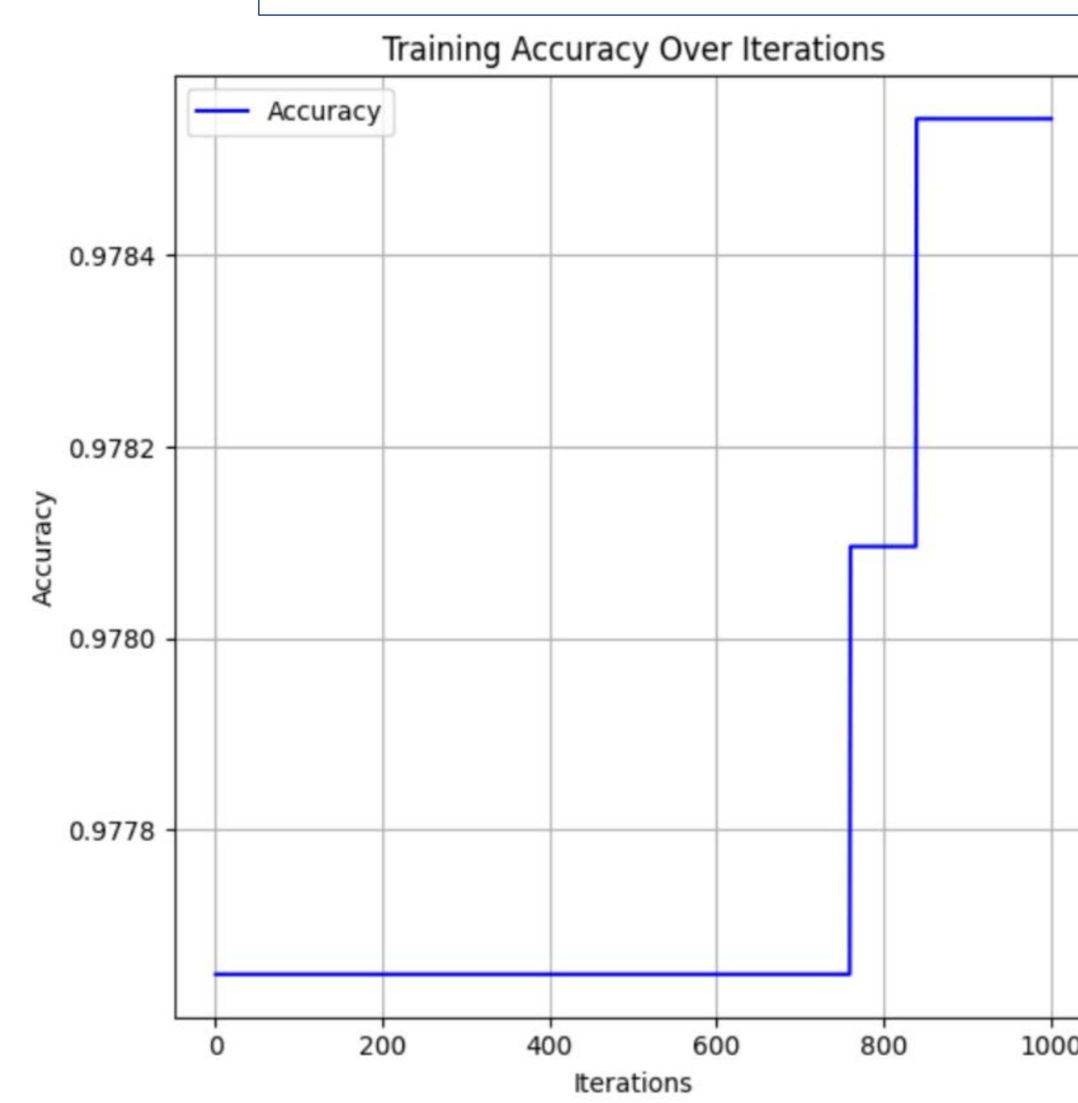
1. **BI-RADS assessment**: 1 to 5
2. **Age**: In years
3. **Shape**: round=1 oval=2 lobular=3 irregular=4
4. **Margin**: circumscribed=1, microlobulated=2 obscured=3 ill-defined=4 spiculated=5
5. **Density**: high=1 iso=2 low=3 fat-containing=4

- **Multi-Layer Perceptron**: Neural network used for this binary classification task
- **Fully Connected Layer 1:** Processes input features through linear transformations (Weights = 120, Biases = 20)
- **ReLU Activation Function**: Introduces non-linearity, mimicking the firing behavior of neurons in spiking neural networks
- **Fully Connected Layer 2**: Processes output from previous layer and maps it to a single output neuron (Weights = 400, Biases = 20)
- **Sigmoid Activation Function:** Provides a bounded output (probability of input sample belonging to positive class - malignant tumor)
- **Binary Output:** 0 for benign, 1 for malignant (Output Layer: Weights = 20, Biases = 1)

Training, Optimization, and Results

- Number of Epochs: **1000**, Learning Rate = **0.01**





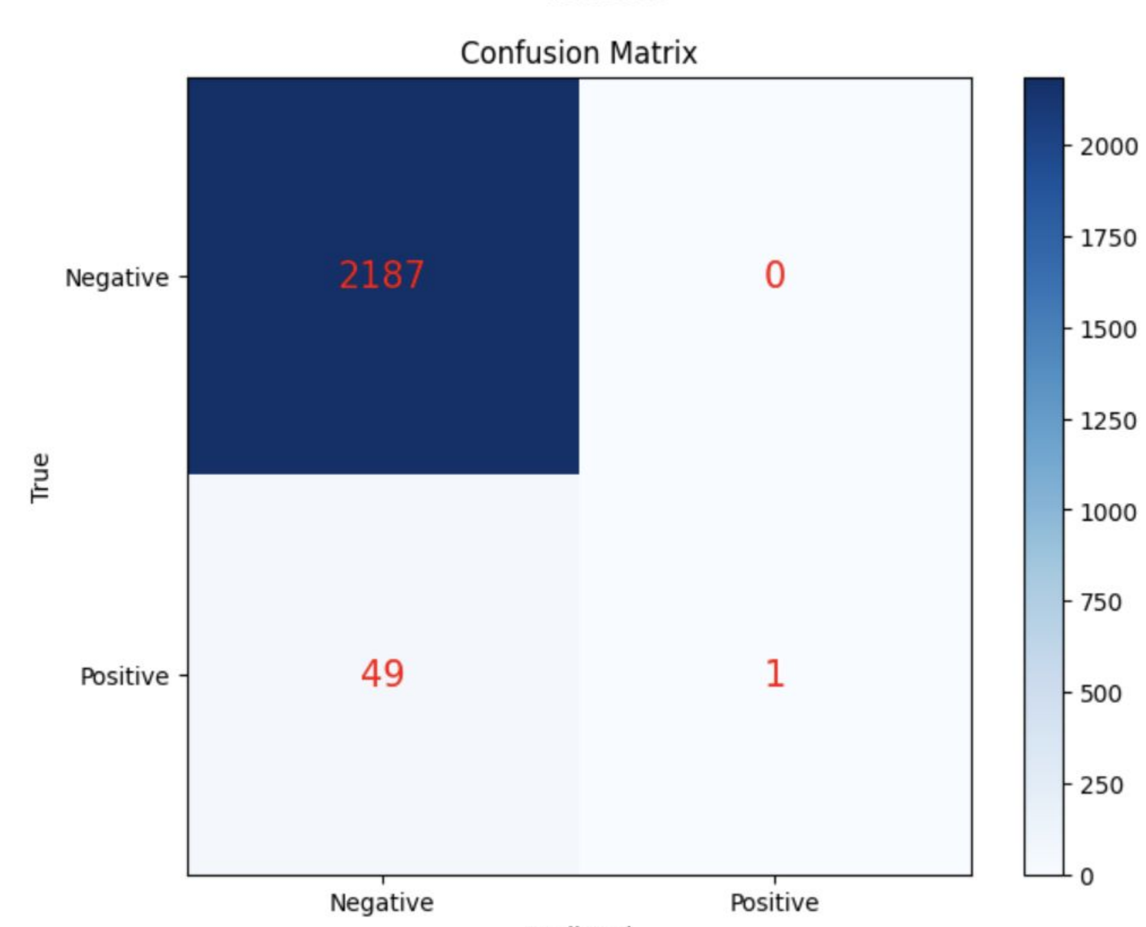
Accuracy is calculated using:

$$Accuracy\ Metric = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}$$

Model has a final **accuracy** of **97.856%**

Classification Report:

	precision	recall	f1-score	support
0	0.98	1.00	0.99	2187
1	1.00	0.02	0.04	50
accuracy			0.98	2237
macro avg	0.99	0.51	0.51	2237
weighted avg	0.98	0.98	0.97	2237



Classification Report:

Precision, Recall, F1:

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

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

$$F1 = \frac{2 \times precision \times recall}{precision + recall}$$

- For **class 0**, **98%** of the predictions are correct
- For **class 1**, **precision** is **1.00** (all predictions are correct)

Future Goals and Acknowledgements

Future Goals:

- Study the effect of quantization (INT8/4) to inference accuracy for various neural network models
- Model the data flow of hardware CiM machines using scripting language and build a compiler to streamline hardware neural network implementation
- Explore TinyML for edge applications using CiM machines.

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