VISION-BASED EXPLAINABLE DIAGNOSIS FRAMEWORK FOR BREAST CANCER

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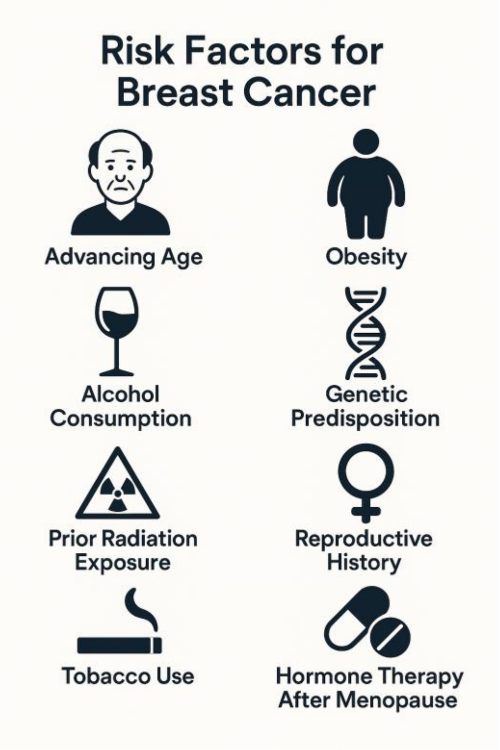
INTRODUCTION & KEY INSIGHTS

- Breast cancer is the most commonly diagnosed cancer among women globally and a leading cause of cancer-related deaths, accounting for approximately 685,000 deaths worldwide in 2020.
- Early and accurate diagnosis is critical for improving patient outcomes and survival rates.
- In South Africa specifically, it is estimated that 1 in 27 women will be diagnosed with breast cancer during their lifetime
- Medical imaging interpretation is complex and subject to variability among clinicians.
- AI and deep learning (CNNs) show promise in automating cancer detection from images.
- Challenges include model generalization across populations and lack of explainability.



LITERATURE REVIEW:DEEP LEARNING IN CADX

CNNs are widely used for medical image classification and detection.

Achieve higher accuracy, sensitivity, and specificity than traditional ML methods
.

Breast cancer imaging modalities: Mammograms, Ultrasound, MRI, PET, and CT.

Many CADx systems integrate CNNs with segmentation models (e.g., U-Net).

Hybrid CNN architectures (YOLO, ResNet, DenseNet, EfficientNet, etc.) enhance feature extraction and accuracy.

Challenges: Dense breast tissue, small tumors, varying image quality.

Explainable AI (XAI)

Tools like Grad-CAM provide heatmaps for decision transparency.

Improves trust and adoption in clinical practice.

Current Limitations:Lack of interpretability (black-box problem). Limited generalization across datasets.

Opportunity: Combine CNNs + segmentation (U-Net) with XAI to achieve accurate and interpretable CADx predictions

COMPREHENSIVE FRAMEWORK

The pipeline integrates preprocessing, segmentation (U-Net), classification (CNN), and explainability (Grad-CAM).

Uses publicly available data from TCIA, supporting reproducibility and clinical relevance.

Adoption of hybrid CNN architectures inspired by state-of-the-art models.

Image Preprocessing

- Automated DICOM Data Pipeline (Extracts raw pixel data from dicom images via automated data mapping pipeline)
- Handles resizing, normalization & One-hot encoding
- Handles data annotation efficiently
- process includes artifact suppression, breast segmentation, and pectoral muscle removal, isolating diagnostically relevant regions

Image Segmentation

- custom U-Net-like Segmentation (NumPy Implementation)
- Manually implements convolution, pooling, upsampling, and activation functions.
- Extract 64 feature channels per image

Explainability (XAI)

- Grad-CAM visualizes image regions influencing model decisions.
- Global average pooling on gradients , Weighted sum of feature maps , ReLU + normalization to highlight important regions
- Generates overlays for multiple classes

Classification

- **Custom CNN** to classify tumors as *benign* or *malignant*.
- Layers & Functions - **Convolution** ,**ReLU** ,**Max-Pooling** ,**Batch Normalization** ,**Dropout** ,**Fully Connected Layers, Sigmoid Output**

COMPREHENSIVE FRAMEWORK

- CNN implementation
- Implements convolution, max pooling, dense, and output layers from scratch using NumPy
- Mini-batch gradient descent with accumulation.
- Gradient clipping to prevent unstable updates
- Uses He/Xavier initialization, dropout, LeakyReLU, and gradient clipping.
- Trains on encoded breast cancer dataset with mini-batch gradient descent
- Layers & Functions - Dense ,ReLU ,Max-Pooling ,Batch Normalization ,Dropout ,Fully Connected Layers, Sigmoid Output
- MaxPooling (forward + backward)
- Saves the best model weights during training for inference

Dense forward	$Z = Wx + b$
Activation	$A = \mathrm{LeakyReLU}(Z)$
Softmax	$p_i = e^{z_i} / \sum e^{z_j}$
Loss	$L = -\sum y \log(p)$
Backprop (output)	$dZ = p - y$
Grad weights	$dW = dZ \cdot A^T$
Grad biases	$db = dZ$
Backprop through ReLU	$dA = W^T dZ, dZ = dA \cdot 1_{Z>0}$

PIPELINE OVERVIEW

Preprocessing & Feature Extraction

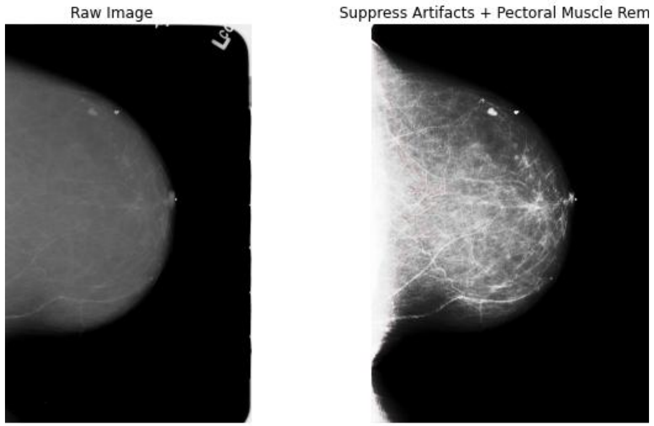
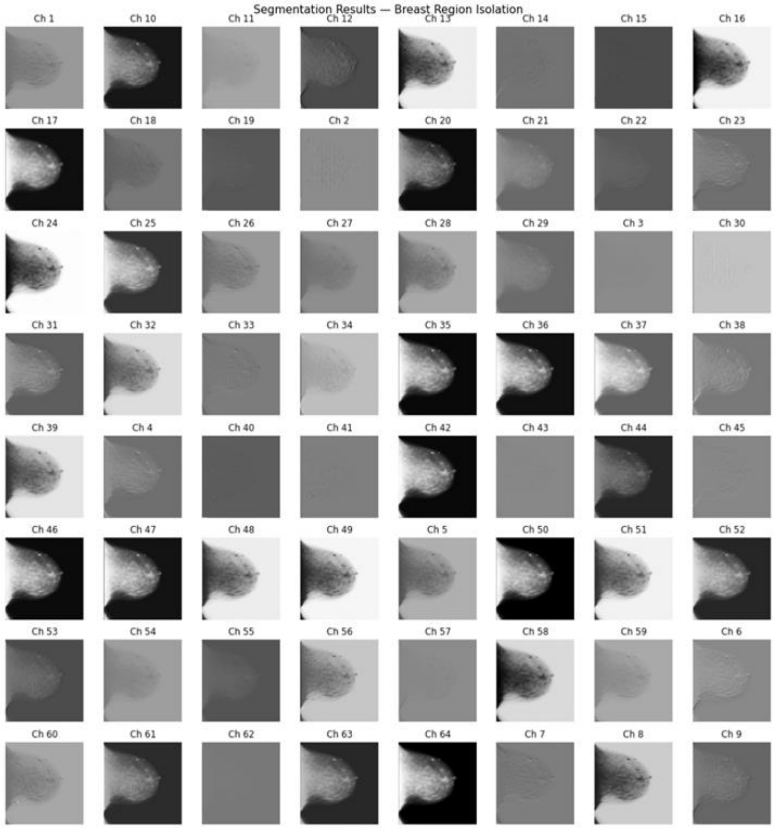


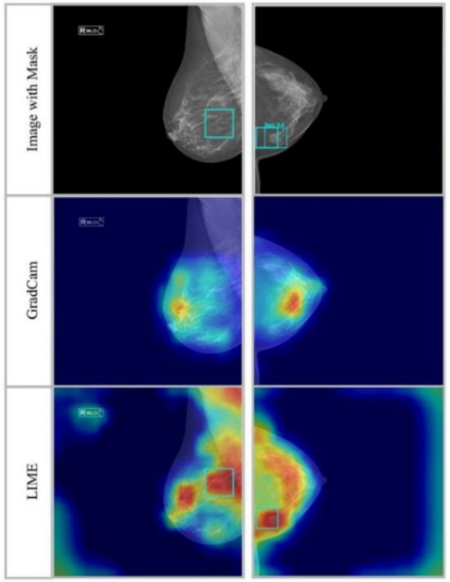
Image Segmentation



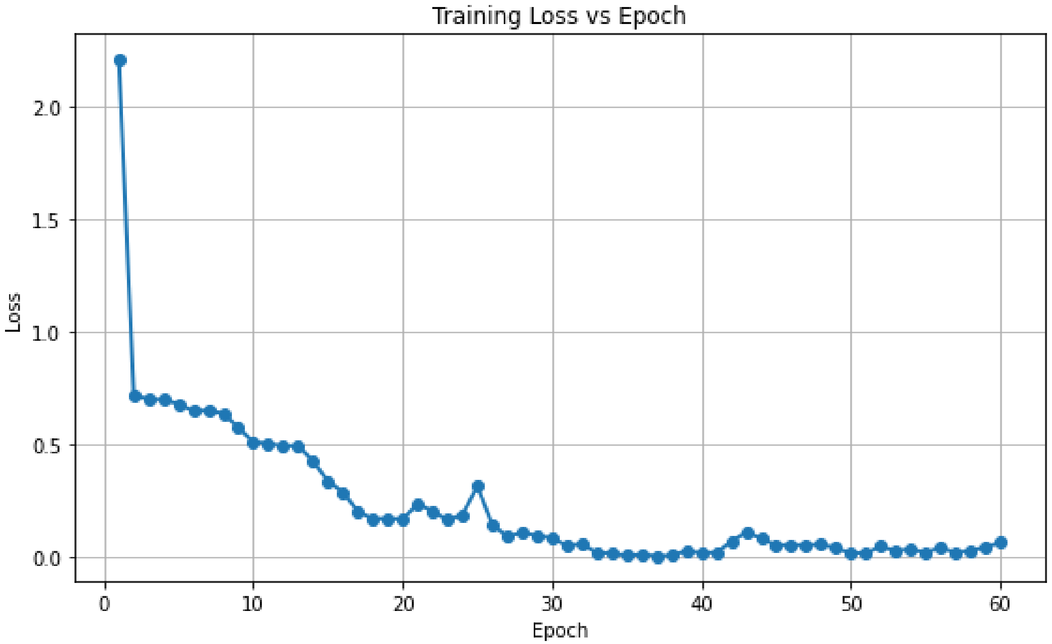
CNN

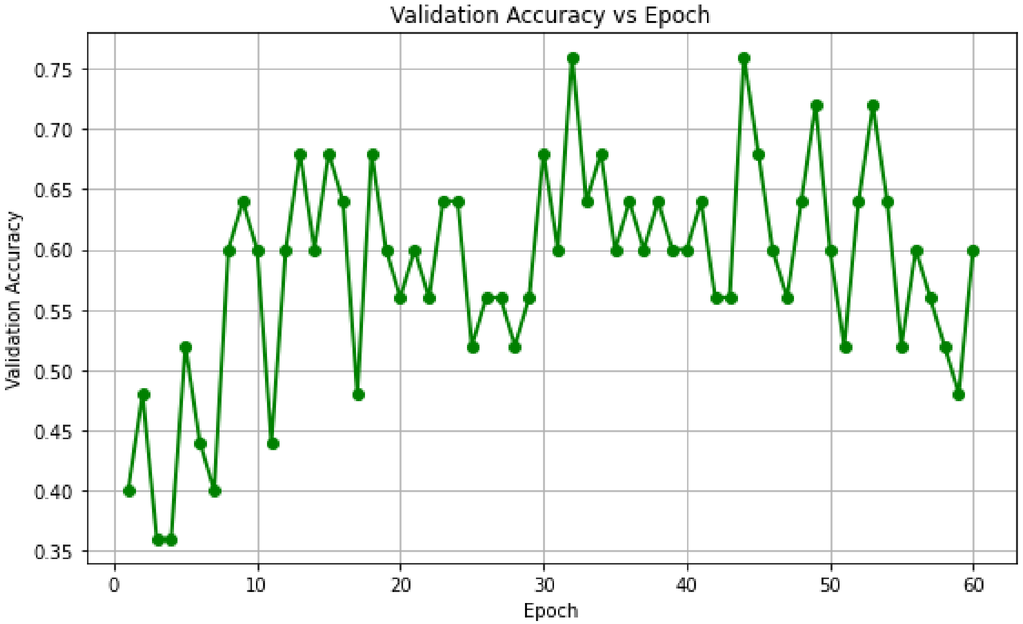
Classification Module

Explainable AI GRAD-CAM



EEXPERIMENTAL DATA





Loss vs Epoch: Plot shows the training loss steadily decreased over the epochs, indicating that the model was learning effectively from the preprocessed data. Initial fluctuations were observed during the early epochs, which gradually stabilized toward the later epochs.

Validation Accuracy vs Epoch: The validation accuracy initially varied across the epochs but eventually reached a maximum at around 76% as illustrated , reflecting good generalization and convergence of the model

EXPERIMENTAL DATA

Class	Precision	Recall	F1-score	Support
0 (BENIGN)	0.769	0.769	0.769	13
1 (MALIGNANT)	0.750	0.750	0.750	12
Weighted Avg	0.760	0.760	0.760	25

CHALLENGES

- EXPLODING & VANISHING GRADIENTS - UNSTABLE UPDATES.
- NO GPU ACCELERATION, PURE NUMPY - LONG TRAINING CYCLES
- MANUAL TUNING - HYPERPARAMETERS DIFFICULT TO OPTIMIZE.
- BALANCING DROPOUT RATE VS. CONVERGENCE SPEED WAS DIFFICULT.
- CONSTRAINED BY COMPUTATIONAL LIMITATIONS

Convolutional Neural Network (CNN)

- Architecture: CNNModel
- Conv Layers: [[32,3],[64,3]]
- Hidden Units: [256,128]
- Dropout Rate: 0.1

Dataset

- Samples: 245
- Classes: 2
- Train/Test Split: 220/25
- Input Shape: [64, 256, 256]

Training Summary

- Epochs: 60
- Batch Size: 32
- Learning Rate: 0.001
- Device: cpu
- Training Time: 00:16:21

PROTOTYPE

- WORKFLOW:
  - Model Performance Metrics
  - Preprocessing and Image segmentation
  - CNN Classification
  - Explainability
  - Diagnostic Report

CONCLUSION AND FUTURE WORK

- PRESENTS A HYBRID DEEP LEARNING BASED CAD SYSTEM FOR BREAST CANCER DETECTION, COMBINING CONVOLUTIONAL NEURAL NETWORK, IMAGE SEGMENTATION AND EXPLAINABILITY
- ENABLING RELIABLE EARLY DETECTION OF BREAST CANCER
- GENERALIZED MODEL CAPABLE OF DIAGNOSING MULTIPLE CANCER TYPES
- AUTOMATED SEMI-SUPERVISED OR UNSUPERVISED LEARNING METHODS