

# TumorTrace: MRI-Based AI for Breast Cancer Detection: Documentation

## 1. Introduction

- **Background:** Brief about breast cancer detection challenges and the role of MRI imaging.
- **Project Goals:** Objectives of TumorTrace in leveraging AI for MRI-based cancer detection.
- **Overview of Workflow:** Summary of the steps involved: data collection, EDA, preprocessing, model training, evaluation, and deployment.

## 2. Exploratory Data Analysis (EDA)

- **Data Overview**
  - Details about the dataset (source, size, format).
  - Description of classes: tumor vs. no tumor.
  - Initial checks on data integrity (missing files, corrupt images).
- **Data Inspection**
  - Visualization of class distributions using bar charts.
  - Sample images from each class with descriptive labels.

Example:

- Tumor class image with annotations highlighting MRI-specific features.
  - No tumor class image with healthy tissue markings.
- **Preprocessing and Augmentation**
  - Resizing images to 224x224 to fit the input requirements of the neural network.

- Normalization using ImageNet statistics for faster convergence.
- Data augmentation techniques for generating diverse training samples.

```
transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.RandomRotation(30),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],
std=[0.229, 0.224, 0.225])
])
```

### 3. Model Training and Evaluation

- **Architecture Selection**

- Why VGG16 was chosen (balance of simplicity and accuracy for image classification).
- Explanation of custom modifications to suit binary classification.

- **Training Configuration**

- Loss Function: Explanation of cross-entropy loss and why it's suitable for classification tasks.
- Optimizer: Use of Adam optimizer and its parameters (learning rate, betas).
- Batch Size and Epochs: Reasoning behind parameter choices.

Example Code:

```
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.0001,
weight_decay=1e-5)
```

- **Evaluation Metrics**

- Metrics: Accuracy, Precision, Recall, F1-score, ROC-AUC, with detailed formulas and usage scenarios.

- Visualizations: Confusion matrix and ROC curve to demonstrate performance.
- **Hyperparameter Tuning**
  - Grid search and validation to find the optimal learning rate, dropout, and batch size.
  - Observations from tuning: Improvements in precision/recall.
- **Results and Insights**
  - Quantitative results: Metrics on the test set.
  - Qualitative insights: Misclassified samples and possible reasons.

## 4. Model Development

### Pretrained Model Customization

A pretrained **VGG16** model is used as the base, modified to adapt to the custom classification task. The model is tailored to handle two classes with the following adjustments:

- Replaced the fully connected layers to match the dataset's output requirements.
- Added dropout for regularization and ReLU activation functions for non-linearity.

### Early Stopping

Implemented a custom `EarlyStopping` class to prevent overfitting by monitoring validation loss:

- Saves the model when a significant improvement in validation loss is detected.
- Stops training after a specified patience period.

### Optimization

Training leverags:

- **Loss Function:** `CrossEntropyLoss` for classification tasks.
- **Optimizer:** `SGD/Adam` for gradient-based optimization.

- **Data Augmentation:** Enhancements like random flips, rotations, and normalization during preprocessing.

## 5. Deployment using Gradio

The final trained model is deployed using **Gradio**, allowing an interactive web interface:

- **Input:** Users upload MRI images.
- **Output:** The model predicts and displays class probabilities or labels.

Key Features:

- Real-time predictions with visual feedback.
- Easy-to-use interface for both developers and end-users.

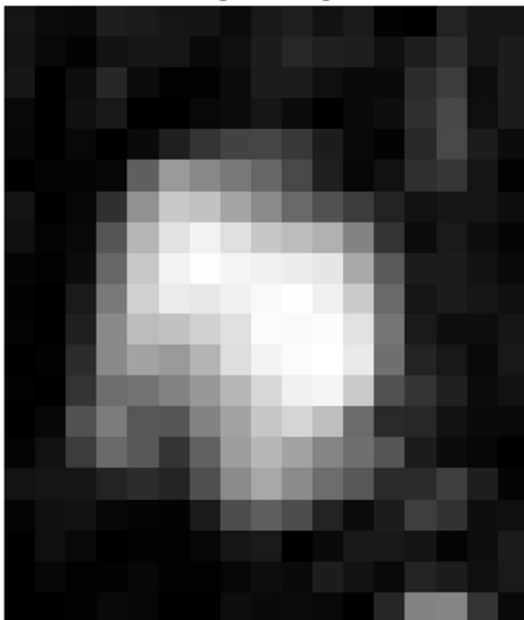
## Results:

Sobel edge detection output:

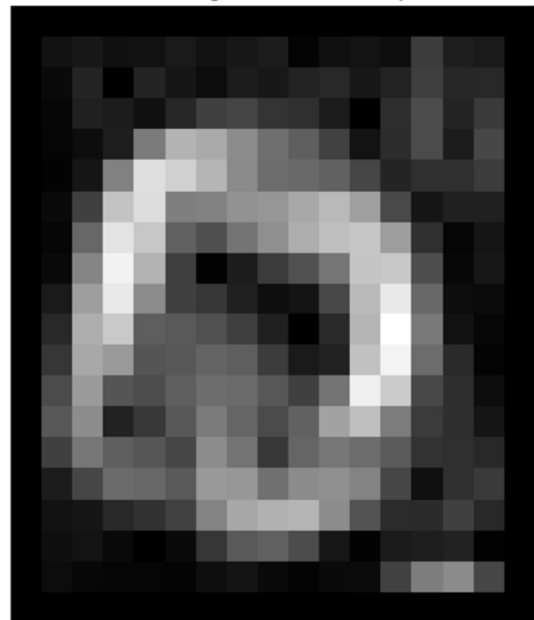
```
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 [ 0 18 24 17 18 26 18 23 28  4 16 19 14 61 30 26  0]
 [ 0 10 37  1 36 22 12 28 24 35 40 24 35 63 39 40  0]
 [ 0  6 32 29 17 39 64 69 53 47 28  1 46 76 37 58  0]
 [ 0  5 13 30 123 179 170 140 111 95 65 19 45 75 28 71  0]
 [ 0  3 22 129 223 208 181 138 109 106 98 70 37 47 47 60  0]
 [ 0 10 64 195 220 127 130 146 150 168 185 159 74 22 33 32  0]
 [ 0  6 103 227 199 97 79 116 143 173 191 198 157 49  5 21  0]
 [ 0  9 133 242 179 63  3 29 61 82 118 197 200 78  8 23  0]
 [ 0 26 158 233 140 64 54 33 14 20 72 186 233 104 13 11  0]
 [ 0 40 174 201 94 89 80 63 32  1 42 181 255 122 18  7  0]
 [ 0 54 168 154 85 88 100 94 60 26 34 193 243 108 42  4  0]
 [ 0 75 155 85 77 95 109 107 87 64 116 239 203 72 46 13  0]
 [ 0 88 141 34 56 88 123 101 75 97 162 191 124 59 46 21  0]
 [ 0 64 119 95 86 70 140 115 56 101 119 108 91 51 47 40  0]
 [ 0 28 70 107 104 89 153 151 113 139 144 131 71 16 49 58  0]
 [ 0 18 22 40 50 65 131 167 177 181 141 83 44 43 64 41  0]
 [ 0 15 19  9  0 10 54 89 98 76 23  3 27 30 34  3  0]
 [ 0 12  7  5  5  4 14 20 10  4 10 11 65 125 139 70  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0]]
```

Sobel edge detection output saved as 'sobel\_edge\_detection\_output.png'

Original Image



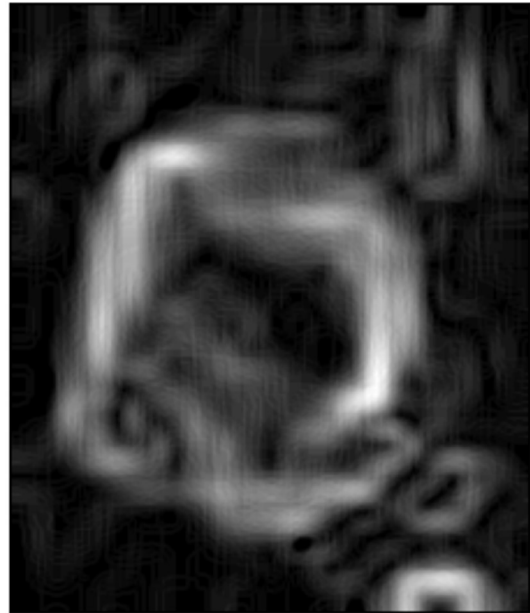
Sobel Edge Detection Output



Resized Input Image



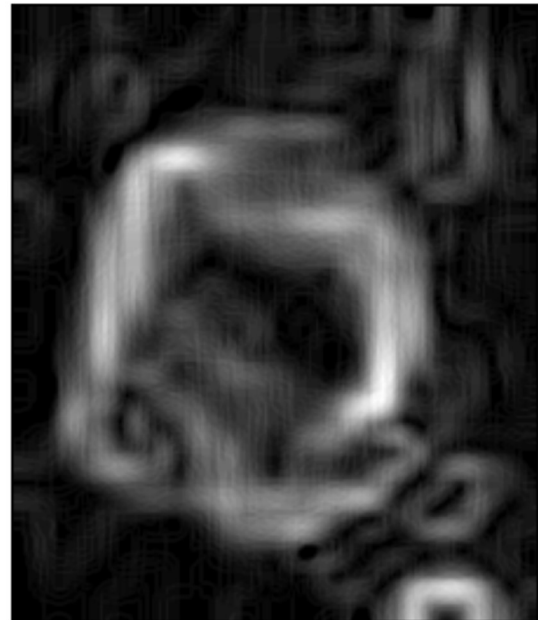
Edge Detection Result



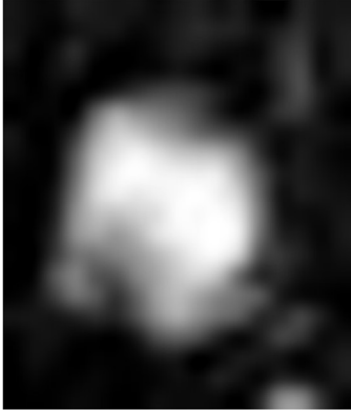
Resized Input Image



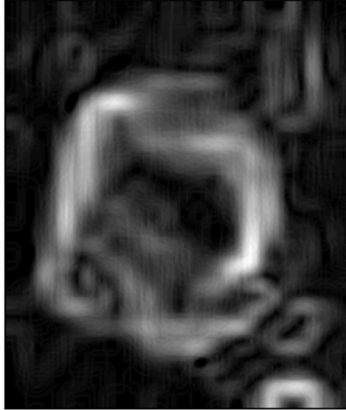
Edge Detection Output



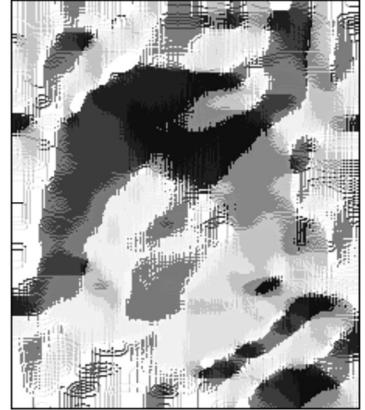
Resized Grayscale Image



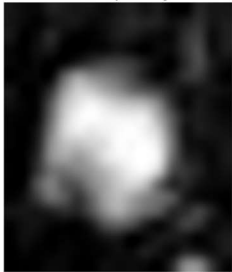
Sobel Edge Detection Result



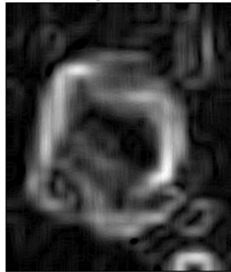
LBP Result



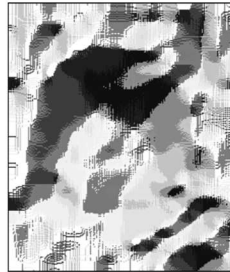
Resized Grayscale Image



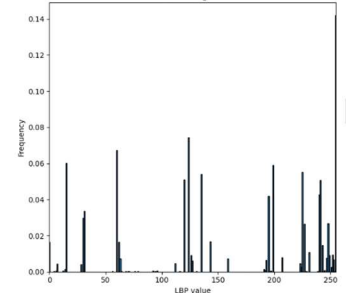
Sobel Edge Detection Result



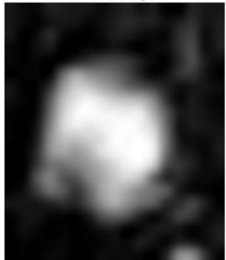
LBP Result



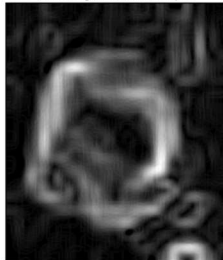
LBP Histogram



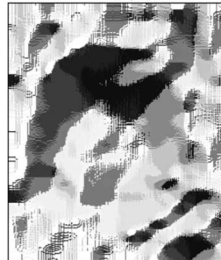
Resized Image



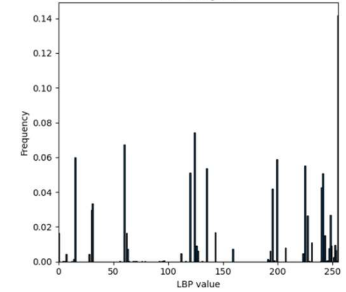
Sobel Edge Detection Output



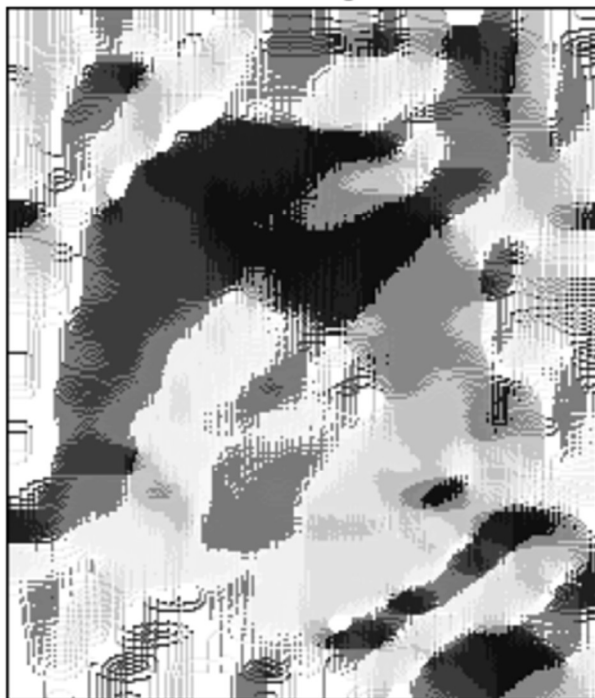
LBP Output



LBP Histogram



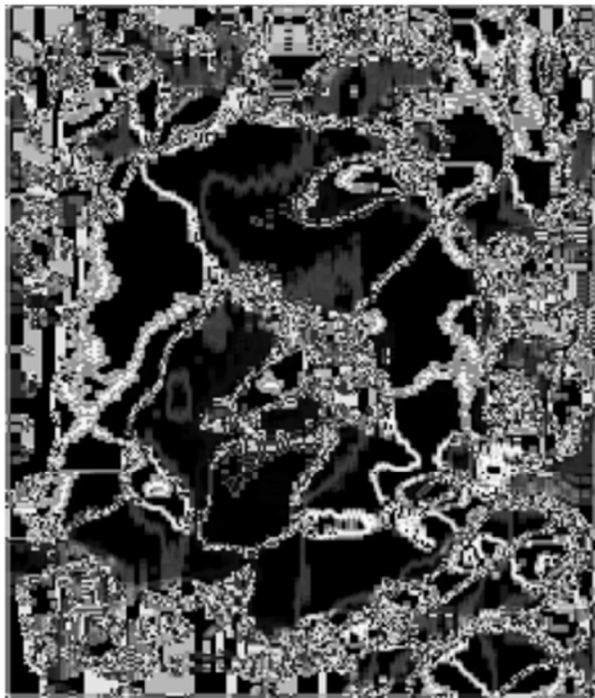
LBP Image



LBP Mean-based Image



LBP Variance-based Image



LBP Median-based Image





Original Image 1



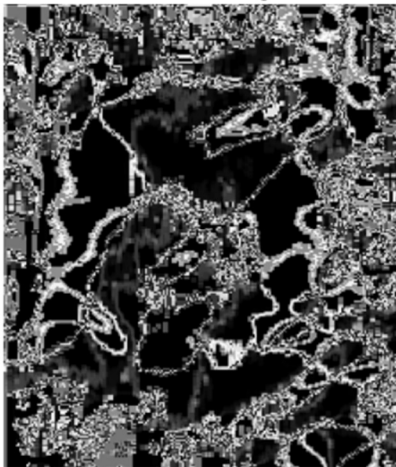
LBP Image 1



LBP Mean Image 1



LBP Variance Image 1



LBP Median Image 1



