Using Machine Learning and Computer Vision to Detect Breast Cancer

Group 3:
Ahmed Ahmed
Mike Moll
Lisa Vo

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Background

Recent breast cancer trends

- About 297,790 new cases in 2023
- About 43,700 women will die in 2023
- 2nd most common cancer among women (behind skin cancer)
- Median age: 62
- Likelihood: 13% or 1 in 8 women

Our Goal

- To train a classifier using support vector machines (SVMs) to predict that a patient has breast cancer based on tabular patient data
- To train another classifier using convolutional neural networks (CNNs) to predict that a patient has breast cancer based on patient mammograms
- To compare the accuracy between SVMs and CNNs in predicting breast cancer in patients

Our Dataset

- Our dataset comes from CBIS-DDSM (Curated Breast Imaging Subset of DDSM) WHICH is an updated and standardized version of the Digital Database for Screening Mammography (DDSM).
- Using data of abnormality type: mass

Why did we choose to compare these two models?

- Our experiment is a reflection of what we've learned in this course
- We are exploring a mix of machine learning, deep learning, and computer vision concepts
- We are comparing two different approaches to classification using two different types of datasets (image and tabular data)

Support Vector Machine

What are Support Vector Machines?

- **Support vector machines** are supervised learning models in machine learning
- Data is mapped to multiple dimensions in a feature space where a separator (“hyperplane”) is optimized between the categories
- Commonly used in classification and regression and can be used on linear and non-linear data

Tabular Data Pre-Processing

- Removed unneeded columns: patient_id, abnormality_type, image file path, cropped image file path, and ROI mask file path
- Replace NaN with mode of corresponding feature

Features

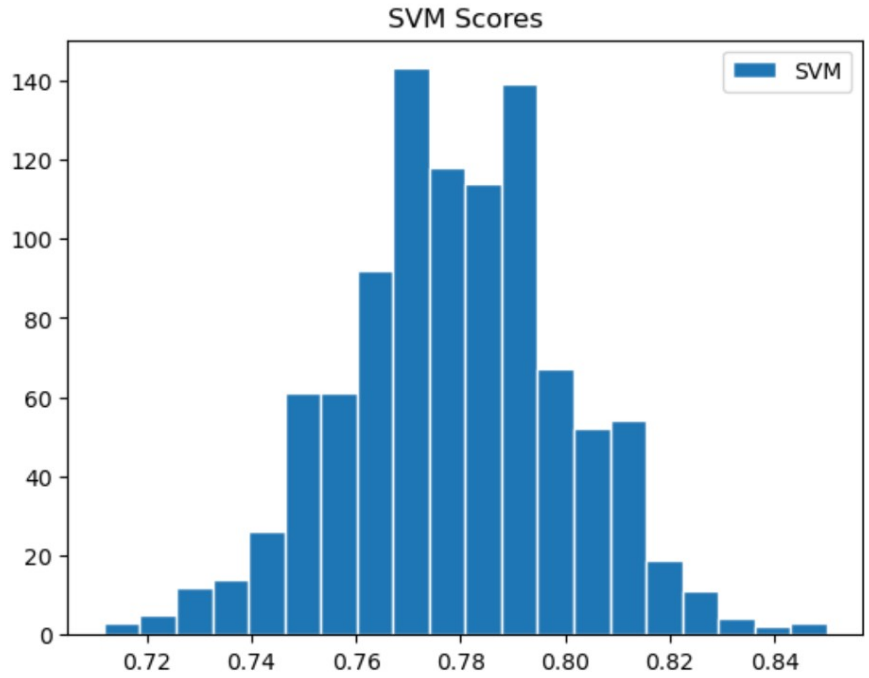
- **Target variable**
  - pathology: “BENIGN”, “MALIGNANT”, “BENIGN_WITHOUT_CALLBACK”
- **Explanatory variables:**
  - breast density, left or right breast, image view, abnormality id, mass shape, mass margins, assessment, and subtlety

Model Training

1. x_train, x_test, y_train, y_test was created from scikit-learn’s train_test_split with test size of 0.20
2. Support Vector Classification (SVC) object used to predict the data points
3. Accuracy scores were calculated from the predictions and y_test data
4. Predictions and accuracy scores calculated 1000 times for score distribution

Discussion & Results (1/2)

Distribution Histogram



Discussion & Results (2/2)

1. Mean accuracy score = 0.78
2. Standard deviation = 0.02
3. Median = 0.78
4. Minimum accuracy score reached = 0.71
5. Maximum accuracy score reached = 0.84

Convolutional Neural Network

What are Convolutional Neural Networks?

- **Convolutional neural networks** are a form of deep learning that is modeled after the human brain
- Consists of input layer, output layer, and at least one intermediate layer that performs the convolution
- Weights are replicated across the nodes of each layer
  - Goal is for each weight to reach an optimal value

Image Pre-Processing

1. Conversion of DICOM images to jpg
2. Three directories of labeled images (Training, Validation, and Test)
3. Each directory contains 3 subfolders of labelled jpg images (Benign, malignant, Benign call back)
4. Image size = 128/ 128
5. Class labels = ['BENIGN', 'MALIGNANT', 'BENIGN_WITHOUT_CALLBACK']

Layers (1/2)

1. Input Image
    - **Dimensions:** 128x128 pixels
    - **Channels:** 3 (RGB)
1. Layers
    - **Convolutional Layer:** 32 filters of size 3x3 with ReLU activation.
    - **Max Pooling Layer:** 2x2 pooling size.
    - **Convolutional Layer:** 64 filters of size 3x3 with ReLU activation.

Layers (2/2)

- **Max Pooling Layer:** 2x2 pooling size.
- **Flattening Layer:** Convert 2D feature maps to 1D feature vector.
- **Dense Layer:** 256 neurons with ReLU activation.
- **Dropout Layer:** 50% dropout rate to prevent overfitting.

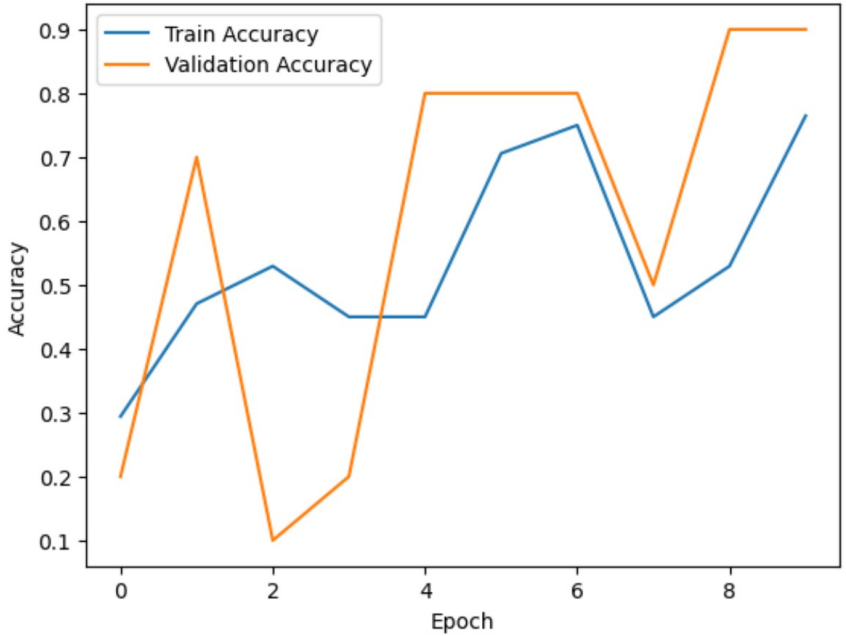
3. **Output Layer:** 3 neurons (for three classes) with Softmax activation.

Post-Model Training

- Model could not perform the prediction process.
- Could be related to incorrect loading or labeling of the images from the directory.
- There's a possibility that the model consistently predicts the same class for all images due to poor training or issues with the training data.

Discussion & Results

Progress of training accuracy and validation accuracy



Algorithm Comparison

SVMs and CNNs

- From a historical standpoint and our experiment, CNNs remain a powerful tool in image processing and prediction
- Our CNN can reach accuracy levels (post-validation) that our SVM classifier could not
  - The highest level of accuracy the CNN reached was 0.90
  - The highest level of accuracy the SVM classifier reached was 0.84
- Using both SVM and CNN can give a more conclusive result in detecting breast cancer

Future Research & Implications

Benefits of Our Experiment

- Deeper understanding of computer vision and machine learning concepts
- Applied concepts learned, at a deeper level
- Expanded technical skills

Potential Improvements in Experiment

- Tabular Data
  - Larger dataset
  - Less missing values
  - Alternative methods to filling missing values
- Images
  - Improve conversion of the images to JPG
  - Improved organization of images

Impact and Implications

- Improved Accuracy
- Efficiency and Scalability
- Personalized Treatment
- Accessibility
- Ethical and Regulatory Considerations
- Integration with Healthcare Systems

Thank you