

Advanced Breast Cancer Prediction System Using Machine Learning & Automated Model Selection

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Project Presentation

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Agenda

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Problem Statement & Motivation

Goal

Predict whether a breast tumor is:

- **Malignant (Cancer)** or
- **Benign (Non-cancerous)**

based on measured tumor features.

- Early detection improves treatment outcomes.
- ML can assist clinicians by providing fast decision support.
- Focus on reliability and interpretability for medical screening.

Dataset Overview

- Dataset: **Breast Cancer Wisconsin (Diagnostic)**
- Type: Tabular, numeric features
- Target:
 - 1 → Malignant
 - 0 → Benign
- Features (examples):
 - radius, texture, perimeter, area
 - smoothness, compactness, concavity
 - symmetry, fractal dimension

Data Preprocessing

- Removed unnecessary column(s) such as `id` (if present).
- Encoded diagnosis:

$$y = \begin{cases} 1, & \text{if diagnosis} = M \\ 0, & \text{if diagnosis} = B \end{cases}$$

- Train-test split (e.g., 80/20) with **stratification**.
- Standardization where needed:

$$x' = \frac{x - \mu}{\sigma}$$

Models Compared

Candidate Models

- **Support Vector Machine (SVM)** (with scaling)
- **Random Forest Classifier**
- **XGBoost Classifier**
- Objective: Select the best model using cross-validation and ROC-AUC.
- Save the final pipeline for consistent inference during deployment.

Training Strategy

- **Stratified K-Fold Cross-Validation** ($k=5$)
- **Hyperparameter Optimization** using RandomizedSearchCV
- Model selection criterion: **Highest ROC-AUC**

Why ROC-AUC?

Useful for medical classification where class separation matters and threshold can be adjusted.

Evaluation Metrics

- Confusion Matrix:

		Predicted Benign	Predicted Malignant
Actual Benign	TN	FP	
Actual Malignant	FN	TP	

- Accuracy, Precision, Recall, F1-score
- ROC Curve and ROC-AUC:

$$AUC = \int_0^1 TPR(FPR) d(FPR)$$

Results Summary

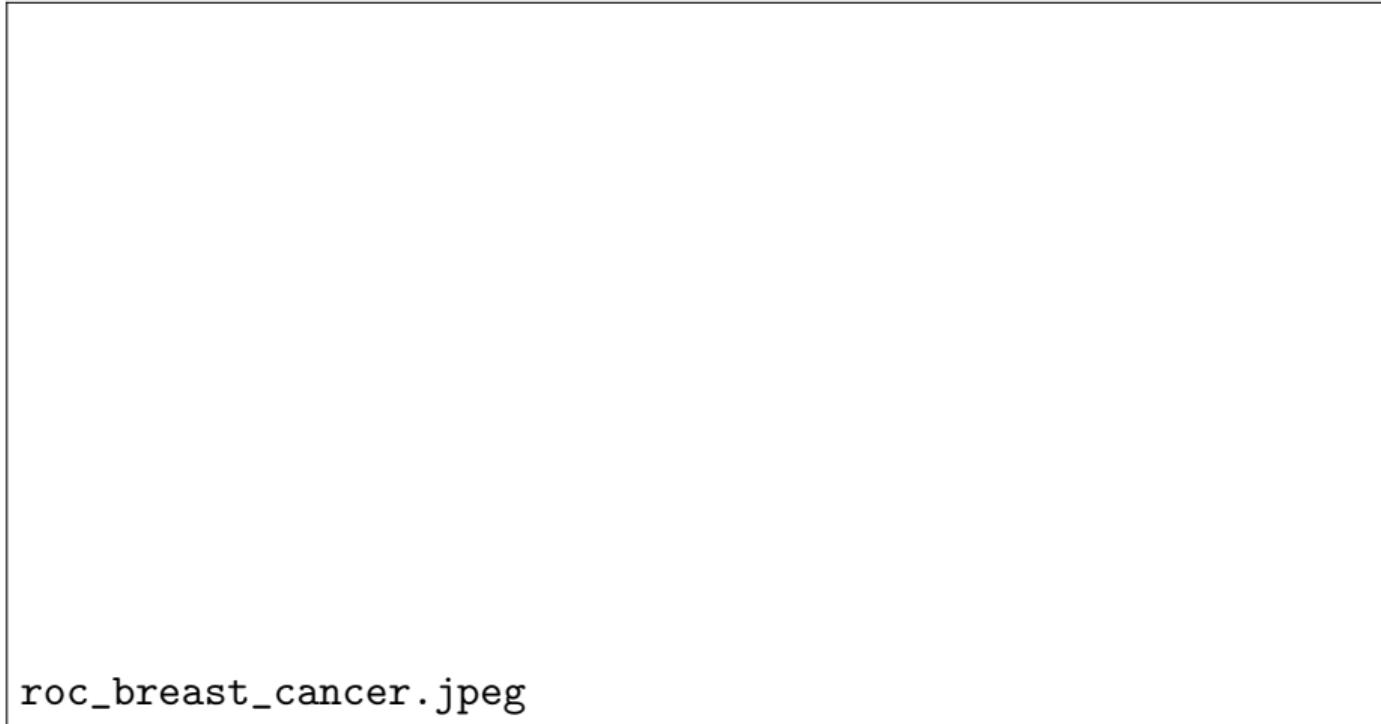
- Best-performing model selected from: SVM / RF / XGBoost
- Reported:
 - ROC-AUC (Cross-Validation)
 - ROC-AUC (Test Set)
 - Confusion matrix and classification report
- Medical focus: prioritize **Recall** for malignant cases when needed.

Key Outcome

An optimized model pipeline saved as `best_pipeline.pkl` for reliable deployment.

ROC Curve Visualization

- The ROC curve compares True Positive Rate vs False Positive Rate.
- Higher curve and larger AUC indicate better separability.



roc_breast_cancer.jpeg

Performance Evaluation

PE_breast_cancer.jpeg

Deployment: Streamlit Web App

Features

- Manual input prediction
- CSV batch prediction + downloadable results
- Probability output + threshold adjustment
- Performance visuals (ROC)
- Educational section: causes, effects, prevention

Artifact Used

`best_pipeline.pkl` contains model + feature columns + threshold.

Demo Flow

- ➊ Open the Streamlit app
- ➋ Manual input:
 - Enter feature values → Predict
 - View label + probability bar
- ➌ CSV mode:
 - Upload CSV → Predict batch
 - View summary: total / malignant / benign
 - Download predictions

Limitations

- Model trained on a specific dataset; performance may vary on real-world clinical data.
- Not a substitute for medical diagnosis.
- Requires consistent feature format and measurement standards.

Ethical Note

Predictions should be used only as decision support and validated by clinicians.

Future Work

- Explainable AI: SHAP/Feature importance dashboards
- Threshold optimization for high-sensitivity screening
- Deep learning with histopathology images (CNN/Transfer Learning)
- Deploy as REST API (FastAPI) + Docker + cloud deployment

Conclusion

- Built an advanced ML pipeline for breast cancer prediction.
- Compared multiple models and selected the best using ROC-AUC.
- Deployed as a user-friendly Streamlit application for real-time and batch predictions.

Thank You!