Hybrid AI-Based Breast Tumor Diagnosis and Decision Support System Using CNN Classification and Rule-Based Expert Reasoning

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Problem Statement

Early and accurate detection of breast tumors is essential for reducing mortality, but diagnosis through mammogram images is challenging due to low contrast, subtle tumor boundaries, radiologist workload, and subjectivity in clinical interpretation. Modern ML models such as CNNs can classify tumors as benign or malignant, but these models alone often lack explainability and domain-driven reasoning. Traditional AI approaches, on the other hand, provide rule-based expert logic but cannot independently interpret medical images.

The problem is to design a hybrid AI system that combines CNN-based tumor classification with a Traditional AI decision-making module to produce a medically meaningful, explainable, and integrated diagnostic support tool.

Motivation

Breast cancer is one of the leading causes of death among women worldwide, particularly in regions where diagnostic resources are limited. Radiologists face heavy workloads, and diagnostic interpretation of mammograms requires high expertise and precision.

A hybrid ML + Traditional AI solution:

- Improves diagnostic reliability using CNN predictions.
- Provides logical, explainable decision rules based on oncology guidelines.
- Helps bridge the gap between data-driven learning and human-like reasoning.
- Supports radiologists through structured recommendations and risk analysis.

This system can serve as a practical, real-world medical decision support tool, enhancing early detection, consistency, and accessibility.

Background

Machine Learning models, especially Convolutional Neural Networks have shown impressive performance in medical imaging tasks, including tumor classification. CNNs can detect patterns and features that are difficult for humans to spot. However, ML models alone lack interpretability.

Traditional AI methods such as **Rule-Based Expert Systems**, **Fuzzy Logic**, and **Graph Search** provide transparent reasoning, but they rely on predefined symbolic knowledge and cannot classify images.

Recent research suggests that hybrid systems combining ML and symbolic reasoning improve reliability, transparency, and usability for clinical decision-making. Such systems leverage the strengths of both paradigms:

- ML for perception
- Traditional AI for reasoning

This aligns perfectly with the requirement of integrating both paradigms in a single unified pipeline.

Related Work

Several studies integrate ML and symbolic AI for medical diagnosis:

1. **CNN-Based Mammogram Classification**
    - Models like ResNet, VGG, and Swin Transformer achieve high accuracy on datasets like CBIS-DDSM and INbreast.
2. **Rule-Based Medical Expert Systems**
    - IF-THEN rules have been widely used for diagnosis and treatment planning (e.g., MYCIN, CADx systems).
3. **Hybrid ML + TAI Systems**
    - Recent literature shows hybrid frameworks for:
        - Diabetic retinopathy screening
        - Lung nodule detection combined with rule-based reasoning
        - Prostate cancer risk scoring using ML + fuzzy inference
4. **Explainable AI in Medical Imaging**
    - Grad-CAM and attention maps help reveal CNN decision logic.

However, very limited work integrates **CNN mammogram classification with rule-based expert logic and optional A* treatment recommendation**, making this project novel and impactful.

Proposed Methodology

The proposed hybrid system contains **three major components**: an ML module, a Traditional AI module, and a web-based interface.

1. Machine Learning Component (CNN Tumor Classifier)

Dataset

- INbreast, CBIS-DDSM, or custom dataset.
- Preprocessing:
    - Resizing, normalization.
    - Optional histogram enhancement.
    - Noise removal filters.

Model Architecture

- Transfer Learning model (ResNet50, MobileNetV2, or Swin Transformer).
- Hyperparameter tuning via grid search or Bayesian optimization.
- Handling imbalance through class weights or augmentation.

Evaluation

- Metrics: Accuracy, Precision, Recall, F1-score, ROC-AUC.
- K-fold cross-validation.
- Robustness testing (noise, contrast shift).

Visualizations

- Loss/accuracy curves.
- Confusion matrix.
- ROC curve.
- Grad-CAM heatmaps.

ML Output Passed to TAI

- Predicted class (benign/malignant)
- Confidence score
- Severity score (scaled probability)

2. Traditional AI Component

A. Rule-Based Expert System (Primary TAI Method)

Uses CNN predictions + patient metadata (age, pain level, symptoms).

Example Rule Structures

- IF malignant AND confidence > 0.85
  THEN risk = high AND recommend = biopsy + oncology referral.
- IF benign AND confidence > 0.90
  THEN risk = low AND recommend = routine 6-month check.

- IF confidence in [0.55–0.75]
  THEN uncertainty = medium → additional imaging required.

B. Fuzzy Logic Integration

Handles uncertainty in ML predictions:

- Low, medium, high confidence membership functions.
- Fuzzy rules for borderline cases.

3. Integration Pipeline

The system follows a modular, ML-driven decision flow:

1. Users upload mammograms via UI.
2. CNN model processes and classifies images.
3. Predictions are fed into the Rule-Based Expert System.
4. Expert System generates:
   - Risk level
   - Explanations
   - Initial recommendations.
5. UI displays integrated results with visualizations.

This fulfills the requirement that **Traditional AI explicitly depends on ML predictions**.

4. User Interface

Technology Options

- **FastAPI + React** (most scalable)

UI Features

- Image upload & preprocessing
- Display:
  - CNN output
  - Confidence scores
  - Grad-CAM heatmaps
- Show expert system results (rules fired + final decision)
- Visualize A* treatment path (if implemented)
- Error handling & accessibility features

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