AI-BASED MAMMOGRAPHY SYSTEM FOR EVALUATION AND DETECTION (AIMED) XERA

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Abstract. This project focuses on developing an X-ray mammography imaging system that enables accurate breast lesion detection with low radiation exposure. On the hardware side, a low-noise, power-efficient Charge Sensitive Amplifier (CSA) was designed using TSMC 180nm CMOS technology. Detector characterization was performed using Modulation Transfer Function (MTF) and Noise Power Spectrum (NPS) metrics for both flat panel and CMOS sensors. On the software side, a deep learning-based pipeline was implemented. First, a lesion detection model based on Faster R-CNN with a ResNet-50 backbone and Feature Pyramid Network (FPN) was trained to locate suspicious regions, achieving 90% accuracy. Then, a ResNet-50 classification model was applied to label the detected lesions as malignant or benign, with an accuracy of 76%. To make the system accessible, a user-friendly web interface was developed, allowing users to upload mammogram images and receive both the tumor location and cancer prediction with visual feedback. This integrated system offers a promising step toward safer and smarter breast cancer diagnosis.

PROJECT DESCRIPTION

Our project focuses on the development of an intelligent breast cancer diagnosis system that combines X-ray image acquisition with AI-assisted lesion detection and classification. The system is designed to support mammography imaging with low-dose X-ray exposure while maintaining high diagnostic accuracy. The project is carried out in collaboration with the company XERA, which aims to improve the efficiency and accessibility of early-stage breast cancer screening. XERA has tasked our team with addressing a major healthcare need: accurate and low-radiation mammographic imaging that can detect small or hard-to-see lesions without increasing health risks to patients.

Many traditional imaging systems either miss these small signs of disease or require high radiation doses to reveal them. This raises concerns about patient safety and diagnostic efficiency. Our goal is to deliver a validated prototype pipeline that brings together detailed detector characterization, efficient analog hardware design, and high-performing deep learning models for medical image analysis.

To achieve this, we carry out two parallel development efforts. On the hardware side, we simulate and model a low-noise, power-efficient Charge Sensitive Amplifier (CSA) using TSMC 180nm CMOS technology. We focus on meeting constraints provided by the company, including achieving a voltage gain of 10 mV/fC, input-referred noise below 100 electrons, and ensuring the design stays under a 61 μW per-pixel power budget. Characterization of both Flat Panel and CMOS detectors is performed using key metrics such as Modulation Transfer Function (MTF) and Noise Power Spectrum (NPS), which help us evaluate image resolution and noise behavior. The hardware system is designed to clearly image fine tissue structures around 20–25 μm while keeping radiation levels as low as possible.

On the software side, we implement a deep learning-based pipeline. First, we use a Faster R-CNN architecture with ResNet-50 and Feature Pyramid Network (FPN) as a backbone for detecting suspicious regions in mammogram images. This model reaches 90% accuracy in locating areas that may indicate the presence of cancer. Following detection, a ResNet-50 classifier is used to analyze these regions and label them as either benign or malignant, achieving 76% classification accuracy. The training pipeline includes preprocessing operations like resizing, contrast enhancement, normalization, and class balancing techniques. We also apply Gradient-weighted Class Activation Mapping (Grad-CAM) visualization tools to highlight which parts of the image the model focused on when making predictions, increasing the model's interpretability for healthcare professionals.

To make the system accessible and flexible, we developed a user-friendly web interface. Users can upload their mammogram images in any size, and the system automatically preprocesses the input. Through the interface, users can choose to apply either the lesion detection model or the tumor classification model, depending on their needs. The interface then displays the prediction results along with visual feedback, making it easy to understand and use.

Overall, the system integrates an X-ray source, detector (FPD or CMOS), signal amplification via CSA, digitization, and a deep learning-based AI analysis pipeline. With its combined hardware and software strengths, this end-to-end solution offers a promising approach for safer, faster, and more accurate breast cancer diagnosis.

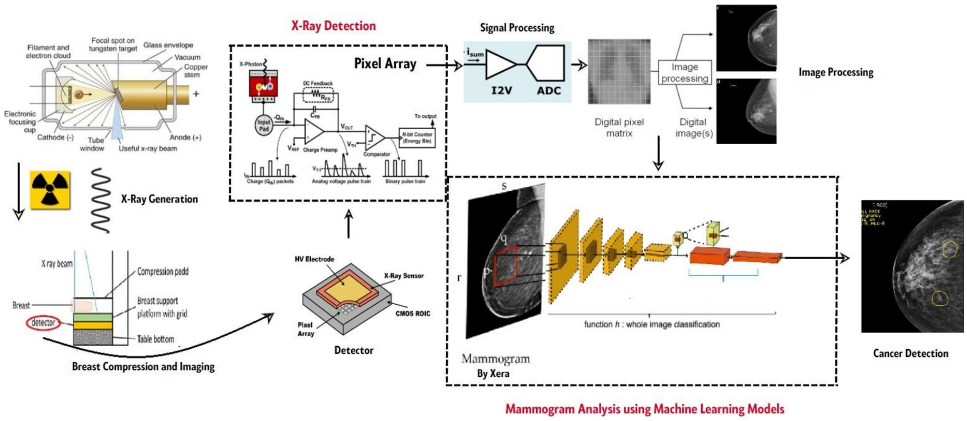

FIGURE 1. Big Picture

MILESTONES

M1 – Literature Review and Preparation

The team divides into hardware and software groups. The hardware team explores photon-counting methods and detector architectures. The software team studies deep learning techniques for object detection and classification via papers.

M2 – Specification Development

The hardware team begins simulations using TSMC 180nm CMOS technology, targeting low-noise CSA design. The software team finalizes tools such as TensorFlow and PyTorch. This milestone clarifies technical requirements and system planning.

M3 – Method Design and Model Selection

The team simulates and analyzes various amplifier configurations, selecting folded cascode for its superior noise performance. Faster R-CNN with ResNet-50 is chosen for lesion detection, and ResNet-50 is prepared for tumor classification. Training pipelines are set up using annotated mammography data with appropriate preprocessing.

M4 – Implementation and Training

The hardware team models the full ROIC signal chain, including input charge simulation and noise analysis, to verify CSA performance under realistic conditions. The software team trains the detection model (Faster R-CNN with ResNet-50 and FPN) and a separate ResNet-50 model for classification. Evaluation includes confusion matrices and Grad-CAM visualizations for interpretability.

M5 – Characterization and Integration

Flat panel and CMOS detectors are characterized using calibration images like flat fields and edge phantoms. Key performance metrics such as MTF, NPS, and PSD are computed to compare detector quality. A user-friendly web interface is built, allowing users to upload mammography images and receive results from either model with Grad-CAM-based visual feedback.

DESIGN DESCRIPTION

The project follows a co-design strategy, combining hardware modeling and software development for an advanced X-ray mammography system. On the hardware side, the approach begins with an extensive literature review on photon-counting detectors and CMOS sensor architectures. Using specifications provided by the company—including a charge range of 800–2000 electrons, 200 fF detector capacitance, 10 mV/fC gain, and input-referred noise below 100 electrons—a Charge Sensitive Amplifier (CSA) is designed in Cadence Virtuoso using TSMC 180nm CMOS technology. After evaluating different amplifier topologies, the folded cascode architecture is selected for its high gain, moderate noise, and superior voltage swing performance.

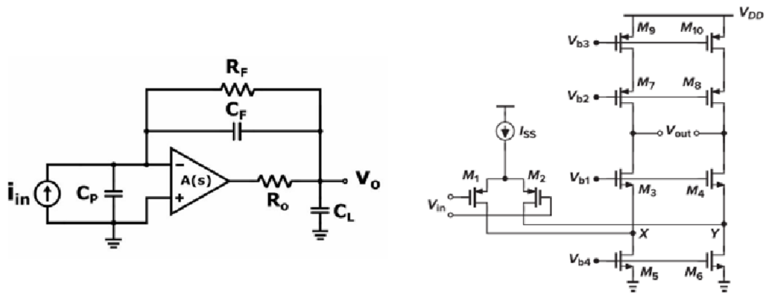

FIGURE 2. Left: Charge Sensitive Amplifier (CSA) front-end configuration. Right: Folded cascode OTA topology used in the amplifier core.

Simulations using Spectre and Maestro are conducted to tune transistor dimensions, set biasing conditions, and sweep performance parameters. The CSA is integrated into a closed-loop configuration with a target 250 ns time constant, suitable for distinguishing closely arriving photon events. For experimental characterization, the Vieworks FXRD-3643VAW flat panel detector system with CsI scintillator is used. Calibration sequences include dark image acquisition, flat field exposure, and sharp-edge imaging with a tungsten plate to prepare for image quality characterization. The same imaging and preprocessing pipeline is applied later to the CMOS-based detector for comparative analysis. All preprocessing involves gain correction, offset removal, and flat field normalization.

In parallel, the software development team explored modern AI-based techniques for medical image analysis. After reviewing a variety of classical and deep learning approaches—including CNNs, HOG, Viola-Jones, U-Net, YOLO, and Transformers—two models were developed to serve different purposes. A ResNet-50-based classification model was implemented in Google Colab, focusing on identifying malignant or benign tissue types from cropped lesion patches. ResNet-50 was selected due to its proven performance in medical imaging tasks, thanks to its deep residual structure which enables efficient gradient flow and strong feature extraction. Due to storage limitations, a smaller dataset was used. Preprocessing steps included grayscale normalization, resizing to 512×512, contrast enhancement, and augmentation methods such as horizontal flipping and angle shifts to handle class imbalance.

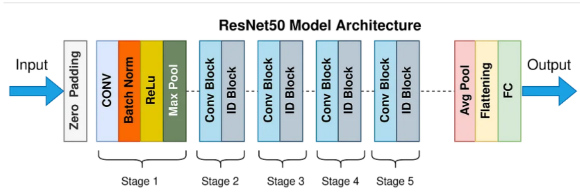

FIGURE 3. ResNet-50 architecture used for lesion classification.

Concurrently, a Faster R-CNN object detection model with a ResNet-50 backbone and Feature Pyramid Network (FPN) was trained on the company's server using the full 340 GB DICOM dataset. This model detects and localizes suspicious areas within full mammogram images by drawing bounding boxes around them. Both models utilized cross-entropy loss with class weighting and the Adam optimizer during training.

To enhance model interpretability, Grad-CAM was used to highlight the image regions that influenced classification outcomes, offering transparent visual feedback.

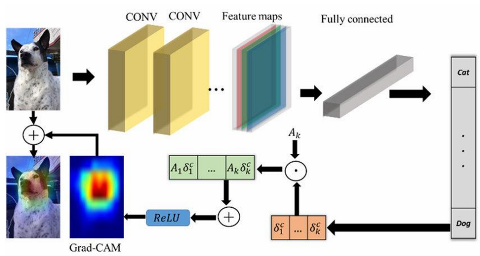

FIGURE 4. Grad-CAM Architecture for Visualization

A user-friendly website is developed, allowing individuals to upload mammography images of any size and choose between lesion detection or classification, with results presented in an easy-to-understand format for both professionals and general users.

RESULTS AND PERFORMANCE EVALUATION

On the hardware side, the folded cascode CSA was designed and simulated using Cadence Spectre, achieving a gain of 45 dB and a bandwidth of 1.02 MHz. Also a complete signal chain was implemented to characterize the detector's response, including modeling of input pulses, signal shaping, and noise components. Then we moved on to the detector characterization; Using edge tungsten images, the Edge Spread Function (ESF), Line Spread Function (LSF), and Modulation Transfer Function (MTF) were calculated. As shown in Figure 5 (left), the MTF curve confirms a spatial resolution of approximately 3.5 lp/mm for the TFT-GadOx detector. Noise behavior was also assessed via the Noise Power Spectrum (NPS) in Figure 5 (right), showing that most noise energy is concentrated in low spatial frequencies, helping to preserve high-frequency image detail. Once the characterization of TFT detector was done we moved on to characterization of the CMOS detector using the exact same methods.

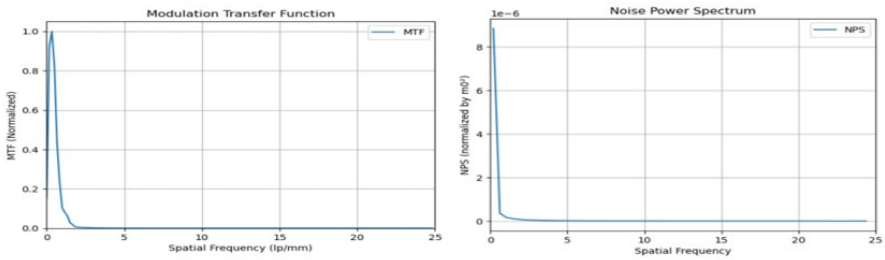

FIGURE 5. Left: MTF up to 4 lp/mm.Right: NPS for TFT detector

On the software side, two deep learning models based on ResNet-50 were implemented and trained on mammogram images. For tumor classification, a ResNet-50 model was used in Google Colab, trained on both a public and the company-provided dataset. Images were preprocessed through resizing to 512×512, grayscale normalization, and data augmentation. A custom two-neuron classification head was added to the model, and training was done using the Adam optimizer with a decaying learning rate over 50 epochs. The final model achieved 76% accuracy. Grad-CAM heatmaps were used for visual interpretability, clearly highlighting tumor areas in both true positive and true negative predictions, as shown in Figure 6.

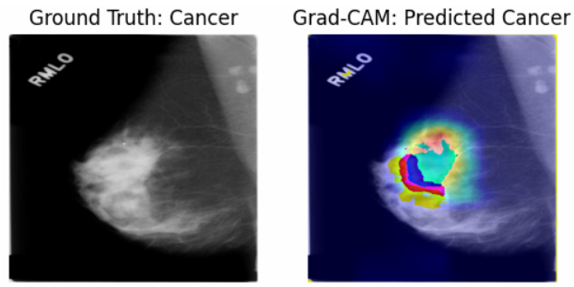

FIGURE 6. Grad-CAM visualization results.

TABLE 1. Evaluation Metrics of ResNet-50 Classification Model

Class	**Precision**	**Recall**	**F1-Score**	**Accuracy**
Benign	0.77	0.87	0.82	0.76
Malignant	0.75	0.59	0.66	

In parallel, an object detection model using Faster R-CNN with ResNet-50 + Feature Pyramid Network (FPN) was trained on the company's 340 GB DICOM dataset using the internal server. This model detects suspicious regions by drawing bounding boxes around lesions in full-size mammogram images.The model achieved 90% accuracy, with high recall on cancerous samples. The detailed performance is given in Table 2.

TABLE 2. Evaluation Metrics of Object Detection Model

Class	Precision	Recall	F1-Score	Support	Accuracy
Healthy	0.99	0.89	0.94	18232	0.90
Cancer	0.46	0.97	0.62	1768	

To make the system accessible, a user-friendly web platform is developed. Users can upload mammogram images of any size and choose between object detection or tumor classification, receiving clear and easy-to-understand prediction results.

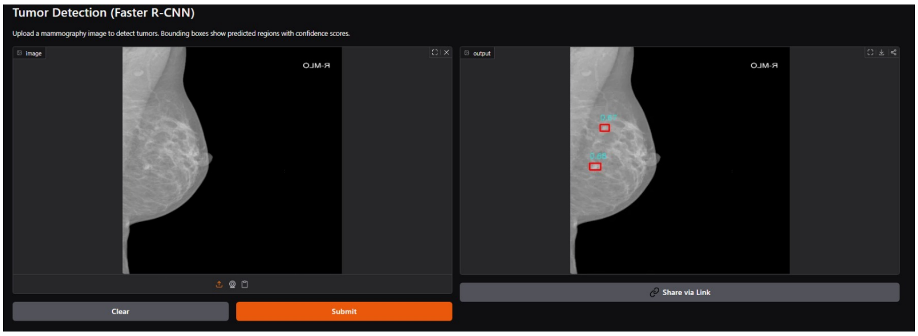

FIGURE 7. Uploading Image by User and Prediction Result

These results demonstrate that both the hardware and software pipelines meet their performance goals. The CSA design achieves the required gain and noise characteristics for low-dose imaging, while the ResNet-based models provide accurate, interpretable results for both lesion detection and tumor classification. Future improvements will focus on combining these models, optimizing inference speed, and further refining the user experience.

CONCLUSIONS AND FUTURE DIRECTIONS

This project successfully developed an AI-supported mammography system by integrating hardware and software components. The folded cascode CSA met performance goals for gain, noise, and bandwidth, validated through MTF and NPS analysis. On the software side, the Faster R-CNN detection model achieved 90% accuracy, while the ResNet-50 classification model reached 76%, both supported by Grad-CAM visualizations. A user-friendly web platform was created to allow real-time predictions from uploaded mammograms. Future work will focus on improving model performance, speeding up inference, and enhancing usability for clinical environments.

REFERENCES

[1] C6 Project Group, *CM3 Report: Object Detection and CMOS Detector Design for X-ray Mammography Imaging*, Bilkent University, Department of Electrical and Electronics Engineering, April 2025.

[2] Nitish Kundu, “Exploring ResNet50: An In-Depth Look at the Model Architecture and Code Implementation,” *Medium*, [Online]. Available: Exploring ResNet50 on Medium

BEHIND THE SCENES