

BREAST CANCER DETECTION WITH EXPLAINABLE AI: GRAD-CAM AND BOUNDING BOX-BASED INTERPRETABILITY

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RESEARCH BACKGROUND

- Breast cancer is the most common cancer in women worldwide.
 - Early detection improves survival rates and treatment outcomes.
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- Traditional mammography is time-consuming and varies by radiologist.
 - AI models achieve high accuracy but face adoption challenges.
 - Lack of interpretability limits clinical trust in AI.
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- Explainable AI (XAI) enhances model transparency with Grad-CAM & bounding boxes.
 - Improving interpretability bridges AI and medical professionals.
 - Class imbalance & generalization must be addressed for reliable AI diagnostics.
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RESEARCH OBJECTIVE

- 1. Develop an AI-based breast cancer detection model with high interpretability using XAI techniques.
- 2. Use Grad-CAM heatmaps and bounding box visualizations to highlight diagnostic features in mammograms.
- 3. Improve model performance by addressing class imbalance and incorporating metadata.

METHODOLOGY

→ Data Source

RSNA Screening Mammography Breast Cancer Detection dataset.

→ Dataset

There are a total of 54706 images in train across 11913 patients.

Metadata : Laterality, view, age, desnsity rating, cancer diagnosis

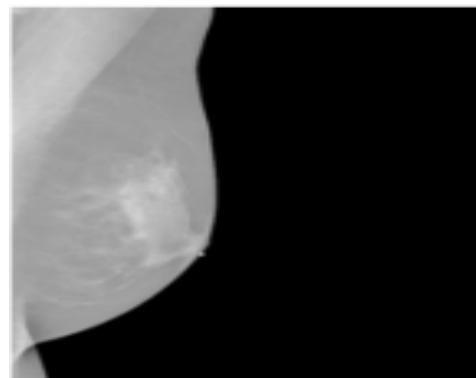
→ Class Imbalance

The dataset exhibited a severe class imbalance, with 1,158 cancer cases compared to 53,548 non-cancer cases, potentially leading to model bias toward the majority class. To address this issue, focal loss was implemented to reduce the emphasis on easily classified samples while prioritizing harder-to-classify cancer cases. Additionally, an up-sampling factor of 10 was applied to the cancer class, ensuring a more balanced distribution and improving the model's ability to detect malignant cases accurately.

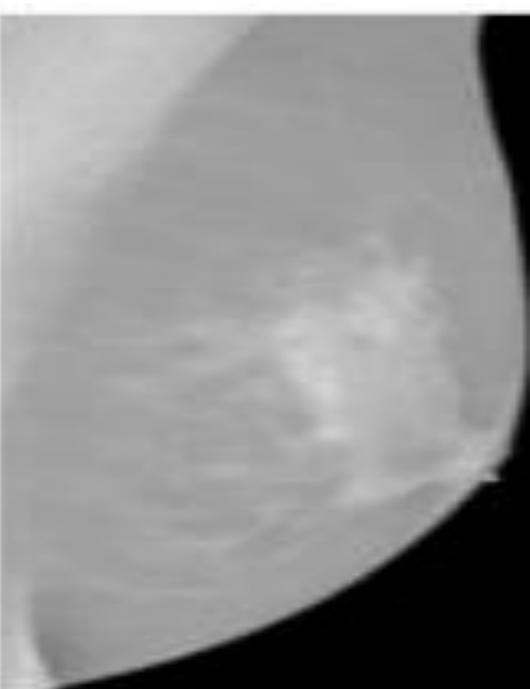
METHODOLOGY

→ Image Data Preprocessing

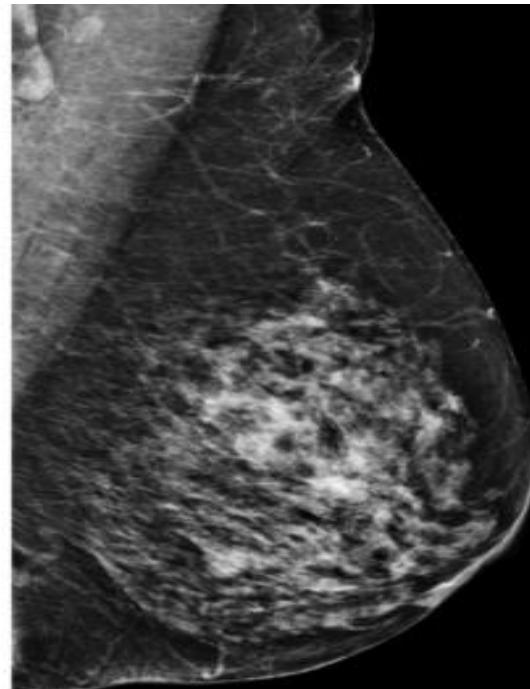
Original Resolution



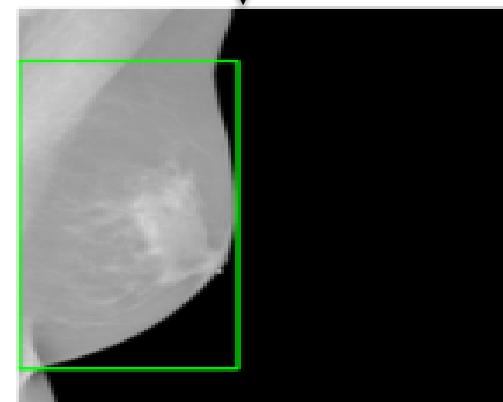
Cropping



Windowing



YOLOX
nano
 416×416



→ Images Augmentation

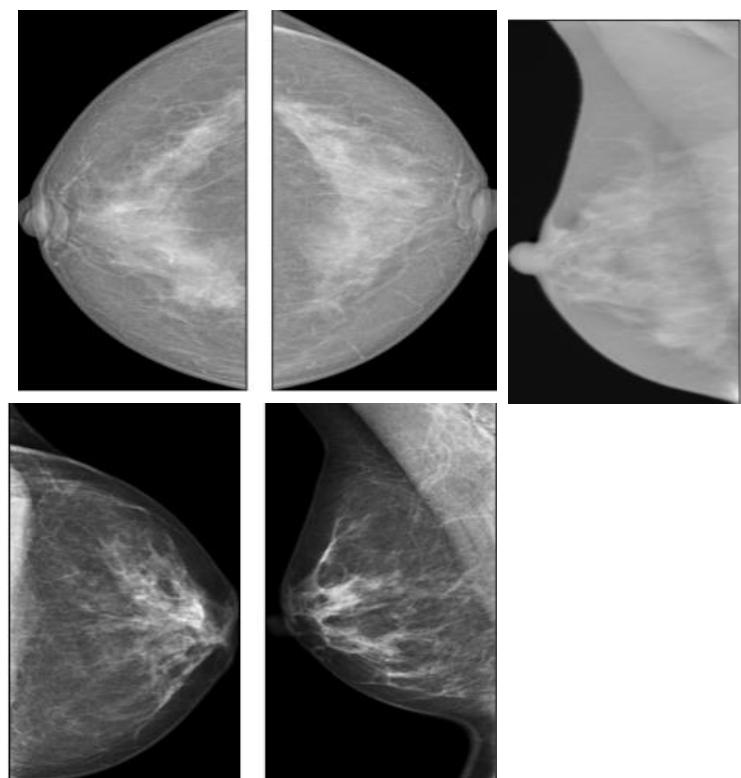
1024

METHODOLOGY

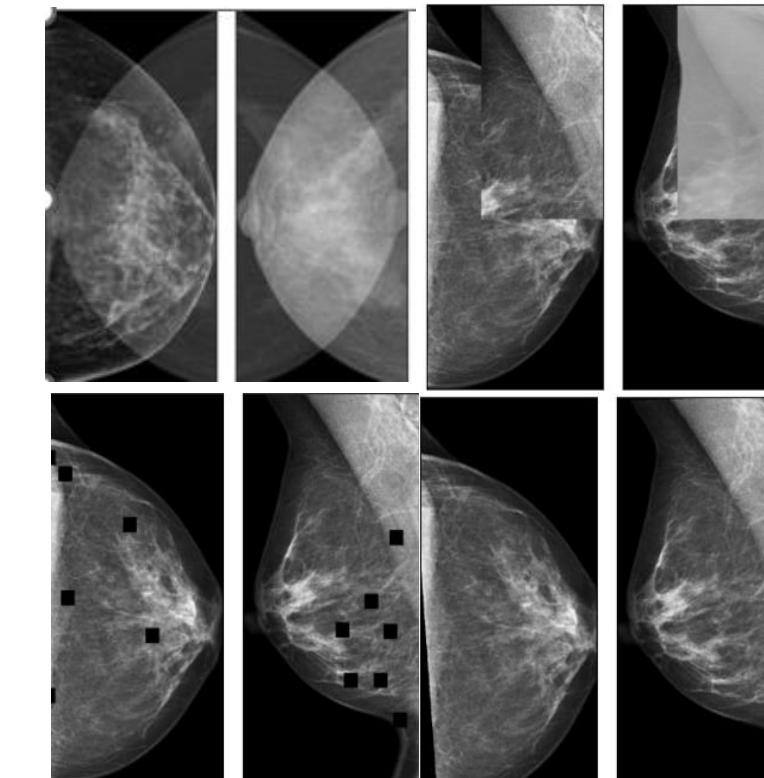
→ Images Augmentation

- Random horizontal flips** → Simulates natural breast variations
- Brightness/contrast adjustments** → Enhances robustness to imaging conditions
- Hue/saturation modifications** → Improves tissue differentiation
- Coarse dropout** → Prevents over-reliance on specific features
- Mix-up augmentation** → Generates synthetic samples for better generalization

Original images



Augmentation Images



METHODOLOGY

→ Models

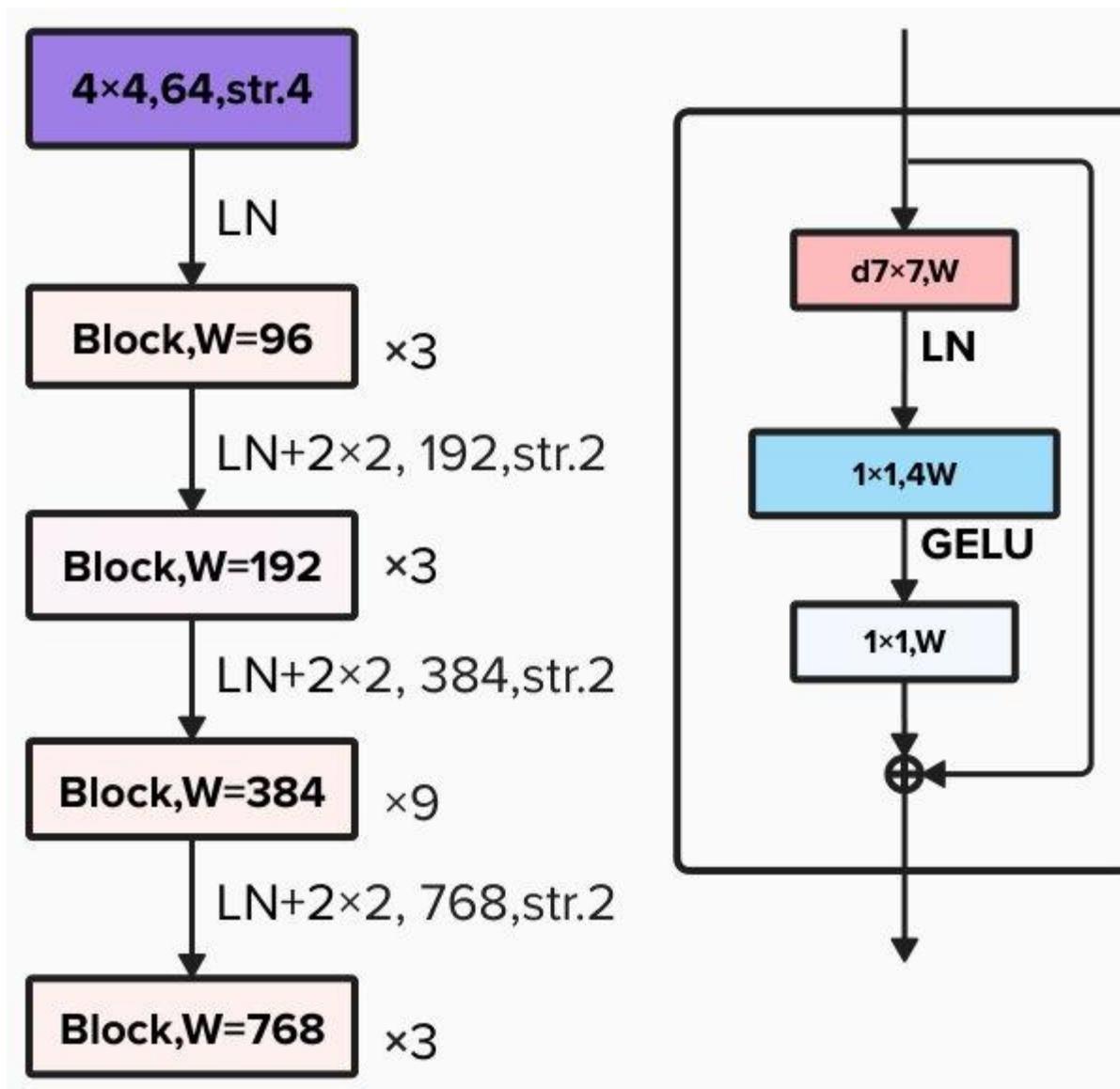


Fig 1:ConvNeXtV1-small

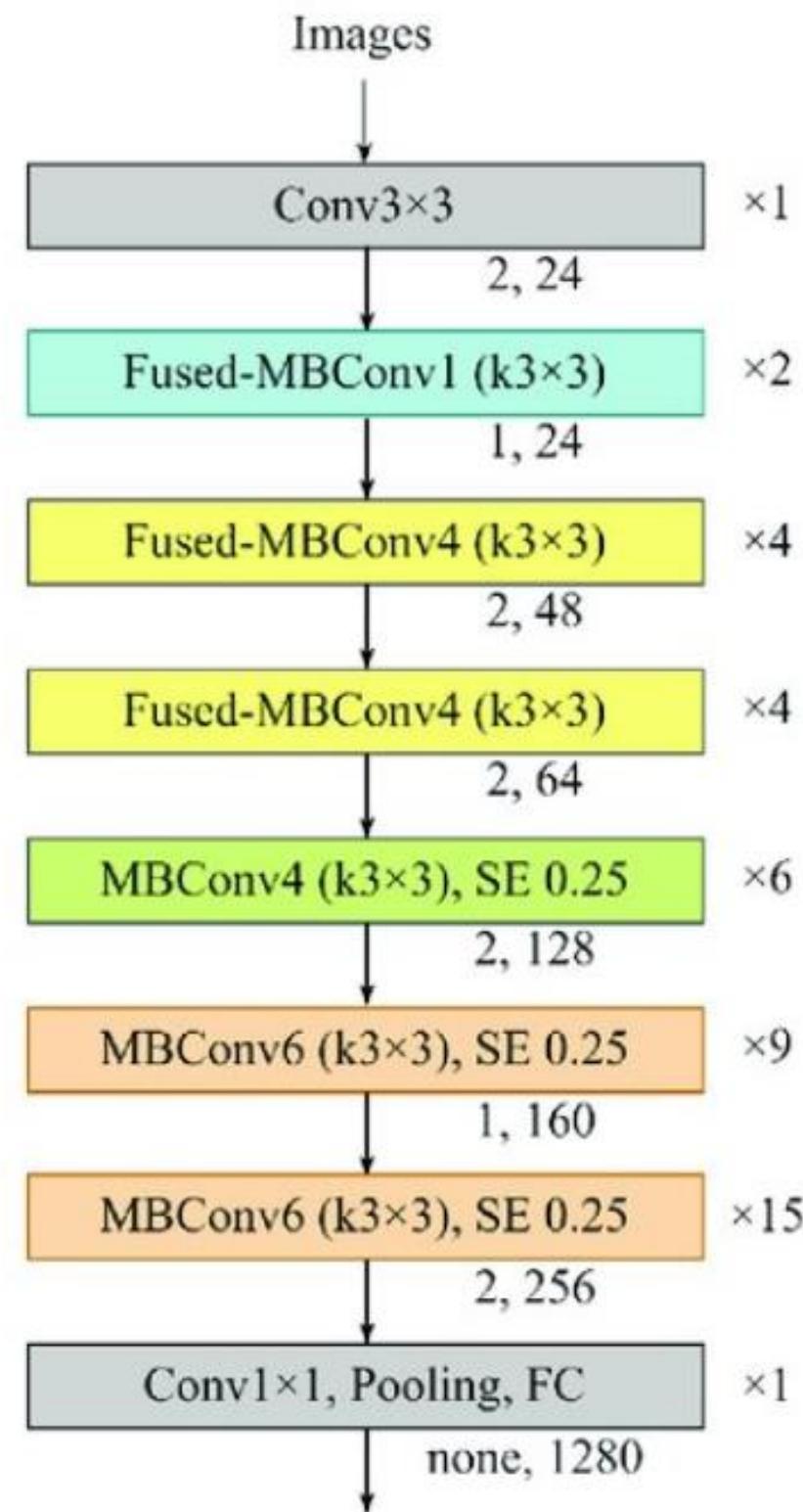


Fig 2: EfficientNetV2

METHODOLOGY

→ Models

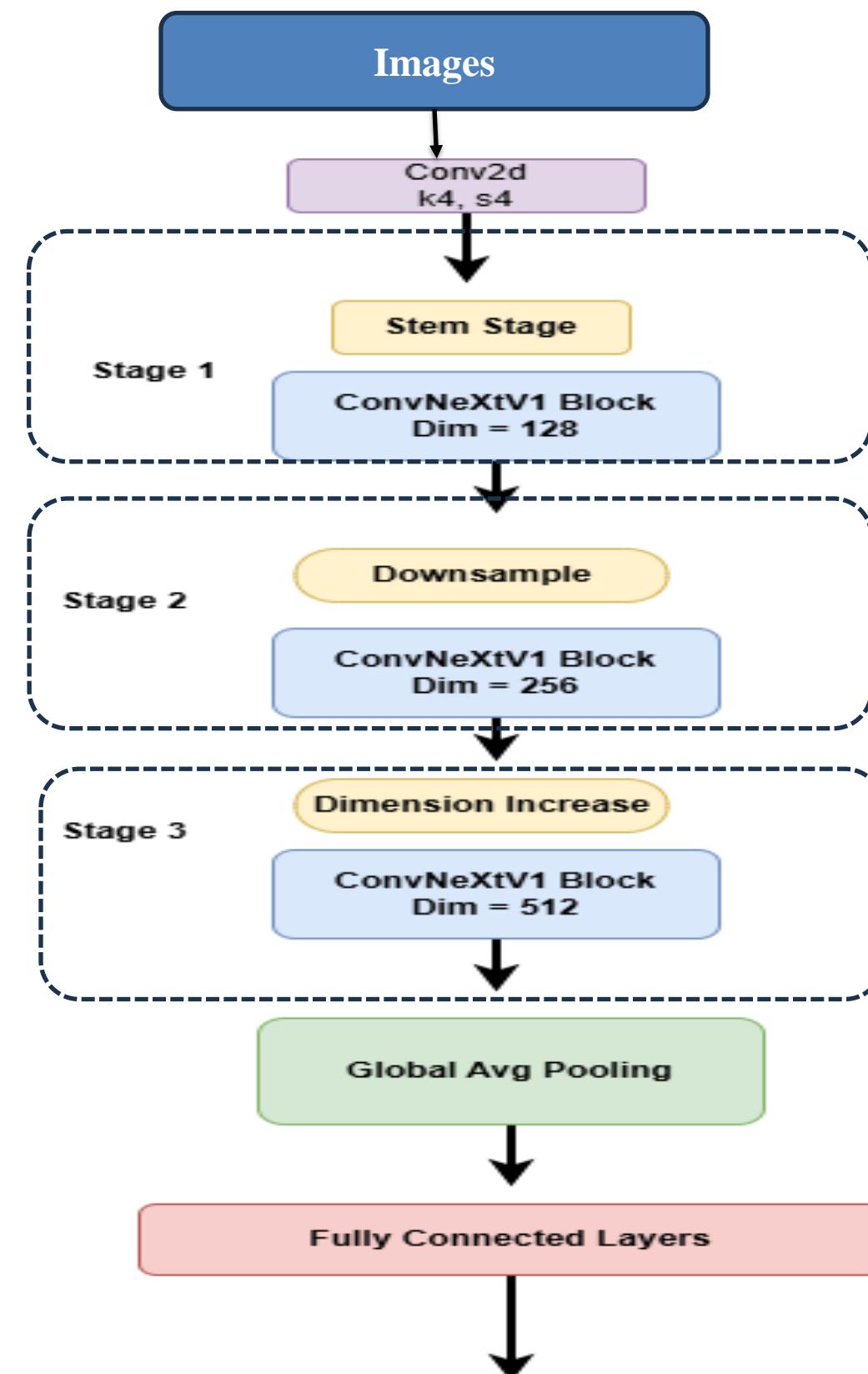


Fig. 1: Implementing ConvNeXtV1- small for advanced breast cancer classification.

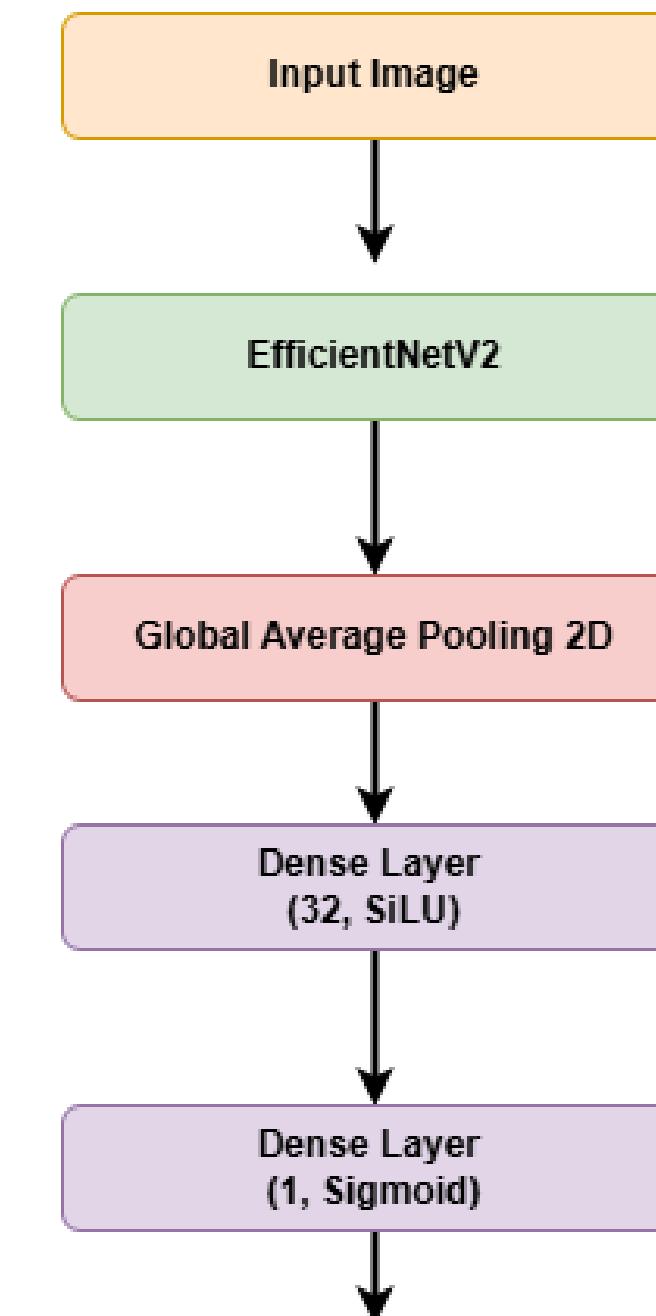
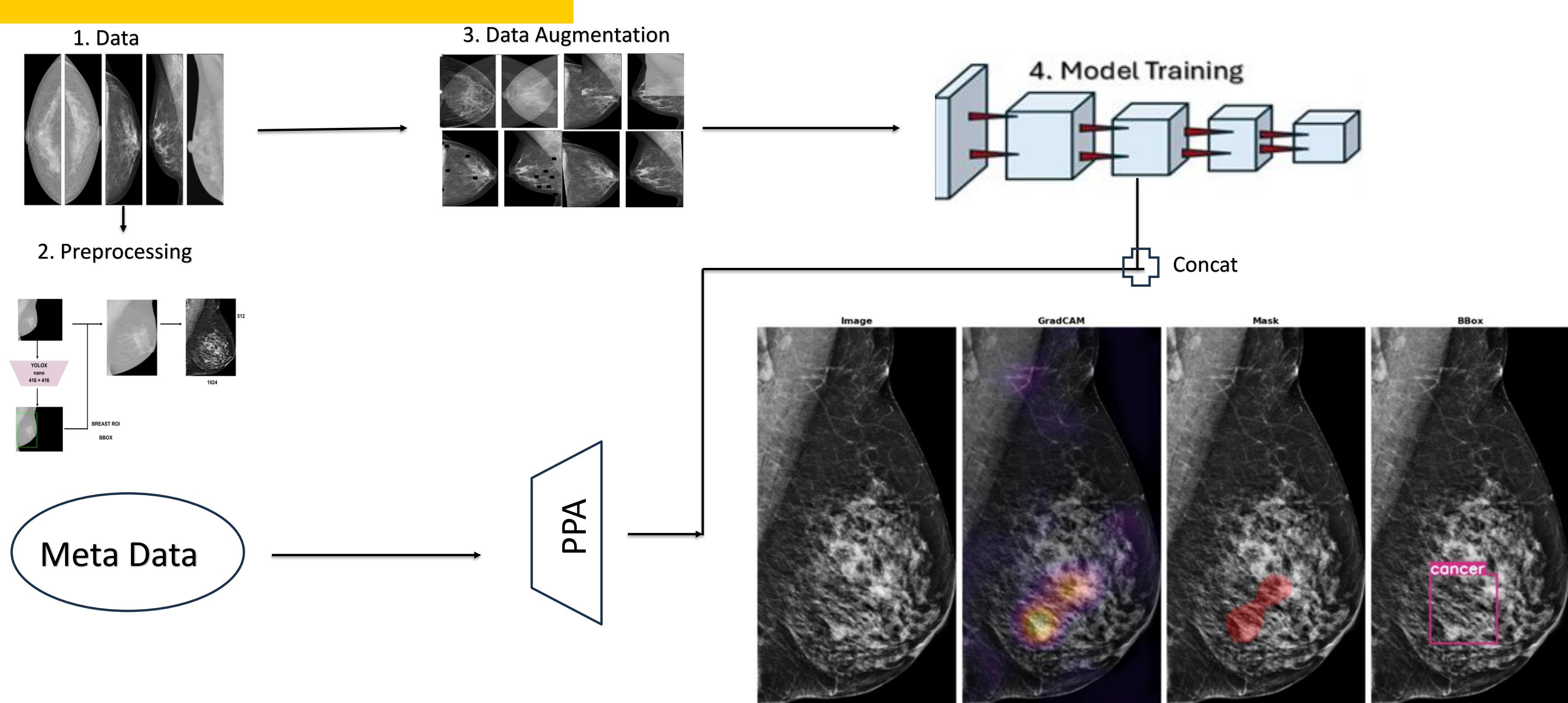


Fig. 2: Implementing EfficientNetV2 for advanced breast cancer classification.

Workflow



Grad cam and BBOX Detecting cancer with Interpretability

Results & Model Performance

Evaluation Metric: Probabilistic F1 (pF1) score

$$pF_1 = 2 \frac{pPrecision \cdot pRecall}{pPrecision + pRecall}$$

$$pPrecision = \frac{pTP}{pTP + pFP}$$

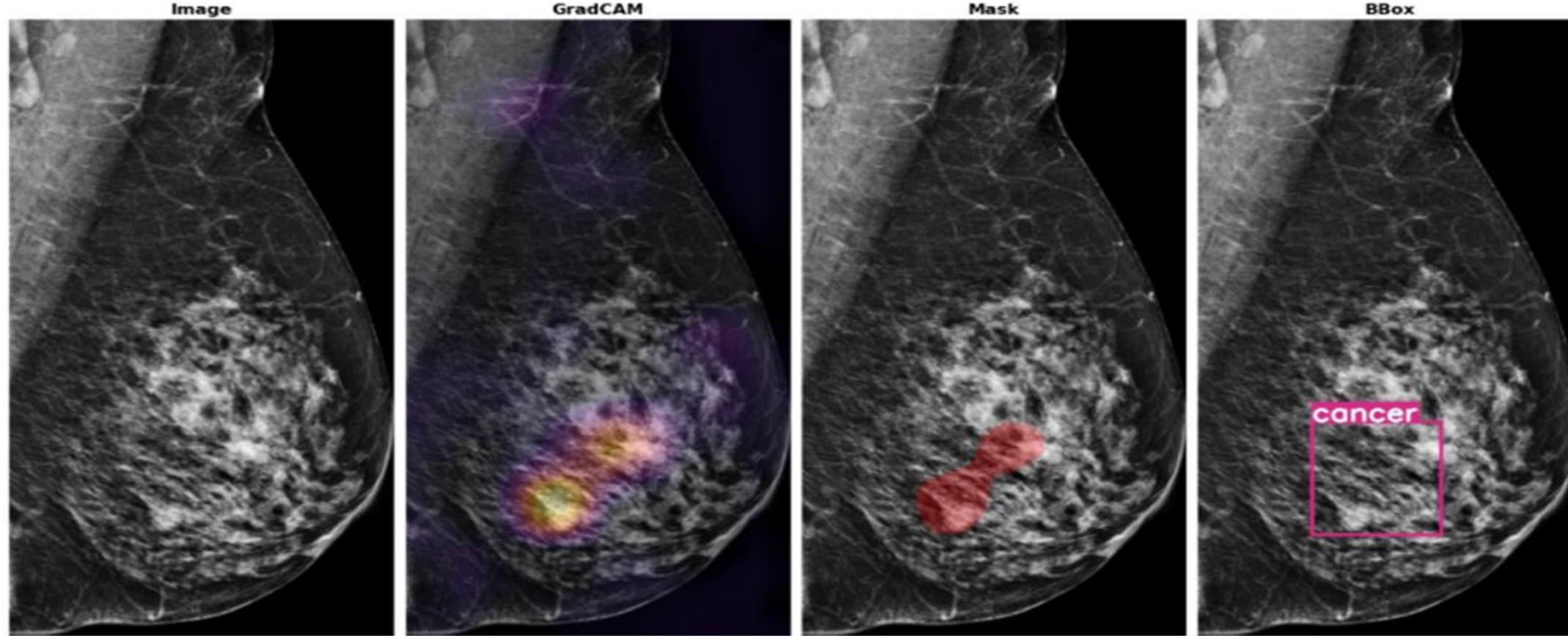
$$pRecall = \frac{pTP}{TP + FN}$$

Results Table:

Model	pF1
ConvNeXtV1-small	0.558
EfficientNetV2	0.331

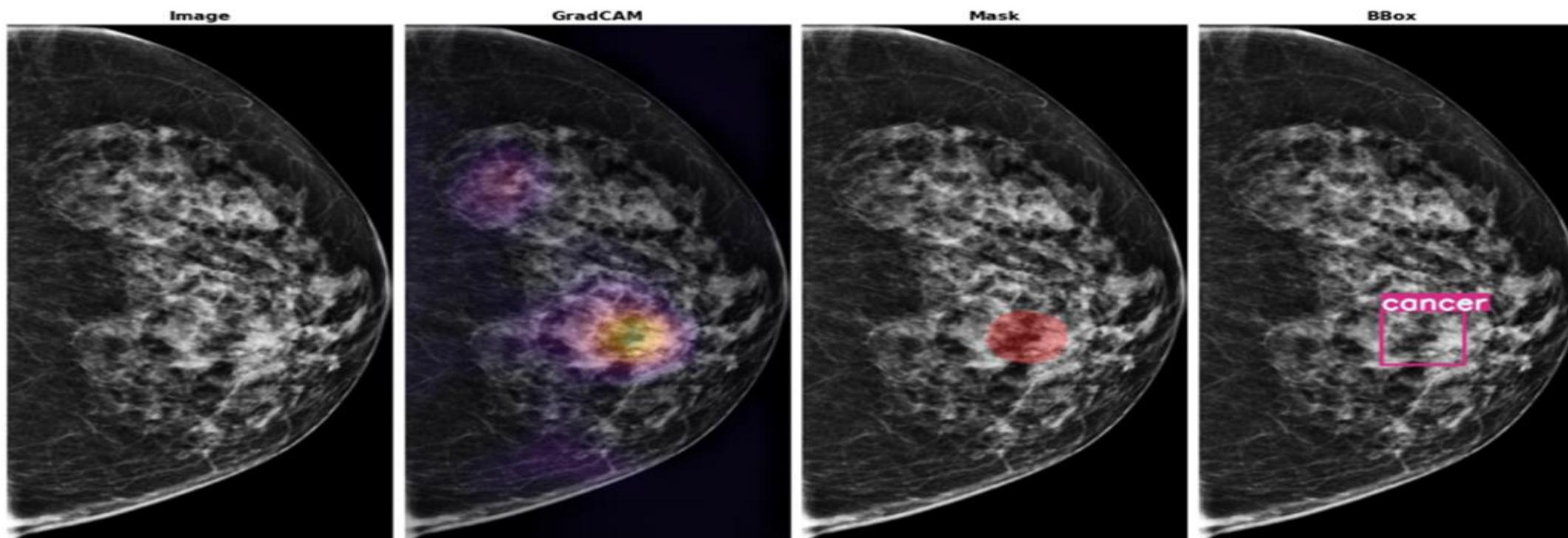
ConvNeXtV1-small **outperformed EfficientNetV2**, showing better feature extraction capabilities.

Visual Results - Grad-CAM & Bounding Boxes



Findings:

1. **Malignant cases:** Strong Grad-CAM activations in tumor regions.
2. **Benign cases:** Highlighted dense breast tissue
3. Bounding boxes **refined lesion localization**, reducing false positives.



Challenges & Limitations

- **Class Imbalance:** Required advanced sampling and label smoothing to mitigate prediction bias.
- **Computational Constraints:** Limited TPU/GPU access hindered larger model experimentation.
- **Dataset Bias:** Potential geographic and ethnic variations may affect generalizability.
- **High-Configuration Needs:** Demanded powerful TPUs/multi-GPU systems for efficient training.

CONCLUSION

- Explainable AI techniques **enhance transparency and trust** in AI-driven breast cancer detection.
- Grad-CAM & bounding boxes **improve lesion localization** and align with radiological assessments.
- The study underscores **the necessity of interpretability in AI-based diagnostics**.

Future Work

- Explore **Transformer-based architectures** (Swin Transformer, Vision Transformer).
- Improve **data augmentation** techniques for robust feature learning.
- Collaborate with radiologists for **real-world validation** of model predictions.

REFERENCES

- He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778.
- Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the inception architecture for computer vision. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2818–2826.
- Zhang, Q., Wu, Y. N., & Zhu, S. C. (2018). Interpretable convolutional neural networks. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 8827–8836.

REFERENCES

- Shen, W., Zhou, M., Yang, F., Yu, D., Dong, D., Yang, C., & Zang, Y. (2019). Multi-crop convolutional neural networks for lung nodule malignancy suspiciousness classification. *Pattern Recognition*, 88, 385–398.
- RSNA Screening Mammography Breast Cancer Detection Dataset. (2023). Available at: <https://www.kaggle.com/competitions/rsna-breast-cancer-detection>
- Wu, J., Hicks, C., & Wang, H. (2019). Interpretable deep learning for automatic diagnosis in breast cancer. *Nature Machine Intelligence*, 1(5), 236–245.

THANK YOU

