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Synopsis Of

Explainable AI-Driven Clinical Thermography for Breast Cancer Detection

A Thesis

To be submitted by

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Of

DOCTOR OF PHILOSOPHY

1 Abstract

Improving breast cancer detection through non-invasive methods is crucial due to its significant impact on women's health worldwide. This thesis introduces a sophisticated artificial intelligence (AI) pipeline to detect breast cancer using infrared breast images, featuring an explainable classifier that enhances interpretability and trust. Infrared thermography offers a promising, non-contact, non-invasive alternative that remains underutilized in clinical practice. This study aims to leverage the untapped potential of infrared imaging, presenting it as a viable complement or alternative to traditional mammography by improving detection rates and patient comfort. The foundation of this thesis is laid by an extensive review of the current literature on IR imaging for breast cancer detection, which has highlighted the standardization of image acquisition protocols. With this knowledge, four distinct IR breast image datasets conforming to these protocols were amassed, allowing for a multifaceted analysis.

The initial contribution of this research is the development of novel denoising auto-encoders using image pyramids to combat the non-local noise inherent in thermographic imaging. By devising a statistical method to ascertain the noise probability distribution, these auto-encoders enhance the image quality, as evidenced by the improved peak signal-to-noise ratios across the datasets. Advancing to the segmentation phase, a Generative Adversarial Network (GAN) model, named IR-GAN, was trained to delineate the breast regions precisely in IR images. This model leverages a U-Net structure with PatchGAN discriminators. It outshines existing segmentation models by applying both reconstruction and adversarial loss. The effectiveness of IR-GAN is reflected in its superior performance metrics, including mean Intersection over Union and Dice scores, evaluated against a variety of datasets featuring breasts of differing shapes and sizes.

The pivotal aspect of the thesis revolves around the classification of IR images for cancer detection. A sophisticated classifier was constructed by refining pre-trained networks such as VGG-19, DenseNet-201, and EfficientNetB7 with carefully tuned hyperparameters and utilizing denoised and segmented breast images. An ensemble of these networks, specifically excluding their classification heads, was discovered to yield enhanced accuracy. The final step in this scholarly endeavour was to augment the classifier's transparency by developing an Attention-Guided Grad-CAM. This modification introduced an attention mechanism into the pre-trained networks. Attention-Guided Grad-CAM produced detailed and accurate heatmaps that offer a granular explanation of the classifier's decisions. The validation of these heatmaps against mammograms and annotated infrared thyroid nodule datasets corroborated their precision and utility in a clinical context.

2 Objectives

In the realm of medical imaging, the quest for non-invasive, accurate diagnostic tools is paramount, particularly in the early detection of diseases such as breast cancer. This research aims to bridge the gap between clinical thermography's capabilities and its practical application, leveraging the power of artificial intelligence (AI) to enhance diagnostic accuracy and interpretability. Against this backdrop, our study sets forth the following objectives:

1. Conduct a thorough literature review to explore the various modalities of clinical thermography, examining current protocols, standardization requirements, and identifying directions for future research.

2. Establish a detailed framework and data management pipeline designed to pre-process, classify, and elucidate AI-based clinical thermography classification results, transforming it into a supportive technology for medical practitioners.

3. Improve classification accuracy within clinical thermography by employing advanced deep learning methodologies, focusing on the development of superior denoising and segmentation strategies.

4. Through a series of deep learning experiments with infrared images, our goal is to develop a non-invasive assistive technology that gains the trust of medical professionals and ultimately contributes positively to patient care.

Abbreviations

Abbreviations	**Abbreviations**
AI : Artificial Intelligence	ABT : Amrita Breast Thermography
VGG : Visual Geometry Group	iPyrDAE : Image Pyramid Denoising Autoencoder
CAM : Class Activation Map	KL : Kullback-Leible
GAN : Generative adversarial networks	PDF : Probability Density Function
IR : Infrared	MLE : Maximum Likelihood Estimate
XAI : Explainable Artificial Intelligence	DAE : Denoising Autoencoder
DMR-IR : Database for Mastology Research	JS : Jensen-Shannon
AAT : Ann Arbor Thermology	GCLM : Gray Level Co-occurrence Matrix

Table 1: List of Abbreviations

3 Existing Gaps Which Were Bridged

In the evolving field of artificial intelligence (AI) for medical diagnostics, particularly in the detection of breast cancer using infrared imaging, a detailed examination of current research reveals following gaps that need addressing.

1. Denoising Importance: Effective denoising is crucial for accurate image analysis and reducing diagnostic errors.

2. Denoising Autoencoders Underutilized: There's minimal research on applying denoising autoencoders to infrared breast images, essential for improving diagnostics.

3. Focus on Tumor Segmentation: Current research primarily targets tumor segmentation, neglecting the segmentation of the entire breast (Yadav and Jadhav, 2022).

4. U-Net's Potential Not Fully Explored: The capabilities of U-Net for comprehensive breast segmentation in infrared imaging are under-explored.

5. Focused Breast Analysis: There's a lack of research on analyzing the entire breast area (segmented bust), which could reveal cancer markers through explinable AI.

6. Limited Dataset Utilization: Studies often use only parts of the DMR-IR dataset, affecting the generalizability of findings.

7. Transfer Learning Under-explored: The application of transfer learning for dataset adaptation in infrared breast imaging has not been widely investigated.

8. Explainable AI Techniques Missing: There is a significant gap in integrating XAI techniques to improve classification decision interpretability in a clinical setting (Shah *et al.*, 2022).

4 Most Important Contributions

- Developed an innovative denoising autoencoder using image pyramids for multi-scale denoising, enhancing image clarity and reliability for diagnostics.
- Created a U-Net-based model integrated with Generative Adversarial Networks (GANs) for precise breast portion segmentation, providing a complete representation of the breast for more detailed diagnostics.
- Implemented a classifier with adaptable pre-trained networks to maintain high accuracy and generalizability across various infrared breast imaging datasets.
- Enhanced the interpretability of AI classification decisions by developing an improved Grad-CAM (Selvaraju *et al.*, 2017) explainer, providing clinicians with intuitive visual explanations of the AI's diagnostic process.

These advancements mark significant strides in improving the detection and diagnosis of breast cancer through infrared imaging, promising avenues for future research and clinical application.

4.1 Datasets Used

The following datasets will be used. The Following table 2 shows the metrics on infrared images available.

1. DMR-IR (Silva *et al.*, 2014): Database of Mastology Research.

2. MammoTherm (Araújo *et al.*, 2017) - Thermographic mammary images database for breast cancer research

3. ABT (Krishna and George, 2021)- Amrita Breast Thermogram

4. AAT (Dey *et al.*, 2023) - Ann Arbor Thermography

To augment the infrared breast image datasets and achieve a total count of 10,000 images while maintaining the original ratio of sick (abnormal) to healthy images, Albumentations (Buslaev *et al.*, 2020) was used. The Table 3 show the size of the infrared images after augmentations.

(a) DMR (Database for Mastology Research): 5,493 images , to be augmented to 7,500 images.

(b) MammoThem: Original count of 371 , to be augmented to 1,500 images.

(c) ABT (Amrita Breast Thermogram): Original count of 60, to be augmented to 500 images.

(d) ANN (Ann Arbor Thermography): Original count 85 , to be augmented to 500 images.

4.2 iPyrDAE - Image pyramid based Denosing Autoencoder

The iPyrDAE (Image Pyramid Denoising AutoEncoder) represents an innovative approach to denoising infrared (IR) breast images, utilizing the concept of image pyramids to tackle noise at multiple scales. By leveraging image pyramids, the DAE processes images at different resolutions, allowing it to effectively identify and mitigate both local and global noise variations. This method enhances the model's ability to discern and address noise without compromising the integrity of the original image. To further refine the denoising process, the Gray Level Co-occurrence Matrix (GLCM) is applied to the input IR images. This matrix, which quantifies the frequency of pixel intensity changes, aids in identifying pixels that likely contribute to noise—characterized by higher contrast and lower correlation, energy, and homogeneity (Gomez *et al.*, 2017). By setting specific thresholds based on these features, pixels are classified as noise or non-noise, enabling a targeted approach to denoising.

Upon identifying noisy pixels, the iPyrDAE formulates hypotheses regarding the noise distribution—considering common types such as gamma, Poisson, and Gaussian—and applies the Probability Density Function (PDF) for each distribution to the noisy regions. By computing the Maximum Likelihood Estimate (MLE) for the parameters of each noise distribution, the model identifies the parameters that best explain the observed noise. This process is complemented by using statistical methods like the Kullback-Leibler (KL) and Jensen-Shannon (JS) divergence to compare the hypothesized noise distributions with the actual noise present in the images. The selection of a noise model is based on the lowest divergence values, indicating the closest fit to the actual noise distribution. The DAE then generates noisy images by adding noise to selected levels of image pyramids and pairs these with clean images for training. Through

Table 2: Infrared breast Image Dataset Metrics

Dataset name	Item	Healthy	Sick	Total
DMR- IR	# Patients/Volunteers	192	46	238
DMR- IR	# Static Protocol Images	787	193	980
DMR- IR	# Dynamic Protocol Images	3642	871	4513
MammoTherm	# Patients/Volunteers	69	38	98
MammoTherm	# Static Protocol Images	235	136	371
ABT	# Static Protocol Images (Sample)	45	15	60
ATT	# Static Protocol Images (Sample)	55	30	85

Table 3: The dataset size after Augmentation

Dataset	Normal Images	Sick Images	Total Images
DMR-IR	6047	1453	7500
MammoTherm	950	550	1500
ABT	375	125	500
AAT	323	177	500

this sophisticated training process, which minimizes the reconstruction error between the denoised output and the clean target images, the iPyrDAE effectively enhances the quality of IR breast images, making it a valuable tool for improving diagnostic accuracy in breast cancer detection. The proposed model successfully achieved a Peak Signal-to-Noise Ratio (PSNR) of 50.10 dB when comparing the denoised images to the original, corrupted input images. The Figure 1 shows the iPyrDAE architecture.

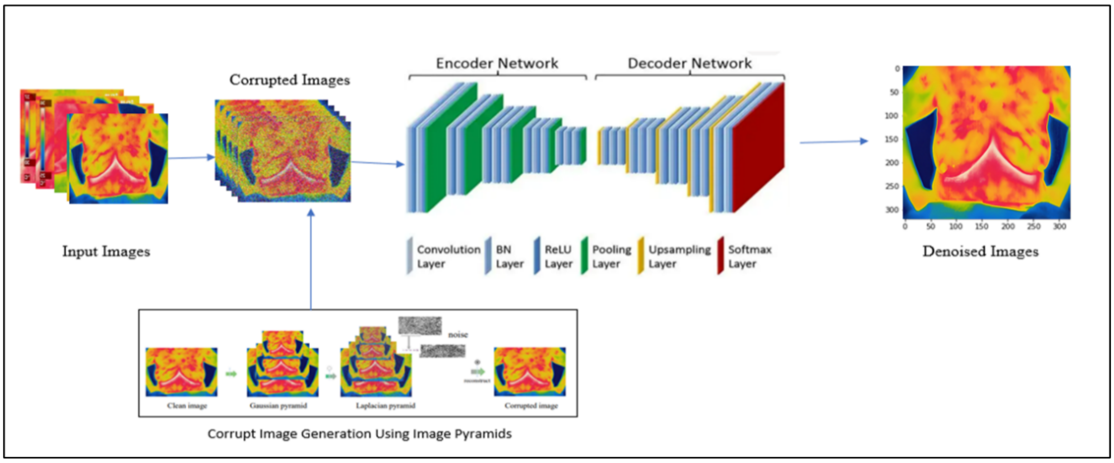

Figure 1: The iPyrDAE showing the Denoising Architecture using auto-encoders

4.3 IR-GAN - A U-Net based GAN for Breast Portion Segmentation

In our approach to segment breast portions from infrared (IR) images, we employed a systematic preprocessing and training strategy to harness the capabilities of U-Net (Gomathi *et al.*, 2020) within a Generative Adversarial Network (GAN) framework. The initial preprocessing involved cropping the images from their original size of 640x480 to 480x480, removing equal parts from both sides to ensure square images that meet U-Net's input requirements. Following this, we applied GrabCut, an automated foreground extraction tool, to generate binary segmentation masks that distinguish the breast area from the background. This step was crucial in preparing our data for the nuanced task of segmentation, where the primary challenge lies in accurately identifying the breast tissue in IR images, which can vary significantly in appearance due to physiological differences and imaging conditions.

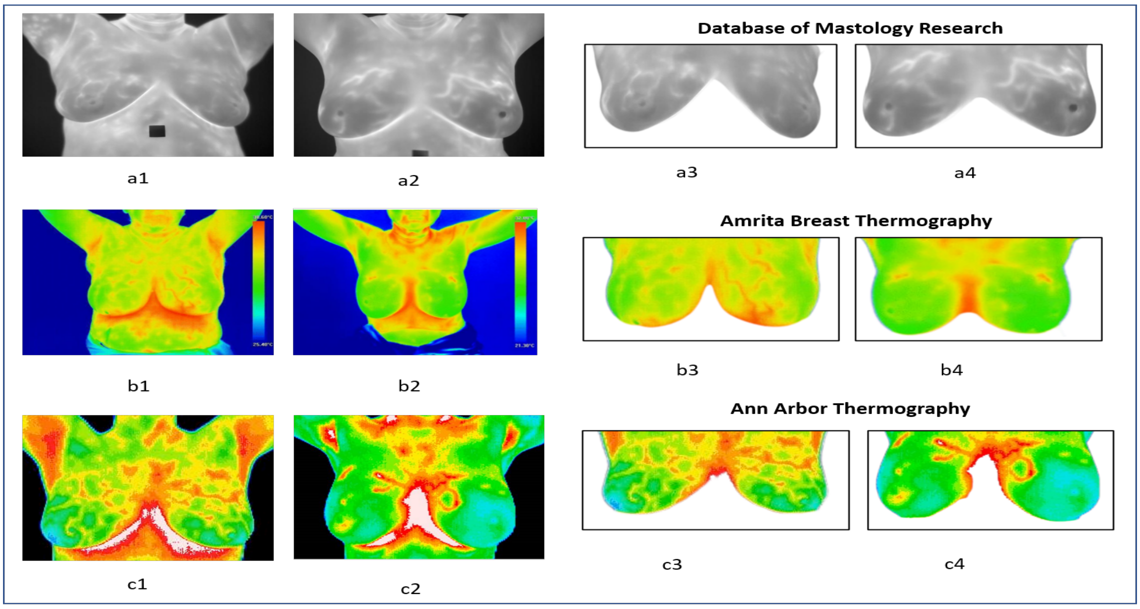

Figure 2: The segmentation output for various datasets. (a1, a2), (b1, b2) & (c1, c2) are input images, whereas (a3, a4), (b3, b4) & (c3, c4) are the segmented images

With the preprocessed images and initial segmentation masks ready, we proceeded to train a U-Net model specifically designed for this task. The trained U-Net then served as the generator in our GAN setup, paired with a PatchGAN discriminator (Innani *et al.*, 2023). This combination allowed for a detailed feedback mechanism, where PatchGAN evaluates small patches of the image to determine their authenticity, thus providing localized enhancements to the segmentation process. The GAN was trained using a combination of adversarial and reconstruction losses, meticulously tuned to ensure that the generated segmentation masks are indistinguishable from real, manually corrected masks and closely match the target masks. This dual-loss strategy proved effective, as evidenced by our model achieving an exceptional mean Intersection over Union (mIoU) of 0.937 on unseen test images, underscoring the accuracy of our segmentation approach. This methodology not only showcases the potential of integrating U-Net with GANs for medical image segmentation but also sets a new benchmark for the precision of breast cancer detection through IR imaging. The Figure 2 shows the breast portion segmentation using IR-GAN.

4.4 Ensemble Classifier with Grad-CAM Explainer

Our goal was to leverage the capabilities of pre-trained networks to classify infrared breast images as normal or cancerous and employ Grad-CAM to elucidate the classification decisions. We constructed classifiers using three prominent pre-trained models: VGG-19 (Tiwari *et al.*, 2021), DenseNet-201 (Zhong *et al.*, 2020), and EfficientNetB7 Tan and Le (2019). Each model was chosen for its unique architectural strengths and proven efficacy in image classification tasks. The aim was to harness their deep learning capabilities to accurately classify infrared breast images. Hyperparameters for each classifier were meticulously tuned to optimize performance. This process involved adjusting learning rates, batch sizes, and regularization parameters to achieve a balance between model complexity and generalization ability. Post-tuning, each classifier demonstrated commendable performance, with accuracy metrics ranging between 90% to 92%. These results underscored the effectiveness of the models in distinguishing between normal and cancerous infrared breast images. To further enhance classification accuracy, we experimented with creating an ensemble of the classifiers in two configurations: utilizing only the classifier heads and another without the heads. This approach yielded a significant accuracy improvement, reaching approximately 95%. The ensemble method capitalized on the diverse strengths of each model, thereby reducing the likelihood of misclassification. The Figure 3 shows the proposed Grad-CAM technique.

Initially, Grad-CAM was applied to visualize salient regions relevant to cancer prediction. However, the initial heatmaps lacked focus and granularity. To address this, we integrated a Squeeze and Excite attention mechanism just before the last layer, prior to softmax, across all three networks. This adjustment re-calibrated Grad-CAM, resulting in more focused and fine-grained visual outputs. The enhanced heatmaps provided clearer insights into the regions of interest, making the Grad-CAM outputs more interpretable for physicians. The model's robustness and replicability were tested on additional datasets, including the DNTR (González *et al.*, 2019), dataset, which comprises infrared images used for diagnosing thyroid nodules. This step was crucial for demonstrating the model's adaptability and potential applicability beyond breast cancer detection. The integration of attention mechanisms with Grad-CAM represents a significant advancement in making AI-driven diagnostic tools more accessible and trustworthy for clinical use. The Figure 4 shows the Grad-CAM output explaining the classfication output for cancer detection.

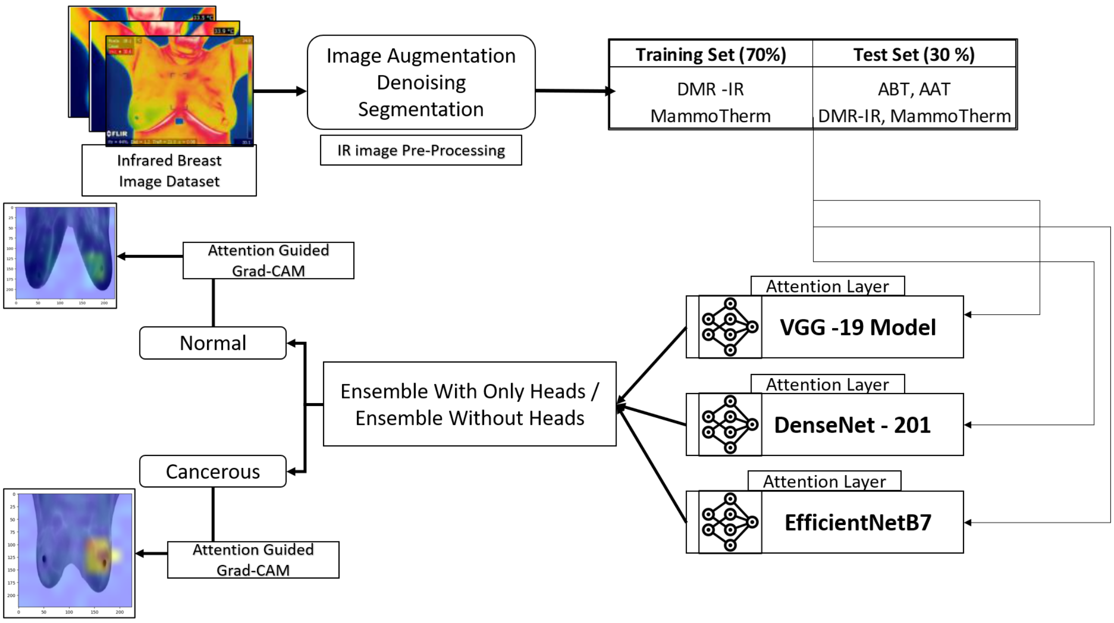

Figure 3: Proposed Attention Guided Grad-CAM

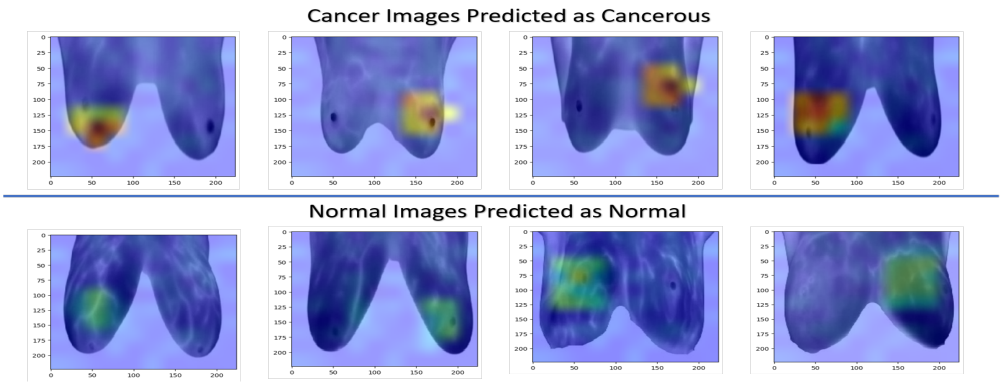

Figure 4: Attention Guided Grad-CAM with salient Features

5 Conclusions

This thesis presents research on using artificial intelligence for breast cancer detection through infrared imaging. It combines image denoising, segmentation of breast tissue, and the application of attention-guided Grad-CAM to enhance model interpretability. The work develops a diagnostic framework that achieves high accuracy and provides insights into its decision-making process. An ensemble classifier, optimized through hyperparameter adjustments and incorporated with a Squeeze and Excite attention mechanism, shows effectiveness, as evidenced by performance across additional medical imaging datasets. This effort highlights the potential of deep learning in medical diagnostics and addresses the demands for reliability and interpretability in clinical applications. Future research will focus on integrating additional Explainable Artificial Intelligence (XAI) techniques such as Visual Question Answering (VQA) to provide detailed explanations of diagnoses and developing methods to grade breast cancer severity based on heatmap intensity analysis. These advancements aim to enhance diagnostic interpretability and accuracy. The thesis contributes to the field of AI-assisted breast cancer detection and establishes a foundation for future research.

6 Organization of the Thesis

The proposed outline of the thesis is as follows:

(a) Chapter 1: Introduction

(b) Chapter 2: Literature Review

(c) Chapter 3: Data Set Description

(d) Chapter 4: iPyrDAE : Infrared Breast Image Denoising Using Image Pyramids and Denosing Autoencoder

(e) Chapter 5: IR-GAN : GAN based Breast portion segmentation using U-Net

(f) Chapter 6:Attention Guided Grad-CAM for Explaining breast cancer classification

(g) Chapter 7: Conclusion and Future Scope

7 List of Publications

Refereed Journals Based on The Thesis

1. Kaushik R., Sivaselvan B. & Kamakoti V. (2023) Clinical Thermography for Breast Cancer Screening: A Systematic Review on Image Acquisition, Segmentation, and Classification, IETE Technical Review,
   DOI: 10.1080/02564602.2023.2238683

2. Kaushik R., Sivaselvan B. & Kamakoti V. Attention guided grad-CAM : an improved explainable artificial intelligence model for infrared breast cancer detection. Multimed Tools Appl (2023).
   https://doi.org/10.1007/s11042-023-17776-7

3. Kaushik R., Sivaselvan B. & Kamakoti V. (2023) IR-GAN: improved generative adversarial networks for infrared breast image segmentation, Quantitative InfraRed Thermography Journal,
   DOI: 10.1080/17686733.2023.2294598

Presentations/Publications in Conferences Based on the Thesis

1. Kaushik R., Sivaselvan B. & Kamakoti V. (2023). iPyrDAE: Image Pyramid-Based Denoising Autoencoder for Infrared Breast Images. In: Pattern Recognition and Machine Intelligence. PReMI 2023. Lecture Notes in Computer Science, vol 14301. Springer, Cham.
   https://doi.org/10.1007/978-3-031-45170-6_41
   Invited for Submitting Extended Version : IET Image Processing Journal

2. Kaushik R., Sivaselvan B. & Kamakoti V. (2023). Integrating Explainable AI With Infrared Imaging and Deep Learning for Breast Cancer Detection. In: 21st OITS International Conference on Information Technology NIT, Raipur. IEEE record no. of the OCIT 2023 is 59427.

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4. Kaushik R., Sivaselvan B. & Kamakoti V. (2023). Enhancing Interpretability in Infrared Breast Cancer Classification: Combining Grad-CAM and Visual Question Answering. In: 10th International Conference on Business Analytics and Intelligence (2023-ICBAI),IISc Bangalore

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