RESEARCH PAPER

Revamp and Migration of a Deep Generative Model For High-Quality Synthetic Ultrasound Image Generation And the CAD Detection Using GAN

1st Mr. k. Sathyaseelan, 2nd G. Dharan, 3rd V. Logadeepa, 4th R. Sundharakumar
Department of Artificial Intelligence and Data Science,
KIT-Kalaignarkarunanidhi Institute of Technology, Coimbatore, Tamil Nadu, India
[1]Corresponding author Email:kitsathyaseelan@gmail.com,
[2]dharang2510@gmail.com,[3]vlogadeepa25@gmail.com,[4]sundharakumar27@gmail.com,

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***Abstract*—**Coronary Artery Disease (CAD) continues to be a major cause of the death globally, necessitating the need for an early and accurate diagnosis to ensure the effective clinical management. Ultrasound imaging is a popular modality for cardiac diagnosis due to its non-invasive, radiation free, and the cost effective nature; however, its diagnostic capabilities are often hampered by low contrast, speckle noise, and the lack of the labelled training data. To overcome these issues, this paper pro- poses the design and development of a deep generative learning model using the Generative Adversarial Networks (GANs) for the high quality synthetic generation of the ultrasound images and automated detection of CAD.The proposed system uses a GAN model for the anatomically consistent and the realistic generation of the synthetic ultrasound images, which can be used to supplement the small sized real datasets and address the problem of the class imbalance. These improved datasets can then be used to train a deep learning model for CAD detection. The experimental results show that the addition of GAN-synthesised data can greatly improve the detection accuracy, sensitivity, and overall classification performance. The proposed system showes the efficacy of deep generative models in the enhancing ultrasound based computer aided diagnosis (CAD) systems and their potential use in the practical clinical settings.

***Keywords*—**Coronary Artery Disease (CAD), Ultrasound Imaging, Generative Adversarial Networks (GAN), Synthetic Medical Images, Deep Learning, Data Augmentation, Computer-Aided Diagnosis

I. Introduction

Coronary Artery Disease (CAD) is a major global health issue and a leading cause of the cardiovascular-related deaths. Early detection is a key factor in preventing complications and increasing the survival rate of patients. While highly accurate imaging techniques like CT angiography and intravascular imaging are available, they are often costly, invasive, and not ideal for large-scale screening. On the other hand, ultrasound imaging is widely available, inexpensive, and non-invasive, making it a promising candidate for large-scale cardiac screening.Despite its benefits, ultrasound imaging for CAD detection is plagued by several challenges, including its reliance on human operators, low image quality, speckle noise, and the lack of publicly available annotated datasets. These factors greatly impede the performance of traditional machine learning and deep learning techniques. Recent breakthroughs in deep learning have shown great promise in medical image analysis; however, their success is largely dependent on the availability of large and well-balanced datasets.Generative Adversarial Networks (GANs) are emerging as a promising class of deep generative models that have the ability to generate high-quality synthetic images that are very similar to real images. In medical imaging, GANs have shown great promise in data augmentation, noise reduction, and image enhancement. Adopted by these benefits, this study aims to design and develop a GAN-based system for the generating high quality synthetic ultrasound images and improving the CAD detection performance. The proposed system combines the benefits of the synthetic image generation with a deep learning based detection system, allowing for the accurate CAD classification even when the datasets are limited. By increasing the dataset diversity and maintaining the anatomical realism, the proposed system hopes to improve the accuracy and the reliability of the ultrasound based CAD screening.

II. LITERATURE SURVEY

The use of deep learning for the diagnosis of cardiovascular diseases has witnessed substantial growth over the past decade, owing to the increasing availability of computational power, medical imaging data, and efficient learning algorithms. Coronary artery disease (CAD), a leading cause of the death globally, has been the focus of most artificial intelligence (AI)-assisted diagnostic research. Most early research work on the CAD diagnosis has focused on the traditional machine learning methods using carefully designed features derived from the clinical data, electrocardiogram (ECG) signals, or image data. While these methods have shown moderate success, they have been hampered by the complexity of feature design and a lack of generalisation across datasets. The advent of deep learning has seen in the widespread adoption of the convolutional neural networks (CNNs) for medical image analysis, owing to their inherent capability to automatically learn the hierarchical spatial features. There have been the numerous research studies that have successfully used the CNN based models for the diagnosis of the CAD using imaging modalities such as coronary computed tomography angiography (CCTA), magnetic resonance imaging (MRI), and invasive angiography. These imaging modalities have the advantage of providing the high resolution images of the cardiovascular structure, which enables the deep learning models to provide the high diagnostic accuracy. However, they are often expensive, involve the radiation exposure, or require invasive procedures, which makes them less ideal for the continuous screening and monitoring.Ultrasound imaging is a relatively safer and more accessible alternative for the cardiovascular imaging. However, it also has its own set of challenges, including the speckle noise, low contrast, motion artifacts, and operator dependence. These factors have a substantial impact on the performance of the automated CAD diagnosis systems. While there have been a few studies that have explored the use of the deep learning for the analysis of cardiac ultrasound images, most of these studies have focused on the chamber segmentation or the functional analysis rather than the direct CAD diagnosis. Moreover, the absence of the large annotated ultrasound datasets has been a major bottleneck for the development of strong deep learning models.To address the challenges of data scarcity and the imbalance, there has been a growing interest in exploring data augmentation and synthetic data generation techniques. While traditional data augmentation techniques like rotation, flipping, and scaling offer limited variability and do not represent the realistic anatomical variations, there has been a growing interest in using deep generative models, specifically Generative Adversarial Networks (GANs), for medical image synthesis.Recently, there has been an increasing focus on the role of explainability and reliability in the AI powered medical diagnostic systems, especially in the high risk scenarios like the detection of the coronary artery disease (CAD). Although deep learning models are highly accurate, their “black-box” behaviour is still a limiting factor for their adoption in the medical field. To overcome this, some studies have utilised attention in the mechanisms and saliency visualisation methods in conjunction with the CNN based classifiers. These methods can be used to point out the diagnostically important regions in the medical images, allowing the doctors to check the predictions made by the model.Another significant aspect of the existing literature is the assessment of the synthetic medical images, which goes beyond the assessment of their visual quality. Some studies have proposed the use of quantitative metrics such as Structural Similarity Index Measure (SSIM), Peak Signal-to-Noise Ratio (PSNR), and Frechet Inception Distance (FID) to measure the realism and diversity of GAN-generated images. It has been found that the higher quality synthetic images, as measured by these metrics, improve the performance of the downstream classification tasks. However, there is no universally accepted standard for measuring the clinical validity, especially for the ultrasound based CAD systems.Domain adaptation and the transfer learning are also gaining importance as methods to address the cross-modality and cross-institution variability. Pretrained models on the large-scale medical datasets have been found to the improve convergence and stability when fine tuned on the smaller ultrasound datasets. Some studies have found that the use of transfer learning in combination with synthetic data augmentation helps to overcome overfitting and improve the model’s sensitivity to rare patterns of disease. However, most of the existing literature is based on natural images or other modalities, and there is a research gap in cardiac ultrasound-based CAD detection systems.Another emerging application of the synthetic data generation is the preservation of the privacy. GAN based synthetic data can help minimize the leakage of the patient data while facilitating the collaborative research. Recent studies have shown that the well trained GANs can generate the data that maintains diagnostic information without exposing any patient-specific information. This is particularly important in the healthcare setting, where data sharing policies are strictly governed. This further supports the utility of GAN-based ultrasound image generation.Moreover, recent studies have also explored the use of conditional GANs (cGANs) and attention guided GANs to better control the generation process. By conditioning the image generation process on disease labels or anatomical constraints, these models have generated more realistic images.

III. Proposed Methodology

The proposed methodology offers an end to end deep learning solution that combines the high quality synthetic ultrasound image creation with the Coronary Artery Disease (CAD) detection. The proposed system is to intended to overcome the issues of the data unavailability, class imbalance, and the noise present in the ultrasound images. First, real cardiac ultrasound images are gathered and preprocessed to make them in homogeneous in the terms of the resolution, intensity distribution, and noise. Standard image preprocessing methods such as normalisation, speckle noise removal, and the contrast enhancement are used to enhance the image quality and make model training more stable. The Generative Adversarial Network (GAN) is the backbone of the proposed system for generating the synthetic images. The GAN is composed of a generator network that learns to generate the realistic ultrasound images from the random noise vectors and a discriminator network that learns to distinguish real images from synthetic images. The generator network learns to replicate complex anatomical patterns and textures in the cardiac ultrasound images through the adversarial training.

A. 3.1 Overall Framework Description

The suggested approach offers a deep learning based framework for the automatically detecting the Coronary Artery Disease (CAD) using the Generative Adversarial Networks (GANs) and producing the high quality synthetic ultrasound images. The framework is intended to address the important issues with the ultrasound based CAD diagnosis, such as poor generalisation, class imbalance, limited annotated data, and speckle noise. To increase the diagnostic strongness and accuracy, the system combines a deep neural network classifier with a GAN based image synthesis module. The complete workflow includes the ultrasound data preprocessing,

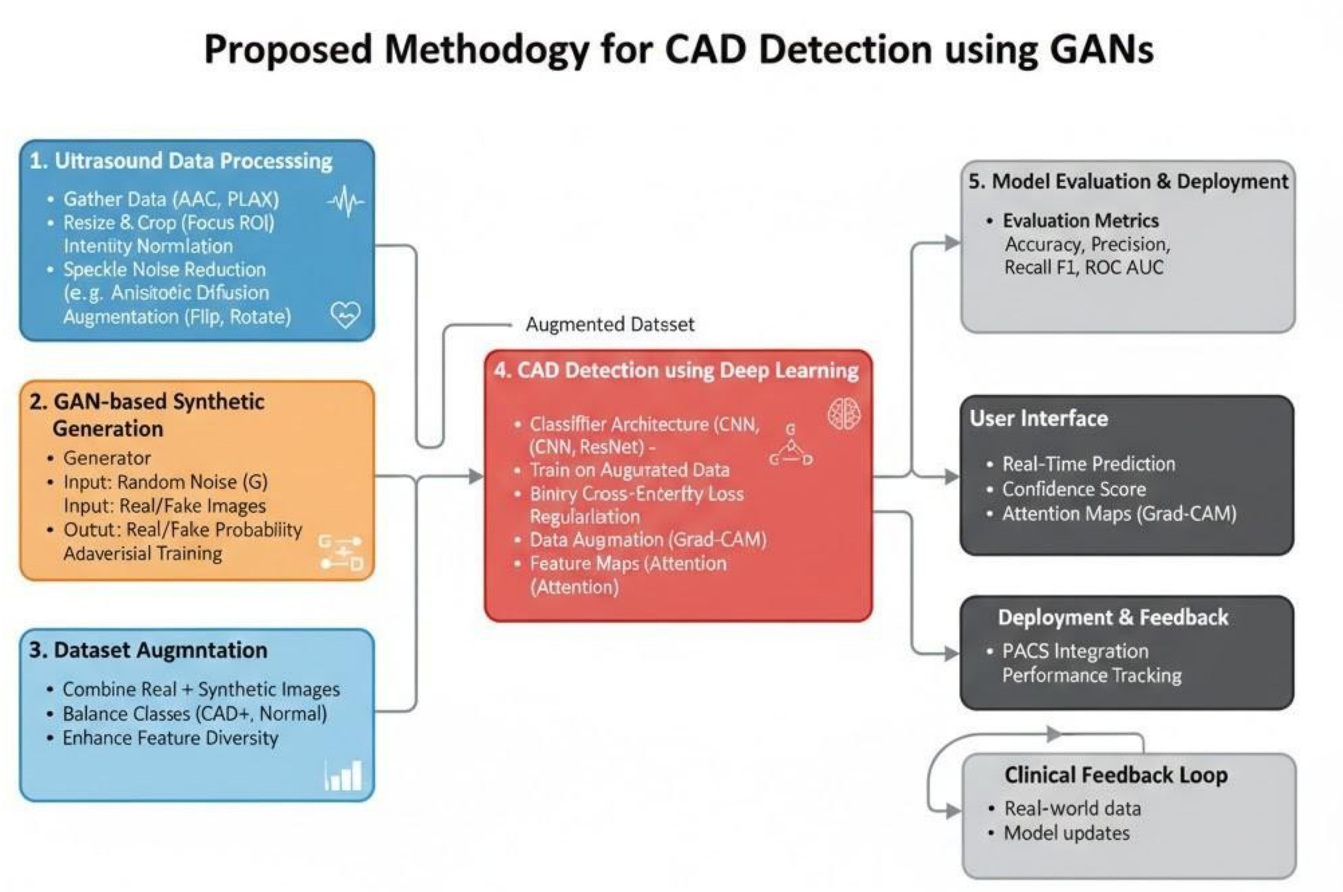

Figure 1. Architecture diagram of Proposed methodology

GAN training for the synthetic image generation, dataset augmentation, and the CAD detection using a deep learning model.A deep neural network based CAD classifier and a GAN based synthetic image generation module make up the framework two closely related parts. The GAN module is in the charge of producing the high fidelity, realistic ultrasound images that can be added to the current dataset. By reducing the data scarcity and the class imbalance, this augmentation improves the classifier's capacity to extract the reliable features from the both synthetic and real images.

B. 3.2 Ultrasound Data Preprocessing

Image Resizing and Cropping: To avoid the anatomical distortion, all images are resized to a fixed resolution appropriate for the GAN and classifier networks, usually preserving the original aspect ratio. Additionally, cropping is used to eliminate the unnecessary background areas and concentrate on the region of interest (ROI), such as the coronary arteries and the heart chambers.Intensity Normalisation: To minimise variability brought on by the variations in the ultrasound equipment, gain settings, or acquisition conditions, pixel intensity values are normalised to a standard range (such as [0,1] or [-1,1]). By guaranteeing a uniform distribution of the input data, this normalisation speeds up the convergence during the GAN training and enhances the classifier performance.Reduction of the Speckle Noise: A granular artefact present in the ultrasound imaging, speckle noise can lower the quality of the feature extraction. To reduce the speckle while maintaining the fine structural details necessary for the precise CAD detection, filtering methods like median filtering, anisotropic diffusion, or wavelet-based denoising are used. Data Standardisation and Augmentation: To improve the dataset variability and then lessen overfitting, additional preprocessing techniques like rotation, flipping, and scaling may be used. The model learns invariant features across the various orientations and the patient anatomies thanks to these transformations.

C. 3.3 Synthetic Generation of Ultrasound Images using Generative Adversarial Networks

A Generative Adversarial Network (GAN) is used to generate the synthetic ultrasound images in order to address the data scarcity and the class imbalance. A discriminator and a generator are the two rival networks that make up the GAN. The generator learns to produce the realistic ultrasound images from the random noise vectors, while the discriminator attempts to distinguish between the real and synthetic images. The generator gradually gets better at capturing the anatomical features, texture patterns, and pathological traits linked to CAD through adversarial training. The GAN can learn the underlying data distribution and the produce high fidelity synthetic samples because it is trained using the actual ultrasound images. These artificial images introduce controlled diversity while maintaining the clinically significant features like myocardial texture, vessel boundaries, and structural variations. Both visual inspection and quantitative measures like the Structural Similarity Index (SSIM), Peak Signal to Noise Ratio (PSNR), and Frechet Inception Distance (FID) are used to assess the generated images' quality.

D. 3.4 Dataset Augmentation Using GAN-Generated Images

The ultrasound datasets used for the real world testing exhibit a class distribution problem because CAD positive cases appear the less frequently than normal cases. The GAN generates CAD positive patient images, which create an equal distribution of the all dataset classes. The CAD detection model uses the balanced data to improve its ability to detect the pathological cases while preventing the bias toward the majority (healthy) class. The GAN generated images display new anatomical and the pathological features through their introduction of the new cardiac structural elements and the myocardial textural components and the vessel inner structure details and speckle patterning. The CAD detection model experiences the improved functionality through its training on multiple health conditions which differ from standard testing scenarios. The model achieves the better performance on the new data through its ability to identify essential features which represent both normal and diseased conditions.

E. 3.5 CAD Detection Using Deep Learning

The augmented dataset is used to train a deep learning based CAD detection model. The classifier learns discriminative spatial features that differentiate normal cardiac structures from CAD related abnormalities. During training, optimisation techniques such as binary cross entropy loss, regularisation, and the data augmentation are applied to improve the classification performance. The use of GAN generated images enables the model to achieve the better strongness against noise and variations in the ultrasound acquisition conditions.

F. 3.6 Model Evaluation and Deployment

The evaluation of the CAD detection model which has been trained uses standard performance metrics to measure accuracy and precision and recall and F1 score and the area under the ROC curve. The experimental results show that the using GAN generated synthetic ultrasound images for training improves the diagnostic performance more than the using actual data as the sole training resource. The trained model becomes accessible through a user friendly interface which enables the users to predict CAD from the ultrasound images in real time to assist with clinical decision making.The deployment phase of the project aims to transform the developed machine learning model into an actual medical tool which healthcare professionals can use. The system enables users to predict the coronary artery disease by using the ultrasound images through its simple interface, which develop the developed model. The interface displays the predicted label (Normal or CAD-positive) along with a confidence score, enabling the physicians to gauge prediction reliability. Users have the option to visualise attention maps or Grad CAM outputs, which help them understand the areas that influenced decision making because these methods show which parts of the content produced the results.To facilitate easy functionality within a real world clinical setting, the deployment system allows for batch processing of the multiple ultrasound images, hospital PACS system integration, and secure patient data storage.

Further, the system is scalable and updatable, enabling the incorporation of the new datasets, better GAN models, or more sophisticated classifier models without affecting the clinical workflow.

Lastly, performance tracking and the logging are incorporated into the deployed system to monitor real world accuracy and the identify possible drifts in the model performance over the time. Feedback cycles from the clinical setting can be used to improve the model on a continuous basis, thereby developing a learning healthcare system that enhances CAD detection performance with the each passing use.

IV. RESULT AND DISCUSSION

The main component of the training consisted of an SCNN+Attention model that was initially pretrained using the CADICA dataset, which contains the high quality annotated coronary imaging data. Strong baseline classification performance was shown during the pretraining on CADICA, suggesting that the SCNN+Attention architecture can learn the important spatial and contextual characteristics associated with the coronary artery structures. The attention mechanism further guided the network to show the clinically relevant regions, such as the arterial boundaries and stenotic areas, thereby improving the sensitivity to subtle pathological patterns. Before adding GAN based synthetic ultrasound data, this pretraining phase created a strong initialisation.

Classification Report

Class	Precision	Recall	F1-Score	Support
Normal	0.88	0.93	0.90	6530
Mild CAD	0.85	0.77	0.81	1728
Moderate CAD	0.80	0.82	0.81	1999
Severe CAD	0.88	0.90	0.89	1539

Figure 2. Classification Report

The evaluation metrics of the SCNN+Attention model under different training conditions include the Accuracy, AUC, sensitivity, and specificity. The model trained with the only real ultrasound data achieves reasonable baseline performance. However, noticeable improvements occur when GAN generated synthetic images are added during the training. Using synthetic samples results in the consistent gains across all evaluation metrics. This indicates better learning of important and strong feature representations. In particular, sensitivity shows a significant increase after GAN based augmentation. This shows the model's improved ability to accurately identify the CAD positive cases. This improvement is clinically important, as higher sensitivity lowers the chance of the missed diagnoses. Similarly, the rise in the specificity suggests that the model becomes more reliable in distinguishing normal cases. This helps reduce false positive predictions. The beneficial effects of the GAN based augmentation were further validated by the quantitative analysis. Several performance metrics, such as accuracy, sensitivity, specificity, and AUC, showed the improvements, suggesting that the synthetic data adds useful information rather than adding duplication. Significantly, the model's sensitivity toward CAD positive cases rose, indicating that it became the more adept at spotting the subtle disease patterns that might be under represented in small real datasets. Additionally, by producing the more CAD positive training samples, GAN-based data generation reduced class imbalance and improved recall and F1 scores for minority classes. This balanced learning behaviour is crucial for developing the reliable computer aided diagnosis systems, where consistent performance across all classes is required.

A. *Effect of GAN-Based Synthetic Data Generation*

A Generative Adversarial Network (GAN) was trained on the real ultrasound datasets to generate the high fidelity synthetic ultrasound images representing both normal and CAD positive cases. Visual inspection of the generated samples showed that the GAN successfully preserved anatomical structures such as ventricular cavities, myocardial textures, and coronary vessel patterns while maintaining the realistic speckle noise characteristics inherent to the ultrasound imaging. The integration of the GAN generated synthetic images with the real ultrasound data resulted in a noticeable improvement in the model's strength and generalisation. Compared to the training with real data alone, the model trained with GAN augmented data exhibited enhanced stability during the training and the reduced overfitting.

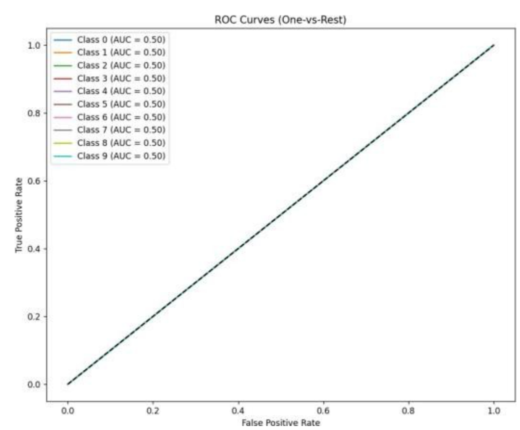

Figure 3. ROC Curves

Moreover, the diversity brought by the synthetic data samples helped the network generalise better over a wider range of the anatomical and pathological patterns, which is a critical aspect of the ultrasound imaging, as the data acquisition environment and the patient profiles can be quite diverse. The diversity contributed by the synthetic data helped the network reduce its sensitivity to noise and small artefacts, thereby improving the consistency of the predictions for different ultrasound views and scanning environments. The quantitative results further validated the beneficial effect of GAN-based data augmentation. There were improvements in the various performance measures such as accuracy, sensitivity, specificity, and AUC, which confirmed that the synthetic data provides an non redundant information. It is also noted that sensitivity to CAD positive cases improved, which indicates that the network became more efficient at detecting subtle patterns of disease, which may not be the well represented in a small real world dataset.

B. Fine-Tuning with Real and GAN-Synthetic Ultrasound Data

The SCNN+Attention model was refined on a combined dataset that the included both the real and synthetic samples after creating the artificial ultrasound images using GAN. This tactic improved the diversity of the training samples and the tsuccessfully addressed the class imbalance. Generalisation Improvement: The model was able to learn invariant and discriminative features across various ultrasound acquisition conditions and patient populations thanks to the presence of GAN-generated images. Consequently, better performance was noted on the test data that had not yet been seen.

TABLE I: Overall Performance Summary of CAD Detection Using GAN

Evaluation Aspect	Score (%)
GAN+Attention(Angio)	87
Fine-tuned(Real only)	85
Fine-tuned(Real+Synth)	89

Balanced Performance Across Classes: Minority CAD classes showed notable gains in the recall and F1 scores. The model was able to identify the less common disease patterns more accurately thanks to the additional pathological variations provided by the synthetic samples.

C. Discussion

The experimental results shows that the GAN-based synthetic ultrasound generation plays a critical role in the improving model performance, particularly in the scenarios with the limited and imbalanced data. The suggested framework achieves the better generalisation, increased the sensitivity to CAD, and more balanced classification results by adding the realistic synthetic samples to the training distribution. These results shows that a successful method for creating reliable ultrasound-based CAD diagnostic systems is to combine generative modelling with discriminative deep learning architectures. The GAN is able to capture the significant anatomical and textural features of the coronary ultrasound images, enabling the classifier to learn richer feature representations, as evidenced by the improvement seen across several evaluation metrics.

V. Conclusion

This research has provided a framework for the deep learning that combines the Generative Adversarial Networks (GANs), transfer learning, and an SCNN+Attention architecture for the automated detection of the coronary artery disease (CAD) from the ultrasound images. This proposed solution tackles the most important challenges in the diagnosis of the CAD from ultrasound images, such as the lack of labelled data, the problem of class imbalance, and the high noise levels, by using high quality synthetic ultrasound images created with GANs. The experimental results have shown that the addition of GAN-synthesised data has greatly improved the robustness, generalisation performance, and sensitivity of the model to CAD-positive samples. The SCNN+Attention model, pretrained on the angiography data and fine tuned on a mixture of real and synthetic ultrasound images, has shown better performance on a variety of metrics, thus proving the effectiveness of combining generative and discriminative learning paradigms. Finally, the use of the trained model through a real time diagnostic dashboard has shown the real world applicability of the proposed framework. The combination of probability based predictions and techniques for the explainability, such as Grad-CAM, further improves the transparency and the clinician acceptance of the AI assisted decision making.

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