UNDERWATER IMAGES NOISE REDUCTION USING HHDNET AND GAN

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for the award of the degree of

B.Tech Computer Science and Engineering (OR Artificial Intelligence and Data Science)

by

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Evaluation Sheet

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Certificate

We, **M.Abhijith Sai - 121CS0064, Mukeshsingh Rajpurohit - 121CS0039** hereby declare that the material presented in the Project Report titled **UnderWater Images Noise Reduction Using HHDNET and GAN** represents original work carried out by me (or us) in the **Department of Computer Science and Engineering** at the **Indian Institute of Information Technology Design and Manufacturing Kurnool** during the years **2023 - 2024**. With my signature, I certify that:

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In my capacity as supervisor of the above-mentioned work, I certify that the work presented in this Report is carried out under my supervision, and is worthy of consideration for the requirements of B.Tech. Project work.

Advisor's Name: Advisor's Signature

Abstract

Enter Abstract Content here...

Acknowledgements

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Abbreviations

FEA	**F**inite **E**lement **A**nalysis
FEM	**F**inite **E**lement **M**ethod
LVDT	**L**inear **V**ariable **D**ifferential **T**ransformer
RC	**R**einforced **C**oncrete

Symbols

D^{el}	elasticity tensor
σ	stress tensor
ε	strain tensor

For/Dedicated to/To my…

Chapter 1

Introduction

1.1 Background of High-Resolution Image Restoration

1.1.1 Importance in Various Fields

Image restoration is essential in fields like medical imaging, satellite surveillance, and digital photography. High-quality imagery significantly impacts decision-making, ranging from diagnostics in healthcare to security analysis in surveillance.

1.1.2 Traditional Restoration Techniques

Traditional methods, such as interpolation and denoising filters, have been commonly used for image restoration. While these methods are effective in controlled environments, they often struggle with the complexities found in real-world images, such as varied textures and high levels of noise.

1.1.3 Challenges in Real-World Image Restoration

Restoring real-world images presents several challenges:

- **Complex Patterns:** Traditional methods often blur or lose essential details when attempting to reduce noise.
- **Noise Consistency:** These techniques are ineffective against diverse noise patterns, resulting in inconsistent outcomes across different image types.

1.2 The Role of Deep Learning in Image Restoration

1.2.1 Introduction of Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) analyze images at multiple abstraction levels, making them effective for complex pattern recognition. CNNs outperform traditional techniques in noise reduction and detail preservation.

1.2.2 Limitations of Standard CNN Approaches

Despite their advantages, standard CNNs face challenges in image restoration:

- **High-Frequency Details:** Even advanced CNNs can struggle to balance noise removal and detail retention, particularly in high-frequency regions.
- **Real-World Noise:** Standard CNNs often lack the adaptability to unpredictable noise, making it difficult to retain essential image features.

1.3 Proposed Solution: HHDNet Model

1.3.1 Overview of HHDNet's Approach

HHDNet introduces a novel approach that combines frequency separation, attention mechanisms, and adversarial training to address existing challenges in image restoration.

1.3.2 Frequency Separation

The model separates high-frequency (detail) and low-frequency (structure) components of an image. This separation allows HHDNet to focus on noise reduction in smoother regions while preserving sharpness in detailed areas.

1.3.3 Attention Mechanisms

By integrating attention mechanisms, HHDNet can dynamically focus on critical regions of the image to enhance detail preservation and noise reduction. This selective focus improves the model's ability to produce high-quality outputs.

1.3.4 Adversarial Training

HHDNet employs adversarial training, involving a competition between generator and discriminator networks, to improve image realism. This approach encourages the generator to produce images that are visually convincing and of high quality.

1.4 HHDNet Architecture and Design

1.4.1 Architectural Components

This section outlines the core components and design decisions within HHDNet. Each architectural choice, including frequency separation, attention mechanisms, and adversarial elements, is discussed with its respective rationale.

1.4.2 Challenges in Development and Training

During the development of HHDNet, challenges such as overfitting, stability, and computational complexity were encountered. This section covers the strategies used to address these issues, including regularization and optimization techniques.

1.5 Project Objectives

1.5.1 Demonstrating Improved Image Clarity

The primary objective of HHDNet is to demonstrate its ability to reduce noise and enhance image clarity. Examples in fields like medical imaging and satellite analysis illustrate the practical applications of HHDNet's improvements.

1.5.2 Application Potential

The enhancements made by HHDNet are applicable across fields requiring high-resolution image restoration. HHDNet's potential impact spans from diagnostics and treatment planning in healthcare to geographic and environmental analysis in satellite imagery.

1.6 Summary and Overview of Report Structure

1.6.1 Summary of Contributions

HHDNet addresses several limitations present in both traditional and CNN-based methods. This section summarizes the motivation, technical challenges, and contributions of the proposed model.

1.6.2 Report Layout

An outline of the report's structure follows, with sections covering HHDNet's model breakdown, functionality, and performance analysis.

Chapter 2

Introduction to Convolutional Neural Networks (CNNs)

2.1 Overview of Convolutional Neural Networks

Convolutional Neural Networks (CNNs) have revolutionized the field of image processing, particularly in tasks like classification, segmentation, and restoration. Unlike traditional machine learning methods, CNNs are designed to process data with a grid-like topology, such as images, making them highly effective for visual tasks. They achieve this by analyzing images at multiple levels of abstraction. A CNN processes an image through several layers, including convolutional layers, pooling layers, and fully connected layers, with each layer extracting increasingly complex features. At the lower layers, CNNs may focus on simple features like edges and textures, while deeper layers capture higher-level patterns such as shapes and objects.

2.1.1 Multi-Layer Approach of CNNs

This multi-layer approach allows CNNs to outperform traditional image processing techniques in areas such as noise reduction, detail preservation, and pattern recognition. For example, CNNs can learn to identify and remove various forms of noise while preserving critical details like edges and textures, which are often lost with conventional filtering methods. As a result, CNNs have become a cornerstone for modern image restoration techniques, enabling significant improvements in tasks such as super-resolution, denoising, and inpainting.

2.1.2 Challenges in CNNs

However, while CNNs are powerful, they are not without their limitations, especially when dealing with complex or real-world noise. One of the primary challenges faced by standard CNN approaches is maintaining a balance between noise removal and detail preservation, particularly in high-frequency regions.

2.2 High-Frequency Details and Noise Removal

High-frequency details, such as fine textures, edges, and intricate patterns, are often essential to the image's overall quality. However, these areas are also where noise tends to be most prominent. Standard CNNs can sometimes blur or smooth these fine details in an effort to remove noise, which can result in a loss of important information and lower the quality of the restored image. This is especially true for images that contain fine-grained textures or intricate details, where noise reduction algorithms may inadvertently blur or distort key elements.

2.2.1 Preservation of Fine Details

Fine textures and edges are critical to the image's realism and perceived quality. CNNs often struggle to preserve these high-frequency elements when the focus is on aggressive noise reduction, leading to trade-offs between noise removal and detail integrity.

2.2.2 Impact of Noise on High-Frequency Details

In images with intricate details, noise can disrupt the clarity of edges and textures. Noise reduction algorithms in CNNs may smooth over these details, which often results in the loss of essential information. This challenge remains an area of active research in improving CNN-based image restoration techniques.

Chapter 3

Proposed Solution: HHDNet Model

3.1 Overview of HHDNet's Approach

HHDNet (High-Resolution Image Restoration with Hybrid Decomposition and Attention Mechanisms) is a novel deep learning model designed to overcome the limitations of standard CNN approaches in image restoration. It integrates a combination of advanced techniques, including frequency separation, attention mechanisms, and adversarial training, to improve the performance of image restoration models.

3.1.1 Key Innovations of HHDNet

HHDNet's primary innovation lies in its ability to separate the frequency components of an image, allowing the model to focus on different regions with varying degrees of attention. This enables the model to better preserve high-frequency details while simultaneously removing noise from low-frequency regions.

3.1.2 Attention Mechanisms and Adversarial Training

Furthermore, HHDNet incorporates attention mechanisms to selectively focus on critical regions of the image. This selective attention ensures that important areas, such as edges and textures, are preserved while less relevant information is discarded. Additionally, the use of adversarial training allows HHDNet to produce more realistic and high-quality images, further enhancing its effectiveness in image restoration tasks.

3.1.3 Advantages over Traditional CNNs

By combining these techniques, HHDNet addresses the challenges posed by traditional CNN-based approaches, offering a more robust solution for restoring images in complex scenarios.

3.2 Frequency Separation

One of the key innovations of the HHDNet model is its use of frequency separation. In image processing, frequency components refer to different levels of detail present in an image. Low-frequency components typically represent larger structures and smoother regions, while high-frequency components capture fine details and sharp edges. By separating the frequency components of an image, HHDNet can address different parts of the image independently, allowing it to perform noise reduction and detail preservation more effectively.

3.2.1 Low-Frequency and High-Frequency Components

In practical terms, this means that HHDNet can focus on smoothing out low-frequency regions, such as uniform backgrounds or homogeneous areas, without affecting high-frequency details like edges or fine textures. Conversely, the model can dedicate more resources to preserving these high-frequency components, ensuring that essential details are not lost during the restoration process.

3.2.2 Tailored Restoration Techniques

Frequency separation also helps HHDNet overcome some of the challenges faced by traditional CNNs. Standard CNNs often struggle to balance noise reduction with detail preservation, particularly in regions with complex textures or intricate patterns. By isolating the high-frequency and low-frequency components, HHDNet can apply tailored restoration techniques to each component, improving overall image quality.

3.3 Attention Mechanisms

Another important feature of HHDNet is the integration of attention mechanisms, which allow the model to focus selectively on the most critical regions of the image. Attention mechanisms have become a key component in many modern deep learning models, as they enable the model to allocate more resources to important features while ignoring less relevant information.

3.3.1 Focusing on Key Details

In the context of image restoration, attention mechanisms are particularly useful for focusing on key details, such as edges, textures, and other high-frequency components. These areas are often the most susceptible to noise, and maintaining their sharpness is critical for achieving high-quality restoration. By dynamically adjusting the model's focus, attention mechanisms ensure that the model prioritizes these critical areas, improving the overall performance of the restoration process.

3.3.2 Collaboration with Frequency Separation

Attention mechanisms in HHDNet work in tandem with the frequency separation approach. Once the frequency components are separated, attention mechanisms can be applied to both the high-frequency and low-frequency components independently. This selective focus allows HHDNet to maintain fine details in important regions of the image while reducing noise in smoother areas, ultimately improving the overall quality of the restored image.

3.4 Adversarial Training

Adversarial training is another critical aspect of HHDNet's design. In this approach, the model is trained in a competitive framework, where two networks, a generator and a discriminator, are pitted against each other. The generator is responsible for creating restored images, while the discriminator evaluates the quality of these images and attempts to distinguish them from real, uncorrupted images. The generator is trained to improve its ability to produce realistic images, while the discriminator becomes more adept at identifying imperfections.

3.4.1 Generator and Discriminator Networks

The adversarial process encourages the generator to produce images that are not only free of noise but also visually convincing and high in quality. This results in more realistic restorations, as the generator learns to mimic the subtle details and textures found in real images.

3.4.2 Effectiveness in Image Restoration

Adversarial training has been particularly effective in image restoration tasks, where the goal is not only to reduce noise but also to preserve the natural appearance of the image. By incorporating adversarial training into HHDNet, the model is able to produce restored images that are both high-quality and visually realistic, addressing some of the shortcomings of traditional CNN-based approaches.

3.5 Conclusion

In conclusion, HHDNet represents a significant advancement in the field of image restoration. By combining frequency separation, attention mechanisms, and adversarial training, HHDNet offers a more robust and effective solution for restoring images in complex scenarios. Its ability to balance noise reduction and detail preservation, while adapting to varying types of noise, makes it a powerful tool for improving the quality of restored images in real-world applications.

Chapter 4

Proposed Solution

4.1 Research Gaps

Underwater image denoising is crucial for applications in marine exploration, archaeology, and robotics, where image clarity is often compromised by environmental factors. However, current methods like **HHDNet** have limitations in terms of visual realism and adaptability to varying noise patterns, especially in complex underwater environments. Key research gaps identified include:

- **Lack of Realism in Denoising**: While models such as HHDNet employ high- and low-frequency separation and dual-branch networks to handle noise, they often fall short in preserving realistic textures and natural appearance in the denoised images.
- **Limited Adaptability to Diverse Noise Types**: HHDNet and similar architectures may not perform well with the diverse and often unpredictable noise patterns found in underwater images, as they lack the ability to dynamically adapt to different noise characteristics.
- **Dependence on Standard Loss Functions**: Standard loss functions like pixel-wise loss and perceptual loss focus primarily on pixel accuracy and structural details but may neglect the nuanced, high-level features necessary for realistic image synthesis.

These gaps motivate the exploration of more advanced denoising methods that can improve realism, adaptability, and feature retention.

4.2 Proposed Solution

To address these research gaps, we propose an enhanced model called **Proposed HHDNet-GAN Model**, which builds on the dual-branch architecture of HHDNet but incorporates a **Generative Adversarial Network (GAN)**. The GAN framework introduces a dynamic, adversarial approach to underwater image denoising, yielding significant improvements in realism, noise adaptability, and detail preservation.

4.2.1 Proposed HHDNet-GAN Model Architecture

Proposed HHDNet-GAN Model combines high-low frequency separation, dual-branch processing, and adversarial learning through a GAN setup. The key components are as follows:

1. **High-Low Frequency Separation**: Similar to HHDNet, Proposed HHDNet-GAN Model separates the input image I into high-frequency and low-frequency components, where high-frequency components capture sharp details and noise, and low-frequency components retain structural information:

   $$I_{\text{low}} = G_{\sigma,k} * I$$

   where $G_{\sigma,k}$ represents a Gaussian kernel. The high-frequency component I_{high} is obtained as:

   $$I_{\text{high}} = |I - I_{\text{low}}|$$

2. **Dual-Branch Network**: Proposed HHDNet-GAN Model utilizes a dual-branch network where:

   - The **High-Frequency Branch** employs the Global Context Extractor (GCE) module, integrating grouped convolutions and cross-attention mechanisms to effectively detect and reduce high-frequency noise while preserving fine details.
   - The **Low-Frequency Branch** uses a residual convolutional module designed to adjust color, brightness, and saturation with minimal distortion, focusing on low-noise regions.

3. **Adversarial Learning with GAN**: Proposed HHDNet-GAN Model incorporates a GAN setup, consisting of a generator (the dual-branch network) and a discriminator.

The discriminator is trained to distinguish between real, clean images and generated (denoised) images, providing feedback that encourages the generator to produce outputs with high visual realism. This adversarial process is crucial for producing outputs that are both structurally accurate and visually natural.

4.2.2 Enhanced Loss Functions

Proposed HHDNet-GAN Model optimizes the denoising process by using a combination of pixel-wise loss, perceptual loss, and adversarial loss:

- **Pixel-wise Loss**: Measures the mean squared error (MSE) between the denoised and target images, ensuring pixel-level accuracy:

$$\mathcal{L}_{\text{pixel}} = \frac{1}{N}\sum_{i=1}^{N}(I^i_{\text{out}} - I^i_{\text{target}})^2$$

- **Perceptual Loss**: Compares feature maps from a pre-trained network, emphasizing the preservation of important structures in the image.
- **Adversarial Loss**: This loss, based on the discriminator's feedback, encourages the generator to produce images that appear more realistic:

$$\mathcal{L}_{\text{adv}} = -\mathbb{E}[\log(D(I_{\text{out}}))]$$

The total loss function is a weighted combination of the pixel-wise, perceptual, and adversarial losses, which together guide the generator to produce outputs that balance pixel-level accuracy, structural coherence, and visual realism.

4.2.3 Summary of Advantages

By integrating a GAN, Proposed HHDNet-GAN Model improves on previous methods such as HHDNet in the following ways:

- **Increased Realism**: The adversarial loss encourages Proposed HHDNet-GAN Model to produce images that closely resemble real, noise-free images, enhancing texture and fine detail preservation.

- **Enhanced Adaptability to Noise Types**: The GAN's dynamic feedback loop enables Proposed HHDNet-GAN Model to learn and adapt to varying noise patterns in underwater environments, making it more flexible and robust.
- **Balanced Detail and Structural Accuracy**: The feedback from the discriminator helps the generator maintain a balance between removing noise and preserving key structural details, resulting in cleaner and more visually appealing images.

In summary, the GAN-based Proposed HHDNet-GAN Model provides a comprehensive and effective solution to the challenges of underwater image denoising, offering improved performance in terms of realism, adaptability, and visual clarity over traditional dual-branch architectures.

Chapter 5

Methodology

5.1 High-Low Frequency Separation

The high-low frequency separation module divides the input image into high-frequency and low-frequency components. A Gaussian blur with a specified kernel size and standard deviation is applied to retain low-frequency information, representing general color and tone:

$$I_{\text{low}} = G_{\sigma,k} * I$$

where $*$ denotes convolution. High-frequency details, including edges and sharp structures, are extracted by subtracting the low-frequency component from the original image:

$$I_{\text{high}} = |I - I_{\text{low}}|$$

This frequency separation allows the model to process high-detail features independently from broader structures, enhancing both fine detail restoration and overall image consistency.

5.2 ConvGroup Module

The ConvGroup module consists of multiple convolutional layers with grouped convolutions and batch normalization. Grouped convolutions enhance specialization by allowing the model to learn feature patterns unique to each frequency component, while batch normalization ensures stable learning. The module employs ReLU activation and residual connections, retaining feature information throughout the network:

$$Y = X + \mathrm{ReLU}(\mathrm{BN}(\mathrm{Conv}(X)))$$

where X is the input, BN is batch normalization, and Y is the output.

5.2.1 Grouped Convolutions

Grouped convolutions help the model to specialize in distinct feature patterns associated with each frequency, enhancing its ability to separate and process high- and low-frequency information.

5.2.2 Batch Normalization

Batch normalization stabilizes the learning process by normalizing inputs within each mini-batch, reducing training time and improving convergence.

5.3 CrossAttention Module

The CrossAttention module enhances feature maps by amplifying essential information in each channel. Using adaptive average and max pooling, the module captures different channel dependencies. The output from both pooling paths is combined with fully connected layers to highlight important features:

$$Y = A_{\mathrm{avg}} \times A_{\mathrm{max}} + X$$

where A_{avg} and A_{max} are results from average and max pooling, respectively.

5.4 Generalized Channel Enhancement (GCE)

GCE serves as an integrated feature enhancement block, combining ConvGroup and CrossAttention modules. This composite module boosts the network's sensitivity to fine details and important structures, particularly under challenging noise conditions. This attention mechanism ensures that high-frequency details are amplified for more refined restoration results.

5.5 Low-Frequency Residual Block

The low-frequency branch includes a residual block with instance normalization and parametric ReLU (PReLU) activation. This module stabilizes low-frequency signals, maintaining structural integrity in the restored image. The design allows the model to process broader, lower-resolution features without degrading finer details handled in the high-frequency path.

5.6 GAN Architecture

The proposed model utilizes a Generative Adversarial Network (GAN) framework, comprising a generator (responsible for image enhancement) and a discriminator. The generator builds on the dual-branch network structure, outputting denoised images, while the discriminator differentiates between real and generated images. This adversarial approach is crucial for producing visually realistic denoising results.

- **Generator:** The generator is structured similarly to the HHDNet-inspired architecture with separate high- and low-frequency processing branches. Its objective is to produce denoised images that are indistinguishable from clean images.
- **Discriminator:** The discriminator aids the generator by providing feedback based on image authenticity, pushing the generator to improve realism and detail preservation in the generated images.

The adversarial interaction between these two components enhances the model's ability to handle complex, high-frequency noise, generating clean images with authentic textures.

5.7 Loss Functions

The model utilizes a combination of pixel-wise, perceptual, and adversarial losses to guide training:

- **Pixel-wise Loss:** This loss measures the mean squared error (MSE) between the restored and target images, ensuring pixel-level accuracy:

$$\mathcal{L}_{\text{pixel}} = \frac{1}{N}\sum_{i=1}^{N}(I_{\text{out}}^{i} - I_{\text{target}}^{i})^2$$

- **Perceptual Loss:** Compares feature maps from a pre-trained model, emphasizing the preservation of important structures and details within images.

- **Adversarial Loss:** Based on the discriminator's feedback, this loss encourages the generator to create more realistic textures:

$$\mathcal{L}_{\text{adv}} = -\mathbb{E}[\log(D(I_{\text{out}}))]$$

The total loss is a weighted sum of these components, guiding the generator to balance structural accuracy with visual realism. This combination enables the model to produce high-quality, clean images suited for underwater applications.

5.8 Overall Working

The proposed model operates by first decomposing an input image into high-frequency and low-frequency components using a Gaussian blur-based separation. This initial step enables the model to separately process fine details and broader structural information, effectively isolating noise patterns prevalent in each frequency band.

1. **High-Low Frequency Separation**: The input image I is divided into high- and low-frequency components. Low-frequency information, which includes general color and tone, is captured through a Gaussian blur operation, resulting in I_{low}. The high-frequency component I_{high}, containing sharp details, is calculated by subtracting I_{low} from the original image.

2. **Dual-Branch Network Processing**: Once separated, each frequency component is processed through a dedicated branch:

    - The **High-Frequency Branch** utilizes the Global Context Extractor (GCE) module, combining convolutional and cross-attention mechanisms to capture and refine fine details while mitigating high-frequency noise.

- The **Low-Frequency Branch** employs residual blocks with instance normalization and parametric ReLU activation, which stabilize and enhance low-frequency signals, preserving the overall structure and tone.

3. **GAN Framework**: The model is structured as a Generative Adversarial Network (GAN), incorporating a generator (dual-branch network) and a discriminator. The generator produces a denoised image by merging the processed high- and low-frequency outputs, while the discriminator evaluates the realism of the generated image. Through adversarial training, the discriminator's feedback drives the generator to produce outputs with enhanced realism and texture detail.

4. **Loss Optimization**: The model is trained using a combination of pixel-wise, perceptual, and adversarial losses. Pixel-wise and perceptual losses ensure accuracy and structural consistency, while the adversarial loss encourages realistic texture generation.

Together, these stages allow the model to adaptively denoise underwater images, effectively balancing noise reduction with visual realism and structural integrity.

Chapter 6

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6.1 Main Section 1

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6.1.1 Subsection 1

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6.1.2 Subsection 2

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6.2 Main Section 2

Sed ullamcorper quam eu nisl interdum at interdum enim egestas. Aliquam placerat justo sed lectus lobortis ut porta nisl porttitor. Vestibulum mi dolor, lacinia molestie gravida at, tempus vitae ligula. Donec eget quam sapien, in viverra eros. Donec pellentesque justo a massa fringilla non vestibulum metus vestibulum. Vestibulum in orci quis felis tempor lacinia. Vivamus ornare ultrices facilisis. Ut hendrerit volutpat vulputate. Morbi condimentum venenatis augue, id porta ipsum vulputate in. Curabitur luctus tempus justo. Vestibulum risus lectus, adipiscing nec condimentum quis, condimentum nec nisl. Aliquam dictum sagittis velit sed iaculis. Morbi tristique augue sit amet nulla pulvinar id facilisis ligula mollis. Nam elit libero, tincidunt ut aliquam at, molestie in quam. Aenean rhoncus vehicula hendrerit.

Appendix A

Sum of Geometric Series

Write your Appendix content here.

The main rule for the use of commas in English is: Keep your sentences clear. Too many commas might be distracting; too few might make the text difficult to read and understand.

Always check your texts on readability. This requires some practice, however, as first you must know which commas are necessary and which are optional.

The following chapters contain explanations on English comma rules. In our exercises you can practise what you've learned.

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Appendix B

Sum of Hyper Series

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Appendix C

Sum of Super Series

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