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MAD Net: A Fast and Lightweight Network for Single-Image Super Resolution

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ABSTRACT:

The paragraph discusses advancements in single-image superresolution (SISR) achieved through deep convolutional neural networks (CNNs). While CNN-based approaches have significantly improved image quality in terms of peak signal-to-noise ratio (PSNR) and structural similarity (SSIM), they often demand substantial computing power, hindering their practical use. Additionally, many existing CNN models fail to fully utilize intermediate features crucial for precise image reconstruction. To tackle these challenges, the article introduces MADNet, a novel lightweight network design. MADNet focuses on enhancing multiscale feature expression and learning feature correlations efficiently. It introduces a Residual Multiscale Module with Attention Mechanism (RMAM) to bolster the representation of informative multiscale features. This module helps in capturing diverse features across different scales, allowing for a more comprehensive understanding of the input image. Moreover, MADNet incorporates a Dual Residual-Path Block (DRPB) to leverage hierarchical features extracted from the original low-resolution images. By integrating these features at multiple levels, MADNet ensures a richer understanding of the image content, which aids in more accurate superresolution. To facilitate effective information flow and feature reuse, MADNet employs dense connections among blocks. These connections enable seamless communication between different

layers, promoting feature propagation and enhancing the overall performance of the network. Importantly, comparative evaluations show that MADNet outperforms existing models while utilizing significantly fewer computational resources, as measured by multiadds and parameters. This efficiency makes MADNet a promising solution for real-world applications where computational resources are limited.

I INTRODUCTION

Single-image superresolution (SISR) is a fundamental challenge in low-level computer vision, aiming to enhance the resolution and quality of a single low-resolution (LR) input image to produce a corresponding high-resolution (HR) output. Recent advancements in deep convolutional neural networks (CNNs) have revolutionized SISR by enabling the learning of complex mappings from LR to HR images. These CNN-based methods have demonstrated remarkable performance improvements by exploiting inherent image relationships within training datasets. From early models like SRCNN to more recent architectures like RCAN, it's evident that deeper models generally yield better performance.

However, despite their successes, CNN-based SISR models encounter several limitations. Firstly, many of these models heavily rely on increased model depth or width, resulting in high computational demands that hinder their practical deployment. Secondly, most existing CNN-based methods fail to effectively leverage multiscale representations and hierarchical features, which are crucial for accurate super resolution.

To address these challenges, there's a pressing need for lightweight architectures capable of efficiently harnessing multiscale features and dense connections. In this context, we introduce an efficient feature extraction network (EFEN) coupled with an upsampling network (UN). The EFEN module is pivotal in our approach, incorporating a residual multiscale module with an attention mechanism (RMAM) to enhance multiscale feature correlation learning. This mechanism enables adaptive feature selection across

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different scales, promoting more informative representations. Additionally, we propose a dual residual-path block (DRPB) to leverage hierarchical features from LR images and a dense connection structure to integrate features from various layers effectively.

II SURVEY OF RESEARCH

Single image super resolution (SISR) constitutes a fundamental challenge in computer vision, aiming to enhance the resolution and quality of a single low-resolution (LR) input image to produce a corresponding high-resolution (HR) output. Early techniques such as nearest neighbor and bilinear interpolation provided initial solutions, but they lacked the ability to capture complex image features, resulting in blurry outputs. The advent of machine learning marked a significant revolution in super resolution research. Sparse coding methods attempted to learn sparse representations of LR image patches, albeit with limited success due to computational complexity and generalization issues.

However, the landscape changed drastically with the emergence of deep learning, particularly convolutional neural networks (CNNs). CNN-based methods, starting with the Super-Resolution Convolutional Neural Network (SRCNN), demonstrated unprecedented performance improvements by directly learning the mapping from LR to HR images. These models effectively captured intricate image features, leading to superior super resolution results compared to traditional methods.

Further advancements in deep learning, notably with the introduction of Generative Adversarial Networks (GANs), propelled the field forward. GAN-based approaches, exemplified by models like SRGAN, introduced a novel framework where a generator network produces HR images from LR inputs, while a discriminator network distinguishes between real and generated HR images. By adversarial optimizing the generator network, GANs achieved realistic and visually pleasing super resolution results.

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III PROPOSED SYSTEM

MadNet is an innovative image super-resolution technique that leverages the power of Residual Networks (ResNet) to reduce model complexity while effectively capturing both external and internal features of an image. By integrating ResNet architecture, MadNet aims to overcome the limitations of traditional super-resolution methods and produce high-quality, visually appealing high-resolution images from low-resolution inputs. ResNet, originally introduced for image classification tasks, has proven to be highly effective in learning intricate features from images while mitigating the challenges of vanishing gradients during deep network training. MadNet capitalizes on these strengths by adapting ResNet's architecture to the super-resolution domain, thereby enhancing its capability to capture both global structures and fine details within images. One distinguishing feature of MadNet is its ability to exploit both external and internal features of an image during the super-resolution process. External features refer to overarching structures and patterns present in the image, while internal features encompass finer details and textures. By incorporating ResNet, MadNet can effectively extract and integrate these features at multiple levels of abstraction, enabling the generation of high-resolution images with enhanced fidelity and perceptual quality. Moreover, by utilizing residual connections within ResNet blocks, MadNet facilitates smoother gradient flow during training, which helps alleviate optimization challenges and accelerates convergence. This not only reduces computational complexity but also enhances the overall efficiency of the super-resolution process.

IV WORKING METHODOLOGY

The methodology of MadNet, an advanced image super-resolution technique, involves several key steps and strategies aimed at effectively generating high-resolution images from low-resolution inputs. Here's an overview of the methodology:

ResNet-Based Architecture Selection: MadNet employs a Residual Network (ResNet)-based architecture as the foundation of its methodology. ResNet is chosen for its ability to learn intricate features from images while mitigating the challenges of vanishing gradients in deep neural networks.

Feature Extraction and Internal Representation: Within the ResNet architecture, MadNet incorporates feature extraction layers responsible for capturing both external structures and internal details of the input image. These layers employ convolutional operations to extract hierarchical features at multiple levels of abstraction.

Residual Blocks for Smoother Gradient Flow: MadNet utilizes residual blocks within the ResNet architecture to facilitate smoother gradient flow during training. These residual blocks incorporate skip connections, allowing gradients to bypass some layers and alleviating optimization challenges. This results in faster convergence and improved efficiency during training.

Upsampling Layers for Resolution Enhancement: MadNet integrates upsampling layers to increase the spatial resolution of the image. These layers interpolate the low-resolution input to produce a high-resolution output, enabling the generation of visually appealing super-resolved images.

Activation Functions for Non-Linearity: Activation functions such as ReLU (Rectified Linear Unit) or Leaky ReLU are applied within MadNet to introduce non-linearity and enable the network to capture complex relationships within the data. These functions enhance the expressive power of the network and facilitate feature learning.

Loss Function Optimization: MadNet minimizes a loss function during training to quantify the discrepancy between the generated high-resolution image and the ground truth high-resolution image. Common loss functions used include Mean Squared Error (MSE) or perceptual loss, which measures differences in feature representations between the generated and ground truth images.

Training and Optimization: MadNet undergoes training using a dataset of paired low-resolution and high-resolution images. During training, the model adjusts its parameters through

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optimization techniques such as stochastic gradient descent (SGD) or its variants, aiming to minimize the loss function and improve the quality of the generated images.

Evaluation and Validation: Throughout the training process, MadNet is evaluated and validated using a separate validation dataset to assess its performance. Metrics such as PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) are commonly used to measure the quality of the generated high-resolution images.

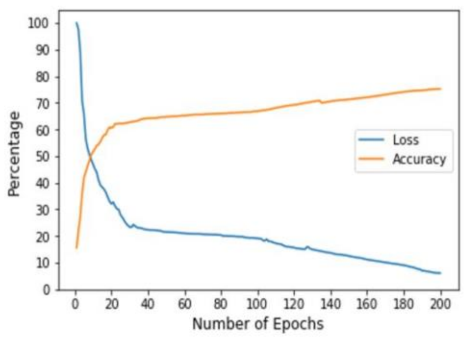

FIG : 7.1.1 MODEL ACCURACY LOSS GRAPH

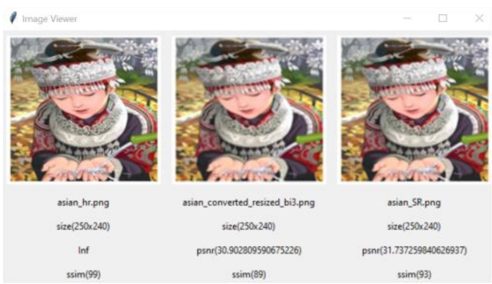

FIG : 7.1.1 OUTPUT IMAGE

CONCLUSION

In conclusion, MadNet presents a promising advancement in the field of image super-resolution, leveraging its innovative architecture and components to generate high-resolution images from low-resolution inputs effectively. With its ResNet-based approach, MadNet achieves a balance between model complexity, feature capture, and optimization efficiency, resulting in superior performance and improved image quality compared to traditional methods.

The future scope for MadNet is vast and encompasses several exciting possibilities:

Performance Optimization: Continued research and development efforts can focus on optimizing MadNet's performance further, improving its speed, efficiency, and scalability. By leveraging advancements in hardware acceleration and parallel processing techniques, MadNet can achieve real-time super-resolution capabilities, making it suitable for a broader range of applications.

Adversarial Training: Exploring adversarial training techniques such as Generative Adversarial Networks (GANs) can enhance MadNet's ability to generate high-fidelity, photorealistic images. By incorporating adversarial loss functions, MadNet can learn more realistic image textures and details, resulting in visually appealing super-resolved outputs.

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