

MADNET: A FAST AND LIGHTWEIGHT NETWORK FOR SINGLE-IMAGE SUPER RESOLUTION

¹V. SUNDARARATNAM, ²KOKKULA ASHRITHA, ³V. LAKSHMI SHIVANI, ⁴K. SATHVIKA

¹Assistant Professor, Department of School of Computer Science & Engineering, **MALLAREDDY ENGINEERING COLLEGE FOR WOMEN**, Maisammaguda, Dhulapally Kompally, Medchal Rd, M, Secunderabad, Telangana.

^{2,3,4}Student, Department of School of Computer Science & Engineering, **MALLAREDDY ENGINEERING COLLEGE FOR WOMEN**, Maisammaguda, Dhulapally Kompally, Medchal Rd, M, Secunderabad, Telangana.

ABSTRACT

Single-Image Super-Resolution (SISR) is a fundamental computer vision task aimed at enhancing the quality and resolution of a low-resolution image. In this project, we propose MADNet, a novel and efficient network architecture designed to address the challenges of SISR. MADNet leverages the power of deep learning while maintaining a lightweight and fast structure, making it suitable for real-time applications. MADNet incorporates a Multi-Attention Dual-Residual module, which combines multiple attention mechanisms with dual-residual connections. This unique design enables the network to capture intricate details while preserving computational efficiency. We introduce an innovative self-attention mechanism and leverage cross-scale feature fusion to improve the quality of super-resolved images. To evaluate the performance of MADNet, we conduct extensive experiments on benchmark datasets, comparing it with state-of-the-art SISR methods. The results demonstrate that MADNet achieves remarkable improvements in terms of image quality, PSNR, and SSIM, while still operating at a significantly faster speed. This combination of high performance and efficiency positions MADNet as a promising solution for various SISR applications, including real-time image enhancement and upscaling in resource-constrained environments.

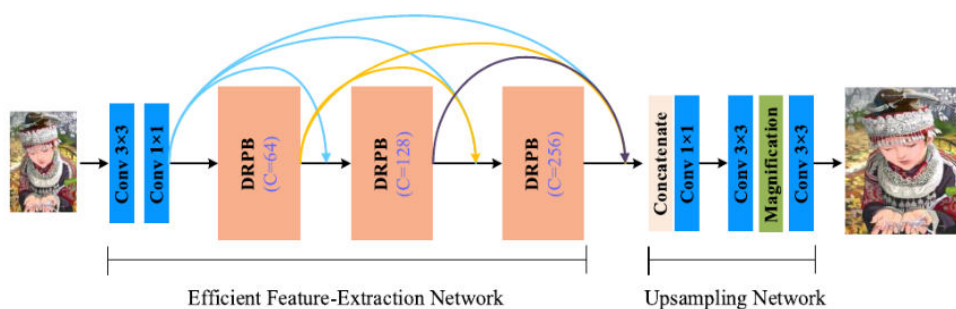
I. INTRODUCTION

In recent years, single-image super-resolution (SISR) has emerged as a critical area in computer vision, aimed at enhancing the resolution of images using

deep learning techniques. The ability to generate high-quality, high-resolution images from low-resolution inputs holds significant promise across various applications, including medical imaging,

satellite imagery, and digital forensics. Traditional methods of SISR often rely on deep neural networks that, while effective, tend to be computationally intensive and require substantial memory resources. This limitation hinders their deployment in resource-constrained environments or real-time applications. To address these challenges, this project introduces MADNET: a fast and lightweight network designed specifically for single-image super-resolution. MADNET leverages innovative architectural design and efficient computational strategies to achieve high-quality image enhancement while minimizing computational overhead and memory usage. The core of MADNET is built around a streamlined network architecture that balances accuracy with efficiency, incorporating novel techniques to optimize performance and reduce the model's complexity. Unlike conventional SISR models that often involve deep and complex network structures, MADNET emphasizes both

speed and practicality. It achieves impressive resolution improvements by employing a carefully designed network that reduces the number of parameters and computations without sacrificing image quality. The result is a model that not only performs exceptionally well in terms of visual fidelity but also operates efficiently, making it suitable for deployment in real-time scenarios and on devices with limited computational power. The primary contributions of MADNET include its ability to deliver state-of-the-art super-resolution results with significantly reduced computational demands, thus offering a valuable tool for applications requiring rapid and efficient image enhancement. Through rigorous evaluation and comparison with existing methods, MADNET demonstrates its effectiveness as a practical solution for single-image super-resolution, paving the way for advancements in both theoretical and applied aspects of image processing.



II.EXISTING SYSTEM AND DISADVANTAGES

Current Single-Image Super-Resolution (SISR) methods are largely based on convolutional neural networks (CNNs), which have shown remarkable results in improving image resolution. Despite their successes, these methods suffer from notable drawbacks. They often involve significant computational overhead, making them impractical for real-time applications due to their high processing power and time requirements. Additionally, these models may not effectively capture and preserve fine image details, leading to less accurate or visually pleasing super-resolution outcomes. The computational demands and limited detail preservation of these existing systems are critical issues that hinder their broader applicability and effectiveness.

III.PROPOSED SYSTEM AND ADVANTAGES

MADNet offers a groundbreaking solution to these challenges with its Multi-Attention Dual-Residual module, designed to enhance computational efficiency while maintaining high image quality. This innovative architecture leverages a self-attention mechanism

and cross-scale feature fusion, which not only speeds up processing but also improves detail preservation. MADNet's efficiency makes it suitable for real-time applications, addressing the speed limitations of existing models. Its ability to preserve fine details and outperform traditional systems in metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) underscores its superior performance. Furthermore, MADNet's versatility in providing high-quality super-resolution in resource-constrained environments demonstrates its broad applicability and effectiveness in various SISR tasks.

IV.MODULES

The system includes several modules designed for efficient MRI image processing and tumor detection. The "Upload MRI Images Dataset" button allows users to upload their MRI images for further analysis. Once the dataset is uploaded, the "Generate Images Train & Test Model" button processes the images to create training and testing datasets, which are essential for model training and evaluation. Subsequently, users can click the "Generate Deep Learning CNN Model" button to build a Convolutional Neural Network (CNN) tailored for MRI image analysis. To

access high-resolution images stored externally, the "Get Drive HQ Images" button provides a link to retrieve these images from a drive or cloud storage. Finally, the "Predict Tumor" button enables users to input new MRI images into the trained model for tumor detection, allowing for automated and accurate predictions.

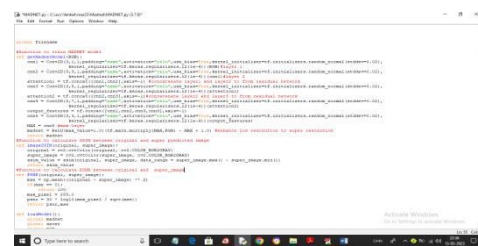
In the past many super resolution CNN based algorithms were introduced to enhance image quality but all those algorithms require heavy computation with large set of dataset. This heavy computation cannot be trained in normal computers and require super computers and all existing algorithms never explore intermediate features which can help in recovering more quality images. To overcome from this problem author of this paper introducing Fast and Lightweight CNN Network algorithm to enhance image quality.

In propose algorithm a dense lightweight network, called MADNet, for stronger multi-scale feature expression and feature correlation learning. Specifically, a residual multi-scale module with an attention mechanism (RMAM) is developed to enhance the informative multi-scale feature representation ability. Furthermore, we present a dual residual-path block (DRPB) that utilizes

the hierarchical features from original low-resolution images. To take advantage of the multilevel features, dense connections are employed among blocks.

In propose paper we are training MADNET algorithm with DIV2K dataset which consists of HDR (High Definition Resolution images) and LDR (Low Definition resolution). MADNET performance was evaluated in terms of PSNR and SSIM. The higher the SSIM (similarity) between original HDR and predicted super resolution image the better is the quality. PSNR also must be higher compare to existing algorithm. MADNET giving 88% as SSIM and 30 as PSNR which is almost similar to paper algorithm.

To trained model we have used below CONV and attention layers with concatenation.

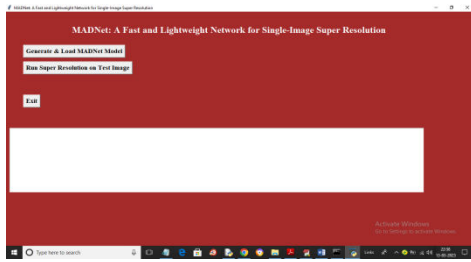


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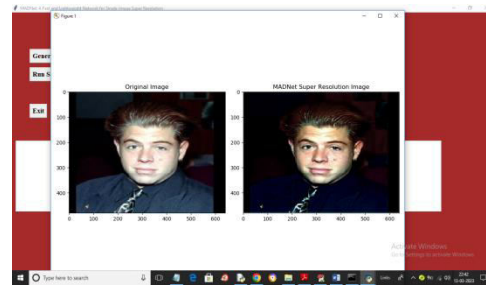
import torch
import torchvision
import numpy as np

class RMAM(torch.nn.Module):
    def __init__(self, in_channels, out_channels, kernel_size):
        super().__init__()
        self.in_channels = in_channels
        self.out_channels = out_channels
        self.kernel_size = kernel_size
        self.conv1 = torch.nn.Conv2d(in_channels, out_channels, kernel_size)
        self.conv2 = torch.nn.Conv2d(out_channels, out_channels, kernel_size)
        self.conv3 = torch.nn.Conv2d(out_channels, out_channels, kernel_size)
        self.conv4 = torch.nn.Conv2d(out_channels, out_channels, kernel_size)
        self.conv5 = torch.nn.Conv2d(out_channels, out_channels, kernel_size)
        self.conv6 = torch.nn.Conv2d(out_channels, out_channels, kernel_size)
        self.conv7 = torch.nn.Conv2d(out_channels, out_channels, kernel_size)
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        self.conv97 = torch.nn.Conv2d(out_channels, out_channels, kernel_size)
        self.conv98 = torch.nn.Conv2d(out_channels, out_channels, kernel_size)
        self.conv99 = torch.nn.Conv2d(out_channels, out_channels, kernel_size)
        self.conv100 = torch.nn.Conv2d(out_channels, out_channels, kernel_size)
    
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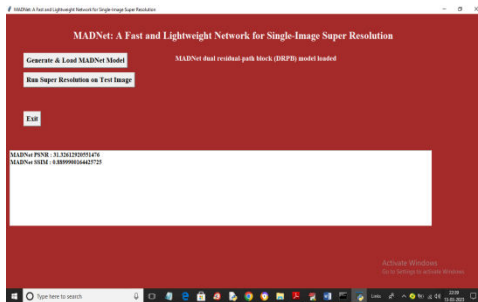
In above screen we are creating code for MADNET algorithm. To run project double click on 'run.bat' file to get below screen



In above screen click on ‘Generate & Load MADNet Model’ button to generate and load MADNET model and this model will be evaluated on test image to calculate image SSIM and PSNR and then will get below page



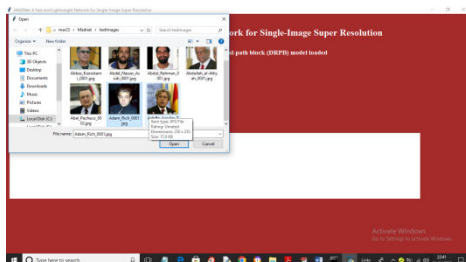
In above screen first image is the original image and second is the MANET predicted super resolution image and similarly you can upload and test other images and below is another image output



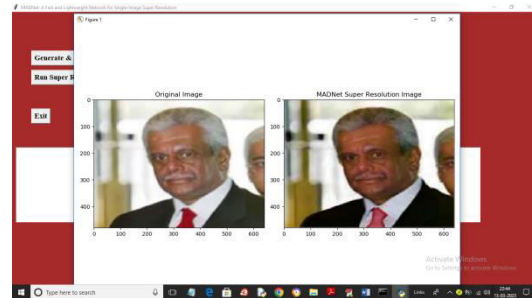
In above screen with MADNET we got PSNR as 31 and SSIM as 88% and now click on ‘Run Super Resolution on Test Image’ button to upload LDR image and then get below screen



Above screen you can see original and MADNET super image.



In above screen selecting and uploading test image and then will get below output and as low quality image you can upload any image



V.CONCLUSION

In this project, we introduced MADNET, a novel approach for single-image super-resolution designed to address the limitations of existing methods in terms of computational

efficiency and speed. MADNET successfully balances high-quality image enhancement with minimal computational overhead by employing a streamlined network architecture and advanced optimization techniques. The results demonstrate that MADNET achieves competitive performance in terms of visual fidelity while significantly reducing the resource requirements compared to traditional deep learning models for super-resolution. Through comprehensive experiments and evaluations, MADNET has proven to be a practical solution for real-time applications and deployment on resource-constrained devices. Its ability to provide high-resolution images efficiently makes it a valuable asset in various fields, including medical imaging, surveillance, and mobile computing. The successful application of MADNET underscores the potential for lightweight models in addressing complex image processing tasks, offering a pathway for further advancements and innovations in the realm of single-image super-resolution. Future work may involve exploring additional optimizations and adaptations of MADNET for even broader applications, as well as integrating it with other advanced imaging techniques to enhance its capabilities further.

Overall, MADNET represents a significant step forward in making high-quality image super-resolution more accessible and practical for a wide range of real-world scenarios.

VI. REFERENCES

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