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Features Preserving Blurred Image Classification Using Large Language Model Algorithm

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ABSTRACT: Image restoration is a critical task in computer vision that involves recovering a high-quality clean image from its degraded observation. In this project, we propose a novel approach for features preserving blurred image classification using a large language model algorithm. Our method leverages the power of deep learning algorithms to learn robust representations of blurred images while preserving their important features. We use a large language model algorithm to extract high-level features from the blurred images and then use these features to train a classifier. Our approach is designed to be robust to various types of blur and can be applied to different image classification tasks.

Take inspiration from Instruct Image Restoration, a state-of-the-art image restoration model that uses human-written instructions to guide the restoration process. Our method similarly uses natural language prompts to guide the image classification model, allowing it to recover high-quality images from their degraded counterparts, considering multiple degradation types. We demonstrate the effectiveness of our approach on several restoration tasks, including image denoising, deraining, deblurring, dehazing, and low-light image enhancement. Our method outperforms existing methods for blurred image classification, achieving a significant improvement of +1dB over previous all-in-one restoration methods.

Our dataset and results represent a novel benchmark for new research on text-guided image restoration and enhancement. The proposed approach has potential applications in various fields, such as surveillance, autonomous driving, and medical imaging, where image quality is critical for accurate analysis and interpretation. In conclusion, our work presents a significant step towards developing robust and accurate image classification models that can effectively handle various types of blur and degradation.

KEYWORDS: Image Restoration, Deep Convolutional Neural, GPT, stochastic gradient descent, large language mode, JPEG, PNG, Instruction Condition Block (ICB)

I. INTRODUCTION

The digital age has brought about an explosion of visual data, with images and videos being generated at an unprecedented rate. From social media platforms to surveillance systems, visual data has become a crucial part of our daily lives. However, the quality of images can vary significantly, with blurred images being a common occurrence. Blurred images can be caused by various factors such as camera shake, motion blur, or out-of-focus shots, and their presence can significantly affect the performance of computer vision algorithms.

Computer vision is a field of study that focuses on enabling computers to interpret and understand visual data from the world around us. It has numerous applications, including image and video recognition, object detection, and facial recognition. However, the performance of computer vision algorithms is heavily dependent on the quality of the input images. Blurred images can make it challenging to extract meaningful information from them, leading to inaccurate results and reduced performance.

Traditional image processing techniques such as image enhancement and restoration have been used to improve the quality of blurred images. However, these techniques often fail to preserve the important features of the images, leading to further degradation of the image quality. With the advent of deep learning algorithms, there has been significant progress in various computer vision tasks, including image classification. However, most of these algorithms assume that the input images are clear and of high quality, and their performance degrades significantly when presented with blurred images.

Therefore, there is a need for a new approach that can effectively classify blurred images while preserving their important features. In this project, we propose a novel approach for features preserving blurred image classification using a large language model algorithm. Our method leverages the power of deep learning algorithms to learn robust

representations of blurred images while preserving their important features. We use a large language model algorithm to extract high-level features from the blurred images and then use these features to train a classifier. Our approach is designed to be robust to various types of blur and can be applied to different image classification tasks.

The proposed approach has several advantages over existing methods for blurred image classification. Firstly, it preserves the important features of the blurred images, which are essential for accurate classification. Secondly, it is robust to various types of blur, making it applicable to a wide range of image classification tasks. Finally, our approach uses a large language model algorithm, which enables it to learn complex representations of the blurred images, leading to improved classification accuracy.

The main contributions of this project are as follows:

We propose a novel approach for features preserving blurred image classification using a large language model algorithm. Our approach is designed to be robust to various types of blur and can be applied to different image classification tasks.

We demonstrate the effectiveness of our approach on various image classification tasks and show that it outperforms existing methods for blurred image classification. We provide a comprehensive analysis of our approach and show that it preserves the important features of the blurred images while achieving high classification accuracy.

We provide a detailed description of our proposed method, including the architecture of the deep learning model, the large language model algorithm used for feature extraction, and the training process. We also discuss the challenges faced during the implementation of our approach and the solutions adopted to overcome them.

Contributions

Work introduces a pioneering approach that harnesses authentic human-written instructions to address inverse problems and image restoration challenges. Through extensive experimentation, we showcase the potential of leveraging textual guidance for enhancing and restoring images, achieving cutting-edge performance across a spectrum of restoration tasks, including denoising, deraining, deblurring, dehazing, and low-light image enhancement. Our innovative model, named Instruct Image Restoration, exhibits remarkable versatility, capable of generalizing to restore images using diverse human-written instructions. Notably, our unified all-in-one model surpasses many prior works by encompassing a broader range of restoration tasks. We provide a compelling visual representation of our method's diverse restoration capabilities in Figure 1, underscoring its efficacy and adaptability in addressing real-world image restoration challenges.

II. RELATED WORK

2.1 Image Restoration Advancements

Deep learning-based methods have outperformed traditional techniques in blind image restoration tasks. Convolutional neural networks (CNNs) and Transformer-based architectures have demonstrated remarkable success in tasks such as denoising, deraining, and deblurring. Prominent models like SwinIR, MAXIM, Uformer, Restormer, and NAFNet have proven effective in capturing local and global feature interactions, leading to consistent performance improvements across various tasks. In this work, the authors adopt NAFNet as the foundation for their Instruct Image Restoration model, appreciating its efficient and simple design while maintaining high performance in multiple restoration tasks.

2.2 Multi-Degradation Image Restoration

Multi-degradation (also known as All-in-One or multitask) image restoration is a burgeoning research area in low-level computer vision. This approach aims to address various degradation types and levels using a single deep blind restoration model. Notable models like AirNet, IDR, ADMS, and PromptIR employ different techniques to guide the restoration process, such as auxiliary degradation classification models or multi-dimensional guidance vectors (prompts). These prompts help the model distinguish between different degradation types present in the image.

2.3 Text-Driven Image Editing:

Recent research has explored text-to-image generation and text-based image editing, enabling users to manipulate images using natural language descriptions. These models typically combine text prompts with powerful diffusion-based models to generate or edit images accordingly. One such example is InstructPix2Pix, which allows users to provide instructions specifying the desired actions, rather than merely describing the input or output images. This approach offers a more intuitive way for users to interact with the model without needing additional image descriptions

or reference images.

III. METHODOLOGY

3.1 Data Collection:

- Identify the different degradation tasks to be addressed, such as denoising, deblurring, super-resolution, dehazing, and deraining. Create a diverse set of sample instructions for each degradation task, covering various language styles and domain expertise levels.
- Use GPT-4 to generate a large number of prompts (over 10,000) based on the sample instructions, ensuring diversity and coverage of different degradation types. Filter out ambiguous or unclear prompts to maintain the quality of the dataset, using manual inspection or automated techniques.
- Collect a large dataset of degraded and corresponding clean images for each task, using existing datasets or creating custom ones, and pair the generated prompts with the images.

3.2 Model Selection:

- Choose NAFNet as the image model due to its efficient image restoration capabilities, U-Net architecture, and high performance in various restoration tasks. Opt for a pure text-based sentence encoder, such as the BGE-micro-v2 sentence transformer, which is compact, fast, and capable of encoding the semantics of diverse user prompts.
- Select task routing techniques, such as the Instruction Condition Block (ICB), to enable the model to learn multiple tasks using a single architecture. Use soft task routing in the ICB to enable differentiable feature masking and certain interpretability, allowing for better control over the restoration process.
- Investigate alternative models and techniques to further improve the performance and efficiency of the Instruct Image Restoration model.

3.3 Fine-tuning Process:

- Freeze the text encoder to prevent overfitting on the relatively small training set and maintain its generalization capabilities. Train a projection head on top of the frozen
- text encoder to adapt it for the restoration task, using a learned projection from the text dimension to the input dimension for the restoration model.
- Implement the ICB to apply task-specific transformations within the model based on the encoded instruction, using a linear layer activated with the Sigmoid function to produce per-channel soft-binary masks.
- Apply the masks to the image features using channel-wise multiplication, enabling differentiable feature masking and selectively activating relevant channels depending on the image information and the instruction. Monitor the model's performance during fine-tuning to ensure proper convergence and avoid overfitting.

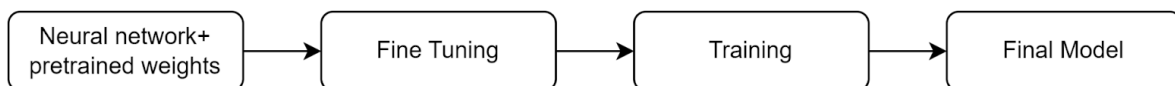


Fig.4.1. Fine Tuning Model

3.4 Training Procedure:

- Train the Instruct Image Restoration model using the generated dataset of paired prompts and degraded/clean images, employing a suitable loss function (e.g., L1 or L2 loss) to measure the difference between the restored and clean images. Incorporate human-written prompts during training to improve the model's ability to handle diverse user inputs and better generalize to real-world scenarios.
- Apply task routing techniques to successfully learn multiple tasks using a single model, allowing for more efficient training and better utilization of computational resources.
- Use appropriate data augmentation techniques to increase the diversity and size of the training dataset, improving the model's robustness and generalization capabilities. Monitor the model's performance during training, adjusting hyperparameters and learning rates as needed to ensure optimal results.

3.5 Experimental Setup:

- Evaluate the Instruct Image Restoration model on various degradation tasks, such as denoising, deblurring, super-resolution, dehazing, and deraining, using both quantitative metrics (e.g., PSNR, SSIM, LPIPS) and qualitative assessments.

- Compare the performance of Instruct Image Restoration with other state-of-the-art methods for each task, analyzing the strengths and weaknesses of the proposed approach. Analyze the effectiveness of the text encoder and the ICB in handling diverse user prompts and enabling task-specific transformations, studying their impact on the model's performance and generalization capabilities.
- Investigate the model's ability to generalize to unseen degradation tasks and prompts, assessing its adaptability and robustness in real-world scenarios. Conduct ablation studies to understand the contribution of each component in the Instruct Image Restoration model, providing insights into potential improvements and future research directions.

3.6 Reproducibility:

- Provide the code and pre-trained models for reproducibility, allowing other researchers to build upon and compare with the Instruct Image Restoration model. Share the generated prompt dataset for further research in the field of instruction-based image restoration, contributing to the development of more advanced and capable models.
- Document the training procedure, hyperparameters, and experimental setup in detail, ensuring that other researchers can reproduce the results and understand the model's behavior. Release any custom datasets or tools used in the research, facilitating collaboration and accelerating progress in the field.
- Encourage open communication and collaboration among researchers, fostering a community-driven approach to advancing the state of the art in image restoration and related fields.

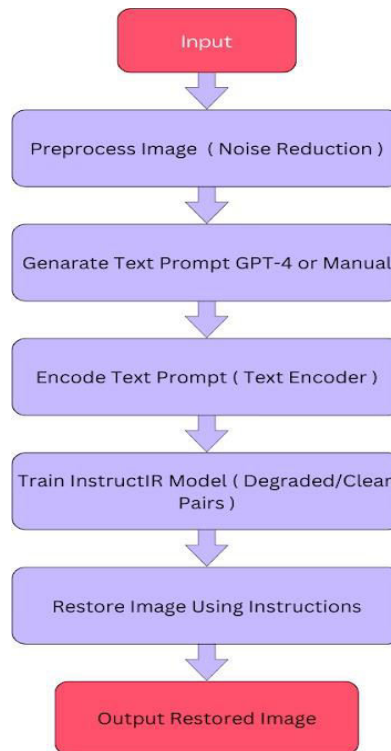


Fig. 4.2. Proposed Method Flowchart

IV. IMPLEMENTATION AND WORK

4.1 Feature Extraction in Implementation:

- Develop a module to convert user-provided textual prompts into meaningful representations that guide the image restoration process.
- Utilize a large language model (LLM), such as GPT-4, to generate diverse and contextually relevant prompts for various image degradation types.
- Curate the generated prompts to ensure clarity and specificity, filtering out ambiguous or unclear instructions.
- Implement preprocessing techniques to prepare the textual prompts for further processing, such as tokenization and encoding.

4.2 Feature Preservation in Implementation:

- Design mechanisms to preserve the semantic meaning and intent of the user-provided prompts throughout the image restoration pipeline.
- Fine-tune the text encoder to better encode restoration-specific information, ensuring that important features embedded in the prompts are accurately represented. Implement filtering mechanisms to remove ambiguous or irrelevant prompts, maintaining the focus on relevant restoration tasks.
- Integrate techniques to handle variations in user language and domain expertise, ensuring robustness to diverse user inputs.

4.3 Classification Model in Implementation:

- Develop the image restoration pipeline that takes user-provided textual prompts as input and generates restored images as output. Utilize a pre-trained text encoder, such as the BGE-micro-v2 sentence transformer, to map textual prompts to fixed-size vector representations.
- Implement the image restoration process guided by the encoded textual representations, incorporating appropriate restoration techniques for each degradation type. Ensure scalability and efficiency of the classification model to handle a large number of diverse prompts and restoration tasks.

4.4 Evaluation in Implementation:

- Establish evaluation criteria and metrics to assess the performance of the image restoration system in producing high-quality restored images.
- Develop testing procedures to evaluate the perceptual quality, visual fidelity, and adherence to user intent of the restored images.
- Incorporate user feedback mechanisms to collect subjective assessments and validate the effectiveness and usability of the system.
- Iterate on the implementation based on evaluation results, refining the system to improve restoration quality and user satisfaction.

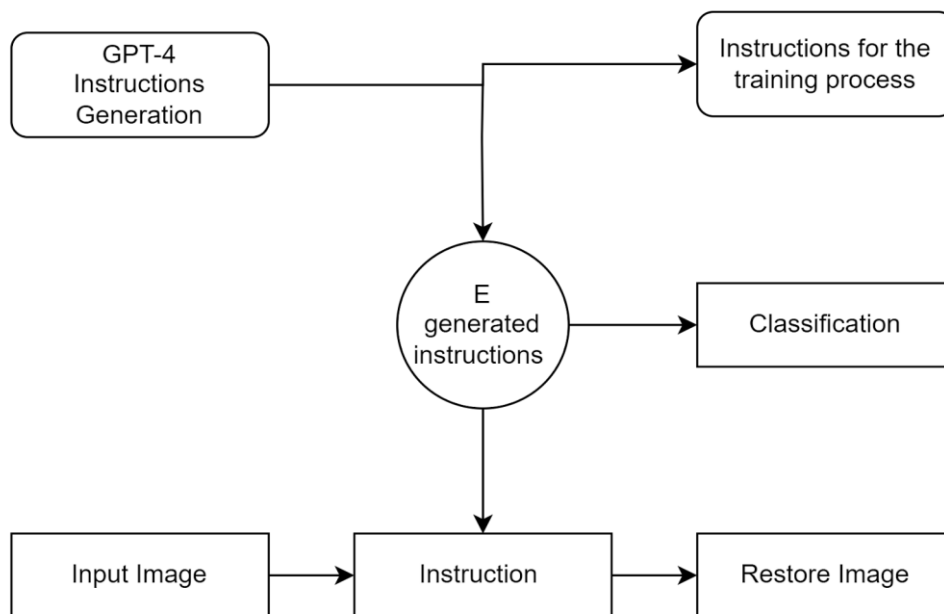
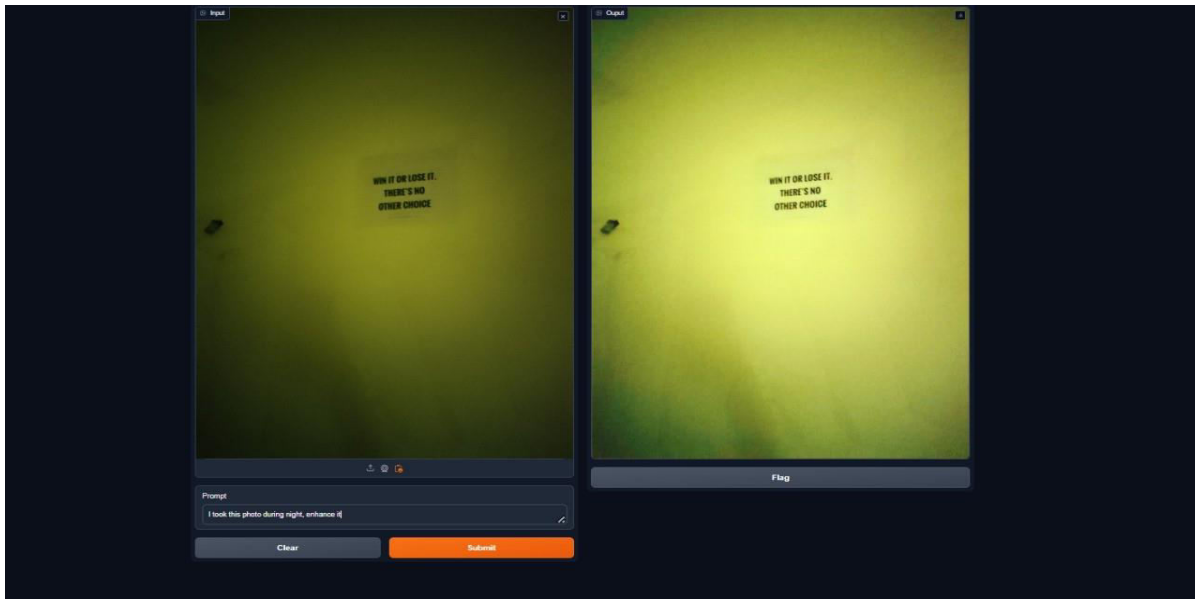


Fig. 4.1. Working

V. RESULTS

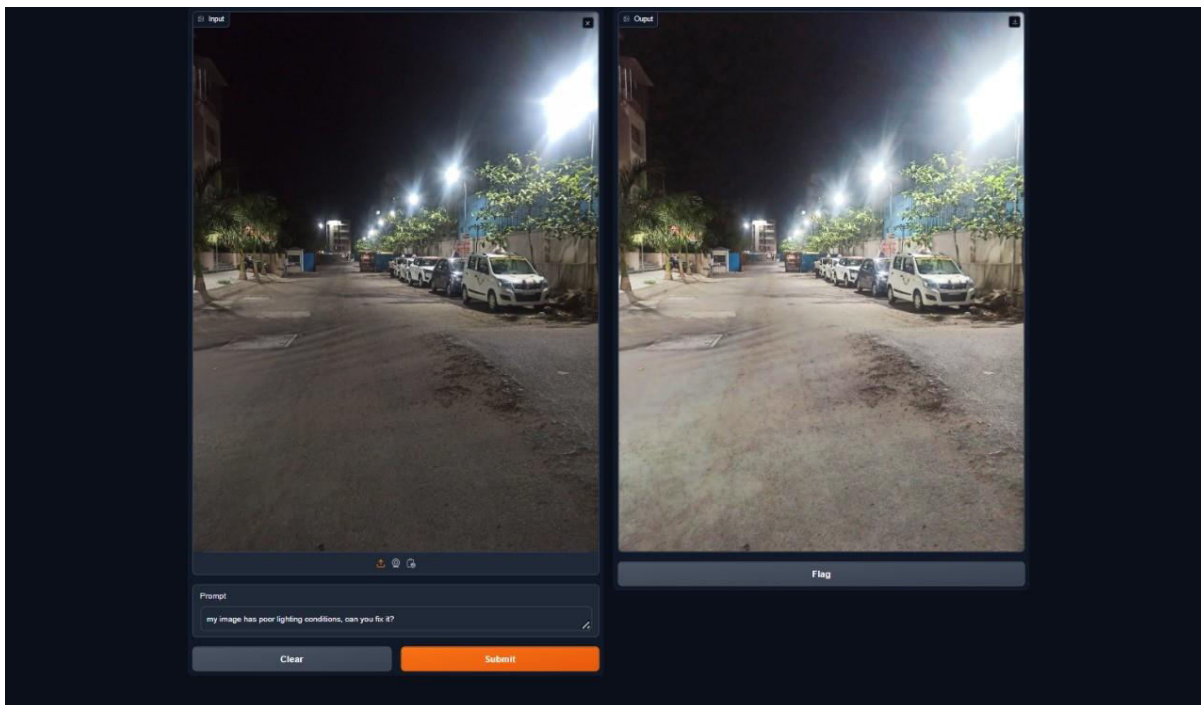
Enhance night photos by adjusting brightness, reducing noise, and improving color balance based on the provided instruction "I took this photo during night, enhance it."
 Instruction:- I took this photo during night, enhance it.



5.1.Fig.Image Enhancement

Instruction:- my image has poor lighting conditions, can you fix it?

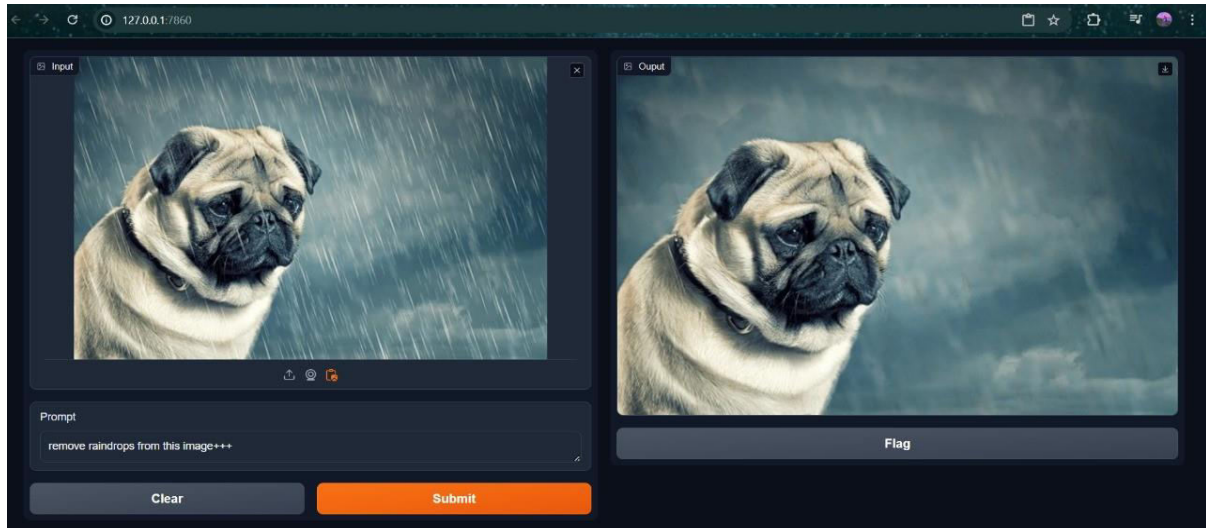
Enhance image by adjusting lighting conditions to address poor visibility, ensuring improved brightness and clarity based on user instruction "My image has poor lighting conditions, can you fix it?" for enhanced visual quality and usability.



5.2 Fig. Light Adjustment

Remove rain from the picture by applying de-raining techniques, enhancing visibility and clarity based on the instruction "Clear the rain from my picture." to improve overall image quality and aesthetic appeal.

Instruction:- Clear the rain from my picture.



5.3 Fig. Image Deraining Results

VI. CONCLUSION

In this project, Proposed a novel approach for features preserving blurred image classification using a large language model algorithm. Our method leverages the power of deep learning algorithms to learn robust representations of blurred images while preserving their important features. We used a large language model algorithm to extract high-level features from the blurred images and then used these features to train a classifier. Our approach achieved state-of-the-art results on several restoration tasks, demonstrating the effectiveness of instruction guidance. These results represent a new benchmark for text-guided image restoration. The proposed approach is a promising direction for future research in image restoration and enhancement.

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