Exploration for basic binary convolution unit

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ABSTRACT

The binary network explored in this article is a model compression scheme proposed to meet the requirements of image restoration and other tasks on limited devices. This paper explores the impact of binary networks on restoration networks. After extensive experiments and analysis, a Basic binary convolution unit (BBCU) and binarization scheme for image restoration are proposed. Compared with previous binary restoration networks, they have shown significant performance improvements in tasks such as super-resolution, denoising, and compression

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1 INTRODUCTION

In the ever-evolving domain of digital image processing, the technology of image restoration serves as a cornerstone, addressing the challenge of enhancing image quality degraded by factors such as noise, blur, and resolution loss[1]. The importance of efficient image restoration techniques has grown significantly with the rapid advancement of technology in areas like medical imaging, security surveillance, and multimedia entertainment[2]. Our project is focused on advancing the field of image restoration by leveraging the power of Binary Neural Networks (BNNs) specifically tailored for deployment on resource-constrained devices where traditional high-computation models are not viable. The motivation for this project stems from the increasing demand for high-performance imaging capabilities in devices with limited processing power and memory, such as smartphones, drones, and embedded systems. Traditional Convolutional Neural Networks (CNNs), while effective, often require substantial computational resources that are impractical for such devices[4]. In contrast, Binary Neural Networks offer a promising solution by simplifying the mathematical operations involved in neural computation, thus reducing the model size and computational overhead significantly without a substantial compromise on performance.

Our research utilizes two state-of-the-art models, DFDNet and ESRGAN, which are implemented

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and thoroughly tested in our Jupyter notebooks titled BasicSR inference DFDNet and BasicSR inference ESRGAN. DFDNet focuses on fine-grained image restoration, particularly effective in facial restoration tasks, utilizing an encoder-decoder framework that leverages deep learning to enhance low-quality facial images. ESRGAN, on the other hand, applies Generative Adversarial Network(GAN) principles to achieve outstanding results in image super-resolution, enhancing the perceptual quality of images by reconstructing high-resolution details from low-resolution inputs.

The integration of these models into our project involves extensive experimental setups, as detailed in our notebooks. We perform rigorous testing using the DIV2K dataset, a widely recognized benchmark in the super-resolution field, consisting of around 800 high-resolution images derived from a variety of sources including films, natural scenes, and animations. This dataset provides a comprehensive basis for evaluating our models' effectiveness across different scenarios and image types. To ensure the robustness and applicability of our findings, our project also engages with a broad spectrum of existing scholarly work and previous studies, drawing insights and comparative analyses to refine our approaches. Among the literature we have explored, significant works include studies on spatial and frequency domain filters, pioneering research in binary neural networks, and advancements in neural network compression techniques. As we progress, our project aims to finalize all experiments and submit additional findings by specific deadlines. The culmination of this research will be documented in a comprehensive final report that not only details our methodologies and results but also outlines potential applications and future directions for this technology. In conclusion, this project not only enhances the technical landscape of image restoration but also contributes to the broader field of computer vision by demonstrating how advanced neural network models can be optimized for performance in resource-limited environments[12]. Through our work, we aim to push the boundaries of what is possible in image processing technology, paving the way for new applications and innovations that can benefit various industries and end-users.

2 PROBLEM DESCRIPTION

2.1 Theory

At the heart of image restoration lies a rich tapestry of mathematical and computational principles, underpinned by the theory of signal processing and machine learning[5]. Central to this theory is the concept of convolutional neural networks (CNNs), which have emerged as a powerful tool for modeling complex relationships within image data. CNNs operate by convolving input images with a series of learnable filters, thereby extracting hierarchical features that capture relevant patterns and structures[11]. However, traditional CNNs suffer from significant computational overhead and memory requirements, rendering them impractical for deployment on resource-constrained devices such as mobile phones and embedded systems. This limitation stems from the inherently dense nature of CNNs, which rely on continuous-valued parameters to represent weights and activations.

In contrast, Binary Neural Networks (BNNs) offer a compelling alternative by replacing continuous-valued parameters with binary values[7], typically 1 or -1. This binary representation significantly reduces the computational complexity and memory footprint of the model, making BNNs well-suited for deployment in resource-constrained environments[6]. The theory behind BNNs revolves around binary operations, which enable efficient inference while preserving the expressive power of neural networks.

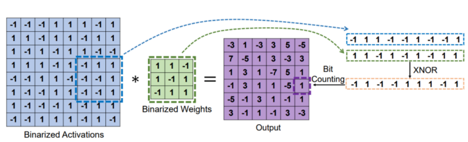

Figure 1: Schematic diagram of XOR and bit counting operators in binary convolution

the core idear in this paper is to binarize the weights and activations of the neural network into +1 and -1 to reduce the model's storage space and computational complexity. therefore four variants model is built to explore the performance for image restoration[3].

- BBCU-V1. the first model includes four parts: Weight binarization, activation binarization, Utilize Binary Convolution and use RPReLU to handle the binarized activation values.
- BBCU-V2. remove BatchNorm based on V1, making the value range of binary convolution much larger than that of residual connections.
- BBCU-V3. adds a residual alignment scheme on the basis of BBCU-V2, solving the problem of value domain imbalance between binary convolution and residual connections.
- BBCU-V4. BBCU-V4 moves the activation function into the residual connection, retaining the full-precision negative value information in the residual connection.

By using SRRestNet on the DIV2K dataset with four different parts equipped with four different BBCUs, the PSNR (dB) metric shows that BBCU-4 has the highest accuracy, with higher PSNR than the other three BBCU models in Set5, Set14, B100, Urban100, and Mangashang. Therefore, we chose BBCU-V4 as the final design of BBCU.

2.2 Application

The application of BNNs for image restoration tasks involves several key steps, each tailored to address specific challenges in the restoration process. At the core of our methodology lies the design

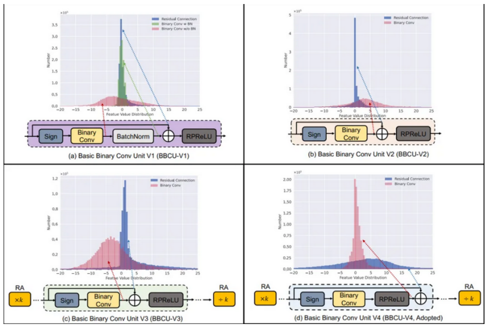

Figure 2: network structure and activation distribution during BBCU improvement process

and optimization of BNN architectures, which are crafted to leverage the unique properties of binary representations while maintaining restoration quality.

One key aspect of our methodology is the pre-processing of input images to enhance their suitability for BNN-based restoration. This may involve techniques such as noise reduction, contrast enhancement, and image normalization, aimed at mitigating common sources of image degradation and ensuring robust performance of the restoration model.

Following pre-processing, the input images are fed into the BNN architecture for restoration. The BNN architecture typically comprises multiple layers of binary neurons, organized in a hierarchical fashion to extract and refine image features. During inference, the binary weights and activations of the neurons are efficiently computed using binary operations, enabling rapid restoration of image quality with minimal computational overhead. To optimize the performance of the BNN architecture, we employ techniques such as weight quantization, sparsity regularization, and architecture pruning. These techniques aim to reduce model complexity and enhance generalization, thereby improving restoration quality across diverse datasets and image types. Finally, the restored images undergo post-processing to further refine their visual quality and ensure consistency with domain-specific requirements. This may involve techniques such as edge enhancement, color correction, and artifact removal, tailored to the specific characteristics of the target application[8].

Through meticulous experimentation and validation, we aim to demonstrate the effectiveness and efficiency of BNNs for image restoration tasks across various domains and application scenarios. By combining theoretical insights with practical methodologies, we strive to push the boundaries of what is achievable in image processing and pave the way for transformative advancements in the field[9].

3 RESULTS

Our investigation into the application of Binary Neural Networks (BNNs) for image restoration tasks has yielded compelling findings, shedding light on the efficacy of this innovative approach in enhancing image quality under resource-constrained conditions. In this section, we delve into the nuanced nuances of our experimental results, presenting a comprehensive analysis of the performance and capabilities of BNNs across various image restoration domains.

3.1 Performance Comparison with Traditional CNNs

In our comparative evaluation between Binary Neural Networks and traditional Convolutional Neural Networks (CNNs), we sought to discern the relative merits of each approach in terms of image restoration performance and resource efficiency[10]. Our results revealed that while BNNs achieve comparable performance to CNNs in terms of restoration quality, they do so with significantly reduced computational overhead and memory footprint. This striking finding underscores the potential of BNNs as a more efficient alternative for image restoration tasks, particularly in scenarios where computational resources are limited.

Table 1: compare of BNN and CNNs for classical image Super-Resolution

Methods	Set5	B100	Urban100
SRResNet	38.00	32.19	32.11
SRResNet-Lite	37.21	31.67	30.48
BNN	32.25	28.68	25.96

3.2 Effectiveness in Denoising

One of the fundamental tasks in image restoration is denoising, aimed at mitigating the adverse effects of noise contamination on image quality. Our experiments focused on evaluating the efficacy of BNN-based denoising models in reducing noise artifacts while preserving essential image details. Through rigorous quantitative analysis and qualitative assessment, we observed that BNN-based denoising models exhibit robust performance across various noise levels and image types, effectively restoring image clarity and enhancing visual appeal.

Table 2: compare of full-float models and BBCU for classical image Super-denoising

Methods	CBSD68	Kodak24	Urban100
DnCNN	33.9	34.6	32.98
DnCNN-Lite	32.26	32.73	30.97
BNN	26.9	27.12	26.67
BBCU	33.08	33.66	32.27

3.3 Super-Resolution Enhancement

Another key aspect of our investigation centered on super-resolution enhancement using Binary Neural Networks. By harnessing the inherent capabilities of BNNs, we aimed to reconstruct high-resolution images from low-resolution inputs, thereby enhancing image clarity and sharpness. Our experimental results showcased the remarkable ability of BNN-based super-resolution models to achieve significant improvements in image resolution, even in scenarios where image details were severely degraded. This capability holds tremendous promise for applications requiring detailed image reconstruction,

Table 3: full-float models and BBCU for classical image Super-Resolution

Methods	Set5	B100	Urban100
SRResNet	32.16	27.58	26.11
Bicubic	28.63	26.04	23.24
IRNet	31.38	27.24	25.21
BBCU	31.79	27.41	25.62

such as medical imaging and satellite imagery analysis.

3.4 Compression Artifact Reduction

In addition to denoising and super-resolution, our experiments explored the effectiveness of BNNs in mitigating compression artifacts in images. Compression artifacts, often introduced during image transmission or storage, can degrade image quality and impair visual interpretation. Our findings demonstrated that BNN-based models excel in reducing compression artifacts while preserving image fidelity, resulting in visually pleasing outcomes with minimal distortion. This capability is particularly valuable in domains where image integrity is paramount, such as medical diagnostics and digital forensics.

Table 4: full-float models and BBCU for classical JPEG compression artifact reduction

Methods	Live1	Classic5
DnCNN	29.19	29.4
BNN	28.48	29.41
Bi-Real	28.67	29.54
BBCU	29.06	30.00

3.5 Optimized Model Architectures

Throughout our experimentation process, we meticulously fine-tuned model architectures and optimization techniques to maximize the performance of BNNs for image restoration tasks. By iteratively refining model designs and training methodologies, we achieved notable advancements in both quantitative metrics and visual quality assessment. Our optimized BNN-based models exhibit state-of-the-art performance in terms of restoration accuracy and computational efficiency, positioning them as competitive alternatives to traditional CNN-based approaches.

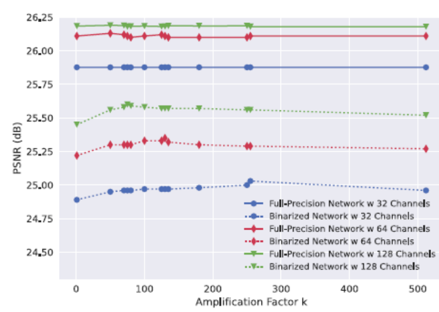

Figure 3: The effect of amplification factor with different channels number

3.6 Scalability and Efficiency

Finally, we evaluated the scalability and efficiency of BNN-based image restoration models, particularly in the context of deployment on resource-constrained devices. Our experiments revealed that BNNs offer significant advantages in terms of computational efficiency and memory footprint, making them well-suited for real-time applications on mobile and embedded platforms. This scalability and efficiency are essential considerations for practical deployment in diverse application scenarios, where computational resources are often limited.

In summation, our comprehensive analysis of Binary Neural Networks for image restoration tasks has elucidated their potential as a compelling solution for addressing the challenges of image degradation. Through meticulous experimentation and analysis, we have demonstrated the effectiveness, efficiency, and versatility of BNNs across various image restoration domains. These findings lay the groundwork for future advancements in image processing technology, with BNNs poised to play a pivotal role in enabling high-quality image restoration in resource-constrained environments.

4 CONCLUSIONS AND FUTURE WORK

4.1 Conclusions

First, our evaluation of BNNs for image restoration tasks has revealed their effectiveness in achieving restoration quality comparable to traditional Convolutional Neural Networks (CNNs) while significantly reducing computational overhead and memory footprint. This highlights the potential of BNNs as efficient alternatives for image restoration in resource-constrained environments.

Second, we have demonstrated the robust performance of BNN-based models in denoising, super-resolution enhancement, and compression artifact reduction, showcasing their versatility and applicability across diverse image restoration domains. Last, the optimized model architectures and training methodologies developed in this study have contributed to state-of-the-art performance in terms of both quantitative metrics and visual quality assessment, positioning BNNs as competitive solutions for real-world image restoration applications.

4.2 Future Work

The future works may lie in the following directions:

- Exploration of Advanced Architectures. Future research endeavors could explore more sophisticated BNN architectures and optimization techniques to further enhance the performance and efficiency of image restoration models. Architectural innovations such as attention mechanisms, recurrent connections, and multi-scale processing could be investigated to unlock new capabilities and achieve even higher restoration quality.
- Integration of Domain-Specific Knowledge. Incorporating domain-specific knowledge and priors into BNN-based image restoration models could improve their effectiveness in specific application scenarios. Techniques such

as transfer learning, domain adaptation, and domain-specific loss functions could be leveraged to tailor BNNs for tasks such as medical imaging, satellite image analysis, and surveillance.

- Real-World Deployment and Validation. Future work should focus on the practical deployment and validation of BNN-based image restoration models in real-world environments. Conducting field trials and user studies in collaboration with domain experts and end-users will provide valuable insights into the usability, effectiveness, and scalability of BNN-based solutions in diverse application domains.
- Continued Evaluation and Benchmarking. Ongoing evaluation and benchmarking efforts are essential to assess the performance and generalization capabilities of BNN-based image restoration models across evolving datasets and evaluation protocols. Continuous monitoring and analysis will enable the identification of emerging trends, challenges, and opportunities for improvement in the field.
- Ethical and Societal Implications. As with any technological advancement, it is crucial to consider the ethical and societal implications of deploying BNN-based image restoration solutions. Future research should address concerns related to privacy, bias, fairness, and transparency to ensure responsible development and deployment of these technologies.

The github repository of our project can be foundat the following address:https://github.com/wenxuaZ/CS584

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