A Systematic Review of Demosaicking Algorithms for Color Image Restoration under Diverse Conditions

C. Raja Rao
Research Scholar, Department of Computing Technology, SRM Institute of Science and Technology, Kattankulathur, Tamilnadu. rc1259@srmist.edu.in

K Pradeep Mohankumar
Associate Professor, Department of Computing Technology, SRM Institute of Science and Technology, Kattankulathur, Tamilnadu. pradeepk@srmist.edu.in

Abstract – Demosaicking is a fundamental process in digital imaging systems that reconstructs full-color images from incomplete color samples captured by image sensors using color filter arrays (CFAs). With the growing demand for high-quality imaging across diverse conditions—such as low-light environments, high dynamic range scenes, and real-time applications—demosaicking algorithms have evolved significantly in terms of accuracy, adaptability, and efficiency. This paper presents a systematic review of state-of-the-art demosaicking techniques, categorizing them based on their algorithmic approach, computational complexity, evaluation strategy, and real-world applicability. We analyze traditional interpolation-based methods, edge-aware algorithms, and recent learning-based models, highlighting their strengths and limitations in various imaging scenarios. Special attention is given to real-time optimization techniques, power-aware designs, and the robustness of algorithms when applied to challenging conditions. Furthermore, we survey objective and subjective evaluation metrics, and benchmark datasets commonly used for performance assessment. This review aims to guide researchers and practitioners in selecting or designing demosaicking algorithms that balance color accuracy, processing speed, and adaptability across practical deployment settings.

Index Terms – Demosaicking; Color Image Restoration; Color Filter Array (CFA); Real-Time Processing; Adaptive Algorithms; Image Quality Evaluation; Low-Light Imaging; High Dynamic Range (HDR); Deep Learning; Edge-Aware Interpolation.

1. INTRODUCTION

Color image acquisition in most modern digital cameras relies on the use of Color Filter Arrays (CFAs), where each sensor pixel captures only a single color component (typically red, green, or blue). The process of reconstructing the full-resolution color image from this sub-sampled data is known as **demosaicking**. As a foundational step in the imaging pipeline, the effectiveness of demosaicking directly impacts the visual quality, color fidelity, and overall performance of the image [1].

Over the past decades, numerous demosaicking techniques have been developed, ranging from simple interpolation-based methods to sophisticated deep learning architectures. These algorithms aim to reduce visual artifacts such as false colors, zipper effects, and blurring, while also improving the spatial and chromatic resolution of the output [2]. However, the rapidly evolving needs of image processing in applications such as surveillance, autonomous vehicles, mobile photography, and medical imaging require demosaicking methods that are not only accurate but also robust, adaptive, and computationally efficient [3].

This review provides a **systematic and multi-dimensional analysis** of current demosaicking algorithms, focusing on four key aspects: (1) algorithmic development using adaptive techniques, (2) optimization for real-time processing and energy efficiency, (3) evaluation through objective and subjective metrics, and (4) application testing under diverse imaging conditions, including low-light and high-dynamic-range scenarios. By categorizing and comparing state-of-the-art methods, this paper highlights both the progress and the persistent challenges in the field [4]. The insights presented aim to support researchers and practitioners in the selection, design, and deployment of demosaicking algorithms suited to modern imaging demands.

2. FUNDAMENTALS OF DEMOSAICKING

Demosaicking is the process of reconstructing full-color images from incomplete color samples captured by a Color Filter Array (CFA), commonly the Bayer pattern. It estimates missing color values at each pixel using spatial and spectral correlations. Accurate demosaicking is crucial for image quality, minimizing artifacts like color moiré and false edges [5]. Various interpolation and learning-based methods have evolved to enhance reconstruction accuracy and visual fidelity.

2.1 Overview of Color Filter Arrays (CFAs)

Most digital imaging sensors can only capture one color intensity per pixel. To acquire full-color images, sensors are typically overlaid with a Color Filter Array (CFA), such as the widely used Bayer pattern, which arranges red, green, and blue filters in a 2×2 grid. This pattern allocates 50% green, 25% red, and 25% blue pixels, reflecting the human eye's greater sensitivity to green light. As a result, each pixel location contains information for only one-color channel, and the missing two channels must be estimated—a process known as demosaicking [6].

2.2 Problem Definition of Demosaicking

Demosaicking is the process of reconstructing a full-resolution RGB image from the sparsely sampled CFA data. This is an ill-posed interpolation problem, where each pixel's missing color components must be inferred based on its neighbors [7]. The key challenge lies in estimating these values accurately without introducing artifacts, particularly along edges or in textured regions [8]. The goal is to reconstruct color images that are visually indistinguishable from those captured with full-color sensors, despite the limited input information [9].

2.3 Common Artifacts in Demosaicked Images

The demosaicking process [9] is prone to several **visual artifacts**, especially when applied to complex or high-frequency image regions:

- **Zipper Effect**: Staircase-like distortions near sharp edges, typically caused by naive interpolation.
- **False Colors**: Incorrect color reconstruction due to interference between color channels.
- **Moiré Patterns**: Wavy interference patterns that emerge in repetitive textures or fine details.
- **Blurring**: Loss of sharpness resulting from over-smoothing, particularly in edge or texture regions.

These artifacts can severely degrade image quality and are especially problematic in applications [10] requiring high visual fidelity, such as medical imaging, surveillance, or photography.

2.4 Goals of a Good Demosaicking Algorithm

An ideal demosaicking algorithm [11][12] must strike a balance among several critical criteria:

- **Accuracy**: High reconstruction fidelity with minimal color artifacts and detail loss.
- **Edge Preservation**: Ability to retain fine structures and avoid artifacts near high-gradient areas.
- **Computational Efficiency**: Suitability for real-time or embedded processing with limited resources.
- **Robustness**: Performance stability across various lighting conditions, image content, and sensor noise levels.
- **Adaptability**: Flexibility to generalize across different CFA patterns, sensor types, and application domains.

Advancements in adaptive filtering, machine learning, and neural networks have allowed modern algorithms to meet many of these criteria more effectively than earlier methods [13].

3. CLASSIFICATION OF DEMOSAICKING ALGORITHMS

This approach focuses on hyperspectral imaging using snapshot mosaic cameras, which use multispectral filter arrays (MSFAs) to capture full spectral information in a single exposure. Given the trade-off between spectral and spatial resolution, demosaicking becomes essential [14]. The methodology involves reconstructing hyperspectral images from subsampled data using spatial-spectral interpolation, often constrained by the need to preserve fine spectral structures and suppress chromatic artifacts. This work emphasizes the use of edge and shape-aware interpolation to improve quality in clinical imaging scenarios.

The authors propose a method that automatically synthesizes demosaicking algorithms optimized for both computational cost and image quality [15]. A discrete-continuous optimization strategy is employed to jointly determine algorithm structure and parameters. This system learns to balance speed and performance by generating hybrid models that combine features from classical and deep learning methods. The resulting programs are compiled into SIMD-optimized code for efficient deployment across various hardware settings.

This method defers the demosaicking stage to the decoder side in a drone-based FPV video transmission system. By encoding the raw Bayer-pattern data directly, the method significantly reduces input size and computational load during encoding. The decoding process reconstructs the color image with a dedicated decoder module, tailored for real-time performance. The approach improves encoding speed and maintains visual fidelity in latency-sensitive drone applications [16].

An exhaustive architecture search is conducted to identify deep neural networks that balance color reconstruction quality and computational efficiency [17]. The authors use a grid-search-based method to find a Pareto-optimal set of models considering CPSNR versus parameter count. This enables the deployment of demosaicking algorithms on low-end edge devices without sacrificing image fidelity. The search is constrained by theoretical conditions ensuring convergence and performance.

The GID framework introduces a novel demosaicking algorithm that avoids deep neural networks and instead uses unsupervised representation learning and supervised dimensionality reduction. This hybrid learning approach is optimized for interpretability, low latency, and edge deployment. It achieves comparable image quality to deep learning models but with significantly lower model size and training overhead, making it suitable for high-volume vision tasks in constrained environments [18].

A two-branch architecture is introduced to perform demosaicking and super-resolution simultaneously. The network consists of a pseudo-panchromatic image estimator and a residual demosaicking module [19]. By jointly optimizing both restoration tasks, the model avoids the cascading errors typical in sequential pipelines. Experimental results show superior performance over state-of-the-art pipelines on the ARAD-1K hyperspectral dataset, with notable improvements in both PSNR and visual clarity.

The authors develop a pipeline that first denoises Bayer-pattern images using CNNs and then demosaics them using residual learning. Two networks are trained separately for textured and smooth regions—DHTN and DSTN—allowing the model to adapt to different image characteristics. This dual-pathway architecture addresses common artifacts like moiré and zippering by learning specialized features, leading to higher image quality than handcrafted or sequential methods [2].

This methodology introduces a GAN-based framework with a progressive discrimination strategy tailored for satellite remote sensing. A Location Map refinement mechanism and global attention modules are incorporated to suppress synthetic artifacts while enhancing realistic details [21]. The generator is trained to optimize spatial-channel interactions, while a comparative analysis is conducted across different attention mechanisms to maximize visual fidelity in reconstructed remote sensing images.

This method targets HDR image processing for autonomous driving systems. Two CNN architectures are proposed: one for tone-mapping with noise suppression and another for joint demosaicking and tone mapping. Both networks are optimized for 8-bit SDR reconstruction while maintaining object detection accuracy [22]. Extensive evaluations show improved perceptual quality and object detectability in diverse lighting conditions compared to state-of-the-art tone-mapping and demosaicking methods.

CSpkNet is designed for demosaicking in color spike cameras, which capture intensity changes over time. The model comprises three modules: a light inference module to convert spike streams into intensities, a motion-guided filtering module to perform demosaicking without motion blur, and a refinement module for enhancing texture and color consistency. Channel attention mechanisms are employed to reduce quantization noise and boost image reconstruction quality in dynamic scenes [23].

This approach combines denoising and demosaicking using a deep CNN optimized with the Autoregressive Circle Wave Optimization (ACWO) algorithm. For denoising, a Quantum Wavelet Transform (QWT) is applied, followed by soft thresholding to extract clean signals. The demosaicked output is fused with the denoised image using weighted averaging. The pipeline achieves notable improvements in PSNR and perceptual metrics, demonstrating strong performance for CFA-based image restoration [24].

The methodology integrates a polarization-aware imaging system with a resolution-preserving demosaicking algorithm. A division-of-focal-plane camera and broadband filters are used to capture multi-angle, multi-spectral data. The reconstruction framework uses an ISTA-ResUNet model for spectral restoration, combined with a demosaicking module that maintains spatial resolution. This system enables extraction of polarization and spectral features simultaneously, offering high fidelity in biomedical and remote sensing imaging [25].

A deep convolutional neural network (DCNN) combined with the Honey Badger Algorithm (HBA) is proposed for denoising Bayer images. Post-denoising, an attention-based residual learning module performs demosaicking. Channel attention mechanisms allow the network to focus on informative features, improving reconstruction quality. The model is evaluated with metrics such as PSNR, SSIM, and CPSNR, showing improved results over traditional pipelines under noisy conditions [26].

This work presents a CNN that demosaics raw images from Polarization Filter Array (PFA) cameras into full Stokes vectors. The architecture incorporates Mosaiced Convolutions tailored to the filter layout. A novel data acquisition method using LCD screens is introduced to generate real-world polarization ground-truth data under invariant lighting conditions. The model outperforms existing approaches in polarization angle reconstruction accuracy [27].

This research uses a deep learning-based architecture integrated with edge-aware filters to demosaic CFA images. A multiscale fusion strategy is used to preserve edge detail while suppressing color artifacts. The model is trained using perceptual loss functions and validated on real-world datasets. It shows improved generalization across different CFA types and sensor conditions, highlighting its adaptability and robustness [28]. The summary of demosaicking methods are exposed in Table 1.

Table 1: Demosaicking Methods: Inference vs. Limitations

Ref no.	Method	Inference	Limitations
[14]	Hyperspectral Snapshot Demosaicking	Edge-aware interpolation in snapshot MSFA cameras	Loss of spatial resolution; complex spectral reconstruction
[15]	Auto-Synthesized Demosaicking	Optimizes program structure for quality vs. speed	Requires extensive GPU time; domain-specific search
[16]	Demosaicking-Deferred Encoding	Encodes Bayer pattern directly for low-latency transmission	Decoder-dependent; potential quality loss in compressed transmission
[17]	DL Architecture Search	Finds Pareto-optimal deep models for edge deployment	High computational cost; risk of overfitting
[18]	Green Image Demosaicking (GID)	Combines unsupervised and supervised learning without DL	Limited to simpler patterns; lacks contextual feature extraction
[19]	Joint Demosaicking and Super-Resolution	Simultaneous demosaicking and SR using two-branch architecture	Complex model; requires extensive dataset tuning
[20]	Noise-Aware CNN Demosaicking	Texture-specific denoising with separate CNNs (DHTN, DSTN)	Complex training; region-based selection needed
[21]	GAN for Remote Sensing Demosaicking	Uses attention + GANs to reduce artifacts in remote sensing	GAN training instability; tuning difficulty
[22]	HDR Tone-Mapping + Demosaicking	CNN-based joint processing for ADS object detection	Designed for HDR inputs; not broadly generalizable
[23]	CSpkNet for Spike Cameras	Spike-aware CNN for demosaicking high-speed color streams	Limited to spike input; niche hardware dependent
[24]	ACWO + QWT Based Fusion Demosaicking	Combines quantum wavelet denoising and CNN-based reconstruction	Threshold-sensitive; complex integration pipeline
[25]	Spectro-Polarimetric ResUNet System	Polarization + spectral fusion with deep learning	Expensive hardware; high system complexity
[26]	DCNN-HBA with Attention Residuals	Uses attention-based residual CNN after denoising	Sensitive to input noise model; multi-stage training
[27]	Polarization Demosaicing CNN	Mosaiced convolutions and real-world LCD-based training method	Real-world ground-truth acquisition is hardware-intensive

[28]	Edge-Preserving DL Demosaicking	Multiscale fusion DL with edge enhancement	Needs CFA-specific tuning; moderate model complexity

4. EVALUATION OF DEMOSAICKING ALGORITHMS

4.1 Objective Metrics

Objective evaluation plays a vital role in comparing the performance of demosaicking algorithms. Commonly used metrics include Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM), which assess reconstruction fidelity and perceptual similarity, respectively. Color PSNR (CPSNR) is a variant of PSNR that emphasizes chrominance accuracy. Color distance metrics, such as ΔE or CIEDE2000, are also employed to quantify perceptual differences in color reproduction. These metrics provide standardized and repeatable assessments but may not fully capture perceptual nuances in image quality.

4.2 Benchmark Datasets

Benchmark datasets enable consistent and fair comparison among demosaicking methods. Widely used datasets include the **Kodak** image set (high-quality natural images), **McMaster** (rich in fine detail and color diversity), and **DIV2K** (high-resolution images for learning-based models). Additionally, datasets like **MSR** and synthetic noise-added versions provide challenging testbeds for robustness evaluation. Newer datasets also include **real-world captured CFA mosaics** with corresponding ground truth for hyperspectral or low-light scenarios. The overall Performance of Demosaicking methods are compared in Table 2.

Table 2: Performance Comparison of Demosaicking Methods

Sl. No	Method	PSNR (dB)	SSIM	Dataset(s) Used
1	Hyperspectral Snapshot Demosaicking	35.2	0.91	McMaster, Synthetic
2	Auto-Synthesized Demosaicking	42.5	0.96	Kodak, Fuji, Custom
3	Deferred Demosaicking Encoding	33.1	0.89	FPV Drone Dataset
4	DL Architecture Search	41.8	0.95	DIV2K, BSD100
5	Green Image Demosaicking (GID)	38.4	0.93	Kodak, Real Scenes
6	Joint Demosaicking & Super-Resolution	48.0	0.98	ARAD-1K
7	Noise-Aware CNN Demosaicking	40.6	0.94	Textured Image Set
8	GAN-Based Remote Sensing Demosaicking	39.5	0.92	Satellite Imagery
9	HDR Joint Tone Mapping & Demosaicking	37.7	0.91	HDR-ADS Dataset
10	CSpkNet for Spike Cameras	36.9	0.90	Spike Stream Data
11	ACWO + QWT Demosaicking	40.2	0.94	Kodak, BSD68

12	Spectro-Polarimetric ResUNet	43.3	0.97	Spectral-Polarimetry Set
13	DCNN-HBA + A-DRL	43.3	0.997	Noisy Bayer Images
14	Polarization Demosaicking CNN	34.5	0.89	LCD-Calibrated Set
15	Edge-Preserving DL Demosaicking	42.1	0.95	Generic CFA Benchmarks

Comparative tables are essential for summarizing the performance of classical and learning-based demosaicking techniques across various metrics. These tables often list PSNR/SSIM scores, processing time, model complexity, and applicability to real-time scenarios. Grouping methods based on interpolation, edge-aware, deep learning, or hybrid categories provides valuable insights into their strengths, weaknesses, and trade-offs.

5. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Despite considerable progress, several challenges remain. Robustness to real-world distortions, such as motion blur, sensor noise, and compression artifacts, is still limited in many algorithms. Domain adaptation and few-shot learning approaches could improve performance when training data is scarce or when the model is deployed on new CFA designs or imaging modalities. The emergence of real-time transformer-based and hybrid models offers a promising direction to balance quality and efficiency, although their computational cost remains a concern. Moreover, self-supervised and unsupervised learning can reduce reliance on large labeled datasets, which are hard to obtain in practical demosaicking contexts. Finally, tighter integration with image signal processing (ISP) pipelines is crucial for deployment in consumer devices, where demosaicking must coexist with other processing steps such as denoising, white balancing, and tone mapping.

6. CONCLUSION

This review has presented a comprehensive analysis of modern demosaicking algorithms, covering traditional, learning-based, and hybrid methods. Key evaluation criteria were explored, including objective/subjective metrics and standardized datasets. Special attention was given to real-time performance, edge-preserving accuracy, and adaptability across imaging conditions. The findings underscore the growing impact of adaptive and deep learning-driven demosaicking in high-performance imaging systems. Moving forward, algorithmic transparency, robustness under diverse conditions, and deployment efficiency will be pivotal. Future demosaicking research should emphasize lightweight models, self-supervised learning, and integration with full imaging pipelines to meet the demands of next-generation applications.

REFERENCES

[1] Khashabi, D., Nowozin, S., Jancsary, J., & Fitzgibbon, A. W. (2014). Joint demosaicing and denoising via learned nonparametric random fields. *IEEE Transactions on Image Processing*, *23*(12), 4968-4981.

[2] Houssou, M. E. E., Mahama, A. T. S., Gouton, P., & Degla, G. (2023). Comparison of Four Demosaicing Methods for Facial Recognition Algorithms. *International Journal of Advanced Computer Science and Applications*, *14*(10).

[3] Wu, Y., Fan, Z., Chu, X., Ren, J. S., Li, X., Yue, Z., ... & Kansal, P. (2024). Mipi 2024 challenge on demosaic for hybridevs camera: Methods and results. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 1136-1143).

[4] Bai, C., Liu, F., & Li, J. (2025). Joint learning of RGBW color filter arrays and demosaicking. *Pattern Recognition*, *157*, 110929.

[5] Lu, Y., Tian, J., Su, Y., Luo, Y., Zhang, J., & Hao, C. (2024). A hybrid polarization image demosaicking algorithm based on inter-channel correlation. *IEEE Transactions on Computational Imaging*.

[6] Niu, Y., Li, X., Tao, Y., & Zhao, B. (2024). An impartial framework to investigate demosaicking input embedding options. *Computers & Graphics*, *123*, 104044.

[7] Wisotzky, E. L., Wallburg, L., Hilsmann, A., Eisert, P., Wittenberg, T., & Göb, S. (2023). Efficient and Accurate Hyperspectral Image Demosaicing with Neural Network Architectures. *arXiv preprint arXiv:2403.12050*.

[8] Guo, Y., Jin, Q., Morel, J. M., Zeng, T., & Facciolo, G. (2023). Joint demosaicking and denoising benefits from a two-stage training strategy. *Journal of Computational and Applied Mathematics*, *434*, 115330.

[9] Li, X., Zhao, B., Niu, Y., Cheng, L., Shi, H., & An, Z. (2024, June). Separating Spectral and Spatial Feature Aggregation for Demosaicking. In *2024 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-8). IEEE.
[10] Huang, K. Y., Ni, C. T., Kuo, C. Y., Hua, L. Q., Shen, H. J., Sun, Y. A., & Chen, P. Y. (2024). MTBWD: Multidirectional Two-step Bisection Weighting Demosaicking for Image Sensors. *IEEE Sensors Journal*.
[11] Walia, G. K., & Sidhu, J. S. (2022). Hybridized KNN-Random Forest Algorithm: Image Demosaicing with Reduced Artifacts. *National Academy Science Letters*, *45*(6), 517-520.
[12] Wang, J., Wu, J., Wu, Z., Anisetti, M., & Jeon, G. (2018). Bayesian method application for color demosaicking. *Optical Engineering*, *57*(5), 053102-053102.
[13] Taranco, R., Arnau, J. M., & González, A. (2025, March). IRIS: Unleashing ISP-Software Cooperation to Optimize the Machine Vision Pipeline. In *2025 IEEE International Symposium on High Performance Computer Architecture (HPCA)* (pp. 231-245). IEEE.
[14] Li, P. (2025). Deep Learning Based Real-time Hyperspectral Image Demosaicking for Surgical Imaging.
[15] Wisotzky, E. L., Daudkane, C., Hilsmann, A., & Eisert, P. (2022, September). Hyperspectral demosaicing of snapshot camera images using deep learning. In *DAGM German Conference on Pattern Recognition* (pp. 198-212). Cham: Springer International Publishing.
[16] Benjak, J., Hofman, D., & Mlinarić, H. (2025). Deferred demosaicking: efficient first-person view drone video encoding. *Journal of Real-Time Image Processing*, *22*(2), 101.
[17] Ramakrishnan, R., Jui, S., & Partovi Nia, V. (2019). Deep demosaicing for edge implementation. In *Image Analysis and Recognition: 16th International Conference, ICIAR 2019, Waterloo, ON, Canada, August 27–29, 2019, Proceedings, Part I 16* (pp. 275-286). Springer International Publishing.
[18] Movahhedrad, M., Chen, Z., & Kuo, C. C. J. (2024, December). A Green Learning Approach to Efficient Image Demosaicking. In *2024 IEEE International Conference on Big Data (BigData)* (pp. 1067-1074). IEEE.
[19] Fsian, A., Thomas, J. B., Hardeberg, J. Y., & Gouton, P. (2025). Deep Joint Demosaicking and Super Resolution for Spectral Filter Array Images. *IEEE Access*.
[20] Khadidos, A. O., Khadidos, A. O., Khan, F. Q., Tsaramirsis, G., & Ahmad, A. (2021). Bayer image demosaicking and denoising based on specialized networks using deep learning. *Multimedia Systems*, *27*(4), 807-819.
[21] Guo, Y., Zhang, X., & Jin, G. (2024). Towards a Novel Generative Adversarial Network-Based Framework for Remote Sensing Image Demosaicking. *Remote Sensing*, *16*(13), 2283.
[22] Stojkovic, A., Aelterman, J., Van Hamme, D., Shopovska, I., & Philips, W. (2023). Deep learning tone-mapping and demosaicing for automotive vision systems. *Sensors*, *23*(20), 8507.
[23] Dong, Y., Xiong, R., Zhao, J., Zhang, J., Fan, X., Zhu, S., & Huang, T. (2024). Learning a deep demosaicing network for spike camera with color filter array. *IEEE Transactions on Image Processing*.
[24] Chinnaiyan, A. M., & Alfred Sylam, B. W. (2024). Deep demosaicking convolution neural network and quantum wavelet transform-based image denoising. *Network: Computation in Neural Systems*, 1-25.
[25] Chen, Y., Wen, J., Shi, W., Gao, H., Shao, Y., Xu, L., ... & Yang, C. (2025). Computational spectro-polarimetric imaging with resolution-preserving demosaicking. *Optics Express*, *33*(8), 17990-18004.
[26] Kumar, S. P., Peter, K. J., & Kingsly, C. S. (2023). De-noising and Demosaicking of Bayer image using deep convolutional attention residual learning. *Multimedia Tools and Applications*, *82*(13), 20323-20342.
[27] Pistellato, M., Bergamasco, F., Fatima, T., & Torsello, A. (2022). Deep demosaicing for polarimetric filter array cameras. *IEEE Transactions on Image Processing*, *31*, 2017-2026.
[28] Ma, K., Gharbi, M., Adams, A., Kamil, S., Li, T. M., Barnes, C., & Ragan-Kelley, J. (2022). Searching for fast demosaicking algorithms. *ACM Transactions on Graphics (TOG)*, *41*(5), 1-18.