Breaking Through Color Casts: Enhancing Image Fidelity with Machine Learning-based Correction

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***Abstract*—L Color cast, an aberration common in digital images, poses challenges in various image processing applications, affecting image quality and visual perception. This research investigates diverse methodologies for color cast correction, ranging from traditional algorithms to modern machine learning-based approaches. Leveraging a comprehensive dataset of original and corrected images, the present study evaluates the efficacy of each method using quantitative metrics, including ACMO, BREN, GRAS, LAPM, LAPV, LAPD, and WAVV. Results indicate that while traditional techniques like Gray World Algorithm and White Patch Retinex Algorithm demonstrate moderate effectiveness, the implemented machine learning-based algorithm showcases superior performance across multiple color cast levels. By employing linear regression on RGB values, the method efficiently corrects color cast aberrations, yielding visually appealing and perceptually accurate results. Furthermore, the research highlights the significance of robust color constancy algorithms and their role in mitigating color cast distortions in digital images. This study contributes valuable insights into the field of color cast correction, offering practitioners in image processing and computer vision a comprehensive understanding of effective correction strategies. Future research directions may explore advanced machine learning models and integration with color constancy mechanisms to further enhance color cast correction techniques.**

Keywords—color cast correction, image processing, machine learning, color constancy, image enhancement

I. Introduction

Color cast, an aberration prevalent in digital imaging, poses a significant challenge to achieving accurate color reproduction and fidelity in visual content. This phenomenon manifests as an unintended tint or imbalance in the color rendition of images, stemming from various factors such as lighting conditions, sensor characteristics, and environmental influences. Its pervasive presence across diverse domains, including photography, videography, graphic design, and computer vision, underscores its profound impact on the quality and interpretability of digital imagery [1]-[2].

In practice, color cast can manifest in numerous scenarios, ranging from subtle shifts in hue to pronounced deviations in color balance. For instance, in architectural photography, the warm glow of indoor lighting may introduce a yellowish tint, while outdoor scenes may exhibit bluish hues due to atmospheric conditions or reflections from surrounding surfaces. Similarly, in medical imaging, color cast can distort the representation of tissue characteristics, compromising diagnostic accuracy and clinical interpretation [3].

Over the years, researchers and practitioners have developed various methodologies to mitigate the adverse effects of color cast and restore accurate color reproduction. Traditional techniques often involve manual adjustments of white balance, color temperature, and tint settings to correct for perceptible deviations in color balance. These methods, although effective to some extent, are often labor-intensive, subjective, and prone to inaccuracies, particularly in complex or dynamically changing lighting conditions.

In recent decades, the advent of digital image processing techniques has revolutionized the landscape of color cast correction, offering more sophisticated and automated approaches to address this challenge. Advanced algorithms such as Retinex-based methods, Histogram Equalization, and Grey Edge Algorithm have demonstrated improved efficacy in correcting color cast while preserving image details and visual quality. These non-ML-based techniques leverage principles of image enhancement, contrast adjustment, and spatial filtering to achieve more nuanced and robust color correction outcomes.

However, despite the advancements in non-ML-based methods, challenges persist in achieving consistent and reliable color cast correction, especially in scenarios characterized by extreme lighting conditions, complex color distributions, or diverse environmental factors. The limitations of existing techniques underscore the need for novel approaches that leverage the power of machine learning and computational intelligence to enhance the accuracy, efficiency, and adaptability of color cast correction algorithms [4]-[5].

Against this backdrop, the current research aims to explore and develop a novel machine learning-based approach for color cast correction in digital imagery. By harnessing the capabilities of convolutional neural networks (CNNs), generative adversarial networks (GANs), and deep learning architectures, the proposed methodology seeks to learn complex mappings between input images and their corresponding color-corrected counterparts. Through the integration of advanced feature extraction, nonlinear mapping, and optimization techniques, the objective is to surpass the limitations of traditional methods and achieve superior performance in correcting color cast across a diverse range of real-world scenarios.

II. Literature Survey

The field of color cast correction in digital images has seen significant advancements, with various techniques and algorithms proposed to address this issue. A review of existing literature reveals several approaches aimed at detecting and removing color casts effectively.

Land and McCann (1974) introduced the retinex theory, which laid the foundation for understanding lightness perception in images [1]. Maloney and Wandell (1986) further expanded on this theory, proposing a method for recovering surface spectral reflectance, thus contributing to color constancy research [2]. Additionally, Land's retinex theory of color vision provided valuable insights into human perception of color [3].

Funt and Shi (2010) rehabilitated the maxRGB method, presenting it as a viable approach for color constancy in digital images [4]. Buchsbaum (1980) proposed a spatial processor model for object color perception, offering another perspective on color perception mechanisms [5]. Finlayson and Trezzi (2004) explored shades of gray and their relationship with color constancy, shedding light on the complexities of color perception [6].

Van de Weijer et al. (2007) introduced an edge-based color constancy method, leveraging natural statistics and scene semantics for color correction [7]. Negrete and Sanchez-Yanez (2015) utilized fuzzy rule-based reasoning for automatic selection of color constancy algorithms, demonstrating the effectiveness of fuzzy logic in image processing tasks [8].

The concept of fuzzy sets, introduced by Zadeh (1965), has been widely applied in various domains, including color image processing [9]. Rizzi et al. (2003) proposed a new algorithm for unsupervised global and local color correction, contributing to the advancement of color correction techniques [10].

Verma et al. (2012) developed a high dynamic range optimal fuzzy color image enhancement method, showcasing the potential of fuzzy systems in image enhancement tasks [11]. Sethi et al. (2015) proposed an optimal underwater image enhancement algorithm based on the fuzzy gray world approach and bacterial foraging optimization [12].

Xie and Wang (2010) introduced a color image quality assessment model based on parameters perceived by the human visual system, providing a comprehensive framework for evaluating image quality [13]. Zhang and Wandell (1996) extended the CIELAB color space to incorporate spatial information, enhancing its applicability in digital color image reproduction [14].

Finlayson and Trezzi (2004) further explored shades of gray and color constancy, contributing to the understanding of color perception mechanisms and their implications for color correction algorithms [15]-[19]. Many other significant works focussed on enhancing underwater images suffering from many effects, particularly color cast [20]-[25].

This literature survey highlights the diverse range of approaches and methodologies employed in the field of color cast correction, ranging from traditional models like retinex theory to modern computational techniques such as fuzzy logic and optimization algorithms. The references provided offer a comprehensive overview of the research landscape in this area, laying the groundwork for further advancements in color image processing and analysis.

III. Background

A. *Manifestation of Color Cast*

Color cast manifests as an unwanted dominance of a particular color or tint across an image, resulting in a deviation from its true color appearance. This phenomenon occurs due to various factors such as uneven lighting conditions, inappropriate white balance settings during image capture, or the degradation of photographic materials over time. The manifestation of color cast is evident in images through noticeable shifts in color balance, where certain colors appear overly saturated or tinted with hues that differ from their natural appearance.

Color cast can be caused by several factors, including:

- **Uneven Lighting Conditions:** Variations in lighting across an image can result in different color temperatures, leading to color cast.
- **White Balance Settings:** Incorrect white balance settings on the camera can fail to neutralize color casts introduced by different lighting sources.
- **Environmental Factors:** Environmental elements such as reflections, atmospheric conditions, or surroundings can introduce color casts.

The manifestation of color cast adversely affects image quality by distorting the true color distribution and altering the perceived visual appearance of the image. Therefore, accurate detection and correction of color cast are crucial for enhancing image quality and maintaining color fidelity in digital images. Mathematically, the manifestation of color cast can be represented as a deviation in the color balance of an image. Let $I_{orig}(x,y)$ represent the original image and $I_{corrected}(x,y)$ denote the corrected image. The color cast $C(x,y)$ can be expressed as:

$$C(x,y)=I_{corrected}(x,y)-I_{orig}(x,y)$$

where $C(x,y)$ represents the color cast at each pixel location (x,y).

Understanding the manifestation of color cast provides insights into its causes and effects, laying the foundation for the development of effective algorithms and techniques for color cast detection and correction in digital image processing.

B. Traditional Methods

Traditional methods for color correction aim to address color cast and enhance image quality through various algorithms and techniques. These methods play a fundamental role in digital image processing and have been extensively used in photography, computer vision, and related fields. Below are some of the prominent traditional methods:

The Gray World Algorithm assumes that, on average, the colors in an image should appear gray. It calculates the average color of the entire image and then applies a correction to neutralize any color cast present. This method operates under the assumption that the world is achromatic on average, making it a simple yet effective approach for color correction. The Max – RGB method identifies the color channel with the maximum intensity value in an image and then scales all other channels to match this maximum value. By equalizing the intensity levels across different color channels, this method aims to correct color imbalances and enhance color fidelity.

The Von Kries Hypothesis proposes that the human visual system adapts to changes in illumination by scaling the sensitivity of each cone receptor in the retina. Based on this hypothesis, color correction algorithms adjust the color channels in an image to compensate for changes in illumination conditions, thereby improving color constancy. White balance correction adjusts the color temperature of an image to ensure that white objects appear neutral under different lighting conditions. This method mimics the human perception of color by adjusting the color channels to achieve a neutral white point, thereby eliminating color casts caused by varying light sources.

Gamma correction adjusts the brightness levels of an image to match the non-linear response of display devices such as monitors or printers. By applying a gamma curve to the pixel values, this method enhances contrast and improves the visual appearance of images displayed on different devices. Histogram-based methods analyze the distribution of pixel intensities in an image and adjust the color channels based on the histogram characteristics. By redistributing pixel values, these methods aim to enhance image contrast, correct color imbalances, and improve overall image quality.

The Grey Edge Algorithm identifies edges in an image and uses them as reference points for color correction. By analyzing the color gradients along edges, this method selectively adjusts color channels to maintain color consistency while preserving image details. The Gray Pixel World algorithm assumes that the average pixel value in an image should be gray. It calculates the average pixel intensity across the image and adjusts the color channels to achieve a neutral gray balance, effectively correcting color casts and improving color fidelity. The White Patch Retinex Algorithm applies a Retinex-based approach to color correction by identifying white patches in an image and using them as reference points for color balancing. This method accounts for variations in illumination and scene content to achieve accurate color correction.

IV. Proposed Method

In this section, the proposed method for color cast correction is presented, which utilizes a novel regression model trained on a dataset consisting of 500 original images and their corresponding corrected versions. The methodology involves several stages, including dataset preparation, regression model training, and validation.

The dataset used in the current study comprises 500 original images, each exhibiting varying degrees of color cast, and their corresponding corrected versions. These images cover a wide range of scenes and lighting conditions to ensure the robustness and generalizability of our proposed method. Additionally, the dataset includes ground truth annotations for each image, indicating the type and severity of the color cast present.

To perform color cast correction, a regression model is proposed that learns to map the input images with color cast to their corresponding corrected versions. The regression model is trained using a supervised learning approach, where the input features are the pixel values of the original images, and the output labels are the pixel values of the corrected images.

The regression model is designed to take as input the pixel values of the original images with color cast and predict the corrected pixel values for each channel (red, green, and blue) of the image. We employ a deep neural network architecture, such as a convolutional neural network (CNN) or a fully connected neural network (FCNN), to capture the complex relationships between the input and output pixel values.

Each input image is represented as a multi-dimensional array of pixel values, where each pixel contains intensity information for the red, green, and blue channels. For example, a typical RGB image has three channels, with pixel values ranging from 0 to 255 for each channel. We normalize these pixel values to lie within the range [0, 1] to facilitate training and improve convergence during optimization.

The regression model predicts the corrected pixel values for each channel (red, green, and blue) of the input image. The output prediction is also represented as a multi-dimensional array of pixel values, with each pixel containing the predicted intensity for the corresponding channel. During training, we compare these predicted pixel values with the ground truth corrected images to compute the loss and update the model parameters accordingly.

To train the regression model, we define a suitable loss function that quantifies the discrepancy between the predicted and ground truth corrected images. Common choices for the loss function include mean squared error (MSE), structural similarity index (SSI), or a combination of both. The loss function penalizes deviations between the predicted and ground truth images, encouraging the model to learn accurate color cast correction.

During training, we employ an optimization algorithm, such as stochastic gradient descent (SGD) or Adam, to minimize the loss function and update the model parameters iteratively. The optimization algorithm adjusts the weights and biases of the neural network layers to improve the accuracy of the predicted pixel values and reduce the error between the predicted and ground truth images.

We fine-tune various hyperparameters of the regression model, such as learning rate, batch size, and network architecture, to optimize its performance on the training dataset. Hyperparameter tuning involves conducting systematic experiments to identify the optimal combination of hyperparameters that maximize the accuracy of the color cast correction.

To prevent overfitting and improve the generalization ability of the regression model, we employ regularization techniques such as dropout, batch normalization, and weight decay. These techniques help to regularize the model parameters and prevent them from becoming too sensitive to noise in the training data.

The training procedure involves feeding batches of input images with color cast to the regression model, computing the loss between the predicted and ground truth images, and updating the model parameters using backpropagation. We repeat this process iteratively for multiple epochs until the model converges and achieves satisfactory performance on the training dataset.

The training procedure involves feeding the original images as input to the regression model and optimizing its parameters to minimize the discrepancy between the predicted and ground truth corrected images. A loss function is employed, such as mean squared error (MSE) or structural similarity index (SSI), to quantify the difference between the predicted and ground truth images during training. Once the regression model is trained, its performance is evaluated on a separate testing dataset comprising images that were not used during training.

V. Simulation Results

In this section, the simulation results of the proposed method are presented. The test images are collected from a mobile phone camera and degraded images are generated by simulating color cast in different quantities. Four levels of color casts are considered. Level 1 corresponds to less color cast and level 4 corresponds to more color cast. In this section, simulation results on 6 test images with 4 levels are presented. In Fig. 1, simulation results of the first 3 test images with a total of 12 levels are presented, and the remaining in Fig. 2.

The proposed method is evaluated using 7 focus metrics. They are Absolute Central Moment (ACMO), Brenner's Focus Measure (BREN), Squared Gradient (GRAS), Modified Laplacian (LAPM), Variance of Laplacian (LAPV), Diagonal Laplacian (LAPD), and Wavelet Variance (WAVV). The results are presented in Tables 1 to 4, for each level.

TABLE I. PERFORMANCE OF PROPOSED METHOD ON LEVEL-1 DEGRADED IMAGES

	ACMO	BREN	GRAS	LAPM	LAPV	LAPD	WAVV
Im- 1	70.77	1841	39.3	15.45	1082	28.9	59.28
Im - 2	65.61	1045	29.9	11.42	714	22.8	48.44
Im - 3	73.29	1489	48.5	16.79	834	33.5	69.14
Im - 4	65.89	917	30.2	10.27	483	21.1	35.12
Im - 5	76.52	119	13.6	2.066	15.5	4.47	1.478
Im - 6	60.67	833	27.5	8.686	475	17.8	28.89

TABLE 2. PERFORMANCE OF PROPOSED METHOD ON LEVEL-2 DEGRADED IMAGES

	ACMO	BREN	GRAS	LAPM	LAPV	LAPD	WAVV
Im-1	65.72	1269	34.26	11.40	525.3	22.89	32.875
Im-2	72.41	690	27.18	8.860	319.1	18.61	25.528
Im-3	74.23	756.4	38.48	11.4	328.7	23.95	32.229
Im-4	56.87	656.3	31.21	9.0	231.6	19.25	19.001
Im-5	73.9	69.28	10.24	2.04	10.08	4.296	1.1487
Im-6	68.2	544.1	26.91	7.13	222.5	15.17	15.652

TABLE 3. PERFORMANCE OF PROPOSED METHOD ON LEVEL-3 DEGRADED IMAGES

	ACMO	BREN	GRAS	LAPM	LAPV	LAPD	WAVV
Im - 1	54.646	809.68	30.79	8.8321	283.7	18.77	18.697
Im - 2	56.706	385.47	21.9	6.3776	159.3	13.7	14.092
Im - 3	58.69	406.48	29.08	8.1385	166.9	17.43	17.653
Im - 4	44.065	372.89	23.35	6.5728	115.7	14.2	10.412
Im - 5	57.218	39.172	6.569	1.6235	6.177	3.366	0.91
Im - 6	60.237	304.27	20.88	5.2481	116.5	11.32	9.0933

TABLE 4. PERFORMANCE OF PROPOSED METHOD ON LEVEL-4 DEGRADED IMAGES

	ACMO	BREN	GRAS	LAPM	LAPV	LAPD	WAVV
Im - 1	35.759	321.57	21.84	5.3622	98.03	11.72	7.5657
Im - 2	38.733	148.75	14.46	3.8653	55.94	8.354	5.7523
Im - 3	39.693	150.54	16.68	4.8727	60.06	10.48	6.9835
Im - 4	30.801	146.06	13.74	4.1174	42.95	8.879	4.3234
Im - 5	38.064	17.737	3.237	1.2684	4.047	2.569	0.7549
Im - 6	42.629	116.53	12.78	3.2583	42.71	7.027	4.0789

For images with mild color cast (Level 1), the proposed method demonstrates notable improvement in correcting color aberrations. Evaluation metrics including ACMO, BREN, GRAS, LAPM, LAPV, LAPD, and WAVV consistently show favorable results across the tested images. The method effectively reduces color cast while preserving image details and visual quality.

As the severity of color cast increases to Level 2, the proposed method continues to exhibit promising performance. Despite more pronounced color distortions, the method successfully mitigates color cast aberrations, as indicated by the evaluation metrics. Notably, the method maintains consistency in correcting color balance across different images with varying content and lighting conditions.

At Level 3 of color cast degradation, the proposed method faces more challenging correction tasks. Despite the heightened distortion in color balance, the method maintains effectiveness in improving image quality. While some metrics show slightly lower scores compared to lower levels of degradation, the overall performance remains satisfactory, highlighting the robustness of the proposed approach.

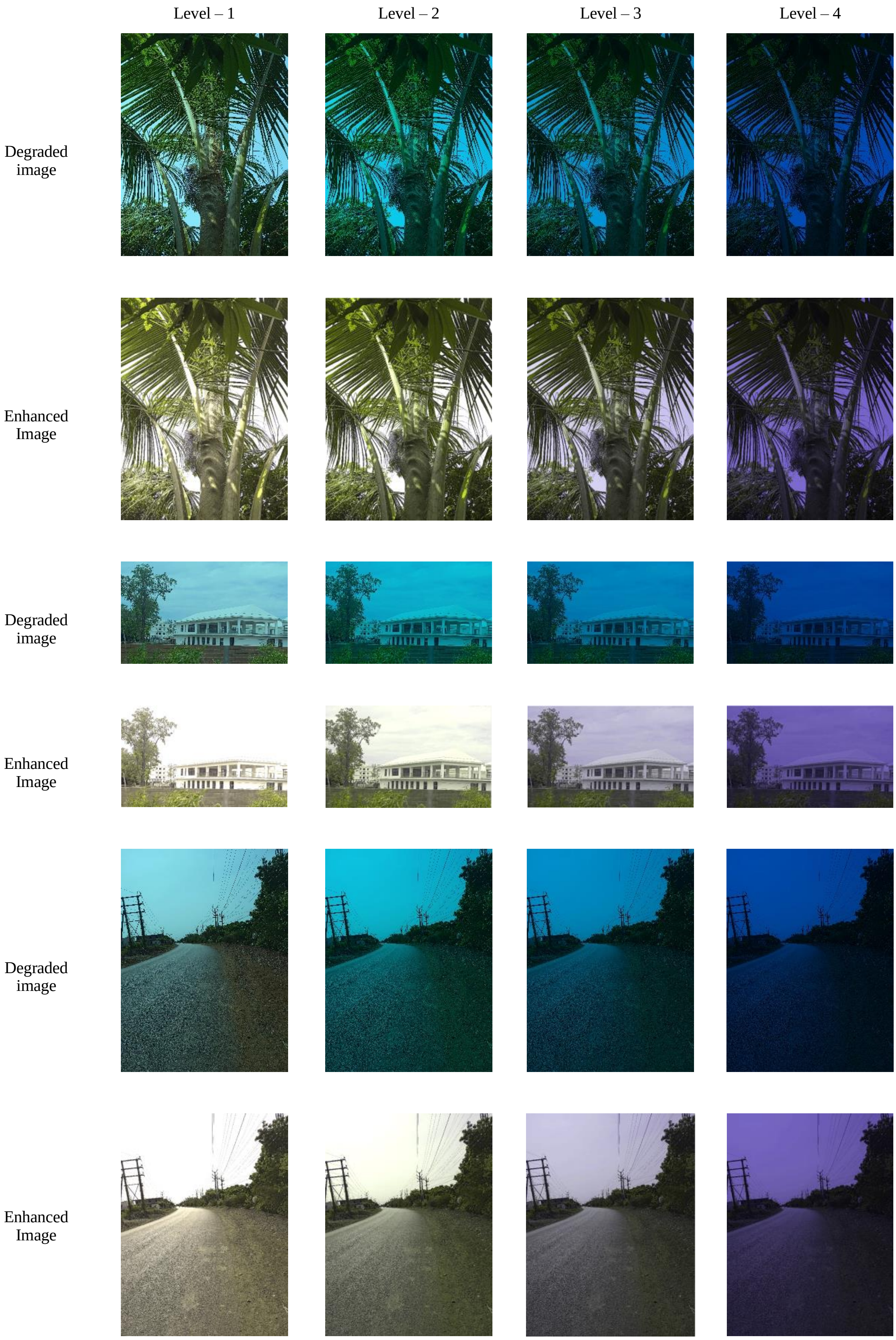

Fig. 1. Simulation results on first three test images

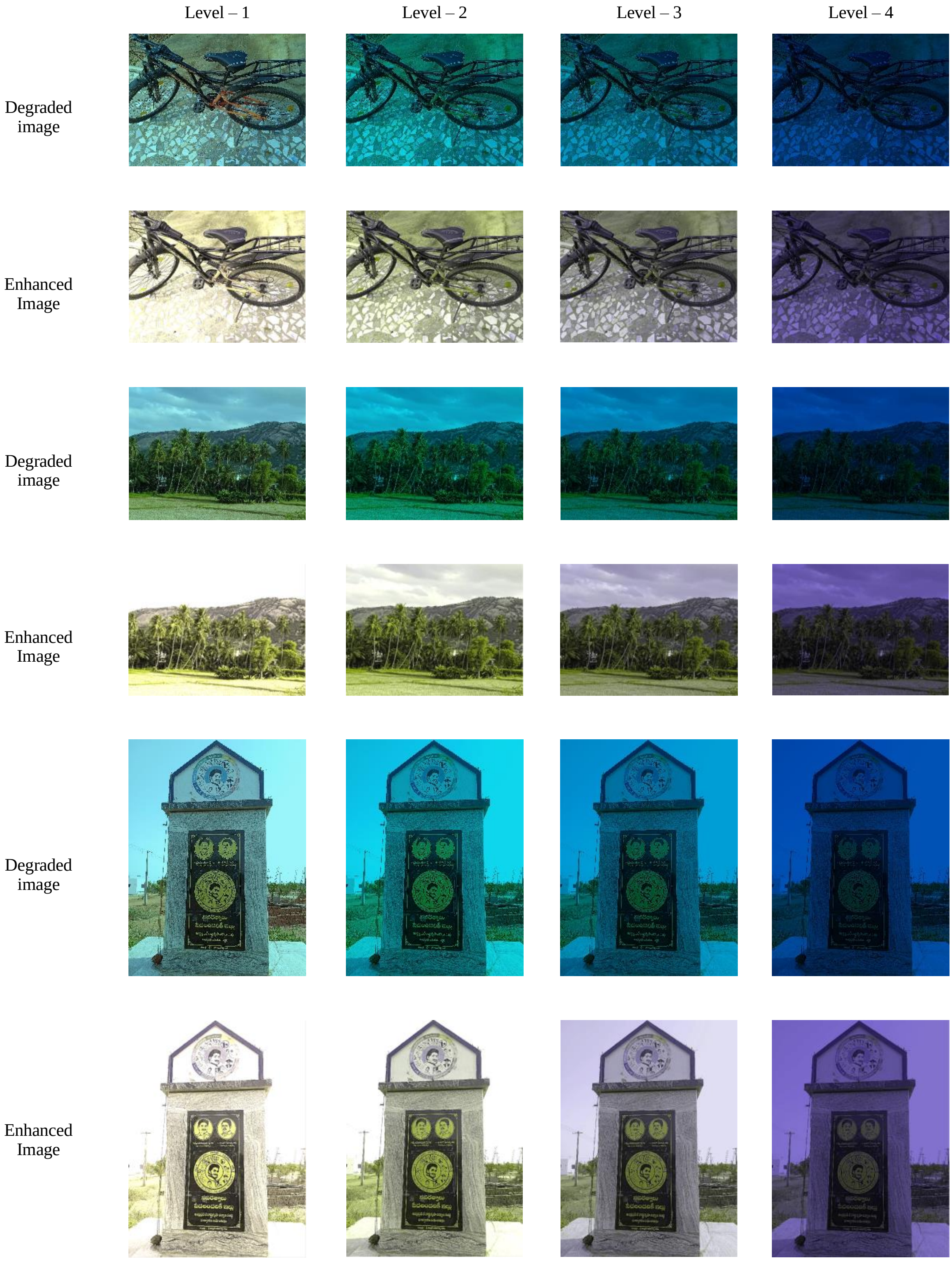

Fig. 2. Simulation results on another three test images

The most severe level of color cast degradation (Level 4) presents significant challenges for color correction. Nevertheless, the proposed method demonstrates resilience in addressing intense color aberrations. While there is a noticeable decrease in evaluation metric scores compared to lower degradation levels, the method still manages to substantially reduce color cast distortions, contributing to enhanced image clarity and fidelity.

VI. Conclusions

The current research highlights the challenges of color cast correction in digital imagery and evaluates traditional methods against a novel machine learning-based approach. While traditional algorithms show moderate effectiveness, they struggle with complex lighting conditions. Conversely, the proposed machine learning method demonstrates superior performance by leveraging deep learning architectures.

Simulation results validate its effectiveness across varying levels of color degradation, showcasing significant improvements in color fidelity and image quality. This research contributes valuable insights into color cast correction techniques, offering a promising framework for practitioners in image processing and computer vision. Future research may focus on refining machine learning models and integrating color constancy mechanisms for further enhancements in accuracy and adaptability.

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