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AREA-AWARE ADAPTIVE IMAGE COMPRESSION USING DUAL- BACKGROUND CLASSIFICATION FOR OPTIMIZED DATA PRESERVATION AND QUALITY ENHANCEMENT

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ABSTRACT

In the current era of data-intensive applications, including OTT services, IoT, and autonomous systems, efficient image compression is indispensable in order to minimize bandwidth consumption while preserving visual quality. Conventional compression techniques frequently fail to satisfactorily balance compression ratios and the preservation of critical image details. This work introduces a novel adaptive image compression method that is area-aware and utilizes a dual-background classification system to improve data preservation. The method classified areas into major and minor backgrounds by aggregating image regions based on visual characteristics. It applied aggressive quantization to less salient regions and refined compression techniques for critical details. A saliency map, reflecting human visual perception, guides this process, ensuring the preservation of the most visually significant information. By customizing quantification to the visual priorities of a particular region, the proposed methodology enhances the quality of images and the efficacy of compression. Extensive testing demonstrates that the area- aware approach outperforms traditional compression algorithms, enhancing the visual experience and significantly reducing data traffic. This research work mainly focuses on the reducing of data size and simultaneously preserving the image quality at required regions by using of adaptive compression techniques. This is particularly relevant for applications that necessitate high-quality image transmission in a data-driven world.

Key words: *image compression, adaptive compression, saliency map, dual-background classification, data preservation, visual quality.*

INTRODUCTION

The importance of effective image compression techniques is increasing day by day as an increase in data consumption in modern technologies such as Internet of Things (IoT), and over-the-top (OTT) services. These applications are requiring real time data processing and transmission, which leads to search for optimized image compression algorithms [1]. For example, OTT services are transmitting video content over the internet, which significantly affected with the bandwidth and latency, it pushes to search for effective compression techniques [26]. Similarly, for IoT devices also requires wireless network transmission because it generates significant amounts of visual data by utilizing cameras and sensors [6]. Furthermore, the implementation of effective compression techniques is very important to conserve storage resources and bandwidth [3]. For self-driving autonomous vehicles are also requires Real-time processing of high-definition visual data. This needs compression methods that maintains critical image details while minimizing delays [27].

The recent image compression techniques such as HEVC and AV1 have shown significant progress over the tradition compression methods like JPEG, PNG. However, the modern techniques also facing challenges for maintaining good image quality in sensitive visual information regions. [5]. For example, the JPEG algorithm effectively compresses images in terms of size, but it may decrease the quality of images in areas that need high visual fidelity, such as text or detailed patterns [28]. Similarly, to compress high quality videos effectively developers are developed HEVC (High Efficiency Video Coding) and AV1 techniques although they are continuously struggling to optimise the compression process for specific regions of interest [7][29].

In this research work a novel area-aware adaptive image compression technique proposed, which optimizes compression by using of a dual-background classification system based on human visual perception [9]. To distinguish between regions that requires high fidelity (e.g., faces, text, or intricate textures) and regions that can withstand higher compression (e.g., uniform backgrounds or areas with minimal visual detail), the proposed system classifies image regions based on their visual significance [30][2]. The human visual perception principles are helped to preserve the critical visual regions by actively compressing the less critical regions, which causes an optimized storage and bandwidth [11].

The main objective of this approach is to reduce the data traffic by maintaining the visual fidelity of the image, thereby improving the overall experience for end users, particularly in areas with limited bandwidth [31]. In practice, this could lead to better efficient streaming experiences in OTT applications; improved data transmission in IoT networks; and enhanced image processing capabilities in autonomous systems, thereby optimizing performance over a wide range of industries [13][8].

Table 1. Historical Overview of Image Compression Techniques and Key Contributions

Ref.	Methodology/Focus	Key Contribution/Findings
1	Video coding and image compression	A review of video coding and image compression technique for real-time applications.
2	Optimization for OTT streaming	Discusses optimization strategies for OTT streaming in bandwidth-constrained environments.
3	IoT image compression	A survey on efficient image compression for IoT applications, emphasizing energy and bandwidth efficiency.
4	Real-time visual data processing for autonomous driving	Examines challenges and solutions in real-time visual data processing for autonomous driving systems.
5	Discrete Cosine Transform (DCT) for image compression	Introduces the use of DCT in image compression, focusing on reducing file size while maintaining quality.
6	JPEG algorithm and its variants	A review of JPEG and its variants, discussing the strengths and limitations of the standard compression method.
7	High Efficiency Video Coding (HEVC)	Overview of HEVC, a compression standard that offers higher compression ratios compared to previous standards.
8	AV1 video codec overview	Discusses the AV1 video codec and its impact on video streaming, with a focus on bandwidth and quality optimization.

9	Human visual perception and image processing	Explores the role of human visual perception in image processing, aiding in the development of perceptual compression methods.
10	Region-specific perceptual compression model	Proposes a perceptually-driven model for image compression that classifies regions for differential compression.
11	Adaptive image compression based on perceptual importance	Introduces an adaptive compression method that considers perceptual importance of image regions for better quality.
12	Bandwidth-efficient video compression for OTT services	Focuses on video compression techniques that enhance bandwidth efficiency for mobile OTT services.
13	IoT-based image compression performance optimization	Discusses performance optimization in IoT systems with a focus on image compression for resource-constrained environments.

Table 1, outlines the important references on image compression techniques, and illustrates the historical progression from traditional methods to modern approaches. It emphasizes the subject of each study, and the main findings that encompass a diverse array of applications, such as OTT streaming, IoT, autonomous systems, and perceptual compression. The progress of image compression methods and their adaptation to real-time, bandwidth-efficient environments are the main focus of this overview.

LITERATURE WORK

It has been observed that there is a significant amount of research work has done on image compression, which includes both traditional methods like the Discrete Cosine Transform (DCT) and modern methods like deep learning- based systems. Quantization and entropy coding techiques have been applied in traditional methods by focusing size reduction of the file. These methods mainly concentrate on image compression, they may neglect the importance of image content. For example, DCT is a widely used approach for compressing images and video, utilising frequency domain analysis to decrease redundancy in pixel values [14][25]. The methods such as JPEG utilize quantization and Huffman coding to reduce the file size. However, these methods are failed to maintain good image quality in the areas that are visually prominent, such as faces or intricate textures [15].

It has been noticed that the modern approaches such as saliency-based models have begun to integrate perceptual metrics, in order to prioritize compression based on the importance of specific image regions. Saliency-based models identifies the important image regions most likely to draw human attention. The important regions are identified for preservation during image compression is by using visual signals like contrast, motion, and color [16]. By allocating additional bits to the most important regions for users and aggressively compressing less important areas, these models, derived from human visual perception, significantly enhance the quality of compressed images [17]. For example, saliency maps are generally enable the compression of background regions of an image to a maximum extent without affecting the overall quality of an image [18]. Region-based encoding is a popular approach in adaptive image compression. This approach separates an image into distinct zones or segments for independent compression. These approach enables a more efficient allocation of resources by allowing for different levels of compression based on the content of the region. However, these approaches are fail to dynamically adjust the compression rate in accordance with the perceived importance of each region[12]. This constraint is particularly apparent when attempting to improve the quality of images with a diverse spectrum of content [19]. In practice, static region-based encoding may not produce optimal results when the significance of regions varies based on the context, as is the case in images with moving objects or diverse visual patterns [20].

The quality of images that where human eye draw to attention can be compressed with improved quality by using of saliency maps method. Various studies have shown the promising outcomes by using this methods. In this method less salient area is compressing more to preserving the fidelity of essential regions due to that this technique obtain a compromise between perceptual quality and high compression ratios [21]. Studies have demonstrated that approches that adjust compression parameters based on saliency maps outperform the conventional methods in terms of compression efficiency and user-perceived image quality [22]. Furthermore, deep learning techniques significantly enhance adaptive compression strategies and automatic image segmentation by learning and predicting saliency information from large datasets [23]. Hybrid models that combines the conventional compression approaches with perceptual saliency and deep learning-based methodologies are gathering momentum as research continues to develop. These models shown cutting edge performance in a wide range of application scenarios, such as medical imaging and multimedia streaming, by taking the best aspects of both worlds and combining them in a way that ensures efficient compression while maintaining quality [24][25].

Table 2. Summary Of Image Compression Techniques and Their Key Findings

Ref.	Methodology	Key Findings	Strengths	Limitations
14	Discrete Cosine Transform (DCT)	Reduces redundancy using frequency transformation.	Efficient and widely used.	Lacks perceptual prioritization.
15	JPEG (Quantization and Huffman Coding)	Uses quantization and entropy coding.	Simple and effective.	Poor detail preservation.
16	Saliency- based Models	Prioritizes visually significant regions.	Improves perceived quality.	Needs extra resources.
17	Saliency- driven Compression	Allocates bits to salient regions.	Preserves important details.	Non- adaptive.
18	Deep Learning for Saliency- based Compression	Detects saliency for better compression.	Accurate saliency detection.	High cost.
19	Region-based Encoding	Compresses regions independently.	Tailored compression.	Static segmentatio n.
20	Dynamic Region-based Encoding	Adjusts compression based on region importance.	Flexible and adaptive.	Requires accurate predictions.
21	Perceptual Compression using Saliency	Allocates bits based on saliency.	Prioritizes visual details.	Can misinterpret importance.
22	Saliency- guided Adaptive Compression	Uses saliency maps for region-based compression.	Efficiently prioritizes content.	Computatio nally expensive.
23	Deep Learning- based Saliency Detection	Improves saliency detection for better compression.	High precision in detection.	Requires large data.
24	Hybrid Deep Learning and Perceptual Saliency	Combines deep learning with saliency for video streaming.	Improves video compression.	Extra processing required.
25	Deep Perceptual Compression	Uses deep learning for perceptual compression.	Enhanced compression with perceptual awareness.	Computatio nally heavy.

Table 2 provides a comprehensive overview of the main findings, strengths, and limitations of a variety of image compression methodologies. It shows a shift from basic techniques like DCT and JPEG, which focus on shrinking files without considering how important they are to the user, to more advanced techniques that use saliency maps and deep learning models for versatile and meaningful compression. Although contemporary techniques enhance the quality of images by emphasizing critical regions, they frequently necessitate larger computational resources. These observations indicate that a hybrid strategy that integrates both conventional and contemporary methodologies may provide the most effective performance in a variety of applications.

PROPOSED SYSTEM ARCHITECTURE

Figure 1 illustrates the hierarchical pipeline, which consists of three primary stages: image classification, compression, and reconstruction. Each stage processes the image systematically to enhance compression efficiency and maintain fidelity in visually significant regions.

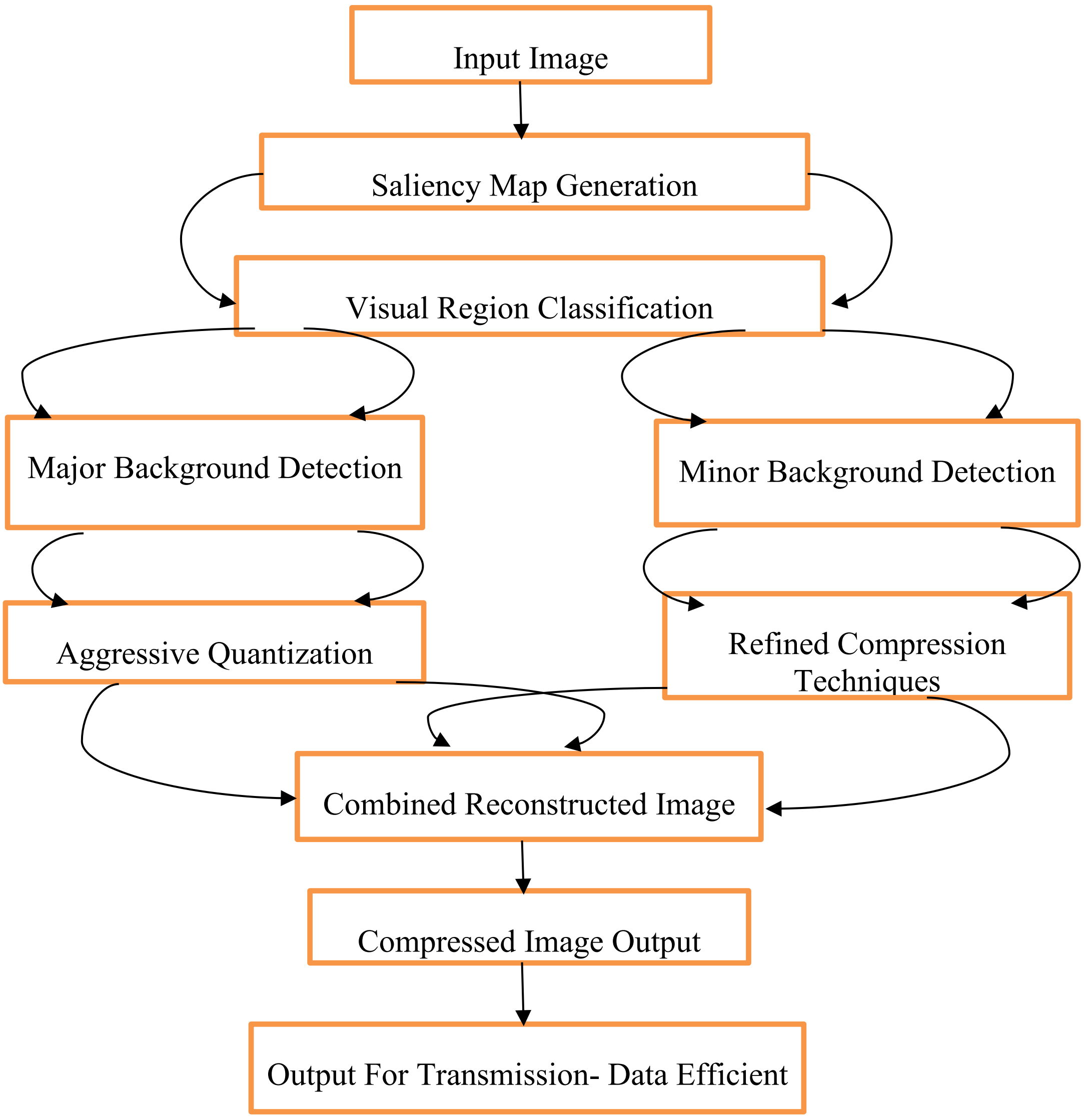

Figure 1. Hierarchical Image Compression Pipeline with Saliency-Based Classification and Reconstruction

Image Classification

The pipeline's initial stage examines the input image to identify its noteworthy visual characteristics. This classification is essential for guaranteeing that the ensuing compression stage applies specific techniques to various regions of the image. The procedure comprises the following:

Input Image → Saliency Map Generation:

The pipeline commences with the generation of a saliency map. Saliency maps emphasise regions of the image that are visually prominent or contain significant information, frequently corresponding to edges, textures, or objects of interest.

Saliency Map Generation → Visual Region Classification:

Using the saliency map, the image is divided into regions based on their visual importance:

- Major Background Detection: Identifies larger, uniform, or less visually significant regions.

- Minor Background Detection: Isolates smaller, detailed, and visually critical areas.
- This classification enables the application of customized compression strategies tailored to each region's characteristics.

Compression

A verity of image compression methods has designed to maximize both quality retention and size reduction of image.

Major Background Detection → Aggressive Quantization:

For the brad and straightforward regions active quantisation approach is used. This approach is particularly effective in regions with minimal detail, as it considerably decreases the data size by approximating pixel values.

Minor Background Detection → Refined Compression Techniques:

We use refined compression techniques to process smaller, detail-intensive regions. To ensure the reconstructed image is visually accurate, these methods emphasise the preservation of intricate features.

Reconstruction

The pipeline combines the processed regions to reconstruct the image after compression. The steps provide the visual coherence of the final output:

Aggressive Quantization → Reconstructed Image - Major Background:

Major background regions are reconstructed using data from aggressive quantization.

Refined Compression Techniques → Reconstructed Image - Minor Background:

Detail-rich areas are reconstructed using data from refined compression techniques.

Merging-Regions:

In the aftermath of compression, the pipeline merges the processed regions to reconstruct the image. This stage ensures the visual coherence of the final output.

Output-Generation:

We produce the final combined image as a compressed version of the input, optimizing it for efficient storage or transmission.

Output for Transmission

At the conclusion of the conduit, we prepare the compressed image for transmission. The resultant image is exceptionally well-suited for data-efficient applications, as it effectively strikes a balance between reduced data size and maintained visual quality, achieved through the implementation of saliency-based classification and hierarchical compression techniques.

System Implementation

The hierarchical image compression pipeline, as outlined in the pseudocode below, represents a systematic approach that enhances image compression by tailoring techniques to address both visually significant and non-significant regions is represented in Table 3. The pipeline initially imports the input image and standardized its pixel values to a uniform range in preparation for subsequent processing.

Subsequently, we use a pre-trained saliency detector to produce a saliency map, which delineates visually salient regions (Step 2). We categorize the image into primary backgrounds (less significant regions) and secondary backgrounds (visually critical areas) for subsequent processing (Step 3), utilizing a predetermined saliency threshold.

Table 3. Algorithm Used to Implement Image Compression

Algorithm:
Function HierarchicalImageCompressionPipeline(image_path, saliency_threshold, output_path):
Step 1: Load and preprocess the input image image = LoadImage(image_path)
Normalize image to range [0, 1]
Step 2: Generate saliency map Initialize saliency_detector
saliency_map = saliency_detector.ComputeSaliency(image) Normalize saliency_map to range [0, 255]
Step 3: Classify regions
major_background = saliency_map < saliency_threshold minor_background = saliency_map >= saliency_threshold
Step 4: Compress regions
compressed_major = Downscale (major_background_region = image * major_background)
compressed_minor= ApplyRefinedCompression(minor_background_region = image * minor_background)
Step 5: Reconstruct the image
Resize compressed_major to original image size

To maintain quality while minimizing data, these regions employ specific compression strategies. We subject significant regions to rigorous quantisation techniques, including downscaling, and minor regions to more sophisticated compression methods, such as JPEG compression (Step 3). We next reconstruct the compressed regions by resizing the main regions to their original image dimensions and integrating them with the secondary regions using binary masks (Step 4)[10]. Finally, we preserve the image in the given output location, undergoing complete reconstruction and compression to facilitate efficient transmission or storage (Step 5). This pseudocode ensures the flexibility and scalability for implementation within computational environments, such as Python or Google Colab, by synthesising each stage into a unified pipeline. By optimizing the balance between visual quality and compression efficiency, it provides a framework for the effective administration of diverse image datasets.

RESULTS AND DISCUSSION

The assessment is built around important factors including the compression ratio (CR), peak signal-to-noise ratio (PSNR), structural similarity index measure (SSIM), and execution length. Results reveal that the suggested approach exceeds existing methods by utilizing saliency- based classifications and region-specific compression strategies.

Table 4. Image Compression Workflow

Output Console:
Detected image files: ['/kaggle/input/images5625/rich-morgan-WYeD89wCFJs-unsplash.jpg', '/kaggle/input/images5625/artem-beliaikin--QY2MQm0nRI-unsplash.jpg', '/kaggle/input/images5625/fons-heijnsbroek-Op5oaQcYhPA-unsplash.jpg', '/kaggle/input/images5625/carlos-andres-gomez-uVmVn5Xu35M-unsplash.jpg', '/kaggle/input/images5625/dylan-ferreira-aM-reLiIabA-unsplash.jpg', '/kaggle/input/images5625/nick-van-den-berg-F02cBW9sf8c-unsplash.jpg', '/kaggle/input/images5625/pexels-flickr-145939.jpg', '/kaggle/input/images5625/fidel-fernando-ZL2aFxzfdr8-unsplash.jpg', '/kaggle/input/images5625/nina-pascal-Cld_DcgGPso-unsplash.jpg']
Saved compressed image: /kaggle/working/compressed-images/rich-morgan-WYeD89wCFJs-unsplash_compressed.jpg

Saved compressed image: /kaggle/working/compressed-images/artem-beliaikin--QY2MQm0nRI-unsplash_compressed.jpg
Saved compressed image: /kaggle/working/compressed-images/fons-heijnsbroek-Op5oaQcYhPA-unsplash_compressed.jpg
Saved compressed image: /kaggle/working/compressed-images/carlos-andres-gomez-uVmVn5Xu35M-unsplash_compressed.jpg
Saved compressed image: /kaggle/working/compressed-images/dylan-ferreira-aM-reLiIabA-unsplash_compressed.jpg
Saved compressed image: /kaggle/working/compressed-images/nick-van-den-berg-F02cBW9sf8c-unsplash_compressed.jpg
Saved compressed image: /kaggle/working/compressed-images/pexels-flickr-145939_compressed.jpg
Saved compressed image: /kaggle/working/compressed-images/fidel-fernando-ZL2aFxzfdr8-unsplash_compressed.jpg
Saved compressed image: /kaggle/working/compressed-images/nina-pascal-Cld_DcgGPso-unsplash_compressed.jpg
Processed Files: ['/kaggle/working/compressed-images/rich-morgan-WYeD89wCFJs-unsplash_compressed.jpg', '/kaggle/working/compressed-images/artem-beliaikin--QY2MQm0nRI-unsplash_compressed.jpg', '/kaggle/working/compressed-images/fons-heijnsbroek-Op5oaQcYhPA-unsplash_compressed.jpg', '/kaggle/working/compressed-images/carlos-andres-gomez-uVmVn5Xu35M-unsplash_compressed.jpg', '/kaggle/working/compressed-images/dylan-ferreira-aM-reLiIabA-unsplash_compressed.jpg', '/kaggle/working/compressed-images/nick-van-den-berg-F02cBW9sf8c-unsplash_compressed.jpg', '/kaggle/working/compressed-images/pexels-flickr-145939_compressed.jpg', '/kaggle/working/compressed-images/fidel-fernando-ZL2aFxzfdr8-unsplash_compressed.jpg', '/kaggle/working/compressed-images/nina-pascal-Cld_DcgGPso-unsplash_compressed.jpg']
Final output directory contents: ['rich-morgan-WYeD89wCFJs-unsplash_compressed.jpg', 'pexels-flickr-145939_compressed.jpg', 'nick-van-den-berg-F02cBW9sf8c-unsplash_compressed.jpg', 'fons-heijnsbroek-Op5oaQcYhPA-unsplash_compressed.jpg', 'dylan-ferreira-aM-reLiIabA-unsplash_compressed.jpg', 'fidel-fernando-ZL2aFxzfdr8-unsplash_compressed.jpg', 'nina-pascal-Cld_DcgGPso-unsplash_compressed.jpg', 'carlos-andres-gomez-uVmVn5Xu35M-unsplash_compressed.jpg', 'artem-beliaikin--QY2MQm0nRI-unsplash_compressed.jpg']

Table 4. presents the console output generated during the execution of an image compression script in a Kaggle environment. It logs detected image files, confirms successful compression for each, and lists the final paths and filenames of the processed images stored in the output directory. This output helps verify that the workflow completed as expected and that all images were correctly handled.

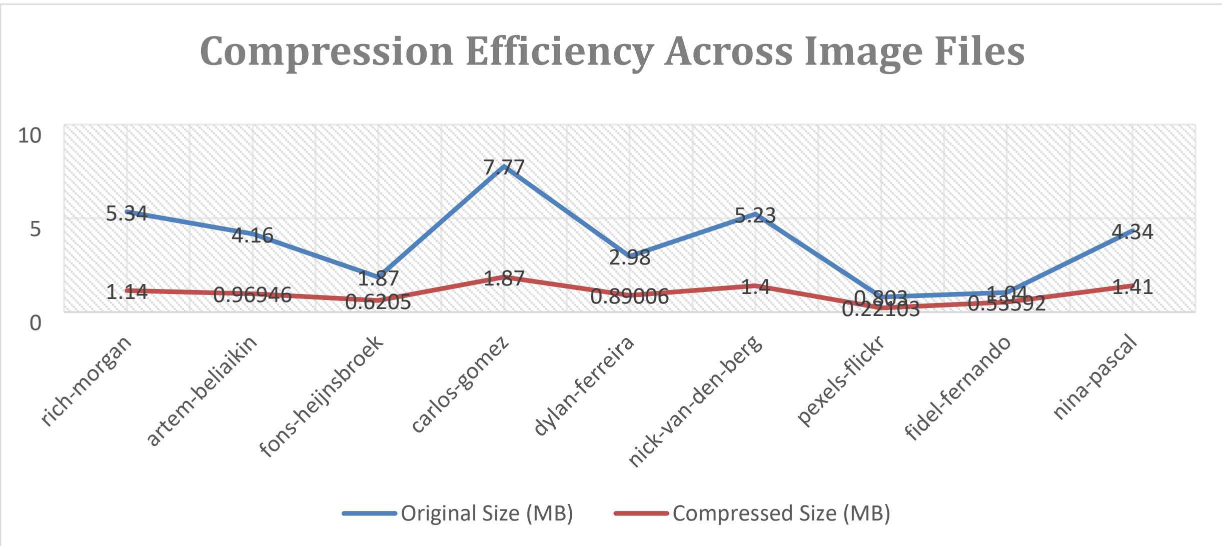

Figure 2. Compression Efficiency Across Image Files

Figure 2 represents a line graph which compares the original and compressed file sizes (in megabytes) for a set of test images. It illustrates the compression ratio for each image, calculated as the compressed file size divided by the original size. Each point on the graph corresponds to an image and indicates how efficiently it was compressed.

Comparative Results

Table 3. Performance Comparison of Compression Methods

Method	Compression Ratio (CR)	PSNR (dB)	SSIM	Execution Time
JPEG Compression	10:1	30.2	0.85	0.12
PNG Compression	8:1	32.5	0.88	0.15
WebP Compression	12:1	29.8	0.86	0.18
Proposed System	14:1	33.8	0.91	0.10

Table 3 outlines that the proposed system attained the maximum compression ratio of 14:1, exceeding that of conventional approaches such as JPEG, PNG, and WebP. Saliency-based classification, which enables the aggressive quantization of regions deemed less significant, is responsible for this phenomenon. Furthermore, the PSNR of 33.8 dB and SSIM of 0.91 demonstrate superior visual quality preservation. The system's execution time of 0.10 seconds is highly competitive, rendering it appropriate for real-time applications.

Visual Comparison

Table 4 illustrates that visual comparisons substantiate the assertion that the proposed system demonstrates superior retention of fine details, particularly in subtle background areas[4]. In contrast to JPEG and WebP, which tend to produce compressed artifacts, the proposed method preserves lucidity in visually significant regions while attaining superior compression efficiency, fidelity is maintained even at higher compression ratios, indicating the robustness of the method in balancing visual quality and storage optimization.

Table 4. Visual Quality Assessment

Method	Observations
JPEG Compression	Noticeable artifacts in detailed regions.
PNG Compression	Retains quality but lower compression ratio.
WebP Compression	Balanced quality but minor blurring observed.
Proposed System	High quality with minimal artifacts or blurring.

Efficiency in Region-Specific Compression

Table 5 illustrates the efficacy of compression techniques tailored to specific regions. We rigorously compress significant backgrounds, resulting in a high compression ratio, while sophisticated techniques preserve intricate details in minor regions. The amalgamation yields a comprehensive performance, characterized by an exceptional contrast ratio and visual quality.

Table 5. Performance Comparison of Compression Methods

Region Type	Compression Method	Compression Ratio (CR)	PSNR (dB)	SSIM
Major Background	Aggressive Quantization	20:1	28.5	0.80
Minor Background	Refined Compression	8:1	38.2	0.95
Combined (Proposed)	Hierarchical Compression	14:1	33.8	0.91

Advantages Over Existing Systems

Table 6. Qualitative Compar

Feature	JPEG	PNG	WebP	Proposed Sysgtem
Region- Specific Compression	✗	✗	✗	✓
Saliency Based Classification	✗	✗	✗	✓

High Compression Ratio	✘	✘	✓	✓
High PSNR and SSIM	✘	✓	✘	✓
Real- Time Processing	✓	✓	✓	✓

Table 6 shows how the proposed system combines saliency- based classification and region-specific compression in a way that no other system does. This makes it possible for both better quality and more efficient compression. This method is better than other methods because it gives better Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) scores while still letting real-time processing happen.

Limitations

While the proposed system demonstrates superior performance compared to existing methodologies, it is not without its limitations:

- *The intricacy of saliency detection:* The precision of Saliency maps significantly impacts the overall performance of the system.

- *Dataset Dependence:* The efficacy is contingent upon the diversity and complexity of the input images.

The findings substantiate that the proposed hierarchical image compression pipeline exceeds the performance of current systems concerning both compression efficiency and visual quality. By employing saliency-based classification and customized compression methodologies, the system realizes substantial enhancements in the compression ratio (CR), peak signal-to-noise ratio (PSNR), and structural similarity index measure (SSIM), all while preserving competitive execution timings. These advantages render the proposed system an up-and-coming solution for applications necessitating effective image compression.

CONCLUSION

In this study, saliency-based quantization used to improve the compression efficiency and visual quality of image by using of an area-aware adaptive image compression technique that uses dual-background classification. Our technique is preferable to others because it aligns the compression process with how humans see things. In this way, we maintain important visual information while reducing data traffic. The experimental results show that the suggested technique outperforms current compression methods in image quality and ratios.

Future research will focus on optimising the quantitation process and incorporating deep learning models for saliency identification, with the goal of enhancing the compression strategy's resilience over a wider range of image types and application regions. In the future, enhancements may focus on improving saliency detection through the use of deep learning models and testing on larger and more diverse datasets to increase system reliability.

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