Optimizing Images for Mobile Internet Browsing

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ABSTRACT

Google's Next Billion Users research estimates a billion more people will purchase their first smartphone by 2025 [10]. There will be significant pressure on the existing web infrastructure considering the increasing demand and decreasing data cost [6]. This project aims to explore and analyze three distinct potential solutions to decrease the data demand through optimal image format techniques.

Images are the most popular resource type on the web [7] and the second largest resource-consuming form of digital content. Lossless image compression format, PNG, is used by 82.0% of all websites [2]. Analysis and utilization of other image compression techniques, such as color quantization, WebP & AVIF formats, and super-resolution using Artificial Intelligence, could significantly decrease website data usage. They would prove particularly effective for low-bandwidth networks and low-end devices.

KEYWORDS

image compression, content delivery network, browser optimization, low carbon images, super-resolution

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1 INTRODUCTION

Some disturbing trends highlight the importance of image delivery optimization solutions. This proposal starts with macro trends and narrows the scope of analysis even further to include websites and image-based media. It is estimated that 1 billion new users will buy their first smartphone by 2025 [10]. By 2025, it is also estimated that 72% of all internet users will solely use smartphones to access the Web [11]. This can put more pressure on the existing web infrastructure. As mobile data becomes increasingly cheaper, it is easier for first-time users to access the Internet [6]. Only 5% of Alexa's top 10 million websites do not use PNG, JPEG, SVG, GIF, WebP, ICO, or BMP formats. In contrast, 79.9% of websites in the same group use PNG format on at least one web page, while JPEG and SVG figures are 74.4% and 50%, respectively [2]. Without a doubt, pictures are almost everywhere on the Internet.

Let us dig deeper into the analysis of the web page to get a more precise picture of the problem. The average mobile page weight increased from 295 KB in January 2012 to 1,939 KB in September 2021, a 560% increase in just under a decade. The weight of the mobile page at the 75th percentile is 3749 KB, and that figure increases to 6890 KB at the 90th percentile. [1] An average mobile web page contains 877 KB of image data, almost 45% of the page's total weight. That is more than double of JavaScript's 430 KB, the second-largest page weight factor. [15] These numbers are a compelling argument for image optimization solutions. Most of the billion first-time users will come from countries with dense populations and bandwidth-constrained internet infrastructures. Images open the Internet to people unfamiliar with English, the Internet's primary language. It also makes the Internet more accessible to people with disabilities who cannot use letters fully: people with learning disabilities and those with visual impairments.

The research in comparative analysis in image formats is not original. There has yet to be an in-depth comparative analysis of different image formats and their impact on mobile web browsing. The study aims to examine and evaluate implementable solutions to reduce the image file size for mobile browsing.

2 RELATED WORK

Web Browsing Optimizations Solutions

Various interesting approaches to reducing page-load time and bandwidth usage exist. Past research proposes different

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ways of reducing the total data delivered to the user. FlexiWeb is a proposed framework that determines when and how to use a middlebox based on the client's network conditions. The FlexiWeb performed better in cases of bad network connection by reducing page load time by 35~42%. [13] A different approach to reducing data is eliminating websites' JavaScript dead code. The dead code elimination of Javascript decreased the downloaded file size by 55% and sped up the page load speed by 25~30%. [9]

Performance Analysis on Image Format

Considerable research exists in the performance analysis of web image compression formats. [8] shows the comparative study of PNG, JPEG, and WebP formats on performance metrics of quality degradation in compression and time consumption. [3] shows a comparative analysis of multiple lossless PNG, JPEG, WebP, FLIF, and AVIF compression techniques. Compression ratio and Bitrate were used as the performance metrics. [12] shows different techniques to optimize web performance. However, there has not been in-depth research on the impact of web compression techniques on mobile browsing.

Super-Resolution

The study of super-resolution in this research employs the ESRGAN model developed by Xintao Wang, as detailed in [16]. Super-resolution, an AI-driven method of enhancing image quality, has been shown to surpass traditional techniques like bicubic interpolation in quality, as discussed in [5].

While there are studies on using super-resolution for streaming low-quality video in real-time to achieve better quality, research specifically addressing the use of super-resolution for mobile browsing is scarce. This paper, therefore, aims to fill this gap by investigating the potential of super-resolution to optimize images for mobile web browsing.

3 METHODOLOGY

Algorithmic color quantization, WebP and AVIF encoding, and super-resolution are explored as methods for optimizing images for mobile browsing. The methods are aimed to reduce the image size for mobile browsing. For each method, two criteria were used to measure the validity: the amount of compression of image file size and its impact on user perception.

3.1 Data Sourcing

The dataset utilized in this capstone research was procured from a preceding research project by Singh [14]. A stratified random sampling technique was employed, whereby 10% of the entire set of JPEG images from the aforementioned project were selected, yielding 2,500 JPEG images for the color quantization study. Additionally, 1,500 png images were used for WebP & AVIF analysis, and 750 jpeg images were used for Super-Resolution study.

3.2 Color Quantization

The analysis is performed with combinations of technical implementations to decrease the image file size.

- **Simple Color Reduction**: Simple Color Reduction is a Color Quantization technique with the smallest O(n) runtime complexity. After determining the number of colors available for each RGB value, each pixel in the image is matched and replaced with the closest available RGB value.
- **Dithering**: Image dithering is a technique used in computer graphics to create the illusion of color depth in images with a limited color palette. The dithering algorithm used for the study is Floyd-Steinberg Dithering for maintaining a high level of detail in the image while reducing the color palette.
- **Median Cut Color Quantization**: Median Cut is a Color Quantization technique with complexity of O(n log n log k) where n is the number of unique colors and k is the desired number of color clusters. The list of all the unique colors in the image is sorted by color space with the highest range. Then, the list is split into two groups recursively until the desired color clusters are reached. Once the desired number of color clusters is reached, all the colors in the clusters are replaced with the average color in the cluster.
- **Octree Color Quantization**: Octree color quantization uses a tree structure to partition the RGB color space, with each level of the tree representing a bit of the red, green, and blue color components. As colors from the image are inserted into the octree, nodes are collapsed if a predefined color limit is exceeded, averaging the colors they contain. The final octree nodes represent the reduced color palette, with each pixel in the image being mapped to the closest color in the tree.

3.3 WebP and AVIF Image Format

- **WebP image format**: WebP compression is an image format developed by Google. The WebP encoding provides superior compression for images on the web. The WebP encoding will be performed with 'cwebp,' a Google-developed tool for converting images to WebP format.
- **AVIF**: AVIF (AV1 Image File Format) encoding is a technique based on the AV1 video codec. The AVIF encoding provides superior compression compared to

JPEG and WebP [4]. We will use the 'libavif' library for the AVIF image encoding.

3.4 Super-Resolution

Super-resolution refers to a technique aimed at elevating the resolution of an image. This process involves initially expanding the dimensions of an image via interpolation methods. Subsequently, a machine learning model is employed to refine and enhance the details within the image, effectively generating higher-quality elements that were not present in the original image.

- **ESRGAN**: The ESRGAN (Enhanced Super-Resolution Generative Adversarial Networks) model, developed by Xintao Wang, stands as one of the most prominent methods in the field of super-resolution. The decision to utilize the ESRGAN model in this study is grounded in its widespread recognition and proven stability. This model has demonstrated remarkable effectiveness in enhancing image resolution while preserving and improving image quality.

3.5 Image Transforamtion

The study employed three distinct methods to transform the sampled images:

3.5.1 ***Method 1: Color Quantization***. Several color quantization techniques were explored, including Simple Color Quantization, Image Dithering, Median Cut, and Octree Color Quantization. The color reduction was benchmarked at 2^6, 2^9, 2^{12}, 2^{15}, 2^{18}, and 2^{21} distinct colors. These benchmarks were chosen to ensure consistent comparison across the various quantization methods. Given that Simple Color Quantization necessitates colors in the form 2^{3n} and Median Cut in the form 2^{2n}, the aforementioned benchmarks were adopted. It's noteworthy that these settings represent a significant reduction from the 16 million colors (or 2^{24} colors) typically supported by the JPEG format.

The Floyd-Steinberg Dithering algorithm was chosen for Image Dithering due to its superior balance between quality and computational efficiency. Simple Color Quantization was favored for its linear time complexity, represented as $O(n)$. Image Dithering was deemed effective in creating a semblance of diverse colors even with a limited palette, thus mitigating perceptible quality degradation. The Median Cut and Octree Color Quantization methods were selected for their proficiency in preserving the original image's color fidelity.

While the k-means clustering algorithm was initially contemplated, it was ultimately excluded from the study due to its prohibitive computational complexity.

The transformed images were subsequently saved in the JPEG format.

3.5.2 ***Method 2: Conversion to WebP and AVIF Post-Color Quantization***. A pivotal objective of this research was to gauge the efficacy of color quantization as a preliminary step prior to the conversion into WebP or AVIF formats. The underlying hypothesis was that by curtailing the color spectrum within an image, the subsequent conversion into WebP or AVIF would be both expeditious and efficient.

Given that both WebP and AVIF employ predictive algorithms for image compression, it was posited that a diminished color palette would augment data redundancy, thereby streamlining the compression process in both formats.

3.5.3 ***Method 3: Varying Lossy Compression of WebP and AVIF***. The study by Singh on converting images to WebP and AVIF formats primarily used a default lossy compression setting of 75. However, both AVIF and WebP formats offer a broad range of adjustable lossy quality settings, from 0 (maximum compression) to 100 (minimum compression). To date, there has been a lack of direct comparative studies on the quality implications of these two compression methods across their entire setting spectrum.

In this research, we aim to explore and compare the effects of varying lossy compression qualities for both WebP and AVIF formats. Specifically, we have selected compression quality settings of 10, 25, 50, and 75 for our analysis. These settings are utilized for two primary purposes: to analyze the percentage of compression achieved at each level and to assess the impact on user perception through a dedicated study.

3.5.4 ***Method 4: Resizing Image Dimension for Super-Resolution***. The fourth method proposed in this study involves the use of super-resolution to enhance images. The strategy is to transmit images with reduced dimensions (specifically, one-fourth the size of the original image) and subsequently upscale them on the user's device. This method posits an innovative approach to image optimization, potentially offering significant bandwidth savings while maintaining image quality.

For the purpose of our compression percentage analysis, the images were resized to half of the maximum device width. This resizing serves as a basis for quantifying the extent of compression achieved. Furthermore, a user perception study was conducted using images upscaled through the ESRGAN model. This part of the study is pivotal in understanding how effectively super-resolution can enhance low-resolution images while preserving, or even improving, the viewer's perceptual experience.

3.6 Evaluation Metrics for Compression

Throughout the image transformation process of Color Quantization, several key metrics were rigorously evaluated, encompassing variations in file size, compression ratios, unique color counts, and conversion times. The compression ratio was computed using the size of the uncompressed original image as the numerator and the size of the compressed file as the denominator. A compression ratio greater than 1 indicates successful compression. Compression Percentage was calculated by the following equation:

$$\text{Compression Percentage} = \left(1 - \frac{\text{Uncompressed Size}}{\text{Compressed Size}}\right) \times 100$$

3.7 Evaluation Metrics for User Perception

Given that color quantization methods did not demonstrate a substantial advantage in compression performance over AVIF and WebP encoding, the user perception survey focused exclusively on evaluating the impact of AVIF & WebP lossy compression and super-resolution techniques.

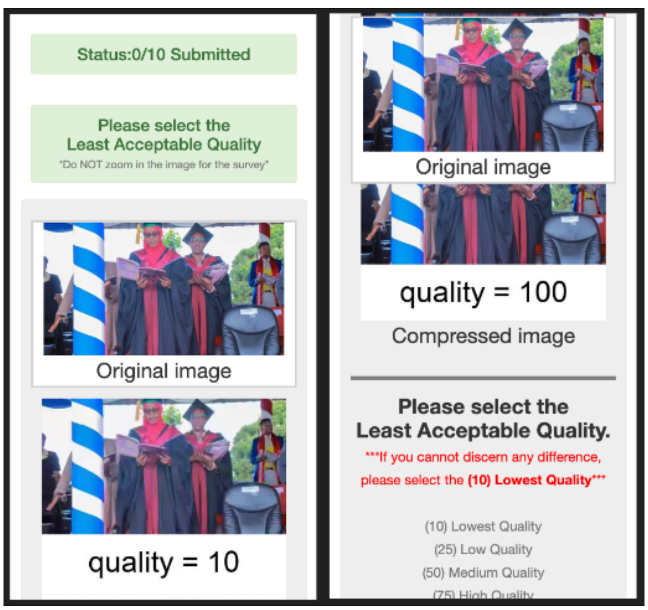

Figure 1: GUI for testing user perception of images with varying levels of lossy compression. The suvey was set to be only performable on mobile device, with zooming feature disabled.

3.7.1 *User Perception Survey for Avif & WebP Lossy Compression*

For this segment of the study, 1500 images were randomly selected for the user perception survey. These images underwent compression in two distinct versions, WebP and AVIF, with quality settings of 10, 25, 50, and 75.

The survey was conducted with 1500 participants, each evaluating 10 images in a randomized sequence. The participants were presented with images at various quality settings and were asked to identify the "least acceptable quality" for each. This approach was designed to gauge the lowest quality threshold that users find tolerable, providing insights into the balance between compression efficiency and perceptual quality.

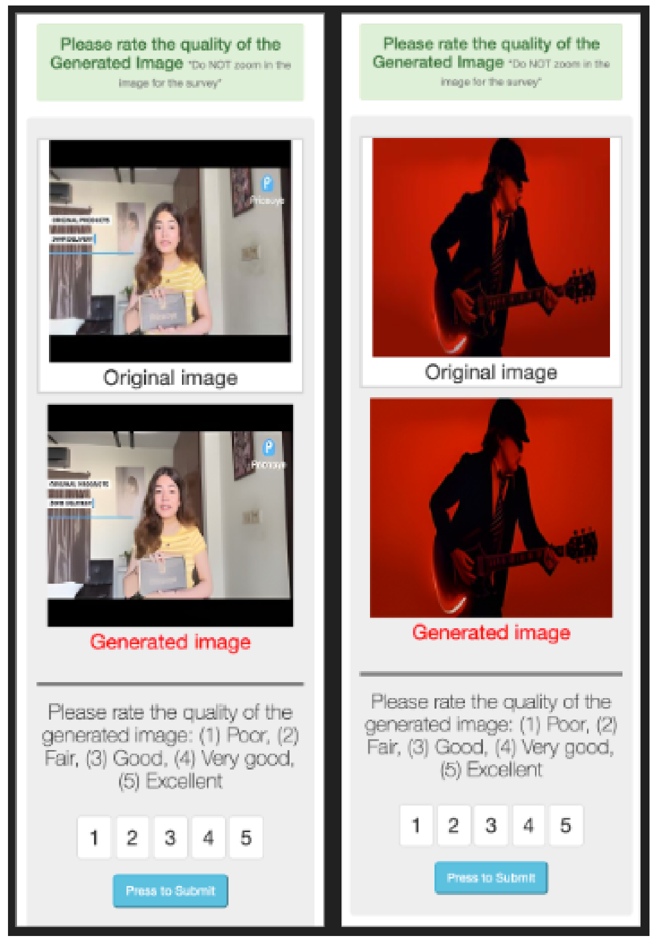

Figure 2: GUI for testing user perception of images of images upscaled with ESRGAN. The suvey was set to be only performable on mobile device, with zooming feature disabled.

3.7.2 *User Perception Survey for Super-Resolution with ESRGAN*

In the super-resolution segment of the user perception study, 750 images were randomly selected. These images were initially resized to half the mobile device screen size (approximately 200px) while maintaining their proportions. They were then upscaled using the ESRGAN model.

A group of 750 participants was involved in this study, each reviewing 10 images in a random order. The participants were shown each ESRGAN-enhanced image alongside its original version. They were asked to evaluate and compare the perceived quality of the generated image against the original. This part of the survey aims to understand user perceptions of the effectiveness of super-resolution in enhancing image quality, particularly in a mobile browsing context.

4 RESULTS

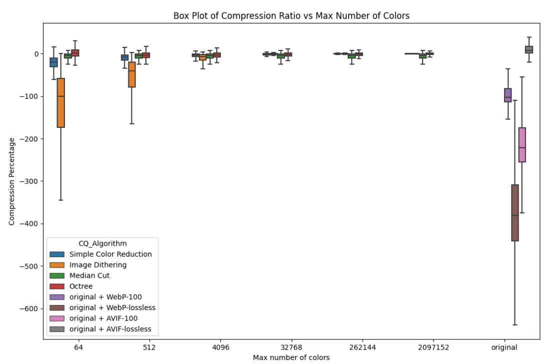

Figure 3: Box plot for Method1 & 2.

4.1 Method 1: Color Quantization

Table 1: Color Quantizations

	Simple	Dither	Median Cut	Octree
Min	0.19	0.05	0.56	0.63
1st Quartile	0.92	0.73	0.90	0.95
2nd Quartile	0.95	0.84	0.95	0.99
3rd Quartile	1.0	1.0	0.99	1.02
Max	5.99	1.06	1.08	2.78

Using color quantization as a standalone technique yielded mixed results concerning file size reduction. Analyzing the first and third quantiles, it is evident that most images processed using color quantization did not achieve significant file size reduction. In certain instances, there was a marginal increase in file size. While the Simple Color Reduction and Octree methods demonstrated some effectiveness in file size reduction, these results were limited to approximately 25% of the total images. This suggests that color quantization may not be a universally effective method for file size reduction.

4.2 Method 2: Color Quantization followed by WebP and AVIF Conversion

The subsequent boxplots elucidate the efficacy of image conversions from the sample images.

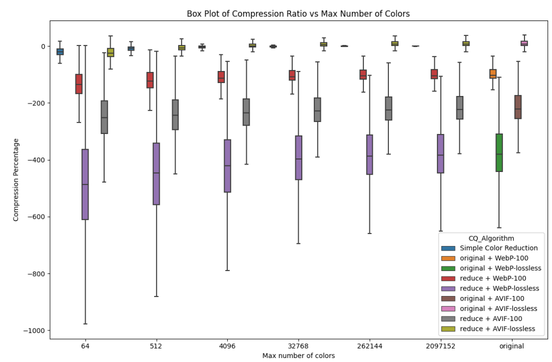

Figure 4: Simple Color Reduction as preprocessing.

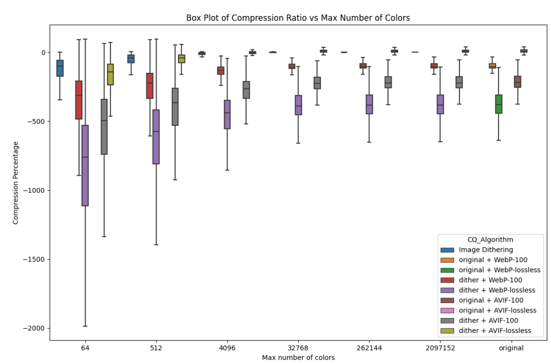

Figure 5: Dithering as preprocessing.

These plots indicate that employing color quantization as a pre-processing step prior to converting images to AVIF or WebP formats may not be optimal. Instead, the data suggests that it may be more expedient and effective to directly utilize the lossy compression features of the WebP and AVIF formats to achieve notable file size reductions.

4.3 Method 3:Varying Lossy Compression of WebP and AVIF

4.3.1 Compression Analysis. The compression analysis, as illustrated in Figure 8, indicates that WebP achieved superior compression at a Quality Setting of 75. Conversely, AVIF

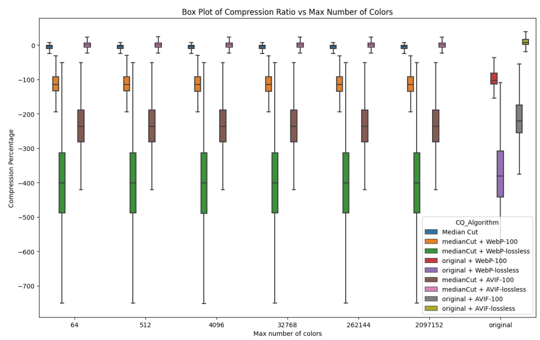

Figure 6: Median Cut as preprocessing.

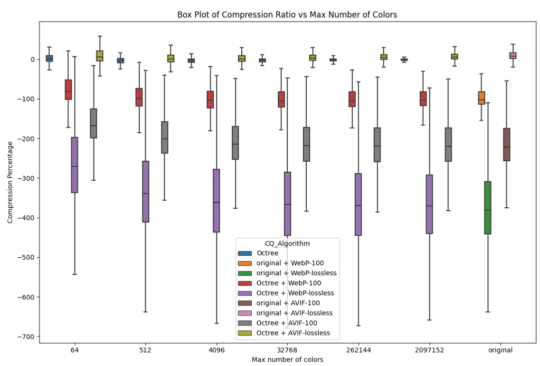

Figure 7: Octree as preprocessing.

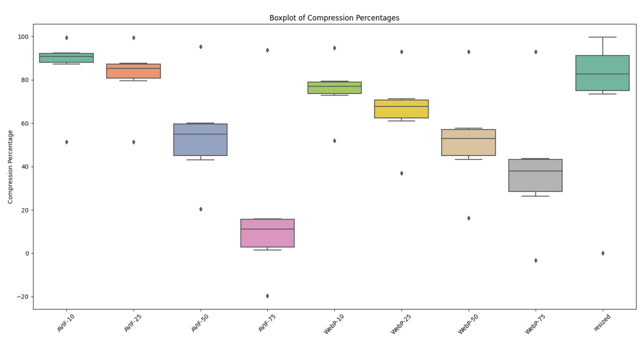

Figure 8: WebP & AVIF & Resizing Compression Percentage

demonstrated greater compression efficiency at lower quality settings, particularly at Quality 25 and Quality 10. Notably, both AVIF and WebP's lossy compression methods significantly outperformed the algorithmic color quantization methods in terms of compression.

It's important to note that while the compression percentages varied between the two image formats based on the quality setting, this does not imply equivalent quality across corresponding settings. This discrepancy necessitated the execution of a user perception survey to assess the visual quality at varying compression levels.

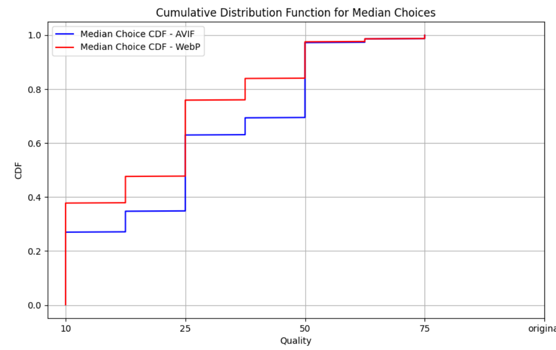

Figure 9: WebP & AVIF User Perception

4.3.2 User Perception Analysis. The analysis of the user perception survey, depicted in Figure 9 through a Cumulative Distribution Function (CDF) of user responses, reveals insightful trends. When asked to select the Least Acceptable Quality, 82% of users indicated a preference for a Quality setting of 50 in WebP, and 65% favored the same setting for AVIF. Interestingly, every participant's median choice was at a quality setting of 75 or lower. This unanimous preference suggests that the default lossy compression settings for both AVIF and WebP are generally satisfactory for the diverse range of images included in the survey.

These findings are significant as they provide a clear indication of user tolerance levels regarding image quality in compressed formats. The results suggest that a balance can be struck between efficient compression and maintaining an acceptable level of image quality, which is crucial for optimizing mobile web browsing experiences.

These findings lend significant support to the idea of converting existing images to WebP and AVIF formats as a means to reduce webpage size, consequently enhancing the browsing experience.

Moreover, when compared to the default lossy compression, which yields an average file size reduction of 41.6% for WebP and 15% for AVIF, adopting a more aggressive lossy compression with a quality setting of 50 can result in compression rates of 55% for WebP and 58% for AVIF. This indicates that further compression is feasible without markedly degrading the user experience for the majority of users. This balance between compression efficiency and maintaining acceptable image quality is a crucial aspect for optimizing web content, especially for mobile browsing environments where both data usage and visual quality are key concerns.

4.3.3 Webpage Impact Analysis. The Webpage Impact analysis was conducted to evaluate the effects of reducing image quality settings from the default 75 to 50, as suggested by the findings of the user perception survey. This analysis aimed to understand the real-world implications of such adjustments on web page performance.

For this experiment, 50 websites from low-income countries and another 50 from high-income countries were randomly selected. The data from these websites, including images and other content, were saved and cached through web crawling using Selenium.

The experimental setup involved loading these websites on a low-end smartphone connected to a proxy server. This server was configured to deliver the cached content with images converted to either WebP or AVIF formats, replacing the original JPG, PNG, and JPEG files. It's important to note that other image formats like GIFs or SVGs were not altered and were served in their original form.

The analysis focused on several key web performance metrics: page size, page load time, first contentful paint (FCP), and speed index. To closely replicate real-world conditions, each website was tested three times for each image format.

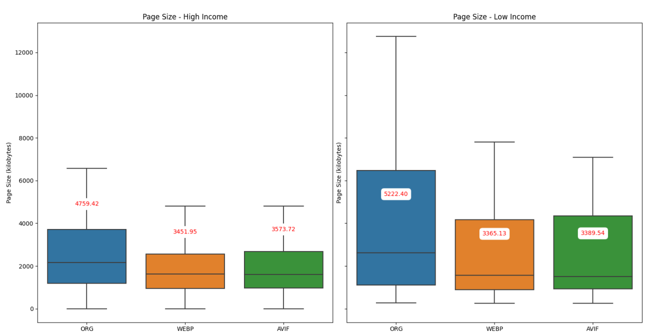

Figure 10: Page Size - Webpage Analysis

Figure 10 in the study illustrates the impact on page size resulting from the conversion of images to WebP and AVIF formats with a lossy compression quality setting of 50. The results indicate a notable decrease in page size—an average reduction of 27% for websites in high-income countries and 36% for those in low-income countries when using WebP. Similarly, for AVIF, the reductions were 25% and 35%, respectively.

Figures 11, 12, and 13 present the effects of these changes on page load time, FCP, and speed index. While there was a general trend of improvement in these metrics with both image formats, it was observed that in some cases, the page load time actually increased with the use of WebP images (Figure 11).

Despite these occasional increases in load time, the overall trend pointed to a clear reduction in page size and enhancements in web performance metrics. This evidence supports the conclusion that implementing lossy compression with WebP and AVIF formats is a promising strategy for reducing data consumption in mobile browsing, particularly in contexts where bandwidth and loading speeds are critical

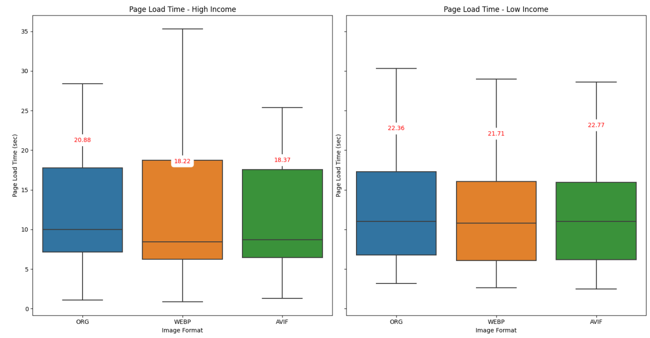

Figure 11: Page Load Time - Webpage Analysis

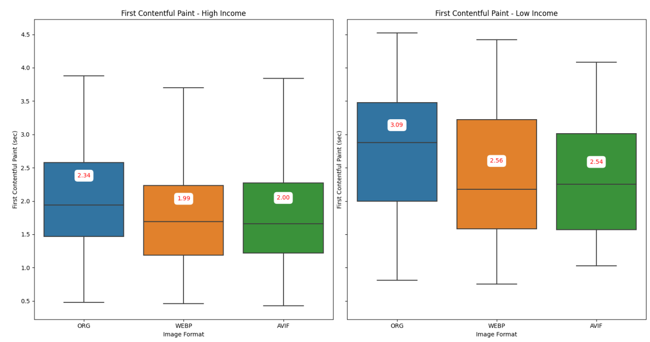

Figure 12: First Contentful Paint - Webpage Analysis

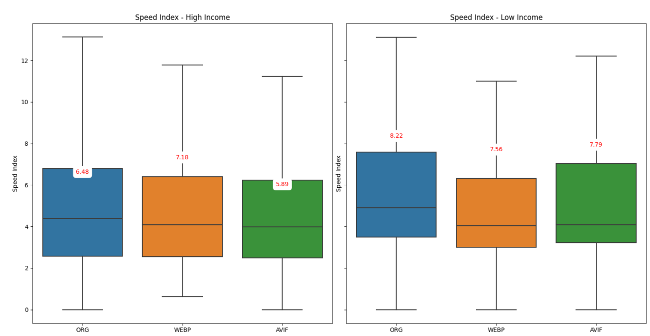

Figure 13: Speed Index - Webpage Analysis

concerns. This finding holds significant potential for improving the accessibility and efficiency of web content, especially in regions with limited internet infrastructure.

4.4 Method 3:Super-Resolution with ESRGAN

Measure	Compression Percentage (%)
Minimum	0.00
1st Quartile	73.45
2nd Quartile	85.29
3rd Quartile	93.22
Maximum	99.75
Mean	80.08

Table 2: Resizing Compression Percentages

4.4.1 Compression Analysis. The analysis of compression, as depicted in Figure 8 and Table 2, reveals that resizing images results in notably stable compression outcomes. This high level of compression can be attributed to two primary factors: 1) the initial compression achieved by resizing images that were not originally optimized for mobile browsers, and 2) further compression obtained by resizing the image to one-fourth of its size optimized for mobile viewing.

The strategy of employing image resizing combined with super-resolution techniques for mobile browsing appears to yield consistently high compression across various applications, regardless of the initial mobile optimization of the images. This indicates a promising avenue for reducing bandwidth usage and enhancing mobile browsing efficiency.

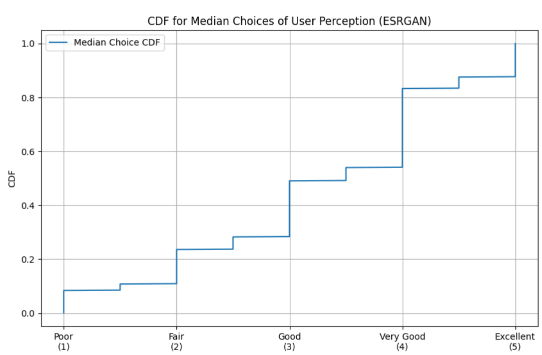

Figure 14: ESRGAN User Perception

4.4.2 User Perception Analysis. As shown in Figure 14, the user perception survey offers varied insights into the effectiveness of using ESRGAN for image upscaling. While over half of the images were deemed satisfactory by users, a closer examination of the images that received lower satisfaction scores reveals a specific trend. Images containing human faces and text were frequently rated as unsatisfactory. This was particularly evident in cases where the super-resolution process introduced artifacts that appeared unnatural to the viewers.

Not all images with human faces and text were poorly received, but those generating noticeable artifacts were especially problematic. As super-resolution algorithms continue to evolve, focusing on optimizing face and text rendering, these artifacts are expected to diminish. However, based on the current findings from the user perception survey, the existing ESRGAN model may not yet be a viable option for widespread application in mobile browsing scenarios, primarily due to these specific limitations in handling certain types of images.

4.5 Ancillary Findings

Supplementing the findings from Method 1 & 2, parameters such as original image size and unique color counts were analyzed during the image conversion process to discern potential characteristics inherent to the WebP and AVIF conversion methodologies. By leveraging the Pearson correlation coefficient, relationships between image file size, unique color count, compression ratio, compression percentage, and compression time were ascertained for both WebP and AVIF conversions. Here are the salient observations from the analyzed samples:

4.5.1 Compression Time & Image File Size. : For WebP conversions (lossless and q=100), the correlation coefficients were 0.41 and 0.57, respectively. This suggests that the compression time lengthens as the file size increases. This trend was not observed for AVIF compressions, regardless of the chosen settings.

4.5.2 Original Number of Colors & Compression Percentage. : Correlation coefficients of -0.44, -0.37, and -0.41 were observed for WebP (lossless), WebP (q=100), and AVIF (q=100) respectively. For AVIF lossless, the coefficient was -0.09. While the number of unique colors in an image does influence the compression percentage, its efficacy as a standalone solution appears limited.

5 CONCLUSION

This research has explored three distinct methodologies for optimizing images for mobile web browsing, specifically examining the potentials of increased lossy compression in WebP and AVIF formats and the application of super-resolution techniques. The findings suggest that both enhanced lossy compression and super-resolution are viable strategies for reducing image file sizes, thereby contributing to a more efficient and user-friendly mobile browsing experience.

Past research on WebP and AVIF formats has predominantly focused on lossless or default compression quality settings. However, our user perception survey, which examined a range of compression qualities, provides compelling evidence that implementing a higher degree of lossy compression can significantly reduce webpage sizes without substantially affecting user experience. This insight opens up new avenues for optimizing web content, particularly in mobile contexts where bandwidth and loading times are critical considerations.

Additionally, the ongoing advancements in super-resolution technology hold promise for future applications. The prospect of on-device image upscaling using such techniques is an exciting development that could further enhance web browsing experiences. Implementing super-resolution at the device level could offer a novel approach to managing image quality and file size.

However, the application of super-resolution in a mobile context raises several important considerations that warrant further investigation. Key among these is the assessment of the impact of super-resolution on device performance, including CPU usage and battery consumption. Additionally, determining the minimum device specifications required for effective implementation of super-resolution is essential to ensure its feasibility and accessibility across a wide range of mobile devices.

In conclusion, while this study has made significant strides in understanding and enhancing image optimization for mobile web browsing, there remains a fertile ground for future research. This includes not only the continued refinement of lossy compression techniques and super-resolution technologies but also a broader assessment of their practical implications for both end-users and the overall web ecosystem.

6 ETHICAL STATEMENT

The user studies were approved by the Institutional Review Board (IRB) and the author who conducted the study is CITI certified. Participation was voluntary, and informed consent was obtained from all participants. All data was processed anonymously.

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