Image Compression Using a Block-Based Genetic Algorithm

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***Abstract*—Image compression is a fundamental problem in computer vision, where the goal is to reduce image size while preserving visual quality. In this project, we explore an artificial intelligence–based approach to image compression using a Genetic Algorithm (GA). Given a high-resolution RGB image of size 2000×1200, the objective is to generate a compressed representation of size 200×120 using learning and optimization rather than traditional resizing techniques. A block-based strategy is adopted to reduce computational complexity, and the compressed image is evaluated using standard image quality metrics and baseline comparisons. The results demonstrate that the proposed method is capable of preserving global image structure and dominant color regions, while highlighting the trade-offs between compression ratio, computational cost, and visual fidelity.**

I. Introduction

Image compression plays a crucial role in modern computing systems, particularly in storage, transmission, and multimedia applications. Traditional compression and resizing techniques such as nearest-neighbor, bilinear, and bicubic interpolation rely on fixed mathematical rules. While these methods are computationally efficient, they do not adapt to image content and may fail to preserve important visual features such as edges, textures, and object boundaries.

Artificial intelligence offers an alternative perspective by framing image compression as a learning or optimization problem. Instead of directly applying predefined formulas, AI-based methods attempt to discover compressed representations that best preserve image information according to a defined objective. In this project, image compression is formulated as an optimization problem and solved using a Genetic Algorithm. The goal is not to outperform industrial compression standards, but to demonstrate how AI techniques can be applied to a real-world computer vision task.

II. Project Planning and Overall Approach

To ensure fair workload distribution and effective collaboration, the project was divided into clearly defined roles among group members. Each role focused on a specific component of the system, including baseline methods, AI optimization, block-based processing, and report preparation.

The overall approach uses a block-based Genetic Algorithm. The original image is divided into smaller regions, and each region is compressed independently using evolutionary optimization. This design reduces computational complexity while allowing the algorithm to adapt to local image characteristics. The compressed blocks are then stitched together to form the final compressed image.

III. Baseline Compression Methods

To evaluate the effectiveness of the proposed AI-based approach, traditional interpolation-based methods were implemented as baselines:

- Nearest-neighbor interpolation
- Bilinear interpolation
- Bicubic interpolation

These baseline methods directly resize the original image to the target resolution without learning or optimization. They serve as reference points for evaluating the quality and behavior of the Genetic Algorithm–based compression.

IV. Genetic Algorithm-Based Compression

A. Representation

Each individual in the Genetic Algorithm population represents a compressed image (or image block). The chromosome is defined as an RGB pixel array of size 200×120, where each gene corresponds to a pixel value in the range $[0, 255]$. This representation allows the algorithm to directly optimize pixel intensities.

B. Fitness Function

The fitness of an individual is evaluated by first upscaling the compressed image back to the original resolution. The reconstructed image is then compared to the original image using Mean Squared Error (MSE). Lower MSE indicates better reconstruction quality and therefore higher fitness.

C. Genetic Operators

The Genetic Algorithm uses standard evolutionary operators. Selection favors individuals with lower reconstruction error. Crossover combines pixel regions from two parent solutions to produce offspring. Mutation introduces small random perturbations to pixel values, encouraging exploration of the search space and preventing premature convergence.

V. Block-Based Processing and Reconstruction

To reduce computational cost, the original image is divided into smaller blocks. Each block is compressed independently using the Genetic Algorithm. Once all blocks are processed, they are combined to form the final compressed image.

This block-based strategy allows the algorithm to preserve local image features more effectively and makes the optimization problem more manageable. However, it may introduce minor artifacts at block boundaries, which are discussed in the results section.

VI. Evaluation Metrics

Compression quality is evaluated using the following metrics:

- Mean Squared Error (MSE)
- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity Index (SSIM)

In addition to numerical metrics, visual comparisons between the original image, compressed representation, and reconstructed image are used to analyze perceptual quality.

VII. Results and Discussion

To evaluate the effectiveness and generality of the proposed approach, the Genetic Algorithm–based compression method was tested on multiple images with different visual characteristics, including an object-focused image, a human portrait, and a natural scene.

Figure 1 shows results for an object-based image with strong color contrast. The Genetic Algorithm preserves dominant color regions and overall shape, although noise is visible in the compressed representation due to the limited number of generations and large search space.

Figure 2 presents results for a human portrait, which represents a more challenging case for compression. While fine facial details are degraded, the reconstructed image retains the global facial structure and illumination patterns, highlighting the algorithm's ability to preserve overall composition.

Figure 3 shows results for a natural scene containing complex textures. The compressed and reconstructed images preserve large-scale structure and scene layout, though fine textures such as snow and foliage are partially smoothed.

Across all test images, the proposed method demonstrates consistent behavior: global structure and dominant visual features are preserved, while fine details are sacrificed due to the aggressive compression ratio (100:1 pixel reduction) and computational constraints. Compared to nearest-neighbor interpolation, the AI-based approach better maintains global coherence, while bilinear and bicubic methods perform well on smooth regions.

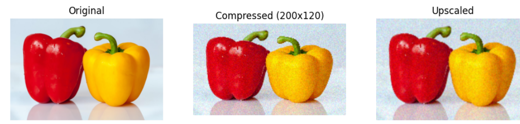

Fig. 1. Results for an object-based image. From left to right: original image, compressed representation generated by the Genetic Algorithm (200×120), and reconstructed image after upscaling.

Fig. 2. Results for a human portrait image. The Genetic Algorithm preserves global facial structure while fine details are partially lost due to high compression.

Fig. 3. Results for a natural scene image. Global scene layout and dominant structures are preserved, while fine textures are smoothed in the reconstructed image.

Comparison of original image, compressed representation generated by the Genetic Algorithm (200×120), and reconstructed image after upscaling. The GA preserves dominant color regions and global structure while sacrificing fine detail due to the high compression ratio.

VIII. Limitations and Future Work

The primary limitation of the proposed approach is computational cost, as Genetic Algorithms require many fitness evaluations to converge. Additionally, block-based processing may introduce boundary artifacts. Future work could explore hybrid methods, adaptive block sizes, alternative fitness functions such as SSIM, and parallel processing to improve efficiency and visual quality.

IX. Conclusion

This project demonstrates that image compression can be treated as an AI optimization problem rather than a fixed resizing task. By using a block-based Genetic Algorithm, the system learns compressed representations that preserve global image structure and dominant visual features. While the method does not aim to outperform industrial compression standards, it successfully illustrates the application of artificial intelligence techniques to a real-world computer vision problem.

X. Group Member Contributions

- **Caleb Edeke**: Implemented baseline compression methods and image quality metrics.
- **Sandhi Howlader**: Developed the Genetic Algorithm and optimization framework.
- **Syed Ahmed**: Implemented block-based processing, AI integration, and final image reconstruction.
- **Alena Binu**: Led report writing, visualization, and final document formatting.

References

[1] OpenCV Library, https://opencv.org
[2] NumPy Documentation, https://numpy.org
[3] scikit-image Documentation, https://scikit-image.org

Appendix

The complete source code, implementation details, and experimental results for this project are available at the following GitHub repository:

https://github.com/SyedAhmed2004/COSC3P71-Image-Compression-GA.git