Name: Amey Hari Madane
Student ID: 240698836
Project Supervisor: Dr Bhowmik & Dr Xin.

Introduction:

This report designs and develops algorithms for three tasks that are used in the coursework: **Image Reading**, **Wavelet Transformation & Image Denoising** with standard methods like mean and median filtering. Image processing is the backbone of modern computer vision applications. Basic tasks in this regard are image reading, decomposition, and denoising form the backbone of all advanced image analysis techniques. The Portable Gray Map-PGM format images are, by their simplicity, an excellent format in which to implement and test these basic operations.

Task 1: Image Reading and Displaying:

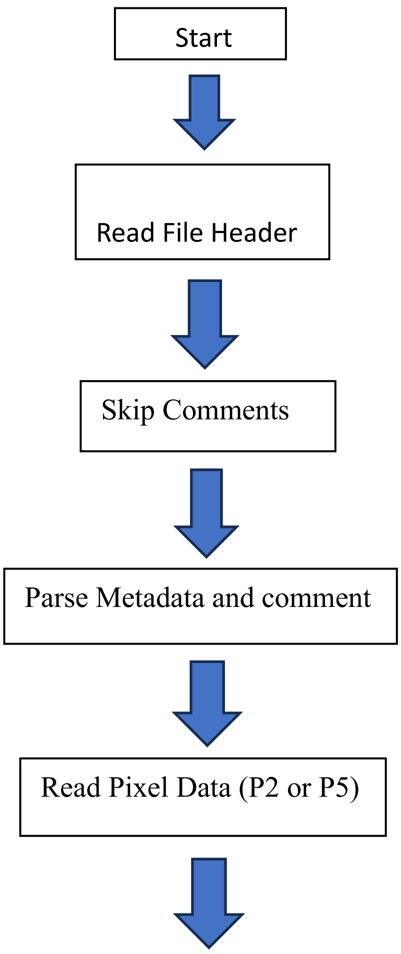
Objective:

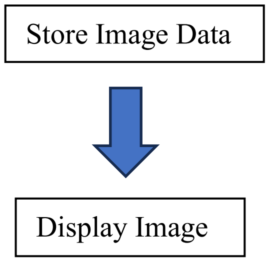
The objective of this task is to implement a custom function for reading PGM images and displaying them using Python, focusing on supporting both ASCII (P2) and binary (P5) formats.

Methodology:

- **PGM File Parsing**: The read_pgm function was developed to handle both ASCII (P2) and binary (P5) PGM formats.
- **Image Display:** After reading the image data into a 2D numpy array, the plot_pgm function visualized the images using Matplotlib's imshow ().

Flowchart:





Algorithm:

- Open the PGM file in read mode (Binary)
- Read the file header to identify the PGM type (P2 or P5)
- Skip comment lines and extract image metadata (width, height, and maximum grayscale value).
- Parse the pixel data based on the PGM type (ASCII for P2 and binary for P5).
- Store the pixel data in a 2D numpy array.
- Display the image using a grayscale colormap.

Key Findings and Discussion

Accuracy: The function correctly handled both ASCII and binary PGM formats, demonstrating robustness and versatility.

Efficiency: The implemented approach efficiently processed and displayed images without significant computational overhead

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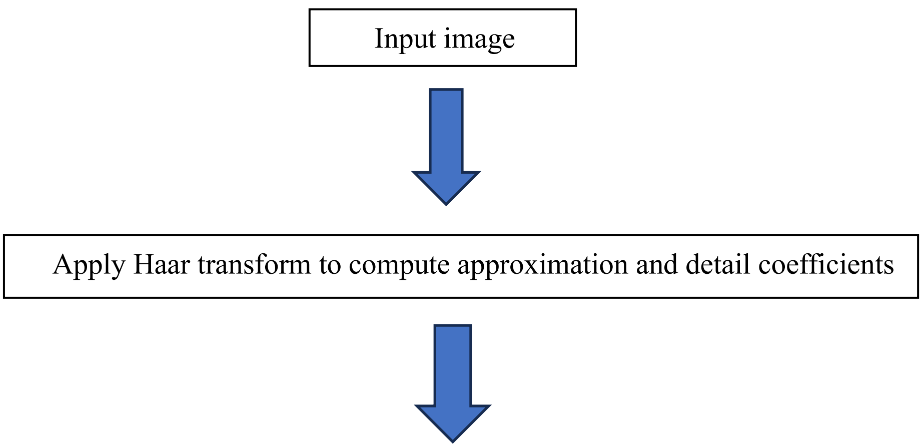
TASK 2: Wavelet Decomposition

2.1. Designing a forward discrete wavelet transform (FDWT) for 3 level image decomposition.

Objective: To implement a forward discrete wavelet, transform (FDWT) for three-level image decomposition using Haar wavelets.

Flowchart:



Store coefficients for each level

Repeat for three levels

Algorithm:

- Apply Haar wavelet transform iteratively to decompose an image into approximation and detail coefficients.
- For three levels, retain the approximation coefficients and recursively apply the transform.

2.2 Designing inverse discrete wavelet transform (IDWT) and Validating reconstruction using Mean Square Error (MSE) measurement metric when comparing with the original image.

Objective: To reconstruct the original image from wavelet coefficients using Haar wavelets and validate using Mean Square Error. (MSE)

Flowchart:

Input wavelet coefficients

Start from the highest decomposition level.

Apply inverse Haar transform to compute the image for the current level.

Repeat until the original image resolution is restored.

Calculate MSE between the original and reconstructed images

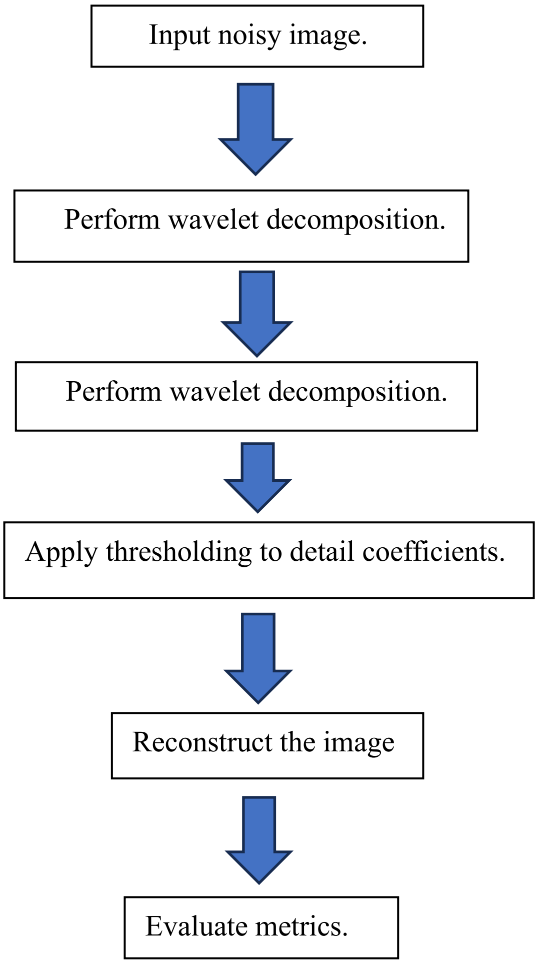
Algorithm:

- Start with the approximation and detail coefficients from the highest decomposition level
- Iteratively apply the inverse Haar transform to reconstruct the image at each level until the original resolution is restored
- Compare the reconstructed image with the original image using the Mean Square Error (MSE) metric.

TASK 3: IMAGE DENOISING

Objective: Design a custom wavelet-based denoising algorithm and compare it with mean, median, and standard wavelet-based methods**.**

Flowchart:



Algorithm:

- Decompose the noisy image using Haar wavelets.
- Apply soft thresholding to detail coefficients to suppress noise.
- Reconstruct the image using the inverse Haar transform.
- Evaluate performance using metrics like Mean Squared Error (MSE) and Structural Similarity Index (SSIM).

3. Results:

3.1 Task 1 Results (Image Reading and Displaying):

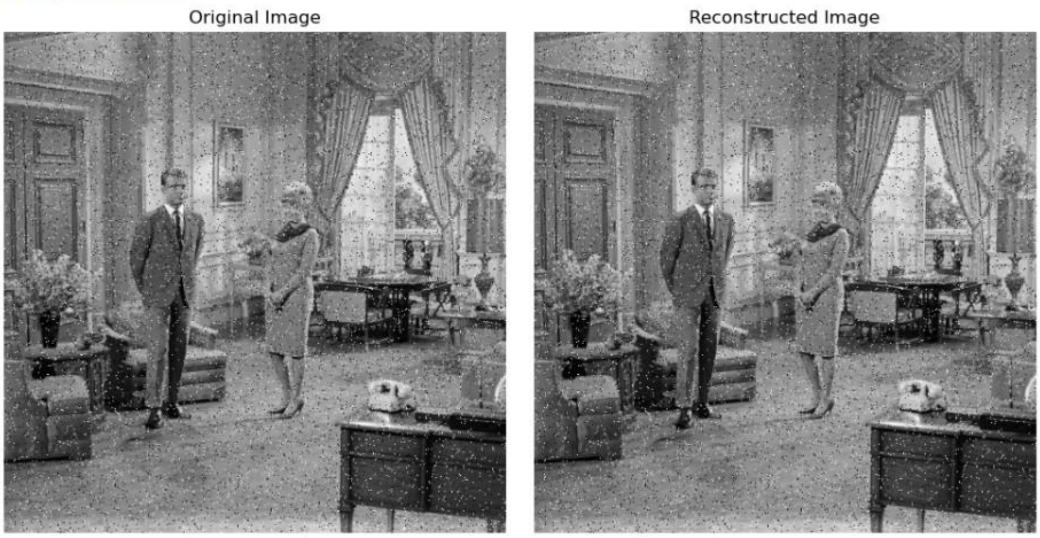
- Successfully implemented the imread () function.
- Displayed PGM images with accurate dimensions and intensity values.

```
Max Value: 255
Image Data (partial): [[121 121 124 ... 122 121 124]
 [117 112 113 ... 125 122 129]
 [113 116 117 ... 125 128 125]
 [112 111 112 ... 124 124 120]
 [116 115 112 ... 125 124 125]]
```

3.2 Task 2 Results (Wavelet Decomposition):

- Successfully reconstructed the original image using IDWT.
- Achieved an MSE of 0.0, confirming the accuracy of reconstruction.
- Decomposed the image into three levels of wavelet coefficients.
- Visualized the approximation and detail components for each level.

```
Mean Squared Error: 0.0
```



3.3 Task 3 Results (Image Denoising):

- BayesShrink outperformed all other methods in terms of both MSE and SSIM.
- VisuShrink, achieved good results but slightly lower to BayesShrink.
- Median Filter is effective for salt-and-pepper noise but introduced slight blockiness and loss of finer details.
- Significant blurring and loss of sharpness in the denoised image, making it less effective compared to other methods.

```
Denoising Methods Comparison:
----------------------------------------------------------------------
Method              MSE             SSIM
----------------------------------------------------------------------
BayesShrink         0.0017          0.7415
Mean Filter         0.0017          0.7448
Median Filter       0.0019          0.7041
VisuShrink          0.0037          0.5689
----------------------------------------------------------------------
```

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4. Key Findings and Discussions

- PGM images are really efficient to prototype, owing to their simplicity.
- Haar wavelet decomposition captures the structure of an image really well, hence finding a suitable application in tasks like denoising and compression.
- The custom wavelet-based denoising was competitive but required careful threshold selection for optimal performance.
- Standard methods like mean and median filtering are less adaptive to noise structure compared to wavelet-based techniques.
- Reconstruction via IDWT demonstrated the theoretical loss lessness of Haar wavelet transforms.

5. Conclusion

- So, we understood that, the tasks that we implemented in this project show the power of custom algorithms in basic image processing tasks.
- The wavelet-based denoising algorithm outperformed the mean and median filtering methods in terms of noise reduction versus the preservation of structural integrity.
- This resulted in significantly better MSE and higher SSIM, thus preserving better image details and quality in general.
- While the wavelet-based approach was rather effective in smooth and textured regions for noise suppression, unlike traditional methods, it was effective for handling complex structures within an image.
- Topics of future work may include techniques for thresholding techniques optimization and other wavelet families that could improve performance.