CS 663 - Assignment 1

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1 Image Subsampling and Interpolation

1.a

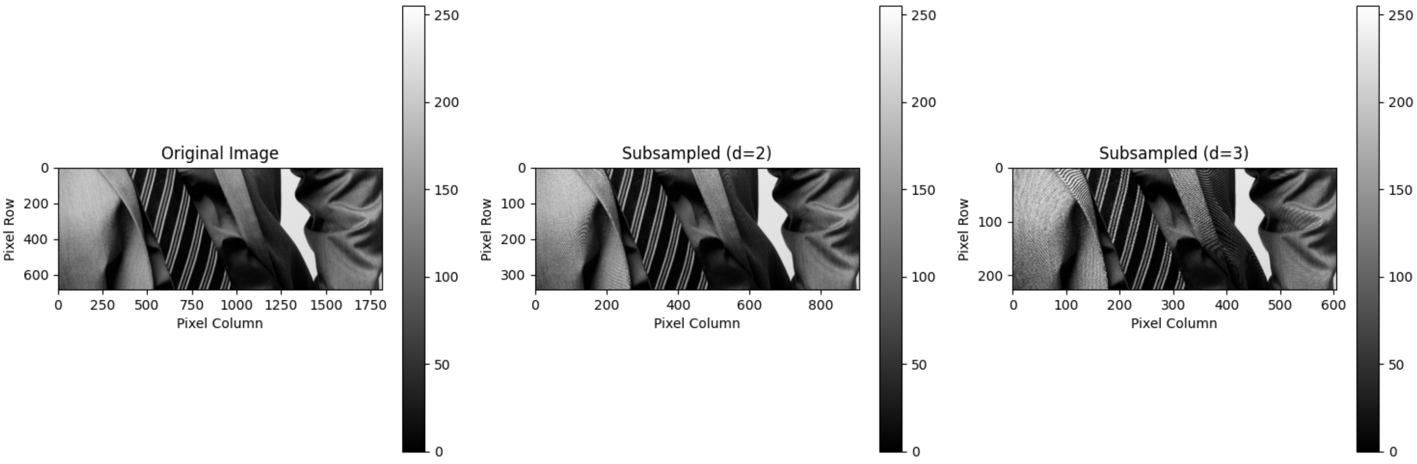

Figure 1: Comparison of Original vs d=2 vs d=3 Image Shrinking

1.b

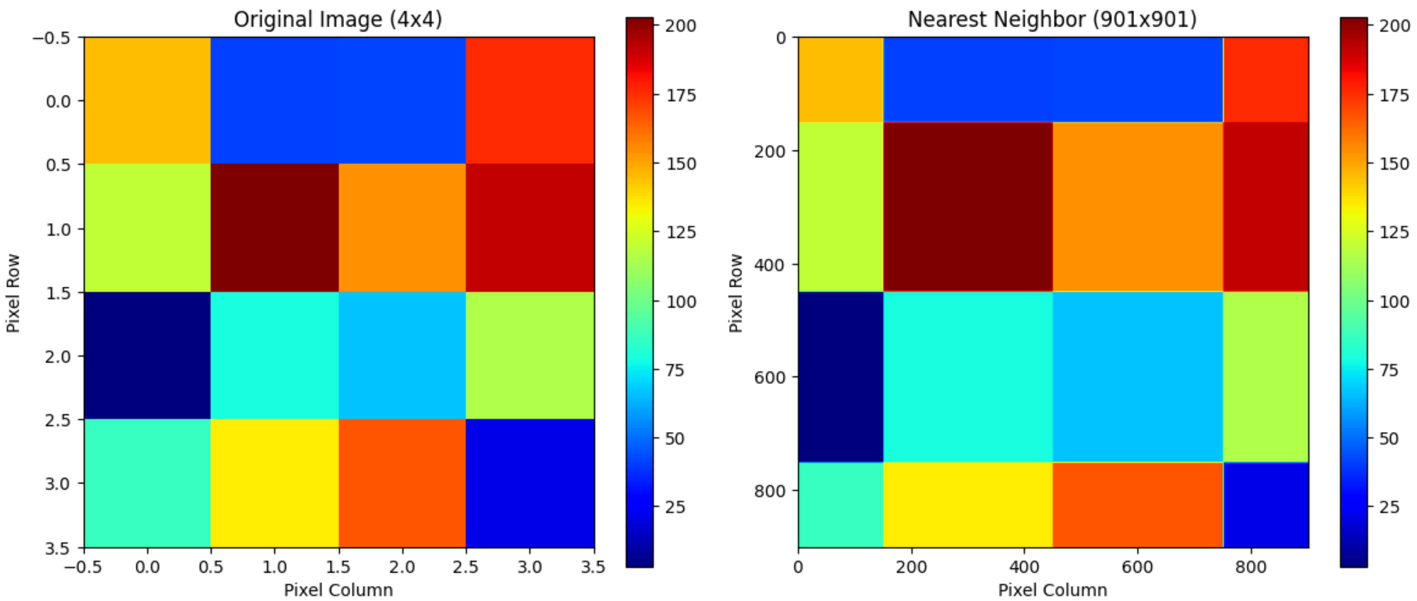

Figure 2: Comparison of Original vs NN Interpolated Enlarged Image

1.c

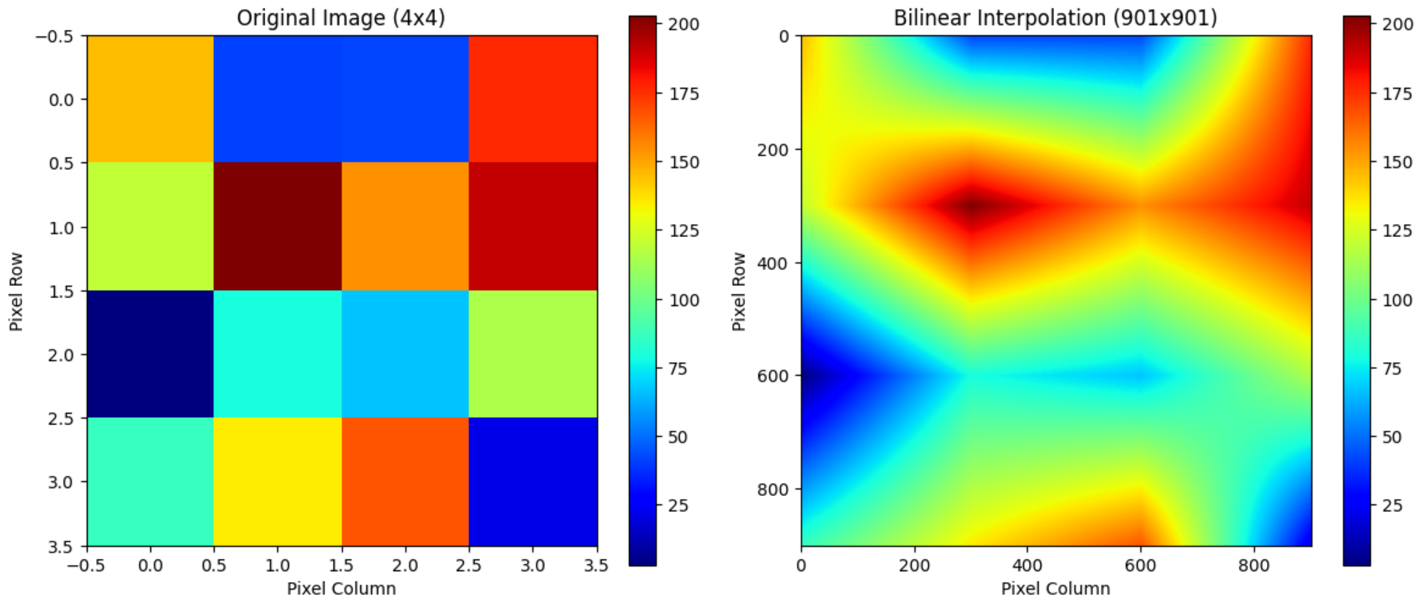

Figure 3: Comparison of Original vs Bilinear Interpolated Enlarged Image

1.d

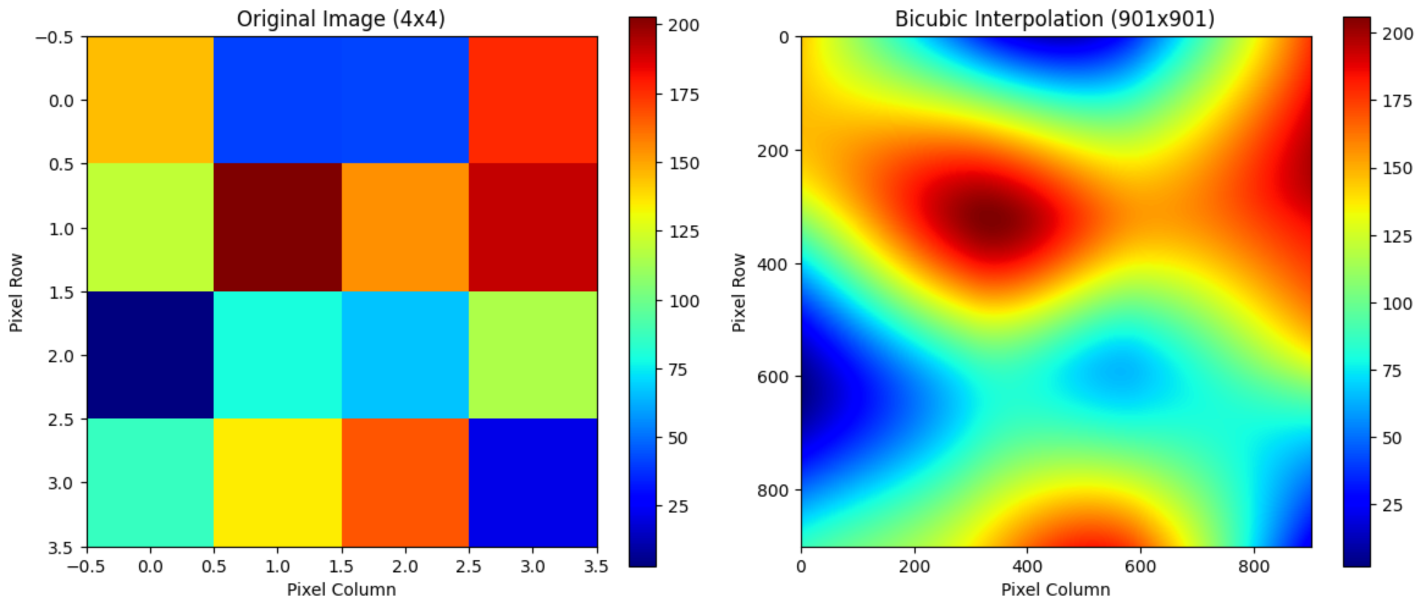

Figure 4: Comparison of Original vs Bicubic Interpolated Enlarged Image

1.e

Angle of rotation = 15^o

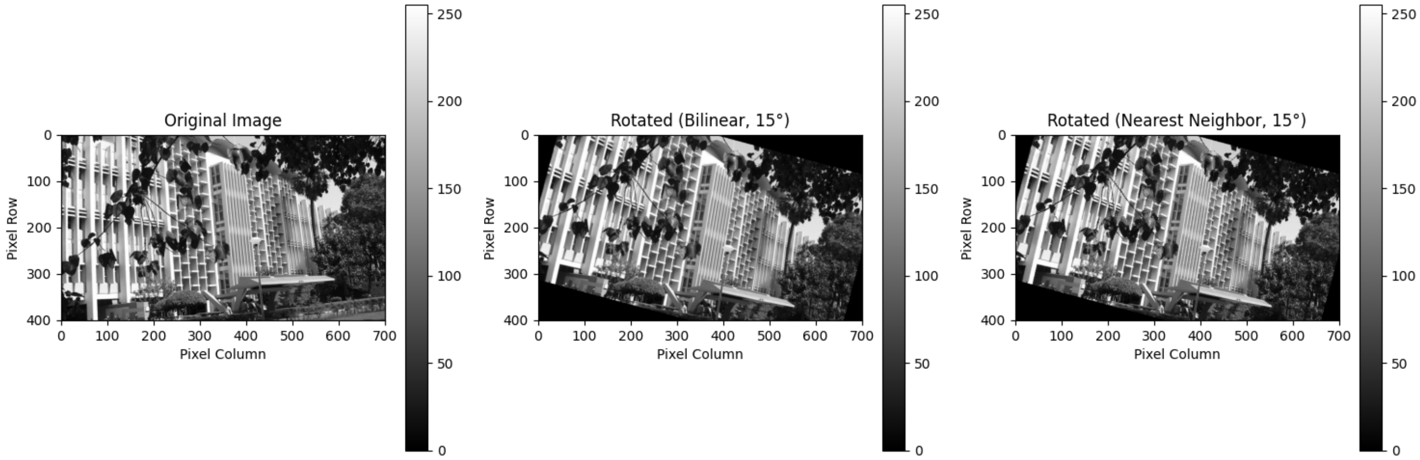

Figure 5: Comparison of Original vs NN Rotated vs Bilinear Rotated Image

1.f

RMSE Results:
Nearest Neighbor: 103.4262
Bilinear: 68.9654
RMSE Bicubic: 65.9247

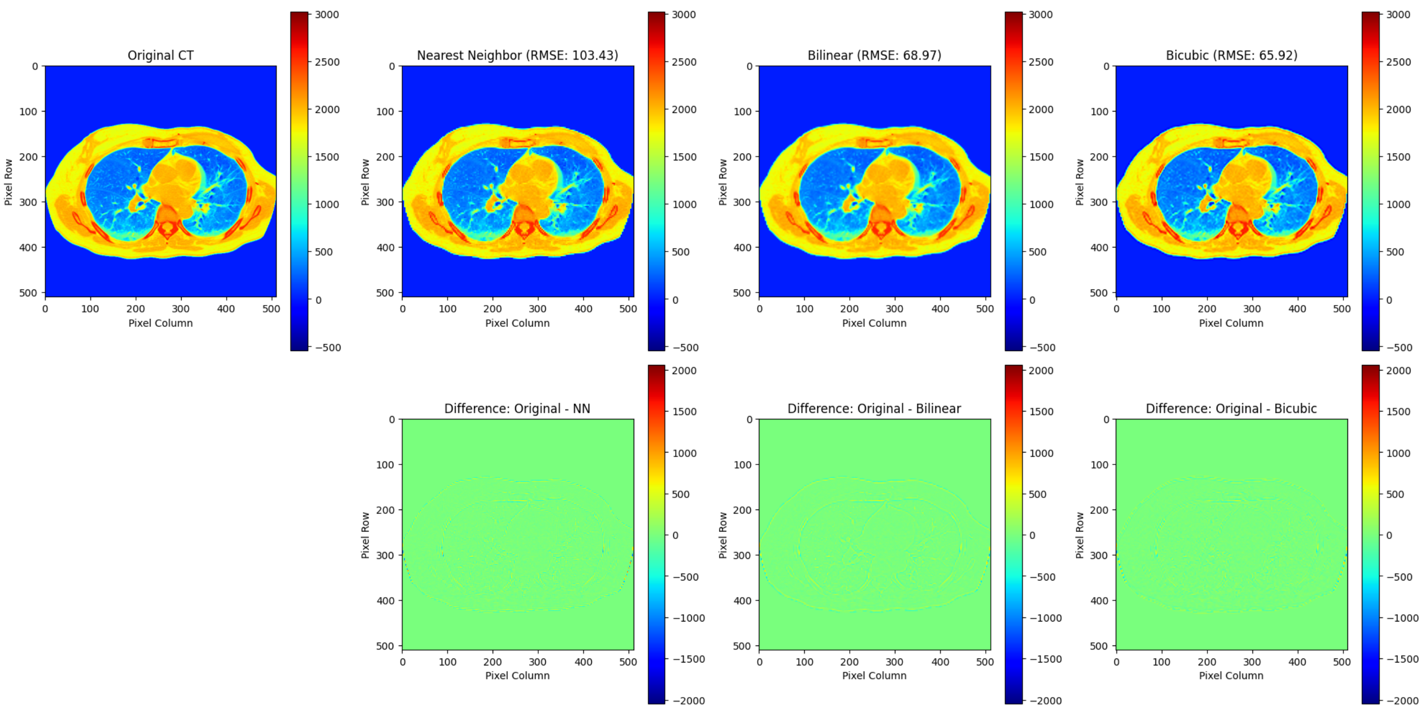

Figure 6: Comparison of Original vs NN vs Bilinear vs Bicubic Upsampled Image

Quality Analysis:
From the enlarged images with same colormap limits:
- Bicubic interpolation typically produces the smoothest results
- Bilinear interpolation provides good balance between smoothness and computational cost
- Nearest neighbour produces blocky artifacts but preserves sharp edges

From the difference images with same colormap limits:
- Bicubic typically has the lowest reconstruction error
- The difference images show where each method introduces artifacts

2 Thresholding

2.a

For Receipt image,
Manual Thresholding: A fixed intensity value is chosen to separate text from background. It can work for the dark text on the light receipt, but the background shading makes it unreliable—too low a threshold captures noise, too high loses faint text.
Otsu's Thresholding: Automatically calculates a global threshold based on the image histogram. Since the image has both light and dark regions, Otsu may misclassify some areas—lighter text could disappear, and darker shadows may appear as false text.
Adaptive Thresholding: Calculates thresholds locally for different regions of the image. This makes it robust to uneven lighting and shadows on the receipt, preserving text details across the whole image.

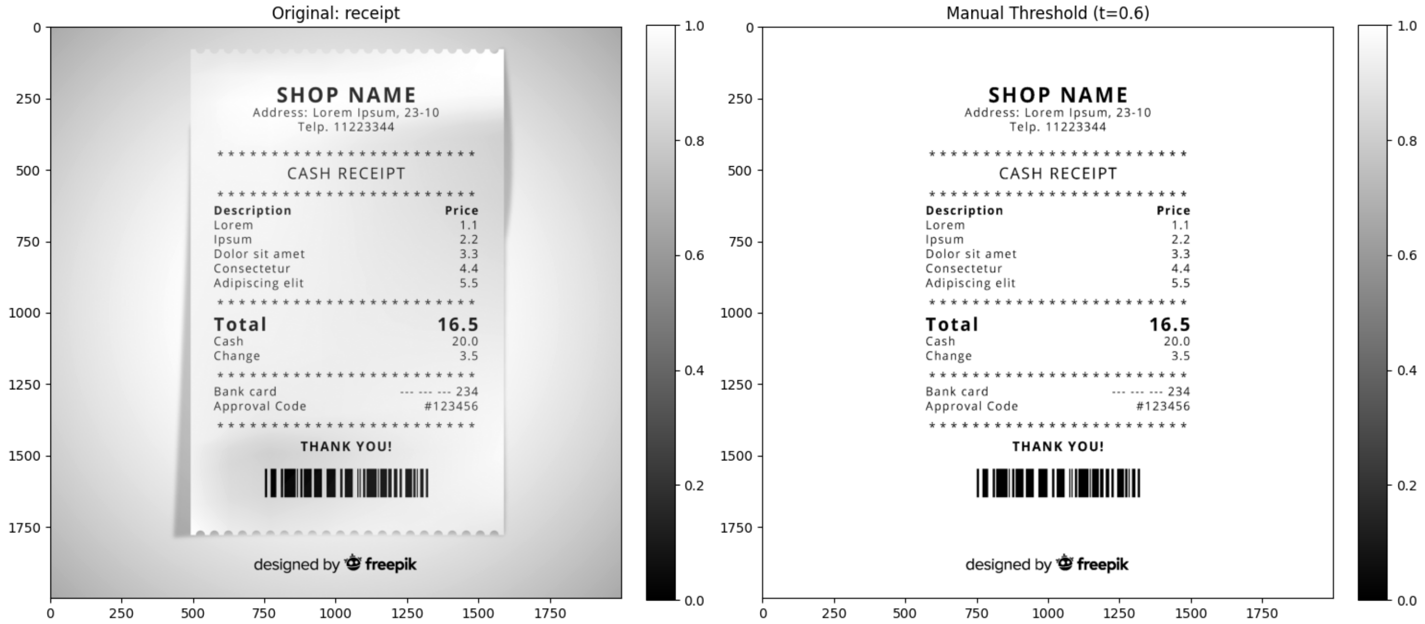

Figure 7: Comparison of Original vs Manual Threshold Image - Receipt

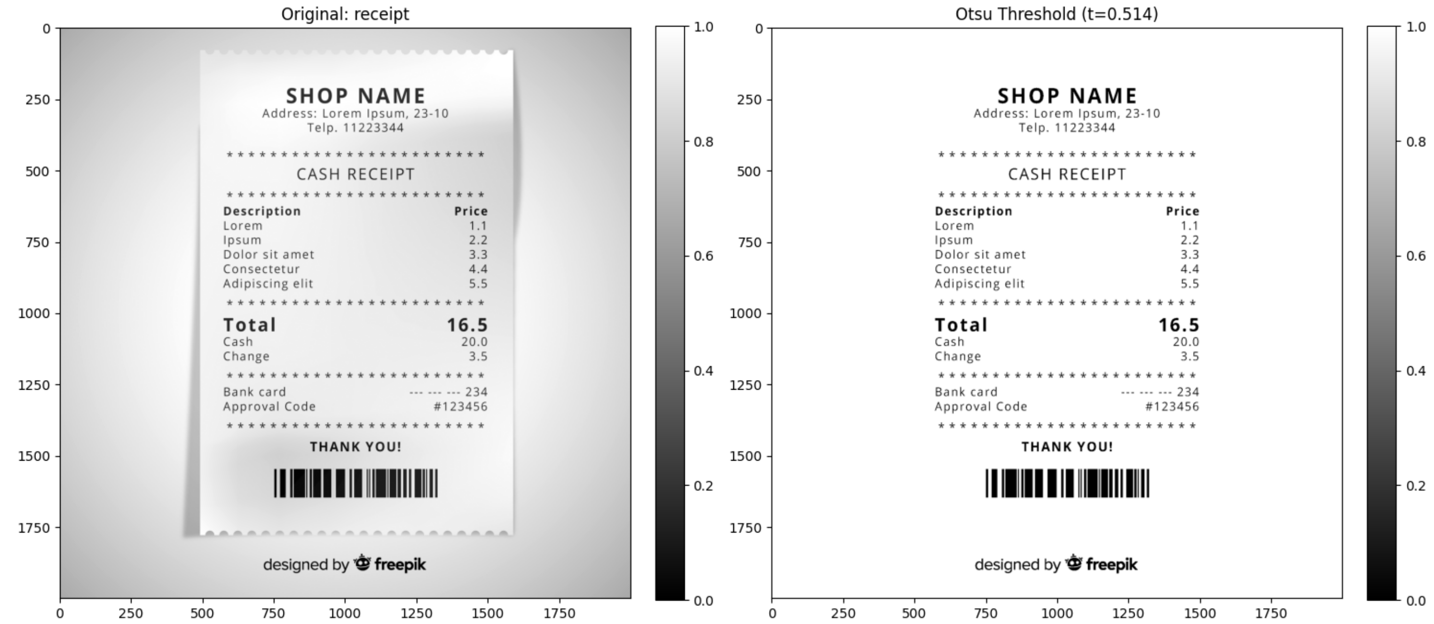

Figure 8: Comparison of Original vs Otsu Threshold Image - Receipt

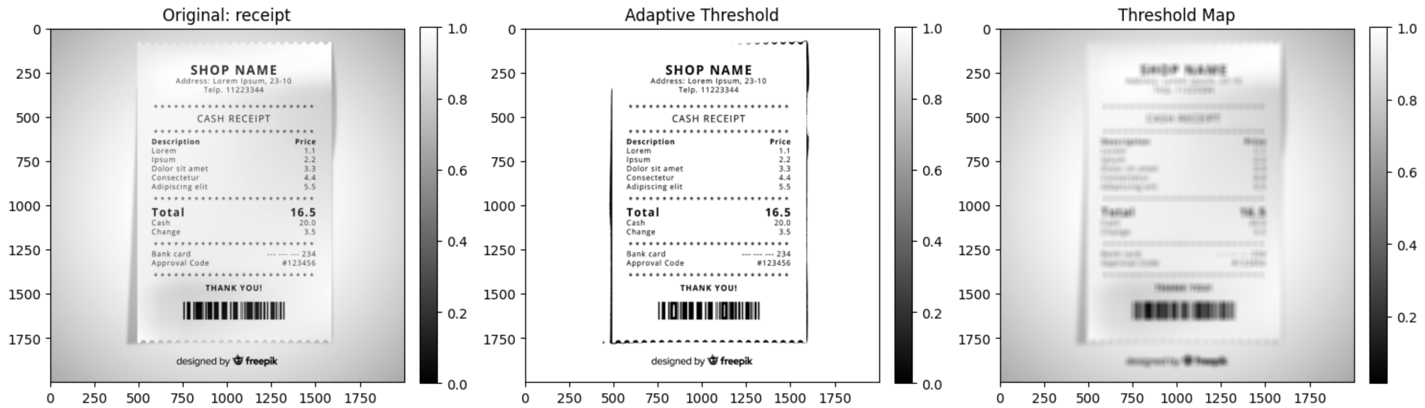

Figure 9: Comparison of Original vs Adaptive Threshold Image - Receipt

2.b

For blackboard image,
Manual Thresholding: A single fixed threshold is unsuitable because the blackboard shows uneven lighting, glare, and chalk smudges. This causes faint strokes to disappear or background noise to be picked up, making it unreliable.

Otsu's Thresholding: Since the image generally has two intensity levels (bright chalk vs dark board), Otsu can separate them reasonably well. However, the presence of glare and non-uniform background reduces the effectiveness of this global method, leading to imperfect segmentation.

Adaptive Thresholding: This method calculates thresholds locally, making it robust against illumination changes and background variations. It captures both faint and bright chalk writing effectively, handling shadows and glare better than the other two methods.

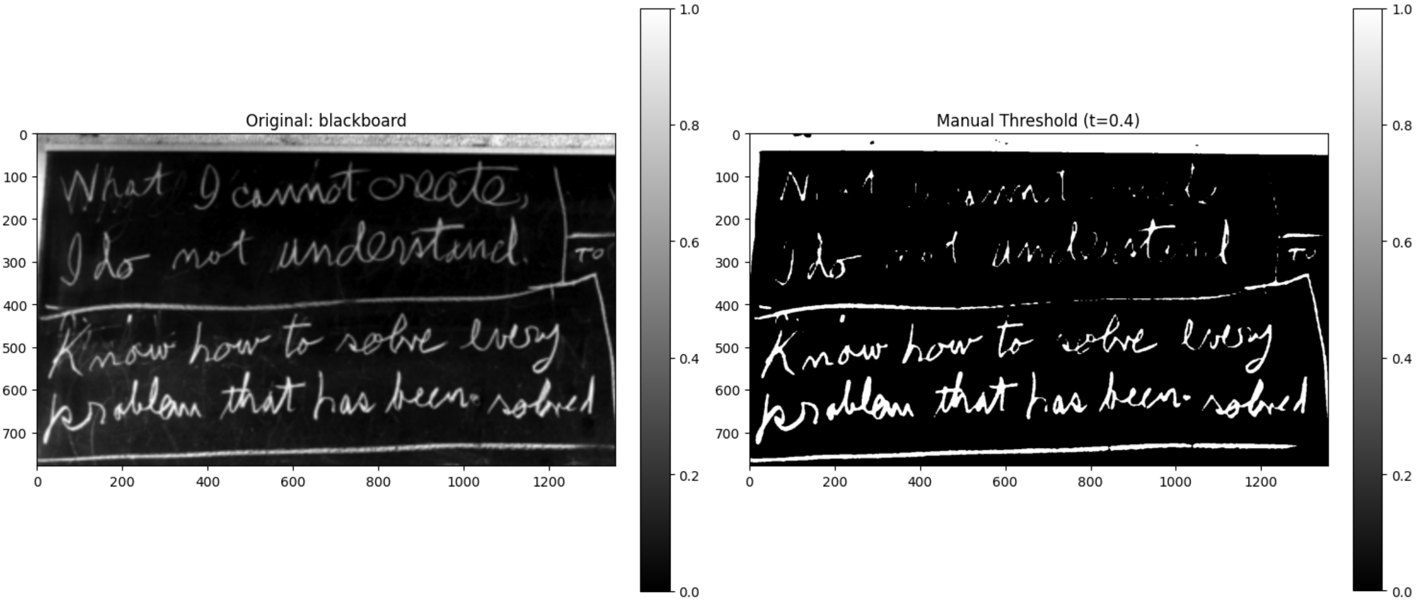

Figure 10: Comparison of Original vs Manual Threshold Image – Blackboard

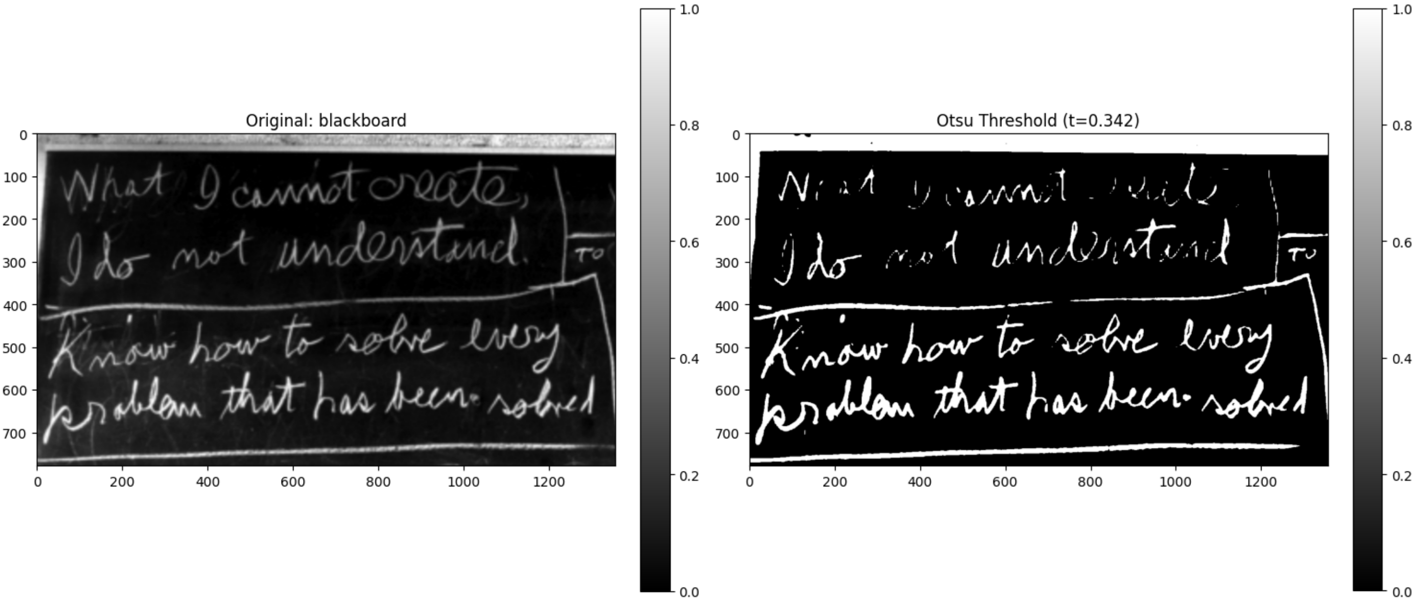

Figure 11: Comparison of Original vs Otsu Threshold Image – Blackboard

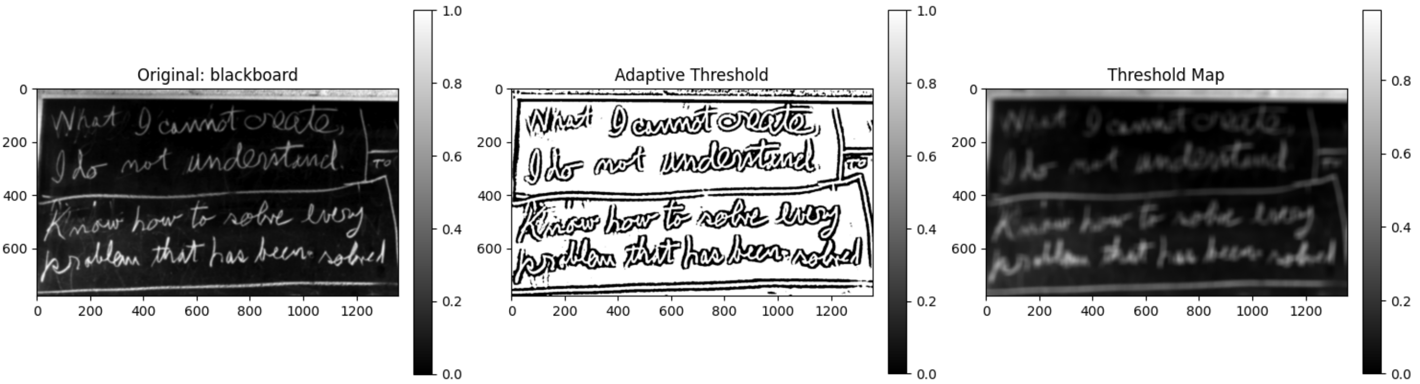

Figure 12: Comparison of Original vs Adaptive Threshold Image – Blackboard

For Lilavati image,
Manual Thresholding: Relies on a single global threshold, which is ineffective for this manuscript because the paper has stains, faded ink, and uneven illumination. A fixed threshold either loses faint text or wrongly classifies background noise as text.
Otsu's Thresholding: Automatically selects a global threshold based on histogram analysis. However, since the manuscript contains multiple intensity levels (dark strokes, faint strokes, stains, and paper texture), the histogram is not clearly bimodal. This leads to misclassification of stains and loss of weak writing.
Adaptive Thresholding: Calculates thresholds locally, making it more robust to background variations and faded ink. It preserves fine details of the script and reduces the effect of stains and uneven shading, making it the most effective method for this historical document.

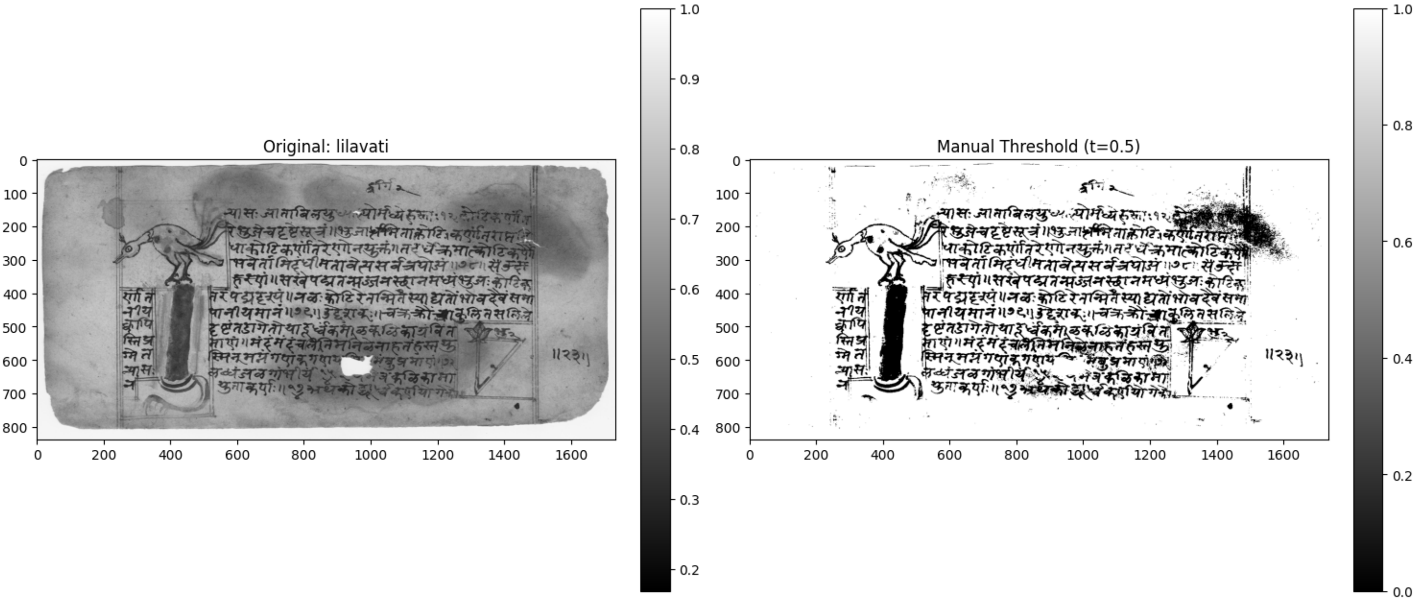

Figure 13: Comparison of Original vs Manual Threshold Image – Lilavati

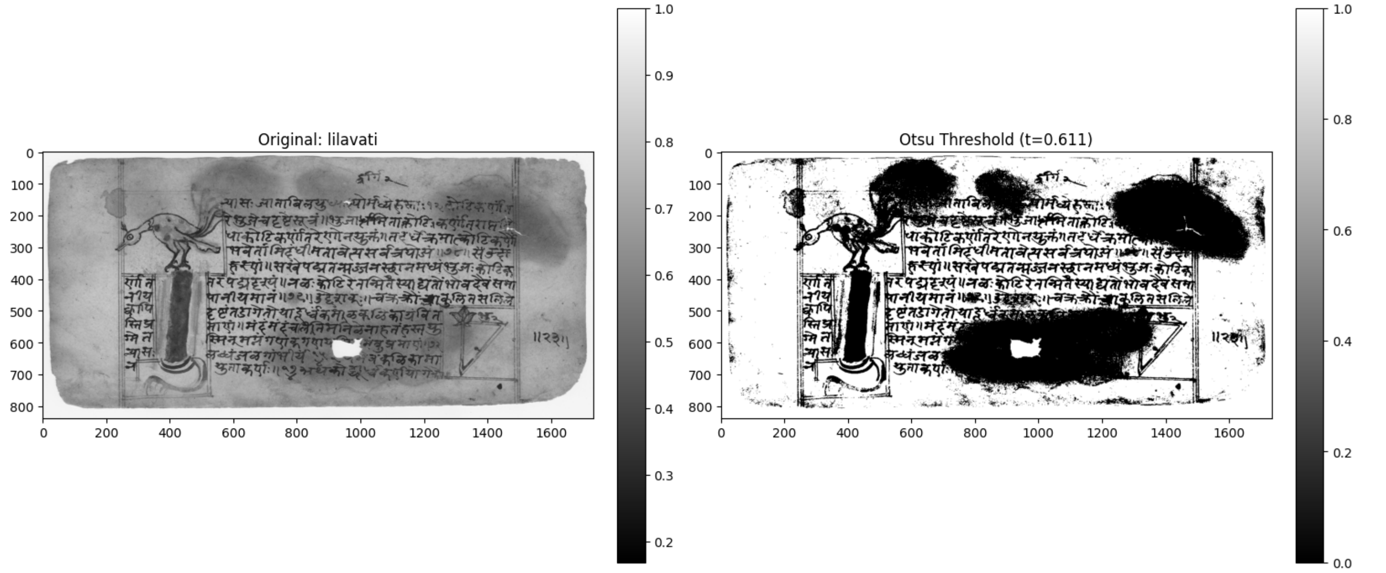

Figure 14: Comparison of Original vs Otsu Threshold Image – Lilavati

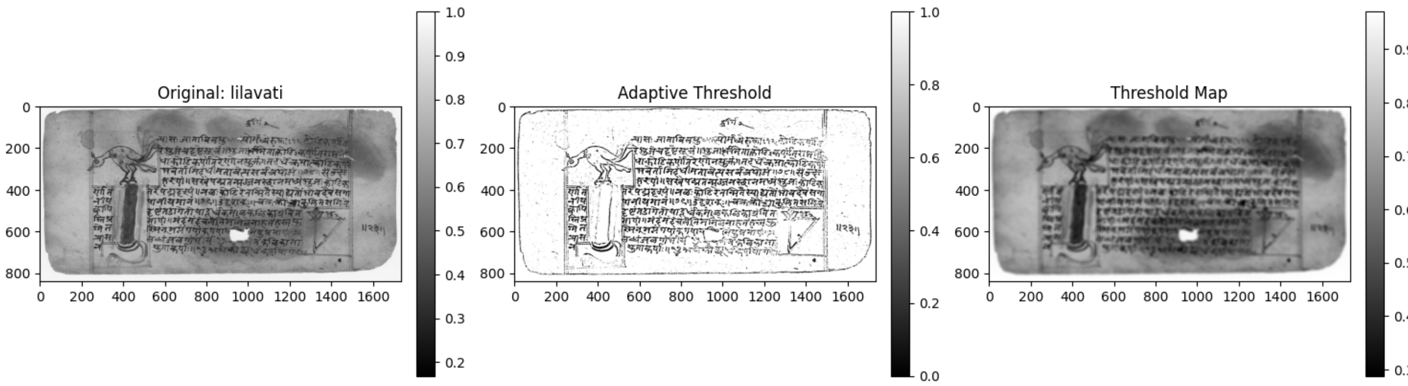

Figure 15: Comparison of Original vs Adaptive Threshold Image – Lilavati

For qr image,
Manual Thresholding: Can work fairly well because the QR code has high contrast (black modules on a white background). However, due to uneven illumination and shading, a single threshold may cause parts of the code to blur or vanish, reducing scan accuracy.
Otsu's Thresholding: Performs well since the image is close to bimodal (black QR patterns vs white background). Otsu can automatically separate the two classes effectively, but uneven lighting in the top-left may still introduce some errors.
Adaptive Thresholding: Best suited, as it adjusts locally to brightness variations. It ensures all parts of the QR code are binarized correctly despite shading, preserving readability and scannability.

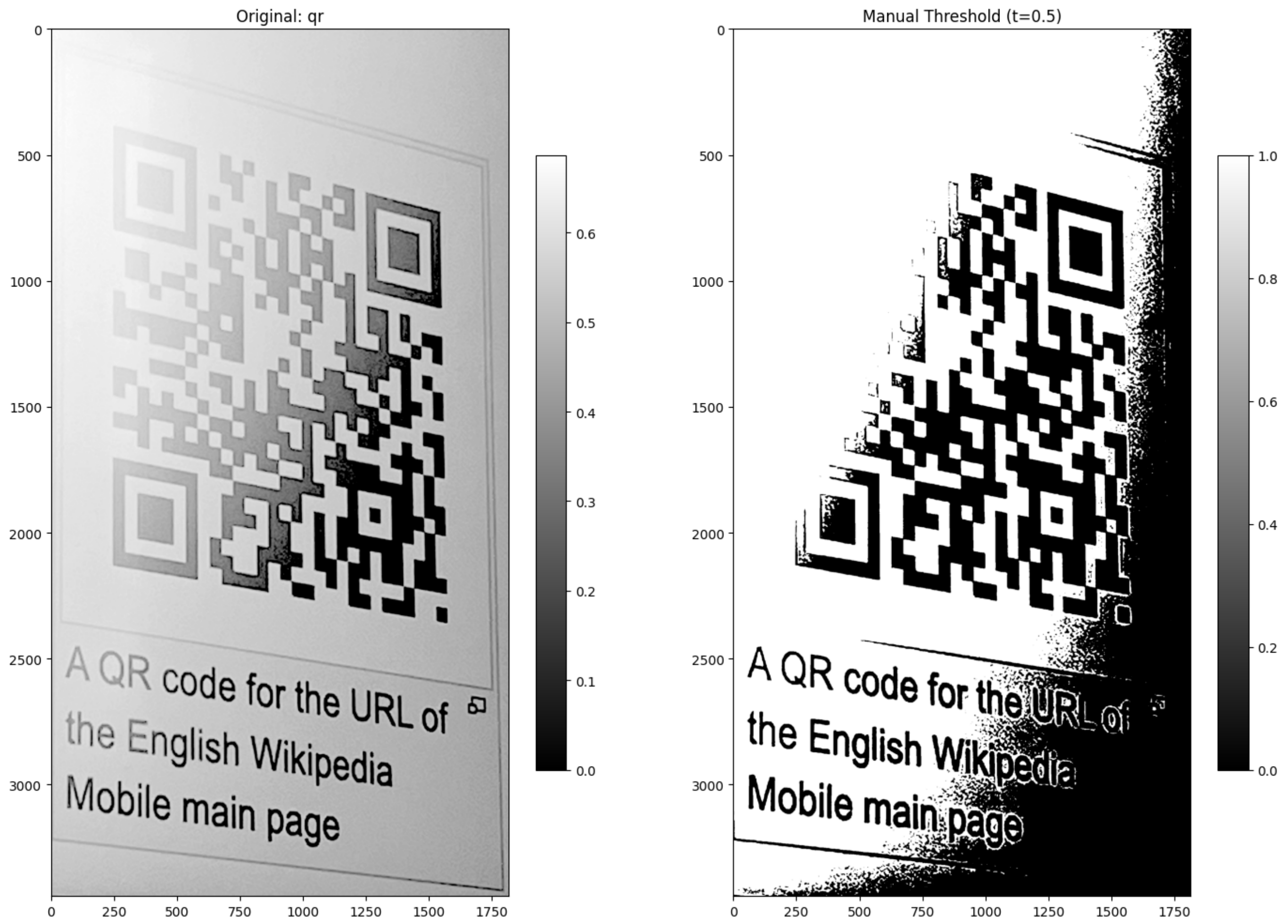

Figure 16: Comparison of Original vs Manual Threshold Image – QR

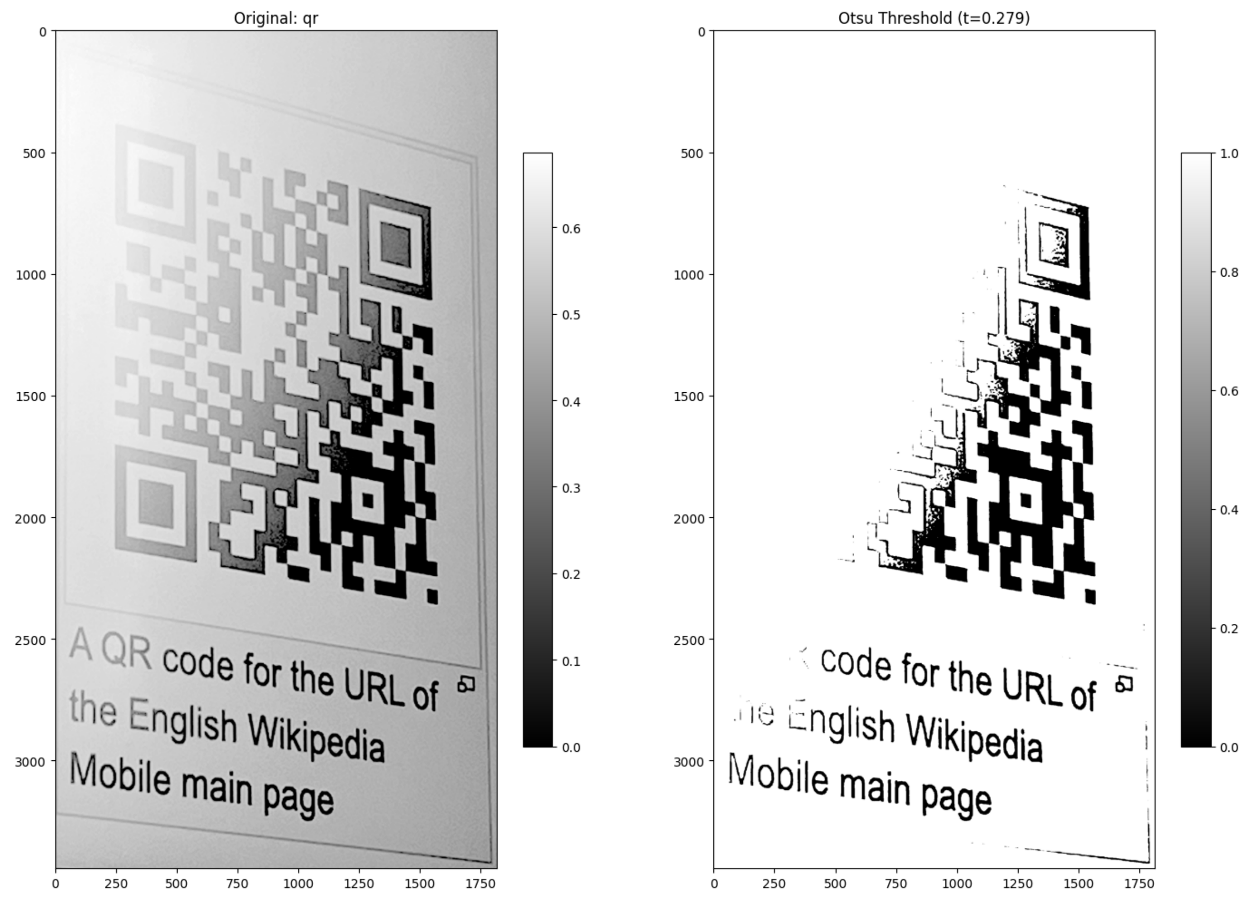

Figure 17: Comparison of Original vs Otsu Threshold Image – QR

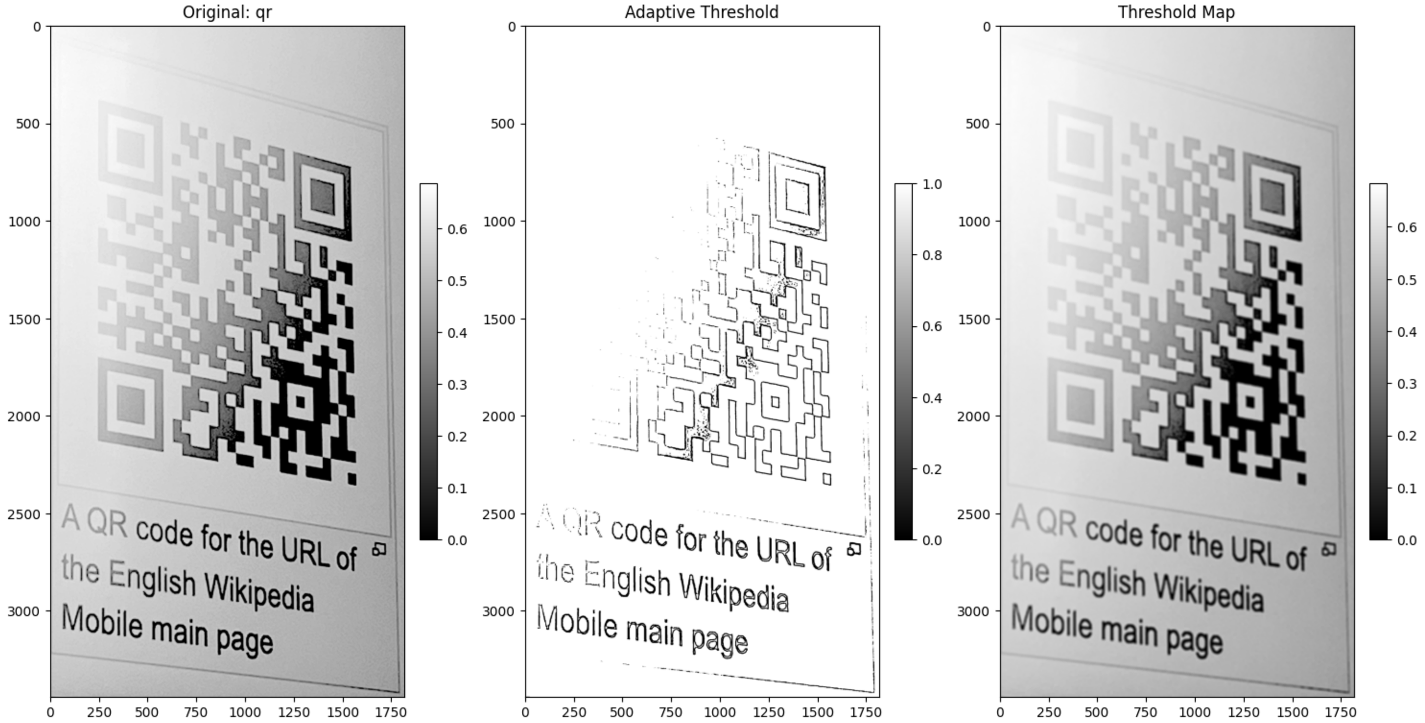

Figure 18: Comparison of Original vs Adaptive Threshold Image – QR

3. Contrast Enhancement

3.a

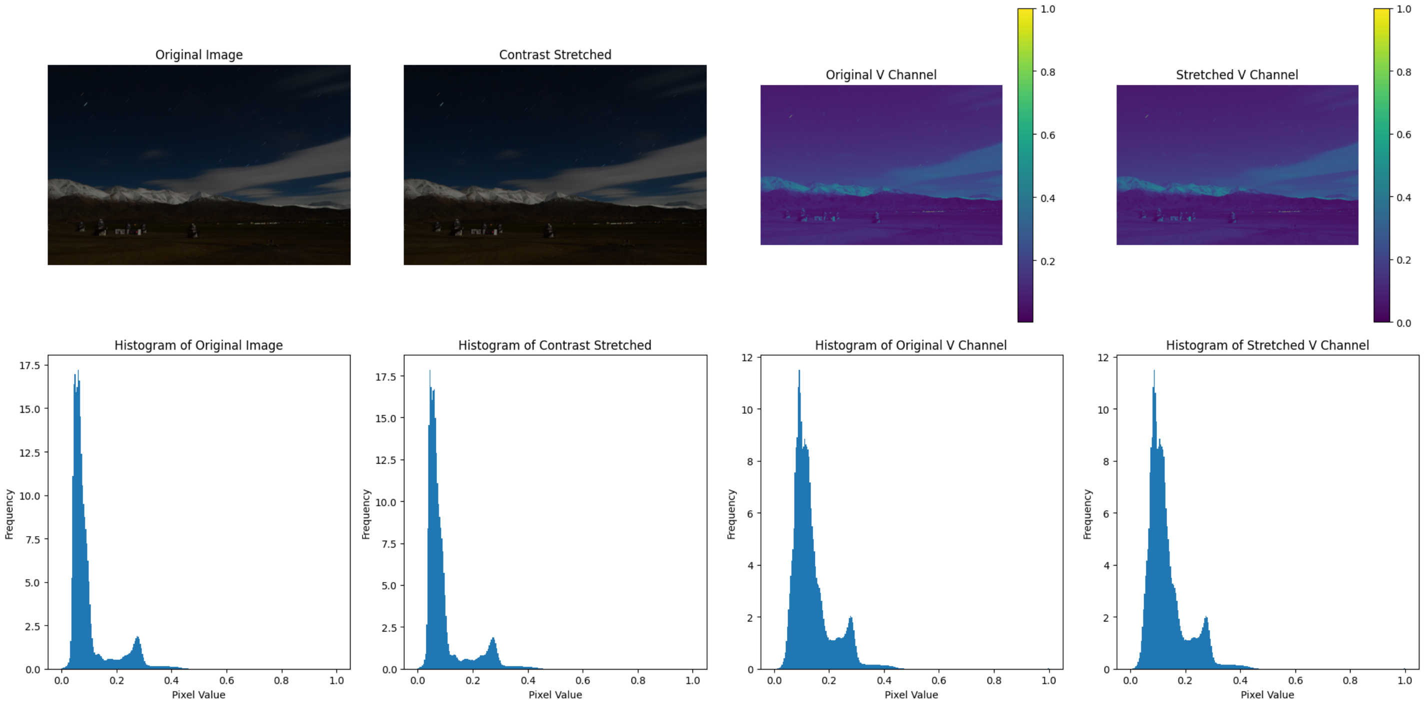

Figure 19: Linear Contrast Enhancement

3.b

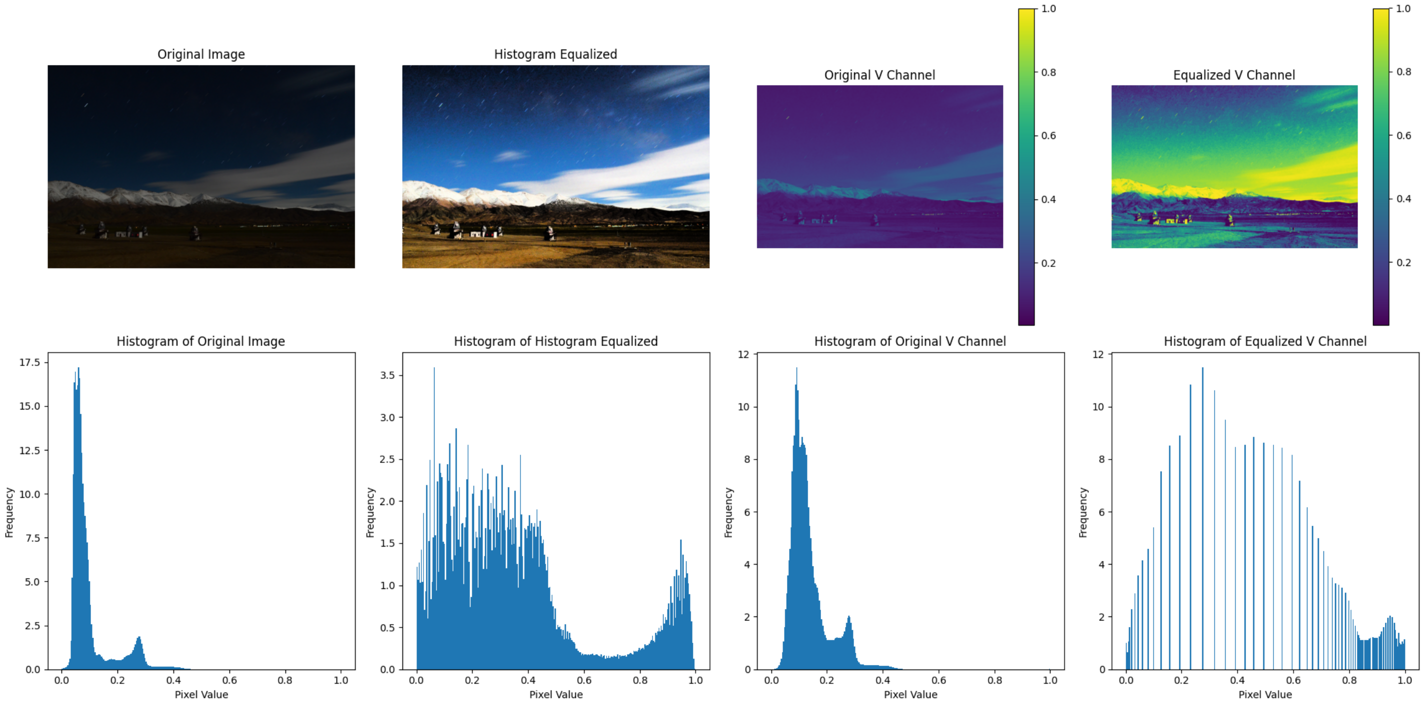

Figure 21: Histogram Equalisation Contrast Enhancement

3.c

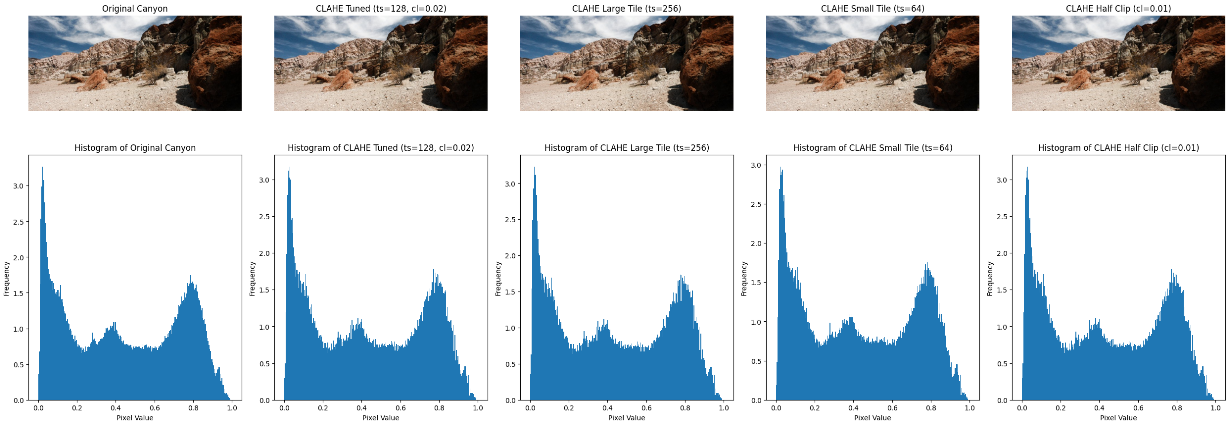

Figure 23: CLAHE Comparison: Canyon

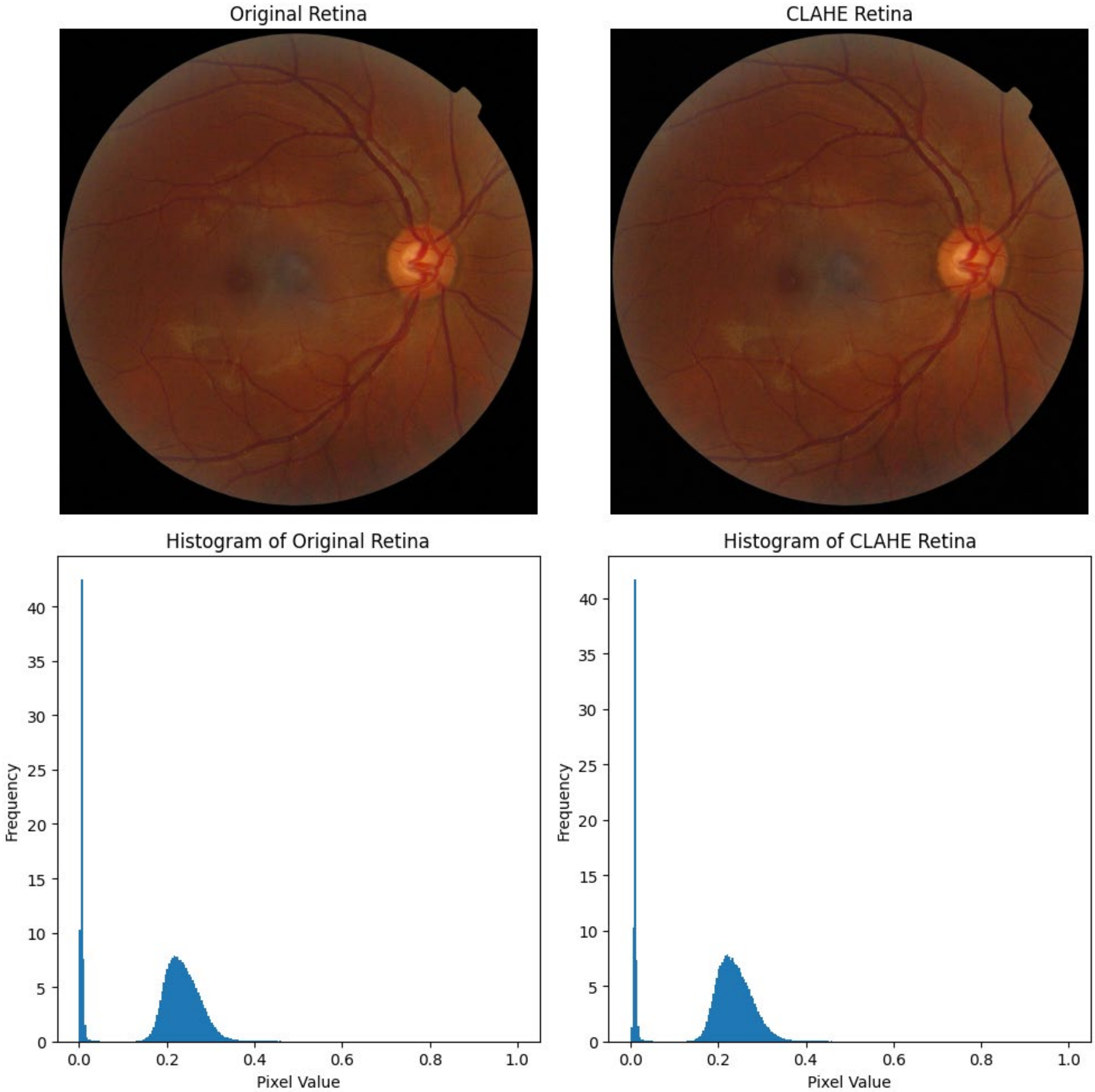

Figure 24: CLAHE Comparison: Retina

3.d

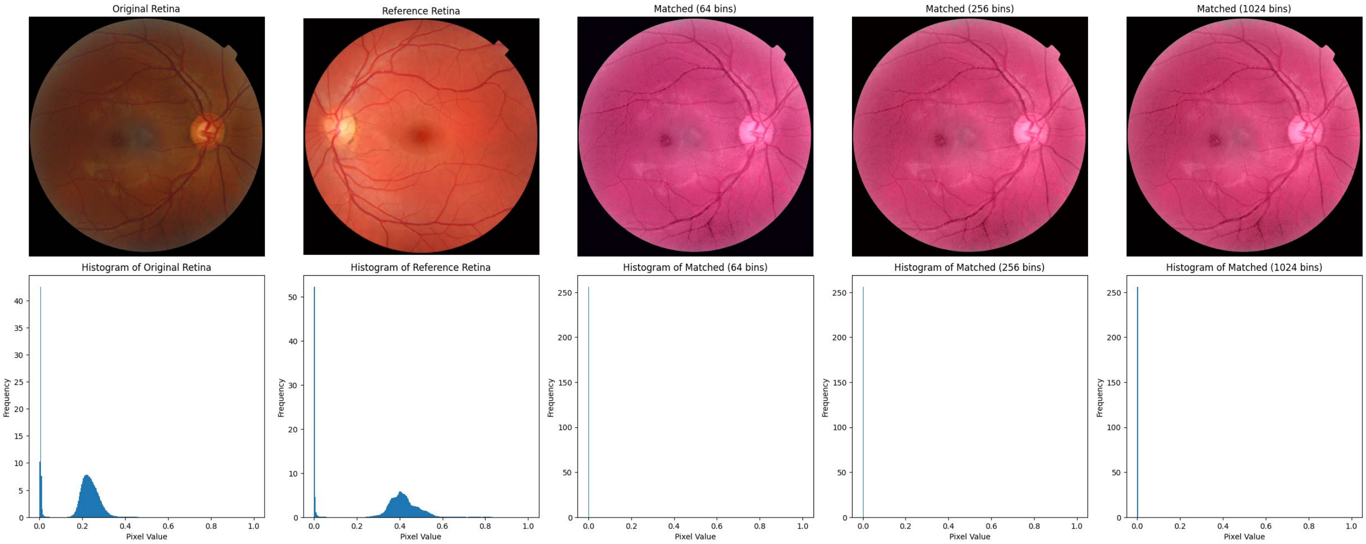

Figure 25: Histogram Matching