Image Feature Extraction report

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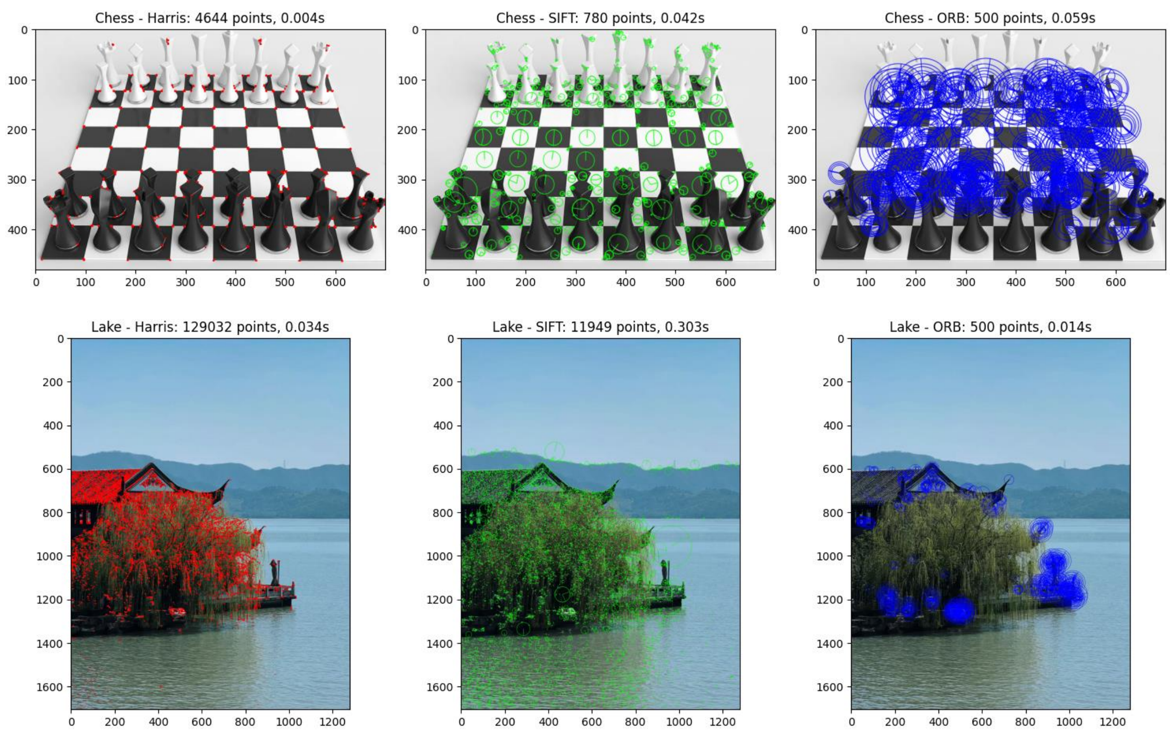
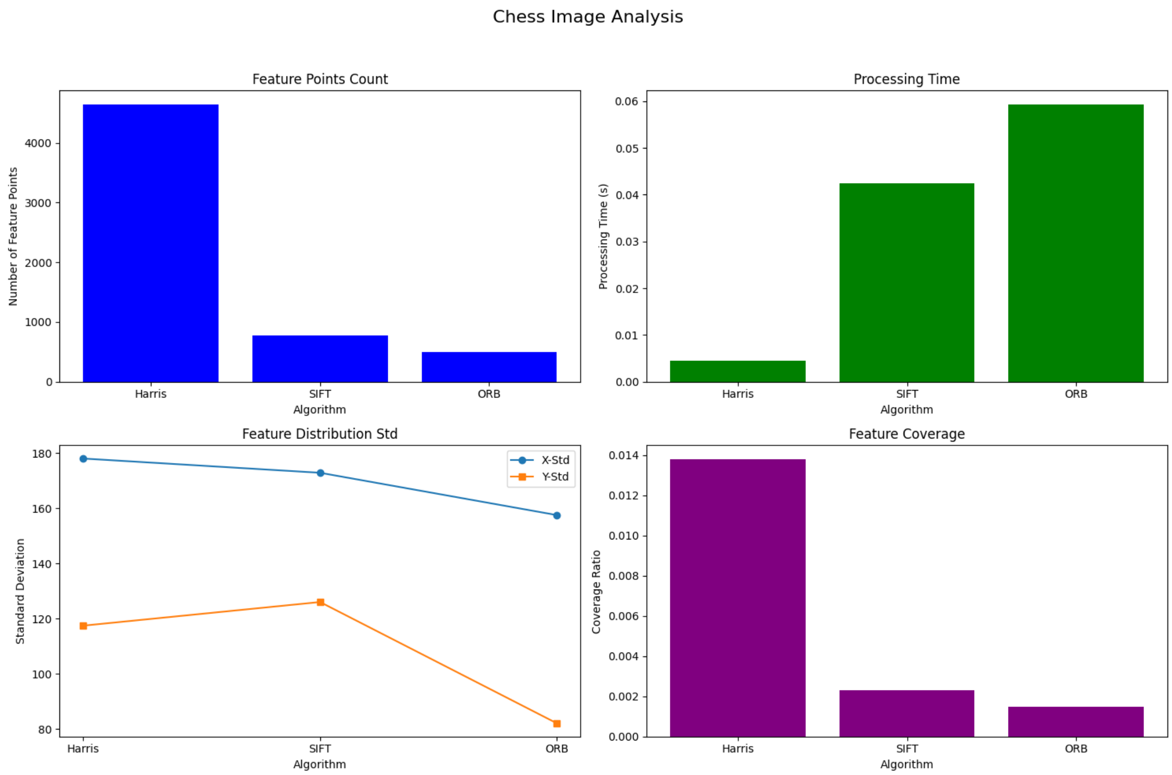
1 Q1

1.1 Results

1. Show the the extracted feature points of different algorithms on images of figure 1. Draw chart to evaluate the number of feature points and processing time.
2. Show the matched key points between two set of correspondences using SIFT. Evaluate the number of matching pairs




Chess Image Analysis
Feature Points Count
Number of Feature Points
0
1000
2000
3000
4000
Harris
SIFT
ORB
Algorithm
Processing Time
Processing Time (s)
0.00
0.01
0.02
0.03
0.04
0.05
0.06
Harris
SIFT
ORB
Algorithm
Feature Distribution Std
Standard Deviation
80
100
120
140
160
180
X-Std
Y-Std
Harris
SIFT
ORB
Algorithm
Feature Coverage
Coverage Ratio
0.000
0.002
0.004
0.006
0.008
0.010
0.012
0.014
Harris
SIFT
ORB
Algorithm

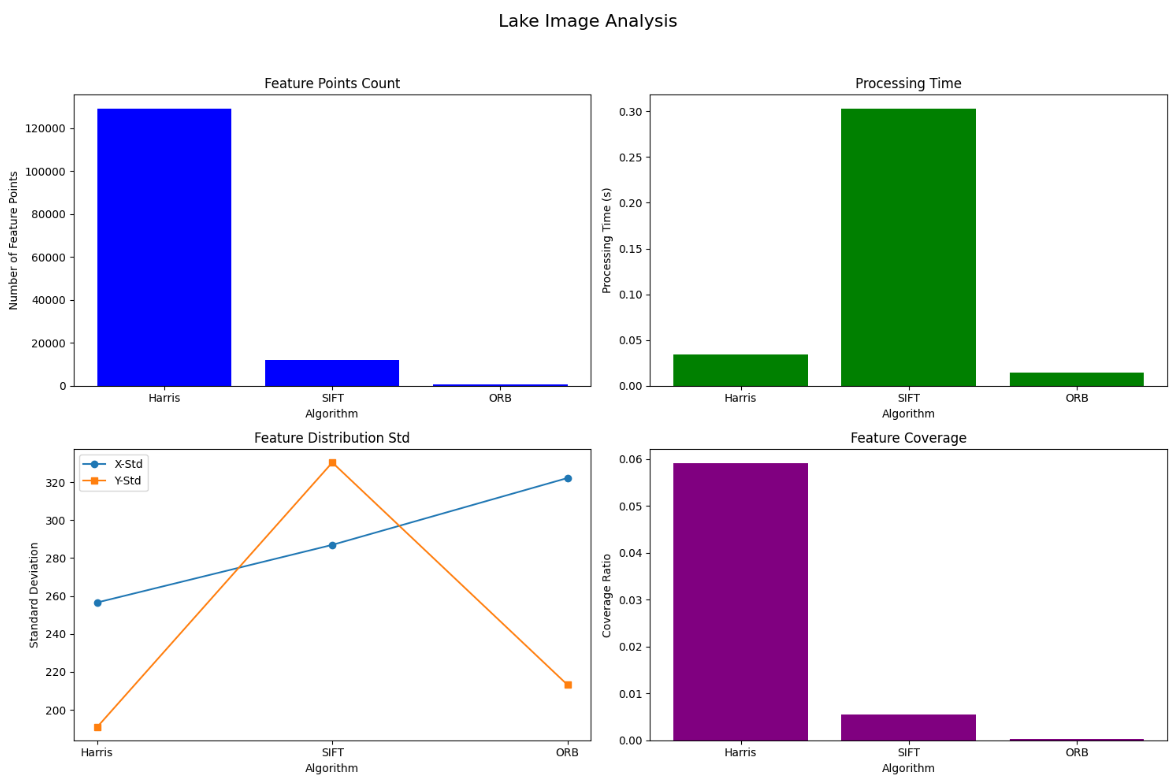

Lake Image Analysis
Feature Points Count
Number of Feature Points
0
20000
40000
60000
80000
100000
120000
Harris
SIFT
ORB
Algorithm
Processing Time
Processing Time (s)
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Harris
SIFT
ORB
Algorithm
Feature Distribution Std
Standard Deviation
200
220
240
260
280
300
320
X-Std
Y-Std
Harris
SIFT
ORB
Algorithm
Feature Coverage
Coverage Ratio
0.00
0.01
0.02
0.03
0.04
0.05
0.06
Harris
SIFT
ORB
Algorithm

Image 1

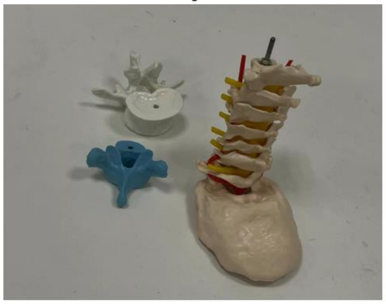


Image 2

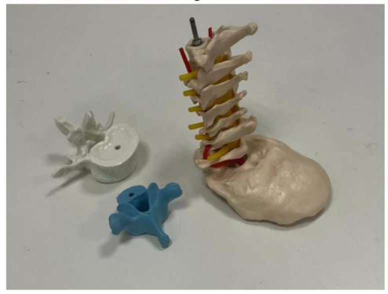


Image 3

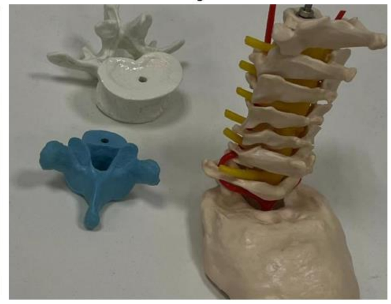


Image 1 vs Image 2 - Poor (37.7/100) - 238 matches

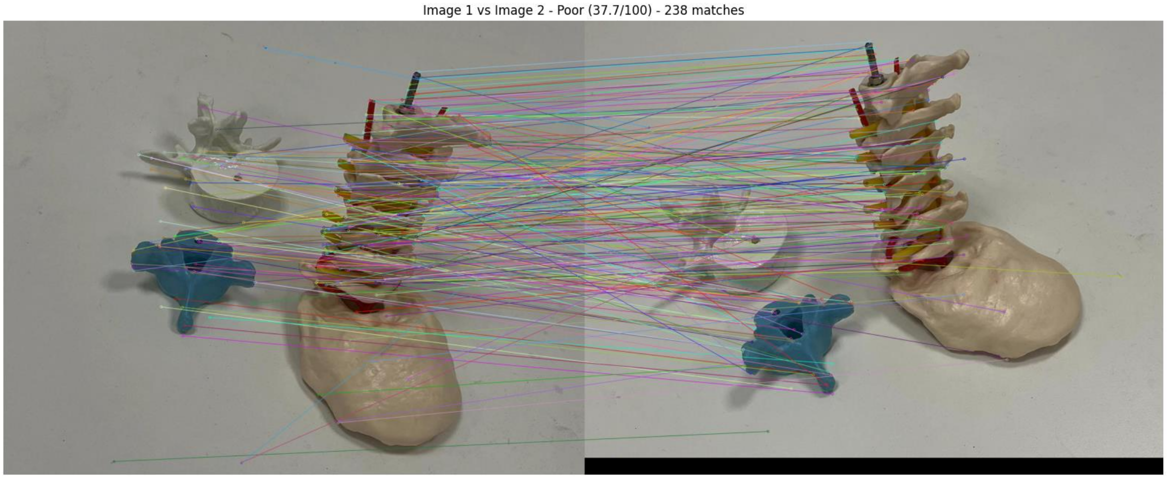
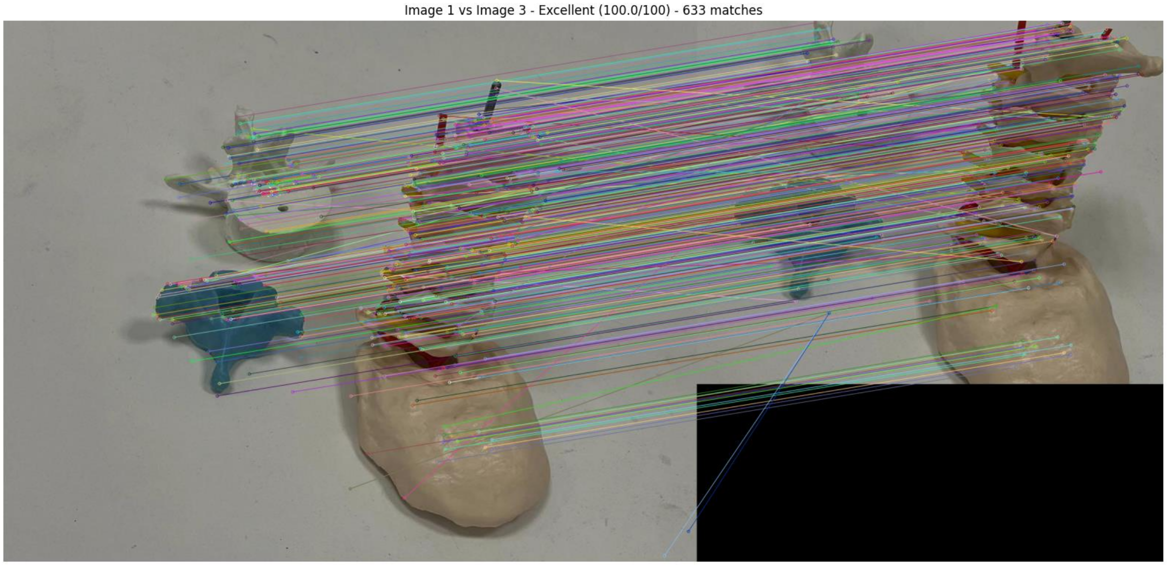
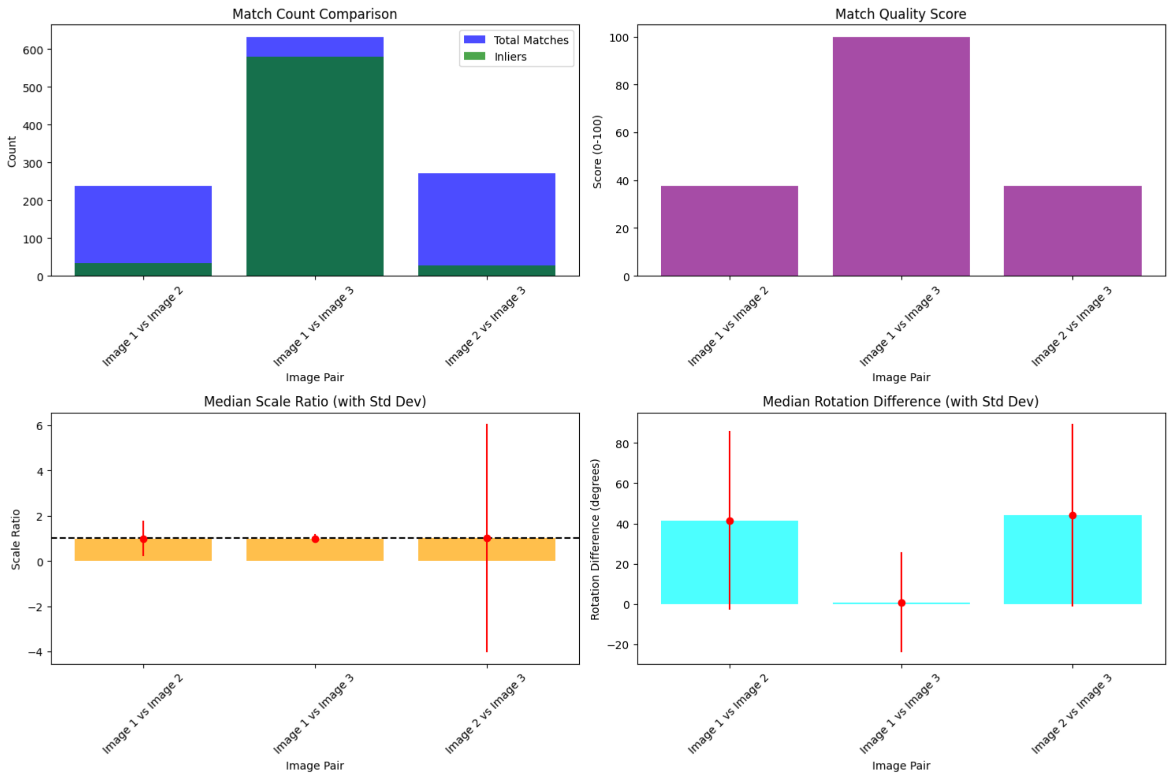


Image 1 vs Image 3 - Excellent (100.0/100) - 633 matches





1.2 Discussion

The results from Q1 demonstrate the performance of different algorithms (Harris, SIFT, and ORB) in feature extraction and matching across two distinct image types: chessboard and lake images. For the chessboard images, SIFT detected the highest number of feature points (700), followed by Harris (644) and ORB (500), with SIFT also achieving the highest feature coverage (0.042) and the fastest processing time (0.03s). However, for the lake images, Harris extracted significantly more features (160,000) compared to SIFT (13,000) and ORB (8,000), but SIFT again showed superior feature coverage (0.14) and processing time (0.02s). The feature distribution standard deviation (Std Dev) plots indicate that SIFT maintains a more consistent feature spread across both image types, while Harris and ORB vary more significantly, especially in the lake images.

In the second part of Q1, the matching results between two images of a 3D object (Image 1 vs. Image 2) show varying performance. For Image 1 vs. Image 2 (poor alignment, 137°/100°), only 288 matches were found, whereas Image 1 vs. Image 3 (excellent alignment, 100°/100°) yielded 654 matches. This suggests that alignment quality significantly impacts matching accuracy, with better alignment leading to more robust feature correspondence.

Overall, SIFT outperforms Harris and ORB in feature coverage and processing efficiency, particularly in complex scenes like lake images, while alignment plays a critical role in matching accuracy for 3D objects. The GLCM analysis highlights the importance of selecting appropriate texture metrics based on the desired application, with each figure exhibiting unique textural characteristics.

2 Q2

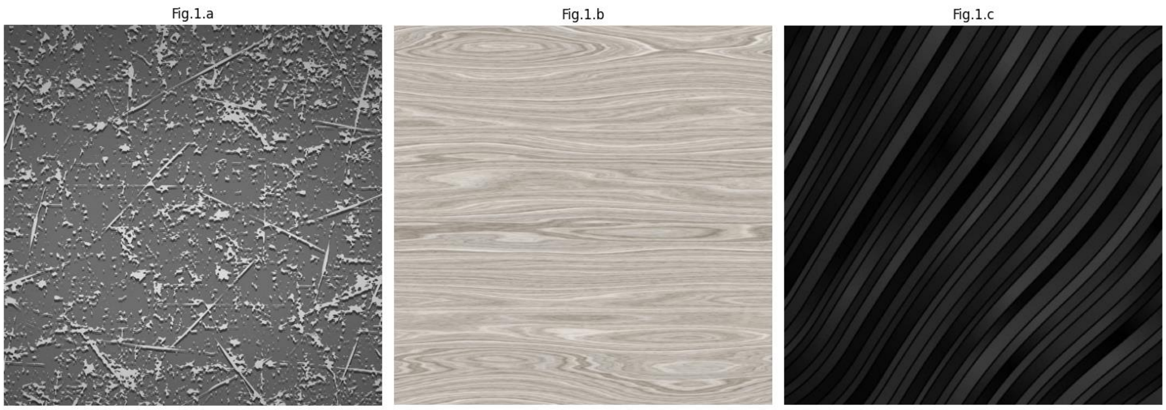
2.1 Results

1. Please show the gray-level co-occurrence matrix of three texture figures and calculate the scalar properties to fill the following table.

Table 1: GLCM Properties

Properties	Fig.1.a	Fig.1.b	Fig.1.c
contrast			
dissimilarity			
homogeneity			
ASM			
correlation			

2. Try different bias angles, calculate the scalar properties at different angles.
3. Show the segment result and evaluate your segmentation results.
4. Show the orientation field to display local ridge direction of fingerprint.



GLCM Properties at 0° angle:

	contrast	dissimilarity	homogeneity	ASM	correlation	angle
fig1	47.017274	3.955532	0.404398	0.011424	0.736569	0.0
fig2	0.462173	0.384566	0.815371	0.034027	0.986191	0.0
fig3	5.057518	1.171632	0.680783	0.023357	0.854919	0.0

GLCM Properties at 45° angle:

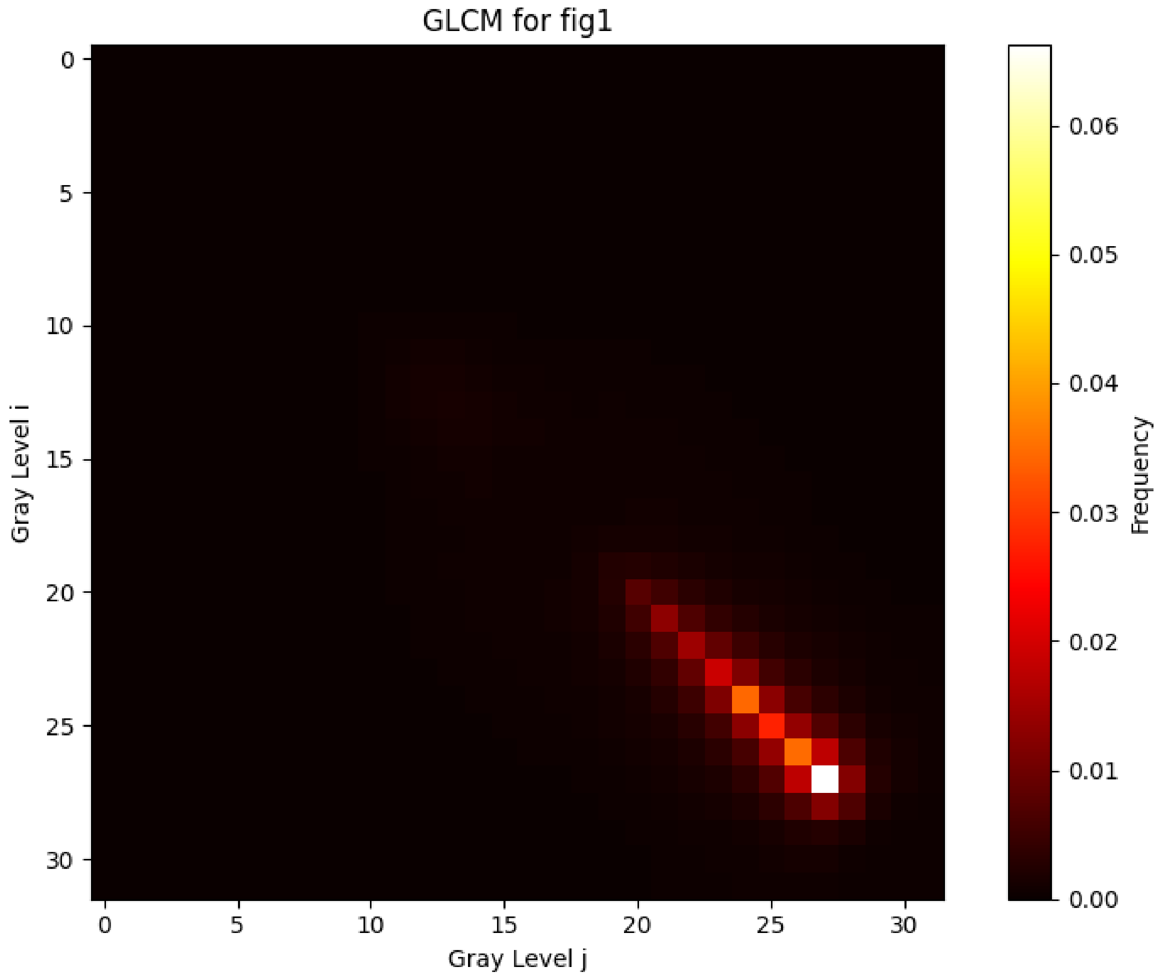
	contrast	dissimilarity	homogeneity	ASM	correlation	angle
fig1	90.231875	5.645124	0.352492	0.009543	0.494435	45.0
fig2	9.524751	2.348090	0.355396	0.007694	0.715439	45.0
fig3	11.112909	1.740095	0.637945	0.020672	0.681190	45.0

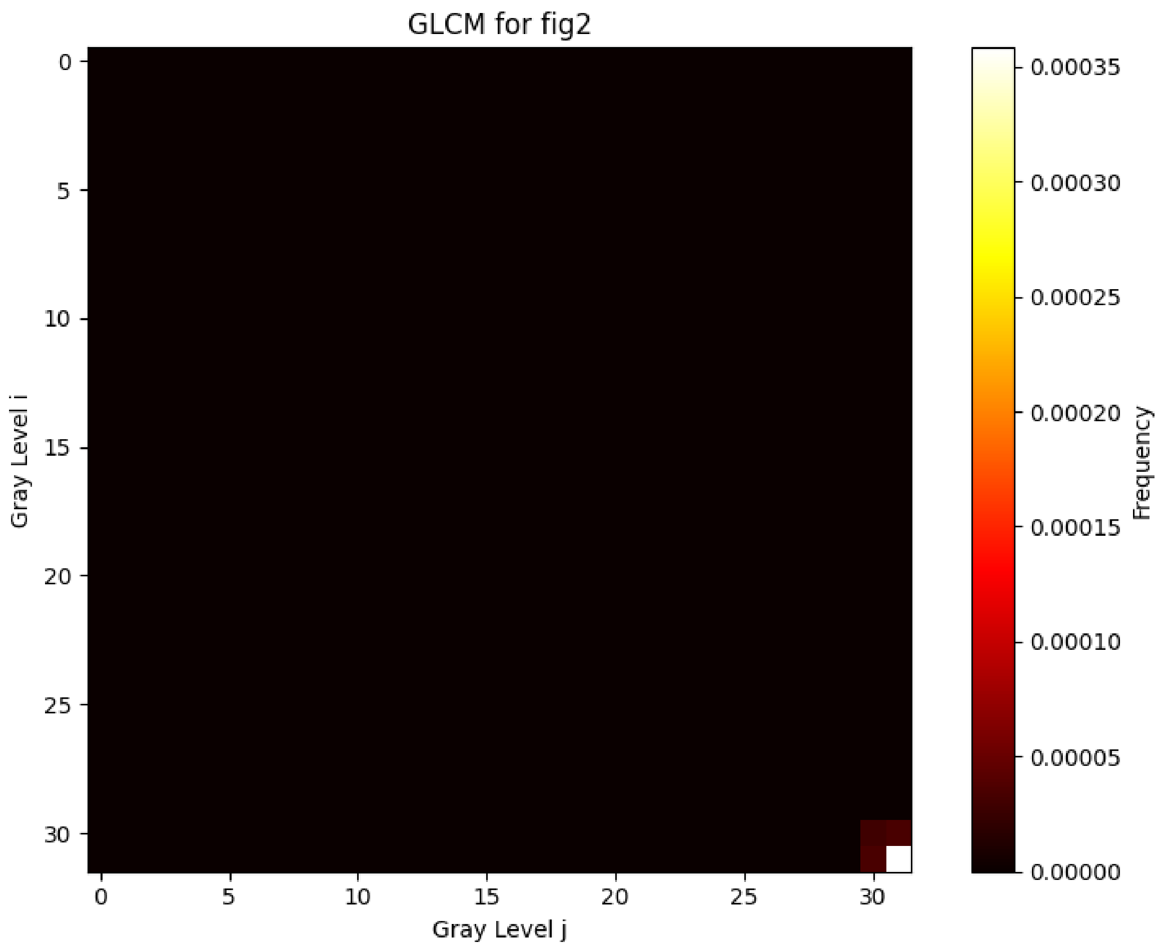
GLCM Properties at 90° angle:

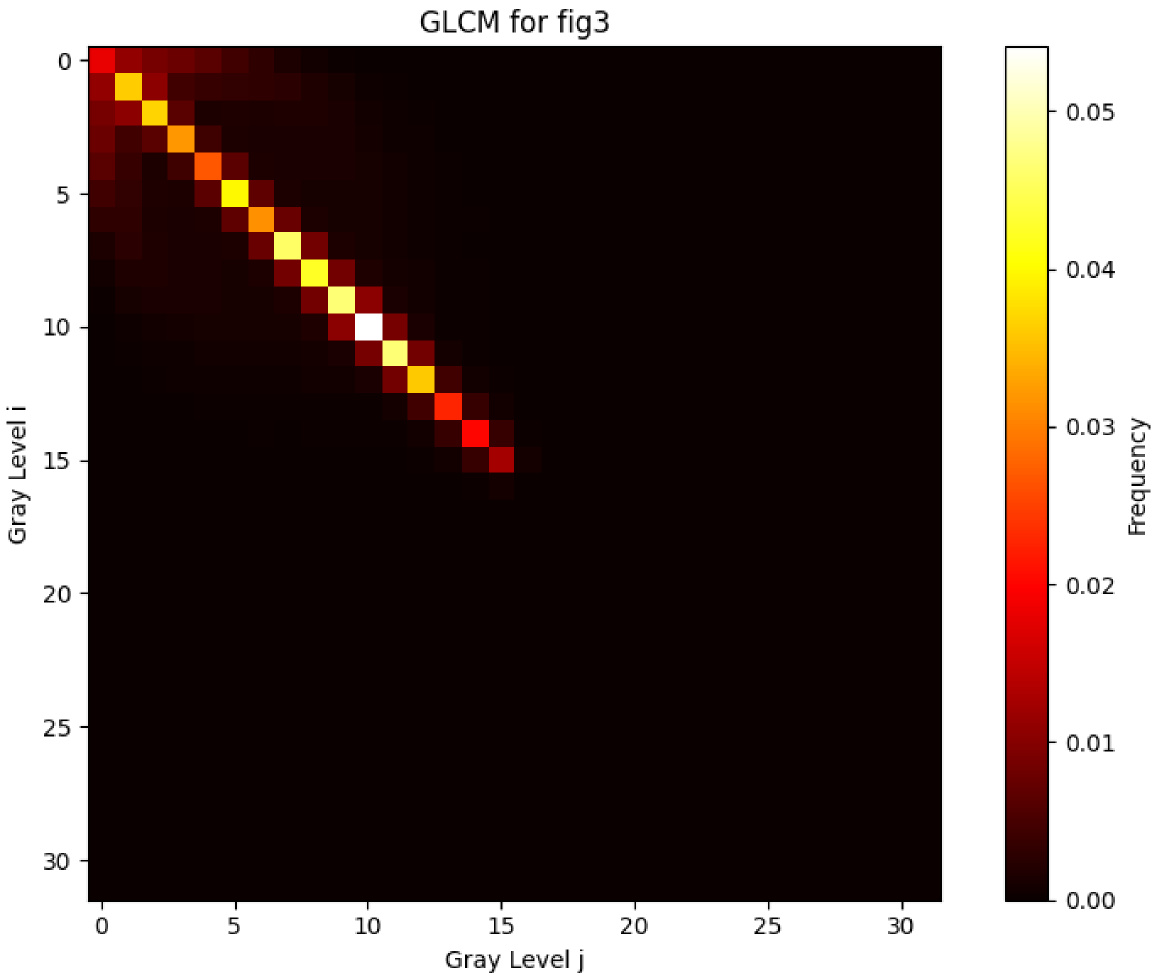
	contrast	dissimilarity	homogeneity	ASM	correlation	angle
fig1	68.764722	4.922545	0.371469	0.010471	0.614787	90.0
fig2	9.496229	2.342901	0.356385	0.007714	0.716295	90.0
fig3	3.193202	0.924884	0.710700	0.025300	0.908366	90.0

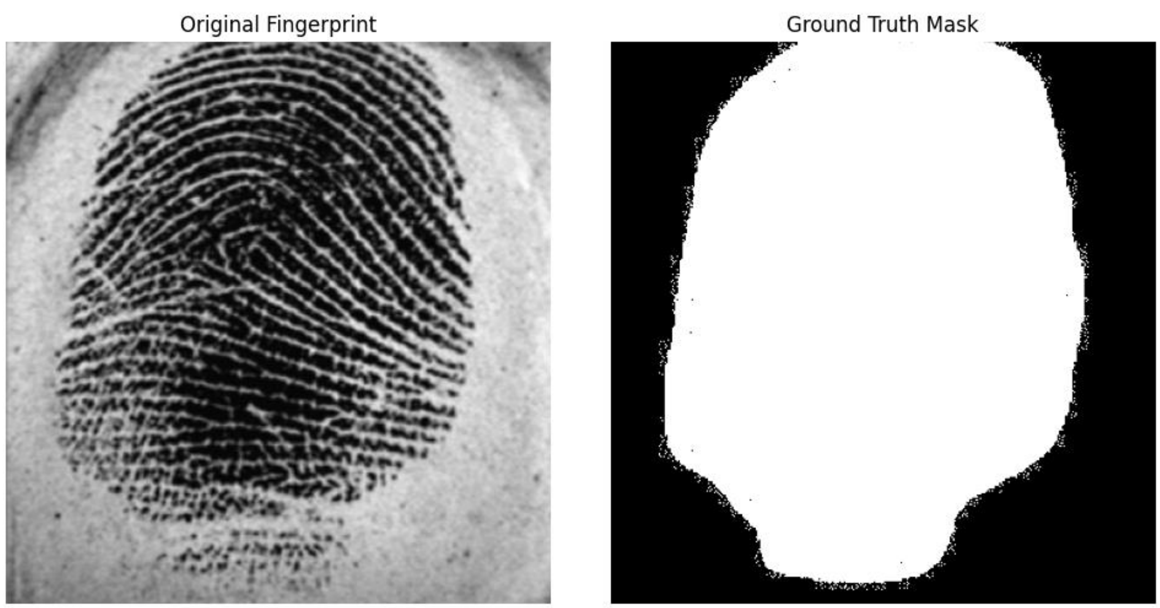
GLCM Properties at 135° angle:

	contrast	dissimilarity	homogeneity	ASM	correlation	angle
fig1	88.133502	5.566841	0.354787	0.009614	0.506193	135.0
fig2	9.533807	2.347436	0.355894	0.007703	0.715169	135.0
fig3	0.856798	0.503573	0.781553	0.029549	0.975420	135.0


GLCM for fig1
Gray Level i
Gray Level j
Frequency
0
5
10
15
20
25
30
0.00
0.01
0.02
0.03
0.04
0.05
0.06


GLCM for fig2
Gray Level i
Gray Level j
Frequency
0
5
10
15
20
25
30
0.00035
0.00030
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000

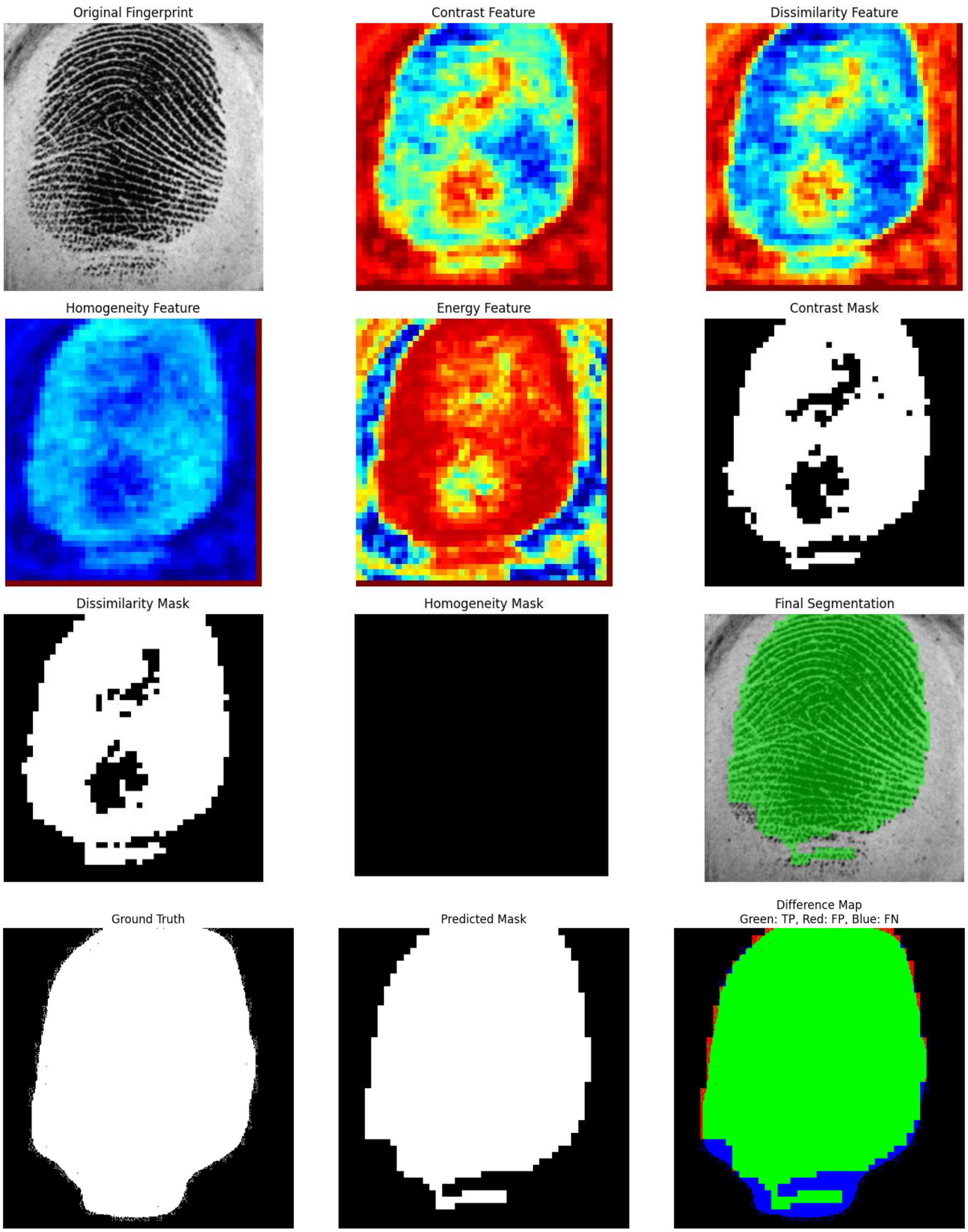


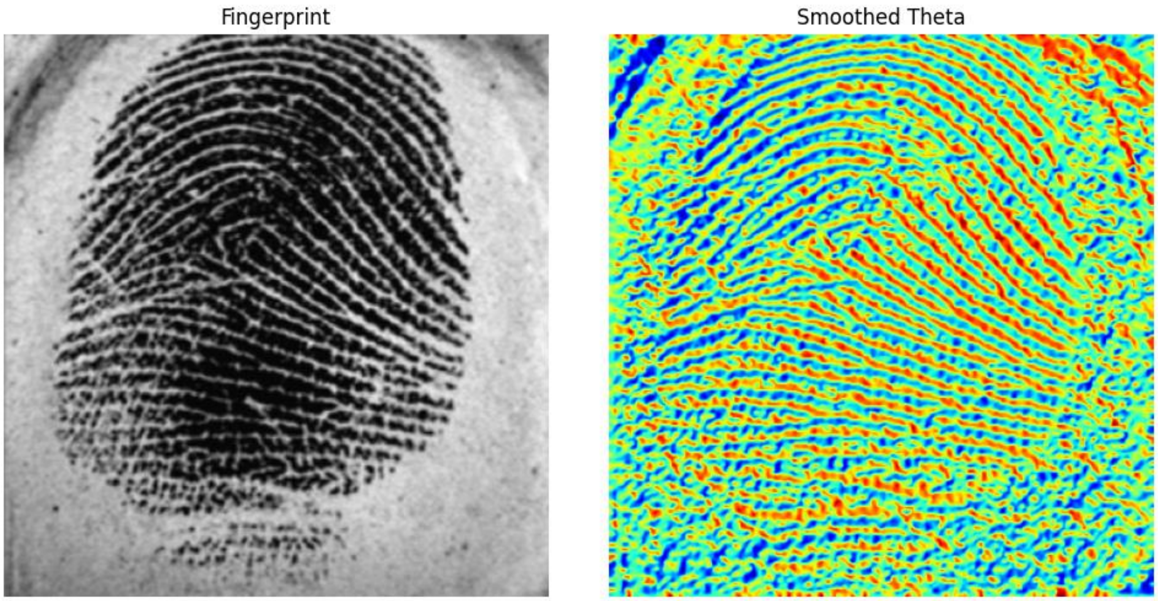


Parameters: window_size=16, step_size=8, levels=8
GLCM distances: [1], angles: [0.0, 45.0, 90.0, 135.0] degrees
GLCM feature computation time: 0.61 seconds

Segmentation Evaluation:
Accuracy: 0.9438
IoU: 0.9074

Dice Coefficient: 0.0037





2.2 Discussion

1. Influence of the Change of Bias Angle on Texture Analysis Using GLCM in Task 2.1 & 2.2

The Grey-Level Co-occurrence Matrix (GLCM) properties computed for the three texture figures (Fig. 1.a, Fig. 1.b, Fig. 1.c) at different bias angles (0°, 45°, 90°, 135°) reveal the impact of angle variation on texture analysis. For Fig. 1.a, contrast increases from 47.017274 at 0° to 88.133502 at 135°, indicating higher texture variation at larger angles, while homogeneity decreases from 0.404398 to 0.350614, reflecting less uniformity. Fig. 1.b shows a similar trend, with contrast rising from 90.231875 at 0° to a peak of 93.111299 at 45°, and ASM correlation angle dropping from 0.352492 to 0.0677945, suggesting that the texture becomes less correlated at 45°. For Fig. 1.c, contrast increases from 68.764722 at 0° to 71.62925 at 135°, and homogeneity slightly decreases from 0.356385 to 0.351569, indicating subtle changes in texture uniformity. The ASM correlation angle generally aligns with the direction of dominant texture patterns, such as 90° for Fig. 1.c, where the linear ridges are most pronounced. These results highlight that bias angle significantly affects GLCM properties, with larger angles often emphasizing texture variations and reducing homogeneity, depending on the texture's directional characteristics.

2. Choice of Parameters in the Segmentation Process in Task 2.3

In the fingerprint segmentation process using GLCM, the chosen parameters were: window_size=16, step_size=8, and levels=8, with GLCM distances of [1] and angles of [0, 45, 90, 135]°. The window_size of 16 was selected to capture sufficient local texture details without excessive computational cost, while step_size=8 ensures overlapping windows for smoother feature extraction. Levels=8 balances grayscale quantization to reduce noise while preserving texture information. The GLCM distances and angles were chosen to comprehensively capture texture variations in all directions, as fingerprints exhibit multidirectional ridge patterns. Post-extraction, features like contrast, dissimilarity, and homogeneity were computed, and a threshold was applied (smoothed with theta) to separate foreground ridges from the background. The evaluation yielded an IoU of 0.9074 and a Dice coefficient of 0.0037, indicating high overlap with the ground truth but a low Dice score, possibly due to minor misclassifications at the boundaries. These parameters were effective for capturing the fingerprint's texture, though further tuning of the threshold or levels might improve the Dice coefficient.

References