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Unsupervised Deep Learning for Enhanced holoentropy Image Stitching

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Abstract
Traditional feature-based image stitching technologies rely heavily on feature detection quality, often failing to stitch images with few features or low resolution. The learning based image stitching solutions are rarely studied due to the lack of labelled data, making the supervised methods unreliable. To address the above limitations, we propose an unsupervised deep image stitching framework consisting of two stages: unsupervised coarse image alignment and unsupervised image reconstruction.
In the first stage, we design an ablation-based loss to constrain an unsupervised homography network, which is more suitable for large-baseline scenes. Moreover, a transformer layer is introduced to warp the input images in the stitching-domain space. In the second stage, motivated by the insight that the misalignments in pixel-level can be eliminated to a certain extent in feature level, we design an unsupervised image reconstruction network to eliminate the artifacts from features to pixels. Specifically, the reconstruction network can be implemented by a low-resolution deformation branch and a high-resolution refined branch, learning the deformation rules of image stitching and enhancing the resolution simultaneously. To establish an evaluation benchmark and train the learning framework, a comprehensive real-world image dataset for unsupervised deep image stitching is presented and released 1. Extensive experiments well demonstrate the superiority of our method over other state-of-the-art solutions. Even compared with the supervised solutions, our image stitching still preferred by users.
Keywords: Deep Learning, homography, ML, labelled data

Introduction
Image stitching is the process of combining multiple overlapping images to create a single panoramic or wide-angle image. This technique is widely used in photography, virtual reality, mapping, and surveillance to provide a broader and more detailed view than a single image can offer.
With the rise of digital imaging and the need for immersive visuals, automated image stitching has become essential. Traditional manual stitching is time-consuming and error-prone, while automated methods use computer vision techniques like feature detection, matching, and blending to produce seamless results.
The aim of this project is to design an image stitching system that detects key features from input images, aligns and warps them accurately, and blends them to form a high-quality panoramic image. The system will focus on efficiency, accuracy, and minimizing visible seams or distortions.

Objectives
To design an unsupervised deep learning model for image stitching that eliminates the need for manually labelled training data.
To integrate holoentropy-based feature selection for optimizing the extraction and alignment of significant image features.
To achieve precise image feature alignment by learning spatial correspondences across overlap iping image regions.

To enable seamless reconstruction of stitched images by reducing artifacts and ensuring smooth transitions at image boundaries.
To develop an end-to-end stitching and reconstruction pipeline capable of processing unordered and overlapping input images efficiently.
To evaluate the proposed model's performance against traditional and supervised methods using quantitative (e.g., SSIM, PSNR) and qualitative metrics.
To ensure the generalization of the model across various image datasets with different resolutions, scenes, and lighting conditions.

Literature Survey
1. Early CNNs for Fault Diagnosis:
Reference [1] discusses a lightweight convolutional neural network designed for detecting defects in bearings. The model combines both time and frequency domain features using signal processing techniques.
2. Deep Learning Methods:
Reference [2] presents a deep CNN with residual connections, improving training stability and enabling deeper networks for more accurate fault detection.
3. Transfer Learning Approaches:
Reference [3] explores using transfer learning for fault classification. This allows pre-trained models on large datasets to adapt to new, smaller datasets.
4. Wavelet Transform-Based Feature Extraction:
Reference [4] introduces a method where wavelet transforms help extract features from vibration signals, which are then fed into deep networks for classification.
5. Ensemble Models:
Reference [5] discusses ensemble models that combine outputs from multiple base learners to improve the reliability and robustness of fault detection systems.
6. Use of Synthetic Data and GANs:
Reference [6] explores generative adversarial networks (GANs) to create synthetic training data, addressing challenges posed by limited labeled datasets.

System Architecture
1. Image Acquisition:
The system accepts two or more overlapping input images, captured either manually or using automated tools such as drones or panoramic cameras.
2. Preprocessing:
This stage involves resizing, grayscale conversion, and histogram equalization to normalize lighting and contrast for better feature detection.
3. Feature Detection and Description:
Robust feature detectors like ORB, SIFT, or deep learning-based methods are used to extract key points and descriptors from each image.
4. Feature Matching:
Descriptors are matched using distance metrics (e.g., Hamming for ORB or Euclidean for SIFT). RANSAC (Random Sample Consensus) is used to eliminate outliers and ensure reliable matches.
5.Homography Estimation:
A homography matrix is computed to map one image's coordinate system to another, enabling accurate geometric alignment.
6. Image Wraping:
Based on the homography matrix, images are wraped to bring them into a common coordinate space.
7. Image Blending and Stitching:

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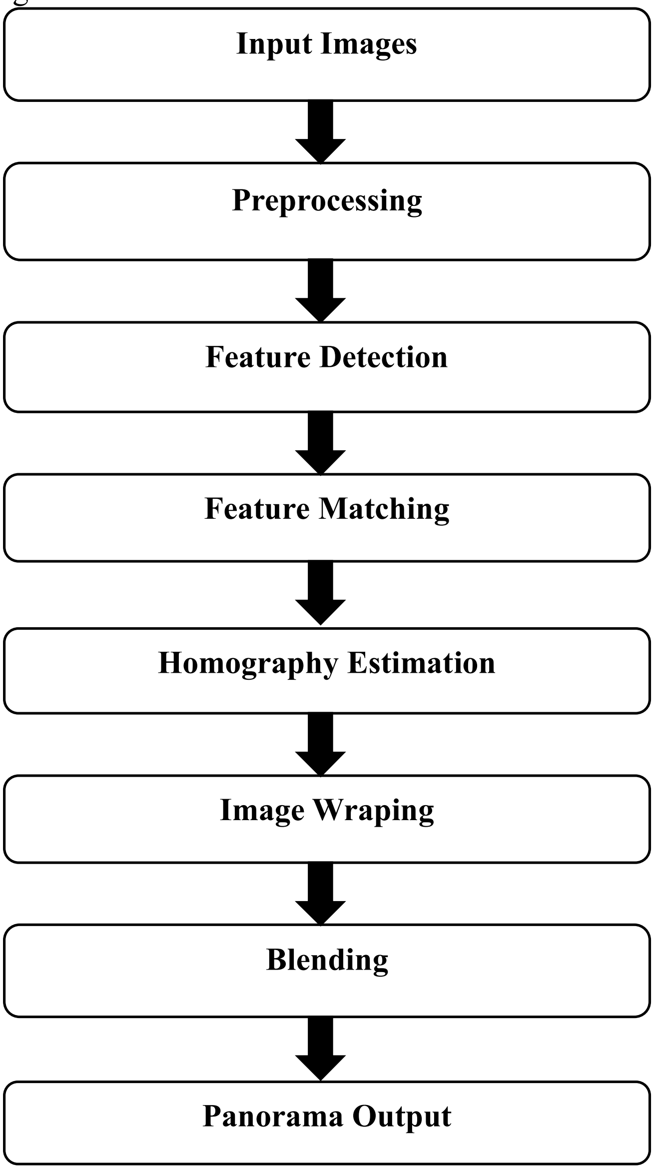
Overlapping areas are blended using methods like linear blending, feathering, or multi-band blending to reduce visible seams.

8. Panorama Output:

The final stitched image is produced, offering a wide-field panoramic view with minimal distortions and artifacts.

. This modular architecture ensures that each stage of image stitching is robust, accurate, and adaptable to varying image conditions.



Results

The proposed image stitching system was tested on a variety of overlapping image sets to evaluate its performance in real-world scenarios. The results demonstrate the effectiveness of the feature detection, matching, warping, and blending modules in producing visually coherent panoramic outputs.

The stitched outputs exhibit smooth transitions between images, minimal ghosting, and accurate alignment of features such as buildings, landscapes, and other structures. This indicates the robustness of the algorithm in handling different types of image inputs.

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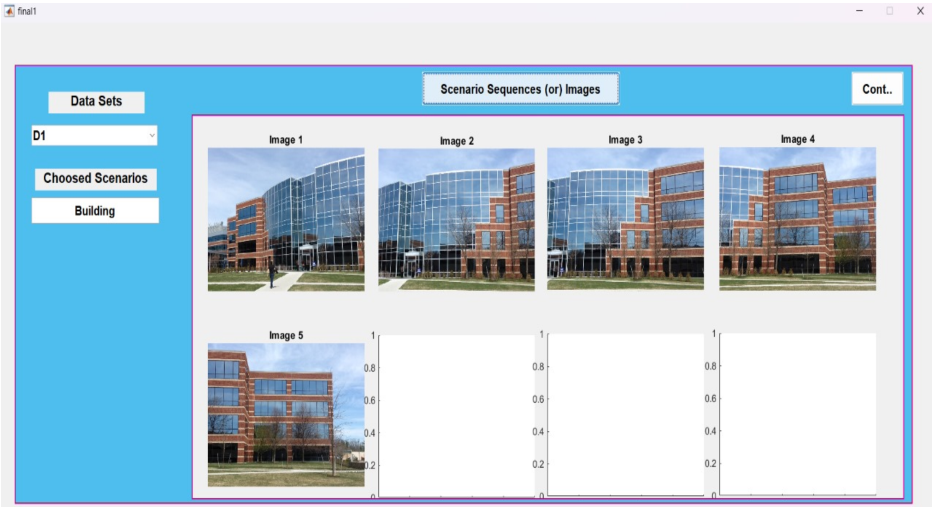
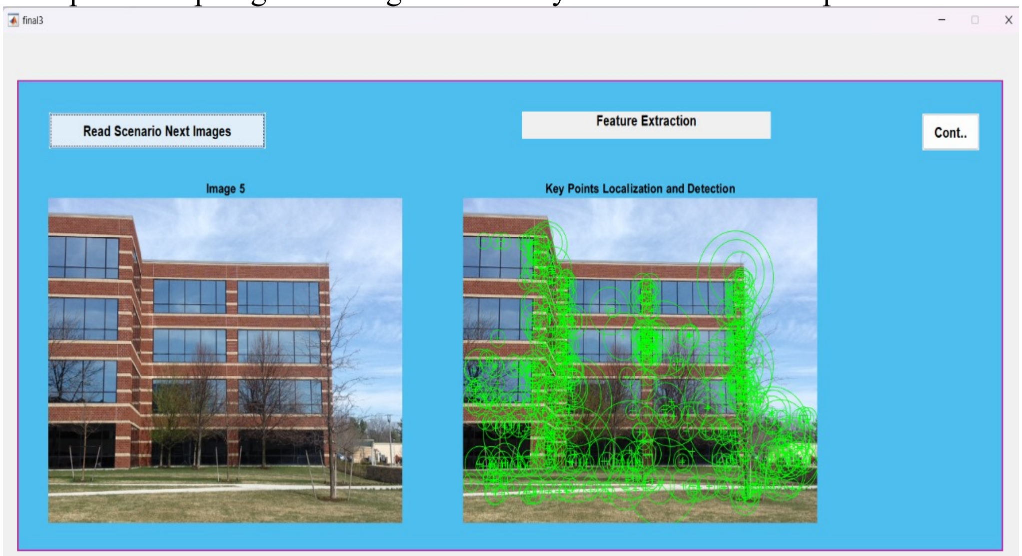
For DATASET 1 : BUILDING



These matched points help align the images accurately to form a seamless panorama.



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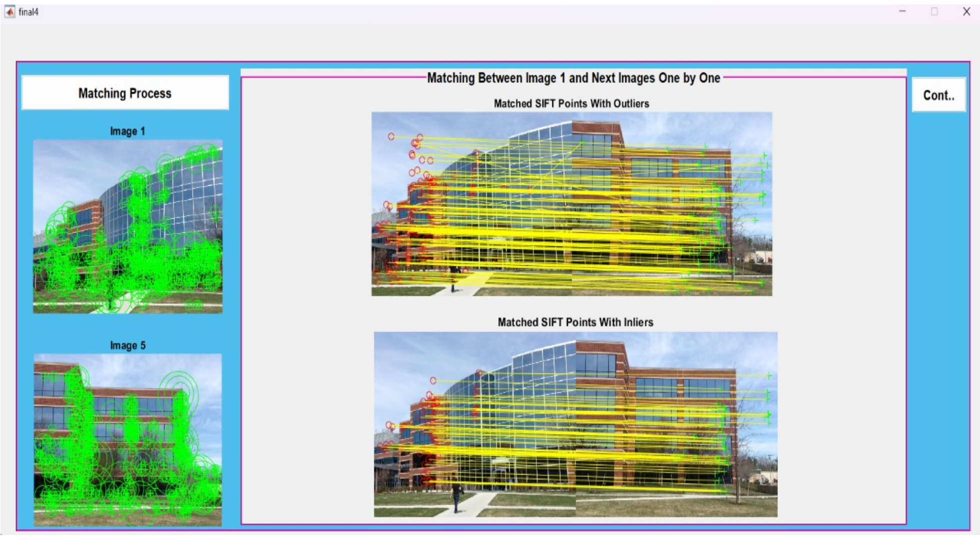
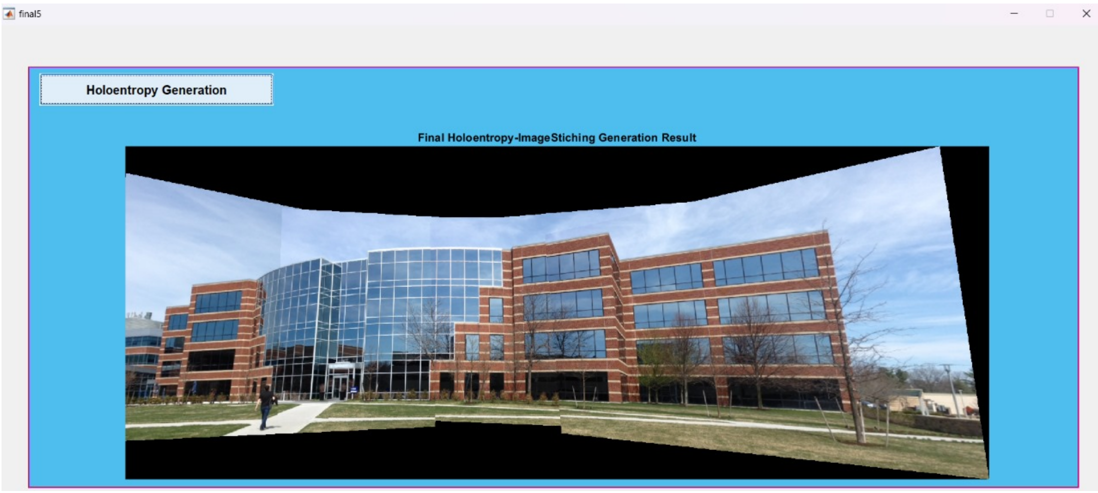


During testing, the system successfully identified key points in each image using the chosen feature detection method and accurately matched them using descriptor matching techniques. The use of homography estimation ensured proper geometric alignment between overlapping regions. Furthermore, the blending process minimized visible seams and handled variations in brightness and exposure across images.

The final output for DATASET 1 :



Overall, the results validate the effectiveness of the proposed system in achieving seamless image stitching, making it suitable for applications in photography, surveillance, mapping, and more.

For DATASET 2 : GLACIER

Detect keypoints in each image using algorithms like ORB or SIFT.

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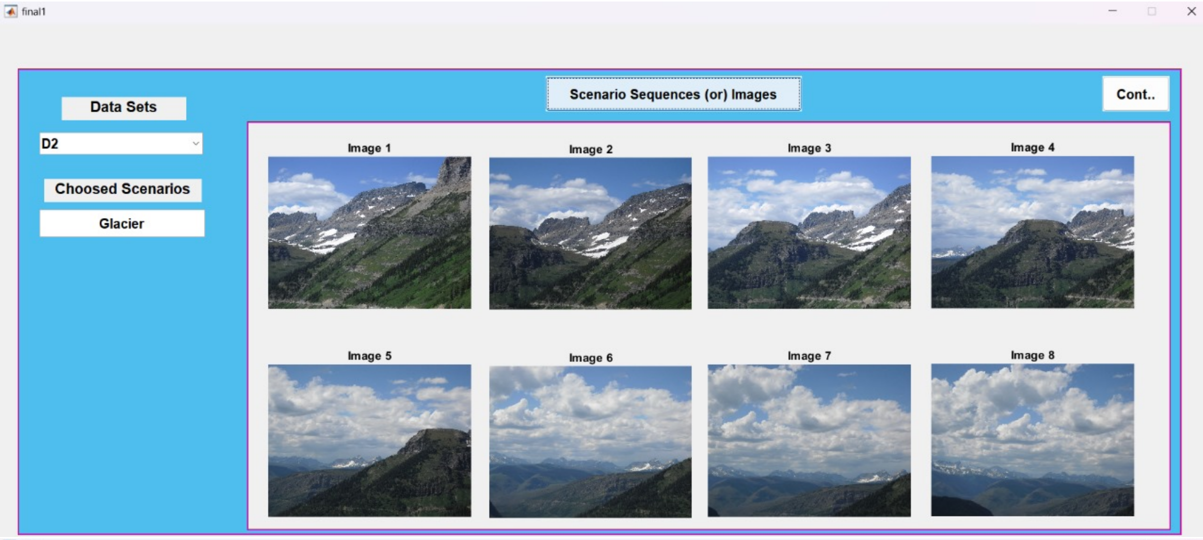
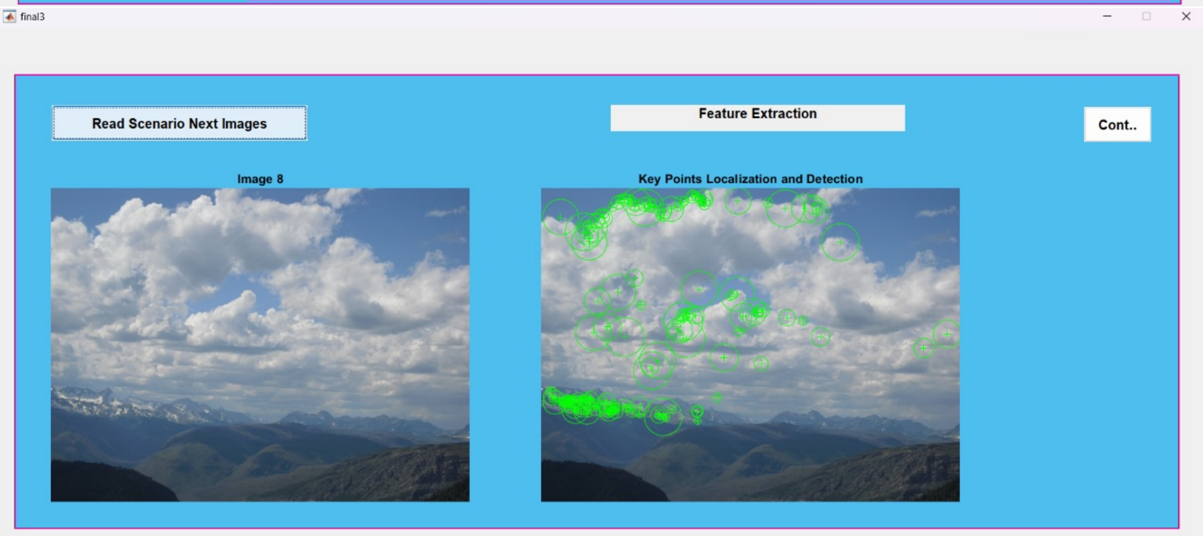
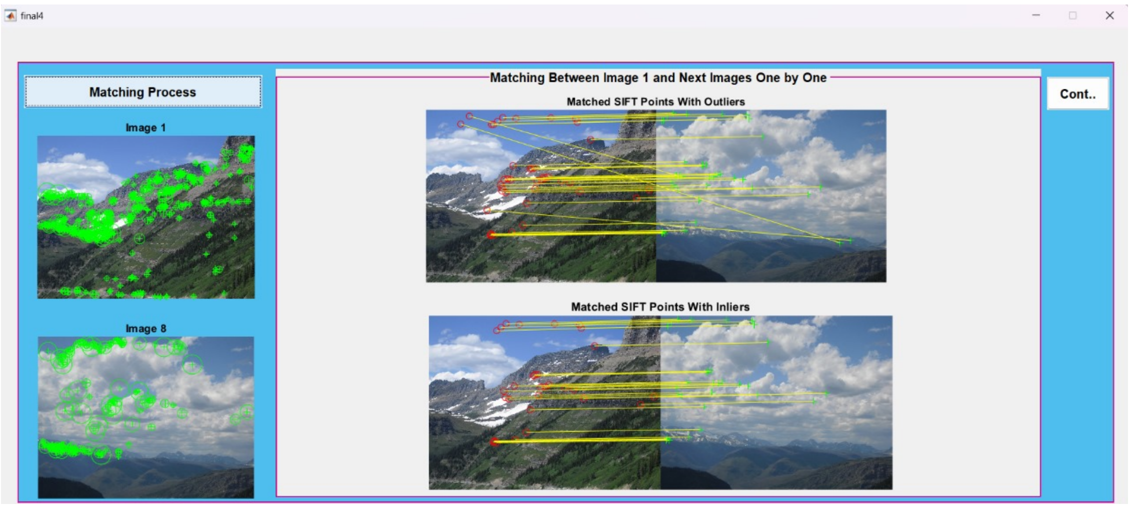




Matching the key points between overlapping images using a descriptor matcher and filter out incorrect matches with RANSAC.



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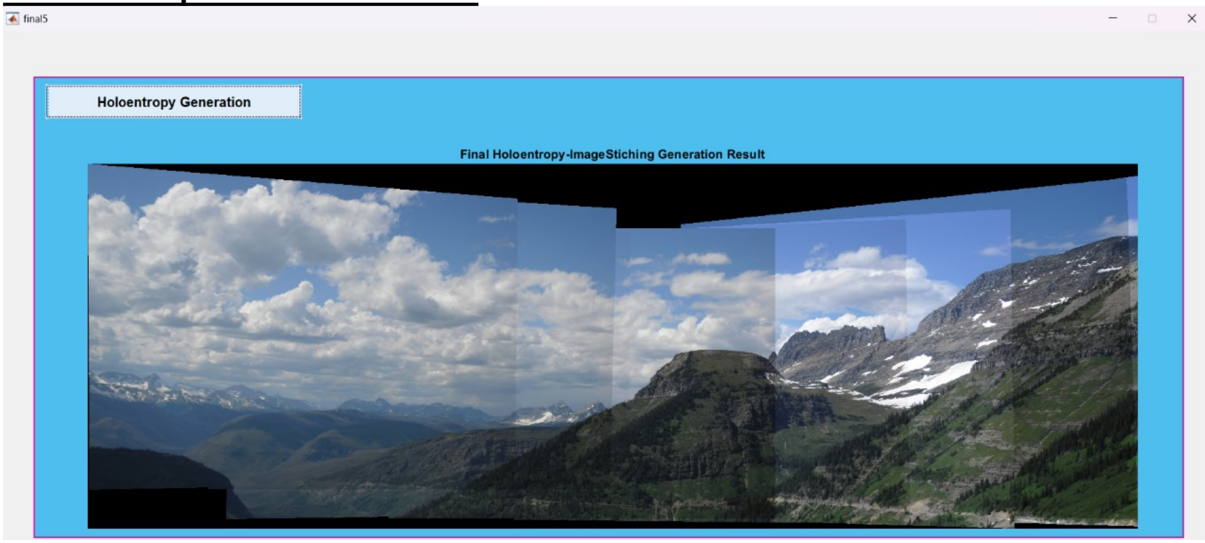
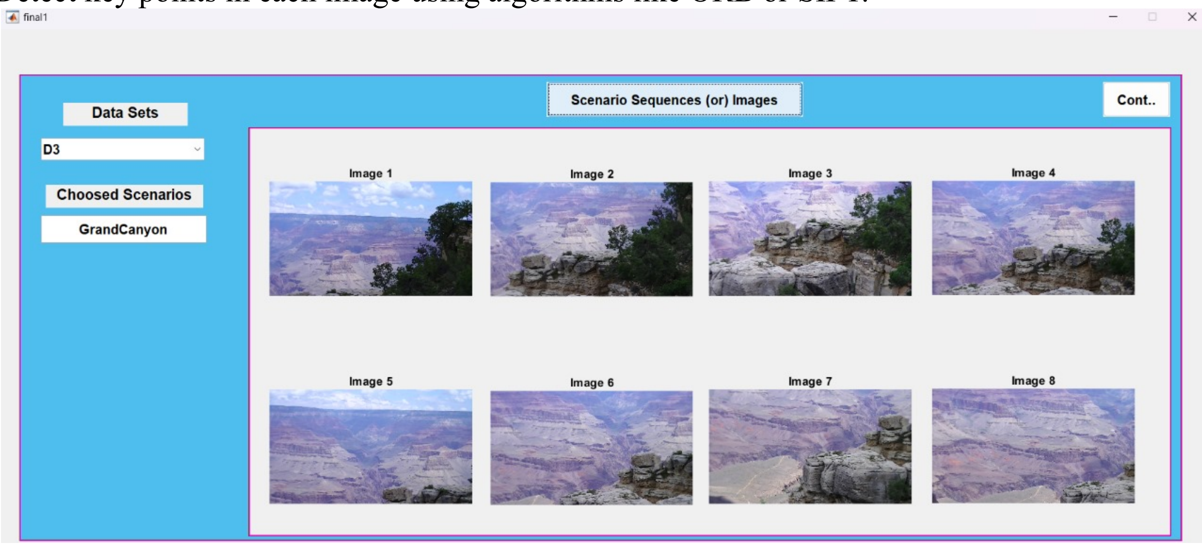
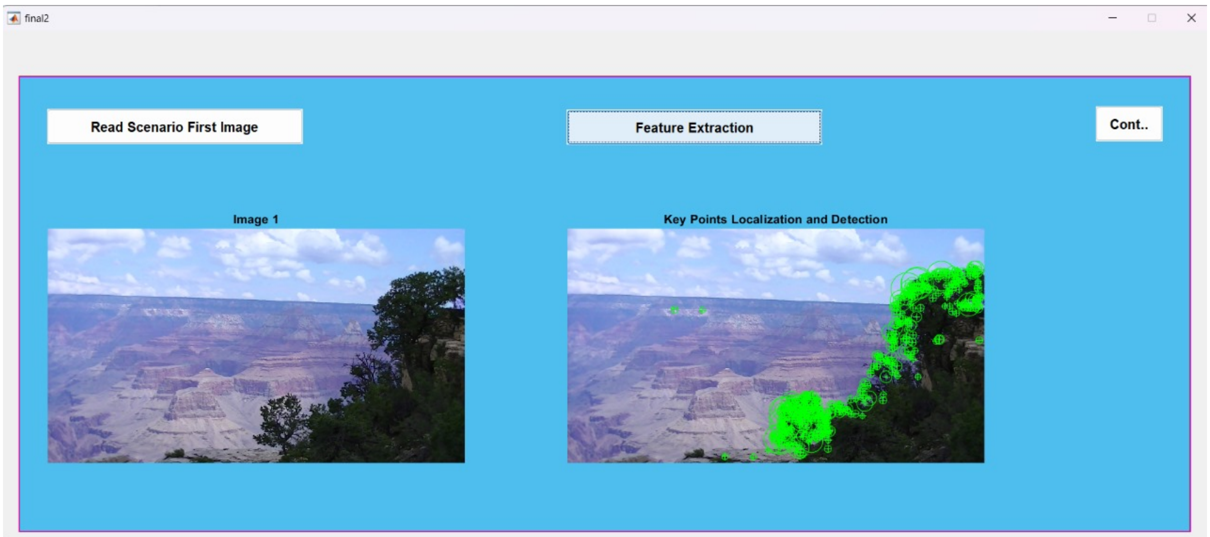
The final output for DATASET 2 :



For DATASET 3 : GRANDCANYON

Detect key points in each image using algorithms like ORB or SIFT.





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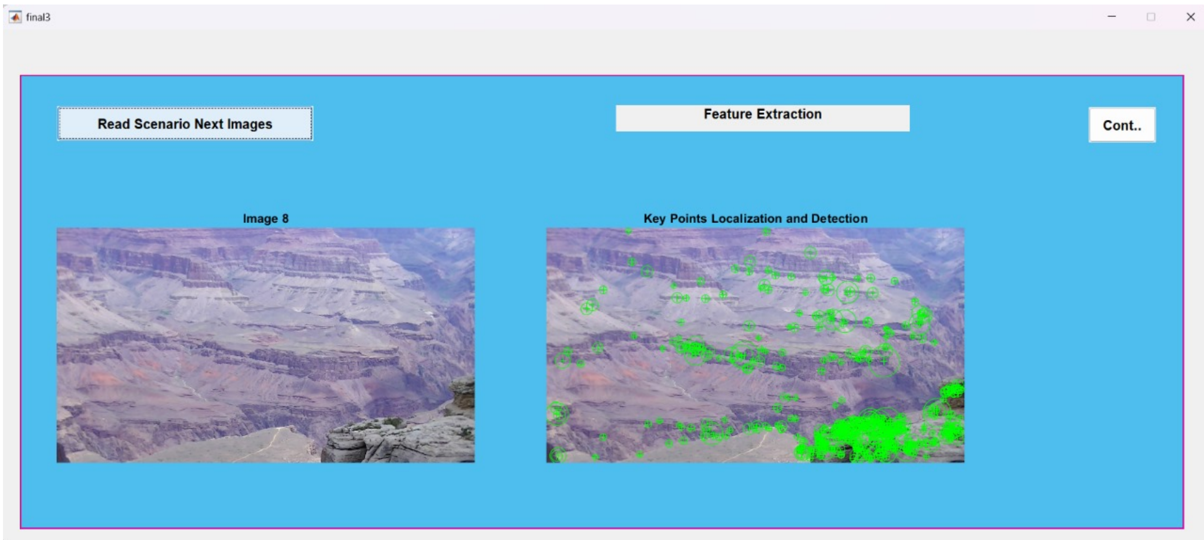
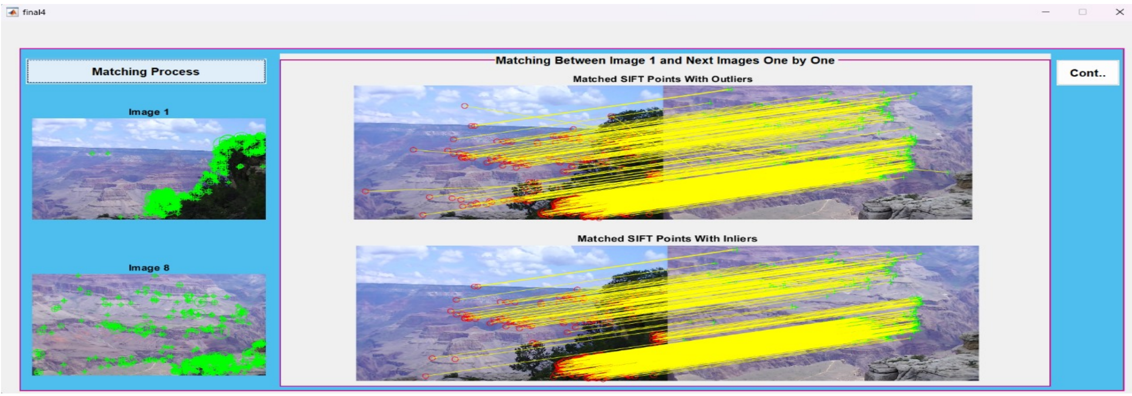
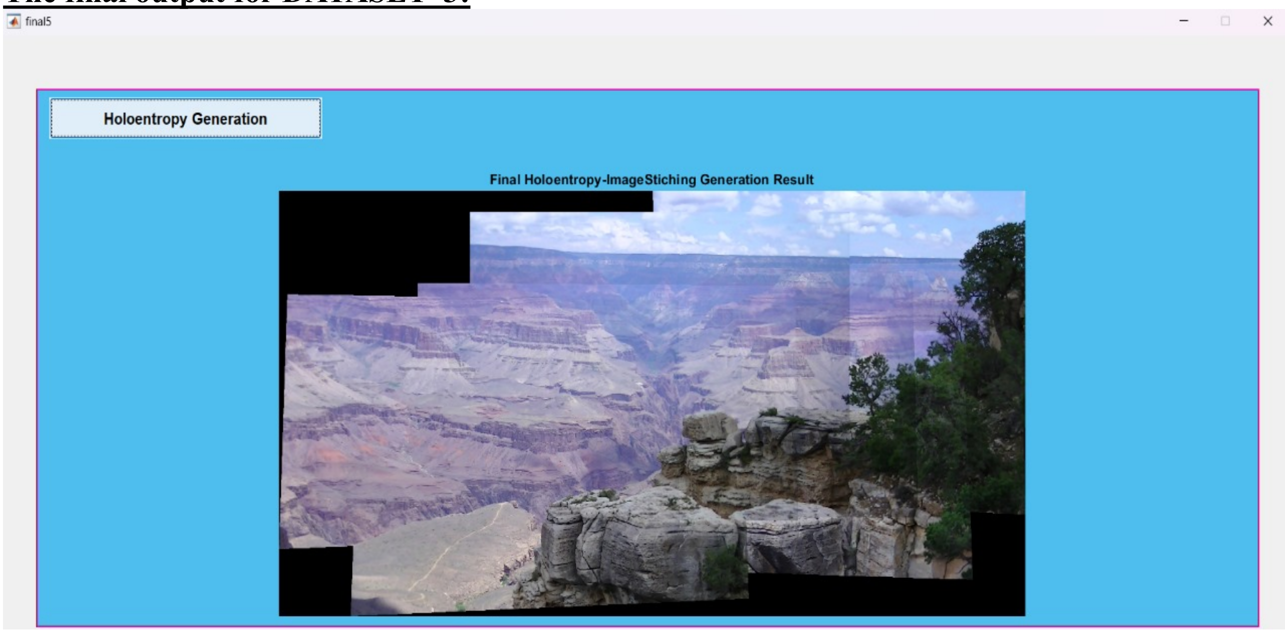


Matching the key points between overlapping images using a descriptor matcher and filter out incorrect matches with RANSAC.



The final output for DATASET 3:



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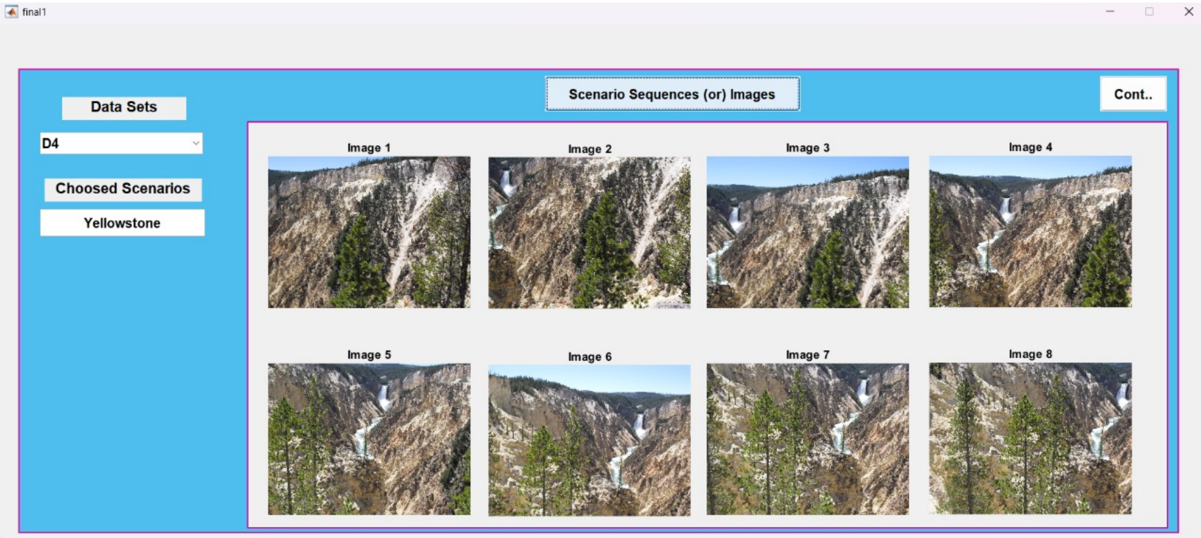
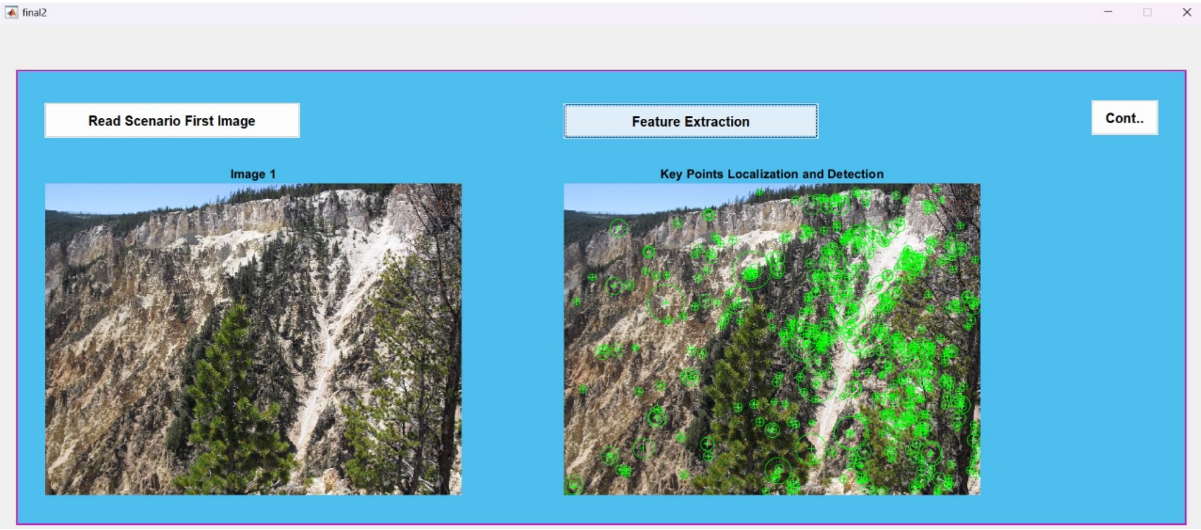
For DATASET 4 : YELLOWSTONE





Matching the key points between overlapping images using a descriptor matcher and filter out incorrect matches with RANSAC.

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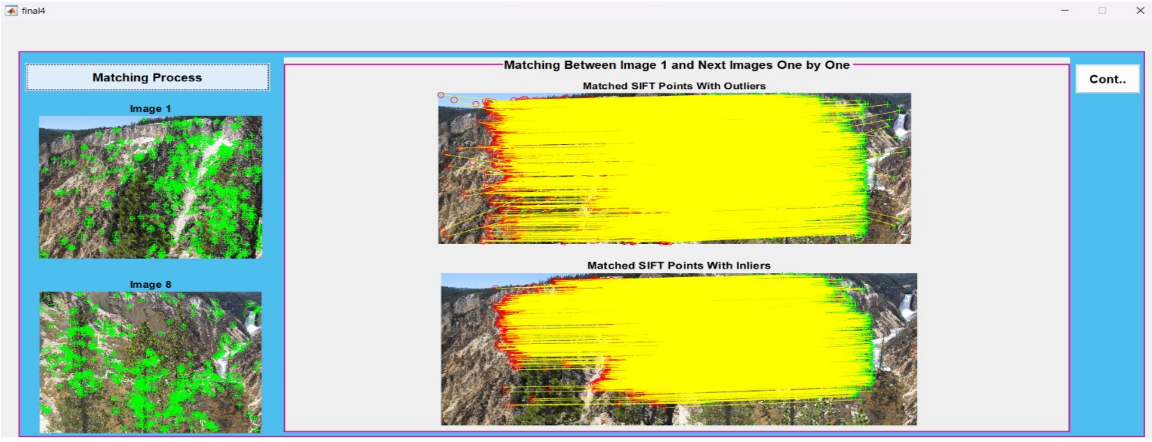
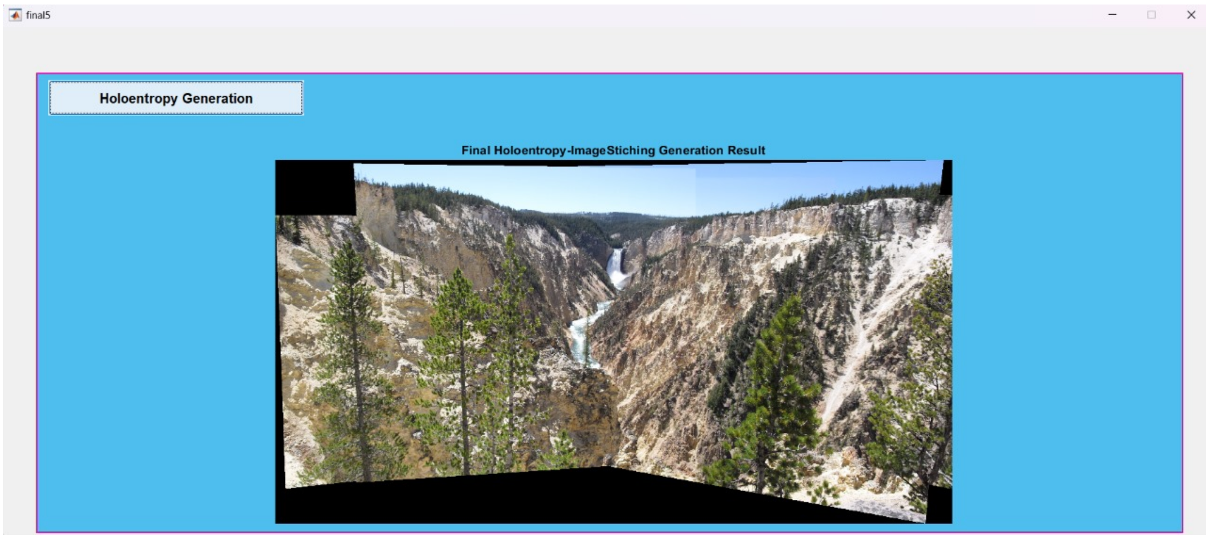


The final output for DATASET 4:



Conclusion

The primary objective of this project was to design and implement an efficient image stitching system capable of generating seamless panoramic views from multiple overlapping images. The developed system employs a combination of classical computer vision techniques, including feature detection (using ORB), feature matching, homography estimation, and image blending.
Through extensive testing on various image sets, the system demonstrated strong performance in aligning and stitching images with minimal artifacts. Key challenges such as feature mismatch, geometric distortion, and visible seams were effectively handled using robust algorithms like RANSAC and multi-band blending. The output images confirmed the system's ability to maintain visual consistency, handle variations in perspective, and preserve scene structure.
This project successfully meets its goal of automating the image stitching process and lays a solid foundation for real-world applications in fields such as photography, remote sensing, surveillance, and digital mapping.

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