Image Blending and Landslide Detection Using U-Net Convolutional Neural Network

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Abstact. The paper develops a sophisticated image blending and landslide detection system specifically designed for aerial datasets captured by drones. Utilizing high-resolution drone imagery, the system leverages OpenCV to seamlessly blending multiple images, providing an accurate and comprehensive representation of the terrain. This blending imagery is crucial for analysing large areas, offering a unified view that allows for better assessment and monitoring of land conditions. The landslide detection component of the system employs U-Net, a convolutional neural network architecture that excels in image segmentation tasks. U-Net's ability to accurately identify and delineate landslide regions within the fusion images ensures precise detection and analysis. This architecture is particularly well-suited for handling the complexities of aerial imagery, such as varying angles, lighting conditions, and terrain features. Real-time monitoring and disaster responses require the ability of the system to segregate landslide-affected and unaffected areas. In assessing the performance of the system, testing has been done on unseen datasets using metrics such as accuracy, precision, recall, and F1 score. These metrics will provide insight into the performance of the system for a wide range of conditions and datasets, ensuring its reliability and robustness. Continuous fine-tuning of the model enhances its adaptability to diverse landscapes and improves its overall detection capability. This research addresses a critical need for efficient analysis of aerial data, particularly in regions prone to natural disasters like landslides. By integrating advanced image blending with cutting-edge landslide detection algorithms, this system has potential applications in environmental monitoring, disaster management, urban planning, and infrastructure assessment, contributing to the innovative use of drone technology in various industries.

Keywords: Image Blending, Landslide Detection, CNN, U-Net, OpenCV.

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1. Introduction

1.1. Drone

The term "drone" identifies the device category of unmanned aerial vehicles able to be controlled by humans by remote control or fly alone using software-controlled flight plans. Drones are designed with sensors, GPS systems, cameras, and a multitude of technologies enabling them to capture data-a number of images and videos from the air. They are commonly used in various industries like agriculture, surveillance, disaster management, environmental monitoring, and photography, as well as for recreational purposes. Drones are known for their versatility and ability to access difficult or dangerous locations.

1.1.1 Applications of Drone

Due to the fact that drones can take photos and videos while hovering over the ground, there is great flexibility in their applications to most industries. Key uses of drones include:

Aerial Photography and Videography**:** Drones are widely used for capturing high-quality images and videos for films, events, real estate, and marketing.

Agriculture: Drones help monitor crop health, manage irrigation, detect pests, and create detailed maps to improve farming efficiency.

Disaster Management: In natural disasters like floods, earthquakes, and landslides, drones assist in assessing damage, locating survivors, and delivering supplies to hard-to-reach areas.

Environmental Monitoring**:** Drones are used to monitor wildlife, track deforestation, survey ecosystems, and collect environmental data, helping with conservation efforts.

Infrastructure Inspection: Critical infrastructures, such as bridges, power lines, wind turbines, and oil rigs, can be inspected by means of drones. They increase safety by reducing the number of manual inspections performed at dangerous locations.

Surveying and Mapping: In construction, mining, and urban planning, drones capture aerial imagery to create detailed maps, 3D models, and topographical surveys.

Surveillance and Security: Drones provide aerial surveillance for military, law enforcement, and private security to monitor large areas and respond to potential threats.

Delivery Services: Drones are being developed for delivering goods, such as medical supplies and packages, in areas where traditional delivery methods are slow or impractical.

Search and Rescue: Drones assist in locating missing people in remote or dangerous areas, enhancing the effectiveness of rescue missions.

Military and Defence: Drones are widely used for reconnaissance, surveillance, and combat operations, offering strategic advantages in warfare.

1.2. Image Blending

Image blending is a process used to combine multiple overlapping images to create a single, high-resolution panoramic or composite image. This technique is commonly used in photography, surveying, and various applications that require a broader view than what a single image can capture.

1.2.1. Key Components of Image Blending

Image Acquisition: Multiple photographs are taken from different angles or positions, often with some overlap between consecutive images.

Feature Detection: The algorithm identifies key points or features in each image that can be used for matching, such as corners, edges, or specific patterns.
Image Matching: The software compares the detected features in overlapping images to find correspondences. This helps align the images accurately.
Transformation and Alignment: The images are transformed and aligned based on the matched features. This may involve rotation, scaling, and translation to ensure that the images fit together seamlessly.
Blending: Once aligned, the images are blended together to create a smooth transition between them. This step often includes adjusting colours and exposure levels to eliminate visible seams or mismatches.

Output Generation: The final result is a single stitched image that provides a wider field of view or a detailed composite image.

1.2.2. Applications of Image Blending

Panoramic Photography**:** To capture wide landscapes or cityscapes.

Medical Imaging: For creating comprehensive images of tissues or organs from multiple scans.
Geographical Mapping: In surveying and cartography for creating detailed maps of large areas.
Virtual Reality: To create immersive environments by blending images taken from various angles.

Image Blending enhances the ability to visualize larger scenes or more detailed information than would be possible with a single photograph.

1.3. Landslide Detection

1.3.1. Landslide

A landslide refers to the downhill motion of rock or earth because of gravity. This is contributed by numerous factors including heavy rainfall, earthquakes, volcanic actions, or even human activities of mining and construction. These slides range in both size and speed from very small and slow-moving slides to very large and quick slides that cause a greater capacity of damage to the surroundings and structures.

1.3.2. Detection Using Drone

Landslide detection using drones uses UAVs equipped with different kinds of sensors and imaging, generally used for monitoring and assessing potential landslide risks. The whole process typically takes this course:

Data Collection: Gathering detailed terrain information using drones equipped with cameras and sensors.
Data Processing: Transforming raw data into usable formats, such as maps and models, for further analysis. Analysis: Using algorithms and models to assess landslide risks based on processed data.
Monitoring and Reporting: Regularly observing high-risk areas and generating reports for stakeholders.

1.3.3. Benefits

Real-Time Data: Drones provide immediate information on changes in the landscape, facilitating quick decision-making.

Enhanced Safety: Reduces the need for personnel to access hazardous areas, minimizing risk during surveys.

2. Literature Work

[1] J N Goh, S K Phang* and W J Chew In this paper, "Real-time and automatic map stitching through aerial images from UAV," an effective real-time approach is being proposed for the generation of an aerial map based on images taken from the camera mounted on a UAV. This algorithm employs feature-based algorithms: ORB, SIFT, and SURF for feature detection and matching, then computes homography for aligning the images. In place of traditional SVD used in RANSAC, matrix multiplication has been used for better computational efficiency. The proposed system demonstrates the capability of real-time mapping with high accuracy, tested in actual scenarios. It is useful for applications such as disaster management or land surveying.

[2] Yulin Xu, Chaojun Ouyang, The paper "Monitoring and characterizing slope movements in the Three Gorges Reservoir area using Sentinel-1 InSAR time series" presents the application of Sentinel-1 Synthetic Aperture Radar data for the identification and monitoring of slope instabilities in the Three Gorges Reservoir area. The interferometric SAR time series technique is used by the authors to identify the deformation trends over time. The study integrates geological insights into radar data to understand spatial and temporal patterns of slope movement for improved hazard prediction and mitigation. Results highlight the enabling role that Sentinel-1 InSAR can have in detecting subtle deformation patterns, early warning systems, and informing local engineering practices.

[3] Jianwei Sun,GuoqinYuan,Laiyun Song and Hongwen Zhang, The paper "Unmanned Aerial Vehicles (UAVs) in Landslide Investigation and Monitoring: A Review" presents a broad overview regarding the application of UAVs in landslide studies. It points out their roles in mapping, monitoring temporal and spatial dynamics, and responding to post-landslide events. Several UAV platforms and sensors are discussed, including RGB, multispectral, and LiDAR, with their respective advantages over traditional surveying methods: low cost, high resolution, and flexibility in difficult environments. Case studies demonstrate how UAVs enable accurate Digital Terrain Models and multi-temporal analyses. The paper also points out challenges such as battery limitation, regulatory hurdles, and integration with emerging technologies including UAV swarms.

[4] Farina P.; Rossi G.; Tanteri L. The use of multi-copter drones for landslide investigations" explains the contribution of UAVs in landslide studies, in particular, those involving geodetic monitoring. The low-cost UAVs equipped with optical sensors, as it pointed out, could capture high-resolution images used in mapping unstable slopes. This study, therefore, includes case studies in Tuscany, Umbria, and Sicily, showing how the multi-copter named Saturn has been used in generating high-accuracy DTMs. Traditional approaches to surveying are compared with the UAV-based one, real-time data acquisition, low cost, and flexibility. This paper will show the contribution of multi-temporal drone data in slope monitoring and landslide investigations.

3. Existing System

3.1. For Image Blending

3.1.1. ORB (Oriented FAST and Rotated BRIEF) features based algorithm

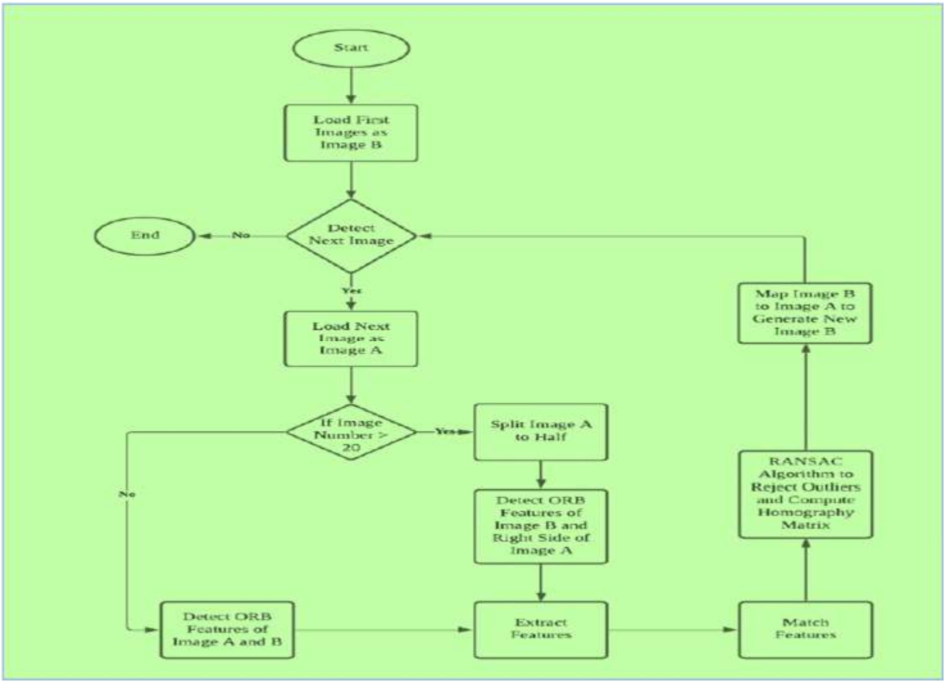

Fig. 1. Image blending workflow

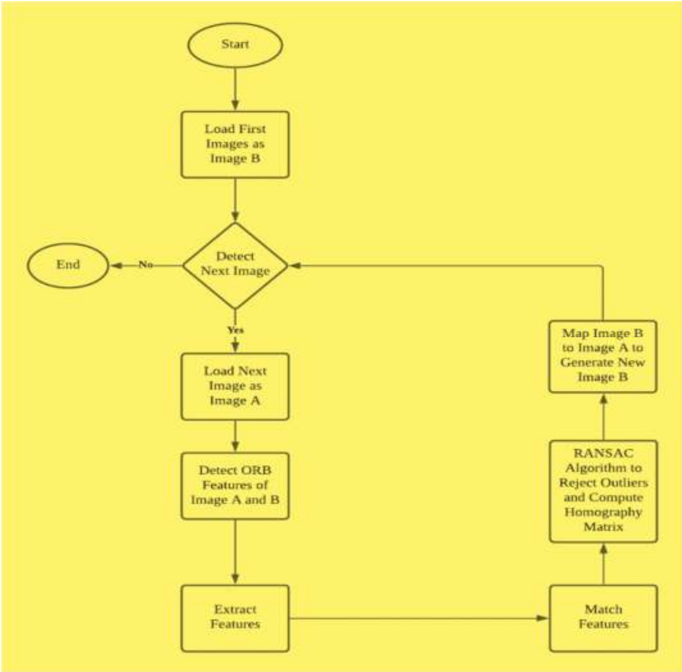

Fig. 2. Image blending workflow for ORB based features algorithm.

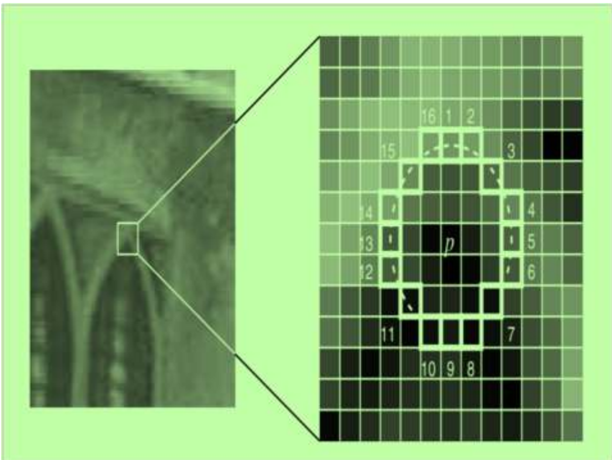

Fig. 3. ORB Feature Based Method.

(i) Gaussian Blur

The Gaussian Blur is used in image processing to perform smoothing of an image by basically reducing noise and detail by averaging the pixel

values in a neighborhood around each pixel, with the weighting determined by a Gaussian function. The effect of this is to blur the image overall, but leave behind coarse structure and soften the fine details.

$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$

The Gaussian kernel $G(x,y,\sigma)$ is convolved over every pixel in the image. Each pixel value of the blurred image $L(x,y)$ is determined as the weighted average of its neighboring pixels in the original image $I(x,y)$.

Gaussian Function is given by :

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

- $L(x,y,\sigma)$: The blurred photo at point (x,y) and scale σ.
- $G(x,y,\sigma)$: The **Gaussian function** used as the blur filter.
- $I(x,y)$:The real image at point (x,y).
- *: Convolution operation, which applies the Gaussian function over the entire image.
- σ: Standard deviation (scale) of the Gaussian, controlling the amount of blur; larger σ produces more blur.
- x and y: Distances from the center of the Gaussian kernel.

(ii) Centroid Calculation:

The **centroid calculation** is a process used in image processing to find the centre of mass (or geometric centre) of a region in an image based on pixel intensity values. The centroid can help identify the position of key points, which is particularly useful in algorithms like ORB for determining the orientation of features.

$$C = (m_{10}/m_{00}, m_{01}/m_{00})$$

$$m00 = x, y\sum I(x, y)$$

$$m10 = x, y\sum x \cdot I(x, y)$$

$$m01 = x, y\sum y \cdot I(x, y)$$

- C: The centroid coordinates, represented as (Cx,Cy).
- m00: The zeroth moment, representing the total intensity of the region.

- m10: The first moment in the x-direction.
- m01: The first moment in the y-direction.

(iii) Final Descriptor

The last descriptor in the ORB (Oriented FAST and Rotated BRIEF) algorithm extracts the peculiarity of a key point while maintaining the uniqueness of the descriptor to rotation-invariance. This allows the keypoint to be matched across different orientations and scales.

$$gn(p, \theta)=fn(p)(xi, yi)\in s\theta$$

- ***gn(p,θ):***

This represents the final descriptor for the key point after considering its orientation θ. The descriptor is a binary string that encodes the relative intensity differences between pixel pairs around the key point.

- ***fn(p):***

This is the basic descriptor generated by the BRIEF (Binary Robust Invariant Scalable Keypoints) algorithm, which compares pixel intensities at specified coordinates around the keypointppp.The descriptor consists of a series of binary comparisons, yielding a string of bits that uniquely represents the local image structure around the keypoint.

- ***(xi,yi)∈sθ:***

sθ refers to the rotated coordinate pairs used for the descriptor based on the angle θ calculated earlier (the orientation of the keypoint).The coordinates (xi,yi) represent the pixel locations used for comparisons in the descriptor. By rotating these coordinates by the angle θ\thetaθ, the algorithm ensures that the descriptor is invariant to the rotation of the keypoint.

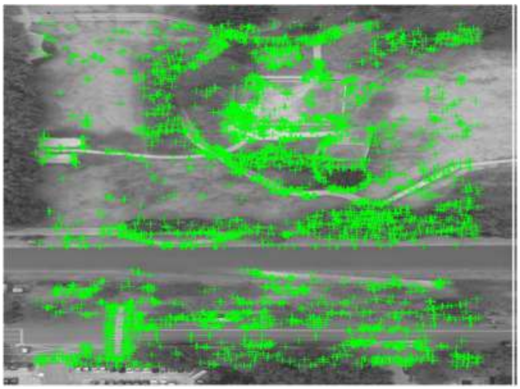

Fig. 4. Gray Scale Image A with ORB

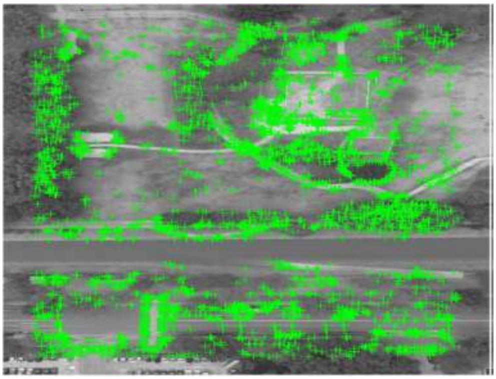

Fig. 5. ORB Feature points plotted with Gray Scale Image B

3.1.2. RANSAC Algorithm

RANSAC is the short form of Random Sample Consensus, which is an algorithm used in image blending-where multiple images are merged to make one panoramic image.In this context, RANSAC is typically used to estimate the geometric transformation (such as homography) needed to align overlapping images accurately. Here's how RANSAC is integrated into the image blending workflow:

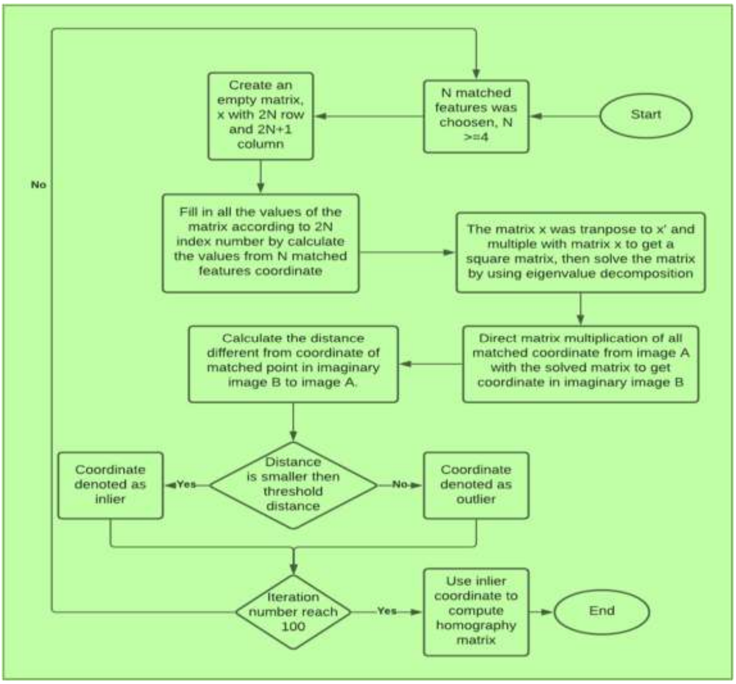

Fig. 6. RANSAC Code Flow Chart.

(i) Outlier Removal with RANSAC:

- Randomly Sample Matches: From the set of matched key points, randomly select a minimal number of correspondences required to compute the homography matrix (typically four pairs for 2D homography).
- Estimate Homography: Calculate the homography matrix using the selected correspondences. The homography matrix relates the points in one image to the corresponding points in another image, effectively modelling the transformation needed to align them.
- Determine Inliers: For each matched point, apply the estimated homography to transform points from one image and check how closely they match their corresponding points in the other image. Points within a certain distance threshold from the transformed points are considered inliers.
- Count Inliers: Keep track of the number of inliers for each estimated homography.

(ii) Homography Matrix :

The **homography matrix** is a fundamental concept in computer vision and image

, where $$\begin{bmatrix} x' \\ y' \\ w' \end{bmatrix} = H \cdot \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \qquad H = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix}$$

4. Data Collection

The drone-captured image datasets have been sourced from Kaggle, a well-known platform for data science and machine learning. These datasets provide a rich variety of aerial imagery, which can be instrumental in training and evaluating models for applications such as landslide detection and image blending.

5. Methodology

5.1. For Image Blending

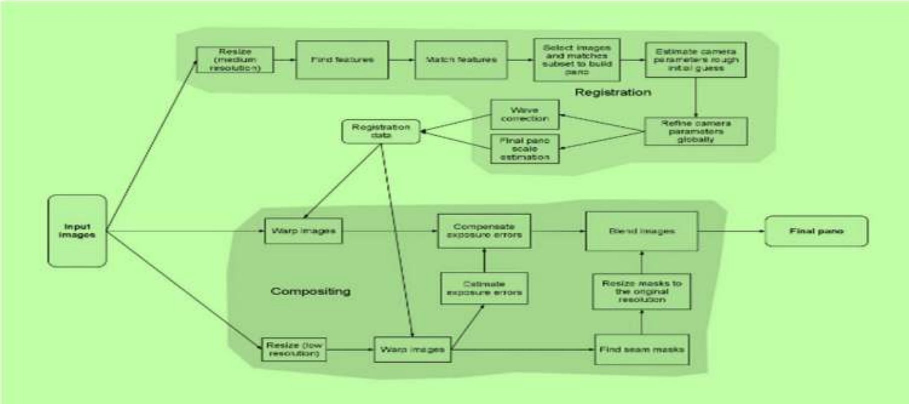

Fig. 7. Flow Control in OpenCV for Image Blending.

Fig. 7: This example illustrates flow control in OpenCV while executing the image blending process, among other processes such as stitching of images, perspective transformation, and 3D re-construction. It returns the relation between two views from similar scenes taken from other viewpoints or under different perspective views.

OpenCV is an open-source, advanced computer vision library of repute, combined with machine learning software. It contains a number of utilities and functions which might be used for implementing project related to real-time computer vision. OpenCV can run on several programming languages: for example, C++, Python, and Java. Most of its code is also highly portable and can work on various operating systems including Windows, macOS, and Linux.

(i) Key Features of OpenCV:

Image Processing: OpenCV has a great set of both basic and advanced functionalities to filter, transform, and geometrically manipulate images.

Feature Detection and Description: It includes algorithms for detecting keypoints and descriptors, enabling tasks like object recognition and tracking.

Machine Learning: OpenCV contains machine learning algorithms that facilitate training and deploying models for various applications, including image classification.

Video Analysis: The library can handle video capture and analysis, making it suitable for real-time applications like surveillance and gesture recognition.

Stitching and Blending: OpenCV has built-in functions for stitching multiple images into a panorama and blending images together, allowing for seamless integration of different views.

(ii) Image Blending with OpenCV

Image blending is a technique used to combine two or more images into a single composite image. This is particularly useful in various applications:

1. Panorama Creation: Blending images taken from different angles
2. to create a wider field of view.
3. Image Enhancement: Combining images taken at different exposures or times to enhance details and colour.
4. Augmented Reality: Overlaying virtual objects onto real-world images for applications like gaming and training.

(iii)Benefits of Using OpenCV for Image Blending

Efficiency: OpenCV is optimized for performance, enabling real-time processing and blending of images.

Robust Algorithms: The library implements state-of-the-art algorithms for image registration, stitching, and blending, ensuring high-quality results.

Versatility: OpenCV can handle various image formats and types, making it adaptable for different projects.

Community Support: As an open-source project, OpenCV has a large community, which means plenty of resources, tutorials, and forums for support.

5.2. For Landslide Detection

U-Net Model (A type of Convolutional Neural Network)

Detection of a landslide could be done with the U-Net model, wherein the deep learning analysis of an aerial or satellite image for the identification of landslide-prone areas is done with CNNs. This U-Net architecture was popularized in image segmentation and especially in medical imaging. However, it has been effective in adaption among many environmental monitoring applications.

5.2.1. U-Net Architecture:

1. U-Net consists of an encoder (down sampling) and a decoder (up sampling) path. The encoder captures context and features from the input images, while the decoder enables precise localization by combining features from the encoder through skip connections.

2. The last layer usually uses softmax as an activation function in multi-class segmentation or sigmoid if the segmentation is binary.

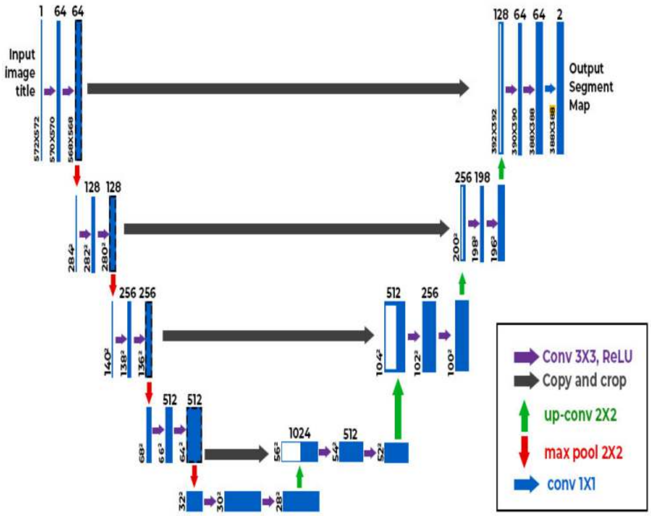

Fig. 8. Architecture of U-Net Model

(a)Contracting path(Encoder) :

- **Convolutional Layer**:

$$\text{Output} = \text{ReLU}(W * X + b)$$

Where W is the weight matrix, X is the input, and b is the bias.

- **Max Pooling Layer** (downsampling):

$$Y = \text{MaxPool}(X)$$

This reduces the spatial dimensions, typically by a factor of 2.

(b)Expansive path(Decoder)

- **Up Sampling Layer**:

$$Y = \text{UpSample}(X)$$

This layer increases the spatial dimensions, often using techniques like nearest neighbor or bilinear interpolation.

- **Concatenation**: Concatenates the corresponding features from the contracting path:

$$Z = \text{concat}(Y, X')$$

Where Y is the output from the upsampling layer, and X' is the corresponding feature map from the contracting path.

- **Convolutional Layer**: Similar to the encoder:

$$\text{Output} = \text{ReLU}(W * Z + b)$$

(c) Final Layer

- **1x1 Convolution**: The final layer uses a 1×1 convolution to map the feature maps to the desired number of classes:

$$\text{Output} = \sigma(W * Z + b)$$

Where σ is the activation function (usually softmax or sigmoid for binary segmentation).

(d) Loss Function

- **Binary Cross-Entropy Loss** (for binary segmentation):

$$\text{Loss} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

Where y_i is the ground truth, and $\hat{y}_i$ is the predicted probability.

VI. EXPERIMENTAL RESULTS

6.1. FOR IMAGE BLENDING:

Fig. 9. Mapping the similarities

Fig. 9 illustrates the process of mapping similarities between two images for effective blending. The colored lines indicate the detection of corresponding features, highlighting the relationships that facilitate seamless integration. This mapping is crucial for aligning the images accurately, ensuring a cohesive final product. By identifying distinct characteristics, the process enhances the blending outcome, whether for panorama creation or image editing. Overall, this technique simplifies the complex task of combining images while maintaining visual integrity. Additionally, this feature mapping technique is essential for applications in augmented reality and visual effects, where precision is paramount. By leveraging advanced algorithms, the blending process achieves a natural look, enriching the viewer's experience.

Fig. 10. Final Blended Image

Fig. 10 showcases the resulting blended image, which is created by seamlessly merging two distinct images into a cohesive panorama. This technique captures a wide-area view, allowing for a broader perspective that individual images cannot provide. The blending process carefully combines features and colors from both images, ensuring a natural transition and visual harmony. As a result, the final output appears as a unified scene, enhancing the viewer's experience. Such blended images are particularly useful in landscape photography, virtual tours, and augmented reality applications, where immersive views are essential. Overall, this image exemplifies the power of blending techniques in transforming separate visuals into a single, expansive composition.

6.2. Landslide Detection

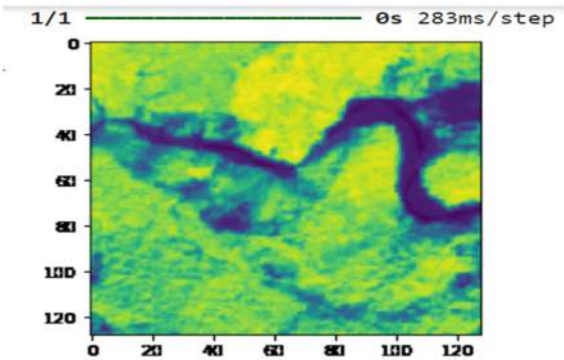

Fig. 11. Original Image

Fig. 11 showcases an aerial image captured by a drone, specifically designed to facilitate our algorithms in detecting landslides. The high-resolution perspective provided by the drone allows for a detailed examination of the terrain, making it easier to identify subtle changes indicative of potential landslide activity. Our algorithms will analyze various features within this image, such as variations in vegetation, soil displacement, and other geological markers. This innovative approach aims to enhance our ability to monitor and predict landslide occurrences, ultimately contributing to improved safety and risk management in vulnerable areas. By leveraging advanced technology, we can gain valuable insights into landscape dynamics and improve disaster preparedness efforts.

Fig. 12. Masked/Segmented Image

Fig. 12 illustrates the masked or segmented image resulting from our analysis, highlighting distinct areas of land based on their stability. In this representation, the black color indicates regions of stable, "good" land, while the white color signifies areas affected by landslides. This clear dichotomy allows for easy visualization and interpretation of the landscape, facilitating quick assessments of risk. The segmentation enhances the effectiveness of our algorithms by focusing attention on critical areas that require further analysis or intervention. By employing this method, we can streamline the monitoring process and enhance our understanding of landslide distribution, ultimately aiding in disaster preparedness and mitigation strategies. This visual clarity is essential for communicating findings to stakeholders and decision-makers.

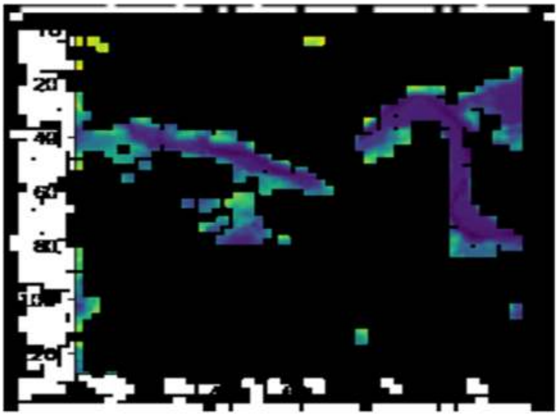

Fig. 13. Detecting only landslide from original image

Fig. 13 presents a focused view that exclusively highlights the landslide-affected areas from the original aerial image. By isolating these regions, this representation allows for a detailed examination of the characteristics and extent of the landslides without the distraction of stable land. This targeted approach is crucial for analyzing the specific factors contributing to the landslide events, such as soil composition, topography, and vegetation loss. By concentrating solely on the landslide sections, we can enhance our understanding of the dynamics at play and develop more effective strategies for monitoring and mitigating risks. This focused visualization not only aids in data analysis but also assists researchers and decision-makers in prioritizing interventions in vulnerable areas. Ultimately, it underscores the importance of precise data representation in disaster management efforts.

7. Conclusion

We do research effectively combined two independent modules: image blending and landslide detection. The image blending module, implemented using OpenCV, produced seamless, large-scale images from multiple aerial shots, ensuring comprehensive terrain coverage. On the other hand, the landslide detection module used a U-Net model to accurately segment landslide-prone areas within the aerial images, providing critical insights for environmental monitoring. These modules form a robust system for real-time assessment and monitoring, with practical applications in disaster response and land management.

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