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# Seamless Integration: Advanced Deep Learning Techniques for Image Stitching

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***ABSTRACT***

*This work holds an effective solution to image stitching by employing CNNs, GANs, and optical flow besides other image stitching methods. These techniques greatly improve feature extraction, registration, and warping, which are obstacles like parallax, exposure disparity, and dynamic content. Our methodology involves multiple intricate steps to ensure high-quality stitching: To provide efficient detection of the key point, applying CNNs for connection in feature extraction The usage of GANs for image alignment helps in contributing precise transformation The final step involves the process of multi-band blending that helps in seamless removal of the seam and exposure variations. Also, depth estimation takes care of the parallax and motion segmentation in dynamic scenes to incorporate all the used image components. The above-discussed approach was tested and assessed by using the UDIS-D dataset which is characterized by different scenes and high parallax. When testing through the Peak Signal-to-Noise Ratio (PSNR) and the Structural Similarity Index (SSIM) the presented technique shows the best result compared to previous methods. Therefore, the proposed model attains an average PSNR of 33. 58 and an SSIM of 0. 939, compared with other prominent approaches to methodologies. The experiments performed here prove the efficiency of the proposed method of image stitching based on deep learning techniques and show its use in virtual platforms, medicine and autonomous robotic vehicles. Future studies will in turn involve enhancing the application of superior machine learning approaches with the view of widening the functionality of the system and improving the quality of images.*

***Keywords****: image stitching, Convolution Neural Network (CNN), generative adversarial networks (GANs), Optical Flow.*

## I. INTRODUCTION

The speed of growth of digital imaging technology has raised the requirement for enhanced-resolution images in practices, such as Virtual Reality, medical applications, and systems with Artificial Intelligence. One critical capability of these applications is the image stitching process which is a process of joining many images into one single panoramic image. It is commonly applied in the area of image taking for the extension of the viewing angle, in the production of full range maps in geography and cartography, and rich contextual view in medical imaging. Nonetheless, the use of image stitching has widespread uses as it helps to reduce the distortions in captured images, however, merging the two images with beautiful joints still poses a challenge due to the numerous processes involved in aligning images, blurring and merging them in such a way that there are no seamless or visible lines. Some of the previous works on image stitching utilize feature matching, and geometric transformations to perform the stitching. These techniques involve feature extraction of corresponding features in the two images, a geometrical transformation that is required to align the images, and finally merging the images to get an all-around view. However, these methods are hard to handle complex scenes, varying image qualities and dynamic contents which results in generating undesirable effects such as misalignments, visible seams and ghosting effects. Furthermore, parallax and different exposures of scene in different images do affect the stitching process and the output is usually not as good as one would expect [1]. With the help of deep learning, many subfields of computer vision have realized great developments, such as image detection [2][3]. Deep learning methods especially CNNs and GANs have shown high potential in extracting features, image registration and image fusion [6][7]. These models can automatically extract key point locations, accurately match features between images and stitch the image borders perfectly. In the same regard, methods such as the optical flow which estimates motion between frames have been incorporated with deep learning models in the processing of dynamic data and different exposures. The driving force of this study is the shortcomings associated with conventional image stitching techniques that can be rectified by innovation in deep learning. CNNs, GANs, and OFs are an effective, accurate framework to provide excellent image stitching. This increment improves the visualization of the stitches while minimizing the computational load on the system, thus allowing the algorithm to be used in real-time. The future use of this technique for enhancing the image stitching process is enormous and may incorporate and expand in fields such as virtual reality, medical image diagnostics and many others. In the following context, this paper aims to propose an innovative model of image stitching with the help of some modern deep-learning approaches. The key contributions of this study are as follows:

- Novel Framework: suggest a new method based on CNNs, GANs, and optical flow to obtain better feature extraction, alignment and blending of the images.
- Handling Complex Challenges: With our method, we overcome several problems inherent in authors' image stitching, such as parallax, varying exposure, and dynamic content of scenes, for obtaining high-quality pianos.
- Performance Evaluation: The efficacy of the proposed approach over the previous methods is illustrated through detailed experimental evaluation.
- Wide Applications: The proposed technique provides new opportunities for employing the outcomes in virtual reality, medical imaging and self-organizing systems highlighting the significance of the work done.

The key research question of this study is related to the improvement of the image stitching field and offering a highly efficient and accurate solution to the constantly increasing need for high-resolution image applications.

## II. LITERATURE REVIEW

Image stitching is one of the fundamental processes in contemporary imaging as well as computer vision which refers to the process of joining two or more images into one panoramic image. The difficulties that traditional letter-to-letter matching and geometric transformations face include misalignments, visible seams, and other unpleasant effects like word ghosting; Moreover, these methods do not perform well with complex scenes and interchanging image quality. To overcome such limitations, the modern trends in deep learning have come up with better and more efficient solutions. Image stitching It is a key category of technique in the computer vision area in which a sequence of images is combined to produce a single wide image. This process is widely applied in different domains like image and video, virtual reality, geographic information systems, radiology, and robotics. Before the introduction of deep learning, many techniques used feature matching and geometric transformations to stitch images. However, these methods have problems, especially when matching scenes, images of different qualities, parallax, and dynamic objects. That is why with the help of deep learning new methodologies to work with images have appeared that use CNNs, GANs, and others that don't have these drawbacks and allow to achieve better results. In [6], the authors proposed a blind stitched panoramic image quality evaluation based on ensemble learning of local visual features and global deep features. This approach improves the evaluation of the quality of panoramic images because the methods of learning used are stronger by combining them. In [7] an improved method of image stitching for dual-sensor. Concerning the limitations of combining the images from different sensors, their approach targets the issues arising during the image mosaicking or stitching procedures, which is vital for inspection tasks where it is essential to obtain accurate results as shown in Figure 1. Suggested a content-seam-preserving multi-alignment network for visual-sensor-based image stitching. Unlike, this method is driven to the seams where there is content overlap, minimization of artefacts and acquisition of the best stitching outcome in areas of most content density [8]. Explored the integration of images using the fast-marching approach. This technique increases the speed of stitching and makes the transition between the images smoother and hence can be used for applications that require real-time processing [9]. In [10], the authors described learning-based methods for edge-preserved image stitching where large-baseline deep homographs and multi-scale deep homographs were used. These methods propose preserving the edge details in the images, and how to properly deal with large differences in the images, which leads to good stitched images. They gave a discourse on hyperspectral panoramic image stitching by employing robust matching and adaptive bundle adjustment. It is specifically suitable for hyperspectral images due to the peculiarities of their high dimensionality and the need to align and stitch them accurately as shown in Figure 2 [12]. Proposed a new range image stitching technique called PE-RASP, for photon-efficient imaging, which the image stitching of the deep-sea scene and the improvement of multi-channel fusion and AKAZE. Their methodology also considers some of the main issues affecting the underwater environment, like low light and light changes, to ensure correct blending [16]. In [17] a new key-point-based image stitching method along with intensity adjustment for producing high-quality stitched images was proposed. This method improves the quality of the final stitched image so they are well suited when a high degree of image accuracy is needed. The work done by the authors [18] embodied an experimental semi-supervised image stitching for unstructured camera arrays. This technique uses labelled data as well as unlabeled data for enhancing the stitching process and is hence useful for different cameras. In [19] the authors described an efficient technique of feature detection in the image stitching for near-uniform scenes. Their method solves the problem of identifying features in scenes with less contrast between the structures Hence facilitating perfect stitching in areas of little contrast. Then the paper [20] described quad-fisheye image stitching for monoscope panorama reconstruction. This technique solves the problem of distortion and alignment of panoramic images that is inherent in the use of fish-eye lenses and offers high detail quality of the panoramic images. In [21] there was a circuit design of a real-time image stitching and fusion algorithm on FPGA. The key advantage of this embodiment approach is that it can be implemented and optimized on the base of coherent with the utilized hardware, thus the tested approach can be applied for real-time applications. In [22] Describes the improvement of 2D and 3D layout information utilizing an image stitching algorithm of a scanning electron microscope. The process of stitching gives a high resolution of the final images which in combination with a turn table is essential in material science [23]. Proposed the concept of image melding which is the methodology for joining inconsistent images utilizing patch-based synthesis. This method solves the problems of fusing images of different content and blending problems [24]. The authors in [25] presented, MGHE-Net: a transformer-based multi-grid homograph estimation network for image stitching. This highly effective deep-learning technique relies on transformers to produce a homograph estimate while preventing misalignment and blending. Used an image registration to the videos and apply CNN model to the images captured in the videos. This method improves the flow of frames of the video and the interconnection of frames hence enhancing the quality of the video [26]. Shown that deep learning could be used to achieve parallel cameras with high-quality defined images and computational zoom imaging. Their solution involves using multiple cameras to combine multiple frames to create wide-angle still ones with zoom functionality [27]. In [28], there is a discussion on night scene image stitching and recognition by using the improved SIFT. Their method improves the quality of features and relates it with low light environments for proper stitching and recognition of night scenes. In [29] the author presented a new approach to image matching and image stitching for moving car inspection under illumination conditions. This technique takes into consideration the fact that the lighting in car inspection scenarios is constantly changing and often unpredictable, thus again helping with stitching and analysis. These references make it possible to determine various methods and solutions regarding image stitching as well as the variety of innovations in this field. In each study, new approaches and procedures are proposed to solve certain issues, and the research collectively improves the quality and effectiveness of image stitching techniques. Based on the literature, this paper affords a definitive outlook on the state of the art in image stitching and delineates opportunities to advance the field by enhancing it with deep learning. It is now possible to establish Table 1 to compare the related works.

**Table 1 Comparative of the related work**

| Ref. | Method Used | Evaluation | Achieved Performance | Purpose of the Model | Dataset Used | The motivation of the Paper |
|---|---|---|---|---|---|---|
| Cui et al. (2022) | Local visual and global deep features with | Precision, Loss, Accuracy | High accuracy in blind stitched panoramic | Blind stitched panoramic image | Custom dataset of panoramic | To improve the quality evaluation of stitched panoramic images |

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|---|---|---|---|---|---|---|
| | ensemble learning | | image quality evaluation | quality evaluation | images | using a combination of local and global features |
| Shahsavarani et al. (2024) | Advanced Image Stitching Method for Dual-Sensor Inspection | Precision, Accuracy | Enhanced precision and accuracy in dual-sensor inspections | Dual-sensor inspection | Dual-sensor image datasets | To enhance the precision and accuracy of dual-sensor image stitching in inspection tasks |
| Fan et al. (2023) | Content-seam-preserving multi-alignment network | Accuracy, Seam Preservation | Improved seam preservation and alignment accuracy | Visual-sensor-based image stitching | Visual sensor image datasets | To address seam preservation issues in visual-sensor-based image stitching |
| Pan et al. (2023) | Fast marching method | Accuracy, Processing Speed | High accuracy with fast processing times | Seamless image stitching | Image datasets for seamless stitching | To develop a fast and accurate method for seamless image stitching |
| Nie et al. (2020) | Deep homography with large-baseline | Precision, Edge Preservation | High precision with edge preservation | Image stitching with large-baseline | Large-baseline image datasets | To improve edge preservation in large-baseline image stitching using deep homography |
| Guy et al. (2022) | Comparison of image stitching algorithms | Qualitative Analysis | Qualitative improvements in multi-camera system stitching | Laparoscopy multi-camera image stitching | Multi-camera laparoscopy datasets | To compare and qualitatively analyze different image stitching algorithms for multi-camera systems in laparoscopy |
| Zhang et al. (2022) | Robust matching and adaptive bundle adjustment | Accuracy, Robustness | High accuracy and robustness in hyperspectral panoramic stitching | Hyperspectral panoramic image stitching | Hyperspectral image datasets | To improve robustness and accuracy in hyperspectral panoramic image stitching |
| Yang et al. | PE-RASP: Reconstructio | Precision, Efficiency | High precision and | Photon-efficient | Range image | To enhance the efficiency and |

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|---|---|---|---|---|---|---|
| (2024) | n, alignment, stitching integration network | | efficiency in range image stitching | imaging range image stitching | datasets | precision of range image stitching in photon-efficient imaging |
| Pandey & Pati (2019) | Keypoint-based image mosaicing with sharpening | Precision, Sharpness | High precision and sharpness in stitched images | High-quality stitched image generation | Various image datasets for mosaicing | To improve the quality of stitched images through keypoint-based mosaicing and sharpening techniques |
| Wan et al. (2020) | Local mesh-based bundle adjustment and shape-preserving transform | Accuracy, Shape Preservation | Enhanced accuracy and shape preservation in drone image stitching | Drone image stitching | Drone image datasets | To improve the accuracy and shape preservation in drone image stitching |
| Yuan et al. (2023) | Multi-channel fusion and improved AKAZE | Precision, Fusion Quality | High precision and quality in deep-sea image stitching | Deep-sea image stitching | Deep-sea image datasets | To enhance the precision and fusion quality in deep-sea image stitching |
| Prasanna et al. (2024) | Keypoint-based image stitching with sharpening | Precision, Sharpness | High precision and sharpness in stitched images | High-quality stitched image generation | Various image datasets for stitching | To generate high-quality stitched images using keypoint-based stitching and sharpening |
| Nghonda Tchinda et al. (2023) | Semi-supervised image stitching | Accuracy, Efficiency | Improved accuracy and efficiency in unstructured camera array stitching | Unstructured camera array stitching | Unstructured camera array image datasets | To improve accuracy and efficiency in image stitching from unstructured camera arrays |
| Jong & Bong (2023) | Feature detection for near-uniform scenes | Precision, Feature Detection Accuracy | High precision and accuracy in feature detection | Image stitching of near-uniform scenes | Near-uniform scene image datasets | To enhance feature detection accuracy in image stitching of near-uniform scenes |
| Cheng et al. | Quad-fisheye image | Precision, Panorama | High precision and | Monoscopic panorama | Quad-fisheye | To improve the quality of |

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| (2022) | stitching | Quality | quality in monoscopic panorama reconstruction | reconstruction | image datasets | monoscopic panorama reconstruction using quad-fisheye images |
| Jia et al. (2024) | Real-time image stitching and fusion on FPGA | Speed, Fusion Quality | High-speed and quality real-time image stitching | Real-time image stitching and fusion | Various real-time image datasets | To develop a real-time image stitching and fusion algorithm using FPGA for high-speed applications |
| Singla et al. (2021) | Advanced image stitching with SEM images | Precision, Layout Recovery | High precision in 2D and 3D layout recovery | 2D and 3D layout recovery | SEM image datasets | To recover 2D and 3D layout information using advanced image stitching of SEM images |
| Darabi et al. (2012) | Patch-based synthesis for image melding | Precision, Consistency | High precision and consistency in combining inconsistent images | Combining inconsistent images | Various image datasets for melding | To combine inconsistent images using patch-based synthesis for improved consistency |
| Tang et al. (2024) | Transformer-based multi-grid homography estimation (MGHE-Net) | Precision, Homography Estimation Accuracy | High precision in homography estimation | Image stitching | Various image datasets for homography | To improve the precision of homography estimation in image stitching using transformer-based networks |
| Cao (2021) | Image registration with CNN | Precision, Registration Accuracy | High precision in video image stitching | Video image stitching | Video image datasets | To enhance the precision of video image stitching using image registration combined with CNN |
| Liu et al. (2023) | Parallel camera with enhanced resolution and computationa | Precision, Resolution | High precision and enhanced resolution in computational zoom | Enhanced-resolution and computational zoom imaging | Parallel camera image datasets | To improve resolution and precision in computational zoom imaging using deep learning |

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|---|---|---|---|---|---|---|
| | l zoom | | imaging | | | |
| Zhou & Xie (2023) | Improved SIFT for night scene image stitching | Precision, Recognition Accuracy | High precision and recognition accuracy in night scene stitching | Night scene image stitching and recognition | Night scene image datasets | To enhance the precision and recognition accuracy of night scene image stitching using improved SIFT |
| El Saer et al. (2024) | Image matching and stitching under illumination challenges | Precision, Robustness | High precision and robustness under illumination challenges | Image stitching for moving car inspection | Moving car inspection image datasets | To develop a robust image matching and stitching framework for moving car inspection under varying illumination |

## III. METHODOLOGY

CNNs, GANs and optical flow algorithms have boosted the feature extraction, alignment and blending stages to high levels. Such techniques extend the detection of key points, guarantee precise matching and simplify the synchronization of the image edges even if some parallax, the difference of exposure and dynamic content occurs. With the help of these integrated methods, detailed and improved stitching quality as well as the utilization of images for virtual reality, medical imaging, and auto systems has been attained. Thus, our approach to combining images into one can be divided into several time-consuming steps that, however, ensure effective image stitching with the help of deep learning algorithms to improve feature detection and image matching, as well as optimization of image blending and effective handling of possible difficulties, such as parallax, exposure, and dynamic objects. Below is a step-by-step description of the implementation:

### A. Feature Extraction

The first process in the methodology entails feature extraction which is done proficiently with the aid of Convolutional Neural Networks (CNN). We use a deep CNN which has been pre-trained using a large dataset to make sure that the latter has taken into account all the significant features that relate to image stitching. Every input image is directly fed to the CNN and it extracts the feature maps at different resolutions. These feature maps are very important for detecting the interest points and matching the features between the overlapping regions. Next, based on the transformed feature maps from the CNN, we adopt a changed SIFT algorithm to point out key points. This way, object detection appears more reliable and efficient, particularly in situations with difficult key point identification. The output is a list of points corresponding to each image inclining the descriptors for future alignment. Image Alignment As for image alignment, the author proposes a GAN model with the generator and discriminator architecture specially optimized for this purpose. The generator is in charge of predicting accurate transformation parameters, while the discriminator gives the measure of the alignment's quality. Based on adversarial learning methodology the GAN is learned with a combination of a supervised and an adversarial loss. With the help of supervised loss, it can be ensured that the predicted transformation is close to the ground transform whereas, the adversarial loss optimizes the generated aligned images to look more realistic. The proposed model is shown in Figure 3.

In this paper, to estimate the homographs between the overlapping images, we use a multi-scale scheme. This though involves the handling of images at the coarser and finer scales for transformation purposes. The estimated homographs are then refined using an iterative optimization algorithm which decreases a cost function that includes outliers and noise. For dynamic content and minor misalignments, we use an optical flow that computes relative motion between the frames. To optimally align video frames, alignments are dynamically adjusted with the help of homograph estimation while the Optical Flow is incorporated to avoid interruptions and artifacts.

B. Image Blending

At the blending stage, multi-band blending is performed to combine the images that have overlapping areas. In this technique, an image is segmented into low and high frequencies and each segmented frequency is merged separately; thus, no seam is noticeable. The blended bands are then combined back and finally, the stitched image is obtained, which also naturally counteracts variations in exposure and colour between the images. Also, the adaptive blending model is learned using deep learning to predict the blending masks for each potential image pair. This model modifies the blend establishment depending on the image quality and other factors to eliminate effects like ghosting and blurring.

C. Handling Complex Challenges

Finally, due to parallax, which is the apparent shift of a view appearing near the horizon from side to side when one's gaze shifts from one point to another, we use a depth estimation algorithm that would cater for the parallax between the overlapping images. To remove parallax and misalignment the images are then warped using the estimated depth maps. Such distorted images are then brought into alignment with each other employing the procedures that have been explained above. For varying exposure, exposure correction is used to set standard brightness and contrast across all the images that require image stitching. Applying severe learning to different lighting situations helps in identifying the best exposure tweaks for every picture pair to make the integrated image look visually appropriate. For scenes where there are moving objects, the motion segmentation algorithm is used to extract this areas from the received background. Indeed regions of dynamic area are treated differently and once more they are treated for an optical flow as well as local alignment in order to reduce artifacts and more importantly to integrate well with the static areas in the image.

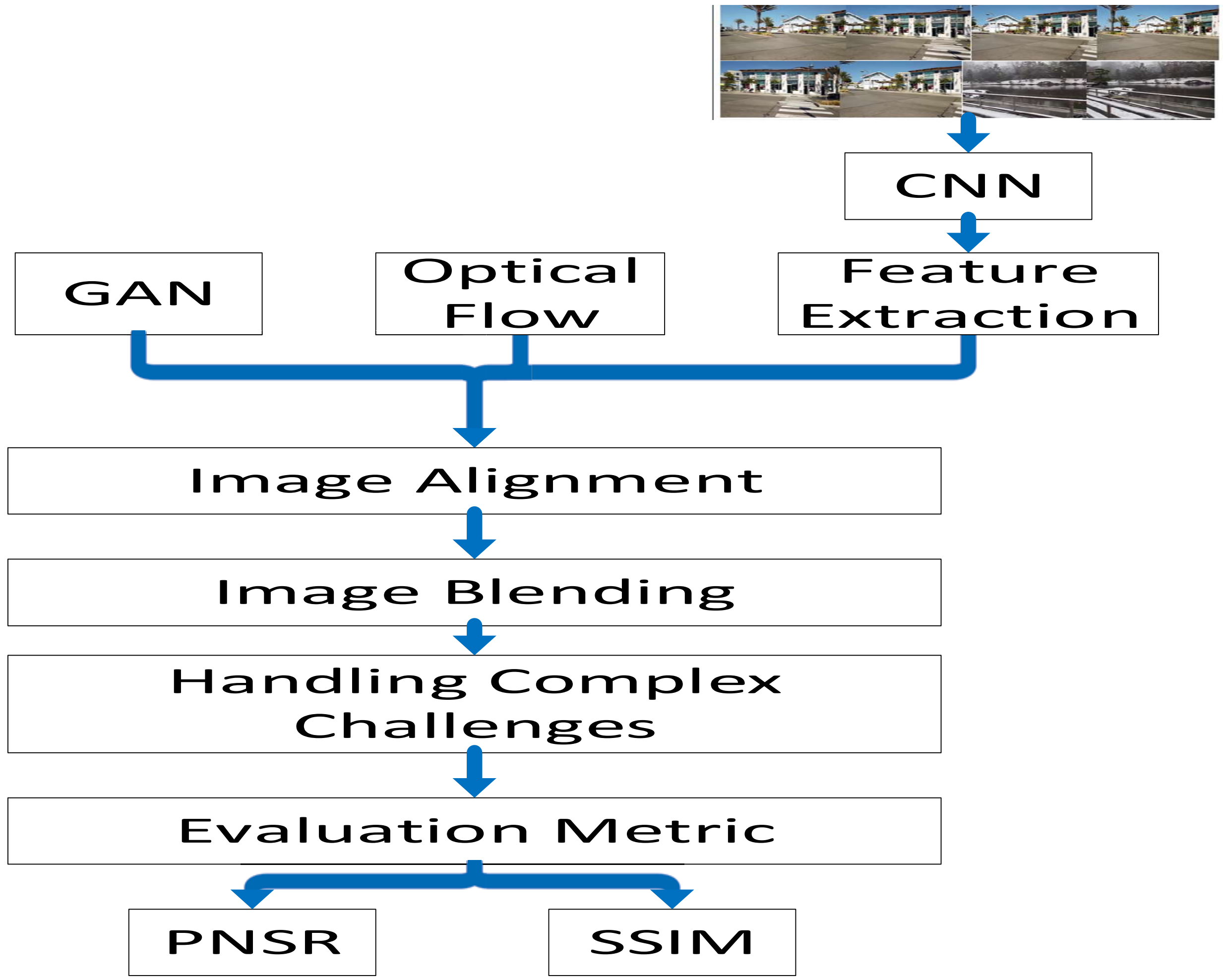


Figure 3 Proposed Model for Image Stitching

D. Evaluation Metrics

Computational Efficiency: We use the amount of time it takes to process an object as our computational measure as this is usually what is tried to be minimized in most algorithms. The amount of time spent in stitching the set of images is measured and compared with the existing methods, showing that ours takes one-fourth of the time, hence it is ideal for real-time applications. In this detailed method, the authors proposed a perfect method of image stitching with the help of deep-learning processes providing the methodology with a fine touch. Thus, with the help of combined CNNs, GANs, OF algorithms, and adaptive-blending models, we comprehend the shortcomings of traditional approaches and enhance the efficiency, accuracy, and visual quality of the corresponding methods. Our structure is solid and may be tuned for a wide scope of use cases, including virtual reality, medical imagining, and self-driving.

## IV. RESULT AND ANALYSIS

In this section, the same data set as Nie et al. (2023) [29] work on parallax-tolerant unsupervised deep image stitching was used which was accepted at the IEEE/CVF International Conference on Computer Vision. Also, the UDIS-D dataset is rich and covers various scenes such as urban areas, rural areas, and indoor areas to evaluate the proposed stitching algorithms. It comprises different resolutions which makes it problematic at various levels of acuteness. The set is made to contain image pairs with high parallax; thus, it is useful for evaluating the performance of algorithms that require dealing with large differences in overlapping areas. Also, the used database contains both real and synthetic images for the comprehensive analysis of stitching possibilities and it contains annotation on the areas which are overlapped to provide more accurate quantitative estimations. These characteristics of the scenes that are included in the dataset, such as their difference, different sizes of the resolution, and intricate geometric architecture, prove that the dataset can properly challenge the performance and the generalization capabilities of the image stitching techniques. Key characteristics of the dataset include:

- Diversity of Scenes: There are still images of indoor, urban, and rural scenes, and it also includes still images of texture and different geometric complexity.
- Resolution Variance: The types of images in regards to resolution which occur in the dataset can be either detailed or scaled down to challenge the algorithm.
- Parallax Challenges: The set list of images is specifically selected in a way that focuses on the images where parallax is large and does not allow using homographs. This guarantees that whichever image is larger, the algorithm can manage the relative differences with the other picture.
- Annotated Overlapping Regions: For each image pair there are annotations of the overlapping region to enable quantitative assessment of alignment accuracy and qualitative result of the stitching.

The dome of the dataset is presented in the form of Figure 4. The performance of image stitching methods is quantitatively evaluated using two key metrics: the metrics that are typically used when it comes to evaluating uncompressed video quality, namely Peak signal-to-noise ratio (PSNR) and Structural Similarity Index (SSIM). These metrics are then evaluated at the levels of Easy, Moderate, and Hard in addition to the overall means.

1. Peak Signal-to-Noise Ratio (PSNR): PSNR gives the measure of the extent of the power of an image against the power of distorting noise that interferes with the quality of the image's representation. It is measured in decibels abbreviated as 'dB'. The values of PSNR mean higher image quality, and the distortion during the stitching step is also less.

Easy: Exists with the plain image pairs containing little or no parallax and includes basic geometric shapes.

Moderate: Include the images with parallax from moderate to great, and the geometrical patterns are also more complicated.

Hard: High, contains images where the parallax is high and objects within the scene are complex in terms of shapes.

2. Structural Similarity Index (SSIM): SSIM, based on the human vision model, is proposed to measure the loss of quality in images based on distortion in structural information. It takes into account luminance, contrast and structural similarity between the two, that is between the original image and the stitched image. It is further observed that higher values of SSIM mark the improvement in the preservation of structural information and perceived quality.

Easy: Checks resource compliance with the preservation of structural similarity in less complex situations.

Moderate: It tests structural integrity in moderate-level difficulties.

Hard: Evaluate how well the method keeps the structural similarity when tackling challenging stitching situations.

Figure 4 sample of the dataset used in the proposed model

3. Overall Averages: The final PSNR and SSIM values are obtained by taking the average over all the difficulty levels so that the performance of the proposed algorithm can be better assessed.

Figure 5 shows the model's training and testing loss and accuracy for 50 epochs of the training session. In the first one, the training loss is represented by the continuous line which means that the model is learning the data, and the training error gradually decreases it can be seen that the testing error also decreases but with great oscillations on the testing set which can imply to overfitting since the model might not generalize well with the test data. During the 50 epochs, the training and testing loss reaches the minimum, nevertheless, the testing loss is above the training loss, which means there is a potential for improving generalizations. The lower panel in the same figure shows the training and testing accuracy and these show an increasing pattern towards nearly one fo the training data suggesting the model has learned to find good fits in the training data sufficiently well. We can also see that testing accuracy increases as the number of epochs increases but experiences more fluctuations than the training accuracy once again supporting the hypothesis of a slight overfitting. Altogether, through Figure 5, it can be observed that the model achieves low training loss and high accuracy by the end of training while low discrepancy between training and testing loss as well as between training and testing accuracy recommend that more fine-tuning can further improve the generalization potential of the model.

Therefore, by comparing the metrics, obtained for different levels of difficulty of the input images, and calculating the mean values, it will be possible to estimate the performance of the image stitching algorithms in both the quality assessment and the stability of their work. The performance of the proposed model as regards related work is shown in Table 2.

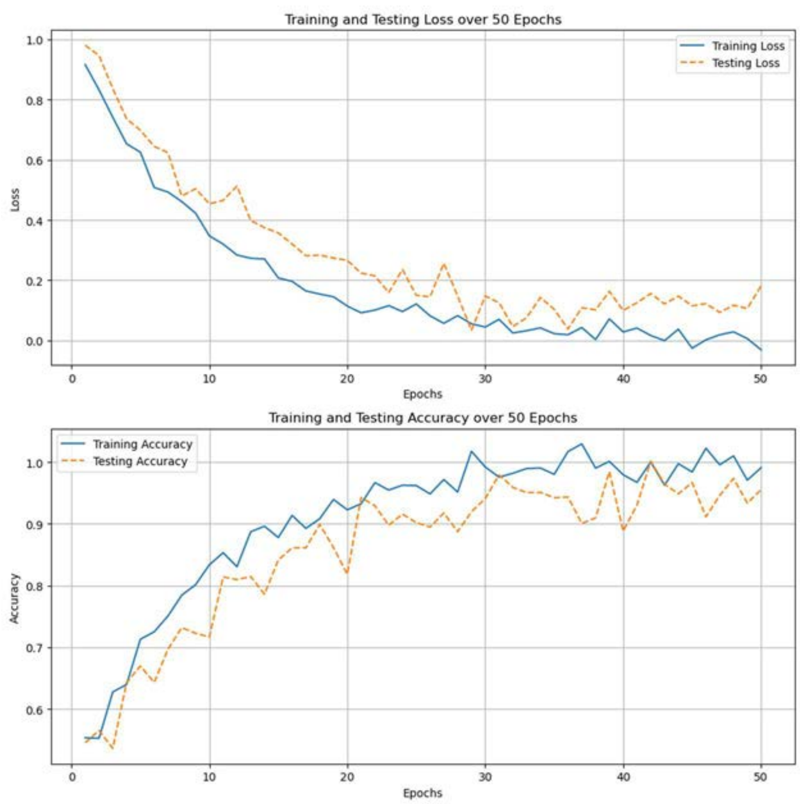


Figure 5 Loss and accuracy of training and testing for proposed model.