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DEEP LEARNING BASED HIGH DYNAMIC RANGE IMAGE RECONSTRUCTION

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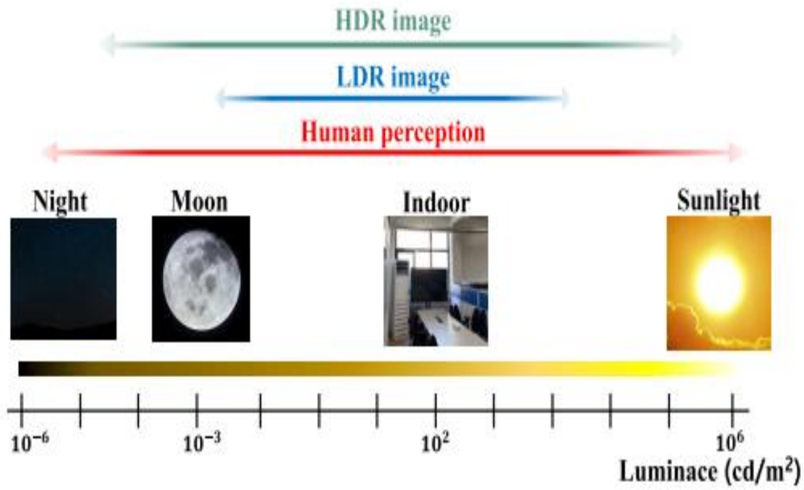
Abstract

When a low dynamic range (LDR) image is converted to a high dynamic range (HDR) image, an image that closely resembles the real world is produced without the use of expensive instruments. Recent advances in deep learning have enabled the creation of HDR photographs that are both realistic and intelligent. This study presents a deep learning method for segmenting the bright and dark portions of an input LDR image and reconstructing an HDR image with similar dynamic ranges in the real world. To create the HDR image, the suggested multi-stage deep learning network brightens bright regions and darkens dark parts, combining features with broader brightness range. The information about missing over-exposed and under-exposed areas is efficiently implemented by dividing the LDR image into bright and dark sections, resulting in a natural HDR image with color and appearance that is similar to reality.

1. Introduction

Significant image processing advancements in recent years have increased the demand for technologies that can produce images with real-world resolution. The most extensively utilized image quality enhancing technology is high dynamic range (HDR).In comparison to that can operate beyond the typical camera sensor restrictions to capture a large dynamic range [1], HDR provides photos with equivalent brightness to the range of human perception, as shown in Fig. 1. As a result, most individuals have restricted access to HDR images.



LDR photos taken with several exposures. The photos are then stitched together to create an HDR image. However, because multiple photos cannot be taken at the same time, the ghost artifact that projects the flow of time appears when the bracketed images are merged. Missing data areas can also be found outside of a specific exposure range

To produce HDR photos from single LDR photographs, inverse tone mapping (ITM) algorithms have been developed. Previous ITM methods, on the other hand, have been insufficient for creating a function that is equivalent to the inverse camera response function (CRF), and acquiring parameters that satisfy all picture situations is problematic.

Convolution neural network (CNN)-based MEF approaches and CNN-based ITM methods have been developed to solve this problem using deep learning methods. By creating and merging multi-exposure pictures, CNN-based MEF algorithms can restore the saturated pixels uniformly. They have trouble restoring saturated pixels that don't exist in the brightness range of multi-exposure photos. To reconstruct HDR images from a single LDR image, CNN-based ITM algorithms have appeared.

To reconstruct HDR images from a single LDR image, CNN-based ITM algorithms have evolved. These methods map the LDR image to the HDR image through a CNN that acts as an inverse CRF. Despite efforts to collect photos that are as close to the source as possible, effective restoration for saturated pixels is still limited

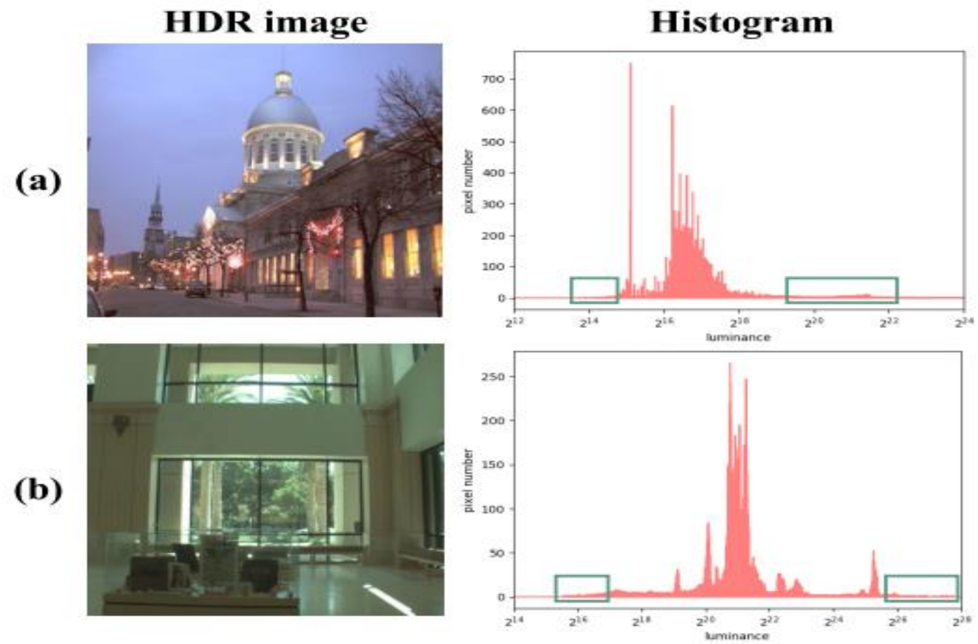
The amount of saturated pixels in the HDR image is limited when compared to the total number of pixels. Weights are changed to reduce the global pixel value discrepancies between the ground truth and inferred images, since image restoration commonly uses loss functions based on L1, L2, or a mean square error (MSE). As a result, the network weights aren't changed as quickly as they should be in order to recover the saturated pixels.

1) The suggested method splits the input image into bright and dark regions, then trains each separately. Over-exposed portions are efficiently restored using bright regions, while under-exposed sections are effectively restored using dark regions. As a result, the proposed method can successfully restore all saturated pixels.

2) The suggested picture segmentation mask creation approach is free of artifacts. When bright and dark sections are mixed, the suggested Mask provides for smooth and clear image segmentation while eliminating boundary plane artifacts.

3) The multi-stage network structure that has been proposed Increases the dynamic range and recovers saturated pixels equally. Bright portions are brightened, while dark regions are darkened to increase the dynamic range. The features are then combined to create the final HDR image.

Histogram of HDR image log2-luminance. The outermost value of the brightness that is likely to be clipped by the CRF is represented by the green box.



II.RELATED WORKS

The article demonstrates the usability of HDR techniques applied to the X-ray images. It is intended for the improvement of diagnostic abilities of the X-ray imaging through the fusion of different exposures obtained with different photon energies (kVp). The article comprises background analysis, proof-of-concept using the generic exposure fusion through the Laplace pyramid and a broad survey of tone mapping techniques. The results of the survey were obtained through the experts systematic quality assessment using an adjective-numerical scale.

We present a method of recovering high dynamic range radiance maps from photographs taken with conventional imaging equipment. In our method, multiple photographs of the scene are taken with different amounts of exposure. Our algorithm uses these differently exposed photographs to recover the response function of the imaging process, up to factor of scale, using the assumption of reciprocity. With the known response function, the algorithm can fuse the multiple photographs into a single, high dynamic range radiance map whose pixel values are proportional to the true radiance values in the scene. We demonstrate our method on images acquired with both photochemical and digital imaging processes. We discuss how this work is applicable in many areas of computer graphics involving digitized photographs, including image-based modeling, image compositing, and image processing. Lastly, we demonstrate a few applications of having high dynamic range radiance maps, such as synthesizing realistic motion blur and simulating the response of the human visual system.

We propose a technique for fusing a bracketed exposure sequence into a high quality image, without converting to HDR first. Skipping the physically-based HDR assembly step simplifies the acquisition pipeline. This avoids camera response curve calibration and is computationally efficient. It also allows for including flash images in the sequence. Our technique blends multiple exposures, guided by simple quality measures like saturation and contrast. This is done in a multiresolution fashion to account for the brightness variation in the sequence. The resulting image quality is comparable to existing tone mapping operators.

High dynamic range (HDR) image generation and display technologies are becoming increasingly popular in various applications. A standard and commonly used approach to obtain an HDR image is the multiple exposures' fusion technique which consists of combining multiple images of the same scene with varying exposure times. However, if the scene is not static during the sequence acquisition, moving objects manifest themselves as ghosting artefacts in the final HDR image. Detecting and removing ghosting artefacts is an important issue for automatically generating HDR images of dynamic scenes. The aim of this paper is to provide an up-to-date review of the recently proposed methods for ghost-free HDR image generation. Moreover, a classification and comparison of the reviewed methods is reported to serve as a useful guide for future research on this topic.

The development of high dynamic range (HDR) imagery has brought us to the verge of arguably the largest change in image display technologies since the transition from black-and-white to color television. Novel capture and display hardware will soon enable consumers to enjoy the HDR experience in their own homes. The question remains, however, of what to do with existing images and movies, which are intrinsically low dynamic range (LDR). Can this enormous volume of legacy content also be displayed effectively on HDR displays? We have carried out a series of rigorous psychophysical investigations to determine how LDR images are best displayed on a state-of-the-art HDR monitor, and to identify which stages of the HDR imaging pipeline are perceptually most critical. Our main findings are: (1) As expected, HDR displays outperform LDR ones. (2) Surprisingly, HDR images that are tone-mapped for display on standard monitors are often no better than the best single LDR exposure from a bracketed sequence.

In recent years many Tone Mapping Operators (TMOs) have been presented in order to display High Dynamic Range Images (HDRI) on typical display devices. TMOs compress the luminance range while trying to maintain contrast. The dual of tone mapping, inverse tone mapping, expands a Low Dynamic Range Image (LDRI) into a HDRI. HsDRIs contain a broader range of physical values that can be perceived by the human visual system. The majority of today's media is stored in low dynamic range. Inverse Tone Mapping Op- erators (iTMOs) could thus potentially revive all of this content for use in high dynamic range display and image-based lighting. We propose an approximate solution to this problem that uses median- cut to find the areas considered of high luminance and subsequently apply a density estimation to generate an Expand-map in order to extend the range in the high luminance areas using an inverse Pho- tographic Tone Reproduction operator. CR Categories: I.3.7 (Computer Graphics): Three-Dimensional Graphics and Realism—Color, shading, shadowing, and texture.

In the last few years, researchers in the field of High Dynamic Range (HDR) Imaging have focused on providing tools for expanding Low Dynamic Range (LDR) content for the generation of HDR images due to the growing popularity of HDR in applications, such as photography and rendering via Image-Based Lighting, and the imminent arrival of HDR displays to the consumer market. LDR content expansion is required due to the lack of fast and reliable consumer level HDR capture for still images and videos. Furthermore, LDR content expansion, will allow the re-use of legacy LDR stills, videos and LDR applications created, over the last century and more, to be widely available. The use of certain LDR expansion methods, those that are based on the inversion of Tone Mapping Operators (TMOs), has made it possible to create novel compression algorithms that tackle the problem of the size of HDR content storage, which remains one of the major obstacles to be overcome for the adoption of HDR. These methods are used in conjunction with traditional LDR compression methods and can evolve accordingly. The goal of this report is to provide a comprehensive overview on HDR Imaging, and an in depth review on these emerging topics.

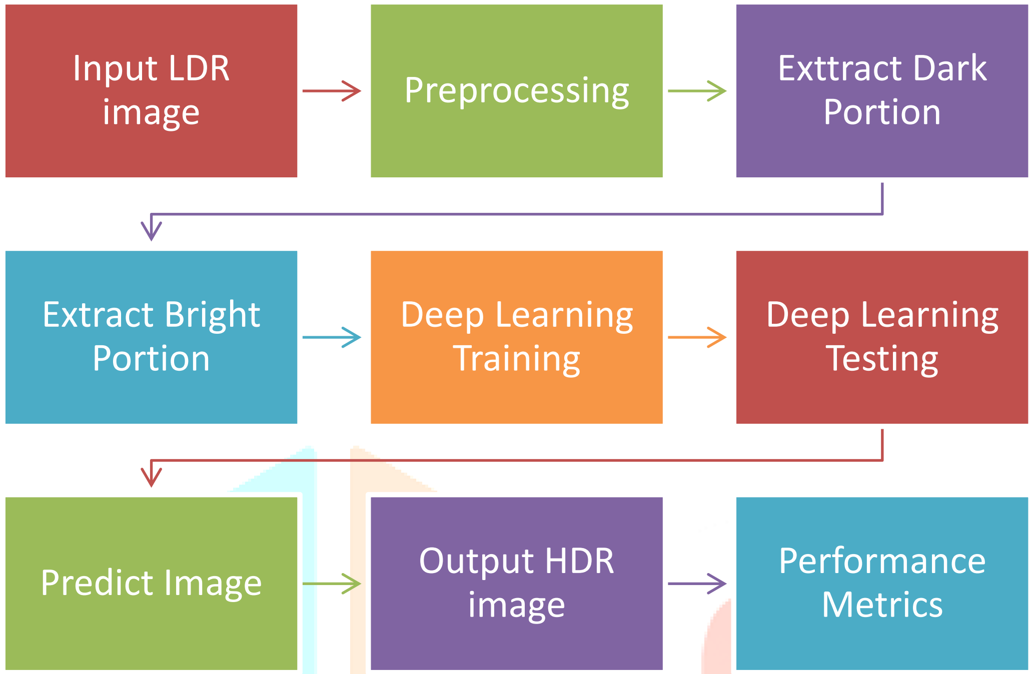
The mismatch between the Low Dynamic Range (LDR) content and the High Dynamic Range (HDR) display arouses the research on inverse tone mapping algorithms. In this paper, we present a physiological inverse tone mapping algorithm inspired by the property of the Human Visual System (HVS). It first imitates the retina response and deduce it to be local adaptive; then estimates local adaptation luminance at each point in the image; finally, the LDR image and local luminance are applied to the inversed local retina response to reconstruct the dynamic range of the original scene. The good performance and high-visual quality were validated by operating on 40 test images. Comparison results with several existing inverse tone mapping methods prove the conciseness and efficiency of the proposed algorithm.

Radiation tolerance in FPGAs is an important field of research particularly for reliable computation in electronics used in aerospace and satellite missions. The motivation behind this research is the degradation of reliability in FPGA hardware due to single-event effects caused by radiation particles. Redundancy is a commonly used technique to enhance the fault-tolerance capability of radiation-sensitive applications. However, redundancy comes with an overhead in terms of excessive area consumption, latency, and power dissipation. Moreover, the redundant circuit implementations vary in structure and resource usage with the redundancy insertion algorithms as well as number of used redundant stages. The radiation environment varies during the operation time span of the mission depending on the orbit and space weather conditions. Therefore, the overheads due to redundancy should also be optimized at run-time with respect to the current radiation level. In this paper, we propose a technique called Dynamic Reliability Management (DRM) that utilizess the radiation data, interprets it, selects a suitable redundancy level, and performs the run-time reconfiguration, thus varying the reliability levels of the target computation modules. DRM is composed of two parts. The design-time tool flow of DRM generates a library of various redundant implementations of the circuit with different magnitudes of performance factors. The run-time tool flow, while utilizing the radiation/error-rate data, selects a required redundancy level and reconfigures the computation module with the corresponding redundant implementation. Both parts of DRM have been verified by experimentation on various benchmarks. The most significant finding we have from this experimentation is that the performance can be scaled multiple times by using partial reconfiguration feature of DRM, e.g., 7.7 and 3.7 times better performance results obtained for our data sorter and matrix multiplier case studies compared with static reliability management techniques. Therefore, DRM allows for maintaining a suitable trade-off between computation reliability and performance overhead during run-time of an application.

To utilize the full potential of new high dynamic range (HDR) displays, a system for the enhancement of bright luminous objects in video sequences is proposed. The system classifies clipped (saturated) regions as lights, reflections or diffuse surfaces using a semi-automatic classifier and then enhances each class of objects with respect to its relative brightness. The enhancement algorithm can significantly stretch the contrast of clipped regions while avoiding amplification of noise and contouring. We demonstrate that the enhanced video is strongly preferred to non-enhanced video, and it compares favorably to other methods.

III.PROPOSED METHOD

It's a difficult task to restore HDR photos from clipped LDR images. Various ways in computer graphics have been studied to overcome this problem, which can be categorized into MEF and ITM.



A.MULTIPLE FUSION METHODS OF EXPOSURE

By mixing bracket photos, De bevel and Malice created an HDR image. Martens et al. fused contrasting elements in multi-exposure photos using a Palladian pyramid and a Gaussian pyramid. The MEF approach is described in detail in references. However, throughout the image merging process, the values of the bracket images were not properly combined, resulting in a halo art effect. To extract the weight values of bracket photos and generate HDR images with equally blended brightness levels, CNN-based MEF algorithms have been presented. Endo et al. used U-Net to bracket photos with different exposure values to create HDR images with large brightness ranges. In a similar vein, Lee et al.

Because MEF approaches typically use more than three LDR pictures, they necessitate a lot of processing time, power, and storage space. To address these issues, Ma et al. developed a rapid MEF technique for generating weight maps for down sampled bracketed pictures using a convolution neural network.

Two exposure fusion (TEF) methods that use only two images have been developed to mitigate the drawbacks of CNN-based MEF methods. Prabhakar et al. suggested a network that merges the brightness information of two LDR images with different exposure times.

However, because TEF approaches necessitate two exposure photographs; the images generated have a significant impact on the outcomes. Furthermore, similar to the CNN-based MEF method, restoring information that may be seen at exposure values other than the preset exposure values is problematic

B.METHODS FOR INVERSE TONE MAPPING

Aksum et al. used gamma correction and linear expansion to create HDR photos. However, unless the input parameters are appropriately specified, efficient range expansion is difficult to achieve. Bantered et al. created HDR photos with a power function and an expansion map [7], as well as an expanded map and the median cut procedure.

These methods, however, necessitate parameters for density estimation, and HDR image inferences have limits when it comes to recovering overexposed areas.

Huo et al. used a physiological ITM method based on the human visual system (HVS) to generate HDR images with fewer parameters, and Masia et al. suggested an automatic global ITM based on gamma expansion. However, the functions used were insufficient to reconstruct the data.

Some proposed solutions, on the other hand, handle a single image by segmenting it into specific ranges. Didyk et al. divided photos into diffuse, reflection, and light zones, then applied different enhancements to each to produce HDR images with a wide brightness range.

Rumple et al. extracted pixels with high luminance and assigned information to saturated pixels using Gaussian filtering and an image pyramid. These methods were successful in restoring saturated pixels, but not in obtaining functions that matched the ground truth level color and texture.

By applying a function to LDR photos, traditional ITM algorithms generate HDR images. Finding a function that is similar to the inverse CRF, on the other hand, is extremely challenging. To overcome this problem, several deep learning algorithms have recently emerged.

Eilertsen et al. used an auto encoder network with a loss function that took into account luminance and reflectivity to create HDR photos. By mixing photos to convert network outputs and LDR images to linear ranges, they were able to create HDR photographs with a higher dynamic range.

The dark regions, in contrast to the light regions created by the CNN, were created using virtual camera curves. As a result, they were unable to effectively recover all waterlogged areas.

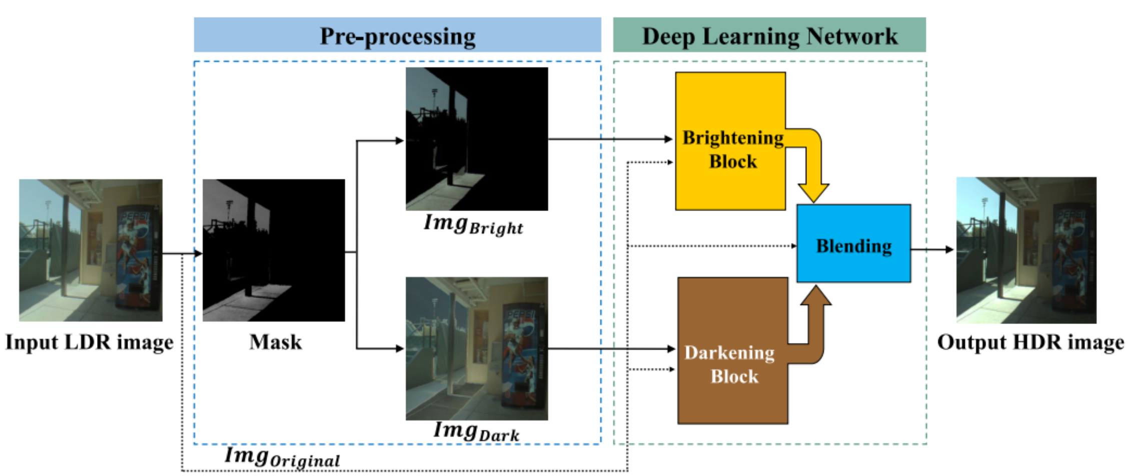
With weighted least squares (WLS) is divided the input LDR image into a low-frequency brightness region and a high-frequency detail region. Then, using a two-stage network, the features of each region were retrieved. Even in low-exposure photos, Cai et al. produced HDR images with improved contrast. However, because they focused on enhancing contrast rather than restoring saturated pixels, they were unable to successfully expand the dynamic range.

Marne rides et al. split global, dilation, and local information from LDR pictures via an end-to-end network into three categories.

Algorithm 1 Finding Threshold

```
Input: H(Histogram), O(Otsu Threshold)
Output: thr (Threshold)
A=[]# Valley point set
T=sum(H)
For j in range(O,252)
      K1=H(j)-H(j-1)<0 and H(j+1)-H(j)>0
      K2= H(j)-H(j-2)<0 and H(j+2)-H(j)>0
      K3= H(j)-H(j-3)<0 and H(j+3)-H(j)>0
      If k1 and k2 and k3:# Find valley point
            V1=var(H(0:j))
             V2=var(H(j+1:255)
             W1=sum(H(0:j))/T
             W2=sum(H(j+1:255))/T
              S=V1*w1+v2*w2
             A.append((s,j))
       End if
End for
If A is not empty:
     thr=max(A)[1]
Else:
   thr=()
End if
```

Liu et al. proposed a method for creating HDR photos with several networks based on a standard camera pipeline layout that produced LDR images. To reverse the process of acquiring LDR images using deep learning, they used dequantization, linearization, hallucination, and refinement networks. They got the final result by sending the LDR image to these networks in order. However, because this method employs many networks, there is a high chance that inference will shift significantly if even one network is not properly learnt.



PSNR: Peak Signal-to-Noise Ratio

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation.

The Formula

$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right)$$

where $MSE = \frac{1}{mn}\sum_0^{m-1}\sum_0^{n-1}\|f(i,j)-g(i,j)\|^2$

SSIM: Structural similarity

The difference with respect to other techniques mentioned previously such as MSE or PSNR is that these approaches estimate *absolute errors*; on the other hand, SSIM is a perception-based model that considers image degradation as *perceived change in structural information*, while also incorporating important perceptual phenomena, including both luminance masking and contrast masking terms. Structural information is the idea that the pixels have strong inter-dependencies especially when they are spatially close. These dependencies carry important information about the structure of the objects in the visual scene.

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{+}c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)}$$

MSE is the mean squared error & it is defined as:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}(O(i,j)-D(i,j))^2$$

Where, **O** represents the matrix data of original image. **D** represents the matrix data of degraded image. **m** represents the numbers of rows of pixels and **i** represents the index of that row of the image. **n** represents the number of columns of pixels and **j** represents the index of that column of the image.

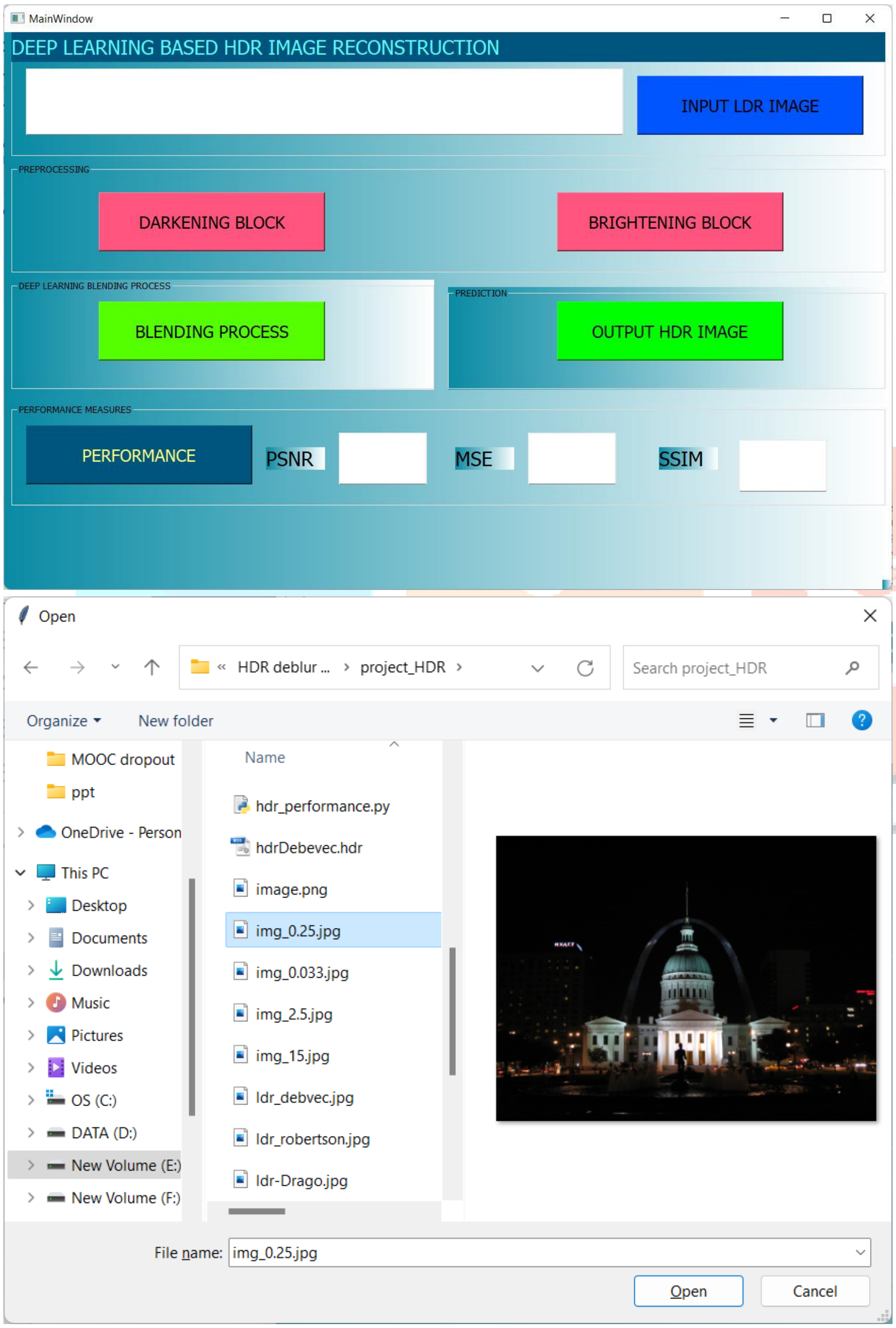
IV. EXPERIMENTAL RESULTS

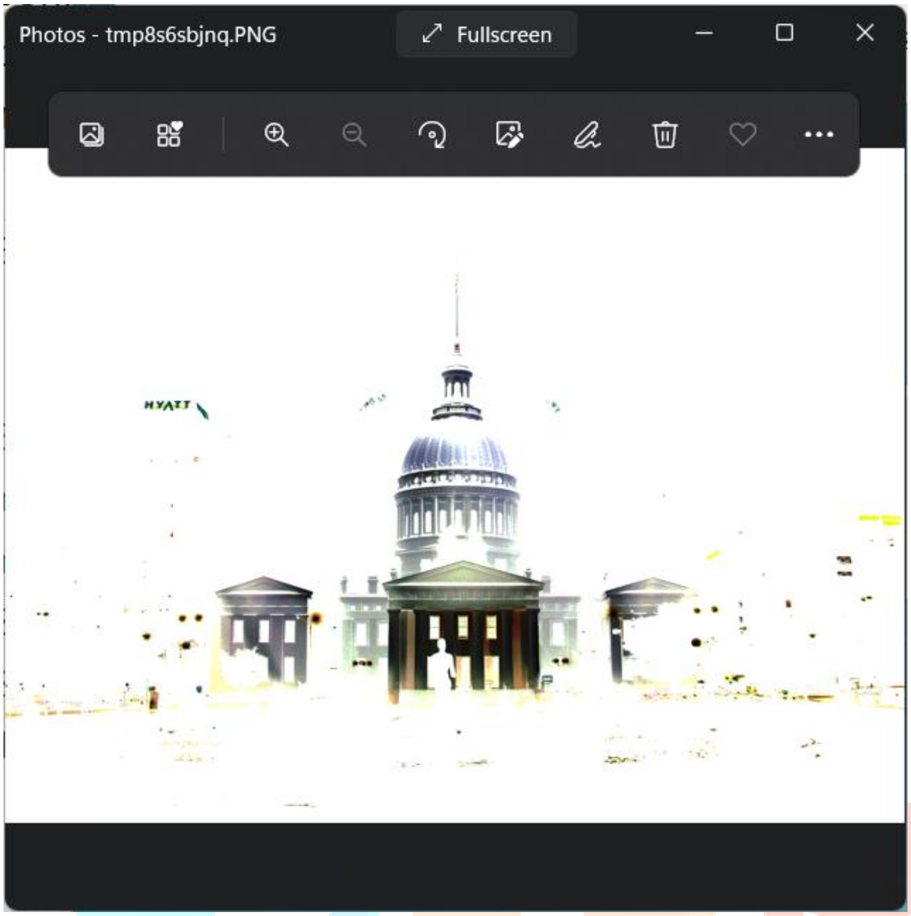
In this section, we explain the functional documentation of the project. It considers various blocks of the modules and the associated forms.

Python v.3.6 was used for training and testing on an Intel i7-7820X CPU with an Nvidia GTX 1080 Ti GPU. To avoid over fitting, we ran 200 training sessions on the 8,118 photos, with the results evaluated every 20 epochs. We utilize the Adam optimizer and start with a learning rate of 0.00007. Each epoch had its weights reset using Xavier initialization, a small batch size of D 8, and 1014 iterations.

The proposed method's overall flow is depicted in Figure 3. During pre-processing, the picture threshold is computed, and the Mask is created. The Mask is then used to segment the LDR picture into bright and dark portions (Img Bright and Img Dark, respectively), with Img Bright and Img Dark serving as inputs to the proposed multi-stage network.

The Brightening block learns ImgBright to create the enhanced brightness value, whereas the Darkening block learns Img Dark to reduce the lower brightness value. Finally, the final HDR image is created by combining the two feature maps with expanded dynamic ranges.

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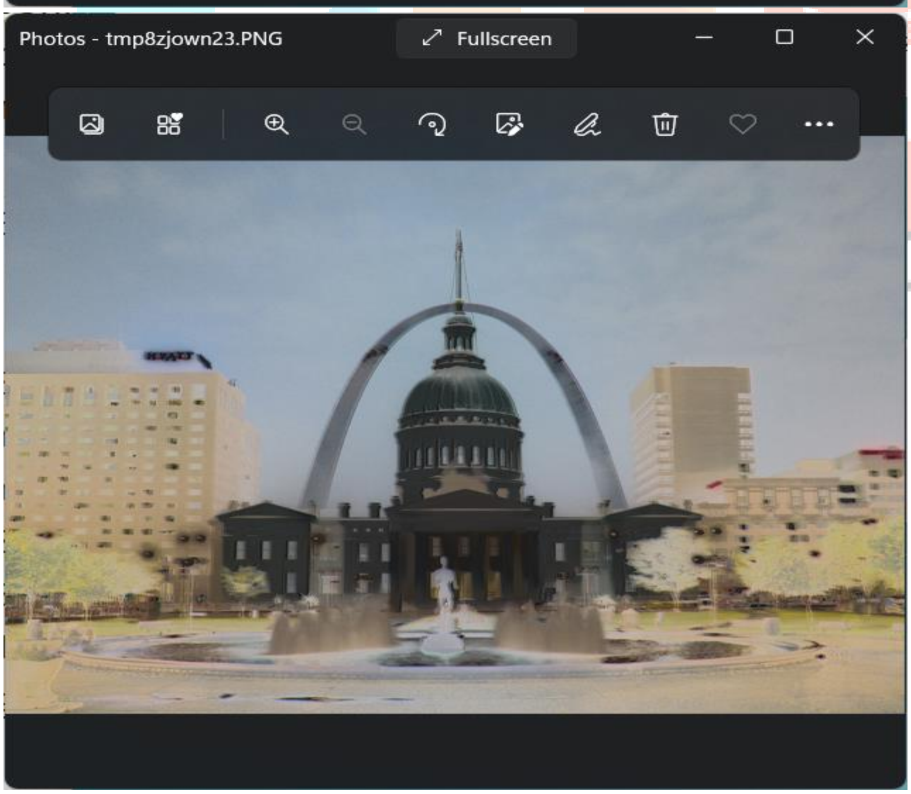
Fullscreen
HYATT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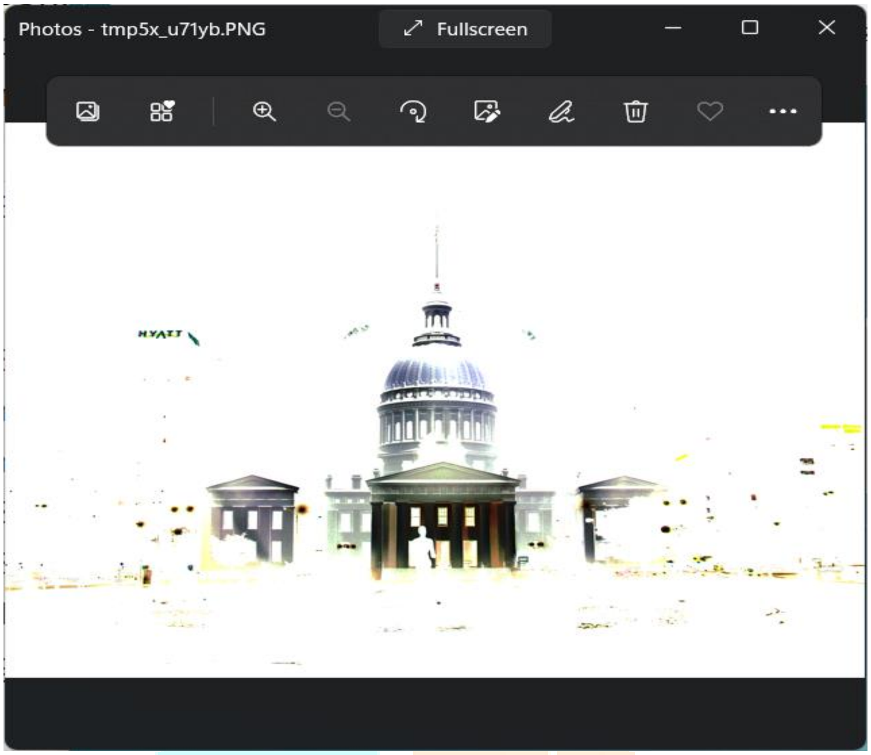
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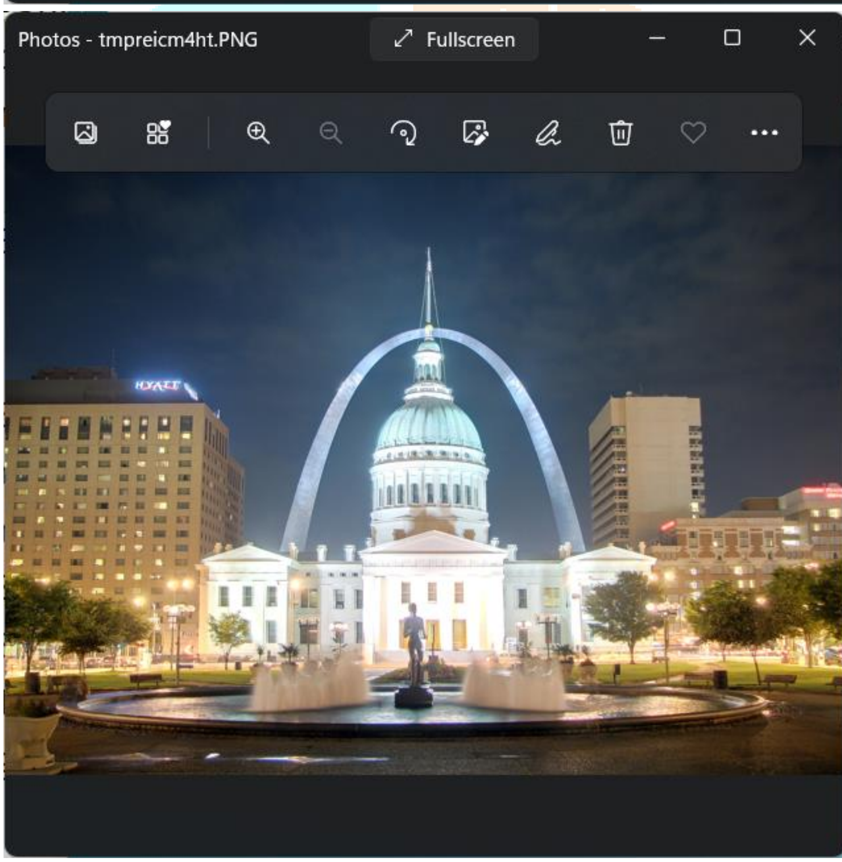
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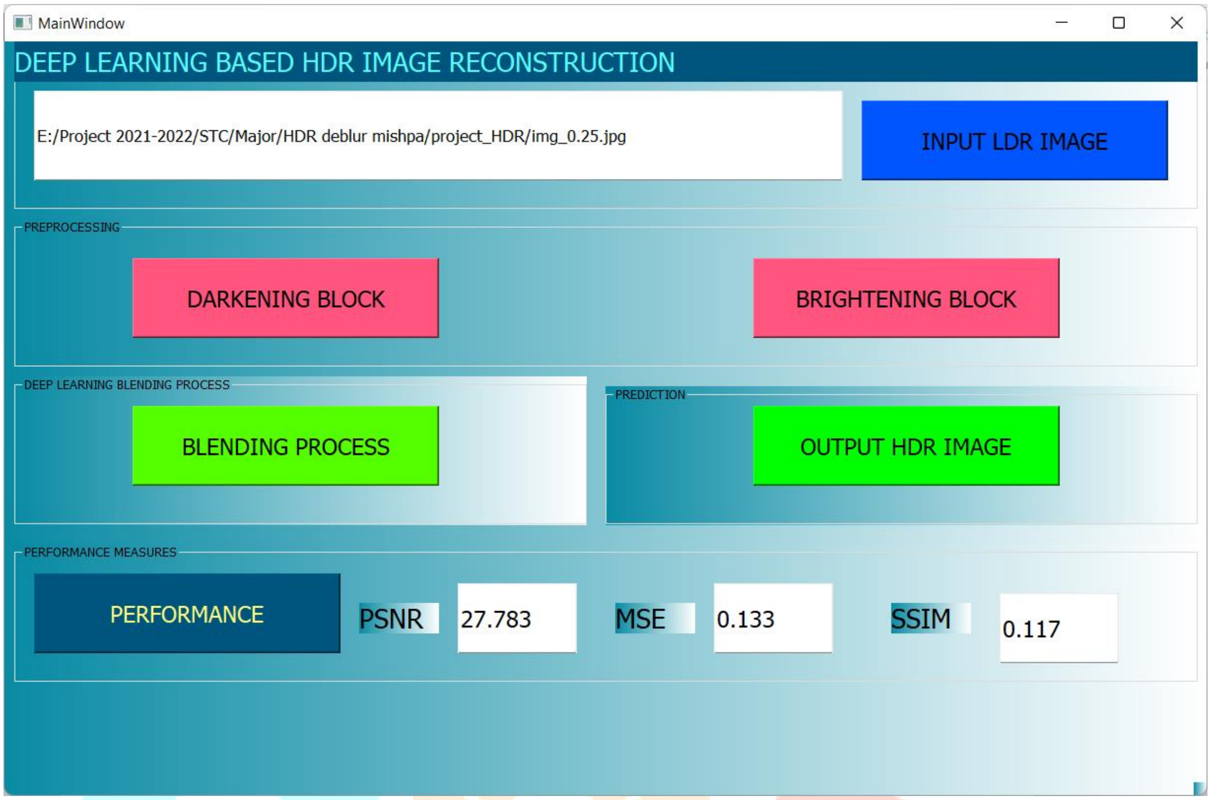

CONCLUSION

HDR recreation from an erratic single uncovered LDR picture is a difficult assignment. To heartily take care of this issue, we have introduced a mixture dynamic reach autoencoder. This is planned and prepared considering the attributes of HDR pictures in the model engineering, preparing information and improvement strategy. The quality and flexibility of the HDR remaking have been shown through various models, as well as in an emotional examination. One of the challenges in HDR image reconstruction is recovering saturated image regions. Quantization artefacts are a less visible issue that can be mitigated using established methods. However, we believe that deep learning can also be used to achieve bit-depth expansion. Existing architectures for compression artefact reduction or super resolution are likely better suited for this application. The recovery of dark parts of a picture that have been lost owing to quantization and noise is a complementary problem to the reconstruction of saturated pixels.

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