Recurrent Exposure Generation for Low-Light Face Detection

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Abstract— This Project introduces an innovative approach to low-light face detection, Exploiting Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and the Zero-Reference Deep Curve Estimation (Zero-DCE) algorithm. The primary goal is to improve the accuracy and reliability of face detection in challenging low-light conditions. Our method integrates LSTM and CNN networks with real-time exposure control, enabling adaptation to dynamic lighting conditions by capturing multiple frames iteratively with varying exposure levels. The incorporation of Zero-DCE facilitates the enhancement of exposure settings, resulting in improved face visibility and noise reduction. Experimental evaluations validate the efficiency of our approach, demonstrating significant advancements in low-light face detection accuracy compared to traditional methods. This project offers a practical adaptable solution with wide-ranging implications for real-world applications, including surveillance, security, and various other domains.

Keywords – Low-light face detection, Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNNs), Zero-Reference Deep Curve Estimation (Zero-DCE), recurrent exposure generation, real-time exposure control, dynamic lighting conditions, noise reduction, surveillance.

I. INTRODUCTION

Photography plays an important role in immortalizing every moment of our lives, be it wedding moments, baby moments, birthday moments, etc. Photos not only preserve our moments forever but can also be used as information or evidence for crimes. For one thing, image enhancement aims to improve the visual/perceptual quality of the overall image, which is not entirely consistent with the purpose of face recognition. For example, smoothing operations to improve noisy images may compromise object identifiability, which is important for detection. This implies tight integration between the enhancement and detection components and points to an end-to-end detection through an enhancement solution. Another reason is that the lighting in the original image can vary greatly from region to region. Therefore, it is difficult to expect a single image with enhanced lighting to be processed properly. Detect facial areas in various lighting conditions. The main goal of our project is to improve the quality of low-light images and identify faces in these images using three main algorithms: Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Zero-Reference Curve Estimator (ZERO). It's about recognizing it. -DCE).) Adjust exposure settings to improve accuracy, improve facial visibility, and reduce noise in challenging low-light conditions.

II. RELATED WORKS

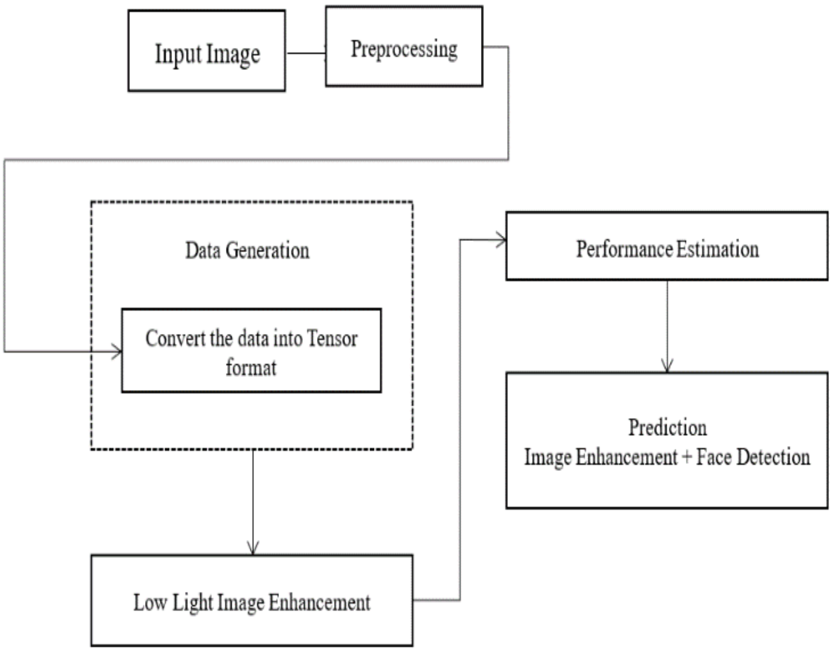
arXiv:2007.10963v1 [cs.CV] 21 Jul 2020

In this work they proposed an end-to-end face detection framework, named REGDet, for dealing with low-light input images. The key component in REGDet is a novel recurrent exposure generation (REG) module that extends ConvGRU to mimic the multi-exposure technique used in photography. The REG module is then sequentially connected with a multi exposure detection (MED) module for detecting faces from images under poor lighting conditions. The proposed method significantly outperforms previous algorithms on a public low light face dataset, with detailed ablation study further validating the effectiveness of the proposed learning component. From an input image, REG generates a sequence of pseudo-exposures to loosely mimic the effect of the highly non-linear process of in-camera multi-exposure. Lightweight recurrent exposure generation module to tackle the non-uniform darkness issues.

III. METHODOLOGY USED

Model Diagram:

This structure offers a broad summary of significant system elements, primary participants in the process, and crucial interconnections.



Algorithms Used:

In this work the experiments are performed by making use of three different Deep Learning algorithms Convolutional Neural Network (CNN), Long short-term Memory (LSTM) and Zero-Reference deep curve estimation (ZERO-DCE) These algorithms are applied on the Dark image dataset, their accuracy is obtained by evaluating the dataset. Each algorithm has been run over the Training dataset and their performance in terms of accuracy is evaluated along with the prediction done in the testing data set.

Convolutional Neural Networks (CNN):

Convolutional Neural Networks (CNNs) have been increasingly utilized in low-light face detection due to their ability to learn hierarchical features directly from images. In the context of low-light face detection, CNNs are employed to extract discriminative features from input images, enabling accurate identification of faces even in challenging lighting conditions. CNNs consist of multiple layers, including convolutional layers that apply filters to input images to extract features, followed by pooling layers to reduce dimensionality and increase robustness to variations in input. These layers are typically followed by fully connected layers for classification or regression tasks. In low-light face detection, CNNs are trained on datasets containing images captured under various lighting conditions, including low-light scenarios. During training, the network learns to extract features that are robust to low-light conditions, enabling it to distinguish between faces and background noise even in dimly lit environments. The network is trained using labelled data, where the labels indicate the presence or absence of a face in the image. Once trained, the CNN can be applied to detect faces in new low-light images by passing the images through the network and analyzing the output.

Long Short-Term Memory (LSTM):

In low-light face detection, Long Short-Term Memory (LSTM) networks offer a dynamic solution by effectively capturing temporal dependencies within sequential data CNN extracting hierarchical features from images, enabling them to discern facial characteristics even under suboptimal lighting conditions. Meanwhile, LSTM networks, renowned for their ability to model temporal dependencies, introduce a crucial element of adaptability by analyzing sequences of frames over time. By integrating LSTM with

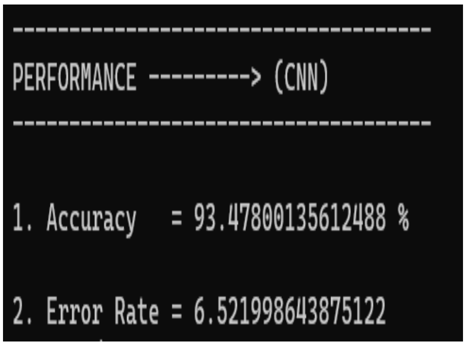
Convolutional Neural Networks (CNNs), the model can adaptively adjust exposure settings in real-time, iteratively capturing multiple frames with varying exposure levels. This intelligent exposure control mechanism enhances face visibility and reduces noise, resulting in significant improvements in low-light face detection accuracy.

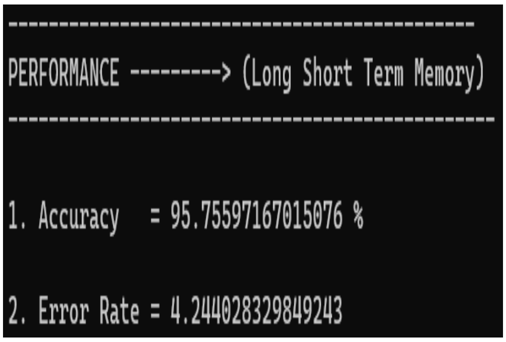
Zero-Reference Deep Curve Estimation (Zero-DCE):

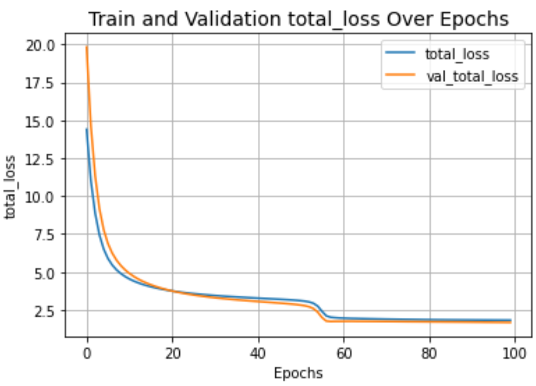
Zero-Reference Deep Curve Estimation, or Zero-DCE, approaches the enhancement of low-light images by employing a deep neural network to estimate an image-specific tonal curve. The network, known as DCE-Net, is lightweight and designed to learn pixel-wise and high-order tonal curves for adjusting the dynamic range of input images. By taking a low-light image as input and generating high-order tonal curves as output, Zero-DCE achieves dynamic range adjustment while preserving neighboring pixel contrast and overall image range. This curve estimation process draws inspiration from curve adjustment tools in photo editing software like Adobe Photoshop, allowing users to manipulate tonal ranges. Notably, Zero-DCE differs from other methods by not requiring input/output image pairs during training, thanks to carefully devised non-reference loss functions that guide the network training process. The DCE-Net itself is a plain convolutional neural network with symmetrical concatenation, featuring seven layers with 32 convolutional kernels per layer, followed by ReLU activation. The final layer employs the Tanh activation function to produce 24 parameter maps, facilitating eight iterations, each requiring three curve parameter maps for the three color channels.

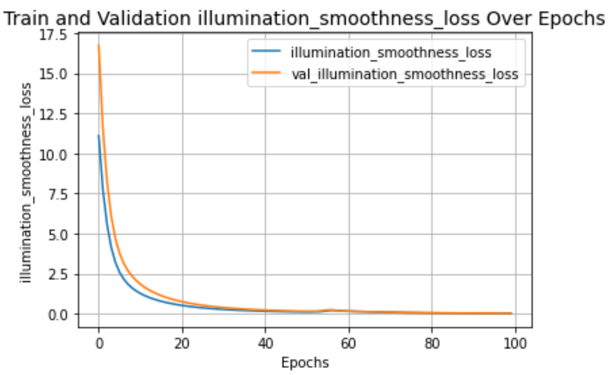
IV. RESULT

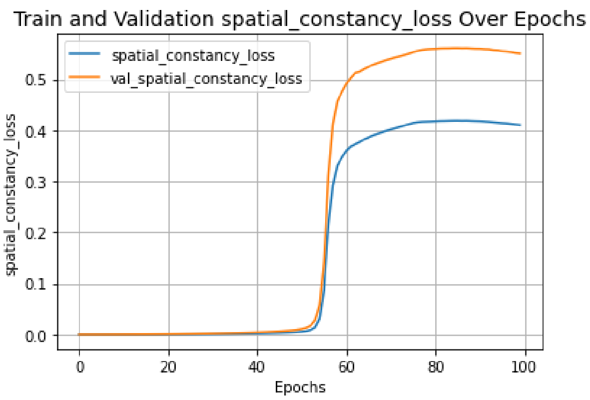
Output interface we can see the accuracy values of each algorithm we are using in this project.

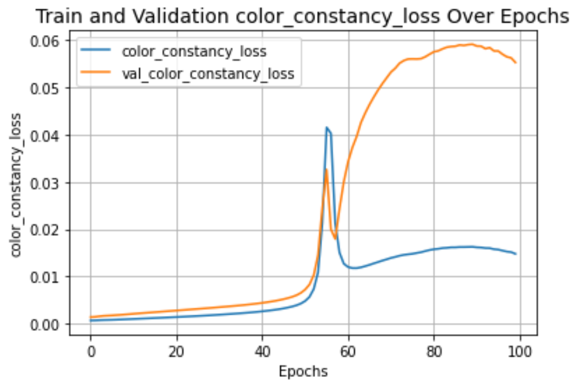


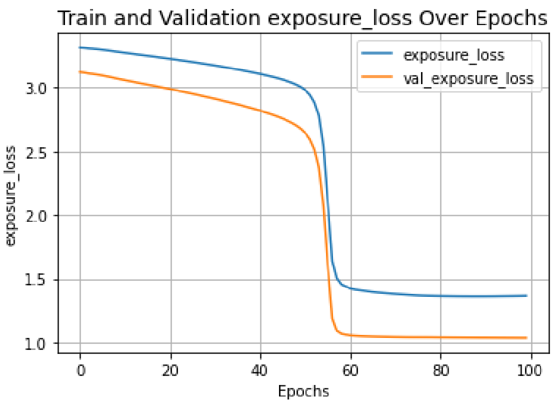






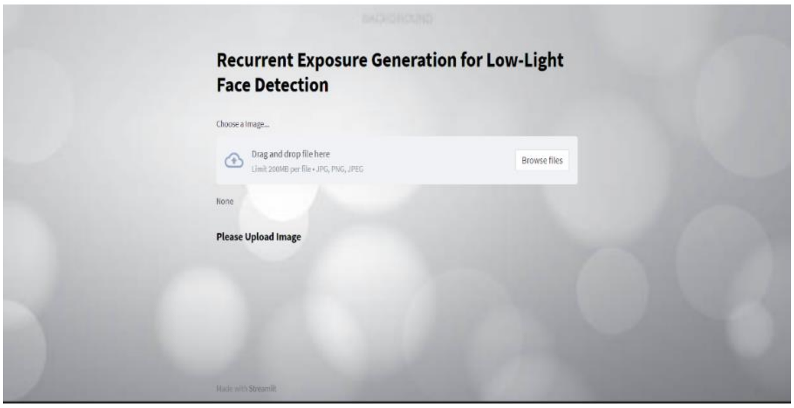




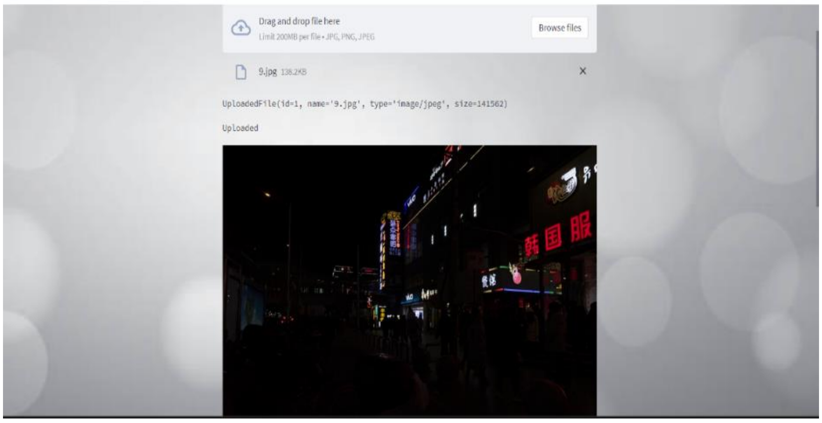


The Web Application interface is given below:

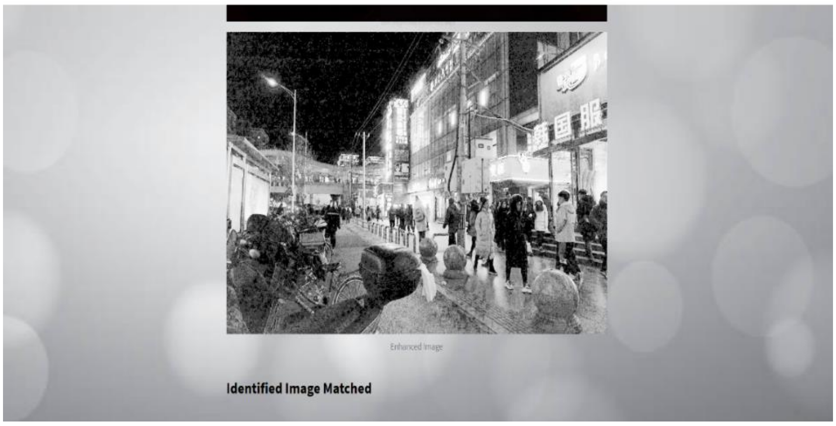
Select input image from the low-light image dataset.



It shows image information and display the uploaded image.



The final output of the prediction model enhances the given low-light image and determines whether the enhanced image is matched with the input image or not.



V. CONCLUSION

In this process, we are using Dark face image dataset to detects the person faces. The dark faces are taken as input and it will applied into image generation, from that module we are going to convert the input as tensor form. Then split the dataset into training dataset and validation dataset using CNN, also used to extract the features from the dark image dataset. LSTM uses these features for further process. After splitting and data generation build the neural network model to enhance the dark images. The Zero DCE-Net is implemented and generates the enhanced images.

In future work, proposed steps can be elaborated to overcome issues of haze and blurriness in case of aerial effects caused in dark face images. The proposed methodology can also be further modified for dark face image enhancement. In future the object detection algorithm will applied and detects the human faces.

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