ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

LOW-LIGHT FACE DETECTION USING DEEP LEARNING

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ABSTRACT

A low-light illumination is always a problem for some face detection models. However, we can solve this problem by applying a low-light image enhancement on the face detection model. This research evaluates four models of low-light image enhancement, which are MirNet, Adaptive Gamma Correction, RetinexNet, and Retinex. These four models are evaluated using LOL dataset by PSNR and SSIM. The evaluation results are applied on RetinaFace model as face detection and tested using Dark Face dataset. The final model on our proposed method is a combination of both Retinex and RetinaFace face detection models. The result of combined model between Retinex and RetinaFace are outperforms other combined methods. The combine method between low-light image enhancement Retinex model and face detection Retinaface model achieved a mean average precision (mAP) of 0.43%. While, without applying low-light image enhancement model on face detection model, RetinaFace only yielded 0.27% on mAP.

Keywords: *Face Detection, Low-light Image Enhancement, Deep Learning, RetinaFace Model, Retinex Model*

1. INTRODUCTION

Photography is an important thing for us to perpetuate every second moment in our lives, for example, wedding moments, birth child moments, birthday moments, and many more. Besides as a perpetuation of our moment, photos can also be used as a medium of information or evidence, such as crimes. Crimes always happen every hour, minute, and second in our lives. To prevent or reduce criminal cases, the government made a plan to install cameras on every street corner. Yet, it doesn't stop bad guys from doing all bad things. However, solid evidence obtained from cameras helps police to identify perpetrators by using face detection which was developed into face recognition. With face detection, the machine can identify the facial area, eyes, nose, and mouth from an input. The input itself can be an image that is taken from a photo or a video. Apart from crimes, face detection helps to advance technology in cameras to make the camera focused on the face. In some cases, cameras and security cameras are unlikely to have the features like night vision and infrared cameras, which can make the camera see the environment in the dark, due to the expensive price of cameras with those features, it's unlikely people bought cameras that have it. In some aspects, this can cause a criminal to exploit the weakness in some cameras, and make their identities hidden in low illumination conditions such as the environment of the night. Fortunately, there's a solution to this problem. The solution has been published by researchers called low-light face detection.

Recent studies in low-light face detection, Such as Wang W, *et al*. utilize features that could self-improve to perform in a much better way in face detection [1]. In another solution Yu J, *et al*. uses a pyramid box to do face detection [2]. Other than that, Liu R, *et al*. uses *Retinex-inspired Unrolling with Architecture Search* (RUAS) a model to perform low-light face detection, which is a retinex inspired model [3]. Lastly, Liang J, *et al*. solution uses a detection with enhancement framework that consist of both *Recurrent Exposure Generation* (REG) and *Multi-Exposure Detection* (MED) [4]. This concludes that regardless there are studies that had proposed a solution for low-light face detection, in this case, there's none that utilize RetinaFace as the face detection method which is the best performing method at WIDER-FACE dataset, and so therefore this paper attempts to use RetinaFace as the face detection module, with the help of low-light image enhancement as the image preprocessing.

Low-light image enhancement have been developed recently to improve under exposure image. Some techniques are Histogram Equalization-based model [5], [6], and the Retinex-based model [7], while the state-of-the-art methods that some studies had proposed are RetinexNet [8] and some even use an additional filter by applying an Adaptive Gamma Correction [9]. This study aims to measure the performance of state-of-the-art methods by using the LOL dataset [10] to compare their achievement to one another quantitative and qualitatively, first by measuring the quality of the image by noise in qualitative ways, and quantitatively by using the measurement of both PSNR [11]and SSIM [11], by doing so we could escalate the founded best method in low-light image enhancement and use it for the step to take for the low-light face detection.

This paper proposed a solution to detect faces in low illumination conditions by applying the best method in low-light image enhancement. The proposed method is divided into two segments. In the first segment, we carry out a measurement of performance for choosing a low image enhancement method by measuring four models: MirNet [12], Adaptive Gamma Correction (AGC) [9], Retinex [13], and RetinexNet [14]. These four models are measured using PSNR and SSIM. While the second segment, we perform a low-light face detection which is RetinaFace. Each low-light image enhancement model is applied to the RetinaFace model. These combined models are evaluated by mAP.

The main contributions of this paper are as follows:

- Evaluating several low-light image enhancement methods as preprocessing for face detection models.
- Applying RetinaFace on low-light image enhancement to detect faces on images in a dark illumination.

2. RELATED WORKS

We divided the related works into 3 sections, which are low-light image enhancement, face detection and low-light face detection.

For face detection and low-light image enhancement, we analyze which model have the best performance and a match combination for our implementation. Whereas the previous works of low-light face detection is to see our work opportunity in this field.

2.1 Low-Light Image enhancement

H. Hao *et al.* developed a model from Retinex into NLHD, where this solution was proposed to improve the brightness of dark images by using the NLHD method [15]. The method was trained using the Wider Face [16] dataset and tested by using the Dark Face dataset. The evaluation result is calculated with NIQE which this model gets a score of 2.76.

A study that suggests a solution to improve an image with low illumination using Whale Optimization and Bezier Curve [6] has been proposed recently by M. Veluchamy *et al.* Using LIME, ExDARK, & Retinex Dataset as training and testing, this method got a good result, where they measured the evaluation using PSNR with a score of 34.45 dB**,** SSIM: 0.901%, PCQI: 0.790%, NIQE: 25.70, and NIQMC: 5.215.

In 2020, M. Fan *et al.* propose a solution to increase brightness in images using the Retinex model [17]. The dataset that is used in this paper is Cityscape & Camvid dataset to train and test the model. the evaluation results show that the PSNR, SSIM, and NIQE are 28.816dB, 0.951%, and 3.048**.**

F. Lv *et al.* write a study to improve the quality of brightness in dark images by increasing the contrast where needed using the under-exposed (ue) attention map method [18]. To train and test this method use the low-light images dataset. The results for PSNR was 27.96dB and SSIM was 0.79%

W. Huang *et al.* did research on increasing contrast in an image using Retinex Model and removing noise in an image using a convolution layer [19]. The solution technique was trained & tested using the real low-light dataset. This technique was measured by PSNR with a score of 23.5236db, SSIM: 0.85%, and MSE: 361.79%.

J. Chai *et al*. create a method that can increase and decrease contrast at high and low exposures in images using a CNN-trained Single Image Contrast Enhancer (SICE) [20]. The multi-exposure image dataset was used to train and test the method. This model got a score of 19.7dB for PSNR, and 0.9347% for FSIM.

2.2 Face Detection

In 2020 S. Zhang *et al*. wrote a result of a study conducted to detect faces with a new model, called RefineFace [21]. The dataset that was used for training was Wider Face and testing were Wider Face, AFW (Annotated Faces in the Wild), PASCAL Face, FDDB, and MAFA (Masked Face). This model was measured with the testing dataset, which are Wider Face dataset with 96.3% accuracy on easy, 95.1% on medium, and 90.2% on hard, for Annotated Faces in the Wild (AFW) dataset: the accuracy precision(AP) is 99.90%, PASCAL FACE dataset with 99.45% AP, the Face Detection Dataset and Benchmark(FDDB) dataset true positive(TP) score was 99.11%, and MASKED Face(MAFA) dataset AP for the masked set with 96.2%, the whole set: 83.9%, and unignored set: 95.7%.

T. M. Hoang *et al*. published a paper about detecting faces using RetinaNet (DCNN architecture) with ResNet as a module + Feature Pyramid Network (FPN) module as feature extraction and assisted with Receptive Context Module (RCM) to strengthen feature maps [22]. The model was trained using Wider Face and tested by Wider Face, FDDB, and MAFA. For the Wider Face dataset, the evaluation on easy, medium, and hard accuracy was 87.2%, 85,6%, and 75,4%, in the FDDB dataset, it got 0.98% in TP, and the MAFA dataset AP score was 77.83%.

Recently, a paper that create a new method of detecting faces using CNN with improvised multiscale (combining global and local features in multi-scale) and ROI (Region of Interest) as a proposal [23] has been published by H. Mliki *et al.* This paper was evaluated using Wider Face dataset that had been split into 40% training set, 10% validation set and 50% as a testing set, beside Wider Face dataset, the FDDB dataset also used on the testing section. The results of the evaluation were Wider Face with 77.23% on precision, Medium 76%, and hard 73.11% with 0.2s as a time cost and on the FDDB dataset, the time cost for this model was 1.4s.

A solution developed by Y. Zhu *et al*. entered 1st place in the Wider Face hard benchmark, they proposed a method for detecting faces using CNN that utilizing RetinaNet architecture and Resnet backbone with Feature Pyramid Network (FPN) and assisted with inception block to increase accuracy in the receptive field (heat map on the face such as eyes, nose, etc.) [24]. For training and testing this model, the Wider Face dataset was used. The results on accuracy are fantastic, using the Wider Face dataset, the easy set got a score of 0.952%, the medium set 0.947%, and the hard set was 0.921%.

In 2019, Zhang *et al*. proposed a method for mobile device face detection by utilizing a Cascaded Convolutional Neural Network (CNN) [25]. The method was trained by using multiple datasets, which are Wider Face, FDDB, CelebFaces Attribut(CelebA), AMI, AWE EAR, IIT Delhi, West Pomeranian University of Technology(WPUT), & their own dataset. While the dataset used in this paper for training is a lot, the dataset that was used for doing experimental testing used only Wider Face with a result that is divided into three categories, that's easy, medium, hard in 0.84, 0.809, 0.603 precision respectively.

Zeng *et al.* developed a new solution model to face detection by using fast cascaded CNN with a multi-tasked learning and network acceleration technique [26]. The method is trained by using Wider Face, Annotated Facial Landmarks in the Wild (AFLW), Celebs. While the testing is done by using FDDB, with a result in Accuracy at 0.98% and speed at 165FPS.

In a recent study by Qezavati *et al*. they did a method development about detecting faces using a scarf/hood using a combination of the Haar Cascade framework and The Support Vector Machine (SVM) algorithm also the Locally Binary Patterns Histogram (LBPH) for face classification and feature extraction. In this study, they used videos taken from Khattam University, totaling 5,000 datasets for training and testing. In the end, the method got 9 False Positive (FP) and 72 True Positive (TP) from 78 faces in the image [27].

A solution was proposed from Qi *et al*. in face detection by using CNN that's applied with Separable Residual Module (SRM) for maintaining a steady accuracy in convolution step [28]. The proposed method was trained by using Wider Face and tested by using both Wider Face and FDDB. The Experimental results that's generated for Wider Face are in 0.869, 0.847, and 0.664 precision respectively to Easy, Medium, and Hard. While for FDDB resulted at a score in 0.947 True Positive.

On other solution about face detection by introducing a method using CNN that used VGG16N architecture and the help of Context agglomeration module (CAM) for combining contextual information to produce an even easier detection on faces [29] was proposed by Shi *et al*. Shi *et al.* used Wider Face dataset to train their model and Wider Face, AFW, PASCAL, and FDDB for testing it. The experimental testing resulted at Wider Face precision at 91.3, 90.3, and 83.1 in precision respectively to easy, medium, and hard. While for both AFW and Pascal Dataset resulted at 99.69 and 98.70 respectively in Average Precision (AP), lastly for FDDB results generated at 0.975 Discrete True Positive.

Zhang *et al*. did an experiment on detecting faces using CNN with RetinaNet architecture by Resnet backbone and Feature Pyramid Network (FPN), especially applying the intersection over union (Iou) Loss Function for regression after classifying the extracted features [30]. Wider Face dataset was utilized to train and test the solution in the experiment. The result on the Wider Face dataset in easy was 96.5%, medium 95.7%, and hard was 91.2%.

Samangouei *et al*. combined a method for a solution in face detection using Faster-RCNN based method with deconvolution in Region Proposal Network (RPN) that was used for determining bounding box [31]. Samangouei *et al*. used the Wider Face dataset for both training and testing, while training only used Wider Face, testing also used FDDB and Pascal datasets for testing. The experimental evaluation in Wider Face resulted at 0.920, 0.913, and 0.850 precision respectively to easy, medium, and hard. While for FDDB resulted at 0.976 discrete true positive, and lastly for Pascal resulted at 98.65 AP.

Yang *et al*. plan to improve the quality of YOLO so that it can detect faces in real-time [32]. In the evaluation, the model was trained and tested using the Celebs Face, FDDB, & Wider Face dataset, the result was measured through size image and cost time. The average for the input of 178*218 image size, the cost time was 0.027199s, the time cost for 450*320 was 0.027246s and last the size image was 2014*680 with 0.029455s time cost.

Chaudhari *et al*. proposed a method using the viola jones algorithm that has been improved to perform a face detection and Neural Network for detecting faces from the eyes [33]. Chaudhari *et al*. used Specs on Faces dataset for Positive Images, and LFW for Negative Images. Both are used for training and testing purposes, resulted in an accuracy at 90%.

A method for face detection was proposed by Li *et al*. using CNN with VGG16 as the backbone that uses Feature Enhance Module (FEN) to enhance featured map that was extracted from convolution image [34]. Li *et al*. used Wider Face for both training and testing with FDDB additionally for testing. Experimental evaluation resulted at Wider Face at 0.966, 0.953, 0.9 respectively to easy, medium, and hard in precision.

Zhang *et al*. proposed a method for solution in face detection by using Faster R-CNN that was improved by increasing the number of layers after the convolution step for feature maps extraction [35]. Zhang *et al*. train and tested the method using Wider Face for both. Which resulted at 95.9, 94.5, 87.9 respectively to easy, medium, hard precision validation.

A RetinaFace model that proposed by Deng *et al*. is a method for face detection by using a multi-task learning strategy, which uses feature pyramids including individual context module to predict face bounding with facial pixel [36]. Deng *et al*. train and tested the method by using Wider Face dataset that resulted at 91.4 AP in hard, 95.6 AP in medium, and 96.3 AP in easy.

2.3 Low-light Face Detection

A paper created by W. Wang *et al*. aims to solve the problem for machines to be able detect faces with dark lighting using the proposed framework, that is a low-level adaptation to adjust low-light brightening, reduce noise, and color bias also a high-level adaptation for self-improving features used [1]. To train the framework, the Wider Face dataset was used, and for testing, it used the Dark Face dataset. At the end of the evaluation, this framework got 44.44% in mean average precision(mAP).

J. Yu *et al*. propose a solution to detect faces in extremely low-light conditions using MSRCR low-light image enhancement and PyramidBox to perform face detection and multi-scale testing [2]. To train the proposed solution, they used the ExDARK dataset and Dark Face dataset, after training the proposed solution was tested using the UFDD dataset and the Dark Face dataset. The results show that this proposed solution got 82.3% for mAP.

R. Liu *et al*. write a proposal for a solution to overcome face detection on a low illumination using Retinex-inspired Unrolling with Architecture Search (RUAS) as a method [3]. The method was trained using Wider Face and tested using Dark Face. The

evaluation result was measured using mAP with 50.13% as a score and LAMR for 72%
.

J. Liang *et al*. create a solution to detect dark faces using Recurrent Exposure generation (REG) and Multi-Exposure Detection (MED) modules to improve performance in face detection [4]. By using the Wider Face dataset as training and the Dark Face dataset as testing, this method got 77.69% in mAP as a result.

2.4 Summary of Related Works

After doing research from reading previous works from researchers, which are W. Wang *et al*, J. Yu *et al*, R. Liu *et al*, and J. Liang *et al*; We can summary that, these works didn't use the best model of face detection in Wider Face hard dataset benchmark. Yet, they used Wider Face dataset as training model in their research. Also, J. Yu *et al* work has the best mAP. Their model achieved 82.3%. It's because, the model was trained and tested using the same dataset, that is Dark Face dataset.

Beside reading from previous works, we also do experiments by comparing one model with another model, we choose the RetinaFace model as our face detection and we combine it with the Retinex model for low-light image enhancement, the reasons are RetinaFace model is a model with high Average Precision (AP) in the Wider Face dataset, which the AP for hard set in Wider Face dataset is 0.914%. Even in the dark illumination, RetinaFace still can detect face with a score of 0.27% in Mean Average Precision(mAP). Yet, because this study wants to improve the mAP in the RetinaFace model, we used Retinex for low-light image enhancement after comparing four models, MirNet, AGC, RetinexNet, and Retinex by quantity and quality that we explain in Chapter 4.

3. THEORY AND METHOD

Deep learning is used for training our method. It increases the accuracy of face detection module. Beside for face detection, deep learning is also used for some low-light image enhancement module to have a better contrast on under exposure image.

3.1 Retinex

Retinex is a concept or theory that has existed for a long time which explains that this concept or theory is taken from the way humans see an object using their Retina and Cortex [37]. This concept or theory continues to be developed by researchers in improving image quality so that the image received by the machine has the same quality as human vision. The researchers made improvements to images that have illumination such as underexposed, noisy images, and foggy images. They do this by separating the reflectance of the image from the illumination in a given image.

3.2 Deep Retinex Decomposition (Retinexnet)

RetinexNet is a developed method from Retinex. The structure of the RetinexNet uses Decom-Net and Enhance-Net to decomposition the image for separating the observed picture into two types of smooth illumination: lighting-independent reflectance and structure-aware smooth illumination and modifies the lighting map to ensure consistency across broad areas while tailoring local distributions through multi-scale concatenation.

3.3 Mirnet

A novel architecture with Convolutional Neural Network (CNN) as a based method to enhance image into high-quality version by using a multi-scale residual block as the core of MirNet. The multi-scale residual block has numerous keys, including parallel multi-resolution convolution streams, information transmission across the multi-resolution streams, spatial and channel attention methods, and attention based multi-scale.

3.4 Adaptive Gamma Correction

Adaptive Gamma Correction is an image enhancement method to enhance a low-light image by using a gamma correction that is calculated for each images according to their gamma value divided into two value low-light image and moderate contrast image, if the value of the mean intensity is lesser than 0.5 means that its categorize as dark image, and in case of its mean intensity is greater than 0.5 means that its categorized as bright image [38].

3.5 Retinaface

RetinaFace is a robust single-stage face detector, developed by Deng *et al*. in 2020. In detecting faces, this model uses a multi-task learning strategy and joint extra-supervised, where this model is designed to predict localization on the face based on the pixels contained in the face. This model has 2 structures, which are Multi-task Loss to minimize errors on the model such as face classification loss, face box regression loss, facial landmark regression loss, and dense regression loss also Dense Regression Branch as a renderer to filter faces and retrieve pixels from rendered filter face.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

In 2020, this model entered the states-of-the art on the Wider Face dataset on the hard difficulty level as no. 2, with an AP of 91.4% after AInnoFace [39].

4. PROPOSED METHOD

The method we propose aims to solve problems that often occur in the face detection model which is low illumination. Some face detection model can detect an input image with low illumination, but the accuracy they have is very low, therefore we tried to solve it by applying a low-light image enhancement technique on face detection model. The workflow of the proposed method is written in Figure 1.

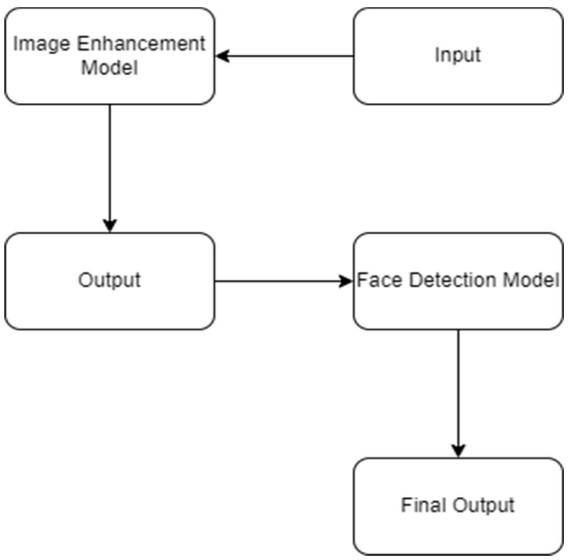

Figure 1. Workflow of proposed method

In general, our method is a combined method between face detection and low-light image enhancement using the RetinaFace model as a face detection model and for the low-light image enhancement model, we use Retinex, RetinexNet, MirNet, and AGC. The low-light image enhancement models are evaluated by PSNR and SSIM using the LOL dataset. After we evaluated the models using the LOL dataset, we evaluate the results that's generated in each image enhancement method and choosing the best low-light image enhancement method to be applied in face detection. The combined method of low-light image enhancement and face detection is evaluated using mAP.

5. EXPERIMENTS

5.1 Dataset

In this study, we used 2 datasets for training and testing our low-light image enhancement model and low-light face detection model, which are LOL dataset and Dark Face dataset.

5.1.1 LOL dataset

LOL dataset [10] was used to train our low image enhancement models and test it to validate the performance result. The dataset contains 500 low-light and normal-light image pairs. The noise in the low-light photographs was created during the photo-taking procedure. The majority of the photographs depict scenes that take place inside. All images have same resolution, which is 400 x 600. The images are shown in Figure 2.

Figure 2. Pair of images in LOL dataset.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

5.1.2 Dark Face dataset

Dark Face dataset [40] was used to perform our performance testing in low-light face detection which provides 6,000 real-world low-light images captured during the nighttime, in this case we could determine whether our study is valid in low illumination condition or not.

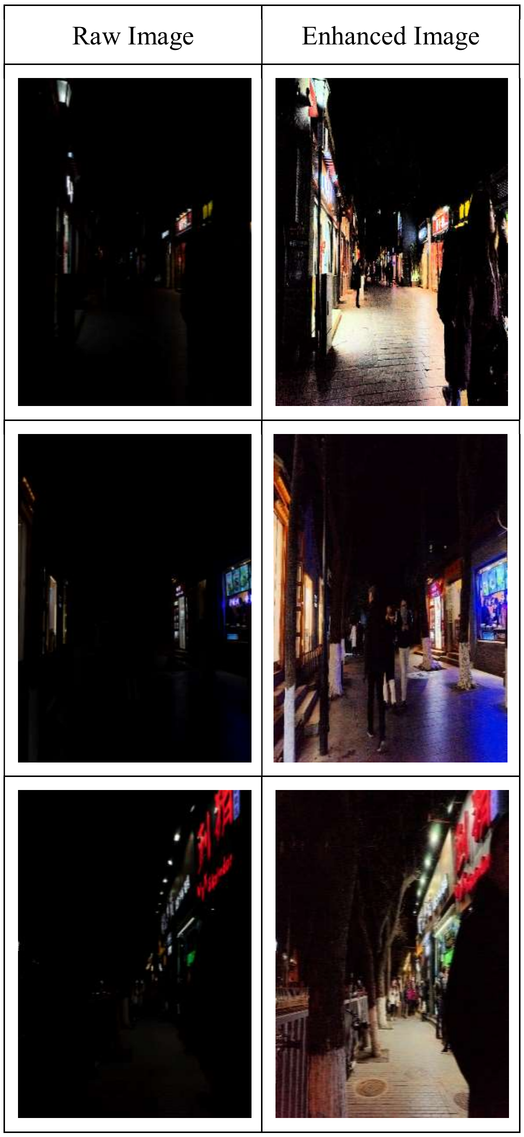

Figure 3. Example of an image from Dark Face dataset.

In the Figure 3, we can see the Dark Face dataset is so dark that even we as human can't see any face in the image. On the other hand, we show the enhanced version with Retinex model so reader can see the faces in the image of Dark Face dataset.

5.2 Experimental Design

5.2.1 Image enhancement experiments

The experiment we did on low-light image enhancement is comparing four models that we used: MirNet, AGC, Retinex, and RetinexNet. For the details, MirNet and RetinexNet are trained using the LOL dataset. The dataset was already split from the source. It is split into pairs of 485 images for training and 15 images for testing. While AGC and Retinex don't need to be trained. After training, we evaluate each model using PNSR and SSIM.

5.2.2 Face detection experiments

While for low-light face detection, we used a pre-trained RetinaFace model which uses Wider Face dataset, whereas for testing we used Dark Face dataset that amounted from 6000, we choose randomly 1000 images in which we conduct performance testing based on mAP.

5.3 Experimental Result

5.3.1. Low-light image enhancement results

After we did some experiments by quantity on the low-light image enhancement model, we can see in Table 1 that MirNet is superior to other models.

Table 1. Evaluation Result on Low-light Image Enhancement Model. MirNet has the highest score in PSNR and SSIM

Model	PSNR (dB)	SSIM
Raw	7.83	0.20185421
AGC	13.60	0.25519422
Retinex	13.40	0.47176218
RetinexNet	16.77	0.41909298
MirNet	19.48	0.7411703

5.3.2 Low-light face detection results

Since the evaluation of low-light image enhancement was done, we move on to test the low-light image enhancement using the Dark Face dataset and predict the output using RetinaFace.

Table 2. Low-light image enhancement evaluation model using Dark face dataset on RetinaFace.

Method	mAP (%)
Raw	0.27
MirNet	0.34
AGC	0.38
RetinexNet	0.39

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Retinex	0.43

As we can see in Table 2, the Retinex model has the highest mAP because the image in the Dark Face dataset has a really low illumination, even in raw RetinaFace model can only have 0.27% mAP.

5.3.3 Qualitative results

(a)Raw **(b)AGC** **(c)RetinexNet**

(d)Retinex **(e)MirNet** **(f)Groundtruth**

Figure 4. Visual Example of Evaluation Result. (a) is the original image of low image from LOL dataset; while (b), (c), (d), and (e) is enhanced LOL dataset image using AGC, RetinexNet, Retinex, and MirNet respectively. (f) is the groundtruth of LOL dataset. Please zoom in for a better view.

We do some analysis on low-light image enhancement results. As we can see on Figure 4, It turns out the Retinex has the brightest color than other models. Then, we conclude that The Retinex model is suitable to be applied to face detection models as an image preprocessing model.

5.4 Discussions

From the result of our experiments, we can see that, RetinaFace model performance is improved. In previous work, RetinaFace model can yield Accuracy Precissions (AP) of 0.914% in Wider Face dataset Hard benchmark, which is Ranked 2. Yet, they can only achieve 0.27% of mAP in Dark Face dataset. While, applying image processing on RetinaFace model, the RetinaFace model performance can obtain 0.43% mAP.

6. CONCLUSION AND FUTURE WORK

In this paper, we have experimented with several method in low image enhancement. The methods are MirNet, AGC, RetinexNet, and lastly Retinex. This low-light image enhancement model is combined with RetinaFace a Face Detection model. The combined model is measured with mAP. The result in low image enhancement shows MirNet is determined as the best performing model according to PSNR and SSIM. While the best results in when the low-light image enhancemen applied to face detection model is Retinex. The mAP score that Retinex got is 0.43%. Yet, the lowest model relatively to mAP scoring in RetinaFace is MirNet with 0.34%.

We can conclude that, applying low light image enhancement as image processing on Retinaface model can improve the Retinaface performance. Without image processing, Retinaface model's mAP score only got 0.27%. But, with image processing, Retinaface model mAP can achieve 0.43%. Furthermore, this strategy can be applied to the best new model on wider face benchmark.

In other words, a better-quality image enhancement doesn't mean that model is applicable on low-light face detection. On the contrary, a brighter image is the better result. In future works, this study could be applied to Face Recognition to identify a person's identity in a low illumination condition and there need to be a study in which uses image enhancement customized for face detection.

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