Masked Face Detection with Illumination Awareness

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***Abstract*—Mask mandate has been applied in many countries in the last two years as a simple but effective way to limit the Covid-19 transmission. Besides the guidance from authorities regarding mask use in public, numerous vision-based approaches have been developed to aid with the monitoring of face mask wearing. Despite promising results have been obtained, several challenges in vision-based masked face detection still remain, primarily due to the insufficient of a quality dataset covering adequate variations in lighting conditions, object scales, mask types, or occlusion levels. In this paper, we investigate the effectiveness of a lightweight masked face detection system under different lighting conditions and the possibility of enhancing its performance with the employment of an image enhancement algorithm and an illumination awareness classifier. A dataset of human subjects with and without face masks in different lighting conditions is first introduced. An illumination awareness classifier is then trained on the collected dataset, the labeling of which is processed automatically based on the difference in detection accuracy when an image enhancement algorithm is taken into account. Experimental results have shown that the combination of the masked face detection system with the illumination awareness and an image enhancement algorithm can boost the system performance to up to 8.6%, 7.4%, and 8.5% in terms of Accuracy, F1-score, and AP-M, respectively.**

***Index Terms*—masked face detection, Covid-19, low-illumination image enhancement**

I. INTRODUCTION

Masked face detection has attracted the attention of researchers over the world in the last two years to aid with the fight against Covid-19 pandemic. Many vision-based approaches have been developed, among which the deep learning ones are more favorable due to the existence of models that can be transferred to the mask face detection domain. As discussed in [1], the major difficulties in this area include but are not limited to face pose, mask type, occlusion, or illumination; each is also a research challenge in computer vision [2].

Regarding the illumination problem in masked face detection, an adequate dataset covering all possible variations might be useful to boost the robustness of a detection model against the brightness and contrast of the input. However, existing datasets such as MFDD, RMFRD, SMFRD [3], MAFA [4] have only addressed the variation in occlusion level, or mask types. On the other hand, image enhancement algorithms can be employed to boost the reliability of detectors in difficult lighting conditions, the applications of which have been verified on pedestrian [5] and face detection tasks [6].

In this paper, we will investigate the improvement feasibility of a simple masked face detection system equipped with some recent effective image enhancement algorithms and an illumination awareness classifier. A dataset with illumination variation is built to train the classifier and test the performance of the system. The contributions of our work are a new masked face dataset and comprehensive experiments to verify the effectiveness of the proposed approach. The rest of the paper is structured as follows: Details of the dataset, the comparative enhancement algorithms, and the classifier are introduced in Section II. Experimental results are reported in Section III. Finally, Section IV concludes the paper.

II. MASKED FACE DETECTION WITH ILLUMINATION AWARENESS

A. Masked Face Detection

A simple masked face detection (MFD) system is first built to identify whether a mask is worn and worn properly on a human subject's face. The system consists of a webcam (HKVISION HS-Y02) and an edge AI computer (Jetson Nano). A light-weight model is then required to implement on the edge device for masked face detection purposes. For the implementation, the following pre-trained models from TensorFlow API are considered: SSD MobileNet-V1 and -V2, SSD ResNet50-V1, and Faster R-CNN ResNet50-V1. These models have been trained on the COCO dataset [7] and customized in this work for the masked face detection task using transfer learning.

Here, we generated a masked face dataset by combining three datasets [8]–[10] consisting of 2241 images of human faces with different types of face coverings. For convenience, we name this dataset for training and validating a masked face detection as MFD2241. The images are categorized into three classes: face with no mask, with properly worn, and improperly worn mask and split into the train and test sets with the ratio of 80:20. As the size of the most bounding boxes are within the $[32^2, 96^2]$ range, AP-M [11] is selected as the evaluation metric for the comparative models.

Table I presents the accuracy and the average processing

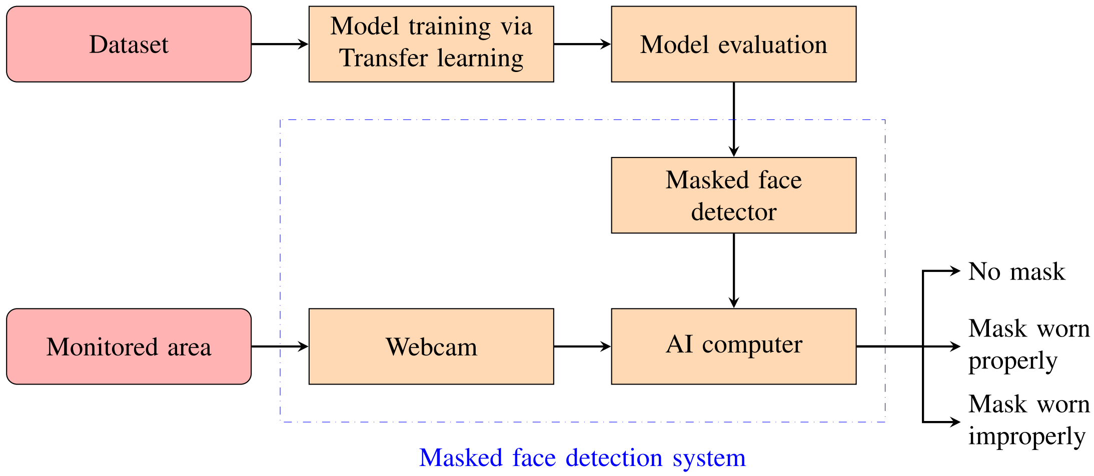


Fig. 1: Processing pipeline of the masked face detection system

TABLE I: PERFORMANCE EVALUATION OF CONSIDERED MODELS FOR MASKED FACE DETECTION

Model	AP-M	fps
SSD MobileNet-V1	0.731	7
SSD MobileNet-V2	0.647	9
SSD ResNet50-V1	0.580	0.5
Faster R-CNN ResNet50-V1	0.630	0.2

time of the considered models on a 2.3 GHz Intel Core i7 with 8 GB DDR3. SSD MobileNetV2 is then selected to embed in the AI computer due to its balance between the accuracy and processing time. The pipeline of the masked face detection system is presented in Fig. 1.

B. Image Illumination Enhancement Algorithms

As discussed in [18], [19], the performance of vision-based approaches using deep learning techniques for social distancing monitoring or masked face detection is impacted in challenged scenarios such as changing illumination. This is critical for monitoring systems installed at locations that are affected by both sun and indoor lighting such as workplace entrances. In such environments, the system should be able to detect masked face subjects not only in good lighting conditions, but also under challenging conditions such as in the dark or under exposure.

A possible solution for this challenge is a classifier to detect ”bright” or ”dark” inputs and apply an image enhancement technique to improve the quality of the ones taken under low lighting conditions. Image enhancement techniques have been developed and successfully applied to low lighting condition scenarios [5], such as nighttime driver face detection [6]. Although promising results have been obtained, the robustness of those algorithms on changing illumination environments have yet to be discussed. For instance, an image is classified as ”enhancement required” in [6] if it is taken after 6pm. Such setting cannot be applied directly in real-life, especially when enhancing an input under good lighting condition could lead to overexposure. Some successful and failure cases of the combination between the MFD and an image enhancement algorithm (Low-Illumination Image Enhancement (LIIE) [5]) is illustrated in Fig. 2. Images taken at low lighting conditions and cannot be detected by MFD (Fig. 2(a) and (b)) are enhanced, leading to a correct recognition of two subjects without and with mask in Fig. 2(d) and (e). In contrast, an enhancement of the input frame taken at a normal lighting condition could lead to an overexposure after enhancement, resulting in a change from a correct to a false recognition of the MFD (Fig. 2(c), (f)).

Here, we collected a dataset of masked face human taken at different lighting conditions, and coupled the proposed masked face detection system with an image enhancement algorithm to build a illumination classifier. Experiments with other image enhancement techniques will then be conducted to verify whether the detection accuracy can be boosted with the classifier. The considered approaches are summarized in Table II.

C. Masked Face Detection with Illumination Awareness

For the training and evaluation of the Illumination Awareness (IA) classifier, images of participated subjects under different lighting conditions are collected. Subjects are asked to stand in front of a camera with different face poses, i.e. rotated at 45 and 90 degree as well as tilted upward and downward at a 20 degree angle. In total, 4178 images are collected, the numbers of which containing subjects wearing masks properly, improperly, and no masks are respectively 1347, 1439, and 1392. For convenience, we name the dataset as Masked Face Dataset with Illumination Change (MFDIC). The categories of MFDIC according to the covering and illumination level is illustrated in Fig. 3.

These images are then classified into two categories depends on their requirement of an illumination enhancement. The labeling of each image is processed automatically by calculating the detection accuracy of the masked face detection

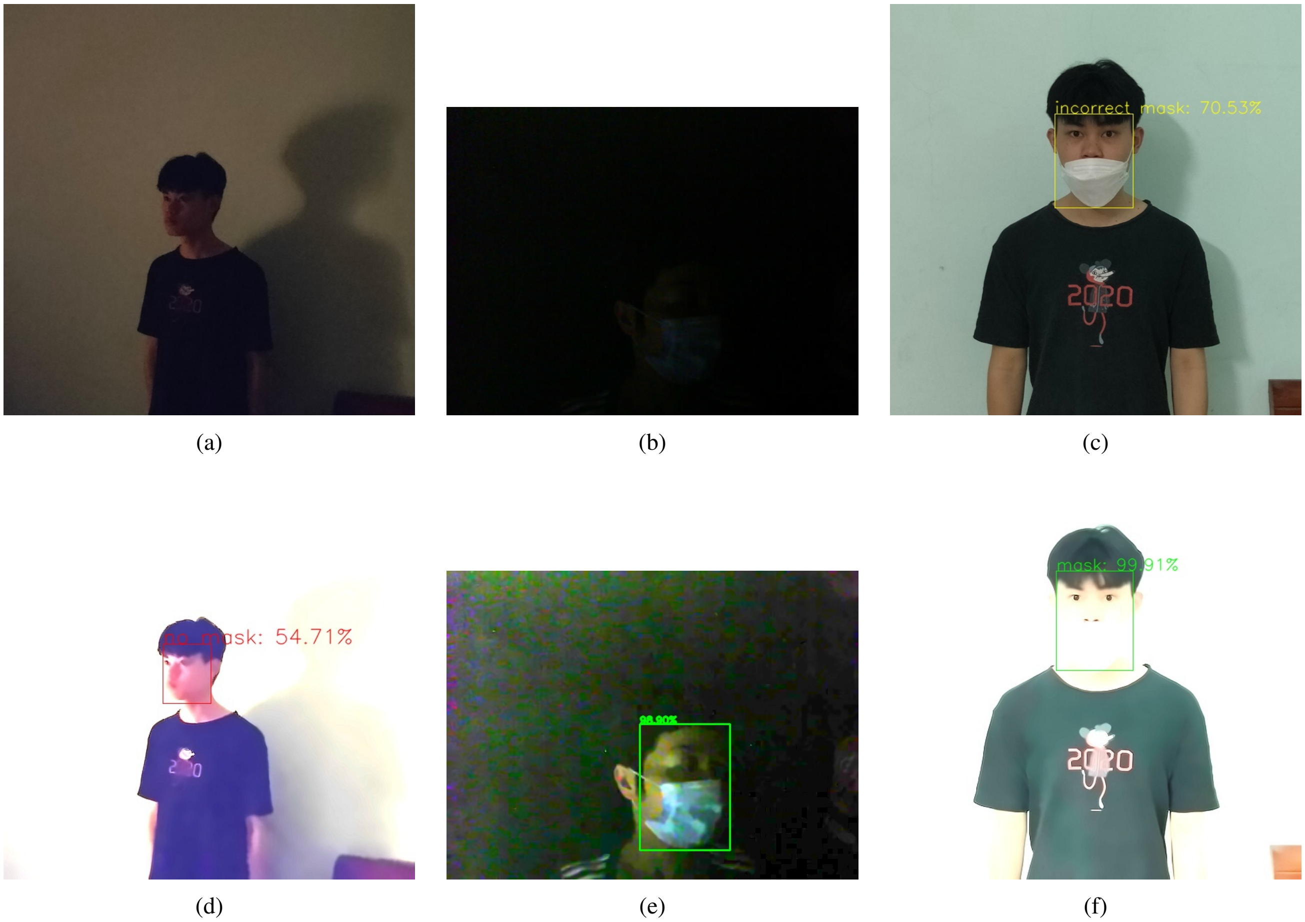


Fig. 2: Successful and failure cases of a combination between the MFD and LIIE in different lighting conditions:
(a) and (b) low illumination with no detection, (d) and (e) successful combination with correct detection on enhanced images; (c) correct detection in normal lighting condition changed to (f) false detection after enhancement due to exposure.

TABLE II: CONSIDERED ILLUMINATION ENHANCEMENT ALGORITHMS

Illumination enhancement algorithm	Brief description
Low-Illumination Image Enhancement (LIIE) [5]	An enhancement approach using hyperbolic tangent curve, block-matching and 3D filtering
Adaptive Attenuation Quantification Retinex (AAQR) [6]	An adaptation of Retinex theory, the quantization range of which is obtained adaptively via attenuation restriction and attenuation prediction
Image De-hazing for Enhancement purposes (IDE) [12]	An adaptation of image de-hazing algorithms combined with inverted low-illumination video frames
Multi-scale Fusion for Illumination Adjustment (MFIA) [13]	A Retinex-inspired method with a fusion of enhanced global luminance and local contrast
Multi Scale Retinex with Color Restoration with Autolevels (MSRCRAL) [14]	An extension of MSRCR [15] eliminating the impact of outliers in the input histogram
Naturalness Preserved Enhancement algorithm (NPE) [16]	An enhancement and naturalness preservation technique using a lightness-order-error measure
Simultaneous Reflection and Illumination Estimation (SRIE) [17]	A reflectance and illumination estimation technique where regularization terms are weighted via a variational model

model on the original input ($A_{\mathrm{w/o}E}$) and the enhanced one ($A_{\mathrm{w}E}$). In this paper, the selected illumination enhancement technique to apply on the input image is LLIE due to its best performance among other comparative approaches on low-illumination images as reported in [5]. An image is classified as "enhancement required" if $A_{\mathrm{w}E} \geq A_{\mathrm{w/o}E}$ and vice versa. The automatic labeling process is illustrated in Fig.4. Out of 4178 collected images, 2507 images are classified as

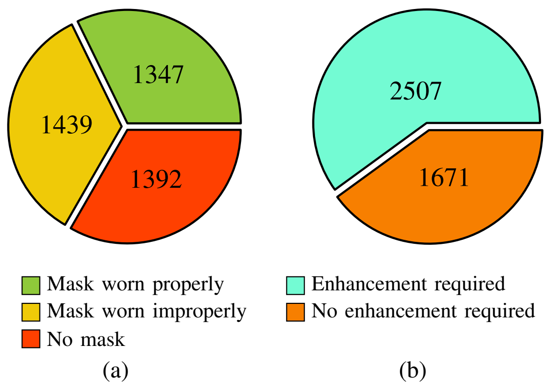


Fig. 3: MFDIC categories according to (a) covering level, and (b) illumination.

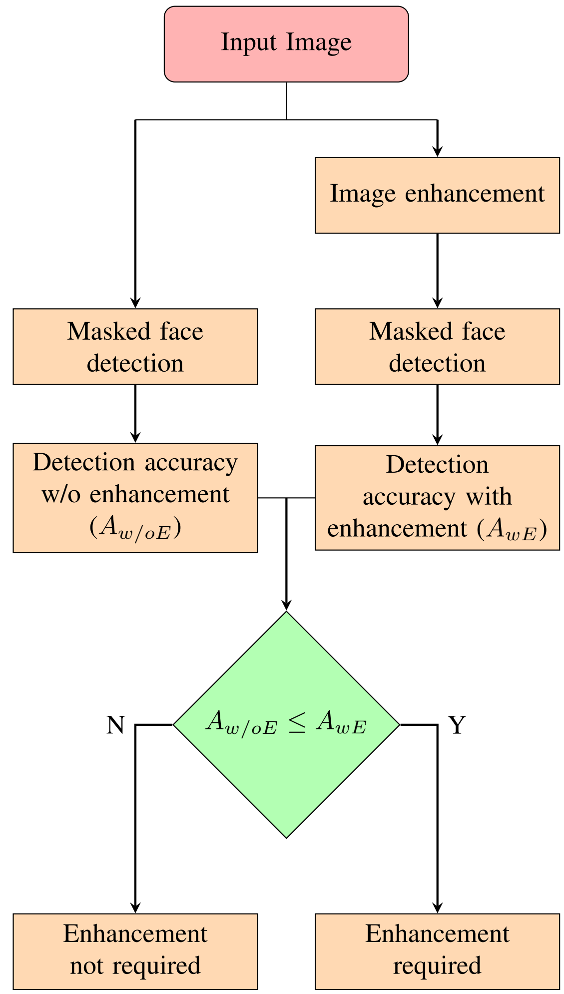


Fig. 4: Illustration of the automatic labeling process.

”enhancement required” while the remaining ones are labeled as ”no enhancement required”. The pipeline of the automatic labeling process is illustrated in Fig. 4.

The collected data is then split into train, validation, and test sets with the ratio of 70:10:20. Data augmentation techniques are also employed in the training dataset to expand the image variations and improve the capability of the trained model. The selected model for this classification task is ResNet-50 [20] due to its competitive performance on the ImageNet 2012 classification dataset [21] while the training time is faster than that of other ResNet variants with more layers.

III. Results and Discussion

Results of the MFD, MFD combined with an image enhancement algorithm (MFD+E), and MFD+E with the illumination awareness classifier (MFD+E+IA) on the MFDIC dataset are reported in Table III. Besides the AP-M, the Accuracy and F1-score are additionally employed as evaluation metrics. First, a drop in AP-M of the MFD on the MFDIC dataset is observed. The reason for this decrease in detection accuracy is due to the complexity of MFDIC compared to that of the source domain MFD2241 where images of participants are taken at different face orientations and illumination levels.

The results of the combination between MFD and an enhancement algorithm show an improvement in terms of AP-M on 5 out of 7 combinations. On a comparison between MFD+E and MFD+E+IA combinations, it is significant to see that the detection accuracy in terms of AP-M is increased with the involvement of the illumination awareness classifier. Out of 7 combinations, only MFD+SRIE performs better without the IA, which could be explained by the training of the classifier on the output of another enhancement algorithm, the LIIE.

In terms of Accuracy, MFD+E performs better than the MFD alone with the involvement of 4 enhancement algorithms, i.e. the MFIA, MSRCRAL, NPE, and SRIE. The Accuracy metrics of the remaining combinations between MFD and LIIE, AAQR, IDE, and MSRCRAL are then significantly boosted with the employment of the IA classifier (3.9% at the lowest and 21.3% at the highest). In contrast, a slight drop of that is experienced on MFIA, NPE, and SRIE.

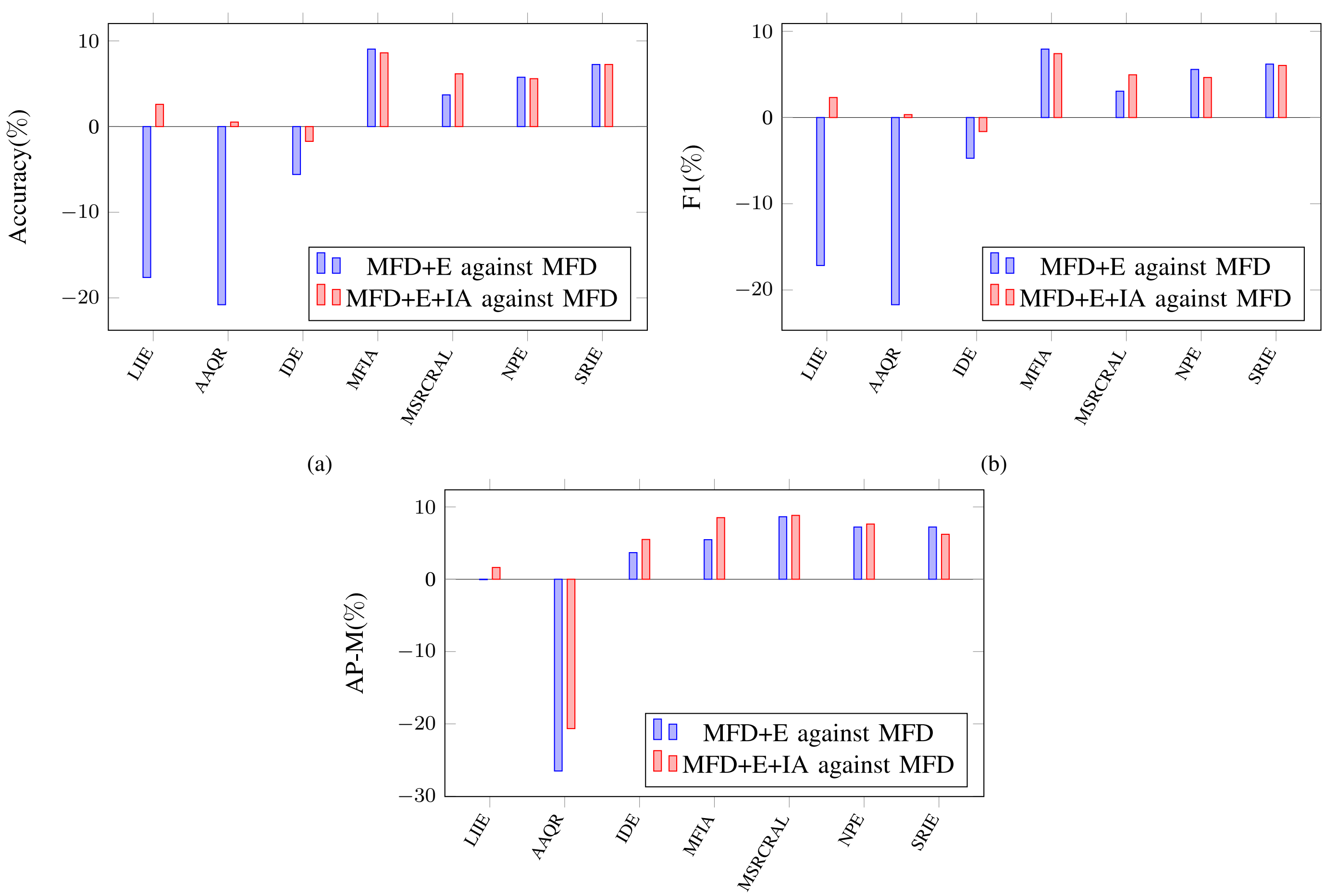
Regarding the F1-score, the involvement of the IA classifier have significantly boosted the performance of 6 out of 7 participated algorithms in this category. Notably, MFD+MFIA+IA outperforms other combinations in all evaluation metrics with a gain of 8.6%, 7.4%, and 8.5% in Accuracy, F1, and AP-M. The application of IA on MFD+E also shows an increment of 3% while the drop in Accuracy and F1 score is less than 0.6%. The performance comparison between MFD+E and MFD+E+IA against MFD is visualized in Fig. 5.

IV. Conclusion

This paper introduced a mask face dataset, the MFDIC, taking into account the illumination variation and the face-covering level at a balanced ratio. The dataset is then employed to train and test the performance of an illumination classifier

TABLE III: ACCURACY EVALUATION OF PARTICIPATED ALGORITHMS ON THE MFDIC DATASET

Algorithms	Metrics	MFD	MFD+E	MFD+E+IA
LIIE [5]	Accuracy(%)		31.272	51.4797
	F1(%)		50.1437	69.625
	AP-M(%)		38.9473	40.6287
AAQR [6]	Accuracy(%)	Accuracy(%)	28.0911	49.4097
	F1(%)	48.8850	45.5959	67.6396
	AP-M(%)		12.4859	18.3477
IDE [12]	Accuracy(%)		43.2929	47.159
	F1(%)		62.5823	65.6793
	AP-M(%)		42.6822	44.5011
MFIA [13]	Accuracy(%)	67.3028	57.9273	57.4908
	F1(%)		75.2392	74.7147
	AP-M(%)	F1(%)	44.4726	47.52
MSRCRAL [14]	Accuracy(%)		52.5832	55.0456
	F1(%)		70.3542	72.2596
	AP-M(%)		47.6458	47.8322
NPE [16]	Accuracy(%)		54.6408	54.4743
	F1(%)	AP-M(%)	72.8824	71.946
	AP-M(%)	39.0011	46.2205	46.6336
SRIE [17]	Accuracy(%)		56.1299	56.1334
	F1(%)		73.4991	73.3455
	AP-M(%)		46.2243	45.216



(a) (b) (c)

Fig. 5: Performance comparison of MFD+E and MFD+E+IA against MFD: (a) Accuracy, (b) F1 and (c) AP-M

on the combination of the masked face detection system with some recent effective image enhancement techniques. Results from the comprehensive experiments have verified the effectiveness of the employment of the enhancement techniques and the illumination classifier. Compared to the MFD alone, a gain in Accuracy, F1-score, and AP-M is observed on 6 out of 7 combinations of MFD+E+IA. The performance of MFD+E+IA is also emphasized compared to that of MFD+E, showing better detection accuracy in terms of all evaluation metrics in most cases.

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