Masked Face Recognition Challenge: The WebFace260M Track Report

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Abstract

According to WHO statistics, there are more than 204,617,027 confirmed COVID-19 cases including 4,323,247 deaths worldwide till August 12, 2021. During the coronavirus epidemic, almost everyone wears a facial mask. Traditionally, face recognition approaches process mostly non-occluded faces, which include primary facial features such as the eyes, nose, and mouth. Removing the mask for authentication in airports or laboratories will increase the risk of virus infection, posing a huge challenge to current face recognition systems. Due to the sudden outbreak of the epidemic, there are yet no publicly available real-world masked face recognition (MFR) benchmark. To cope with the above-mentioned issue, we organize the Face Bio-metrics under COVID Workshop and Masked Face Recognition Challenge in ICCV 2021. Enabled by the ultra-large-scale WebFace260M benchmark and the Face Recognition Under Inference Time conStraint (FRUITS) protocol, this challenge (WebFace260M Track) aims to push the frontiers of practical MFR. Since public evaluation sets are mostly saturated or contain noise, a new test set is gathered consisting of elaborated 2,478 celebrities and 60,926 faces. Meanwhile, we collect the world-largest real-world masked test set. In the first phase of WebFace260M Track, 69 teams (total 833 solutions) participate in the challenge and 49 teams exceed the performance of our baseline. There are second phase of the challenge till October 1, 2021 and on-going leaderboard. We will actively update this report in the future.

1. Introduction

Due to the boom of CNNs, standard face recognition (SFR) systems have achieved a remarkable success, which usually work with mostly non-occluded faces. However, there are a number of circumstances where faces are occluded by facial masks, rising the masked face recognition (MFR) problem.

During the global COVID-19, people are encouraged to wear masks in public areas, making primary facial features invisible. Few SFR systems can work well with this situation, but removing the mask for authentication will increase the risk of virus infection. Recently, some commercial vendors [27] have developed face recognition algorithms capable of handling face masks, and an increasing number of research publications [13, 15, 14, 18, 5] have surfaced on this topic. However, due to the sudden outbreak of the epidemic, there are yet no publicly available large-scale MFR benchmark.

To address the above-mentioned issue, we organize the Face Bio-metrics under COVID Workshop and Masked Face Recognition Challenge in ICCV 2021. Face benchmarks empower researchers to train high-performance face recognition systems. Enabled by the ultra-large-scale WebFace260M benchmark [41], this challenge aims to push the frontiers of practical MFR. On the other hand, evaluation protocols and test set play an essential role in analysing face recognition performance. Since public evaluation sets are mostly saturated or contain noise, we adopt the Face Recognition Under Inference Time conStraint (FRUITS) protocol in WebFace260M Track in this workshop. Besides, a new test set is gathered consisting of elaborated 2,478 celebrities and 60,926 faces. Meanwhile, we collect the world-largest real-world masked test set.

This paper is the official report of WebFace260M Track in the MFR workshop and challenge. We detail the training data, evaluation protocols, submission rules, test set and metric in SFR and MFR, ranking criterion, baseline solution, and preliminary competition results. The challenge was launched at June 7, 2021. In the first phase of WebFace260M Track, 69 teams from academia and industry participate in the challenge and 49 teams exceed the performance of our baseline. Total 833 solutions are submitted, covering various network designs and training strategies. There are second phase of the challenge till October 1, 2021 and on-going leaderboard. We will actively update this report in the future.

Dataset	# Identities	# Images	Images/ID	Cleaning	# Attributes	Availability	Publications
CASIA-WebFace [37]	10 K	0.5 M	47	Auto	-	Public	Arxiv 2014
CelebFaces [31]	10 K	0.2 M	20	Manual	40	Public	ICCV 2015
UMDFaces [6]	8 K	0.3 M	45	Semi-auto	4	Public	IJCB 2017
VGGFace [28]	2 K	2.6 M	1,000	Semi-auto	-	Public	BMVC 2015
VGGFace2 [8]	9 K	3.3 M	363	Semi-auto	11	Public	FG 2018
MS1M [17]	0.1 M	10 M	100	No	-	Public	ECCV 2016
MS1M-IBUG [12]	85 K	3.8 M	45	Semi-auto	-	Public	CVPRW 2017
MS1MV2 [10]	85 K	5.8 M	68	Semi-auto	-	Public	CVPR 2019
MS1M-Glint [1]	87 K	3.9 M	44	Semi-auto	-	Public	-
MegaFace2 [24]	0.6 M	4.7 M	7	Auto	-	Public	CVPR 2017
IMDB-Face [34]	59 K	1.7 M	29	Manual	-	Public	ECCV 2018
Facebook [32]	4 K	4.4 M	1,100	-	-	Private	CVPR 2014
Facebook [33]	10 M	500 M	50	-	-	Private	CVPR 2015
Google [29]	8 M	200 M	25	-	-	Private	CVPR 2015
MillionCelebs [38]	0.6 M	18.8 M	30	Auto	-	Private	CVPR 2020
WebFace260M	**4 M**	**260M**	**65**	No	-	Public	CVPR 2021
WebFace42M	**2 M**	**42M**	**21**	Auto	7	Public	CVPR 2021

Table 1: Training data for deep face recognition. The cleaned WebFace42M is the largest public training set in terms of both # identities and # images.

2. Training Data and Evaluation Protocols

2.1. WebFace260M Data

WebFace260M [41] is current largest public face recognition dataset, covering noisy 4M identities/260M faces and cleaned 2M identities/42M faces. With such large data size, this dataset takes a significant step towards closing the data gap between academia and industry as shown in Table 1. The celebrity name list consists of two parts: the first one is borrowed from MS1M (1 million, constructed from Freebase) and the second one (3 millions) is collected from the IMDB database. Based on the name list, celebrity faces are searched and downloaded via Google image search engine [2]. The WebFace42M training set is obtained by a Cleaning Automatically utilizing Self-Training (CAST) pipeline. Noise ratio of WebFace42M is lower than 10% (similar to CASIA-WebFace [37] and Glint360K [4]) based on the sampling estimation. After CAST, duplicates of each subject are removed when their cosine similarity is higher than 0.95. Furthermore, the feature center of each subject is compared with popular benchmarks (*e.g.* the test set in this challenge, LFW families [19, 40, 39], FaceScrub [26], IJB-C [22] *et al.*), and overlaps are removed if the cosine similarity is higher than 0.7.

2.2. FRUITS Protocol

Most existing face recognition evaluation protocols [19, 30, 23, 40, 39, 20, 22, 36, 21] target the pursuit of accuracy. However, face recognition in real-world application scenarios is always restricted by inference time. Lightweight face recognition challenge [11] takes a step toward this goal by constraining the FLOPs and model size of submissions, which is not a straightforward solution. Besides, it neglects the face detection and alignment module cost. Strict submission policy of NIST-FRVT [3] hinders researchers to freely evaluate their algorithms. In WebFace260M Track of this challenge, we follow the Face Recognition Under Inference Time conStraint (FRUITS) protocol. Referring to [41], inference time is measured on a single core of an Intel Xeon CPU E5-2630-v4@2.20GHz processor (no GPU hardware is provided), and the constraint of 1000 milliseconds is adopted.

2.3. Submission Rules

The WebFace260M Track of our challenge[1] has two phases. For the first phase, the number of max submissions per day is 5. For the second phase, the number of max submissions per day is 3. The full WebFace260M data has been open for all applicants, as long as their agreements[2] are qualified. Mask data-augmentation is allowed, for example this method[3]. The applied mask augmentation tool should be reproducible. External dataset and pre-trained models are both prohibited in the second phase. Participants could submit their submission package[4] to the submission server[5] and get scores by our online evaluation. Participants should run the code for verification on the provided docker file to ensure the correctness of feature and time constraints.

[1] https://www.face-benchmark.org/challenge.html

[2] https://www.face-benchmark.org/doc/license_agreement_for_webface260m_dataset.pdf

[3] https://github.com/deepinsight/insightface/tree/master/recognition/_tools_

[4] https://github.com/WebFace260M/webface260m-iccv21-mfr

[5] https://competitions.codalab.org/competitions/32478

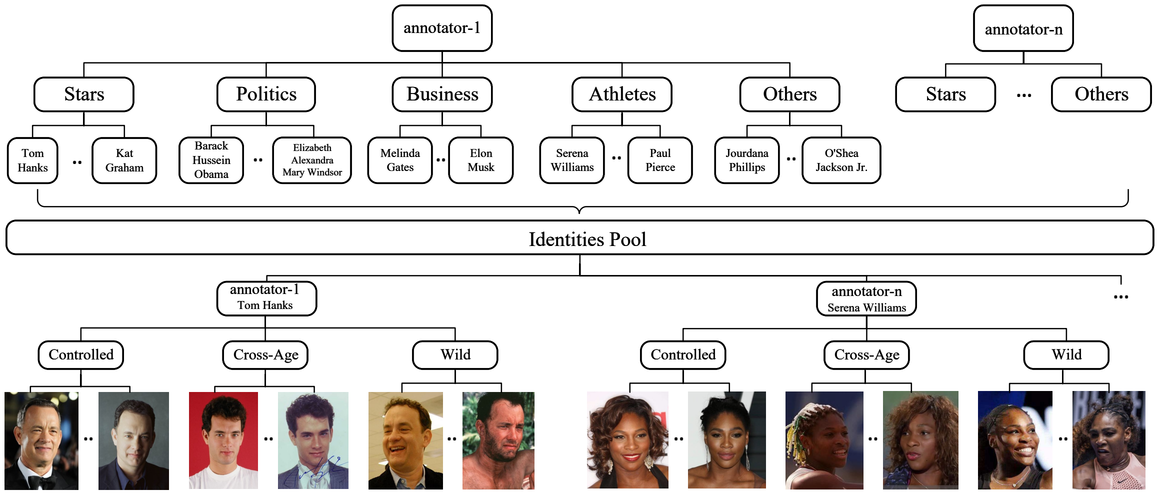

Figure 1: The collecting pipeline of test set.

Figure 2: The annotation interface of our test set collecting system. Top part is gathered celebrities images, while bottom part shows cosine similarities.

Both the models for face detection and recognition should be converted to ONNX format. Participants must package the code directory for submission and see the results on the leaderboard[6]. Test images are invisible during challenges.

3. Standard Face Recognition

3.1. Test Set

To compare deep CNN face matchers utilizing FRUITS protocol, we manually construct a elaborated test set. It is well known that recognizing strangers (especially when they are similar-looking) is a difficult task even for experienced researchers. So we choose to select our familiar celebrities, which ensure the high-quality of the test set.

The collecting pipeline of test set is illustrated in Figure 1. Each annotator is asked to write about 100 names of celebrities including stars, politics, business, athletes *et al*. Different name lists are exclusive, and a identities pool is maintained by merging lists. It is noting that annotators are encouraged to collect gender-balanced and race-balanced identities lists.

The final identities pool consists of 2,748 names. For each celebrity, responsible annotator need to collect his/her faces from reliable sources of information. Targeting at analysing recognition performance in different application scenarios, 3 subclass is defined to guide collection:

Controlled image: *Controlled* faces collection targets to evaluate ID photo such as visa and driving license. *Controlled* face in our test set is defined as: near frontal, five landmarks are visible, normal expression, not low-resolution.

Wild image: *Wild* subclass aims to collect faces in unconstrained scenarios, including large pose, partial occlusion, resolution variation, illumination variation *et al*.

Cross-age image: This subclass collects faces whose age is obviously different from *Controlled* and *Wild* faces, including *Cross-age-10* (more than 10-years gap) and *Cross-age-20* (more than 20-year gap).

For each subclass of a certain celebrity, we gather about 7 faces (*i.e.* 20 faces/identity) to construct test set as shown in Figure 1. Furthermore, we design a interface to assist annotators to judge the difficulty and quality of the collected faces. In Figure 2, collected images for a celebrity, its intra-class scores, its highest inter-class scores with other identities are illustrated respectively. Based on scores indicator

[6] https://competitions.codalab.org/competitions/32478#results

Eva.	Attributes	# Identities	# Faces	# Impostor	# Genuine
SFR	**All**	**2,478**	**57,715**	**3,328,950,920**	**2,070,305**
	Cross-age-10	-	-	1,667,036,254	553,174
	Cross-age-20	-	-	842,366,636	123,560
	Controlled	-	22,135	489,657,590	300,635
	Wild	-	35,580	1,264,898,172	1,038,228
	Cross-scene	-	-	1,574,395,158	731,442
MFR	**All**	**2,478**	**60,926**	-	-
	Masked	862	3,211	-	-
	Nonmasked	2,478	57,715	-	-
	Controlled-Masked	-	-	71,042,982	32,503
	Wild-Masked	-	-	114,193,476	53,904
	All-Masked	-	-	185,236,458	86,407

Table 2: The statistics of our test set.

from this system, annotators are encouraged to gather hard case (For example, less than 0.5 similarity score for intra-class, more than 0.5 for inter-class). Besides, noisy faces could be effectively filtered (For example, if the score of one face is less than 0.5 compared with all other intra-class images, it should be paid more attention).

The statistics of final test is listed in Table 2. There are elaborately constructed 2,478 identities and 57,715 faces in total for SFR. 3,328,950,920 impostors and 2,070,305 genuine pairs could be constructed. Protected attributes (gender, race) as well as different scenarios (*Controlled*, *Wild*, *Cross-age*) are accurately annotated for each subject. *Cross-age* and *Cross-scene* comparisons are also conducted in corresponding subset.

3.2. Metric

Based on the FRUITS protocol and the new test set, we perform 1:1 face verification across various attributes for SFR evaluation. Table 2 shows numbers of imposter and genuine in different verification settings. *All* means impostors are paired without attention to any attribute, while later comparisons are conducted on age and scenario subsets. *Cross-age* refers to cross-age (more than 10 and 20 years) verification, while *Cross-scene* means pairs are compared between controlled and wild settings. Different algorithms are measured on False Non-Match Rate (FNMR) [3], which is defined as the proportion of mated comparisons below a threshold set to achieve the False Match Rate (FMR) specified. FMR is the proportion of impostor comparisons at or above that threshold. It is worth noting that **Lower FNMR at the same FMR is better**.

4. Masked Face Recognition

4.1. Test Set

In contrast with simulated [27, 25] or relatively small [5, 9, 7, 35] masked face test sets, a real-world comprehensive benchmark for evaluating MFR is developed in this challenge. Based on the SFR identities, we further collect masked faces for these celebrities. Specifically, as shown in Table 2, there are carefully selected 3,211 masked faces among 862 identities. Subjects with real-world mask are illustrated in Figure 4.

Figure 3: Celebrities with and without real-world mask.

4.2. Metric

For MFR, assessment is performed with *Mask-Nonmask* comparisons. Specifically, there is one face with mask in imposter and genuine, while another face is from standard face sets. According to the attribute of face without mask, we evaluate the performance of algorithms under *Controlled-Masked*, *Wild-Masked*, and *All-Masked* settings listed in Table 2.

4.3. Competition Ranking

The competition is ranked according to both MFR and SFR metrics. To reduce a tendency that models overfit on masked or standard face recognition, the main series of evaluation metrics are designed to show a weighted sum to consider both masked and standard faces at the same time. As shown in Table 3, the overall ranking is ascend ordered by the *All (MFR&SFR)* metric: *All (MFR&SFR)* = 0.25 $\times$ *All-Masked* + 0.75 $\times$ *All (SFR)*. At the same time, *Wild* and *Controlled* metrics can also be computed as: *Wild (MFR&SFR)* = 0.25 $\times$ *Wild-Masked* + 0.75 $\times$ *Wild (SFR)*; *Controlled (MFR&SFR)* = 0.25 $\times$ *Controlled-Masked* + 0.75 $\times$ *Controlled (SFR)*. It is worth noting that

Rank	Participant	All (MFR&SFR)	Wild (MFR&SFR)	Controlled (MFR&SFR)	All (SFR)	Wild (SFR)	Controlled (SFR)	Detection time	Recognition time	Total time
1	Ethan.y	$0.0980^{(1)}$	$0.1283^{(5)}$	$0.0500^{(1)}$	$0.0393^{(12)}$	$0.0627^{(13)}$	$0.0032^{(6)}$	156	760	916
2	victor-2021	$0.1017^{(2)}$	$0.1222^{(1)}$	$0.0694^{(3)}$	$0.0162^{(1)}$	$0.0270^{(1)}$	$0.0018^{(1)}$	157	496	653
3	sleepybear	$0.1036^{(3)}$	$0.1246^{(2)}$	$0.0699^{(5)}$	$0.0168^{(2)}$	$0.0276^{(2)}$	$0.0020^{(2)}$	162	498	660
4	wjtan99	$0.1056^{(4)}$	$0.1279^{(4)}$	$0.0698^{(4)}$	$0.0187^{(3)}$	$0.0306^{(4)}$	$0.0021^{(3)}$	97	897	994
5	hukangli	$0.1056^{(4)}$	$0.1278^{(3)}$	$0.0698^{(4)}$	$0.0187^{(3)}$	$0.0305^{(3)}$	$0.0021^{(3)}$	97	899	996
6	min.yang	$0.1131^{(5)}$	$0.1366^{(6)}$	$0.0758^{(6)}$	$0.0228^{(4)}$	$0.0367^{(5)}$	$0.0026^{(4)}$	158	453	611
7	wzw	$0.1272^{(6)}$	$0.1530^{(7)}$	$0.0833^{(11)}$	$0.0267^{(7)}$	$0.0432^{(8)}$	$0.0028^{(5)}$	49	744	793
8	vuvko	$0.1315^{(7)}$	$0.1575^{(8)}$	$0.0872^{(12)}$	$0.0248^{(6)}$	$0.0407^{(7)}$	$0.0028^{(5)}$	157	926	1083
9	lcx2	$0.1318^{(8)}$	$0.1699^{(13)}$	$0.0689^{(2)}$	$0.0585^{(27)}$	$0.0911^{(30)}$	$0.0061^{(19)}$	186	371	557
10	linkpal2021	$0.1319^{(9)}$	$0.1622^{(11)}$	$0.0828^{(10)}$	$0.0346^{(9)}$	$0.0561^{(10)}$	$0.0033^{(7)}$	162	769	931
11	tuolaji	$0.1340^{(10)}$	$0.1610^{(10)}$	$0.0909^{(15)}$	$0.0242^{(5)}$	$0.0399^{(6)}$	$0.0026^{(4)}$	167	286	453
12	crishawy	$0.1340^{(10)}$	$0.1610^{(10)}$	$0.0909^{(15)}$	$0.0242^{(5)}$	$0.0399^{(6)}$	$0.0026^{(4)}$	158	861	1019
13	betterone	$0.1341^{(11)}$	$0.1608^{(9)}$	$0.0882^{(13)}$	$0.0291^{(8)}$	$0.0476^{(9)}$	$0.0032^{(6)}$	157	948	1105
14	cheng3qing	$0.1377^{(12)}$	$0.1685^{(12)}$	$0.0812^{(8)}$	$0.0538^{(24)}$	$0.0782^{(24)}$	$0.0062^{(20)}$	159	688	847
15	nayesoj	$0.1389^{(13)}$	$0.1724^{(14)}$	$0.0814^{(9)}$	$0.0498^{(19)}$	$0.0761^{(23)}$	$0.0042^{(11)}$	164	346	510
16	amyburden	$0.1503^{(14)}$	$0.1807^{(15)}$	$0.0996^{(17)}$	$0.0413^{(13)}$	$0.0639^{(14)}$	$0.0048^{(16)}$	158	659	817
17	mind_ft	$0.1503^{(14)}$	$0.1813^{(16)}$	$0.1003^{(18)}$	$0.0377^{(10)}$	$0.0603^{(11)}$	$0.0040^{(9)}$	160	340	500
18	jyf	$0.1591^{(15)}$	$0.2026^{(19)}$	$0.0769^{(7)}$	$0.0878^{(41)}$	$0.1267^{(42)}$	$0.0097^{(30)}$	158	320	478
19	Wison	$0.1596^{(16)}$	$0.1906^{(17)}$	$0.1093^{(20)}$	$0.0386^{(11)}$	$0.0624^{(12)}$	$0.0037^{(8)}$	164	570	734
20	ncvl01	$0.1685^{(17)}$	$0.1996^{(18)}$	$0.1133^{(21)}$	$0.0457^{(15)}$	$0.0683^{(16)}$	$0.0042^{(11)}$	157	819	976
21	Daniel2018	$0.1736^{(18)}$	$0.2172^{(26)}$	$0.0994^{(16)}$	$0.0723^{(33)}$	$0.1115^{(38)}$	$0.0075^{(26)}$	158	330	488
22	simonss	$0.1745^{(19)}$	$0.2043^{(20)}$	$0.1196^{(22)}$	$0.0462^{(16)}$	$0.0682^{(15)}$	$0.0043^{(12)}$	157	1164	1321
23	hihi123	$0.1767^{(20)}$	$0.2106^{(23)}$	$0.1133^{(21)}$	$0.0456^{(14)}$	$0.0730^{(19)}$	$0.0042^{(11)}$	184	644	828
24	Sungmin	$0.1780^{(21)}$	$0.2086^{(22)}$	$0.1210^{(24)}$	$0.0473^{(18)}$	$0.0697^{(17)}$	$0.0044^{(13)}$	136	1160	1296
25	HIT_face	$0.1780^{(21)}$	$0.2083^{(21)}$	$0.1224^{(25)}$	$0.0470^{(17)}$	$0.0701^{(18)}$	$0.0041^{(10)}$	226	639	865
26	thesherlock	$0.1826^{(22)}$	$0.2124^{(24)}$	$0.1285^{(28)}$	$0.0501^{(21)}$	$0.0744^{(21)}$	$0.0045^{(14)}$	162	439	601
27	fh_nj	$0.1827^{(23)}$	$0.2144^{(25)}$	$0.1249^{(26)}$	$0.0508^{(22)}$	$0.0758^{(22)}$	$0.0048^{(16)}$	158	316	474
28	liu_xiang886	$0.1859^{(24)}$	$0.2329^{(32)}$	$0.0897^{(14)}$	$0.1103^{(46)}$	$0.1543^{(48)}$	$0.0127^{(33)}$	157	317	474
29	ppnn	$0.1867^{(25)}$	$0.2251^{(29)}$	$0.1056^{(19)}$	$0.0937^{(44)}$	$0.1282^{(43)}$	$0.0133^{(34)}$	159	827	986
30	MCPRL_aiwa	$0.1882^{(26)}$	$0.2182^{(27)}$	$0.1328^{(30)}$	$0.0500^{(20)}$	$0.0741^{(20)}$	$0.0045^{(14)}$	158	657	815
31	tongtong	$0.1923^{(27)}$	$0.2246^{(28)}$	$0.1332^{(31)}$	$0.0529^{(23)}$	$0.0792^{(25)}$	$0.0047^{(15)}$	159	318	477
32	billzeng	$0.1923^{(27)}$	$0.2246^{(28)}$	$0.1332^{(31)}$	$0.0529^{(23)}$	$0.0792^{(25)}$	$0.0048^{(16)}$	157	319	476
33	runauto	$0.1938^{(28)}$	$0.2311^{(31)}$	$0.1224^{(25)}$	$0.0741^{(34)}$	$0.1066^{(35)}$	$0.0071^{(24)}$	157	733	890
34	yossibiton	$0.1944^{(29)}$	$0.2263^{(30)}$	$0.1345^{(32)}$	$0.0552^{(25)}$	$0.0818^{(27)}$	$0.0049^{(17)}$	167	83	250
35	haoyayu365	$0.1970^{(30)}$	$0.2345^{(33)}$	$0.1321^{(29)}$	$0.0566^{(26)}$	$0.0892^{(28)}$	$0.0061^{(19)}$	156	396	552
36	dler	$0.2064^{(31)}$	$0.2389^{(34)}$	$0.1464^{(41)}$	$0.0538^{(24)}$	$0.0807^{(26)}$	$0.0051^{(18)}$	181	1060	1241
37	f.gomes	$0.2092^{(32)}$	$0.2459^{(36)}$	$0.1407^{(34)}$	$0.0676^{(30)}$	$0.0999^{(32)}$	$0.0064^{(21)}$	157	1285	1442
38	AntonS	$0.2093^{(33)}$	$0.2450^{(35)}$	$0.1411^{(35)}$	$0.0698^{(31)}$	$0.1017^{(33)}$	$0.0069^{(23)}$	157	337	494
39	Jim_1021	$0.2106^{(34)}$	$0.2553^{(40)}$	$0.1204^{(23)}$	$0.0978^{(45)}$	$0.1384^{(46)}$	$0.0101^{(31)}$	156	829	985
40	linghu8812	$0.2117^{(35)}$	$0.2510^{(38)}$	$0.1352^{(33)}$	$0.0828^{(39)}$	$0.1200^{(41)}$	$0.0072^{(25)}$	157	857	1014
41	tib6913	$0.2141^{(36)}$	$0.2501^{(37)}$	$0.1453^{(39)}$	$0.0720^{(32)}$	$0.1044^{(34)}$	$0.0066^{(22)}$	157	192	349
42	meixitu2	$0.2171^{(37)}$	$0.2501^{(37)}$	$0.1529^{(46)}$	$0.0630^{(28)}$	$0.0901^{(29)}$	$0.0069^{(23)}$	157	295	452
43	Cavall	$0.2174^{(38)}$	$0.2583^{(44)}$	$0.1418^{(37)}$	$0.0792^{(37)}$	$0.1172^{(39)}$	$0.0066^{(22)}$	157	389	546
44	HYL_Dave	$0.2174^{(38)}$	$0.2562^{(41)}$	$0.1444^{(38)}$	$0.0751^{(36)}$	$0.1112^{(37)}$	$0.0069^{(23)}$	157	173	330
45	zhangge00hou	$0.2187^{(39)}$	$0.2565^{(42)}$	$0.1469^{(42)}$	$0.0742^{(35)}$	$0.1090^{(36)}$	$0.0071^{(24)}$	157	647	804
46	maguih	$0.2188^{(40)}$	$0.2566^{(43)}$	$0.1469^{(42)}$	$0.0742^{(35)}$	$0.1090^{(36)}$	$0.0071^{(24)}$	158	651	809
47	jinhong.zhang	$0.2202^{(41)}$	$0.2539^{(39)}$	$0.1524^{(45)}$	$0.0661^{(29)}$	$0.0934^{(31)}$	$0.0071^{(24)}$	12	341	353
48	cmkyec	$0.2286^{(42)}$	$0.2781^{(46)}$	$0.1413^{(36)}$	$0.0932^{(43)}$	$0.1419^{(47)}$	$0.0103^{(32)}$	158	247	405
49	nikkonew	$0.2295^{(43)}$	$0.2681^{(45)}$	$0.1545^{(47)}$	$0.0816^{(38)}$	$0.1185^{(40)}$	$0.0077^{(27)}$	156	321	477
50	litian1045	$0.2342^{(44)}$	$0.2816^{(48)}$	$0.1483^{(44)}$	$0.0871^{(40)}$	$0.1341^{(45)}$	$0.0094^{(29)}$	157	172	329

Table 3: The leaderboard of first phase. Results outperforming the baseline (Participant: *litian1045*) are shown.

scores of different metrics is computed at corresponding FNMR@FMR=10-5.

5. Baseline Solutions

5.1. Implementation Details

In order to fairly evaluate the performance of different face recognition models, we reproduce representative algorithms in one Gluon codebase with the hyper-parameters referred to the original papers. Default batch size per GPU is set as 64 unless otherwise indicated. Learning rate is set as 0.05 for a single node (8 GPUs), and follows the linear scaling rule [16] for the training on multiple nodes (*i.e.* $0.05\times$# machines). We decrease the learning rate by $0.1\times$ at 8, 12, and 16 epochs, and stop at 20 epochs for all models. During training, we only adopt the flip data augmentation. Note that other data augmentations such as adding simulated mask are encouraged to boost MFR performance.

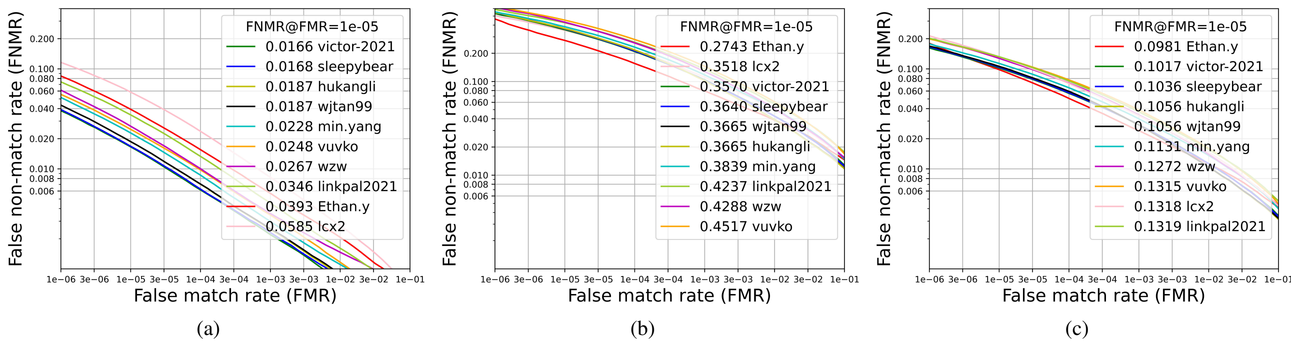

Figure 4: FMR-FNMR plots of SFR, MFR, and final combined MFR&SFR results.

layer name	50-layer	output size
Input Image Crop		112×112×3
	3×3, 64, stride 1	112×112×64
Conv2_x	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix} \times 3$	$56 \times 56 \times 64$
Conv3_x	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix} \times 4$	$28 \times 28 \times 128$
Conv4_x	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix} \times 14$	$14 \times 14 \times 256$
Conv5_x	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix} \times 3$	$7 \times 7 \times 512$
FC		512

Table 4: The network configuration of our baseline model. Convolutional building blocks are shown in brackets with the numbers of blocks stacked. Down-sampling is performed by the second conv in conv2_1, conv3_1, conv4_1, and conv5_1 with a stride of 2.

5.2. Baseline Model and Results

The configuration of the baseline model is ResNet-50 backbone, ArcFace loss, with WebFace12M (30%) training data. The backbone architecture is shown in Table 4. The evaluation results of the baseline model (Participant: *litian1045*) are shown in the last row of Table 3. The FNMR@FMR=1e-5 across different attributes (*All (MFR&SFR)*, *Wild (MFR&SFR)*, *Controlled (MFR&SFR)*, *All (SFR)*, *Wild (SFR)*, *Controlled (SFR)*) is 0.2342, 0.2816, 0.1483, 0.0871, 0.1341, 0.0094, respectively. The time cost of detection, recognition and total is 157 ms, 172 ms, 329 ms, respectively.

6. Preliminary Results of First Phase

First phase was held between June 7, 2021 to August 11, 2021. During this phase, 69 teams submit a total of 833 effective solutions to the challenge. Table 3 gives a detailed result for each participant with their ranks. As shown in Table 3 and Figure 4, *Ethan.y* ranks the 1st place in main *All (MFR&SFR)* metric with 0.0980 as well as *Controlled (MFR&SFR)* with 0.0500, while *victor-2021* wins *Wild (MFR&SFR)* with a score of 0.1222. For SFR metrics, *victor-2021* ranks the 1st place among *All (SFR)*, *Wild (SFR)* and *Controlled (SFR)* with 0.0162, 0.0270 and 0.0018. Since the FNMR of MFR is much higher than that in SFR, the MFR performance dominates the final ranks. It is worth noting that during first phase, a model is allowed to be evaluated if its *Total time* (which is a sum of *Detection time* and *Recognition time*) is no more than 2000ms. In the final ranks (second phase), we only rank models with a *Total time* less than 1000ms. As shown in Table 3, there are 9 participants who have submitted models to the leaderboard with *Total time* more than 1000ms. Since the challenge is still going on, more details of top-ranked solution would be updated in the future.

7. Conclusion

To address the MFR problem during epidemic, we organize the Face Bio-metrics under COVID Workshop and Masked Face Recognition Challenge in ICCV 2021. Enabled by the WebFace260M and FRUITS, this challenge (WebFace260M Track) aims to push the frontiers of practical MFR. This report details the training data, evaluation protocols, submission rules, test set and metric in SFR and MFR, ranking criterion, baseline solution, and preliminary competition results. In the first phase of WebFace260M Track, 69 teams (total 833 solutions) participate in the challenge and 49 teams exceed the performance of our baseline. We will actively update this report in the future.

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