NISTIR 8331

Ongoing Face Recognition Vendor Test (FRVT) Part 6B: Face recognition accuracy with face masks using post-COVID-19 algorithms

Mei Ngan
Patrick Grother
Kayee Hanaoka

This publication is available free of charge from:
https://doi.org/10.6028/NIST.IR.8331

NIST
National Institute of Standards and Technology
U.S. Department of Commerce

NISTIR 8331

Ongoing Face Recognition Vendor Test (FRVT) Part 6B: Face recognition accuracy with face masks using post-COVID-19 algorithms

Mei Ngan
Patrick Grother
Kayee Hanaoka
Information Access Division
Information Technology Laboratory

This publication is available free of charge from:
https://doi.org/10.6028/NIST.IR.8331

November 2020

U.S. Department of Commerce
Wilbur L. Ross, Jr., Secretary

National Institute of Standards and Technology
Walter Copan, NIST Director and Undersecretary of Commerce for Standards and Technology

Certain commercial entities, equipment, or materials may be identified in this document in order to describe an experimental procedure or concept adequately. Such identification is not intended to imply recommendation or endorsement by the National Institute of Standards and Technology, nor is it intended to imply that the entities, materials, or equipment are necessarily the best available for the purpose.

National Institute of Standards and Technology Interagency or Internal Report 8331
Natl. Inst. Stand. Technol. Interag. Intern. Rep. 8331, 83 pages (November 2020)

This publication is available free of charge from:
https://doi.org/10.6028/NIST.IR.8331

Executive Summary

OVERVIEW

This is the second of a series of reports on the performance of face recognition algorithms on faces occluded by protective face masks [2] commonly worn to reduce inhalation and exhalation of viruses. Inspired by the COVID-19 pandemic response, this is a continuous study being run under the Ongoing Face Recognition Vendor Test (FRVT) executed by the National Institute of Standards and Technology (NIST). In our first report [8], we tested "pre-pandemic" algorithms that were already submitted to FRVT 1:1 prior to mid-March 2020. This report augments its predecessor with results for more recent algorithms provided to NIST after mid-March 2020. While we do not have information on whether or not a particular algorithm was designed with face coverings in mind, the results show evidence that a number of developers have adapted their algorithms to support face recognition on subjects potentially wearing face masks. The algorithms tested were one-to-one algorithms submitted to the FRVT 1:1 Verification track. Future editions of this document will also report accuracy of one-to-many algorithms.

WHAT'S NEW

This report includes

- ▷ Results from evaluating 65 face recognition algorithms provided to NIST since mid-March 2020
- ▷ Assessment of when both the enrollment and verification images are masked (in addition to when only the verification image is masked)
- ▷ Results for red and white colored masks (in addition to light-blue and black)
- ▷ Cumulative results for 152 algorithms evaluated to date (submitted both prior to and after mid-March 2020)

MOTIVATION

Traditionally, face recognition systems (in cooperative settings) are presented with mostly non-occluded faces, which include primary facial features such as the eyes, nose, and mouth. However, there are a number of circumstances in which faces are occluded by masks such as in pandemics, medical settings, excessive pollution, or laboratories. Inspired by the COVID-19 pandemic response, the widespread requirement that people wear protective face masks in public places has driven a need to understand how cooperative face recognition technology deals with occluded faces, often with just the periocular area and above visible. An increasing number of research publications have surfaced on the topic of face recognition on people wearing masks along with face-masked research datasets [10]. A number of commercial providers have announced the availability of face recognition algorithms capable of handling face masks, and this report documents performance results for 65 algorithms submitted to NIST after mid-March 2020. This report includes results for all algorithms evaluated to date. At the time of this writing, we are not aware of any large-scale, independent, and publicly reported evaluation on the effects of face mask occlusion on face recognition.

WHAT WE DID

The NIST Information Technology Laboratory (ITL) quantified the accuracy of face recognition algorithms on faces occluded by masks applied digitally to a large set of photos that has been used in an FRVT verification benchmark since 2018. These algorithms were submitted to FRVT 1:1 and includes 65 new algorithms provided to NIST since mid-March 2020. While we do not have information on whether or not a particular algorithm was designed with face coverings in mind, the algorithms were submitted with the expectation that NIST would execute them on masked face images. Using the original unmasked images to form a baseline for accuracy, we measured the impact of occlusion by digitally applying a mask to the face and varying mask shape, mask color, and nose coverage.

We ran these algorithms over a large set of photographs collected in U.S. governmental applications that are currently in operation: **application photographs** from a global population of applicants for immigration benefits and **border crossing photographs** of travelers entering the United States. Both datasets were collected for authorized travel or immigration processes.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

WHAT WE DID (CONTINUED)

The application photos (used as reference images) have good compliance with image capture standards. The border crossing photos (used as probe images) are not in good compliance with image capture standards given possible constraints on capture equipment, duration, facilities, and environment. We evaluated the case where the application photos were left unmasked, and synthetic masks were applied to the border crossing photos. This mimics an operational scenario where a person wearing a mask attempts to authenticate against a prior visa or passport photo. We also evaluated when both the application photos and border crossing photos were masked. This mimics, for example, a seamless travel scenario through an airport where a masked face image captured at check-in is enrolled and used during subsequent authentication attempts of the passenger still wearing a face mask. Together these datasets allowed us to process a total of 6.2 million images through a cumulative total of 152 algorithms.

Our use of software to apply masks to face images has the following advantages: it allows very rapid characterization of the effect of masks on face recognition; it allows controlled exploration of factors such as mask size, shape, and color; it affords repeatability, which is key to the fair comparison of algorithms; it scales to very large datasets - in our study, some 6.2 million photographs - which allows fine-grained characterization of false positive rates in addition to false negative rates. Conversely, our use of digital masks presents a number of limitations - please see the *Limitations* section of this executive summary for a more detailed discussion on the limitations of this study.

WHAT WE FOUND

The following results represent observations on algorithms provided to NIST both before and after the COVID-19 pandemic to date. We do not have information on whether or not a particular algorithm was designed with face coverings in mind. The results documented capture a snapshot of algorithms submitted to the FRVT 1:1 in face recognition on subjects potentially wearing face masks.

▷ **False rejection performance**: All algorithms submitted after the pandemic continue to give increased false non-match rates (FNMR) when the probes are masked. While a few pre-pandemic algorithms still remain within the most accurate on masked photos, some developers have submitted algorithms after the pandemic showing significantly improved accuracy and are now among the most accurate in our test. Using border crossing images, without masks, the most accurate algorithms will fail to authenticate about 0.3% of persons while falsely accepting no more than 1 in 100000 impostors (i.e. FNMR$= 0.003$ at FMR$= 0.00001$). With the highest coverage mask we tested and the most accurate algorithms, this failure rate rises to about 5% (FNMR = 0.05) among all algorithms. This is noteworthy given that around 70% of the face area is occluded by the mask. However, many algorithms submitted since mid-March 2020 remain much less tolerant: some algorithms that are quite competitive with unmasked faces (FNMR < 0.01) still fail to authenticate between 10% to 40% of masked images (FNMR $\rightarrow 0.4$).

See Figures 6, 7 and Table 5

For the case where both the enrollment and verification images are masked, interestingly, many algorithms show a reduction in false non-match rates compared to when only the verification image is masked, at a fixed threshold. While the reduction in FNMR is favorable, we observe much larger false match rates when both images are masked. These findings are discussed in subsequent sections of this executive summary. *See Figure 37*

In cooperative access control applications, false rejections can traditionally be remedied by users making second attempts. This is effective when users correct pose, expression, or illumination aspects of their presentation. With masked faces, however, a second attempt may not be effective if the failure is a systematic property of the algorithm.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

WHAT WE FOUND (CONTINUED)

▷ **Evolution of algorithms on face masks**: We observe that a number of algorithms submitted since mid-March 2020 show notable reductions in error rates with face masks over their pre-pandemic predecessors. When comparing error rates for unmasked versus masked faces, the median FNMR across algorithms submitted since mid-March 2020 has been reduced by around 25% from the median pre-pandemic results. The figure below presents examples of developer evolution on both masked and unmasked datasets. For some developers, false rejection rates in their algorithms submitted since mid-March 2020 decreased by as much as a factor of 10 over their pre-pandemic algorithms, which is evidence that some providers are adapting their algorithms to handle face masks. However, in the best cases, when comparing results for unmasked images to masked images, false rejection rates have increased from 0.3%-0.5% (unmasked) to 2.4%-5% (masked). The current performance of face recognition with face masks is comparable to the state-of-the-art on unmasked images in mid-2017 [4].

Figure 1: Examples of developer evolution of accuracy on masked and unmasked datasets.

See Figures 6, 5, and 7

▷ **False acceptance performance**: As most systems are configured with a fixed threshold, it is necessary to report both false negative and false positive rates for each group at that threshold. When comparing a masked probe to an unmasked enrollment photo, in most cases, false match rates (FMR) are reduced by masks. The effect is generally modest with reductions in FMR usually being smaller than a factor of two. This property is valuable in that masked probes do not impart adverse false match security consequences for verification.

However, when both the enrollment and verification images are masked, most algorithms give elevated false match rates, with FMR ranging from 10 to 100 times higher than when only the probe is masked or both images are unmasked, at the same threshold. This behavior applies to most algorithms tested, with the exception of particular algorithms submitted by Idemia (idemia-006) and Pensees (pensees-001). These two algorithms generate approximately constant FMR across any masked/unmasked combination, and similarly, yield approximately constant FNMR across masked-probe and masked-enrollment-and-probe combinations. *See Figure 37*

▷ **Mask-agnostic face recognition**: All 1:1 verification algorithms submitted to the FRVT test since the start of the pandemic are evaluated on both masked and unmasked datasets. The test is designed this way to mimic operational reality: some images will have masks, some will not (especially enrollment samples from a database or ID card). And to the extent that the use of protective masks will exist for some time, our test will continue to evaluate algorithmic capability on verifying all combinations of masked and unmasked faces.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

WHAT WE FOUND (CONTINUED)

At least two developers - Idemia and Pensees - have developed algorithms that work with any combination of masked and unmasked images, favorably generating approximately constant FMR across any masked/unmasked combination.

Figure 2: FNMR and FMR calibration curves on masked/unmasked combinations.

An example of an integrated approach might be: 1) inclusion of a mask detector 2) on an unmasked image, extract features from both the full face and the periocular region 3) on a detected masked image, extract features from the periocular region 4) at match time, compare full-face templates when both images are unmasked, and periocular templates otherwise.

- **Coverage of the masks**: Masks that occlude more of the face give larger false non-match rates. We surveyed over the extent to which the mask covers the nose, from not at all ("low") to typical ("medium") to near the eyes ("high"). We baselined those with unmasked faces with the result that FNMR increases by factors of around 6, 20, and 30 respectively for the median algorithm submitted since mid-March 2020. However, as noted, algorithms vary considerably in the their tolerance of coverage. Readers should consult tabulated values for specific algorithms.

  See Table 5 and Figures 9, 11

  We included the "low" option not because it is a common position for a mask but as an option for authentication applications where it would be tenable to ask the user to pull the mask down to just below the nose for the duration of the authentication attempt.

- **Color of the masks**: We considered white, light-blue, red, and black masks. Many algorithms have higher error rates in black and red masks than light-blue and white masks. The reason for observed accuracy differences between mask color is unknown but is a point for consideration by impacted developers. Mask color also affects the rate at which some algorithms fail to produce a template from an image. *See Figure 24 and Table 9*

- **Shape of the masks**: The shape of the masks matters. Full-face-width masks generally cover more of the face than rounder N95 type masks. Post-pandemic algorithm results show that wide-width masks generally give false negative rates about a factor of 1.5 higher than do rounder type masks. *See Figure 8*

- **Failure to detect and template:** The false negative rates in this report include the effects of both face detection and localization errors, and low-similarity matching errors. We separately include tables detailing how often an algorithm does not make a template from an input image. While many algorithms give low failure-to-template rates, some give high values ranging close to 100%. Conversely, the successful creation of a template does not guarantee proper facial localization. Such localization failures will not be captured as a failure to detect and template event but will impact accuracy rates nonetheless. *See Table 9 and Figure 10*

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

LIMITATIONS As a simulation, this study likely doesn't fully capture the effects of masks on face recognition. Particularly the following points should be weighed by readers in the near term. Some of these will be addressed in subsequent work at NIST.

- **Train algorithms:** As with all NIST evaluations, we regard the software as a black box whose parameters (models) remain fixed for the entirety of its use without learning from the test data. We do not train or fine-tune algorithms.
- **Evaluate one-to-many algorithms:** We have only run one-to-one verification algorithms with masks. This elicits data on the effect of masks on the underlying feature extraction and discrimination of algorithms and can therefore be be expected to give first-order indications of the effect on one-to-many identification algorithms.
- **Consider the effect of eye occlusion:** We did not address the effect of eye-glasses or eye-protection. While our dataset includes examples of people wearing glasses, we didn't collect such data nor simulate it with digital addition.
- **Test with images of real masks:** Given time and resource constraints, we didn't collect photos of subjects wearing masks. The possible downsides of this are several. First, our digital masks are tailored to faces; while a few don't fit realistically, mass-produced real masks may not fit all actual persons correctly either. We were not able to pursue an exhaustive simulation of the endless variations in color, design, shape, texture, bands, and ways masks can be worn. Second, because many cameras run with exposure-control, it is possible that a dark mask will cause less light to be reflecting and the camera to increase gain on the sensor causing overexposure of the periocular region. Likewise a white mask could lead to underexposure problems. Third, it is possible that some cameras that include a face detector, may fail to focus or acquire a masked face correctly.
- **Use textured masks:** All masks synthesized by NIST in this study have a uniform color. The consequences of this are that we do not capture the impact of mask texture or pattern on face recognition. The possibility exists for patterned masks to induce higher facial localization errors, which is not captured in our current study. We received a suggestion that such information may serve as a soft biometric, in that a subject that always wears the same textured mask will be more identifiable. We don't intend to encourage algorithm development along this line, because as mass-produced high-efficacy masks become more common, mask diversity may actually drop.
- **Study demographic effects on masked images:** This report estimates overall performance of existing algorithms on recognition of faces occluded by masks. We deferred tabulating accuracy for different demographic groups until more capable mask-enabled algorithms have been submitted to FRVT.
- **Evaluate algorithms on non-cooperative, unconstrained imagery:** This report documents results for matching masked webcam images to unmasked portrait-style photos. While the properties of the two sets of images differ, subjects are operating in cooperative mode and are for the most part, looking at the camera.
- **Consider effects of human examination:** This report does not consider the various ways humans are involved in face recognition systems. For example, analysts can correct face detection or localization errors induced by masks, prior to automated recognition. Likewise, humans are often tasked with adjudication of images following a rejection or other exception from an automated system. Analysis of human capability and role is pertinent to those operations, but is beyond the scope of this study.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

IMPLICATIONS AND FUTURE WORK

Know Your Algorithm: Operational implementations usually employ a single face recognition algorithm. Given algorithm-specific sensitivities to masks and other image or subject properties, it is incumbent upon the system owner to know their algorithm. While publicly available test data from NIST and elsewhere can inform owners, it will usually be informative to specifically measure accuracy of the operational algorithm on the operational image data collected with actual masks.

NIST plans on releasing a series of reports, iteratively assessing different aspects and use cases of face masking on recognition performance.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

ACKNOWLEDGMENTS

This work was conducted in collaboration with the Department of Homeland Security's Science & Technology Directorate (S&T), Office of Biometric Identity Management (OBIM), and Customs and Border Protection (CBP). Additionally, the authors are grateful to staff in the NIST Biometrics Research Laboratory for infrastructure supporting rapid evaluation of algorithms.

DISCLAIMER

Specific hardware and software products identified in this report were used in order to perform the evaluations described in this document. In no case does identification of any commercial product, trade name, or vendor, imply recommendation or endorsement by the National Institute of Standards and Technology, nor does it imply that the products and equipment identified are necessarily the best available for the purpose.

INSTITUTIONAL REVIEW BOARD

The National Institute of Standards and Technology's Research Protections Office reviewed the protocol for this project and determined it is not human subjects research as defined in Department of Commerce Regulations, 15 CFR 27, also known as the Common Rule for the Protection of Human Subjects (45 CFR 46, Subpart A).

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Contents

EXECUTIVE SUMMARY I

ACKNOWLEDGMENTS VII

DISCLAIMER VII

INSTITUTIONAL REVIEW BOARD VII

1 FACE MASK EFFECTS 1
1.1 STATUS . . . 1
1.2 INTRODUCTION . . . 1

2 IMAGE DATASETS 2
2.1 APPLICATION IMAGES . . . 2
2.2 WEBCAM IMAGES . . . 2
2.3 SYNTHETICALLY MASKED IMAGES . . . 3

3 METRICS 5
3.1 MATCHING ACCURACY . . . 5
3.2 FAILURE TO ENROLL . . . 5

4 ALGORITHMS 5

5 RESULTS 9
EVOLUTION OF ALGORITHM PERFORMANCE WITH FACE MASKS . . . 9
FNMR - SUMMARY . . . 15
MASK VS. NO MASK . . . 22
MASK SHAPE . . . 22
MASK NOSE COVERAGE . . . 22
ROLE OF FTE . . . 24
IMPACT OF MASK NOSE COVERAGE AND SHAPE . . . 24
IMPACT OF MASK COLOR . . . 38
FNMR AND FMR VS. THRESHOLD . . . 52

APPENDIX A DLIB MASKING METHODOLOGY 71

List of Tables

1 DATASET SUMMARY . . . 2
2 ALGORITHM SUMMARY . . . 6
3 ALGORITHM SUMMARY . . . 7
4 ALGORITHM SUMMARY . . . 8
5 FALSE NON-MATCH RATE . . . 12
6 FALSE NON-MATCH RATE . . . 13
7 FALSE NON-MATCH RATE . . . 14
8 FALSE NON-MATCH RATE . . . 15
9 FAILURE TO ENROL RATES . . . 19
10 FAILURE TO ENROL RATES . . . 20
11 FAILURE TO ENROL RATES . . . 21
12 FAILURE TO ENROL RATES . . . 22

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

List of Figures

1 Examples of developer evolution of accuracy on masked and unmasked datasets. . . . iii
2 FNMR and FMR calibration curves on masked/unmasked combinations. . . . iv
3 Enrollment image examples . . . 2
4 Synthetic face mask examples . . . 4
5 Accuracy gains . . . 10
6 Pre vs. post-covid algorithms . . . 11
7 FNMR gain . . . 16
8 FNMR gain . . . 17
9 FNMR gain . . . 18
10 Role of FTE . . . 23
11 DET unmasked versus masked - shape and coverage . . . 25
12 DET unmasked versus masked - shape and coverage . . . 26
13 DET unmasked versus masked - shape and coverage . . . 27
14 DET unmasked versus masked - shape and coverage . . . 28
15 DET unmasked versus masked - shape and coverage . . . 29
16 DET unmasked versus masked - shape and coverage . . . 30
17 DET unmasked versus masked - shape and coverage . . . 31
18 DET unmasked versus masked - shape and coverage . . . 32
19 DET unmasked versus masked - shape and coverage . . . 33
20 DET unmasked versus masked - shape and coverage . . . 34
21 DET unmasked versus masked - shape and coverage . . . 35
22 DET unmasked versus masked - shape and coverage . . . 36
23 DET unmasked versus masked - shape and coverage . . . 37
24 DET unmasked versus masked - color . . . 39
25 DET unmasked versus masked - color . . . 40
26 DET unmasked versus masked - color . . . 41
27 DET unmasked versus masked - color . . . 42
28 DET unmasked versus masked - color . . . 43
29 DET unmasked versus masked - color . . . 44
30 DET unmasked versus masked - color . . . 45
31 DET unmasked versus masked - color . . . 46
32 DET unmasked versus masked - color . . . 47
33 DET unmasked versus masked - color . . . 48
34 DET unmasked versus masked - color . . . 49
35 DET unmasked versus masked - color . . . 50
36 DET unmasked versus masked - color . . . 51
37 masked-to-unmasked vs. masked-to-masked . . . 53
38 masked-to-unmasked vs. masked-to-masked . . . 54
39 masked-to-unmasked vs. masked-to-masked . . . 55
40 masked-to-unmasked vs. masked-to-masked . . . 56
41 masked-to-unmasked vs. masked-to-masked . . . 57
42 masked-to-unmasked vs. masked-to-masked . . . 58
43 masked-to-unmasked vs. masked-to-masked . . . 59
44 masked-to-unmasked vs. masked-to-masked . . . 60
45 masked-to-unmasked vs. masked-to-masked . . . 61
46 masked-to-unmasked vs. masked-to-masked . . . 62
47 masked-to-unmasked vs. masked-to-masked . . . 63
48 masked-to-unmasked vs. masked-to-masked . . . 64
49 masked-to-unmasked vs. masked-to-masked . . . 65
50 masked-to-unmasked vs. masked-to-masked . . . 66
51 masked-to-unmasked vs. masked-to-masked . . . 67
52 masked-to-unmasked vs. masked-to-masked . . . 68
53 masked-to-unmasked vs. masked-to-masked . . . 69
54 Dlib masking methodology . . . 71

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

1 Face Mask Effects

1.1 Status

NIST has conducted the second out of a series of tests aimed at quantifying face recognition accuracy for people wearing masks. Our initial approach has been to apply masks to faces digitally (i.e., using software to apply a synthetic mask). This allowed us to leverage large datasets that we already have. This report documents results for 1:1 verification algorithms. In our first report [8], we tested "pre-pandemic" algorithms that were already submitted to FRVT 1:1 prior to mid-March 2020. This report augments its predecessor with results for more recent algorithms provided to NIST **after the COVID-19 pandemic**. While we do not have information on whether or not a particular algorithm was designed with face coverings in mind, the algorithms were submitted with the expectation that NIST would execute them on masked face images. In addition to reporting results for when only the verification image is masked, we also document the effects for the case when both enrollment and verification images are masked. This report quantifies the effect of masks on both false negative and false positives match rates and tracks developer evolution of face recognition accuracy with face masks.

The FRVT evaluation is an ongoing test that remains open to new participation. Comments and suggestions should be directed to frvt@nist.gov.

1.2 Introduction

The majority of face recognition systems have been deployed in applications where subjects make cooperative presentations to a camera, for example as part of an application for a benefit or ID credential, or as during access control. With very few exceptions such images would not include face masks or other occlusions. However, with the COVID-19 pandemic, we can anticipate a demand to authenticate persons wearing masks, for example in immigration settings, without the need to the subjects to remove those masks. This presents a problem for face recognition, because regions of the face occluded by masks - the mouth and nose - include information useful for both recognition and, potentially, the detection stage that precedes it.

Previous work on face recognition of occluded faces has been directed at situations such as crime scenes where subjects were actively un-cooperative i.e. acting to evade face detection and recognition. Those applications are often characterized by image properties (low resolution, video compression, uncontrolled head orientation) that are known [5] to degrade recognition accuracy.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

2 Image Datasets

2.1 Application Images

The images are collected in an attended interview setting using dedicated capture equipment and lighting. The images are of size 300x300 pixels. The images are all high-quality frontal portraits collected in immigration offices and with a white background. As such, potential quality related drivers of high false match rates (such as blur) can be expected to be absent. The images are encoded as ISO/IEC 10918 i.e. JPEG. Over a random sample of 1000 images, the images have compressed file sizes (mean: 42KB, median: 58KB, 25-th percentile: 15KB, and 75-th percentile: 66KB). The implied bit-rates are mostly benign and superior to many e-Passports. When these images are provided as input into the algorithm, they are labeled with the type "ISO".

Figure 3: Examples of images with properties similar to the enrollment application photos used in this study. The subjects in the photos are all NIST employees.

2.2 Webcam Images

These images are taken with a camera oriented by an attendant toward a cooperating subject. This is done under time constraints, so there are roll, pitch, and yaw angle variations. Also, background illumination is sometimes bright, so the face is under exposed. Sometimes, there is perspective distortion due to close range images. The images are generally in poor conformance with the ISO/IEC 19794-5 Full Frontal image type. The images have mean interocular distance of 38 pixels. The images are all live capture. When these images are provided as input into the algorithm, they are labeled with the type "WILD". Examples of such images are included in Figure 4 and Figure 4 in NIST Interagency Report 8271. Results for verification of these images (unmasked) appear in FRVT Part 1 - Verification both compared against images of the same type, and with those described in section 2.1.

Description	#
Total images	6 244 865
Application (enrollment) images	1 019 232
Subjects in application images	1 019 232
Webcam (verification) images	5 225 633
Subjects in webcam (verification) images	2 535 329
Mated comparisons	3 225 633
Impostor comparisons	200 000 000
Subjects in mated comparisons	535 329
Subjects in impostor comparisons	3 019 232

Table 1: Summary quantities of the dataset used in this evaluation.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

2.3 Synthetically Masked Images

In this test, synthetically-generated masks were overlaid on top of 1) just the probe image (webcam images described in Section 2.2) or 2) both the enrollment (application photos described in Section 2.1) and probe images. The Dlib [7] C++ toolkit version 19.19 was used to detect and establish key facial points on the face, and with the facial points, solid masks of different shape, height, and color were drawn on the face. The exact Dlib facial points and details used to generate the masks are documented in Appendix A. In the event that Dlib was unable to detect a face in the image, eye coordinates were used to generate a mask leveraging standardized token frontal geometry [1].

Examples of synthetically-masked probe images are presented in Figures 4.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 4: Examples of synthetically-generated face masks used in this study. The original images are from the NIST MEDS-II Dataset [3]. They were collected in operational settings using the same camera and procedure as is used for the border images that form the mainstay of the experiments in this report.

3 Metrics

3.1 Matching accuracy

Given a vector of N genuine scores, u, the false non-match rate (FNMR) is computed as the proportion below some threshold, T:

$$\text{FNMR}(T) = 1 - \frac{1}{N}\sum_{i=1}^{N} H(u_i - T) \tag{1}$$

where $H(x)$ is the unit step function, and $H(0)$ taken to be 1.

Similarly, given a vector of N impostor scores, v, the false match rate (FMR) is computed as the proportion above T:

$$\text{FMR}(T) = \frac{1}{N}\sum_{i=1}^{N} H(v_i - T) \tag{2}$$

The threshold, T, can take on any value. We typically generate a set of thresholds from quantiles of the observed impostor scores, v, as follows. Given some interesting false match rate range, $[\text{FMR}_L, \text{FMR}_U]$, we form a vector of K thresholds corresponding to FMR measurements evenly spaced on a logarithmic scale

$$T_k = Q(1 - \text{FMR}_k) \tag{3}$$

where Q is the quantile function, and FMR_k comes from

$$\log_{10}\text{FMR}_k = \log_{10}\text{FMR}_L + \frac{k}{K}\,[\log_{10}\text{FMR}_U - \log_{10}\text{FMR}_L] \tag{4}$$

Detection error tradeoff (DET) characteristics are plots of FNMR(T) vs. FMR(T). These are plotted with $\text{FMR}_U \to 1$ and FMR_L as low as is sustained by the number of impostor comparisons, N. This is somewhat higher than the "rule of three" limit $3/N$ [6] because samples are not independent, due to re-use of images.

3.2 Failure to Enroll

Failure to enroll (FTE) is the proportion of failed template generation attempts. Failures can occur because the software throws an exception, or because the software electively refuses to process the input image. This would typically occur if a face is not detected. FTE is measured as the number of function calls that give EITHER a non-zero error code OR that give a "small" template. This is defined as one whose size is less than 60 bytes. This second rule is needed because some algorithms incorrectly fail to return a non-zero error code when template generation fails yet do return a valid default data structure.

The effects of FTE are included in the accuracy results of this report by regarding any template comparison involving a failed template to produce a low similarity score. Thus higher FTE results in higher FNMR and lower FMR.

4 Algorithms

The FRVT activity is open to participation worldwide, and the test will evaluate submissions on an ongoing basis. There is no charge to participate. The process and format of algorithm submissions to NIST are described in the FRVT 1:1 Verification Application Programming Interface (API) [9] document. Participants provide their submissions in the form of libraries compiled on a specific Linux kernel, which are linked against NIST's test harness to produce executables. NIST provides a validation package to participants to ensure that NIST's execution of submitted libraries produces the expected output on NIST's test machines.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

This report documents the results of algorithms submitted to FRVT 1:1 for testing both before (prior to mid-March 2020) and after the COVID-19 pandemic. Table 4 lists the algorithms that were tested. Note that algorithms that are expired or retired are not included in this report.

	Developer	Algorithm	Submission Date
1	3Divi	3divi-004	2019-07-22
2	3Divi	3divi-005	2020-08-28
3	ACI Software	acisw-003	2020-08-03
4	ADVANCE.AI	advance-002	2019-12-19
5	ASUSTek Computer Inc	asusaics-000	2019-10-24
6	AYF Technology	ayftech-001	2020-07-06
7	Acer Incorporated	acer-000	2020-01-08
8	Acer Incorporated	acer-001	2020-06-30
9	Ai First	aifirst-001	2019-11-21
10	AiUnion Technology	aiunionface-000	2019-10-22
11	Aigen	aigen-001	2020-10-06
12	Akurat Satu Indonesia	ptakuratsatu-000	2020-09-11
13	AlphaSSTG	alphaface-002	2020-02-20
14	Anke Investments	anke-005	2019-11-21
15	Antheus Technologia	antheus-000	2019-12-05
16	Antheus Technologia	antheus-001	2020-06-25
17	Aware	aware-005	2020-02-27
18	Awidit Systems	awiros-001	2019-09-23
19	Awidit Systems	awiros-002	2020-10-28
20	Beihang University-ERCACAT	ercacat-001	2020-07-06
21	Beijing Alleyes Technology	alleyes-000	2020-03-09
22	BioID Technologies SA	bioidtechswiss-000	2019-11-15
23	BioID Technologies SA	bioidtechswiss-001	2020-08-28
24	Bresee Technology	bresee-000	2020-08-07
25	CSA IntelliCloud Technology	intellicloudai-001	2019-08-13
26	CTBC Bank	ctbcbank-000	2019-06-28
27	Camvi Technologies	camvi-004	2019-07-12
28	Canon Information Technology (Beijing)	cib-000	2019-12-11
29	Canon Information Technology (Beijing)	cib-001	2020-08-05
30	China University of Petroleum	upc-001	2019-06-05
31	Chinese Univeristy of Hong Kong	cuhkee-001	2020-03-18
32	Chosun University	chosun-000	2020-02-12
33	Chosun University	chosun-001	2020-07-01
34	Chunghwa Telecom	chtface-002	2019-12-07
35	Chunghwa Telecom	chtface-003	2020-06-24
36	Cortica	cor-001	2020-09-24
37	Cybercore	cybercore-000	2020-08-26
38	Cyberlink Corp	cyberlink-004	2020-02-27
39	Cyberlink Corp	cyberlink-005	2020-07-31
40	DSK	dsk-000	2019-06-28
41	Dahua Technology	dahua-004	2019-12-18
42	Dahua Technology	dahua-005	2020-08-13
43	Decatur Industries Inc	decatur-000	2020-08-18
44	Deepglint	deepglint-002	2019-11-15
45	DiDi ChuXing Technology	didiglobalface-001	2019-10-23
46	Expasoft LLC	expasoft-000	2020-01-06
47	Expasoft LLC	expasoft-001	2020-09-03
48	FaceSoft	facesoft-000	2019-07-10
49	Fiberhome Telecommunication Technologies	fiberhome-nanjing-002	2020-08-10
50	Fujitsu Research and Development Center	fujitsulab-000	2020-02-04
51	Fujitsu Research and Development Center	fujitsulab-001	2020-09-30
52	GeoVision Inc	geo-000	2020-06-29
53	Glory	glory-002	2019-11-12
54	Gorilla Technology	gorilla-005	2020-03-11
55	Gorilla Technology	gorilla-006	2020-07-31
56	Guangzhou Pixel Solutions	pixelall-003	2019-10-15
57	Guangzhou Pixel Solutions	pixelall-004	2020-07-02

Table 2: List of algorithms included in this report. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

	Developer	Algorithm	Submission Date
58	Hengrui AI Technology	hr-003	2020-09-25
59	ID3 Technology	id3-005	2020-08-04
60	ITMO University	itmo-007	2020-01-06
61	Idemia	idemia-005	2019-10-11
62	Idemia	idemia-006	2020-07-06
63	Imageware Systems	iws-000	2020-08-12
64	Imagus Technology Pty	imagus-001	2019-10-22
65	Imperial College London	imperial-002	2019-08-28
66	Incode Technologies Inc	incode-006	2020-02-20
67	Incode Technologies Inc	incode-007	2020-08-25
68	Innef Labs	innefulabs-000	2020-09-04
69	Innovative Technology	innovativetechnologyltd-002	2020-02-26
70	Innovatrics	innovatrics-006	2019-08-13
71	Institute of Information Technologies	iit-002	2019-12-04
72	Intel Research Group	intelresearch-001	2020-01-14
73	Intel Research Group	intelresearch-002	2020-07-24
74	Intellivision	intellivision-002	2019-08-23
75	Kakao Enterprise	kakao-003	2020-02-26
76	Kedacom International Pte	kedacom-000	2019-06-03
77	Kneron Inc	kneron-005	2020-02-21
78	Kookmin University	kookmin-001	2020-09-28
79	Lomonosov Moscow State University	intsysmsu-002	2020-03-12
80	Lookman Electroplast Industries	lookman-004	2019-06-03
81	Luxand Inc	luxand-000	2019-11-07
82	MVision	mvision-001	2019-11-12
83	Momentum Digital	sertis-000	2019-10-07
84	Momentum Digital	sertis-001	2020-07-30
85	Moontime Smart Technology	mt-000	2019-06-03
86	Moontime Smart Technology	mt-002	2020-07-02
87	N-Tech Lab	ntech-008	2020-01-06
88	NSENSE Corp	nsensecorp-001	2020-10-20
89	Netbridge Technology Incoporation	netbridgetech-001	2020-01-08
90	Netbridge Technology Incoporation	netbridgetech-002	2020-08-11
91	Neurotechnology	neurotechnology-008	2020-01-08
92	Neurotechnology	neurotechnology-009	2020-07-07
93	Nodeflux	nodeflux-002	2019-08-13
94	NotionTag Technologies Private Limited	notiontag-000	2019-06-12
95	Oz Forensics LLC	oz-001	2020-07-29
96	PXL Vision AG	pxl-001	2020-06-30
97	Panasonic R+D Center Singapore	psl-005	2020-07-06
98	Paravision (EverAI)	paravision-004	2019-12-11
99	Pensees Pte	pensees-001	2020-08-17
100	Rank One Computing	rankone-009	2020-06-26
101	Rank One Computing	rankone-010	2020-11-05
102	Remark Holdings	remarkai-002	2019-11-21
103	Rokid Corporation	rokid-000	2019-08-01
104	Samsung S1 Corp	s1-001	2019-12-06
105	Satellite Innovation/Eocortex	eocortex-000	2020-08-26
106	Scanovate	scanovate-001	2019-11-12
107	Scanovate	scanovate-002	2020-06-26
108	Securif AI	securifai-001	2020-10-06
109	Sensetime Group	sensetime-003	2019-06-04
110	Shanghai Jiao Tong University	sjtu-002	2020-02-12
111	Shanghai Jiao Tong University	sjtu-003	2020-11-02
112	Shanghai Ulucu Electronics Technology	uluface-002	2019-07-10
113	Shanghai University - Shanghai Film Academy	shu-002	2019-12-10
114	Shanghai University - Shanghai Film Academy	shu-003	2020-06-24

Table 3: List of algorithms included in this report. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

	Developer	Algorithm	Submission Date
115	Shenzhen AiMall Tech	aimall-002	2020-03-12
116	Shenzhen AiMall Tech	aimall-003	2020-08-12
117	Shenzhen Intellifusion Technologies	intellifusion-002	2020-03-18
118	Staqu Technologies	staqu-000	2020-07-15
119	Star Hybrid Limited	starhybrid-001	2019-06-19
120	Su Zhou NaZhiTianDi intelligent technology	nazhiai-000	2020-06-25
121	Synology Inc	synology-000	2019-10-23
122	TUPU Technology	tuputech-000	2019-10-11
123	Taiwan AI Labs	ailabs-001	2019-12-18
124	Tech5 SA	tech5-004	2020-03-09
125	Tech5 SA	tech5-005	2020-07-24
126	Tencent Deepsea Lab	deepsea-001	2019-06-03
127	Tevian	tevian-005	2019-09-21
128	Tevian	tevian-006	2020-09-11
129	Trueface.ai	trueface-000	2019-10-08
130	Trueface.ai	trueface-001	2020-07-20
131	Universidade de Coimbra	visteam-000	2020-01-14
132	Veridas Digital Authentication Solutions S.L.	veridas-004	2020-07-21
133	Via Technologies Inc	via-001	2020-01-08
134	Videmo Intelligente Videoanalyse	videmo-000	2019-12-19
135	Videonetics Technology Pvt	videonetics-002	2019-11-21
136	Viettel Group	vts-000	2020-11-04
137	Vigilant Solutions	vigilantsolutions-007	2019-06-27
138	Vigilant Solutions	vigilantsolutions-008	2020-08-03
139	VinAI Research VietNam	vinai-000	2020-09-24
140	VisionLabs	visionlabs-008	2020-01-06
141	VisionLabs	visionlabs-009	2020-07-27
142	Vocord	vocord-008	2020-01-031
143	Winsense	winsense-001	2019-10-16
144	X-Laboratory	x-laboratory-001	2020-01-21
145	Xforward AI Technology	xforwardai-000	2020-02-06
146	Xforward AI Technology	xforwardai-001	2020-09-25
147	Xiamen University	xm-000	2020-10-19
148	YooniK	yoonik-000	2020-06-24
149	Yuan High-Tech Development	yuan-000	2020-06-30
150	iQIYI Inc	iqface-000	2019-06-04
151	iQIYI Inc	iqface-002	2020-07-30
152	iSAP Solution Corporation	isap-002	2020-09-01

Table 4: List of algorithms included in this report. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

5 Results

This section includes accuracy results for the 152 one-to-one verification algorithms listed in Section 4, of which 65 were submitted to FRVT after mid-March 2020 and are labeled in blue in figures and tables throughout this report. We do not include speed and computational resource requirements - they are given in Table 1 in the FRVT 1:1 report. Missing entries generally mean the algorithm was not run on that particular mask variation due to time and resource constraints. The results, which span many pages, are comprised of:

- ▷ **Evolution of algorithm performance with face masks**: Figure 5 shows the evolution of performance with face masks for developers that have submitted algorithms since mid-March 2020.
- ▷ **FNMR - summary**: Figure 6 gives a summary of false non-matches rates between pre and post-COVID algorithms with a common type of mask. FNMR values are stated at a fixed threshold calibrated to give FMR = 0.00001 on unmasked images.
- ▷ **FNMR - detailed**: Table 5 tabulates false non-match rates by color, shape, and nose coverage. It includes also FNMR without any mask. FNMR values are stated at a fixed threshold calibrated to give FMR = 0.00001 on unmasked images.
- ▷ **Mask vs. no mask**: The scatter plot in Figure 7 shows variation across all algorithms of FNMR without masks against FNMR with a common type of mask, broken out by pre and post-COVID algorithms.
- ▷ **Mask shape**: The scatter plot in Figure 8 shows for all algorithms the increase in false negative results for wide masks vs. narrower round masks, broken out by pre and post-COVID algorithms.
- ▷ **Mask nose coverage**: The scatter plot in Figure 9 shows for all algorithms the increase in false negative rates for masks that substantially cover the nose and those pulled beneath the nose, broken out by pre and post-COVID algorithms.
- ▷ **FTE**: Table 9 gives empirical failure-to-template results by color, shape, and nose coverage. The table was produced using 10 000 images of each kind of mask.
- ▷ **FTE as contributor to FNMR**: The FNMR results include failure-to-template rates (FTE). Figure 10 shows the proportion of template generation failures, broken out by pre and post-COVID algorithms.
- ▷ **DET - impact of mask nose coverage and shape**: This section of figures shows detection error tradeoff characteristics for each algorithm, across different mask nose coverages and shapes.
- ▷ **DET - impact of mask color**: This section of figures shows detection error tradeoff characteristics for each algorithm, across mask colors.
- ▷ **FNMR and FMR vs. threshold**: This section of figures shows the explicit dependence of false non-match rate and false match rate on threshold.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

Figure 5: Evolution of accuracy with face masks for developers that have submitted algorithms since mid-March 2020. Red line represents results on a masked dataset (masked probe), and for reference, the blue and green lines are results for unmasked datasets. FNMR on masked dataset is for medium, wide, lightblue masks. The horizontal gold line shows where FNMR=10%.

2020/11/30 08:35:54
This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 6: For each algorithm, each dot shows FNMR @ FMR=0.00001, where the threshold is set for FMR on unmasked probe images. The results are for when the probe is masked, and the enrollment image is unmasked. Gray dots represent results for algorithms submitted prior to mid-March 2020 (pre-COVID), and blue dots represent algorithms submitted thereafter (post-COVID).

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

	Algorithm	NOT MASKED	MASK COLOR = LIGHTBLUE						COLOR = BLACK			COLOR = RED	COLOR = WHITE
	Name		SHAPE = WIDE			SHAPE = ROUND			SHAPE = WIDE			SHAPE = WIDE	SHAPE = WIDE
	COVERAGE		LO	MED	HI	LO	MED	HI	LO	MED	HI	MED	MED
1	3divi-004	0.0130^{87}	0.4123^{99}	0.6760^{117}	-	-	-	-	-	-	-	-	-
2	3divi-005	0.0088^{62}	0.1006^{70}	0.2895^{67}	0.3670^{48}	0.0783^{50}	0.1918^{49}	-	0.1185^{50}	0.3057^{53}	0.4272^{49}	-	-
3	acer-000	0.8432^{147}	0.9995^{123}	0.9999^{147}	-	-	-	-	-	-	-	-	-
4	acer-001	0.0219^{108}	0.2587^{92}	0.5835^{105}	0.6719^{62}	0.1536^{57}	0.4325^{57}	0.6831^{48}	0.3132^{56}	0.6304^{64}	0.7143^{55}	-	-
5	acisw-003	0.7160^{145}	0.9810^{116}	0.9970^{139}	0.9970^{72}	-	-	-	0.9883^{64}	0.9997^{76}	-	-	-
6	advance-002	0.0328^{117}	-	0.2351^{52}	-	-	-	-	-	-	-	0.2333^{45}	-
7	aifirst-001	0.0079^{54}	0.0778^{56}	0.2567^{55}	-	-	-	-	-	-	-	0.2624^{49}	-
8	aigen-001	0.0159^{99}	0.1268^{78}	0.3790^{83}	0.4432^{56}	-	0.2880^{56}	-	0.1956^{54}	0.4761^{59}	0.6329^{54}	0.3189^{51}	0.3754^{39}
9	ailabs-001	0.0243^{110}	-	0.6792^{118}	-	-	-	-	-	-	-	-	-
10	aimall-002	0.0133^{91}	-	0.3919^{84}	-	-	-	-	-	-	-	-	-
11	aimall-003	0.0045^{19}	0.0188^{16}	0.0781^{20}	0.1325^{21}	0.0175^{15}	0.0524^{24}	0.1021^{23}	0.0223^{16}	0.0913^{20}	0.1577^{25}	0.0738^{13}	0.0800^{17}
12	aiunionface-000	0.0094^{66}	0.0917^{66}	0.2935^{68}	-	-	-	-	-	-	-	-	-
13	alleyes-000	0.0044^{18}	-	0.1038^{26}	-	0.0181^{19}	0.0542^{26}	0.1050^{24}	0.0262^{24}	0.1287^{31}	0.1991^{31}	0.1066^{21}	0.1098^{23}
14	alphaface-002	1.0000^{152}	1.0000^{125}	1.0000^{150}	-	-	-	-	-	-	-	-	-
15	anke-005	0.0062^{44}	0.0671^{49}	0.3207^{74}	-	-	-	-	-	-	-	-	-
16	antheus-000	0.7319^{146}	0.9994^{122}	0.9999^{146}	-	-	-	-	-	-	-	-	-
17	antheus-001	0.6608^{142}	0.9988^{121}	0.9998^{145}	0.9998^{73}	0.9993^{65}	0.9998^{67}	0.9998^{54}	0.9993^{66}	0.9998^{77}	0.9998^{64}	-	-
18	asusaics-000	0.0090^{64}	-	0.3616^{81}	-	-	-	-	-	-	-	-	-
19	aware-005	0.0308^{116}	0.4962^{103}	0.8876^{127}	-	-	-	-	-	-	-	-	-
20	awiros-001	0.1233^{133}	0.6823^{110}	0.8635^{125}	-	-	-	-	-	-	-	-	-
21	awiros-002	0.2283^{137}	0.6356^{107}	0.8671^{126}	0.9221^{68}	-	-	-	0.7703^{62}	0.9068^{73}	-	0.8628^{57}	0.8508^{42}
22	ayftech-001	0.0828^{129}	0.6740^{108}	0.9132^{131}	0.9333^{70}	0.5865^{63}	0.8519^{64}	0.9538^{53}	0.7540^{61}	0.9048^{72}	0.9705^{62}	-	-
23	bioidtechswiss-000	0.0050^{24}	0.0308^{23}	0.1155^{28}	0.1840^{30}	0.0223^{24}	0.0632^{28}	0.1207^{28}	0.0331^{27}	0.1163^{27}	0.1786^{27}	0.1167^{23}	0.1167^{25}
24	bioidtechswiss-001	0.0037^{6}	0.0225^{21}	0.0945^{24}	0.1519^{25}	0.0180^{18}	0.0524^{25}	0.1070^{26}	0.0254^{21}	0.0986^{23}	0.1571^{23}	0.0979^{19}	0.0945^{22}
25	bresee-000	0.9802^{148}	0.9968^{120}	0.9989^{141}	-	-	-	-	0.9975^{65}	-	-	-	-
26	camvi-004	0.0063^{45}	0.0697^{51}	0.2179^{50}	-	-	-	-	-	-	-	0.3337^{52}	-
27	chosun-000	1.0000^{153}	1.0000^{135}	1.0000^{152}	-	-	-	-	-	-	-	-	-
28	chosun-001	0.0582^{128}	0.5759^{104}	0.9091^{129}	0.9263^{69}	0.5021^{62}	0.8531^{65}	0.9278^{51}	0.5158^{58}	0.9031^{71}	0.9409^{60}	-	-
29	chtface-002	0.0108^{76}	0.1423^{80}	0.4303^{90}	-	-	-	-	-	-	-	-	-
30	chtface-003	0.0084^{56}	0.1008^{71}	0.3201^{73}	-	0.0774^{49}	0.2393^{54}	0.4387^{44}	0.1232^{52}	0.3309^{56}	0.5044^{51}	-	-
31	cib-000	0.0249^{111}	0.0757^{54}	0.1670^{37}	-	-	-	-	-	-	-	0.3825^{53}	0.1859^{36}
32	cib-001	0.0036^{5}	0.0149^{10}	0.0731^{19}	0.1095^{16}	0.0125^{5}	0.0336^{9}	0.0690^{7}	0.0175^{9}	0.0731^{15}	0.1137^{10}	0.0863^{17}	0.0779^{16}
33	clova-000	0.0087^{60}	0.0881^{64}	-	0.5017^{58}	-	-	-	0.0950^{47}	0.3051^{52}	-	-	-
34	cor-001	0.0053^{29}	0.0504^{42}	0.1802^{43}	0.2470^{39}	0.0300^{31}	0.0864^{31}	-	0.0364^{31}	0.1328^{32}	0.1828^{28}	0.1527^{29}	-
35	ctbcbank-000	0.0133^{89}	0.1594^{87}	0.7448^{123}	-	-	-	-	-	-	-	-	-
36	cuhkee-001	0.0041^{13}	0.0143^{9}	0.0572^{13}	0.0963^{13}	0.0143^{9}	0.0333^{8}	0.0715^{8}	0.0164^{8}	0.0652^{10}	0.1193^{11}	-	-
37	cybercore-000	0.1096^{131}	-	0.9097^{130}	-	-	-	-	-	-	-	-	-
38	cyberlink-004	0.0061^{42}	0.0538^{45}	0.2115^{49}	-	-	-	-	-	-	-	0.2591^{48}	-
39	cyberlink-005	0.0055^{30}	0.0376^{32}	0.1374^{32}	0.1808^{29}	0.0388^{42}	0.1018^{35}	0.2695^{39}	0.0451^{38}	0.1610^{37}	0.3991^{46}	0.4285^{55}	0.1316^{26}
40	dahua-004	0.0038^{9}	0.0328^{27}	0.1784^{41}	0.2026^{32}	-	-	-	0.0226^{18}	0.1186^{28}	0.1983^{30}	-	-
41	dahua-005	0.0034^{4}	0.0155^{11}	0.0660^{17}	0.1135^{19}	0.0127^{7}	0.0340^{10}	0.0829^{13}	0.0137^{6}	0.0601^{8}	0.1019^{8}	0.0579^{6}	0.0613^{10}
42	decatur-000	0.0384^{119}	-	0.6440^{111}	-	-	-	-	-	-	-	-	-
43	deepglint-002	0.0039^{11}	0.0077^{1}	0.0237^{1}	0.0455^{1}	0.0078^{1}	0.0141^{1}	0.0292^{1}	0.0083^{1}	0.0254^{1}	0.0513^{1}	0.0234^{1}	0.0248^{1}
44	deepsea-001	0.0110^{79}	0.1218^{75}	0.3094^{71}	0.3778^{52}	0.0922^{54}	0.2217^{52}	0.4469^{47}	-	-	-	-	-
45	didiglobalface-001	0.0050^{25}	-	0.0986^{25}	0.1517^{23}	0.0255^{25}	0.0515^{22}	0.0979^{20}	0.0291^{25}	0.1033^{25}	0.1558^{22}	0.1241^{24}	0.1655^{32}

Table 5: This table summarizes False Non-Match Rate (FNMR) on unmasked and masked probe images. FNMR is the proportion of mated comparisons below a threshold set to achieve FMR=1e-05 on unmasked probe images. False Match Rate (FMR) is the proportion of impostor comparisons at or above that threshold. The red superscripts give rank over all algorithms in that column. Missing entries generally mean the algorithm was not run on that particular mask variation due to time and resource constraints. Algorithms with FTE=1.00 were not run at all. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

2020/11/30 08:35:54
This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

	Algorithm	NOT MASKED	MASK COLOR = LIGHTBLUE						COLOR = BLACK			COLOR = RED	COLOR = WHITE
	Name		SHAPE = WIDE			SHAPE = ROUND			SHAPE = WIDE			SHAPE = WIDE	SHAPE = WIDE
	COVERAGE		LO	MED	HI	LO	MED	HI	LO	MED	HI	MED	MED
46	dsk-000	0.1961^{134}	0.9108^{113}	0.9929^{138}	-	-	-	-	-	-	-	-	-
47	eocortex-000	0.1187^{132}	-	0.9694^{134}	-	-	-	-	-	-	-	-	-
48	ercacat-001	0.0096^{69}	0.0187^{15}	0.0616^{15}	0.0994^{14}	0.0173^{14}	0.0357^{11}	0.0728^{10}	0.0200^{13}	0.0663^{12}	0.1114^{9}	0.0679^{12}	0.0648^{12}
49	expasoft-000	0.0519^{126}	0.3186^{96}	0.6796^{119}	-	-	-	-	-	-	-	-	-
50	expasoft-001	0.0492^{124}	-	0.6414^{110}	-	-	-	-	-	-	-	-	-
51	facesoft-000	0.0057^{36}	0.0397^{34}	0.1428^{33}	-	-	-	-	-	0.1573^{36}	-	0.1446^{28}	0.1428^{29}
52	fiberhome-nanjing-002	0.0133^{90}	0.1554^{86}	0.4734^{96}	-	-	-	-	0.1641^{53}	-	-	-	-
53	fujitsulab-000	0.0180^{103}	-	0.5052^{101}	-	-	-	-	-	-	-	-	-
54	fujitsulab-001	0.0078^{53}	0.0330^{28}	0.0427^{6}	0.0608^{4}	0.0311^{32}	0.0363^{12}	0.0666^{5}	0.0407^{34}	0.0985^{21}	0.1525^{21}	0.0898^{18}	0.0776^{15}
55	geo-000	0.0902^{130}	0.5765^{105}	0.9236^{132}	-	-	0.8082^{63}	0.9311^{52}	0.6214^{60}	0.9428^{74}	0.9541^{61}	-	-
56	glory-002	0.0109^{78}	-	0.2729^{64}	-	-	-	-	-	-	-	-	-
57	gorilla-005	0.0117^{83}	0.1463^{82}	0.5037^{99}	-	-	-	-	-	-	-	-	-
58	gorilla-006	0.0085^{57}	0.0495^{41}	0.1805^{44}	0.2883^{43}	0.0385^{41}	0.1134^{42}	-	-	0.2260^{46}	0.3419^{43}	0.1980^{40}	-
59	hr-003	0.0049^{23}	0.0133^{5}	0.0419^{5}	0.0613^{5}	0.0122^{3}	0.0247^{4}	0.0475^{4}	0.0142^{7}	0.0527^{6}	0.0914^{5}	0.0542^{5}	0.0476^{7}
60	id3-005	0.0145^{96}	0.1181^{74}	0.3540^{80}	-	-	-	-	-	-	-	-	-
61	idemia-005	0.0111^{81}	0.2051^{90}	0.6469^{113}	0.6968^{64}	0.1349^{56}	0.4387^{58}	-	0.2786^{55}	0.7402^{69}	0.8119^{56}	-	-
62	idemia-006	0.0048^{22}	0.0327^{26}	0.0539^{10}	0.0911^{10}	0.0322^{33}	0.0440^{19}	0.0946^{17}	0.0359^{29}	0.0714^{14}	0.1489^{19}	0.0607^{8}	0.0564^{9}
63	iit-002	0.0141^{94}	-	0.3078^{70}	-	-	-	-	-	-	-	-	-
64	imagus-001	0.0276^{113}	0.3488^{98}	0.6510^{114}	-	-	-	-	-	-	-	-	-
65	imperial-002	0.0055^{31}	0.0320^{25}	0.1350^{31}	0.1972^{31}	0.0258^{26}	0.0775^{30}	0.1556^{29}	0.0359^{30}	0.1510^{35}	0.2302^{36}	0.1533^{30}	0.1432^{30}
66	incode-006	0.0095^{68}	-	0.3725^{82}	-	-	-	-	-	-	-	-	-
67	incode-007	0.0058^{37}	0.0470^{38}	0.1790^{42}	0.2393^{38}	0.0323^{34}	0.1040^{37}	0.1779^{31}	0.0561^{41}	0.1891^{43}	0.2754^{39}	0.1978^{39}	-
68	innefulabs-000	0.0155^{98}	-	0.2971^{69}	-	-	-	-	-	-	-	-	-
69	innovativetechnologyltd-002	0.0251^{112}	0.2701^{93}	0.6454^{112}	-	-	-	-	-	-	-	-	-
70	innovatrics-006	0.0059^{40}	0.0543^{48}	0.2210^{51}	0.3118^{44}	0.0369^{37}	0.1109^{40}	0.1984^{33}	0.0557^{40}	0.1909^{44}	0.2764^{40}	0.1936^{38}	-
71	intellicloudai-001	0.0095^{67}	0.1044^{72}	0.4394^{92}	-	-	-	-	-	-	-	-	-
72	intellifusion-002	0.0056^{35}	0.0539^{46}	0.1690^{39}	-	-	-	-	-	0.1822^{42}	-	0.2556^{47}	0.2119^{37}
73	intellivision-002	0.0463^{123}	0.5999^{106}	0.9028^{128}	-	-	-	-	-	-	-	-	-
74	intelresearch-001	0.0220^{109}	0.2254^{91}	0.6184^{108}	-	-	-	-	-	-	-	-	-
75	intelresearch-002	0.0111^{80}	0.0458^{36}	0.1598^{35}	0.2085^{33}	0.0384^{40}	0.1025^{36}	0.2568^{38}	0.0598^{42}	0.1764^{41}	0.2583^{38}	0.1857^{36}	0.1595^{31}
76	intsysmsu-002	0.0089^{63}	0.0827^{60}	0.3138^{72}	-	-	-	-	-	-	-	-	-
77	iqface-000	0.0128^{86}	0.0885^{65}	0.2867^{66}	-	-	-	-	-	-	-	-	-
78	iqface-002	0.0086^{58}	0.0193^{17}	0.0445^{7}	0.0725^{7}	0.0184^{21}	0.0317^{6}	0.0671^{6}	0.0215^{15}	0.0643^{9}	0.0997^{7}	0.0633^{10}	0.0448^{5}
79	isap-002	0.0094^{65}	-	0.4090^{87}	-	-	-	-	-	-	-	-	-
80	itmo-007	0.0098^{72}	0.0840^{61}	0.2685^{60}	-	-	-	-	-	-	-	-	-
81	iws-000	0.6797^{143}	0.9960^{118}	0.9997^{144}	-	-	-	-	-	-	-	-	-
82	kakao-003	0.0170^{101}	0.1541^{85}	0.4123^{88}	-	-	-	-	-	-	-	-	-
83	kedacom-000	0.0391^{120}	0.3444^{97}	0.6188^{109}	0.6848^{63}	0.2663^{59}	0.5975^{60}	-	-	-	-	-	-
84	kneron-005	0.0296^{115}	-	0.4567^{94}	-	-	-	-	-	-	-	-	-
85	kookmin-001	0.0357^{118}	0.4479^{101}	0.7378^{122}	0.8497^{66}	0.2933^{60}	0.6006^{61}	-	0.4160^{57}	0.7365^{68}	0.8917^{58}	0.8642^{58}	0.7432^{41}
86	lookman-004	0.0398^{121}	-	0.6520^{115}	-	-	-	-	-	-	-	-	-
87	luxand-000	0.2167^{136}	0.9732^{115}	0.9988^{140}	-	-	-	-	-	-	-	-	-
88	mt-000	0.0075^{51}	0.0768^{55}	0.2700^{61}	0.3736^{50}	0.0482^{43}	0.1746^{46}	-	0.0749^{43}	0.3084^{54}	0.4239^{48}	-	-
89	mt-002	0.0043^{15}	0.0215^{18}	0.0713^{18}	0.1114^{17}	0.0162^{12}	0.0404^{15}	0.0777^{12}	0.0225^{17}	0.0877^{19}	0.1399^{18}	0.0804^{15}	0.0757^{14}
90	mvision-001	0.0137^{92}	-	0.3987^{85}	-	-	-	-	-	-	-	-	-

Table 6: This table summarizes False Non-Match Rate (FNMR) on unmasked and masked probe images. FNMR is the proportion of mated comparisons below a threshold set to achieve FMR=1e-05 on unmasked probe images. False Match Rate (FMR) is the proportion of impostor comparisons at or above that threshold. The red superscripts give rank over all algorithms in that column. Missing entries generally mean the algorithm was not run on that particular mask variation due to time and resource constraints. Algorithms with FTE=1.00 were not run at all. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

2020/11/30 08:35:54
This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

	Algorithm	NOT MASKED	MASK COLOR = LIGHTBLUE						COLOR = BLACK			COLOR = RED	COLOR = WHITE
	Name		SHAPE = WIDE			SHAPE = ROUND			SHAPE = WIDE			SHAPE = WIDE	SHAPE = WIDE
	COVERAGE		LO	MED	HI	LO	MED	HI	LO	MED	HI	MED	MED
91	nazhiai-000	0.0043[16]	0.0184[13]	0.0835[21]	0.1318[20]	0.0156[11]	0.0463[20]	0.0947[18]	0.0177[10]	0.0764[16]	0.1271[14]	0.0792[14]	0.0854[20]
92	netbridgetech-001	0.2673[139]	0.8940[112]	0.9878[137]	-	-	-	-	-	-	-	-	-
93	netbridgetech-002	0.0083[55]	0.0781[57]	0.2723[63]	0.3522[46]	0.0528[45]	0.1551[44]	-	0.0875[46]	0.2863[51]	0.4151[47]	-	-
94	neurotechnology-008	0.0100[73]	0.0794[58]	0.3450[77]	0.4460[57]	0.0818[51]	0.1834[48]	0.3127[40]	0.0953[48]	0.4893[60]	0.5472[52]	-	-
95	neurotechnology-009	0.0051[26]	0.0351[31]	0.1768[40]	0.2537[41]	0.0268[27]	0.0953[33]	0.2034[34]	0.0414[35]	0.2180[45]	0.3192[42]	0.1658[32]	-
96	nodeflux-002	0.0424[122]	0.4177[100]	0.7307[121]	-	-	-	-	-	-	-	-	-
97	notiontag-000	0.6814[144]	0.9966[119]	0.9992[142]	-	-	-	-	-	-	-	-	-
98	nsensecorp-001	1.0000[151]	1.0000[126]	1.0000[151]	1.0000[74]	-	-	-	1.0000[67]	1.0000[78]	-	1.0000[60]	1.0000[44]
99	ntechlab-008	0.0033[2]	0.0179[12]	0.0642[16]	0.1126[18]	0.0137[8]	0.0413[18]	0.0953[19]	0.0208[14]	0.0842[18]	0.1348[17]	0.0645[11]	0.0840[19]
100	oz-001	0.0152[97]	0.1969[89]	0.5887[106]	-	-	-	-	-	-	-	-	-
101	paravision-004	0.0088[61]	0.0124[4]	0.0281[2]	0.0476[2]	0.0125[6]	0.0181[3]	0.0313[2]	0.0135[4]	0.0327[3]	0.0581[3]	0.0332[3]	0.0313[3]
102	pensees-001	0.0106[75]	0.0309[24]	0.0461[8]	0.0921[12]	0.0326[36]	0.0413[17]	0.0893[15]	0.0333[28]	0.0579[7]	0.1217[12]	0.1338[26]	0.0462[6]
103	pixelall-003	0.0086[59]	0.0746[52]	0.2680[58]	-	-	-	-	-	-	-	-	-
104	pixelall-004	0.0078[52]	0.0524[44]	0.1676[38]	0.2141[35]	0.0495[44]	0.1131[41]	0.2254[37]	0.0849[45]	0.2461[47]	0.3158[41]	0.3148[50]	0.1791[34]
105	psl-005	0.0056[34]	0.0433[35]	0.1904[47]	0.2576[42]	0.0292[30]	0.1054[39]	0.2210[36]	0.0433[37]	0.1681[39]	0.2223[34]	0.1851[35]	-
106	ptakuratsatu-000	0.0059[41]	0.0542[47]	0.1897[46]	0.2485[40]	0.0380[39]	0.1047[38]	-	0.0502[39]	0.1652[38]	0.2360[37]	0.2003[41]	-
107	pxl-001	0.0511[125]	0.4879[102]	0.8183[124]	0.8754[67]	0.3675[61]	0.7276[62]	0.9182[50]	0.5416[59]	0.8047[70]	0.8718[57]	-	-
108	rankone-009	0.0065[46]	0.0951[67]	0.3450[76]	0.3709[49]	0.1004[55]	0.2244[53]	0.4467[46]	-	0.5624[61]	0.9343[59]	-	-
109	rankone-010	0.0065[47]	0.1514[84]	0.5452[102]	0.3915[53]	-	-	-	-	0.7196[67]	-	0.5811[56]	0.5719[40]
110	remarkai-002	0.0073[49]	0.0685[50]	0.2352[53]	-	-	-	-	-	-	-	0.2406[46]	-
111	rokid-000	0.0117[82]	0.1448[81]	0.4346[91]	-	-	-	-	-	-	-	-	-
112	s1-001	0.0277[114]	0.6776[109]	0.9459[133]	-	-	-	-	-	-	-	-	-
113	scanovate-001	0.2403[138]	-	0.5973[107]	-	-	-	-	-	-	-	-	-
114	scanovate-002	0.0119[84]	0.1304[79]	0.4006[86]	0.5142[59]	0.0757[48]	0.2206[51]	0.3622[42]	0.1215[51]	0.3172[55]	0.4633[50]	-	-
115	securifai-001	0.5185[140]	0.9381[114]	0.9835[136]	0.9880[71]	0.9146[64]	0.9788[66]	-	0.9352[63]	0.9853[75]	0.9949[63]	0.9867[59]	0.9829[43]
116	sensetime-003	0.0045[21]	0.0185[14]	0.0544[11]	0.0912[11]	0.0221[23]	0.0365[13]	0.0739[11]	0.0232[20]	0.0654[11]	0.1230[13]	-	-
117	sertis-000	0.0066[48]	0.0751[53]	0.2685[59]	-	-	-	-	-	-	-	-	-
118	sertis-001	0.0179[102]	-	0.5774[104]	0.6655[61]	-	-	-	-	0.5632[62]	-	-	-
119	shu-002	1.0000[150]	-	1.0000[149]	-	-	-	-	-	-	-	-	-
120	shu-003	0.0053[28]	0.0465[37]	0.1839[45]	0.2148[36]	0.0379[38]	0.1148[43]	0.2196[35]	0.0422[36]	0.1702[40]	0.2210[33]	0.1901[37]	-
121	sjtu-002	0.0052[27]	0.0475[40]	0.1912[48]	-	-	-	-	-	-	-	0.2090[42]	-
122	sjtu-003	0.0043[14]	0.0340[30]	0.1239[29]	0.1609[26]	-	-	-	-	0.1008[24]	-	0.1333[25]	0.1323[27]
123	staqu-000	0.0108[77]	0.1251[77]	0.3537[79]	0.4429[55]	0.0913[53]	0.2434[55]	0.4447[45]	-	0.3862[58]	0.6319[53]	-	-
124	starhybrid-001	0.0104[74]	0.1923[88]	0.5033[98]	-	-	-	-	-	-	-	-	-
125	synology-000	0.0123[85]	-	0.4459[93]	-	-	-	-	-	-	-	-	-
126	tech5-004	0.0045[20]	0.0218[19]	0.0839[22]	0.1389[22]	0.0172[13]	0.0464[21]	0.0905[16]	0.0228[19]	0.0818[17]	0.1288[16]	0.0826[16]	0.0830[18]
127	tech5-005	0.0037[7]	0.0224[20]	0.0941[23]	0.1518[24]	0.0180[17]	0.0524[23]	0.1066[25]	0.0254[22]	0.0986[22]	0.1571[24]	0.0979[20]	0.0945[21]
128	tevian-005	0.0061[43]	0.0961[68]	0.5044[100]	-	-	-	-	-	0.6178[63]	-	-	-
129	tevian-006	0.0038[10]	0.0140[7]	0.0547[12]	0.0894[9]	0.0184[20]	0.0325[7]	0.1013[22]	0.0183[11]	0.1281[30]	0.1507[20]	0.1437[27]	0.0659[13]
130	trueface-000	0.0143[95]	0.1512[83]	0.4164[89]	-	-	-	-	-	-	-	-	-
131	trueface-001	0.0097[71]	0.0978[69]	0.3483[78]	0.4310[54]	0.0710[47]	0.2064[50]	0.3846[43]	-	0.3752[57]	-	-	-
132	tuputech-000	0.2014[135]	0.8743[111]	0.9731[135]	-	-	-	-	-	-	-	-	-
133	uluface-002	0.0073[50]	0.0796[59]	0.2450[54]	-	-	-	-	-	-	-	0.3939[54]	-
134	upc-001	0.0167[100]	-	0.4723[95]	-	-	-	-	-	-	-	-	-
135	veridas-004	0.0202[107]	0.2783[94]	0.6697[116]	0.7334[65]	0.1941[58]	0.5025[59]	0.6906[49]	-	0.6592[66]	-	-	-

Table 7: This table summarizes False Non-Match Rate (FNMR) on unmasked and masked probe images. FNMR is the proportion of mated comparisons below a threshold set to achieve FMR=1e-05 on unmasked probe images. False Match Rate (FMR) is the proportion of impostor comparisons at or above that threshold. The red superscripts give rank over all algorithms in that column. Missing entries generally mean the algorithm was not run on that particular mask variation due to time and resource constraints. Algorithms with FTE=1.00 were not run at all. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

2020/11/30 08:35:54
This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

	Algorithm	NOT MASKED	MASK COLOR = LIGHTBLUE						COLOR = BLACK			COLOR = RED	COLOR = WHITE
	Name		SHAPE = WIDE			SHAPE = ROUND			SHAPE = WIDE			SHAPE = WIDE	SHAPE = WIDE
	COVERAGE		LO	MED	HI	LO	MED	HI	LO	MED	HI	MED	MED
136	via-001	0.0097^{70}	0.1234^{76}	0.3406^{75}	-	-	-	-	-	-	-	-	-
137	videmo-000	0.0140^{93}	-	0.5509^{103}	-	-	-	-	-	-	-	-	-
138	videonetics-002	0.6032^{141}	0.9941^{117}	0.9996^{143}	-	-	-	-	-	-	-	-	-
139	vigilantsolutions-007	0.0194^{104}	0.2849^{95}	0.6839^{120}	-	-	-	-	-	-	-	-	-
140	vigilantsolutions-008	0.0195^{105}	-	0.4970^{97}	0.5521^{60}	-	-	-	-	0.6365^{65}	-	-	-
141	vinai-000	0.0056^{33}	0.0388^{33}	0.1587^{34}	0.2130^{34}	0.0286^{29}	0.0965^{34}	-	0.0364^{32}	0.1487^{34}	0.2024^{32}	0.1691^{33}	0.1710^{33}
142	visionlabs-008	0.0034^{3}	0.0139^{6}	0.0579^{14}	0.1014^{15}	0.0154^{10}	0.0412^{16}	0.1004^{21}	0.0187^{12}	0.0664^{13}	0.1284^{15}	0.0614^{9}	0.0618^{11}
143	visionlabs-009	0.0028^{1}	0.0095^{3}	0.0355^{4}	0.0667^{6}	0.0123^{4}	0.0307^{5}	0.0719^{9}	0.0123^{3}	0.0423^{4}	0.0943^{6}	0.0399^{4}	0.0395^{4}
144	visteam-000	0.9960^{149}	1.0000^{124}	1.0000^{148}	-	-	-	-	-	-	-	-	-
145	vocord-008	0.0038^{8}	0.0140^{8}	0.0500^{9}	0.0762^{8}	0.0176^{16}	0.0393^{14}	0.0892^{14}	0.0135^{5}	0.0459^{5}	0.0771^{4}	0.0607^{7}	0.0482^{8}
146	vts-000	0.0199^{106}	0.0870^{62}	0.2755^{65}	0.3566^{47}	-	-	-	-	0.2584^{50}	-	0.2249^{43}	0.2976^{38}
147	winsense-001	0.0058^{38}	0.0473^{39}	0.1626^{36}	0.2244^{37}	0.0325^{35}	0.0946^{32}	0.1853^{32}	0.0406^{33}	0.1471^{33}	0.2231^{35}	0.1622^{31}	0.1843^{35}
148	x-laboratory-001	0.0058^{39}	0.0517^{43}	0.2569^{56}	-	-	-	-	-	-	-	0.2333^{44}	-
149	xforwardai-000	0.0056^{32}	0.0235^{22}	0.1064^{27}	0.1615^{27}	0.0197^{22}	0.0606^{27}	0.1156^{27}	0.0255^{23}	0.1091^{26}	0.1608^{26}	0.1108^{22}	0.1101^{24}
150	xforwardai-001	0.0041^{12}	0.0087^{2}	0.0289^{3}	0.0536^{3}	0.0087^{2}	0.0180^{2}	0.0377^{3}	0.0090^{2}	0.0303^{2}	0.0544^{2}	0.0313^{2}	0.0294^{2}
151	xm-000	0.0044^{17}	0.0334^{29}	0.1255^{30}	0.1682^{28}	0.0275^{28}	0.0774^{29}	0.1648^{30}	0.0324^{26}	0.1274^{29}	0.1839^{29}	0.1706^{34}	0.1381^{28}
152	yoonik-000	0.0520^{127}	0.1056^{73}	0.2675^{57}	0.3773^{51}	0.0895^{52}	0.1823^{47}	0.3214^{41}	0.1027^{49}	0.2582^{49}	0.3628^{44}	-	-
153	yuan-000	0.0130^{88}	0.0871^{63}	0.2704^{62}	0.3516^{45}	0.0654^{46}	0.1661^{45}	-	0.0805^{44}	0.2492^{48}	0.3645^{45}	-	-

Table 8: This table summarizes False Non-Match Rate (FNMR) on unmasked and masked probe images. FNMR is the proportion of mated comparisons below a threshold set to achieve FMR=1e-05 on unmasked probe images. False Match Rate (FMR) is the proportion of impostor comparisons at or above that threshold. The red superscripts give rank over all algorithms in that column. Missing entries generally mean the algorithm was not run on that particular mask variation due to time and resource constraints. Algorithms with FTE=1.00 were not run at all. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

2020/11/30 08:35:54
This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

Figure 7: At a fixed threshold, a plot of FNMR with and without masks. The displacement of the dark red line relative to the black "parity" line shows a large increase in FNMR with masks for pre-COVID algorithms. The reduction in distance (relative to the black line) observed in the gold line indicates a reduction in median FNMR with masks for post-COVID algorithms. The value in the title is the median increase multiplier.

2020/11/30 08:35:54
This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 8: At a fixed threshold, a plot of FNMR with round versus wide masks. The displacement of the dark red (pre-COVID algorithms) and gold (post-COVID algorithms) lines relative to the black "parity" line shows a modest increase in FNMR with wide masks, with median post-COVID results showing nominal FNMR reductions. The value in the title is the median increase multiplier.

2020/11/30 08:35:54
This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 9: At a fixed threshold, a plot of FNMR with low versus high masks. The displacement of the dark red (pre-COVID algorithms) and gold (post-COVID algorithms) lines relative to the black "parity" lines shows a considerable increase in FNMR with high vs. low nose coverage masks, with median post-COVID results showing modest FNMR reductions. The value in the title is the median increase multiplier.

2020/11/30 08:35:54
This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331
FNMR(T) "False non-match rate"
FMR(T) "False match rate"

	Algorithm Name	COLOR = WHITE SHAPE = WIDE			COLOR = LIGHTBLUE SHAPE = WIDE			COLOR = LIGHTBLUE SHAPE = ROUND			COLOR = RED SHAPE = WIDE			COLOR = BLACK SHAPE = WIDE		
	COVERAGE	LO	MED	HI	LO	MED	HI	LO	MED	HI	LO	MED	HI	LO	MED	HI
1	3divi-004	0.514	0.659	0.627	0.420	0.599	0.603	0.378	0.663	0.769	0.290	0.691	0.864	0.653	0.920	0.939
2	3divi-005	0.003	0.012	0.029	0.002	0.013	0.030	0.007	0.011	0.026	0.005	0.040	0.077	0.002	0.006	0.012
3	acer-000	0.048	0.105	0.139	0.035	0.080	0.114	0.052	0.078	0.137	0.168	0.321	0.445	0.107	0.197	0.270
4	acer-001	0.020	0.048	0.091	0.019	0.051	0.096	0.025	0.034	0.060	0.025	0.080	0.147	0.026	0.088	0.157
5	acisw-003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
6	advance-002	0.019	0.046	0.096	0.020	0.045	0.096	0.026	0.037	0.085	0.028	0.088	0.174	0.034	0.104	0.200
7	aifirst-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
8	aigen-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
9	ailabs-001	0.071	0.208	0.248	0.061	0.194	0.233	0.102	0.177	0.314	0.096	0.319	0.389	0.116	0.310	0.465
10	aimall-002	0.073	0.129	0.225	0.095	0.152	0.260	0.107	0.159	0.236	0.086	0.122	0.230	0.049	0.071	0.154
11	aimall-003	0.011	0.038	0.097	0.014	0.047	0.113	0.020	0.041	0.085	0.013	0.039	0.103	0.012	0.033	0.081
12	aiunionface-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
13	alleyes-000	0.006	0.023	0.062	0.006	0.020	0.056	0.007	0.012	0.028	0.007	0.035	0.088	0.010	0.043	0.104
14	alphaface-002	0.025	0.056	0.099	0.024	0.054	0.095	0.033	0.044	0.072	0.041	0.104	0.174	0.027	0.071	0.132
15	anke-005	0.009	0.028	0.066	0.011	0.030	0.069	0.012	0.018	0.041	0.013	0.036	0.079	0.009	0.056	0.091
16	antheus-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
17	antheus-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
18	asusaics-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
19	aware-005	0.053	0.151	0.218	0.039	0.129	0.211	0.046	0.089	0.244	0.095	0.380	0.516	0.091	0.236	0.449
20	awiros-001	0.195	0.370	0.450	0.162	0.298	0.379	0.161	0.258	0.355	0.388	0.650	0.772	0.198	0.415	0.642
21	awiros-002	0.101	0.212	0.215	0.103	0.202	0.220	0.187	0.261	0.356	0.071	0.272	0.296	0.232	0.405	0.455
22	ayftech-001	0.237	0.610	0.587	0.251	0.615	0.609	0.301	0.553	0.728	0.105	0.405	0.626	0.193	0.596	0.758
23	bioidtechswiss-000	0.005	0.022	0.061	0.006	0.028	0.070	0.010	0.021	0.046	0.006	0.025	0.068	0.006	0.021	0.058
24	bioidtechswiss-001	0.004	0.014	0.044	0.004	0.017	0.046	0.006	0.011	0.026	0.005	0.020	0.051	0.007	0.022	0.056
25	bresee-000	0.005	0.022	0.049	0.005	0.020	0.049	0.009	0.014	0.034	0.010	0.051	0.108	0.008	0.041	0.097
26	camvi-004	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
27	chosun-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
28	chosun-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
29	chtface-002	0.033	0.100	0.154	0.026	0.081	0.126	0.031	0.056	0.107	0.110	0.321	0.480	0.042	0.144	0.270
30	chtface-003	0.022	0.075	0.125	0.018	0.059	0.099	0.023	0.039	0.077	0.080	0.259	0.418	0.030	0.108	0.224
31	cib-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
32	cib-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
33	clova-000	0.035	0.089	0.149	0.033	0.081	0.136	0.039	0.059	0.128	0.071	0.245	0.361	0.049	0.146	0.252
34	cor-001	0.002	0.010	0.031	0.003	0.013	0.035	0.004	0.008	0.020	0.004	0.013	0.032	0.004	0.011	0.031
35	ctbcbank-000	0.179	0.794	0.803	0.171	0.786	0.865	0.205	0.620	0.915	0.433	0.857	0.913	0.189	0.806	0.895
36	cuhkee-001	0.009	0.029	0.069	0.009	0.031	0.074	0.014	0.025	0.057	0.012	0.048	0.115	0.013	0.048	0.140
37	cybercore-000	0.194	0.376	0.371	0.222	0.447	0.453	0.267	0.461	0.751	0.191	0.432	0.554	0.367	0.678	0.805
38	cyberlink-004	0.014	0.042	0.096	0.013	0.039	0.091	0.018	0.029	0.063	0.020	0.096	0.177	0.018	0.064	0.136
39	cyberlink-005	0.012	0.035	0.080	0.011	0.029	0.067	0.014	0.021	0.043	0.016	0.072	0.147	0.015	0.049	0.114
40	dahua-004	0.033	0.150	0.087	0.027	0.126	0.094	0.047	0.121	0.190	0.012	0.071	0.187	0.011	0.057	0.183
41	dahua-005	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
42	decatur-000	0.014	0.036	0.074	0.014	0.033	0.069	0.018	0.028	0.058	0.032	0.065	0.135	0.033	0.069	0.135
43	deepglint-002	0.002	0.009	0.028	0.002	0.012	0.031	0.004	0.006	0.017	0.003	0.014	0.035	0.003	0.010	0.024
44	deepsea-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
45	didiglobalface-001	0.025	0.056	0.099	0.024	0.054	0.095	0.033	0.044	0.072	0.041	0.104	0.174	0.027	0.071	0.132

Table 9: This table summarizes Failure to Enroll (FTE) rates surveyed over 10 000 images of each mask variant. FTE is the proportion of failed template generation attempts. Failures can occur because the software throws an exception, or because the software electively refuses to process the input image as would occur if the algorithms does not detect a face or determines that the face has insufficient information. FTE is measured as the number of function calls that give EITHER a non-zero error code OR that give a "small" template containing fewer than 60 bytes. This second rule is needed because some algorithms incorrectly fail to return a non-zero error code when template generation fails but do produce a skeletal template. The effects of FTE are included in the accuracy results of this report by regarding any template comparison involving a failed template to produce a low similarity score. Thus higher FTE results in higher FNMR and lower FMR. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

2020/11/30 08:35:54
This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

	Algorithm Name	COLOR = WHITE SHAPE = WIDE			COLOR = LIGHTBLUE SHAPE = WIDE			COLOR = LIGHTBLUE SHAPE = ROUND			COLOR = RED SHAPE = WIDE			COLOR = BLACK SHAPE = WIDE		
	COVERAGE	LO	MED	HI	LO	MED	HI	LO	MED	HI	LO	MED	HI	LO	MED	HI
46	dsk-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
47	eocortex-000	0.692	0.862	0.861	0.653	0.841	0.860	0.647	0.887	0.904	0.800	0.960	0.990	0.814	0.950	0.990
48	ercacat-001	0.002	0.007	0.014	0.002	0.006	0.013	0.002	0.002	0.006	0.002	0.008	0.016	0.003	0.009	0.017
49	expasoft-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
50	expasoft-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
51	f8-001	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
52	facesoft-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
53	fujitsulab-000	0.006	0.013	0.018	0.006	0.013	0.019	0.008	0.011	0.018	0.024	0.059	0.066	0.014	0.033	0.045
54	fujitsulab-001	0.008	0.014	0.032	0.006	0.011	0.020	0.005	0.005	0.008	0.014	0.038	0.108	0.012	0.025	0.066
55	geo-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
56	glory-002	0.059	0.106	0.128	0.056	0.101	0.124	0.053	0.074	0.126	0.062	0.148	0.239	0.054	0.154	0.279
57	gorilla-005	0.006	0.018	0.040	0.007	0.018	0.038	0.009	0.012	0.024	-	-	-	0.012	0.037	0.071
58	gorilla-006	0.003	0.008	0.014	0.003	0.008	0.013	0.002	0.003	0.005	0.005	0.013	0.034	0.005	0.014	0.031
59	hr-002	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
60	hr-003	0.003	0.008	0.013	0.003	0.009	0.012	0.006	0.008	0.014	0.005	0.011	0.022	0.005	0.009	0.017
61	id3-005	0.143	0.256	0.304	0.169	0.364	0.424	0.196	0.287	0.539	0.192	0.395	0.527	0.216	0.389	0.557
62	idemia-005	0.002	0.008	0.028	0.002	0.007	0.023	0.002	0.004	0.015	0.002	0.015	0.037	0.002	0.010	0.029
63	idemia-006	0.002	0.008	0.028	0.002	0.007	0.023	0.002	0.004	0.015	0.002	0.013	0.035	0.002	0.010	0.029
64	iit-002	0.012	0.036	0.074	0.013	0.043	0.091	0.015	0.027	0.072	0.016	0.060	0.137	0.015	0.087	0.185
65	imagus-001	0.016	0.040	0.074	0.014	0.037	0.066	0.023	0.029	0.056	0.023	0.084	0.135	0.021	0.085	0.149
66	imperial-002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
67	incode-006	0.002	0.008	0.020	0.002	0.008	0.018	0.002	0.003	0.007	0.002	0.010	0.028	0.002	0.012	0.031
68	incode-007	0.003	0.013	0.034	0.003	0.013	0.031	0.003	0.006	0.014	0.004	0.016	0.045	0.004	0.020	0.060
69	innefulabs-000	0.007	0.024	0.064	0.009	0.028	0.069	0.014	0.027	0.053	0.008	0.025	0.060	0.009	0.025	0.064
70	innovativetechnologyltd-002	0.082	0.176	0.232	0.074	0.172	0.233	0.091	0.131	0.265	0.132	0.269	0.391	0.149	0.362	0.516
71	innovatrics-006	0.002	0.017	0.051	0.003	0.018	0.054	0.005	0.012	0.035	0.007	0.045	0.103	0.005	0.037	0.087
72	innovatrics-007	0.001	0.005	0.015	0.002	0.005	0.017	0.003	0.003	0.007	0.003	0.012	0.038	0.002	0.009	0.026
73	intellicloudai-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
74	intellifusion-002	0.000	0.001	0.004	0.000	0.000	0.001	0.000	0.000	0.002	0.001	0.035	0.112	0.000	0.001	0.004
75	intellivision-002	0.073	0.213	0.267	0.068	0.210	0.261	0.143	0.204	0.340	0.308	0.517	0.618	0.137	0.396	0.469
76	intelresearch-001	0.088	0.212	0.242	0.086	0.213	0.257	0.132	0.191	0.316	0.052	0.176	0.265	0.068	0.230	0.358
77	intelresearch-002	0.006	0.016	0.031	0.007	0.017	0.032	0.008	0.011	0.025	0.008	0.021	0.046	0.008	0.023	0.052
78	intsysmsu-002	0.008	0.055	0.117	0.007	0.047	0.110	0.015	0.033	0.100	0.010	0.078	0.191	0.036	0.105	0.231
79	iqface-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
80	iqface-002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
81	isap-001	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
82	isap-002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
83	itmo-007	0.008	0.034	0.086	0.009	0.046	0.106	0.017	0.034	0.071	0.009	0.039	0.102	0.011	0.034	0.082
84	iws-000	0.489	0.829	0.795	0.476	0.827	0.804	0.627	0.800	0.937	0.387	0.873	0.895	0.512	0.961	0.984
85	kakao-003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
86	kedacom-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
87	kneron-005	0.063	0.184	0.206	0.058	0.166	0.212	0.094	0.146	0.276	0.080	0.292	0.309	0.101	0.440	0.505
88	kookmin-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
89	lookman-004	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
90	luxand-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 10: This table summarizes Failure to Enroll (FTE) rates surveyed over 10 000 images of each mask variant. FTE is the proportion of failed template generation attempts. Failures can occur because the software throws an exception, or because the software electively refuses to process the input image as would occur if the algorithms does not detect a face or determines that the face has insufficient information. FTE is measured as the number of function calls that give EITHER a non-zero error code OR that give a "small" template containing fewer than 60 bytes. This second rule is needed because some algorithms incorrectly fail to return a non-zero error code when template generation fails but do produce a skeletal template. The effects of FTE are included in the accuracy results of this report by regarding any template comparison involving a failed template to produce a low similarity score. Thus higher FTE results in higher FNMR and lower FMR. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

2020/11/30 08:35:54
This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

	Algorithm Name	COLOR = WHITE SHAPE = WIDE			COLOR = LIGHTBLUE SHAPE = WIDE			COLOR = LIGHTBLUE SHAPE = ROUND			COLOR = RED SHAPE = WIDE			COLOR = BLACK SHAPE = WIDE		
	COVERAGE	LO	MED	HI	LO	MED	HI	LO	MED	HI	LO	MED	HI	LO	MED	HI
91	mobai-000	0.186	0.306	0.323	0.200	0.299	0.329	0.204	0.275	0.386	0.403	0.643	0.755	0.219	0.397	0.527
92	mt-000	0.005	0.021	0.061	0.006	0.024	0.063	0.011	0.021	0.045	0.006	0.024	0.058	0.007	0.023	0.059
93	mt-002	0.001	0.004	0.007	0.001	0.004	0.006	0.001	0.001	0.003	0.001	0.005	0.013	0.002	0.005	0.009
94	mvision-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
95	nazhiai-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
96	netbridgetech-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
97	netbridgetech-002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
98	neurotechnology-008	0.008	0.029	0.035	0.007	0.025	0.032	0.007	0.010	0.020	0.007	0.047	0.041	0.019	0.107	0.082
99	neurotechnology-009	0.006	0.018	0.026	0.005	0.015	0.023	0.004	0.005	0.014	0.009	0.030	0.043	0.015	0.100	0.086
100	nodeflux-002	0.402	0.598	0.538	0.440	0.671	0.628	0.482	0.681	0.877	0.393	0.672	0.772	0.602	0.835	0.915
101	notiontag-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
102	nsensecorp-001	0.074	0.139	0.196	0.089	0.174	0.241	0.073	0.119	0.264	0.073	0.137	0.204	0.083	0.219	0.291
103	ntechlab-008	0.064	0.126	0.196	0.053	0.011	0.183	0.003	0.095	0.018	0.003	0.016	0.043	0.003	0.016	0.042
104	oz-001	0.010	0.030	0.057	0.010	0.034	0.066	0.024	0.031	0.063	0.036	0.164	0.209	0.007	0.027	0.040
105	paravision-004	0.002	0.011	0.027	0.002	0.010	0.024	0.003	0.004	0.009	0.003	0.019	0.056	0.003	0.016	0.043
106	pensees-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
107	pixelall-003	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
108	pixelall-004	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
109	psl-005	0.004	0.015	0.038	0.003	0.014	0.036	0.006	0.011	0.029	0.006	0.025	0.061	0.008	0.020	0.047
110	ptakuratsatu-000	0.001	0.005	0.015	0.002	0.005	0.017	0.003	0.003	0.007	0.003	0.012	0.038	0.002	0.009	0.026
111	pxl-001	0.096	0.268	0.329	0.082	0.208	0.273	0.090	0.161	0.294	0.272	0.579	0.712	0.116	0.302	0.500
112	rankone-009	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.001
113	rankone-010	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
114	remarkai-002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
115	rokid-000	0.194	0.372	0.370	0.220	0.444	0.450	0.265	0.457	0.749	0.191	0.431	0.553	0.367	0.677	0.806
116	s1-001	0.647	0.943	0.911	0.617	0.930	0.915	0.616	0.919	0.954	0.613	0.957	0.960	0.646	0.962	0.962
117	scanovate-001	0.544	0.601	0.596	0.515	0.553	0.579	0.513	0.565	0.664	0.766	0.914	0.960	0.554	0.676	0.806
118	scanovate-002	0.008	0.019	0.046	0.008	0.018	0.045	0.008	0.012	0.027	0.010	0.025	0.079	0.012	0.036	0.101
119	securifai-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
120	sensetime-003	0.009	0.029	0.069	0.009	0.031	0.074	0.014	0.025	0.057	0.012	0.048	0.115	0.013	0.048	0.140
121	sertis-000	0.002	0.012	0.034	0.002	0.012	0.032	0.003	0.005	0.013	0.003	0.016	0.047	0.005	0.020	0.052
122	sertis-001	0.002	0.006	0.017	0.002	0.006	0.014	0.001	0.002	0.005	0.002	0.007	0.017	0.003	0.009	0.020
123	shu-002	0.011	0.031	0.080	0.009	0.026	0.083	0.023	0.037	0.103	0.026	0.126	0.227	0.016	0.056	0.167
124	shu-003	0.003	0.006	0.013	0.002	0.004	0.008	0.003	0.005	0.009	0.008	0.031	0.070	0.004	0.014	0.040
125	sjtu-002	0.011	0.031	0.080	0.009	0.026	0.083	0.023	0.037	0.103	0.026	0.126	0.227	0.016	0.056	0.167
126	sjtu-003	0.002	0.004	0.009	0.002	0.003	0.006	0.002	0.003	0.006	0.005	0.022	0.049	0.003	0.009	0.028
127	staqu-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
128	starhybrid-001	0.192	0.468	0.461	0.149	0.406	0.483	0.137	0.321	0.487	0.478	0.761	0.781	0.133	0.372	0.565
129	synesis-006	0.001	0.003	0.007	0.001	0.003	0.007	0.001	0.001	0.003	0.001	0.005	0.011	0.001	0.004	0.008
130	synesis-007	0.007	0.021	0.047	0.008	0.028	0.056	0.013	0.025	0.056	0.007	0.046	0.114	0.018	0.124	0.134
131	synology-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
132	synology-002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
133	tech5-004	0.005	0.022	0.061	0.006	0.028	0.070	0.010	0.021	0.046	0.006	0.025	0.068	0.006	0.021	0.058
134	tech5-005	0.004	0.015	0.044	0.004	0.017	0.046	0.006	0.012	0.026	0.005	0.020	0.051	0.007	0.022	0.057
135	tevian-005	0.125	0.463	0.370	0.148	0.650	0.557	0.208	0.359	0.705	0.086	0.667	0.679	0.131	0.786	0.787

Table 11: This table summarizes Failure to Enroll (FTE) rates surveyed over 10 000 images of each mask variant. FTE is the proportion of failed template generation attempts. Failures can occur because the software throws an exception, or because the software electively refuses to process the input image as would occur if the algorithms does not detect a face or determines that the face has insufficient information. FTE is measured as the number of function calls that give EITHER a non-zero error code OR that give a "small" template containing fewer than 60 bytes. This second rule is needed because some algorithms incorrectly fail to return a non-zero error code when template generation fails but do produce a skeletal template. The effects of FTE are included in the accuracy results of this report by regarding any template comparison involving a failed template to produce a low similarity score. Thus higher FTE results in higher FNMR and lower FMR. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

2020/11/30 08:35:54
This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

	Algorithm	COLOR = WHITE			COLOR = LIGHTBLUE						COLOR = RED			COLOR = BLACK		
	Name	SHAPE = WIDE			SHAPE = WIDE			SHAPE = ROUND			SHAPE = WIDE			SHAPE = WIDE		
	COVERAGE	LO	MED	HI	LO	MED	HI	LO	MED	HI	LO	MED	HI	LO	MED	HI
136	tevian-006	0.012	0.089	0.160	0.010	0.066	0.124	0.028	0.041	0.146	0.034	0.266	0.408	0.016	0.256	0.307
137	trueface-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
138	trueface-001	0.078	0.163	0.217	0.071	0.153	0.217	0.084	0.119	0.268	-	-	-	0.147	0.317	0.474
139	tuputech-000	0.517	0.679	0.684	0.626	0.758	0.765	0.502	0.619	0.714	0.652	0.893	0.926	0.661	0.904	0.933
140	uluface-002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
141	upc-001	0.002	0.005	0.012	0.002	0.005	0.012	0.002	0.002	0.005	0.002	0.010	0.027	0.003	0.007	0.018
142	veridas-003	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
143	veridas-004	0.047	0.139	0.202	0.041	0.112	0.164	0.048	0.085	0.154	0.106	0.401	0.568	0.054	0.213	0.383
144	via-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
145	videmo-000	0.019	0.067	0.125	0.018	0.051	0.106	0.023	0.040	0.089	0.122	0.352	0.368	0.027	0.100	0.296
146	videonetics-002	0.338	0.581	0.557	0.330	0.569	0.542	0.378	0.559	0.785	0.344	0.693	0.735	0.396	0.702	0.848
147	vigilantsolutions-007	0.062	0.168	0.220	0.052	0.137	0.193	0.069	0.126	0.206	0.098	0.408	0.634	0.072	0.273	0.493
148	vigilantsolutions-008	0.062	0.168	0.218	0.051	0.136	0.189	0.068	0.124	0.202	0.096	0.407	0.633	0.072	0.268	0.492
149	vinai-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
150	visionlabs-008	0.013	0.035	0.083	0.012	0.031	0.072	0.019	0.038	0.097	0.016	0.040	0.096	0.024	0.061	0.124
151	visionlabs-009	0.011	0.037	0.082	0.010	0.035	0.076	0.018	0.042	0.097	0.016	0.052	0.120	0.024	0.065	0.150
152	visteam-000	0.058	0.150	0.210	0.048	0.118	0.176	0.052	0.092	0.156	0.160	0.372	0.506	0.074	0.202	0.369
153	vocord-008	0.013	0.046	0.087	0.011	0.052	0.089	0.031	0.059	0.111	0.013	0.079	0.127	0.009	0.050	0.093
154	vts-000	0.011	0.029	0.072	0.012	0.028	0.074	0.015	0.020	0.048	0.014	0.043	0.129	0.016	0.051	0.149
155	winsense-001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
156	xforwardai-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
157	xforwardai-001	0.006	0.025	0.069	0.007	0.031	0.079	0.011	0.021	0.052	0.007	0.030	0.079	0.007	0.022	0.060
158	xm-000	0.003	0.006	0.013	0.002	0.004	0.008	0.003	0.004	0.009	0.008	0.031	0.070	0.005	0.013	0.038
159	yoonik-000	0.029	0.061	0.138	0.027	0.060	0.142	0.037	0.049	0.124	0.040	0.094	0.219	0.039	0.099	0.257
160	yoonik-001	0.015	0.052	0.110	0.017	0.055	0.113	0.024	0.035	0.072	0.031	0.093	0.170	0.026	0.086	0.175
161	yuan-000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 12: This table summarizes Failure to Enroll (FTE) rates surveyed over 10 000 images of each mask variant. FTE is the proportion of failed template generation attempts. Failures can occur because the software throws an exception, or because the software electively refuses to process the input image as would occur if the algorithms does not detect a face or determines that the face has insufficient information. FTE is measured as the number of function calls that give EITHER a non-zero error code OR that give a "small" template containing fewer than 60 bytes. This second rule is needed because some algorithms incorrectly fail to return a non-zero error code when template generation fails but do produce a skeletal template. The effects of FTE are included in the accuracy results of this report by regarding any template comparison involving a failed template to produce a low similarity score. Thus higher FTE results in higher FNMR and lower FMR. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

2020/11/30 08:35:54
This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 10: For each algorithm the rightmost dot shows FNMR @ FMR=0.00001 (as reported throughout this report). The left most dot shows the failure-to-template (FTE) rate over the masked verification set of 5.2M images. The gap between the two dots is attributable to low similarity score. Some FTE rates are zero - rates below 0.001 are shown as 0.001.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

The following plots are detection error tradeoff (DET) characteristics for each algorithm, across different mask nose coverages and shapes.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 11: DET curves showing error rates on unmasked and masked probe images, broken out by mask shape and nose coverage. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 12: DET curves showing error rates on unmasked and masked probe images, broken out by mask shape and nose coverage. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 13: DET curves showing error rates on unmasked and masked probe images, broken out by mask shape and nose coverage. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 14: DET curves showing error rates on unmasked and masked probe images, broken out by mask shape and nose coverage. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 15: DET curves showing error rates on unmasked and masked probe images, broken out by mask shape and nose coverage. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 16: DET curves showing error rates on unmasked and masked probe images, broken out by mask shape and nose coverage. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 17: DET curves showing error rates on unmasked and masked probe images, broken out by mask shape and nose coverage. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 18: DET curves showing error rates on unmasked and masked probe images, broken out by mask shape and nose coverage. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 19: DET curves showing error rates on unmasked and masked probe images, broken out by mask shape and nose coverage. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 20: DET curves showing error rates on unmasked and masked probe images, broken out by mask shape and nose coverage. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 21: DET curves showing error rates on unmasked and masked probe images, broken out by mask shape and nose coverage. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 22: DET curves showing error rates on unmasked and masked probe images, broken out by mask shape and nose coverage. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 23: DET curves showing error rates on unmasked and masked probe images, broken out by mask shape and nose coverage. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

The following plots are detection error tradeoff (DET) characteristics for each algorithm, across different mask colors.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 24: DET curves showing error rates on unmasked and masked probe images, broken out by mask color. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 25: DET curves showing error rates on unmasked and masked probe images, broken out by mask color. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 26: DET curves showing error rates on unmasked and masked probe images, broken out by mask color. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 27: DET curves showing error rates on unmasked and masked probe images, broken out by mask color. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 28: DET curves showing error rates on unmasked and masked probe images, broken out by mask color. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 29: DET curves showing error rates on unmasked and masked probe images, broken out by mask color. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 30: DET curves showing error rates on unmasked and masked probe images, broken out by mask color. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 31: DET curves showing error rates on unmasked and masked probe images, broken out by mask color. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 32: DET curves showing error rates on unmasked and masked probe images, broken out by mask color. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 33: DET curves showing error rates on unmasked and masked probe images, broken out by mask color. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 34: DET curves showing error rates on unmasked and masked probe images, broken out by mask color. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

Figure 35: DET curves showing error rates on unmasked and masked probe images, broken out by mask color. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 36: DET curves showing error rates on unmasked and masked probe images, broken out by mask color. Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

The following plots show the explicit dependence of false non-match rate (FNMR) and false match rate (FMR) on score threshold for each algorithm, across different masked/unmasked combinations.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 37: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 38: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 39: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 40: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 41: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 42: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 43: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 44: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 45: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 46: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 47: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

Figure 48: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 49: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 50: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 51: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 52: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Figure 53: FNMR and FMR calibration curves on unmasked-to-unmasked (both unmasked), masked-to-unmasked with medium, wide, lightblue masks (one masked), masked-to-masked with medium, wide, lightblue masks (both masked (w-w)), and masked-to-masked with medium, round, white masks (enrollment image) and medium, wide, lightblue masks (verification image) (both masked (r-w)). Algorithms in black were submitted prior to mid-March 2020, and algorithms in blue were submitted thereafter.

FNMR(T) "False non-match rate"
FMR(T) "False match rate"

References

[1] ISO/IEC 19794-5:2011 - Information technology - Biometric data interchange formats - Part 5: Face image data.

[2] N95 Respirators, Surgical Masks, and Face Masks. https://www.fda.gov/medical-devices/personal-protective-equipment-infection-control/n95-respirators-surgical-masks-and-face-masks.

[3] NIST Special Database 32 - Multiple Encounter Dataset (MEDS-II). https://www.nist.gov/itl/iad/image-group/special-database-32-multiple-encounter-dataset-meds.

[4] Patrick Grother, Mei Ngan, and Kayee Hanaoka. NISTIR 8311 - Ongoing FRVT Part 6A: Face recognition accuracy with face masks using pre-COVID-19 algorithms. Interagency Report 8311, National Institute of Standards and Technology, July 2017. https://pages.nist.gov/frvt/reports/11/frvt_11_report_2017_07_29.pdf.

[5] Patrick Grother, George Quinn, and Mei Ngan. Face in video evaluation (five) face recognition of non-cooperative subjects. Interagency Report 8173, National Institute of Standards and Technology, March 2017. https://doi.org/10.6028/NIST.IR.8173.

[6] J. Hanley and A. Lippman-Hand. If nothing goes wrong, is everything all right? interpreting zero numerators. *JAMA*, 249 13:1743–5, 1983.

[7] Davis E. King. Dlib-ml: A machine learning toolkit. *Journal of Machine Learning Research*, 10:1755–1758, 2009. http://dlib.net.

[8] Mei Ngan, Patrick Grother, and Kayee Hanaoka. NISTIR 8311 - Ongoing FRVT Part 6A: Face recognition accuracy with face masks using pre-COVID-19 algorithms. Interagency Report 8311, National Institute of Standards and Technology, July 2020. https://doi.org/10.6028/NIST.IR.8311.

[9] Patrick Grother and Mei Ngan and Kayee Hanaoka. NIST Ongoing Face Recognition Vendor Test (FRVT) 1:1 Verification Application Programming Interface (API), April 2019. https://pages.nist.gov/frvt/api/FRVT_ongoing_11_api_4.0.pdf.

[10] Zhongyuan Wang, Guangcheng Wang, Baojin Huang, Zhangyang Xiong, Qi Hong, Hao Wu, Peng Yi, Kui Jiang, Nanxi Wang, Yingjiao Pei, Heling Chen, Yu Miao, Zhibing Huang, and Jinbi Liang. Masked face recognition dataset and application, 2020.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331

Appendix A Dlib Masking Methodology

(a) wide, high coverage

(b) round, high coverage

(c) wide, medium coverage

(d) round, medium coverage

(e) wide, low coverage

(f) round, low coverage

Figure 54: This figure shows the Dlib facial points used to create the various synthetic masks used in this report. For wide masks, the specified Dlib facial points were used to generate a closed polygon and two additional points were interpolated between each dlib facial point used for smoothing purposes. For round masks, the specified Dlib facial points were used to generate an ellipse. The Dlib C++ toolkit version 19.19, configured with the common histogram of gradients (HoG)-based face detector and 68 face landmark shape predictor was used to generate the 68 facial landmarks.

This publication is available free of charge from: https://doi.org/10.6028/NIST.IR.8331