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NISTIR 8271 DRAFT SUPPLEMENT

Face Recognition Vendor Test (FRVT)

Part 2: Identification

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Information Access Division
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This document is a draft supplement of NIST Interagency Report 8271

2021/06/22

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

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June 2021

U.S. Department of Commerce
Wynn Coggins, Acting Secretary

National Institute of Standards and Technology
James Altoff, Under Secretary of Commerce for Standards and Technology and Director, acting

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RELEASE NOTES

2021-06-22: Regarding the seventh draft of the update to NIST Interagency Report 8271:

- ▷ We have added results for algorithms from three new participants: Line Corporation, Rendip, and Samsung S1 Corp
- ▷ We have added results for algorithms from five returning developers: Imagus Technology, Kneron, Tevian, Visidon, and Xforward AI Technology.
- ▷ The algorithm-specific report cards (examples: 1, 2, and 3) now include figures showing how low threshold values can be used to reduce candidate list lengths for human review, while (usually) elevating miss rates (FNIR) only modestly. The reports also feature some minor additions and clarifications.
- ▷ A new report, *FRVT Part 7: Identification for Paperless Travel and Immigration*, will be released in mid 2021. It documents the use of 1:N algorithms in positive access control and immigration status update travel applications where the enrolled population size is as low as 420 people, so much smaller than in this report (FRVT Part 2).

2021-03-26: Regarding the sixth draft of the update to NIST Interagency Report 8271:

- ▷ We have added results for algorithms from three returning developers: Neurotechnology, Guangzhou Pixel Solutions, and Tech5 SA.
- ▷ We have added results on the webpage and in the report for a new ageing dataset in which border crossing photos are searched against a gallery of border crossing photos collected between 10 and 15 years prior to the mated search photos. See section 2 for a description of the images. Table 1 has a new entry describing the experiment.
- ▷ We will mostly discontinue running the mugshot ageing test, reserving it for algorithms that show high accuracy on the new border-crossing set.

2021-03-26: Regarding the fifth draft of the update to NIST Interagency Report 8271:

- ▷ In addition have added results for first algorithms from two new participants: Viettel Group and Veridas Digital Authentication Solutions.
- ▷ We have added results for algorithms from two returning developers: Idemia and Cognitec Systems.
- ▷ In addition to the report, the results page and its hyperlinked report cards have been updated.

2021-02-08: Regarding the fourth draft of the update to NIST Interagency Report 8271:

- ▷ We have added results for eight algorithms submitted by eight developers: Cyberlink, Dermalog, Imagus, Paravision, Sensetime, Trueface, Vigilant Solutions, and X-Forward AI. With the exception of Trueface, all of these developers have participated previously.
- ▷ We anticipate updating this report again in the first week of March 2021.
- ▷ The main results page has been revised with tabs for the investigative and lights-out identification tables, and a new tab dedicated to speed and resource consumption.
- ▷ The report cards (example here) hyperlinked from the results page have been revised to improve content and format.

2020-12-14: Regarding third draft of the update to NIST Interagency Report 8271:

- ▷ We have added results for fifteen algorithms submitted by thirteen developers. The four first-time participants are: Acer, Akurat Satu Indonesia, Canon, and Xforward AI Technology. The ten returning developers are: AllGoVision, Cyberlink Corp, Dahua Technology, Deepglint, Guangzhou Pixel Solutions, IIT Vision, Innovatrics, Rank One Computing, Scanovate, Sensetime Group, Synesis, and VisionLabs.

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- ▷ We have added two new datasets to the evaluation: First a set of "visa-border" photos, representing search of an airport immigration lane photo against a database of closely ISO standard portraits; second a "visa-kiosk" set representing search of a photo collected in a registered traveller kiosk against the same ISO portrait gallery. The images are described in section 2.1.
- ▷ As in previous reports, we include results for searching mugshots against a mugshot gallery containing a single image of each of 12 million people. However we have suspending running searches against a gallery in which multiple lifetime photos per person are present, because this is computationally expensive. We retain a N = 3 million search test dedicated to ageing in which mugshots taken up to 18 years after the first photograph are searched - see Table 5.
- ▷ Tables containing computational resource information, Table 2. . ., now include duration of the finalization step, in which search algorithms can, at their option, build fast-search data structures.
- ▷ We have linked revised per-algorithm PDF report cards from the main results page.
- ▷ We have regenerated all figures and tables to drop algorithms submitted before June 2018. Results for prior algorithms appear in archived editions of this report.
- ▷ Going forward, we anticipate producing more frequent updates to this report. Developers may submit one algorithm to this evaluation every four calendar months.

2020-03-24: Regarding the second draft of the update to NIST Interagency Report 8271:

- ▷ Adds results for three algorithms from three developers, Dermalog, Innovatrics, and Synesis.
- ▷ Adds Table 5 on ageing showing the increase in false negative rates with time elapsed between two photos. Some of the results were contained in graphs in prior editions of this report, but the table adds results for some newly submitted algorithms.
- ▷ Adjusts frontal mugshot results (for recent and lifetime consolidated galleries) to include the effect of removing some images that should not have been included in image test sets. These images were mostly profile views, images of tattoos containing faces, images of faces on tee shirts, and images of photographs on walls behind the intended subject. This affects many tables and reduces false negative identification rates for all algorithms. The reduction is larger for "recent" enrollments than for "lifetime consolidated" ones with the consequence that accuracy on recent images is now superior.

2020-02-26: Regarding the first draft of the update to NIST Interagency Report 8271:

- ▷ Adds results for 38 algorithms from 31 different developers, eleven of whom are entirely new to the 1:N track of FRVT. These are Allgovision, Cyberlink, Deepsea Tencent, Farbar F8, Imperial College London, Intsys MSU, Kedacom, Kneron, Pixelall, and Scanovate.

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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).

ACKNOWLEDGMENTS

The authors are grateful for the support and collaboration of the 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.

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Executive Summary

This document is a draft revision of the September 2019 report NIST Interagency Report 8271. That report gave extensive documentation of face recognition applied to mugshots. This report extends that by adding more two more challenging datasets containing images with serious departures from canonical frontal image standards. The report also adds results for algorithms submitted to NIST since in 2019 and 2020. The algorithms, which implement one-to-many identification of faces appearing in two-dimensional images, are prototypes from the research and development laboratories of mostly commercial suppliers, and are submitted to NIST as compiled black-box libraries implementing a NIST-specified C++ test interface. The report therefore does not describe how algorithms operate. The report lists accuracy results alongside developer names and will therefore be useful for comparison of face recognition algorithms and assessment of absolute capability. The report is accompanied by a webpage with sortable results.

The evaluation uses six datasets: frontal mugshots, profile view mugshots, desktop webcam photos, visa-like immigration application photos, immigration lane photos, and registered traveler kiosk photos. These datasets are sequestered at NIST, meaning that developers do not have access to them for training or testing. This aspect is important because face recognition algorithms are very often deployed without the developer having access to the customers image data. A possible exception to this would be in a cloud-based application where the operational image data is uploaded to a cloud operated by a face recognition developer.

The major result in NIST IR 8271 was that massive gains in accuracy have been achieved in the years 2013 to 2018 and these far exceed improvements made in the prior period, 2010 to 2013. While the industry gains were broad - at least 30 developers' algorithms outperformed the most accurate algorithm from late 2013, there remains a wide range of capability. While this report shows accuracy gains only over the period 2018-2020, the most accurate algorithm reported here is substantially more accurate than anything reported in NIST IR 8271. This is evidence that face recognition development continues apace, and that FRVT reports are but a snapshot of contemporary capability.

From discussion with developers, the accuracy gains stem from the adoption of deep convolutional neural networks. As such, face recognition has undergone an industrial revolution, with algorithms increasingly tolerant of poorly illuminated and other low quality images, and poorly posed subjects. One related result is that a few algorithms correctly match side-view photographs to galleries of frontal photos, with search accuracy approaching that of the best c. 2010 algorithms operating on purely frontal images. The capability to recognize under a 90-degree change in viewpoint - pose invariance - has been a long-sought milestone in face recognition research.

With good quality portrait photos, the most accurate algorithms will find matching entries, when present, in galleries containing 12 million individuals, with rank one miss rates of approaching 0.1%. The remaining errors are in large part attributable to long-run ageing, facial injury and poor image quality. Given this impressive achievement - close to perfect recognition - an advocate might claim that cooperative face recognition is a solved problem, a statement that can be refuted with the following context and caveats:

- ▷ **Mugshots vs. less constrained captures:** The low error rates reported here are attained using mostly excellent cooperative live-capture mugshot images collected with an attendant present. Recognition in other circumstances, particularly those without a dedicated photographic environment and human or automated quality control checks, will lead to declines in accuracy. This is documented here for side-view images, poorer quality webcam images, and, particularly, for newly introduced ATM-style kiosk photos that were not originally intended for automated face recognition. In this case, recognition error rates are much higher, often in excess of 20% even with the more accurate algorithms which variously remain intolerant of face cropping (at image edge) and of large downward head pitch.

- ▷ **Algorithm accuracy spectrum:** Recognition accuracy is very strongly dependent on the algorithm and, more

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Figure 1: Identification miss rates across the false positive range. N = 12 million individuals are enrolled with one recent image.

generally, on the developer of the algorithm. False negative error rates in a particular scenario range from a few tenths of one percent to beyond fifty percent. This is tabulated exhaustively later: For example Table 8 shows accuracy across datasets. Figure 1 here compares algorithms on mugshot searches in a consolidated gallery of 12 million subjects and 12 million photos. Many algorithms do not achieve the low error rates noted above, and while many of those may still be useful and valuable to end-users, only the most accurate excel on poor quality images and those collected long after the initial enrollment sample.

▹ **Versioning:** While results for up to ten algorithms from each developer are reported here, the intra-provider accuracy variations are usually smaller than the inter-provider variations. That said different versions give an

order of magnitude fewer misses. Some developers demonstrate speed-accuracy tradeoffs[1]. See Figs. 18, 19.

▷ **Low similarity scores:** In thousands of mugshot cases the correct gallery image is returned at rank 1 but its similarity score is nevertheless low, below some operationally required score threshold. This is not so important when face recognition is used for "lead generation" in investigational applications because human reviewers are specifically required to review potentially long candidate lists and the threshold is effectively 0. In applications where search volumes are higher and labor is not available to review the results from searches, a higher threshold must be applied. This reduces the length of candidate lists and false positive identification rates at the expense of increased false negative miss rates. The tradeoff between the two error rates is reported extensively later.

▷ **Population size:** As the number of enrolled subjects grows, some mates are displaced from rank one, decreasing accuracy. As tabulated later for N up to 12 million, false negative rates generally rise slowly with population size. This enables use of face recognition in very large populations. However in most positive and negative identification applications[2], a score threshold is set to limit the rate at which non-mate searches produce false positives. This has the consequence that some mated searches will report the mate below threshold, i.e. a miss, even if it is at rank 1. The utility of this is that many non-mated searches will return no candidate identities at all. As the error-tradeoff characteristic shows, investigational miss rates on the right side are very low but then rise steadily (in the center region) as threshold is increased to support "lights-out" applications, and ultimately rise quickly (left side) as discussed below. Thus, if we demand that just one in one thousand non-mate searches produce any false positives, the most accurate algorithms there (Sensetime-004 and NEC-3) would fail on between 3 and 5% of mated searches. Even though the graph shows results for the most accurate algorithms, all but two would fail to find the mate in more than 8% of mated searches. While the two most accurate algorithms produce a relatively flat error tradeoff until the threshold is raised to limit false positives to about 1 in 400 non-mated searches[3]

Thereafter, as the threshold is raised to further reduce false positives, miss rates rise rapidly. This means that low false positive identification rates are inaccesible with these algorithms, a result that does not apply for ten-finger identification algorithms. The rapid rise occurs because the lower mate scores are mixed with very high non-mate scores, the low scores from poor image quality and ageing, the high non-mates from the presence of lookalikes persons (doppelgangers), twins (discussed next) and, ultimately, the presence of a few unconsolidated subjects i.e. persons present under multiple IDs.

▷ **False negatives from ageing:** A large source of error in long-run applications where subjects are not re-enrolled on a set schedule is ageing. Changes in facial appearance increase with the time elapsed between photographs. These will depress similarity scores and eventually cause false negatives. All faces age and while this usually proceeds in a graceful and progressive manner, drug use can accelerate this [28]. Elective surgery may be effective in delaying it although this has not been formally quantified with face recognition. As ageing is essentially unavoidable, it can only be mitigated by scheduled re-capture, as in passport re-issuance. To quantify ageing effects, we used the more accurate algorithms to enroll the earliest image of 3.1 million adults and then search with 10.3 million newer photos taken up to 18 years after the the initial enrollment photo. Figure 2 puts ageing

[1] For example, NEC-0 prepares templates much faster than NEC-2 but gives twenty times more misses. Dermalog-5 executes a template search much more quickly than Dermalog-6 but is also much less accurate.

[2] In a positive identification application such as a registered traveler system, a user is making an implicit claim to be enrolled in the system - most users will be. In a negative application, such as with deportees, the implicit claim is that the subejct is not enrolled - most will not be.

[3] The gallery size here is 12 million people, one image per person. Given 331 201 non-mated searches, an exhaustive implementation of one-too-many search would execute almost 4 trillion comparisons. At a false positive identification rate of 0.0025 the number of false positives is, to first order, 828 corresponding to single-comparison false match rate of 828 / 4 trillion = 2.1 10^{-10} i.e. about 1 in 5 billion. Strictly this FMR computation is meaningful only for algorithms that implement 1:N search using N 1:1 comparisons, which is not always the case.

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into context by contrasting it with the increase in false negatives that occurs when the number of individuals in an enrollment database becomes larger and the chance of a false positive increases such that higher thresholds may become necessary[4].

The Figure shows, from to bottom, increases in false negative identification rates (FNIR) with the algorithm being tested. This applies to increases due to N on the left side, and increases due to ageing on the right side. The relative spacing of the dots shows that for all algorithms the dependency of FNIR on N (up to 12 million) is considerably less than on ΔT (up to 18 years).

In the inset table, accuracy is seen to degrade progressively with time, as mate scores decline and non-mates displace mates from rank 1 position. More accurate algorithms tend to be less sensitive to ageing. The more accurate algorithms give fewer errors after 18 years of ageing than middle tier algorithms give after four. Note also we do not quantify an ageing rate - more formal methods [2] borrowed from the longitudinal analysis literature have been published for doing so (given suitable repeated measures data). See Figures 60, 80 and 90.

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[4]Some algorithms implement stragegies to automatically adjust scores to account for increased population size. This relieves the system owner of having to increase thresholds as N increases.

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Figure 2: Identification miss rates as a function of enrolled population size, N, and time-lapse, ΔT.

Figure 3: Intra- and inter-twin scores

- **False positives from twins:** By enrolling 640 000 mugshots, adding photos of one twin, and then searching photos of those subjects and their twin the inset figure shows, for one typical algorithm, the similarity is generally greater when searching twins against themselves (A) than when searching twins against their sibling (B) but very often still above even stringent thresholds i.e. those corresponding to one in one thousand searches producing a false positive. Thus twins will very often produce a high-scoring non-match on a candidate list and a false alarm in an online identification system. The plot of Fig. 3 shows that fraternal twins are sometimes correctly rejected at those thresholds - including most different sex twins (at center). Figure **??** shows substantially similar behavior for all algorithms tested. In an investigative search, a twin would typically appear at rank 1, or rank 2 if their sibling happened to also be the gallery. Twins (and triplets etc.) constituted 3.3% of all live births [17] in recent years[5], and because that number is higher today than when the individuals in current adult databases were born, the false positives that arise from twins are now, and will increasingly be, an operational problem. Relative to the United States, twins are born with considerable regional variation. For example they are much less common in East Asia, and much more common in Sub-Saharan Africa [21].

  The presence of twins in the mugshot database is inevitable given its size, around 12.3 million people. As this is not an insignificant sample of the domestic United States population, people with other familial ties will be present also. The data was collected over an extended period and because location information is not available, we are unable to estimate the proportion of the domestic population that is present in the dataset. However, if we assume twins are neither more or less disposed to arrest than the general population, we can estimate that hundreds of thousands of individuals in the dataset are twins. This will affect false positive rates because we randomly set aside 331 201 individuals for nonmate searches, and some proportion of those will be twins with siblings in the gallery.

- **Database integrity:** An operational error rate should be added to all false negative rates in this report reflecting the proportion of images in a real database that are un-matchable. Such anomalies arise from images that: do not contain a face; include multiple persons; cannot be decoded; are rotated by 90° or 180°; depict a face on clothing; and others introduced by a long tail of various clerical errors. While the mugshot trials in this report have been constructed to minimize such effects, they are a real problem in actual operations.

This report is being updated continuously as new algorithms are submitted to FRVT, and run on new datasets. Participation in the one-to-many identification track is independent of participation in the one-to-one verification track of FRVT.

[5]See the CDC's National Vital Statistics Report for 2017: https://www.cdc.gov/nchs/data/nvsr/nvsr67/nvsr67_08-508.pdf

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Scope and Context

Audience: This report is intended for developers, integrators, end users, policy makers and others who have some familiarity with biometrics applications. The methods and metrics documented here will be of interest to organizations engaged in tests of face recognition algorithms. Some of these have been incorporated in the ISO/IEC 19795 Part 1 Biometric Testing and Reporting Framework standard, now nearing publication.

Prior benchmarks: Automated face recognition accuracy has improved massively in the two decades since initial commercialization of the various technologies. NIST has tracked that improvement through its conduct of regular independent, free, open, and public evaluations. These have fostered improvements in the state of the art. This report serves as an update to the NIST Interagency Report 8271 on performance of face identification algorithms, published in September 2019.

Demographics: In December 2019, NIST published a first report on demographic dependencies in face recognition, NIST Interagency Report 8280 that documented age, sex and race differentials in one-to-one and one-to-many false positive and false negative rates.

Scope: NIST IR 8271 documented recognition results for four databases containing in excess of 30.2 million still photographs of 14.4 million individuals. That constituted the largest public and independent evaluation of face recognition ever conducted. It includes results for accuracy, speed, investigative vs. identification applications, scalability to large populations, use of multiple images per person, images of cooperative and non-cooperative subjects.

The report also includes results for ageing, recognition of twins, and recognition of profile-view images against frontal galleries. It otherwise does not address causes of recognition failure, neither image-specific problems nor subject-specific factors including demographics. Separate reports on demographic dependencies in face recognition will be published in the future. Additionally out of scope are: performance of live human-in-the-loop transactional systems like automated border control gates; human recognition accuracy as used in forensic applications; and recognition of persons in video sequences (which NIST evaluated separately [9]). Some of those applications share core matching technologies that *are* tested in this report.

Images: Five kinds of images are employed; these are either compared with images of the same kind, or against others from different capture environments as follows. The primary dataset is a set of law enforcement mugshot images (Fig. 5) which are enrolled and then searched with three kinds of images: other mugshots (i.e. within-domain); profile-view photographs (90 degree cross-view); and lower quality webcam images (Fig. 6) collected in similar detention operations (cross-domain). Additionally we compare high quality visa-like photos collected in immigration offices, with: medium quality border crossing images collected in primary immigration lanes; poor quality images collected in ATM-like registered traveller kiosks.

Participation and industry coverage: The report includes performance figures for prototype algorithms from the research laboratories of commercial developers and a few universities. This represents a substantial majority of the face recognition industry, but only a tiny minority of the academic community. Participation was open worldwide. While there is no charge for participation, developers incur some software engineering expense in implementing their algorithms behind the NIST application programming interface (API). The test is a black-box test where the function of the algorithm, and the intellectual property associated with it, is hidden inside pre-compiled libraries.

Recent technology development: Most face recognition research with deep convolutional neural networks (CNNs) has been aimed at achieving invariance to pose, illumination and expression variations that characterize photojournalism and social media images. The initial research [18, 22] employed large numbers of images of relatively few ($\sim 10^4$) individuals to learn invariance. Inevitably much larger populations ($\sim 10^7$) were employed for training [11, 20] but the benchmark, Labeled Faces in the Wild with (essentially) an equal error rate metric [12], represents an easy task,

one-to-one verification at very high false match rates. While a larger scale identification benchmark duly followed, Megaface [15], its primary metric, rank one hit rate, contrasts with the high threshold discrimination task required in most large-population applications of face recognition, namely credential de-duplication, and background checks. There, identification in galleries containing up to 10^8 individuals must be performed using a) very few images per individual and b) stringent thresholds to afford very low false positive identification rates. This track of FRVT was launched to measure the capability of the new technologies, including in these two cases. FRVT has included open-set identification tests since 2002, reporting both false negative and positive identification rates [7].

	Positive identification	Negative identification	Post-event investigation
Example	Access to a gym or cruise ship	Watchlist e.g. Detection of deportee or duplicate drivers license applications	Crime scene photos, or of detainee without ID documents.
Claim of identity	Implicit claim to be enrolled	Implicit claim to not be enrolled	No claim: Inquiry
Threshold	High, to implement security objective	High, to limit false positives	Zero
Num. candidates	1	0	L, set by request to algorithm
Human role	Review candidate to assist user in resolution of false negatives, or to detect impostor	Review candidate to determine false positive or correct hit	Review multiple candidates, refer possible hits to examiners see [26]
Intended human involvement frequency	Rare – approx. the false negative identification rate plus prior probability of impostor	Rare – approx. the false positive identification rate plus prior probability of an actual mate	Always
Performance metric of interest	**FNIR at low FPIR. See sec. 3.1, 3.2 and Tables 10, 19**	**FNIR at low FPIR. See sec. 3.1, 3.2 and Tables 10, 19**	**FNIR at ranks 1... 50, say. FPIR = 1. See sec. 3.2 and Table 12, 14, 16**

Performance metrics for applications: This report documents the performance of one-to-many face recognition algorithms. The word "performance" here refers to recognition accuracy and computational resource usage, as measured

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by executing those algorithms on massive sequestered datasets.

This report includes extensive tabulation of recognition error rates germane to the main use-cases for face search technology. The Figure below, inspired by the Figure 1 in [23] differentiates different applications of the technolgy. The last row directs readers to the main tables relevant to those applications, respectively threshold-based and rank-based metrics that are special cases of the metrics given in section 3. The terms negative identification and positive identification are taken from the ISO/IEC 2382-37:2017 standardized biometrics vocabulary.

The algorithms are specifically configured for these applications by setting thresholds and candidate list lengths. Both rank-based metrics and threshold-based metrics include tradeoffs. In investigation, overall accuracy will be reduced if labor is only available to review a few candidates from the automated system. Note that when a fixed number of candidates are returned, the false positive identification rate of the automated face recognition engine will be 100%, because a probe image of anyone not enrolled will still return candidates. In identification applications where false positives must be limited to satisfy reviewer labor availability or a security objective, higher false negative rates are implied. This report includes extensive quantification of this threshold-based tradeoff. See Sec. 3

Template diversity: The FRVT is designed to evaluate black-box technologies with the consequence that the templates that hold features extracted from face images are entirely proprietary opaque binary data that embed considerable intellectual property of the developer. Despite migration to CNN-based technologies there is no consensus on the optimal feature vector dimension. This is evidenced by template sizes ranging from below 100 bytes to more than four kilobytes. This diversity of approaches, suggests there is no prospect of a standard template something that would require a common feature set to be extracted from faces. Interoperability in automated face recognition remains solidly based on images and documentary standards for those, in particular the ICAO portrait [27] specification deriving from the ISO/IEC 19794-5 Token frontal [24] standard, which are similar to certain ANSI/NIST Type 10 [26] formats.

Training: The algorithms submitted to NIST have been developed using image datasets that developers do not disclose. The development will often include application of machine learning techniques and will additionally involve iterative training and testing cycles. NIST itself does not perform any training and does not refine or alter the algorithm in any way. Thus the model, data files, and libraries that define an algorithm are fixed for the duration of the tests. This reflects typical operational reality where recognition software, once installed, is fixed and constant until upgraded. This situation persists because on-site training of algorithms on customer data is atypical essentially because training is not a turnkey process.

Automated search and human review: Virtually all applications using automated face search require human review of the outputs at some frequency: Always for investigational applications; rarely in positive identification applications, after rejection (false or otherwise); and rarely in negative identification applications, after an alarm (false or otherwise). The human role is usually to compare a reference image with the query image or the live-subject if present, to render either a definitive decision on "exclusion" (different subjects), or "identification" (same subject), or a declaration that one or both images have "no value" and that no decision can be made. Note that automated face recognition algorithms are not built to do exclusion - low scores from a face comparison arise from different faces *and* poor quality images of the same face.

Human reviewers make recognition errors [5, 19, 25] and are sensitive to image acquisition and quality. Accurate human review is supported by high resolution - as specified in the Type 50, 51 acquisition profiles of the ANSI/NIST Type 10 record [26], and by multiple non-frontal views as specified in the same standard. These often afford views of the ear. Organizations involved in image collection should consider supporting human adjudication by collecting high-resolution frontal and non-frontal views, preparing low resolution versions for automated face recognition [24], and retaining both for any subsequent resolution of candidate matches. Along these lines, the ISO/IEC Joint Technical

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Committee 1 subcommittee 37 on biometrics has just initiated projects on image quality assessment and face-aware capture.

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Release Notes

FRVT Activities: Since February 2017, NIST has been evaluating one-to-one verification algorithms on an ongoing basis. NIST then restarted FRVT's one-to-many track in February 2018, inviting participants to send up to prototype algorithms. Both tracks allows developers to submit updated algorithms to NIST at any time but no more frequently than four calendar months. This more closely aligns development and evaluation schedules. Results are posted to the web within a few weeks of submission. Details and full report are linked from the Ongoing FRVT site.

FRVT Reports: The results of the FRVT appear in the series NIST Interagency Reports tabulated below. The reports were developed separately and released on different schedules. In prior years NIST has mostly reported FRVT results as a single report; this had the disadvantage that results from completed sub-studies were not published until all other studies were complete.

Date	Link	Title	No.
2014-03-20	PDF	FRVT Performance of Automated Age Estimation Algorithms	7995
2015-04-20	PDF	Face Recognition Vendor Test (FRVT) Performance of Automated Gender Classification Algorithms	8052
2014-05-21	PDF	FRVT Performance of face identification algorithms	8009
2017-03-07	PDF	Face In Video Evaluation (FIVE) Face Recognition of Non-Cooperative Subjects	8173
2017-11-23	PDF	The 2017 IARPA Face Recognition Prize Challenge (FRPC)	8197
2018-11-27	PDF	Face Recognition Vendor Test - Part 2: Identification	8271
2019-09-11	PDF	Face Recognition Vendor Test - Part 2: Identification	8271
2019-12-11	PDF	Face Recognition Vendor Test - Part 3: Demographic Effects	8280
2020-01-03	WWW	Face Recognition Vendor Test (FRVT) - Part 1 Verification	Draft

Details appear on pages linked from `https://www.nist.gov/programs-projects/face-projects`.

Appendices: This report is accompanied by appendices which present exhaustive results on a per-algorithm basis. These are machine-generated and are included because the authors believe that visualization of such data is broadly informative and vital to understanding the context of the report.

Typesetting: Virtually all of the tabulated content in this report was produced automatically. This involved the use of scripting tools to generate directly type-settable LaTeX content. This improves timeliness, flexibility, maintainability, and reduces transcription errors.

Graphics: Many of the Figures in this report were produced using the ggplot2 package running under R, the capabilities of which extend beyond those evident in this document.

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1 Introduction

One-to-many identification represents the largest market for face recognition technology. Algorithms are used across the world in a diverse range of biometric applications: detection of duplicates in databases, detection of fraudulent applications for credentials such as passports and driving licenses, token-less access control, surveillance, social media tagging, lookalike discovery, criminal investigation, and forensic clustering.

This report contains a breadth of performance measurements relevant to many applications. Performance here refers to accuracy and resource consumption. In most applications, the core accuracy of a facial recognition algorithm is the most important performance variable. Resource consumption will be important also as it drives the amount of hardware, power, and cooling necessary to accommodate high volume workflows. Algorithms consume processing time, they require computer memory, and their static template data requires storage space. This report documents these variables.

1.1 Open-set searches

FRVT tested open-set identification algorithms. Real-world applications are almost always "open-set", meaning that some searches have an enrolled mate, but some do not. For example, some subjects have truly not been issued a visa or drivers license before; some law enforcement searches are from first-time arrestees[6]. In an "open-set" application, algorithms make no prior assumption about whether or not to return a high-scoring result, and for a mated search, the ideal behaviour is that the search produces the correct mate at high score and first rank. For a non-mate search, the ideal behavior is that the search produces zero high-scoring candidates.

Many academic benchmarks execute only closed-set searches. The proportion of mates found in the rank one position is the default accuracy metric. This hit rate metric ignores the score with which a mate is found; weak hits count as much as strong hits. This ignores the real-world imperative that in many applications it is necessary to elevate a threshold to reduce the number of false positives.

[6]Operationally closed-set applications are rare because it is usually not the case that all searches have an enrolled mate. One counter-example, however, is a cruise ship in which all passengers are enrolled and all searches should produce exactly one identity. Another example is forensic identification of dental records from an aircraft crash.

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2 Evaluation datasets

This report documents accuracy for four kinds of images - mugshots, webcam, profiles and wild - as described in the following sections.

2.1 Immigration-related images

This report includes benchmark tests sharing a common enrollment of high quality frontal portrait images collected while subject make applications for various immigration benefits. We then search that with two kinds of images, webcam images collected during in-bound immigration and also images collected from registered travelers using a ATM-style kiosk. These are described below and depicted in Figure 4.

a) Application b) Immigration Lane c) Kiosk

Figure 4: Example photos.

- **Application reference photos**: The images are collected in an attended interview setting using dedicated capture equipment and lighting. The images, at size 300x300 pixels, are smaller than normally indicated by ISO. 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 10918-1 i.e. JPEG. Older images had a compression ration of about 16:1, while newer images, since 2010, are more lightly compressed at 4:1. When these images are provided as input into the algorithm, they are labeled with the type "iso". This report enrols 1 600 000 application images, one per person.

- **Border crossing photos**: Most images are have width 320 and height 240 pixels. They are JPEG compressed at 16:1 i.e. filesize just below 15KB. The images present challenges for face recognition in that subjects often exhibit non-zero yaw and pitch (associated with the rotational degrees of freedom of the camera mount), low contrast (due to varying and intense background lights), and poor spatial resolution (due to inexpensive cameras). There are often subjects standing in the background, usually at very low resolution (see Figure 4b). In such cases, algorithms should detect all faces and determine which is the largest and most centered. When these images are provided as input into the algorithm, they are labeled with the type "wild".

- **Kiosk photos**: These photos were collected from subjects whose attention was focused on interaction with an immigration kiosk. They images were not intended for use with automated face recognition. The camera is situated above a display which the user touches, and is triggered either without directing the subject to look at it, or without waiting for the subject to comply. The images are therefore characterized by pitch-down pose, sometimes exceeding 45 degrees, as in Figure 4c. Yaw-angle variation is mild, with most images close to frontal. The images

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have width 320 pixels and height 240 pixels and therefore tall individuals are sometimes cropped. This is often just above the eyes and can occur at the nose or mouth. Conversely, short individuals are sometimes cropped such that only the top part of the face is visible. In a quite small number of cases, there other subjects standing just behind the primary subject such that algoriths should detect all faces and determine which is the largest and most centered. Background ceiling lighting is often visible and this sometimes leads to under-exposure of the face When these images are provided as input into the algorithm, they are labeled with the type "wild".

2.2 Law enforcement images

The main mugshot dataset used is referred to as the FRVT 2018 set. This set was collected over the period 2002 to 2017 in routine United States law enforcement operations. This set yields three subsets

- **Mugshots**: Mugshots comprise about 86% of the database. They have reasonable compliance with the ANSI/NIST ITL1-2011 Type 10 standard's subject acquisition profiles levels 10-20 for frontal images [26]. The most common departure from the standard's requirements is the presence of mild pose variations around frontal - the images of Figure 5 are typical. The images vary in size, with many being 480x600 pixels with JPEG compression applied to produce filesizes of between 18 and 36KB with many images outside this range, implying that about 0.5 bits are being encoded per pixel. When these images are provided as input into the algorithm, they are labeled with the type "mugshot". Example images appear in Fig. 5

  NIST Interagency Report 8238 includes a comparison of this set of mugshots with the smaller and easier sets of mugshots used in tests run in 2010 and 2014.

- **Profile images**: Profile-view images have been collected in law enforcement for more than 100 years, as human capability is improved with orthogonal information. The profile images used in this report were collected during the same session as the frontal mugshot photograph, in the same standardized photographic setup. These would not therefore be used with automated face recognition. A small subset, 200 000 images, were set aside for testing. When these images are provided as input into the algorithm, they are labeled with the type "wild". Example images appear in Fig. 7

- **Webcam images**: The remaining 14% of the images were collected using an inexpensive webcam attached to a flexible operator-directed mount. These images are all of size 240x240 pixels, that are in considerable violation of most quality-related clauses of all face recognition standards. As evident in the figure, the most common defects are non-frontal pose (associated with the rotational degrees of freedom of the camera mount), low contrast (due to varying and intense background lights), and poor spatial resolution (due to inexpensive camera optics) - see examples in Fig 6. The images are overly JPEG compressed, to between 4 and 7KB, implying that only 0.5 to 1 bits are being encoded per color pixel. When these images are provided as input into the algorithm, they are labeled with the type "wild". Example images appear in Fig. 6

These are drawn from NIST Special Database 32 which may be downloaded here.

These images were partitioned in galleries and probesets for the various experiment listed in Table 1.

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Figure 5: Six mated mugshot pairs representative of the FRVT-2014 (LEO) and FRVT-2018 datasets. The images are collected live, i.e. not scanned from paper. Image source: NIST Special Database 32 the Multiple Encounter Deceased Subjects dataset.

Figure 6: Twelve webcam images representative of probes against the FRVT-2018 mugshot gallery. The first eight images are four mated pairs. Such images present challenges to recognition including pose, non-uniform illumination, low contrast, compression, cropping, and low spatial sampling rate. Image source: NIST Special Database 32 the Multiple Encounter Deceased Subjects dataset.

Figure 7: **[Profile views]** *The three images are a frontal enrollment, subsequent frontal probe, and same-session ninety degree profile view. While collection of both frontal and profile views has been typical in law enforcement for more than a century, the recognition of profile to frontal views has essentially been impossible. However, reasonbly high accuracy results is now possible - see section E.*

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Image				
Encounter	1	...	$K_i - 1$	K_i
Capture Time	T_1	...	T_{K_i-1}	T_{K_i}
Role RECENT	Not used	Not used	Enrolled	Search
Role LIFETIME	Enrolled	Enrolled	Enrolled	Search

Figure 8: Depiction of the "recent" and "lifetime" enrollment types. Image source: NIST Special Database 32

2.3 Enrollment strategies

Many operational applications include collection and enrollment of biometric data from subjects on more than one occasion. This might be done on a regular basis, as might occur in credential (re-)issuance, or irregularly, as might happen in a criminal recidivist situation [4]. The number of images per person will depend on the application area. In civil identity credentialing (e.g. passports, driver's licenses), the images will be acquired approximately uniformly over time (e.g. ten years for a passport). While the distribution of dates for such images of a person might be assumed uniform, a number of factors might undermine this assumption[7]. In criminal applications, the number of images would depend on the number of arrests. The distribution of dates for arrest records for a person (i.e. the recidivism distribution) has been modeled using the exponential distribution but is recognized to be more complicated[8].

In any case, the 2010 NIST evaluation of face recognition showed that considerable accuracy benefits accrue with retention and use of *all* historical images [6].

To this end, the FRVT API document provides $K \geq 1$ images of an individual to the enrollment software. The software is tasked with producing a single proprietary undocumented "black-box" template[9] from the K images. This affords the algorithm an ability to generate a *model* of the individual, rather than to simply extract features from each image on a sequential basis.

As depicted in Figure 8, the i-th individual in the FRVT 2018 dataset has K_i images. These are labelled as x_k for $k = 1 \ldots K_i$ in chronological order of capture date. To measure the utility of having multiple enrollment images, this report evaluates three kinds of enrollment:

- ▷ **Recent**: Only the second most recent image, x_{K_i-1} is enrolled. This strategy of enrollment mimics the operational policy of retaining the imagery from the most recent encounter. This might be done operationally to ameliorate the effects of face ageing. Obviously retaining only the most recent image should only be done if the identity of the person is trusted to be correct. For example, in an access control situation retention of the most recent successful *authentication* image would be hazardous if it could be a false positive.

- ▷ **Lifetime-consolidated**: All but the most recent image are enrolled, $x_1 \ldots x_{K_i-1}$. This subject-centric strategy might be adopted if quality variations exist where an older image might be more suitable for matching, despite the ageing effect.

[7] For example, a person might skip applying for a passport for one cycle, letting it expire. In addition, a person might submit identical images (from the same photography session) to consecutive passport applications at five year intervals.
[8] A number of distributions have been considered to model recidivism, see for example [3].
[9] There are no formal face template standards. Template standards only exist for fingerprint minutiae - see ISO/IEC 19794-2:2011.

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Figure 9: **Enrollment strategies**. *The figure shows the three kinds of enrollment databases examined in this report. Image source: NIST Special Database 32*

	ENROLLMENT				SEARCH			
	TYPE SEE	POPULATION			MATE		NON-MATE	
	SECTION 2.3	FILTER	N-SUBJECTS	N-IMAGES	N-SUBJECTS	N-IMAGES	N-SUBJECTS	N-IMAGES
Mugshot trials from enrollment of single images								
1	RECENT	NATURAL	640 000	640 000	154 549	154 549	331 254	331 254
2	RECENT	NATURAL	1 600 000	1 600 000				
3	RECENT	NATURAL	3 000 000	3 000 000				
4	RECENT	NATURAL	6 000 000	6 000 000				
5	RECENT	NATURAL	12 000 000	12 000 000				
Cross-domain								
13	MUGSHOTS AS ON ROW 2				82 106 WEBCAM	82 106 WEBCAM	331 254 WEBCAM	331 254 WEBCAM
Cross-view								
14	MUGSHOTS AS ON ROW 2				100 000 PROFILE	100 000 PROFILE	100 000 PROFILE	100 000 PROFILE
Mugshot ageing								
17	OLDEST	NATURAL	3 068 801	3 068 801	2 853 221	10 951 064	0	0
Border crossing ageing								
17	OLDEST	NATURAL	1 600 000	1 600 000	1 922 437	1 922 437	1 920 000	1 920 000
Visa-border								
19	PRIOR	NATURAL	1 600 000 VISA	1 600 000 VISA	80 000 BORDER	80 000 BORDER	80 000 BORDER	80 000 BORDER
20	VISA AS ON ROW 18				21 016 BORDER	21 016 BORDER	21 016 BORDER	21 016 BORDER

Table 1: **Enrollment and search sets**. *Each row summarizes one identification trial. Unless stated otherwise, all entries refer to mugshot images. The term "natural" means that subjects were selected without heed to demographics, i.e. in the distribution native to this dataset. The probe images were collected in a different calendar year to the enrollment image. Missing values in rows 2-12 are the same as in row 1.*

▷ **Lifetime-unconsolidated**: Again all but the most recent image are enrolled $x_1 \ldots x_{K_i-1}$ but now separately, with different identifiers, such that the algorithm is not aware that the images are from the same face. This kind of event- or encounter-centric enrollment is very common when operational constraints preclude reliable consolidation of the historical encounters into a single identity. This aspect also prevents the recognition algorithm from a) building a holistic model of identity (as is common in speaker recognition systems) and b) implementing fusion, for example template-level fusion of feature vectors, or post-search score-level fusion. The result is that searches will typically yield more than one image of a person in the top ranks. This has consequences for appropriate metrics, as detailed in section 3.2.1

NIST first evaluated this kind of enrollment in mid 2018, and the results tables include some comparison of accuracy available from all three enrollment styles.

In all cases, the most recent image, x_{K_i}, is reserved as the search image. For the 1.6 million subject enrollment partition of the FRVT 2018 data, $1 \leq K_i \leq 33$ with $K_i = 1$ in 80.1% of the individuals, $K_i = 2$ in 13.4%, $K_i = 3$ in 3.7%, $K_i = 4$ in 1.4%, $K_i = 5$ in 0.6%, $K_i = 6$ in 0.3%, and $K_i > 6$ is 0.2% for everyone else. This distribution is substantially dependent on United States recidivism rates.

We did not evaluate the case of retaining only the highest quality image, since automated quality assessment is out of scope for this report. We do not anticipate that such strategies will prove beneficial when the quality assessment apparatus is imperfect and unvalidated.

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3 Performance metrics

This section gives specific definitions for accuracy and timing metrics. Tests of open-set biometric algorithms must quantify frequency of two error conditions:

- ▷ **False positives**: Type I errors occur when search data from a person who has never been seen before is incorrectly associated with one or more enrollees' data.
- ▷ **Misses**: Type II errors arise when a search of an enrolled person's biometric does not return the correct identity.

Many practitioners prefer to talk about "hit rates" instead of "miss rates" - the first is simply one minus the other as detailed below. Sections 3.1 and 3.2 define metrics for the Type I and Type II performance variables.

Additionally, because recognition algorithms sometimes fail to produce a template from an image, or fail to execute a one-to-many search, the occurrence of such events must be recorded. Further because algorithms might elect to not produce a template from, for example, a poor quality image, these failure rates must be combined with the recognition error rates to support algorithm comparison. This is addressed in section 3.5.

Finally, section 3.7 discusses measurement of computation duration, and section 3.8 addresses the uncertainty associated with various measurements. Template size measurement is included with the results.

3.1 Quantifying false positives

It is typical for a search to be conducted into an enrolled population of N identities, and for the algorithm to be configured to return the closest L candidate identities. These candidates are ranked by their score, in descending order, with all scores required to be greater than or equal to zero. A human analyst might examine either all L candidates, or just the top $R \leq L$ identities, or only those with score greater than threshold, T. The workload associated with such examination is discussed later, in 3.6.

False alarm performance is quantified in two related ways. These express how many searches produces false positives, and then, how many false positives are produced in a search.

False positive identification rate: The first quantity, FPIR, is the proportion of non-mate searches that produce an adverse outcome:

$$\text{FPIR}(N,T) = \frac{\text{Num. non-mate searches where one or more enrolled candidates are returned with score at or above threshold}}{\text{Num. non-mate searches attempted.}} \tag{1}$$

Under this definition, FPIR can be computed from the highest non-mate candidate produced in a search - it is not necessary to consider candidates at rank 2 and above. FPIR is the primary measure of Type I errors in this report.

Selectivity: However, note that in any given search, several non-mate may be returned above threshold. In order to quantify such events, a second quantity, selectivity (SEL), is defined as the *number* of non-mates returned on a candidate list, averaged over all searches.

$$\text{SEL}(N,T) = \frac{\text{Num. non-mate enrolled candidates returned with score at or above threshold}}{\text{Num. non-mate searches attempted.}} \tag{2}$$

where $0 \leq$ SEL(N, T) $\leq$L. Both of these metrics are useful operationally. FPIR is useful for targeting how often an

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adverse false positive outcome can occur, while SEL as a number is related to workload associated with adjudicating candidate lists. The relationship between the two quantities is complicated - it depends on whether an algorithm concentrates the false alarms in the results of a few searches or whether it disburses them across many. This was detailed in FRVT 2014, NISTIR 8009. It has not yet been detailed in FRVT 2018.

3.2 Quantifying hits and misses

If L candidates are returned in a search, a shorter candidate list can be prepared by taking the top $R \leq L$ candidates for which the score is above some threshold, $T \geq 0$. This reduction of the candidate list is done because thresholds may be applied, and only short lists might be reviewed (according to policy or labor availability, for example). It is useful then to state accuracy in terms of R and T, so we define a "miss rate" with the general name **false negative identification rate** (FNIR), as follows:

$$\text{FNIR}(N, R, T) = \frac{\text{Num. mate searches with enrolled mate found outside top R ranks or score below threshold}}{\text{Num. mate searches attempted.}} \quad (3)$$

This formulation is simple for evaluation in that it does not distinguish between causes of misses. Thus a mate that is not reported on a candidate list is treated the same as a miss arising from face finding failure, algorithm intolerance of poor quality, or software crashes. Thus if the algorithm fails to produce a candidate list, either because the search failed, or because a search template was not made, the result is regarded as a miss, adding to FNIR.

Hit rates, and true positive identification rates: While FNIR states the "miss rate" as how often the correct candidate is either not above threshold or not at good rank, many communities prefer to talk of "hit rates". This is simply the **true positive identification rate**(TPIR) which is the complement of FNIR giving a positive statement of how often mated searches are successful:

$$\text{TPIR}(N, R, T) = 1 - \text{FNIR}(N, R, T) \quad (4)$$

This report does not report true positive "hit" rates, preferring false negative miss rates for two reasons. First, costs rise linearly with error rates. For example, if we double FNIR in an access control system, then we double user inconvenience and delay. If we express that as decrease of TPIR from, say 98.5% to 97%, then we mentally have to invert the scale to see a doubling in costs. More subtly, readers don't perceive differences in numbers near 100% well, becoming inured to the "high nineties" effect where numbers close to 100 are perceived indifferently.

Reliability is a corresponding term, typically being identical to TPIR, and often cited in automated (fingerprint) identification system (AFIS) evaluations.

An important special case is the **cumulative match characteristic**(CMC) which summarizes accuracy of mated-searches only. It ignores similarity scores by relaxing the threshold requirement, and just reports the fraction of mated searches returning the mate at rank R or better.

$$\text{CMC}(N, R) = 1 - \text{FNIR}(N, R, 0) \quad (5)$$

We primarily cite the complement of this quantity, $\text{FNIR}(N, R, 0)$, the fraction of mates *not* in the top R ranks.

The **rank one hit rate** is the fraction of mated searches yielding the correct candidate at best rank, i.e. CMC(N, 1). While this quantity is the most common summary indicator of an algorithm's efficacy, it is not dependent on similarity scores, so it does not distinguish between strong (high scoring) and weak hits. It also ignores that an adjudicating reviewer is often willing to look at many candidates.

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3.2.1 False negative rates for unconsolidated galleries

As detailed in section 2.3 a common type of gallery, here referred to as the lifetime unconsolidate type, is populated with all images of an individual without any association between them. That is, the gallery construction algorithm is not provided with any ID labels that would support processing of a person's images jointly. This constrasts with the lifetime consolidate type where an algorithm may explicitly fuse features from multiple images of a person, or select a best image. In such cases, where the number of enrolled images is a random variable, we define two false negative rates as follows.

The first demands that the algorithm place any of the K_i mates in the top $R \geq 1$ ranks. The proportion of searches for which this does not occur forms a false negative identification rate:

$$\text{FNIR}_{\text{any}}(N, R, T) = 1 - \frac{\text{Num. mate searches where any enrolled mate is found in the top R ranks and at-or-above threshold}}{\text{Num. mate searches attempted.}} \tag{6}$$

The second demands that the algorithm place all K_i mates in the top $R \geq K_i$ ranks. The proportion of searches for which this does not occur forms a false negative identification rate:

$$\text{FNIR}_{\text{all}}(N, R, T) = 1 - \frac{\text{Num. mate searches where all enrolled mates are found in the top R ranks and at-or-above threshold}}{\text{Num. mate searches attempted.}} \tag{7}$$

Placing all mates in the top ranks is a more difficult task than correctly retrieving any image, so it holds that: $\text{FNIR}_{\text{all}} \geq \text{FNIR}_{\text{any}}$. This is evident in the results presented for November 2018 algorithms in Tables starting at **??**.

The information retrieval community might prefer to compute and plot *precision* and *recall*; this is a valid approach, but we advance the two metrics above because they relate to our normal definition of consolidated FNIR, and they cover the two extreme use-cases of wanting any hit vs. all hits.

3.3 DET interpretation

In biometrics, a false negative occurs when an algorithm fails to match two samples of one person – a Type II error. Correspondingly, a false positive occurs when samples from two persons are improperly associated – a Type I error.

Matches are declared by a biometric system when the native comparison score from the recognition algorithm meets some threshold. Comparison scores can be either similarity scores, in which case higher values indicate that the samples are more likely to come from the same person, or dissimilarity scores, in which case higher values indicate different people. Similarity scores are traditionally computed by fingerprint and face recognition algorithms, while dissimilarities are used in iris recognition. In some cases, the dissimilarity score is a distance possessing metric properties. In any case, scores can be either mate scores, coming from a comparison of one person's samples, or nonmate scores, coming from comparison of different persons' samples.

The words "genuine" or "authentic" are synonyms for mate, and the word "impostor" is used as a synonym for nonmate. The words "mate" and "nonmate" are traditionally used in identification applications (such as law enforcement search, or background checks) while genuine and impostor are used in verification applications (such as access control).

An error tradeoff characteristic represents the tradeoff between Type II and Type I classification errors. For identification this plots false negative vs. false positive identification rates i.e. FNIR vs. FPIR parametrically with T. Such plots

are often called detection error tradeoff (DET) characteristics or receiver operating characteristic (ROC). These serve the same function − to show error tradeoff − but differ, for example, in plotting the complement of an error rate (e.g. TPIR = 1 − FNIR) and in transforming the axes, most commonly using logarithms, to show multiple decades of FPIR. More rarely, the function might be the inverse of the Gaussian cumulative distribution function.

The slides of Figures 10 through 15 discuss presentation and interpretation of DETs used in this document for reporting face identification accuracy. Further detail is provided in formal biometrics testing standards, see the various parts of ISO/IEC 19795 Biometrics Testing and Reporting. More terms, including and beyond those to do with accuracy, appear in ISO/IEC 2382-37 Information technology – Vocabulary – Part 37: Harmonized biometric vocabulary.

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Figure 10: **DET as the primary performance reporting mechanism**.

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Figure 11: **DET as the primary performance reporting mechanism**.

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Figure 12: **DET as the primary performance reporting mechanism**.

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Figure 13: **DET as the primary performance reporting mechanism**.

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Figure 14: **DET as the primary performance reporting mechanism**.

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Figure 15: **DET as the primary performance reporting mechanism**.

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Figure 16: **DET as the primary performance reporting mechanism**.

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Figure 17: **DET as the primary performance reporting mechanism**.

3.4 Best practice testing requires execution of searches with and without mates

FRVT embeds 1:N searches of two kinds: Those for which there is an enrolled mate, and those for which there is not. The respective numbers for these types of searches appear in Table 1. However, it is common to conduct only mated searches[10]. The cumulative match characteristic is computed from candidate lists produced in mated searches. Even if the CMC is the only metric of interest, the actual trials executed in a test should nevertheless include searches for which no mate exists. As detailed in Table 1 the FRVT reserved disjoint populations of subjects for executing true non-mate searches.

3.5 Failure to extract features

During enrollment some algorithms fail to convert a face image to a template. The proportion of failures is the failure-to-enroll rate, denoted by FTE. Similarly, some search images are not converted to templates. The corresponding proportion is termed failure-to-extract, denoted by FTX.

We do not report FTX because we assume that the same underlying algorithm is used for template generation for enrollment and search.

Failure to extract rates are incorporated into FNIR and FPIR measurements as follows.

- ▷ **Enrollment templates**: Any failed enrollment is regarded as producing a zero length template. Algorithms are required by the API [10] to transparently process zero length templates. The effect of template generation failure on search accuracy depends on whether subsequent searches are mated, or non-mated: Mated searches will fail giving elevated FNIR; non-mated searches will not produce false positives so, to first order, FPIR will be reduced by a factor of $1-\text{FTE}$.

- ▷ **Search templates and 1:N search**: In cases where the algorithm fails to produce a search template from input imagery, the result is taken to be a candidate list whose entries have no hypothesized identities and zero score. The effect of template generation failure on search accuracy depends on whether searches are mated, or non-mated: Mated searches will fail giving elevated FNIR; Non-mated searches will not produce false positives, so FPIR will be reduced. Thus given a measurement of false negative and positive rates made over only those where failures-to-extract did not occur, those rates - call them $\text{FNIR}^\dagger$ and $\text{FPIR}^\dagger$ - could be adjusted by an explicit measurement of FTX as follows

$$\text{FNIR} = \text{FTX} + (1 - \text{FTX})\text{FNIR}^\dagger \tag{8}$$

$$\text{FPIR} = (1 - \text{FTX})\text{FPIR}^\dagger \tag{9}$$

This approach is the correct treatment for positive-identification applications such as access control where cooperative users are enrolled and make attempts at recognition. This approach is not appropriate to negative identification applications, such as visa fraud detection, in which hostile individuals may attempt to evade detection by submitting poor quality samples. In those cases, template generation failures should be investigated as though a false alarm had occurred.

[10] For example, the Megaface benchmark. This is bad practice for several reasons: First, if a developer knows, or can reasonably assume, that a mate always exists, then unrealistic gaming of the test is possible. A second reason is that it does not put FPIR on equal footing with FNIR and that matters because in most applications, not all searches have mates - not everyone has been previously enrolled in a driving license issuance or a criminal justice system - so addressing between-class separation becomes necessary.

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3.6 Fixed length candidate lists, threshold independent workload

Suppose an automated face identification algorithm returns L candidates, and a human reviewer is retained to examine up to R candidates, where $R \leq L$ might be set by policy, preference or labor availability. For now, assume also that the reviewer is not provided with, or ignores, similarity scores, and thresholds are not applied. Given the algorithm typically places mates at low (good) ranks, the number of candidates a reviewer can be expected to review can be derived as follows. Note that the reviewer will:

- ▷ Always inspect the first ranked image — Frac. reviewed = 1
- ▷ Then inspect those candidates where mate not confirmed at rank 1 — Frac. reviewed = 1-CMC(1)
- ▷ Then inspect those candidates where mate not confirmed at rank 1 or 2 — Frac. reviewed = 1-CMC(2)

etc. Thus if the reviewer will stop after a maximum of R candidates, the expected number of candidate reviews is

$$M(R) = 1 + (1 - CMC(1)) + (1 - CMC(2)) + \ldots + (1 - CMC(R-1)) \tag{10}$$

$$= R - \sum_{r=1}^{R-1} CMC(r) \tag{11}$$

A recognition algorithm that front-loads the cumulative match characteristic will offer reduced workload for the reviewer. This workload is defined only over the searches for which a mate exists. In the cases where there truly is no mate, the reviewer would review all R candidates. Thus, if the proportion of searches for which a mate does exist is β, which in the law enforcement context would be the recidivism rate [3], the full expression for workload becomes:

$$M(R) = \beta \left(R - \sum_{r=1}^{R-1} CMC(r) \right) \quad + \quad (1-\beta)R \tag{12}$$

$$= R - \beta \sum_{r=1}^{R-1} CMC(r) \tag{13}$$

3.7 Timing measurement

Algorithms were submitted to NIST as implementations of the application programming interface(API) specified by NIST in the Evaluation Plan [10]. The API includes functions for initialization, template generation, finalization, search, gallery insert, and gallery delete. Two template generation functions are required, one for the preparation of an enrollment template, and one for a search template.

In NIST's test harness, all functions were wrapped by calls to the C++ std::chrono::high resolution clock which on the dedicated timing machine counts 1ns clock ticks. Precision is somewhat worse than that however.

3.8 Uncertainty estimation

3.8.1 Random error

This study leverages operational datasets for measurement of recognition error rates. This affords several advantages. First, large numbers of searches are conducted (see Table 1) giving precision to the measurements. Moreover, for the two mugshot datasets, these do not involve reuse of individuals so binomial statistics can be expected to apply to recognition error counts. In that case, an observed count of a particular recognition outcome (i.e. a false negative or false positive) in M trials will sustain 95% confidence that the actual error rate is no larger than some value.

As an example, the minimum number of mugshot searches conducted in this report is M =154 549, and for an observed FNIR around 0.002, the measurement supports a conclusion that the actual FNIR is no higher than 0.00228 at 99% confidence level. On the false positive side, we tabulate FNIR at FPIR values as low as 0.001. Given estimates based on 331 254 non-mate trials, the actual FPIR values will be below 0.00115 at 99% confidence. In conclusion, large scale evaluation, without reuse of subjects, supports tight uncertainty bounds on the measured error rates.

3.8.2 Systematic error

The FRVT 2018 dataset includes anomalies discovered as a result of inspecting images involved in recognition failures from the most accurate algorithms. Two kinds of failure occur: False negatives (which, for the purpose here, include failures to make templates) and false positives.

False negative errors: We reviewed 600 false negative pairs for which either or both of the leading two algorithms did not put the correct mate in the top 50 candidates. Given 154 549 searches, this number represents 0.39% of the total, resulting in FNIR ~ 0.0039. Of the 600 pairs:

- ▷ **A: Poor quality**: About 20% of the pairs included images of very low quality, often greyscale, low resolution, blurred, low contrast, partially cropped, interlaced, or noisy scans of paper images. Additionally, in a few cases, the face is injured or occluded by bandages or heavy cosmetics.
- ▷ **B: Ground truth identity label bugs**: About 15% of the pairs are not actually mated. We only assigned this outcome when a pair is clearly not mated.
- ▷ **C: Profile views**: About 35% included an image of a profile (side) view of the face, or, more rarely, an image that was rotated 90 degrees in-plane (roll).
- ▷ **D: Tattoos**: About 30% included an image of a tattoo that contained a face image. These arise from mis-labelling in the parent dataset metadata.
- ▷ **E: Ageing**: There is considerable time-lapse between the two captures.

All these estimates are approximate. Of these, the tattoo and mislabled images can never be matched. These constitute an accuracy floor in the sample implying that FNIR cannot be below 0.0018[11]. The profile-views, low-quality images, and images with considerable ageing can, in principle, be successfully matched - indeed some algorithms do so - so are not part of the accuracy floor.

[11] This value is the sum of two partial false negative rates: FNIR_B = 0.15 * 0.0039 plus FNIR_D = 0.3 * 0.0039

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For the microsoft-4 algorithm the lowest miss rate from (recent entry in Table 17) is FNIR(640 000, 50, 0) = 0.0018. This is close to the value estimated from the inspection of misses. It is below the 0.0039 figure because the algorithm does match some profile and poor quality images, that the yitu-2 algorithm does not.

For many tables (e.g. Table 17), the FNIR values obtained for the FRVT-2018 mugshots could be corrected by reducing them by 0.0018. The best values would then be indistinct from zero. The results in this report *were not* adjusted to account for this systematic error.

False positive errors: As shown in Figure 1 and discussed in Figure 14 many of the DET characteristics in this report exhibit a pronounced turn upward at low false positive rates. The shape can be caused by identity labelling errors in the ground truth of a dataset, specifically persons present in the database under two IDs such that some proportion of non-mate pairs are actually mated. To look for such possibilities, we merged the highest 1000 non-mate pairs produced by three different algorithms which resulted in 1839 unique pairs. This constitutes 0.56% of all non-mate searches. We assert that it is *very* difficult for human reviewers to assign the pairs into the following three categories: twins; doppelgangers; or ground-truth errors (instances of the same person under two IDs). Given this difficulty we made no attempt to correct any possible ground truth errors except by removing 57 pairs in the following categories:

- **A: Profile views**: Thirteen pairs included one or two profile-view images. As described in Figure 165, these can cause false positives.
- **B: Same-session photographs**: For twelve pairs, the images were identical or trivially altered (e.g. cropped) versions of the same photo. These were present under a different ID likely due to some clerical or procedural mistake.
- **C: Tattoos of faces**: There were fourteen instances of tattoo photographs that contained faces causing false matches.
- **D: T-shirt faces**: There were six instances of T-shirt photographs (of Bob Marley and Che Guevara) being detected instead of the face and causing false positives.
- **E: Background faces**: There were twelve instances of one subject appearing in the background of two otherwise correct portrait photos.

Note we did not remove any images where there was a chance that the pair was actually a different person.

In any case, the results in this report have not been adjusted for this systematic error.

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4 Results

This section gives extensive results for algorithms submitted to FRVT 2018. Three page "report cards" for each algorithm are contained in a separate supplement. Performance metrics were described in section 3. The main results are summarized in tabular form with more exhaustive data included as DET, CMC and related graphs in appendices as follows:

- ▷ The three tables 2-4 list algorithms alongside full developer names, acceptance date, size of the provided configuration data, template size and generation time, and search duration data.
  - The **template generation duration** is most important to applications that require fast response. For example, an eGate taking more than two seconds to produce a template might be unacceptable. Note that GPUs may be of utility in expediting this operation for some algorithms, though at additional expense. Two additional factors should be considered[12][13].
  - The **search duration** is the time taken for a search of a search template into a gallery of N enrollment templates. This performance variable, together with the volume of searches, is influential on the amount of hardware needed to sustain an operational deployment. This is measured here with the algorithm running on a single core of a contemporary CPU. Search is most simply implemented as N computations of a distance metric followed by a sort operation to find the closest enrollments. However, considerable optimization of this process is possible, up to and including fast-search algorithms that, by various means, avoid computation of all N distances.
  - The **template size** is the size of the extracted feature vector (or vectors) and any needed header information. Large template sizes may be influential on bus or network bandwidth, storage requirements, and on search duration. While the template itself is an opaque data blob, the feature dimensionality might be estimated by assuming a four-bytes-per-float encoding. There is a wide range of encodings. For the more accurate algorithm, sizes range from 256 bytes to about 2KB bytes, indicating essentially no consensus on face modeling and template design.
  - The **template size multiplier** column shows how, given k input images, the size of the template grows. Most implementations internally extract features from each image and concatenate them, and implement some score-level fusion logic during search. Other implementations, including many of the most accurate algorithms, produce templates whose size does not grow with k. This could be achieved via selection of the best quality image - but this is not optimal in handling ageing where the oldest image could be the best quality. Another mechanism would be feature-level fusion where information is fused from all k inputs. In any case, as a black-box test, the fusion scheme is proprietary and unknown.
  - The size of the **configuration data** is the total size of all files resident in a vendor-provided directory that contains arbitrary read-only files such as parameters, recognition models (e.g caffe). Generally a large value for this quantity may prohibit the use of the algorithm on a resource-constrained device.

[12] The FRVT 2018 API prohibited threading, so some gains from parallelism may be available on multiple-cores or multiple processors, if the feature extraction code could be distributed across them.

[13] Note also that factors of two or more may be realizable by exploiting modern vector processing instructions on CPUs. It is not clear in our measurements whether all developers exploited Intel's AVX2 instructions, for example. Our machine was so equipped, but we insisted that the same compiled library should also run on older machines lacking that instruction. The more sophisticated implementations may have detected AVX2 presence and branched accordingly. The less sophisticated may be defaulted to the reduced instruction set. Readers should see the FRVT 2018 API document for the specific chip details.

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▷ Tables 17-18 report core rank-based accuracy for mugshot images. The population size is limited to N = 1.6 million identities because this is the largest gallery size on which all algorithms were executed. Notable observations from these tables are as follows:

- **Accuracy gains since 2018**: NIST Interagency Report 8238 documented massive gains over those reported in the FRVT 2014 report, NIST Interagency Report 8009. Further gains are documented in this report. Comparing the most accurate algorithm in November 2018, NEC-3, the value of FNIR(N, L, T) reduced from 0.0031 to 0.0024 for the Sensetime-004 algorithm with N = 12 million recent images. The tables show broader gains: many developers have made advances since 2018 with between two and five-fold reduction in errors.
- **Wide range in accuracy**: The rank-1 miss rates vary from FNIR(N, 1, 0) = 0.0012 for sensetime-004 up to about 0.5 for the very fast but inaccurate microfocus-x algorithms. Among the developers who are superior to NEC in 2013, the range is from 0.002 to 0.035 for camvi-3. This large accuracy range is consistent with the buyer-beware maxim, and indicates that face recognition software is far from being commoditized.

▷ Tables 21-22 report threshold-based error rates, FNIR(N, L, T), for N = 1.6 million for mugshot-mugshot accuracy on FRVT 2014, FRVT 2018, and also (in pink) mugshot-webcam accuracy using FRVT 2018 enrollments. Notable observations from these tables are as follows:

- **Order of magnitude accuracy gains since 2014**: As with rank-based results, the gains in accuracy are substantial, though somewhat reduced. At FPIR = 0.01, the best improvement over NEC in 2014 is a 27 fold reduction in FNIR using the NEC_2 algorithm. At FPIR = 0.001, the largest gain is a six-fold reduction in FNIR via the NEC_3 algorithm.
- **Broad gains across the industry**: About 19 companies realize accuracy better than the NEC benchmark from 2014. This is somewhat lower than the 28 developers who succeeded on the rank-1 metric. This may be due to the ubiquity of, and emphasis on, the rank-1 metric in many published algorithm development papers.
- **Webcam images**: Searches of webcam images give FNIR(N, T) values around 2 to 3 times higher than mugshot searches. Notably the leading developers with mugshots are approximately the same with poorer quality webcams. But some developers e.g. Camvi, Megvii, TongYi, and Neurotechnology do improve their relative rankings on webcams, perhaps indicating their algorithms were tailored to less constrained images.

▷ Tables 13, 15, 16 and show, respectively, high-threshold, rank 1, and rank 50 FNIR values for all algorithms performing searches into five different gallery sizes, N = 640 000, N = 1 600 000, N = 3 000 000, N = 6 000 000 and 12 000 000. The FPIR = 0.001 table is included to inform high-volume duplicate detection applications. The Rank-1 table is included as a primary accuracy indicator. The Rank-50 table is included to inform agencies who routinely produce 50 candidates for human-review. The notable results are:

- **Slow growth in rank-based miss rates:** FNIR(N, R) generally grows as a power law, aN^b. From the straight lines of many graphs of Figure 20 this is clearly a reasonable model for most, but not all, algorithms. The coefficient a can be interpreted as FNIR in a gallery of size 1. The more important coefficient b indicates scalability, and often, $b \ll 1$, implies very benign growth in FNIR. The coefficients of the models appear in the Tables 15 and 16.
- **Slow growth in threshold-based miss rates:** FNIR(N, T) also generally grows as a power law, aN^b except at the high threshold values corresponding to low FPIR values. This is visible in the plots of Figure 36 which

show straight lines except for FPIR = 0.001, which increase more rapidly with N above 3 000 000. Each trace in those figures shows FNIR(N, T) at fixed FPIR with both N and T varying. Thus at large N, it is usually necessary to elevate T to maintain fixed FPIR. This causes increased FNIR. Why that would no-longer obey a power-law is not known. However, if we expect large galleries to contain individuals with familial relations to the non-mate search images - in the most extreme case, twins - then suppression of false positives becomes more difficult. This is discussed in the Figures starting at Fig. 10

▷ Figure **??** shows false positives from twins against their enrolled siblings, broken out by type of twin: fraternal or identical. The Figure is based on the enrollment of 104 single images on one of a pair of twins, and then the search of 2354 second images. Note that the dataset is heavily skewed towards identical twins which is not representative of the true population. There is also a skew towards same sex fraternal twin pairs compared to different sex fraternal twin pairs again not representative of the true population.

The notable results are:

- For all algorithms tested, the 1087 mated searches (Twin A vs. Twin A) produce scores almost always above typical operational thresholds, with (not shown) matches at rank 1. The images are of good quality, so this is the result expected from the rest of this report.
- For the 1066 identical twin searches (AB), almost all produce the twin at rank 1, with a few producing the mate at further down the candidate lists rank and low score.
- For the 169 fraternal searches (AB) from same sex pairs, most algorithms give a large number of very high scores, implying false positives at all thresholds. However, there there are long tails containing lower scores that are correctly below threshold. In general, scores that are higher in this distribution are all rank 1 whereas the lower scores have much higher ranks.
- (Not shown) Of the 169, there are 24 fraternal searches (AB) involving different sex twins. Here most algorithms correctly report scores well below the lowest threshold, and usually not on the candidate list at all.

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Figure 18: **[Mugshot Dataset] Speed-accuracy tradeoff**. *For developers of the more accurate algorithms the plot shows the tradeoff of high-threshold recognition miss-rates, FNIR(N, N, T) for FPIR(N, T) = 0.003, and template generation time. Developers are coded by color. Template size is encoded by the size of the circle. Some labels are quite distant from the respective point, to avoid superposing text. Without any other influences, the assumption would be that taking time to localize the face, and extract features, would lead to better accuracy. The most notable result, for NEC, is that their slower algorithms are much more accurate than the version that extract features in fewer than 90 milliseconds.*

Figure 19: **[Mugshot Dataset] Speed-accuracy tradeoff**. *For developers of the more accurate algorithms the plot shows the tradeoff of rank-one recognition miss-rates, FNIR(N, 1, 0), and template generation time. Developers are coded by color. Template size is encoded by the size of the circle. Some labels are quite distant from the respective point, to avoid superposing text. Without any other influences, the assumption would be that taking time to localize the face, and extract features, would lead to better accuracy. This occurs for NEC with their slower algorithm being much accurate than the version that extract features in fewer than 90 milliseconds.*

	DEVELOPER	SHORT	SEQ.	VALIDATION	CONFIG[1]	LIB[1]	TEMPLATE GENERATION			FINALIZE[2]	SEARCH DURATION[5] MILLISEC					
	FULL NAME	NAME	NUM.	DATE	DATA (MB)	DATA (MB)	SIZE (B)	MULT[3]	TIME (MS)[4]	TIME (S)	L=1	L=50	L=50	L=50	L=50	POWER LAW
										N=1.6M	N=1.6M	N=1.6M	N=3M	N=6M	N=12M	(μs)
1	3Divi	3divi	5	2018-10-26	186	51	^{139}4096	k	^{82}638	^{111}28	$^{(68)}$538	$^{(68)}$537	$^{(61)}$1377	$^{(59)}$2614	$^{(55)}$5530	$^{93}0.07N^{1.1}$
2	3Divi	3divi	6	2018-10-26	187	51	^{31}528	k	^{83}640	^{21}5	$^{(11)}$33	$^{(12)}$33	-	-	-	
3	Acer Incorporated	acer	000	2020-08-12	35	67	^{24}512	-	^{14}198	^{13}4	$^{(49)}$295	$^{(50)}$295	$^{(40)}$623	$^{(53)}$2302	$^{(48)}$4915	$^{119}0.00N^{1.3}$
4	Akurat Satu Indonesia	ptakuratsatu	000	2020-10-23	0	572	^{33}538	-	^{148}905	^{152}28633	$^{(6)}$15	$^{(6)}$16	$^{(6)}$17	$^{(5)}$17	$^{(4)}$17	$^{3}6827.74N^{0.1}$
5	Alchera Inc	alchera	2	2018-10-30	7	14	^{107}2048	k	^{6}114	^{136}63	$^{(126)}$2923	$^{(129)}$2929	-	-	-	
6	Alchera Inc	alchera	3	2018-10-30	251	14	^{100}2048	k	^{67}531	^{137}63	$^{(127)}$2955	$^{(130)}$2956	$^{(110)}$6546	$^{(111)}$15013	$^{(111)}$35262	$^{114}0.10N^{1.2}$
7	Alivia / Innovation Sys	isystems	3	2018-10-30	350	784	^{85}2048	1	^{130}825	^{88}16	$^{(57)}$385	$^{(58)}$389	$^{(48)}$979	$^{(48)}$1822	$^{(71)}$9348	$^{120}0.00N^{1.3}$
8	AllGoVision	allgovision	000	2019-07-30	168	150	^{89}2048	k	^{43}404	^{46}12	$^{(129)}$3226	$^{(132)}$3193	$^{(108)}$6129	$^{(108)}$12449	$^{(108)}$25835	$^{49}1.40N^{1.0}$
9	AllGoVision	allgovision	001	2020-07-14	283	126	^{99}2048	-	^{119}777	^{52}13	$^{(128)}$3174	$^{(131)}$3183	$^{(107)}$6073	$^{(106)}$12284	$^{(107)}$25701	$^{47}1.42N^{1.0}$
10	Anke Investments	anke	0	2018-10-30	779	27	^{125}2072	k	^{48}429	^{86}16	$^{(78)}$675	$^{(82)}$748	$^{(66)}$1483	$^{(65)}$2968	$^{(59)}$6148	$^{68}0.21N^{1.1}$
11	Anke Investments	anke	1	2018-10-30	779	27	^{126}2072	k	^{49}430	^{80}15	$^{(82)}$707	$^{(85)}$769	-	-	-	
12	Anke Investments	anke	002	2019-06-27	341	401	^{120}2056	k	^{78}623	^{60}13	$^{(77)}$624	$^{(77)}$682	$^{(59)}$1306	$^{(55)}$2403	$^{(52)}$5082	$^{42}0.30N^{1.0}$
13	Aware	aware	5	2018-10-30	368	27	^{134}3100	k	^{124}792	^{120}34	$^{(15)}$95	$^{(18)}$98	$^{(16)}$203	$^{(15)}$371	$^{(12)}$252	$^{13}4.13N^{0.7}$
14	Aware	aware	6	2018-10-30	368	27	^{2}124	k	^{123}789	^{2}2	$^{(28)}$158	$^{(28)}$162	-	-	-	
15	Ayonix	ayonix	1	2018-10-29	74	2	^{45}1036	k	^{2}12	^{41}11	$^{(45)}$279	$^{(46)}$279	-	-	-	
16	Ayonix	ayonix	2	2018-10-30	74	2	^{46}1036	1	^{1}11	^{65}14	$^{(44)}$279	$^{(45)}$276	$^{(32)}$535	$^{(30)}$1087	$^{(30)}$2284	$^{56}0.11N^{1.0}$
17	Camvi Technologies	camvitech	4	2018-10-30	233	220	^{39}1024	1	^{97}686	^{118}31	$^{(12)}$33	$^{(11)}$32	$^{(10)}$38	$^{(9)}$40	$^{(7)}$48	$^{4}8492.66N^{0.1}$
18	Camvi Technologies	camvitech	5	2018-10-30	257	220	^{38}1024	1	^{115}751	^{116}31	$^{(10)}$31	$^{(9)}$30	-	-	-	
19	Canon Inc	cib	000	2020-10-19	426	127	^{154}8196	-	^{92}674	^{140}113	$^{(130)}$3589	$^{(134)}$3604	$^{(111)}$6738	$^{(109)}$13495	$^{(109)}$27114	$^{22}2.33N^{1.0}$
20	Cloudwalk - Hengrui AI Technology	hr	000	2021-02-10	501	392	^{105}2048	-	^{147}905	^{73}15	$^{(46)}$282	$^{(44)}$276	$^{(34)}$539	$^{(37)}$1268	$^{(41)}$3177	$^{96}0.03N^{1.1}$
21	Cognitec Systems GmbH	cognitec	2	2018-10-30	463	26	^{110}2052	k	^{18}225	^{106}27	$^{(115)}$1733	$^{(117)}$1763	$^{(99)}$3660	$^{(97)}$7279	$^{(96)}$13895	$^{46}0.83N^{1.0}$
22	Cognitec Systems GmbH	cognitec	3	2018-10-30	465	26	^{115}2052	k	^{28}297	^{84}16	$^{(114)}$1719	$^{(118)}$1791	$^{(98)}$3638	$^{(96)}$7277	$^{(99)}$14904	$^{62}0.66N^{1.0}$
23	Cognitec Systems GmbH	cognitec	004	2021-03-08	384	60	^{116}2052	-	^{13}192	^{58}13	$^{(113)}$1673	$^{(116)}$1727	$^{(92)}$2904	$^{(90)}$5801	$^{(88)}$11707	$^{19}1.15N^{1.0}$
24	Cyberlink Corp	cyberlink	000	2019-06-12	217	93	^{113}2052	1	^{86}654	^{114}30	$^{(80)}$696	$^{(79)}$701	$^{(62)}$1379	$^{(60)}$2639	$^{(61)}$6214	$^{58}0.28N^{1.0}$
25	Cyberlink Corp	cyberlink	001	2019-10-07	459	102	^{111}2052	1	^{46}423	^{112}28	$^{(81)}$698	$^{(78)}$700	$^{(60)}$1350	$^{(88)}$5524	$^{(91)}$12031	$^{118}0.00N^{1.3}$
26	Cyberlink Corp	cyberlink	002	2020-07-31	333	109	^{150}4140	-	^{111}724	^{144}6875	$^{(107)}$1353	$^{(133)}$3198	$^{(109)}$6138	$^{(105)}$12205	$^{(94)}$13106	$^{15}16.71N^{0.8}$
27	Cyberlink Corp	cyberlink	003	2021-01-05	333	100	^{152}6212	-	^{100}691	^{123}35	$^{(64)}$488	$^{(80)}$723	$^{(64)}$1415	$^{(63)}$2886	$^{(56)}$5643	$^{79}0.12N^{1.1}$
28	Dahua Technology Co Ltd	dahua	0	2018-10-29	276	167	^{106}2048	k	^{38}374	^{102}22	-	$^{(42)}$258	-	-	-	
29	Dahua Technology Co Ltd	dahua	1	2018-10-29	276	167	^{79}2048	k	^{34}369	^{108}28	-	$^{(41)}$257	$^{(38)}$602	$^{(35)}$1202	$^{(39)}$3007	$^{103}0.02N^{1.2}$
30	Dahua Technology Co Ltd	dahua	002	2019-12-02	607	137	^{98}2048	k	^{96}685	^{98}19	$^{(37)}$243	$^{(43)}$269	$^{(55)}$1189	$^{(64)}$2950	$^{(64)}$6732	$^{124}0.00N^{1.5}$
31	Dahua Technology Co Ltd	dahua	003	2020-11-18	889	154	^{74}2048	-	^{110}723	^{91}18	$^{(47)}$283	$^{(40)}$249	$^{(30)}$468	$^{(29)}$935	$^{(28)}$1871	$^{23}0.16N^{1.0}$
32	Deepglint	deepglint	001	2019-11-15	448	265	^{136}4096	-	^{94}676	^{121}35	$^{(79)}$677	$^{(110)}$1495	$^{(70)}$1724	$^{(61)}$2747	$^{(62)}$6246	$^{14}25.27N^{0.8}$
33	Dermalog	dermalog	5	2018-10-26	0	440	^{3}128	1	^{66}528	^{143}3155	$^{(1)}$0	$^{(1)}$0	$^{(1)}$0	$^{(1)}$0	$^{(1)}$0	$^{5}66.21N^{0.2}$
34	Dermalog	dermalog	6	2018-10-26	0	453	^{12}256	1	^{62}507	^{3}2	$^{(25)}$142	$^{(25)}$144	$^{(21)}$269	$^{(20)}$531	$^{(19)}$1294	$^{63}0.05N^{1.0}$
35	Dermalog	dermalog	007	2020-02-12	0	424	^{4}128	1	^{45}410	^{1}1	$^{(18)}$98	$^{(16)}$96	$^{(18)}$218	$^{(16)}$429	$^{(16)}$1013	$^{86}0.01N^{1.1}$
36	Dermalog	dermalog	008	2021-01-25	0	531	^{22}512	-	^{35}370	^{15}4	$^{(52)}$335	$^{(37)}$246	$^{(29)}$462	$^{(28)}$924	$^{(27)}$1849	$^{26}0.15N^{1.0}$
37	FarBar Inc	f8	001	2019-10-03	266	19	^{108}2048	k	^{128}810	^{63}14	-	-	-	-	-	
38	Gorilla Technology	gorilla	2	2018-10-29	91	1252	^{50}1132	k	^{31}338	^{105}24	$^{(26)}$145	$^{(26)}$146	$^{(22)}$293	$^{(21)}$612	$^{(23)}$1509	$^{84}0.02N^{1.1}$
39	Gorilla Technology	gorilla	3	2018-10-26	94	1252	^{127}2156	k	^{69}559	^{148}12020	-	$^{(121)}$2047	-	-	-	
40	Gorilla Technology	gorilla	004	2020-01-06	182	1244	^{128}2192	k	^{40}388	^{125}41	$^{(48)}$286	$^{(49)}$285	$^{(56)}$1191	$^{(56)}$2416	$^{(51)}$5036	$^{117}0.00N^{1.3}$
41	Gorilla Technology	gorilla	005	2021-02-22	306	1420	^{153}6288	-	^{59}483	^{139}78	$^{(86)}$802	$^{(86)}$799	$^{(67)}$1514	$^{(72)}$4454	$^{(67)}$8820	$^{105}0.05N^{1.2}$
42	Guangzhou Pixel Solutions Co Ltd	pixelall	002	2019-07-01	0	165	^{132}2560	k	^{12}190	^{77}15	$^{(105)}$1296	$^{(107)}$1334	$^{(85)}$2526	$^{(81)}$5136	$^{(84)}$11045	$^{57}0.52N^{1.0}$
43	Guangzhou Pixel Solutions Co Ltd	pixelall	003	2019-11-05	0	690	^{129}2560	k	^{104}703	^{103}22	$^{(102)}$1273	$^{(104)}$1307	$^{(82)}$2474	$^{(82)}$5198	$^{(85)}$11141	$^{64}0.46N^{1.0}$
44	Guangzhou Pixel Solutions Co Ltd	pixelall	004	2020-07-02	0	538	^{130}2560	k	^{50}449	^{90}17	$^{(101)}$1259	$^{(103)}$1300	$^{(81)}$2465	$^{(87)}$5492	$^{(86)}$11443	$^{72}0.34N^{1.1}$
45	Guangzhou Pixel Solutions Co Ltd	pixelall	005	2021-03-23	0	717	^{131}2560	-	^{134}840	^{40}11	$^{(111)}$1606	$^{(111)}$1528	$^{(87)}$2609	$^{(78)}$4926	$^{(89)}$11770	$^{36}0.73N^{1.0}$
46	Hikvision Research Institute	hikvision	5	2018-10-29	593	9	^{53}1408	1	^{75}607	^{83}16	$^{(91)}$883	$^{(92)}$895	$^{(72)}$1908	$^{(68)}$3792	$^{(72)}$9387	$^{94}0.10N^{1.1}$
47	Hikvision Research Institute	hikvision	6	2018-10-29	593	9	^{54}1408	1	^{73}598	^{85}16	$^{(89)}$871	$^{(91)}$877	-	-	-	
48	Idemia	idemia	5	2018-10-29	417	48	^{20}352	1	^{37}371	^{20}5	$^{(22)}$137	$^{(23)}$138	$^{(27)}$437	$^{(25)}$724	$^{(24)}$1630	$^{111}0.01N^{1.2}$
49	Idemia	idemia	6	2018-10-29	417	48	^{19}352	1	^{36}370	^{19}4	$^{(23)}$137	$^{(22)}$138	$^{(28)}$442	$^{(27)}$827	$^{(25)}$1646	$^{113}0.01N^{1.2}$
50	Idemia	idemia	007	2020-01-17	738	113	^{37}860	1	^{125}794	^{64}14	$^{(27)}$151	$^{(27)}$152	$^{(42)}$683	$^{(41)}$1481	$^{(40)}$3022	$^{122}0.00N^{1.4}$
51	Idemia	idemia	008	2021-03-15	378	65	^{18}300	-	^{52}451	^{11}3	$^{(21)}$132	$^{(21)}$131	$^{(19)}$247	$^{(18)}$501	$^{(17)}$1013	$^{33}0.07N^{1.0}$
52	Imagus Technology Pty Ltd	imagus	005	2021-01-15	222	311	^{84}2048	-	^{122}786	^{62}14	$^{(36)}$236	$^{(52)}$313	$^{(41)}$651	$^{(39)}$1361	$^{(31)}$2461	$^{92}0.03N^{1.1}$

Notes	
1	Configuration size does not capture static data present in libraries. Libraries are included but the size also includes any ancillary libraries for image processing (e.g. openCV) or numerical computation (e.g. blas).
2	Finalization is the processing of converting N = 1600000 templates into a searchable data structure an operation which can be a simple copy, or the building of an index or tree, for example. The duration of the operation may be data dependent, and may not be linear in the number of input templates.
3	This multiplier expresses the increase in template size when k images are passed to the template generation function.
4	All durations are measured on Intel®Xeon®CPU E5-2630 v4 @ 2.20GHz processors. Estimates are made by wrapping the API function call in calls to std::chrono::high_resolution_clock which on the machine in (3) counts 1ns clock ticks. Precision is somewhat worse than that however.
5	Search durations are measured as in the prior note. The power-law model in the final column mostly fits the empirical results in Figure 166. However in certain cases the model is not correct and should not be used numerically.

FNIR(N, R, T) = False neg. identification rate
FPIR(N, T) = False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

Table 2: Summary of algorithms and properties included in this report. The blue superscripts give ranking for the quantity in that column. Missing search durations, denoted by "-", are absent because those runs were not executed, usually because we did not run on the larger galleries. Caution: The power-law model is sometimes an incorrect model. It is included here only to show broad sublinear behavior, which is flagged in green. The models should not be used for prediction.

	DEVELOPER	SHORT	SEQ.	VALIDATION	CONFIG[1]	LIB[1]	TEMPLATE GENERATION			FINALIZE[2]	SEARCH DURATION[5] MILLISEC					
	FULL NAME	NAME	NUM.	DATE	DATA (MB)	DATA (MB)	SIZE (B)	MULT[3]	TIME (MS)[4]	TIME (S) N=1.6M	L=1 N=1.6M	L=50 N=1.6M	L=50 N=3M	L=50 N=6M	L=50 N=12M	POWER LAW (μs)
53	Imagus Technology Pty Ltd	imagus	006	2021-05-27	248	369	^{91}2048	-	^{146}904	^{33}9	$^{(51)}$317	$^{(36)}$234	$^{(31)}$499	$^{(38)}$1273	$^{(33)}$2727	$^{110}0.01N^{1.2}$
54	Imperial College London	imperial	000	2019-08-28	461	15	^{69}2048	1	^{70}577	^{51}13	$^{(54)}$360	$^{(57)}$379	$^{(68)}$1626	$^{(70)}$4057	$^{(82)}$10291	$^{125}0.00N^{1.5}$
55	Incode Technologies Inc	incode	2	2018-10-29	71	31	^{104}2048	1	^{25}289	^{82}15	$^{(62)}$411	$^{(59)}$404	-	-	-	
56	Incode Technologies Inc	incode	3	2018-10-29	133	31	^{87}2048	1	^{102}697	^{72}15	$^{(61)}$408	$^{(62)}$412	$^{(45)}$847	$^{(42)}$1608	$^{(46)}$4486	$^{88}0.05N^{1.1}$
57	Incode Technologies Inc	incode	004	2019-06-24	254	50	^{96}2048	1	^{57}475	^{44}12	$^{(55)}$365	$^{(56)}$378	$^{(65)}$1482	$^{(43)}$1660	$^{(38)}$2954	$^{70}0.12N^{1.1}$
58	Innovatrics	innovatrics	4	2018-10-30	0	400	^{49}1076	k	^{41}399	^{145}10902	$^{(5)}$8	$^{(4)}$8	$^{(4)}$11	$^{(2)}$9	$^{(3)}$13	$^{9}668.38N^{0.2}$
59	Innovatrics	innovatrics	005	2019-09-30	0	455	^{32}538	1	^{131}827	^{147}11897	$^{(4)}$8	$^{(5)}$8	$^{(3)}$9	$^{(3)}$9	$^{(2)}$9	$^{1}4055.65N^{0.1}$
60	IrexAI	irex	000	2021-02-09	724	46	^{133}3080	-	^{135}844	^{97}19	$^{(76)}$616	$^{(74)}$600	$^{(52)}$1120	$^{(58)}$2477	$^{(57)}$5863	$^{75}0.13N^{1.1}$
61	Kedacom International Pte	kedacom	001	2019-09-16	239	36	^{17}292	1	^{63}507	^{4}2	$^{(84)}$764	$^{(83)}$760	$^{(73)}$1940	$^{(66)}$2983	$^{(63)}$6623	$^{60}0.31N^{1.0}$
62	Kneron	kneron	000	2020-03-03	366	13	^{70}2048	k	^{65}523	^{56}13	$^{(123)}$2535	$^{(126)}$2506	$^{(105)}$4752	$^{(103)}$9696	$^{(106)}$20926	$^{61}0.95N^{1.0}$
63	Kneron	kneron	001	2021-06-10	270	69	^{90}2048	-	^{56}472	^{30}9	$^{(124)}$2690	$^{(128)}$2642	-	-	-	
64	Line Corporation	line	000	2021-06-02	138	397	^{72}2048	-	^{58}481	^{28}8	$^{(135)}$5433	$^{(139)}$5418	$^{(115)}$10144	-	-	$^{21}3.65N^{1.0}$
65	Lomonosov Moscow State University	intsysmsu	000	2019-08-19	375	168	^{68}2048	1	^{76}614	^{57}13	$^{(63)}$430	$^{(64)}$431	$^{(47)}$860	$^{(44)}$1730	$^{(54)}$5353	$^{101}0.03N^{1.1}$
66	Lookman Electroplast Industries	lookman	3	2018-10-28	203	24	^{16}292	1	^{30}336	^{10}3	$^{(83)}$739	$^{(81)}$745	$^{(63)}$1394	$^{(62)}$2817	$^{(65)}$8286	$^{82}0.13N^{1.1}$
67	Lookman Electroplast Industries	lookman	4	2018-10-28	184	24	^{35}548	1	^{29}320	^{18}4	$^{(92)}$981	$^{(93)}$998	-	-	-	
68	Lookman Electroplast Industries	lookman	005	2019-09-16	239	36	^{34}548	1	^{61}506	^{14}4	$^{(93)}$1005	$^{(94)}$1008	$^{(86)}$2597	$^{(86)}$5446	$^{(68)}$8939	$^{80}0.19N^{1.1}$
69	Megvii/Face++	megvii	1	2018-10-28	1703	41	^{144}4096	1	^{80}631	^{119}32	$^{(69)}$552	$^{(72)}$561	$^{(58)}$1222	$^{(54)}$2321	$^{(58)}$5968	$^{87}0.08N^{1.1}$
70	Megvii/Face++	megvii	2	2018-10-28	1735	42	^{141}4096	1	^{81}635	^{117}31	$^{(70)}$553	$^{(70)}$558	-	-	-	
71	MicroFocus	microfocus	5	2018-10-29	94	26	^{11}256	k	^{22}262	^{7}2	$^{(33)}$182	$^{(32)}$186	$^{(25)}$354	$^{(24)}$708	$^{(21)}$1425	$^{32}0.11N^{1.0}$
72	MicroFocus	microfocus	6	2018-10-29	94	26	^{10}256	k	^{21}262	^{9}2	$^{(34)}$183	$^{(31)}$186	-	-	-	
73	Microsoft	microsoft	5	2018-10-29	381	155	^{40}1024	1	^{87}658	^{42}11	$^{(110)}$1606	$^{(113)}$1673	$^{(95)}$3076	$^{(93)}$6302	$^{(95)}$13160	$^{41}0.79N^{1.0}$
74	Microsoft	microsoft	6	2018-10-29	478	155	^{41}1024	1	^{90}671	^{76}15	$^{(112)}$1642	$^{(112)}$1618	$^{(100)}$3710	$^{(94)}$6401	$^{(93)}$12892	$^{53}0.68N^{1.0}$
75	N-Tech Lab	ntech	5	2018-10-30	1685	113	^{65}1940	k	^{108}711	^{134}55	$^{(39)}$243	$^{(39)}$246	$^{(33)}$538	$^{(31)}$1100	$^{(35)}$2867	$^{97}0.02N^{1.1}$
76	N-Tech Lab	ntech	6	2018-10-30	1686	117	^{64}1940	k	^{133}831	^{135}63	$^{(38)}$243	$^{(38)}$246	$^{(35)}$546	$^{(32)}$1104	$^{(36)}$2873	$^{99}0.02N^{1.1}$
77	N-Tech Lab	ntechlab	007	2019-06-25	2450	51	^{135}3348	k	^{126}795	^{138}73	$^{(58)}$393	$^{(63)}$427	$^{(44)}$780	$^{(47)}$1768	$^{(43)}$3499	$^{59}0.16N^{1.0}$
78	N-Tech Lab	ntechlab	008	2020-01-06	1111	51	^{51}1300	k	^{68}554	^{124}36	$^{(32)}$179	$^{(29)}$184	$^{(24)}$341	$^{(23)}$683	$^{(20)}$1395	$^{30}0.11N^{1.0}$
79	N-Tech Lab	ntechlab	009	2021-03-01	1208	42	^{52}1300	-	^{145}899	^{122}35	$^{(31)}$178	$^{(30)}$184	$^{(23)}$336	$^{(22)}$676	$^{(26)}$1704	$^{71}0.05N^{1.1}$
80	NEC	nec	2	2018-10-30	705	35	^{60}1616	k	^{84}642	^{94}18	$^{(59)}$405	$^{(61)}$409	$^{(50)}$1072	$^{(45)}$1755	$^{(45)}$4255	$^{89}0.06N^{1.1}$
81	NEC	nec	3	2018-10-30	774	110	^{61}1712	k	^{88}665	^{100}21	$^{(3)}$7	$^{(3)}$7	$^{(5)}$14	$^{(8)}$40	$^{(9)}$82	$^{106}0.00N^{1.2}$
82	Neurotechnology	neurotech	5	2018-10-30	266	53	^{9}256	k	^{42}402	^{8}2	$^{(87)}$835	$^{(88)}$839	$^{(69)}$1690	$^{(67)}$3219	$^{(69)}$8955	$^{76}0.19N^{1.1}$
83	Neurotechnology	neurotech	6	2018-10-30	564	53	^{8}256	k	^{112}726	^{6}2	$^{(88)}$839	$^{(89)}$842	-	-	-	
84	Neurotechnology	neurotech	007	2019-10-03	57	51	^{13}256	k	^{7}161	^{5}2	$^{(95)}$1118	$^{(96)}$1110	$^{(76)}$2143	$^{(71)}$4397	$^{(70)}$9045	$^{40}0.55N^{1.0}$
85	Neurotechnology	neurotechnology	008	2021-03-22	355	49	^{30}514	-	^{127}800	^{17}4	$^{(98)}$1167	$^{(99)}$1149	$^{(78)}$2266	$^{(75)}$4573	$^{(75)}$9586	$^{44}0.55N^{1.0}$
86	Newland Computer Co Ltd	newland	2	2018-10-30	96	27	^{71}2048	-	^{137}855	^{78}15	$^{(145)}$8741	$^{(150)}$8854	$^{(126)}$17892	$^{(123)}$39356	-	$^{85}1.32N^{1.1}$
87	Noblis	noblis	1	2018-10-30	114	176	^{93}2048	1	^{16}206	^{74}15	$^{(103)}$1273	$^{(102)}$1272	-	-	-	
88	Noblis	noblis	2	2018-10-30	153	176	^{151}6144	1	^{64}517	^{127}43	$^{(122)}$2513	$^{(127)}$2522	$^{(106)}$5649	$^{(107)}$12432	$^{(113)}$44262	$^{115}0.04N^{1.3}$
89	Paravision (EverAI)	everai	2	2018-10-30	224	304	^{82}2048	1	^{33}366	^{115}30	$^{(43)}$278	$^{(48)}$283	-	-	-	
90	Paravision (EverAI)	everai	3	2018-10-30	438	304	^{77}2048	1	^{109}717	^{110}28	$^{(42)}$278	$^{(47)}$281	$^{(36)}$572	$^{(33)}$1146	$^{(29)}$2278	$^{54}0.12N^{1.0}$
91	Paravision (EverAI)	everai-paravision	004	2019-06-19	527	128	^{140}4096	1	^{91}672	^{130}45	$^{(71)}$559	$^{(71)}$559	$^{(88)}$2611	$^{(95)}$6445	$^{(97)}$14519	$^{123}0.00N^{1.5}$
92	Paravision (EverAI)	paravision	005	2019-12-11	543	154	^{145}4096	1	^{132}830	^{132}48	$^{(72)}$561	$^{(73)}$564	$^{(49)}$1056	$^{(51)}$2298	$^{(49)}$4966	$^{69}0.16N^{1.1}$
93	Paravision (EverAI)	paravision	007	2021-02-01	529	235	^{138}4096	-	^{103}701	^{133}48	$^{(73)}$569	$^{(69)}$558	$^{(51)}$1086	$^{(49)}$2111	$^{(44)}$4254	$^{17}1.11N^{0.9}$
94	Quantasoft	quantasoft	1	2018-10-30	276	452	^{88}2048	k	^{39}385	^{22}6	$^{(146)}$15422	$^{(151)}$14858	$^{(124)}$14717	-	$^{(103)}$18323	
95	Rank One Computing	rankone	4	2018-10-09	0	101	^{1}85	k	^{3}36	^{23}7	$^{(19)}$101	$^{(19)}$101	$^{(15)}$190	-	-	$^{20}0.07N^{1.0}$
96	Rank One Computing	rankone	5	2018-10-24	0	101	^{5}133	k	^{4}92	^{24}7	$^{(24)}$140	$^{(24)}$144	$^{(20)}$266	$^{(19)}$525	$^{(18)}$1049	$^{18}0.11N^{1.0}$
97	Rank One Computing	rankone	006	2019-06-03	0	133	^{6}165	k	^{20}245	^{27}8	-	-	-	-	-	
98	Rank One Computing	rankone	007	2019-11-12	0	137	^{7}165	k	^{23}272	^{26}7	$^{(20)}$116	$^{(20)}$115	$^{(17)}$215	$^{(17)}$439	$^{(15)}$877	$^{31}0.07N^{1.0}$
99	Rank One Computing	rankone	009	2020-06-26	0	105	^{14}260	k	^{11}185	^{39}11	$^{(16)}$95	$^{(17)}$96	$^{(14)}$181	$^{(14)}$362	$^{(14)}$727	$^{25}0.06N^{1.0}$
100	Rank One Computing	rankone	010	2020-11-05	0	135	^{15}261	-	^{15}198	^{36}10	$^{(17)}$95	$^{(15)}$95	$^{(13)}$178	$^{(13)}$357	$^{(13)}$714	$^{24}0.06N^{1.0}$
101	Realnetworks Inc	realnetworks	2	2018-10-30	105	104	^{147}4104	k	^{19}241	^{109}28	$^{(117)}$2008	$^{(122)}$2048	$^{(102)}$4194	$^{(101)}$8642	$^{(100)}$15035	$^{35}1.08N^{1.0}$
102	Realnetworks Inc	realnetworks	003	2019-06-12	93	102	^{62}1848	k	^{10}173	^{50}13	$^{(97)}$1145	$^{(97)}$1132	$^{(75)}$2142	$^{(83)}$5241	$^{(83)}$10495	$^{78}0.21N^{1.1}$
103	Realnetworks Inc	realnetworks	004	2019-10-17	94	102	^{63}1848	1	^{9}171	^{38}11	$^{(96)}$1143	$^{(98)}$1137	$^{(77)}$2149	$^{(77)}$4740	$^{(78)}$9693	$^{67}0.36N^{1.0}$
104	Remark Holdings	remarkai	000	2019-06-12	234	1092	^{80}2048	k	^{85}650	^{49}12	$^{(139)}$5776	$^{(141)}$5703	$^{(117)}$11604	$^{(122)}$32133	$^{(122)}$91436	$^{116}0.05N^{1.3}$

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5	Search durations are measured as in the prior note. The power-law model in the final column mostly fits the empirical results in Figure 166. However in certain cases the model is not correct and should not be used numerically.

Table 3: Summary of algorithms and properties included in this report. The blue superscripts give ranking for the quantity in that column. Missing search durations, denoted by "-", are absent because those runs were not executed, usually because we did not run on the larger galleries. Caution: The power-law model is sometimes an incorrect model. It is included here only to show broad sublinear behavior, which is flagged in green. The models should not be used for prediction.

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	DEVELOPER	SHORT	SEQ.	VALIDATION	CONFIG[1]	LIB[1]	TEMPLATE GENERATION			FINALIZE[2]	SEARCH DURATION[5] MILLISEC					
	FULL NAME	NAME	NUM.	DATE	DATA (MB)	DATA (MB)	SIZE (B)	MULT[3]	TIME (MS)[4]	TIME (S)	L=1	L=50	L=50	L=50	L=50	POWER LAW
										N=1.6M	N=1.6M	N=1.6M	N=3M	N=6M	N=12M	(μs)
105	Remark Holdings	remarkai	0	2018-10-30	187	847	[81]2048	k	[71]593	[67]14	[(138)]5685	[(142)]5723	-	-	-	
106	Remark Holdings	remarkai	1	2018-10-30	187	847	[83]2048	k	[47]427	[71]14	[(137)]5680	[(143)]5761	[(120)]12475	[(120)]28726	[(120)]59618	[107]$0.37N^{1.2}$
107	Rendip	rendip	000	2021-05-21	0	416	[103]2048	-	[143]890	[31]9	[(40)]249	[(54)]368	[(43)]697	[(40)]1452	[(37)]2926	[73]$0.08N^{1.1}$
108	Samsung S1 Corp	s1	000	2021-06-03	257	196	[137]4096	-	[138]865	[99]20	[(143)]6715	[(148)]6794	[(123)]13032	[(119)]26372	[(119)]55723	[52]$2.82N^{1.0}$
109	Scanovate Ltd	scanovate	000	2020-01-15	250	446	[92]2048	1	[105]705	[69]14	[(109)]1419	[(109)]1412	[(94)]3008	[(104)]11616	[(90)]12012	[108]$0.10N^{1.2}$
110	Scanovate Ltd	scanovate	001	2020-09-10	250	446	[97]2048	-	[93]675	[55]13	[(106)]1321	[(106)]1320	[(83)]2502	[(80)]5047	[(80)]10163	[37]$0.65N^{1.0}$
111	Sensetime Group	sensetime	0	2018-10-30	525	6	[149]4104	k	[101]693	[126]41	[(65)]498	[(65)]501	[(57)]1212	[(50)]2281	[(50)]5032	[83]$0.09N^{1.1}$
112	Sensetime Group	sensetime	1	2018-10-30	525	6	[148]4104	k	[79]628	[131]48	[(67)]516	[(66)]502	[(53)]1146	[(52)]2301	[(47)]4765	[81]$0.09N^{1.1}$
113	Sensetime Group	sensetime	002	2019-06-03	523	6	[119]2056	k	[74]603	[92]18	[(53)]359	[(55)]370	[(71)]1897	[(73)]4508	[(74)]9543	[126]$0.00N^{1.5}$
114	Sensetime Group	sensetime	003	2019-12-02	769	76	[121]2056	1	[149]910	[96]19	[(134)]4885	[(138)]4989	[(119)]12325	[(116)]24712	[(115)]49445	[91]$0.67N^{1.1}$
115	Sensetime Group	sensetime	004	2020-08-10	456	29	[42]1032	-	[99]690	[48]12	[(121)]2490	[(125)]2477	[(104)]4654	[(102)]9402	[(105)]19651	[39]$1.22N^{1.0}$
116	Sensetime Group	sensetime	005	2020-12-17	631	39	[44]1032	-	[155]980	[37]11	[(120)]2459	[(135)]3939	[(112)]7398	[(110)]14768	[(104)]19016	[16]$14.03N^{0.9}$
117	Shaman Software	shaman	6	2018-10-26	0	200	[102]2048	k	[106]706	[68]14	[(75)]603	[(75)]612	-	-	-	
118	Shaman Software	shaman	7	2018-10-26	0	200	[101]2048	k	[107]707	[70]14	[(74)]602	[(76)]614	[(54)]1187	[(57)]2448	[(53)]5083	[55]$0.25N^{1.0}$
119	Shanghai Yitu Technology	yitu	4	2018-10-30	2119	136	[123]2070	1	[144]897	[129]45	[(104)]1288	[(101)]1203	[(80)]2440	[(84)]5241	[(77)]9671	[51]$0.52N^{1.0}$
120	Shanghai Yitu Technology	yitu	5	2018-10-30	2043	136	[124]2070	1	[136]853	[128]44	[(100)]1237	[(100)]1199	[(84)]2513	[(79)]5013	[(76)]9620	[48]$0.55N^{1.0}$
121	Smilart	smilart	4	2018-10-30	65	89	[25]512	k	[8]167	[16]4	[(147)]16137	[(152)]15633	-	-	-	
122	Smilart	smilart	5	2018-10-30	562	89	[78]2048	k	[51]450	[66]14	-	-	-	-	-	
123	Synesis	synesis	003	2019-07-04	143	17	[67]2048	k	[17]211	[45]12	[(66)]507	[(67)]502	[(79)]2297	[(74)]4564	[(73)]9452	[121]$0.00N^{1.4}$
124	Synesis	synesis	3	2018-10-30	237	150	[143]4096	k	[5]99	[113]29	[(85)]789	[(87)]801	[(74)]1941	[(69)]3888	[(66)]8810	[98]$0.07N^{1.1}$
125	Synesis	synesis	005	2020-09-08	494	24	[146]4104	-	[117]756	[104]24	[(90)]877	[(90)]865	[(96)]3182	[(76)]4658	[(79)]9750	[109]$0.06N^{1.2}$
126	Tech5 SA	tech5	001	2019-08-19	1394	116	[55]1536	k	[142]887	[35]10	[(56)]383	[(84)]766	[(90)]2767	[(92)]6149	[(60)]6178	[90]$0.12N^{1.1}$
127	Tech5 SA	tech5	002	2021-04-07	727	112	[29]513	-	[152]940	[12]4	[(133)]4682	[(147)]6689	[(121)]12541	[(117)]25145	[(117)]50239	[27]$4.18N^{1.0}$
128	Tencent Deepsea Lab	deepsea	001	2019-07-29	250	323	[86]2048	1	[114]737	[47]12	[(94)]1021	[(95)]1020	[(91)]2774	[(89)]5767	[(92)]12341	[112]$0.06N^{1.2}$
129	Tevian	tevian	5	2018-10-30	773	15	[75]2048	1	[44]405	[75]15	[(60)]405	[(60)]408	[(46)]854	[(46)]1757	[(42)]3380	[66]$0.14N^{1.0}$
130	Tevian	tevian	006	2021-04-16	769	19	[43]1032	-	[72]597	[34]10	[(50)]295	[(51)]295	[(37)]578	[(34)]1187	[(34)]2741	[74]$0.06N^{1.1}$
131	Thales	cogent	2	2018-10-30	681	39	[47]1043	k	[153]945	[107]27	[(118)]2017	[(123)]2144	[(103)]4298	[(100)]8472	[(102)]16429	[38]$1.08N^{1.0}$
132	Thales	cogent	3	2018-10-30	681	39	[48]1043	k	[151]940	[32]9	[(99)]1230	[(105)]1311	[(89)]2687	[(85)]5398	[(81)]10184	[45]$0.62N^{1.0}$
133	Thales	cogent	004	2021-02-10	1376	59	[118]2053	-	[154]947	[61]14	[(125)]2903	[(119)]1911	[(97)]3566	[(98)]7498	[(101)]16370	[65]$0.64N^{1.0}$
134	TigerIT Americas LLC	tiger	2	2018-10-29	416	518	[117]2052	k	[53]461	[79]15	[(116)]1816	[(120)]1921	[(101)]3833	[(99)]7526	[(98)]14820	[50]$0.83N^{1.0}$
135	TigerIT Americas LLC	tiger	3	2018-10-30	416	518	[114]2052	k	[54]461	[154]37431	[(35)]191	[(33)]189	-	-	-	
136	Toshiba	toshiba	0	2018-10-30	961	105	[59]1548	k	[141]876	[43]12	[(142)]6153	[(144)]6236	[(118)]12221	[(118)]25355	[(116)]49448	[104]$0.36N^{1.2}$
137	Toshiba	toshiba	1	2018-10-30	961	105	[122]2060	k	[140]875	[155]44701	[(141)]6007	[(145)]6355	-	-	-	
138	Trueface.ai	trueface	000	2021-01-27	247	119	[66]2000	-	[32]363	[53]13	[(41)]271	[(53)]327	[(39)]614	[(36)]1239	[(32)]2678	[43]$0.15N^{1.0}$
139	Veridas Digital Authentication Solutions S.L.	veridas	001	2021-03-05	347	875	[94]2048	-	[139]872	[54]13	[(136)]5493	[(140)]5469	[(116)]10350	[(114)]20655	[(112)]41264	[28]$3.40N^{1.0}$
140	Viettel Group	vts	000	2021-03-12	250	257	[73]2048	-	[60]492	[142]2295	[(2)]4	[(2)]4	[(2)]6	[(4)]11	-	[12]$0.61N^{0.6}$
141	Vigilant Solutions	vigilant	5	2018-10-30	335	122	[57]1544	k	[118]762	[95]19	-	[(115)]1720	-	-	-	
142	Vigilant Solutions	vigilant	6	2018-10-30	337	122	[56]1544	k	[129]816	[101]21	-	[(114)]1713	-	-	-	
143	Vigilant Solutions	vigilantsolutions	007	2021-01-08	340	51	[58]1544	-	[77]616	[89]16	[(108)]1354	[(108)]1352	[(93)]2911	[(91)]5966	[(87)]11466	[77]$0.27N^{1.1}$
144	Visidon	visidon	1	2018-10-30	166	42	[109]2052	k	[89]667	[81]15	[(131)]4370	[(137)]4472	[(113)]8454	[(112)]17262	[(110)]34288	[34]$2.40N^{1.0}$
145	Visidon	vd	002	2021-05-18	248	42	[112]2052	-	[98]687	[29]9	[(119)]2089	[(124)]2336	-	-	-	
146	VisionLabs	visionlabs	6	2018-10-30	360	17	[26]512	1	[26]289	[151]20290	[(13)]36	[(13)]36	[(11)]39	[(10)]44	[(8)]53	[8]$3211.93N^{0.2}$
147	VisionLabs	visionlabs	7	2018-10-30	360	17	[23]512	1	[27]289	[153]34666	[(14)]63	[(14)]63	[(12)]72	[(12)]80	[(10)]115	[10]$2076.32N^{0.2}$
148	VisionLabs	visionlabs	008	2019-06-18	348	17	[21]512	1	[24]272	[149]12747	[(8)]23	[(7)]24	[(7)]26	[(6)]29	[(5)]33	[6]$2539.61N^{0.2}$
149	VisionLabs	visionlabs	009	2020-08-04	689	20	[28]512	-	[55]467	[150]13245	[(9)]23	[(8)]29	[(8)]34	[(11)]61	[(11)]145	[11]$8.88N^{0.6}$
150	VisionLabs	visionlabs	010	2021-02-05	1042	20	[27]512	-	[113]731	[146]11837	[(7)]21	[(10)]32	[(9)]36	[(7)]39	[(6)]43	[7]$3183.79N^{0.2}$
151	Vocord	vocord	5	2018-10-30	1035	185	[36]768	k	[120]780	[25]7	[(29)]158	[(34)]204	[(26)]383	[(26)]767	[(22)]1466	[29]$0.12N^{1.0}$
152	Vocord	vocord	6	2018-10-30	1035	185	[155]10240	k	[121]785	[141]243	[(30)]170	[(35)]216	-	-	-	
153	Xforward AI Technology	xforwardai	000	2020-07-24	236	171	[95]2048	-	[116]753	[59]13	[(132)]4603	[(149)]7647	[(125)]15723	[(115)]23900	[(118)]53729	[95]$0.56N^{1.1}$
154	Xforward AI Technology	xforwardai	001	2021-01-21	332	50	[76]2048	-	[95]677	[87]16	[(140)]5887	[(136)]4384	[(114)]8798	[(113)]18553	[(114)]48993	[102]$0.32N^{1.1}$
155	Xforward AI Technology	xforwardai	002	2021-05-24	691	50	[142]4096	-	[150]930	[93]18	[(144)]6957	[(146)]6400	[(122)]12659	[(121)]31077	[(121)]65158	[100]$0.52N^{1.1}$

Notes	
1	Configuration size does not capture static data present in libraries. Libraries are included but the size also includes any ancillary libraries for image processing (e.g. openCV) or numerical computation (e.g. blas).
2	Finalization is the processing of converting N = 1600000 templates into a searchable data structure an operation which can be a simple copy, or the building of an index or tree, for example. The duration of the operation may be data dependent, and may not be linear in the number of input templates.
3	This multiplier expresses the increase in template size when k images are passed to the template generation function.
4	All durations are measured on Intel®Xeon®CPU E5-2630 v4 @ 2.20GHz processors. Estimates are made by wrapping the API function call in calls to std::chrono::high_resolution_clock which on the machine in (3) counts 1ns clock ticks. Precision is somewhat worse than that however.
5	Search durations are measured as in the prior note. The power-law model in the final column mostly fits the empirical results in Figure 166. However in certain cases the model is not correct and should not be used numerically.

Table 4: Summary of algorithms and properties included in this report. The blue superscripts give ranking for the quantity in that column. Missing search durations, denoted by "-", are absent because those runs were not executed, usually because we did not run on the larger galleries. Caution: The power-law model is sometimes an incorrect model. It is included here only to show broad sublinear behavior, which is flagged in green. The models should not be used for prediction.

MISS RATES		INVESTIGATION, FNIR(N, R = 1, T = 0)								IDENTIFICATION, FNIR(N, R = L, T $\geq$ 0) FOR FPIR = 0.001							
#	ALGORITHM	(0, 2]	(2, 4]	(4, 6]	(6, 8]	(8, 10]	(10, 12]	(12, 14]	(14, 18]	(0, 2]	(2, 4]	(4, 6]	(6, 8]	(8, 10]	(10, 12]	(12, 14]	(14, 18]
1	3DIVI-005	^{93}0.0207	^{92}0.0304	^{92}0.0415	^{92}0.0533	^{92}0.0646	^{92}0.0735	^{92}0.0884	^{93}0.1148	^{96}0.1580	^{93}0.2316	^{93}0.3033	^{93}0.3740	^{93}0.4285	^{93}0.4742	^{94}0.5329	^{92}0.5975
2	ANKE-000	^{90}0.0162	^{90}0.0245	^{90}0.0333	^{90}0.0428	^{90}0.0515	^{90}0.0615	^{90}0.0780	^{89}0.1028	^{91}0.1132	^{91}0.1761	^{91}0.2402	^{91}0.3057	^{90}0.3640	^{90}0.4200	^{90}0.4928	^{90}0.5680
3	ANKE-002	^{44}0.0055	^{45}0.0074	^{45}0.0090	^{44}0.0103	^{43}0.0116	^{44}0.0135	^{43}0.0162	^{42}0.0202	^{49}0.0329	^{49}0.0560	^{51}0.0843	^{52}0.1169	^{52}0.1481	^{52}0.1820	^{52}0.2280	^{51}0.2831
4	AWARE-005	^{101}0.0328	^{101}0.0519	^{101}0.0712	^{99}0.0910	^{99}0.1078	^{99}0.1235	^{99}0.1457	^{99}0.1831	^{101}0.3605	^{102}0.4949	^{102}0.5948	^{102}0.6783	^{103}0.7393	^{103}0.7905	^{103}0.8408	^{104}0.8831
5	AWARE-006	^{105}0.0702	^{105}0.1110	^{105}0.1502	^{105}0.1899	^{105}0.2253	^{106}0.2614	^{105}0.3045	^{105}0.3659								
6	AYONIX-002	^{108}0.3360	^{109}0.4389	^{109}0.5144	^{109}0.5814	^{109}0.6340	^{109}0.6818	^{109}0.7297	^{110}0.7774	^{105}0.8288	^{106}0.9013	^{106}0.9375	^{106}0.9603	^{106}0.9744	^{107}0.9837	^{107}0.9893	^{107}0.9927
7	CAMVI-004	^{104}0.0623	^{104}0.0944	^{104}0.1243	^{104}0.1548	^{103}0.1812	^{103}0.2056	^{103}0.2344	^{101}0.2672	^{86}0.0810	^{86}0.1267	^{83}0.1721	^{83}0.2203	^{83}0.2619	^{81}0.3040	^{80}0.3543	^{76}0.4124
8	CAMVI-005	^{106}0.0849	^{106}0.1255	^{106}0.1631	^{106}0.1989	^{106}0.2298	^{105}0.2585	^{104}0.2915	^{104}0.3246								
9	CIB-000	^{11}0.0022	^{11}0.0030	^{12}0.0037	^{12}0.0044	^{13}0.0049	^{13}0.0057	^{13}0.0069	^{13}0.0062	^{20}0.0139	^{21}0.0240	^{22}0.0373	^{23}0.0525	^{23}0.0689	^{21}0.0859	^{21}0.1109	^{21}0.1454
10	CLOUDWALK-HR-000	^{5}0.0019	^{4}0.0024	^{5}0.0029	^{4}0.0032	^{3}0.0032	^{3}0.0036	^{1}0.0041	^{1}0.0020	^{1}0.0029	^{1}0.0041	^{1}0.0054	^{1}0.0064	^{1}0.0073	^{1}0.0085	^{1}0.0102	^{1}0.0112
11	COGENT-000	^{85}0.0128	^{86}0.0184	^{88}0.0250	^{88}0.0327	^{88}0.0407	^{87}0.0488	^{85}0.0611	^{85}0.0794	^{72}0.0559	^{74}0.0923	^{71}0.1342	^{71}0.1812	^{70}0.2243	^{70}0.2675	^{68}0.3240	^{72}0.3992
12	COGENT-001	^{86}0.0128	^{85}0.0184	^{87}0.0250	^{87}0.0327	^{87}0.0407	^{86}0.0488	^{86}0.0611	^{84}0.0794	^{73}0.0559	^{73}0.0923	^{72}0.1342	^{72}0.1812	^{71}0.2243	^{69}0.2675	^{69}0.3240	^{73}0.3992
13	COGENT-002	^{64}0.0081	^{61}0.0105	^{58}0.0123	^{59}0.0137	^{57}0.0157	^{57}0.0175	^{55}0.0215	^{55}0.0280	^{64}0.0499	^{63}0.0827	^{62}0.1207	^{62}0.1639	^{62}0.2037	^{61}0.2432	^{62}0.2972	^{63}0.3638
14	COGENT-003	^{66}0.0082	^{62}0.0108	^{60}0.0128	^{62}0.0145	^{61}0.0168	^{63}0.0191	^{64}0.0239	^{61}0.0312	^{75}0.0582	^{75}0.0971	^{75}0.1417	^{75}0.1918	^{75}0.2380	^{76}0.2836	^{78}0.3440	^{79}0.4207
15	COGENT-004	^{54}0.0066	^{48}0.0080	^{40}0.0085	^{34}0.0080	^{26}0.0083	^{26}0.0092	^{27}0.0106	^{30}0.0130	^{58}0.0410	^{60}0.0720	^{60}0.1099	^{60}0.1539	^{59}0.1974	^{62}0.2443	^{65}0.3043	^{65}0.3757
16	COGNITEC-000	^{100}0.0265	^{98}0.0423	^{98}0.0588	^{98}0.0757	^{97}0.0894	^{97}0.1014	^{97}0.1169	^{96}0.1381	^{95}0.1522	^{94}0.2330	^{94}0.3051	^{94}0.3751	^{94}0.4300	^{94}0.4779	^{93}0.5307	^{91}0.5913
17	COGNITEC-001	^{88}0.0149	^{89}0.0228	^{87}0.0312	^{87}0.0399	^{89}0.0479	^{89}0.0546	^{88}0.0656	^{86}0.0806	^{88}0.0963	^{88}0.1562	^{88}0.2157	^{88}0.2771	^{88}0.3287	^{88}0.3771	^{87}0.4343	^{86}0.4959
18	COGNITEC-002	^{72}0.0101	^{75}0.0138	^{76}0.0170	^{76}0.0201	^{76}0.0237	^{75}0.0264	^{73}0.0309	^{72}0.0389	^{67}0.0517	^{66}0.0879	^{67}0.1269	^{68}0.1707	^{66}0.2098	^{63}0.2463	^{61}0.2919	^{61}0.3535
19	COGNITEC-003	^{73}0.0104	^{76}0.0140	^{77}0.0174	^{77}0.0205	^{77}0.0238	^{76}0.0266	^{74}0.0311	^{74}0.0401	^{66}0.0504	^{65}0.0855	^{64}0.1235	^{64}0.1662	^{63}0.2045	^{60}0.2403	^{60}0.2854	^{59}0.3451
20	COGNITEC-004	^{59}0.0073	^{58}0.0099	^{57}0.0118	^{54}0.0130	^{54}0.0147	^{56}0.0163	^{52}0.0189	^{51}0.0239	^{48}0.0325	^{48}0.0548	^{47}0.0798	^{46}0.1074	^{45}0.1325	^{46}0.1591	^{43}0.1952	^{42}0.2414
21	CYBERLINK-002	^{45}0.0055	^{40}0.0068	^{36}0.0075	^{30}0.0078	^{27}0.0084	^{27}0.0094	^{28}0.0107	^{26}0.0114	^{27}0.0180	^{28}0.0302	^{28}0.0460	^{27}0.0643	^{28}0.0837	^{28}0.1058	^{27}0.1370	^{27}0.1787
22	CYBERLINK-003	^{30}0.0041	^{29}0.0052	^{22}0.0057	^{20}0.0058	^{20}0.0061	^{20}0.0068	^{16}0.0078	^{19}0.0078	^{15}0.0109	^{15}0.0175	^{16}0.0259	^{16}0.0356	^{16}0.0468	^{16}0.0594	^{16}0.0787	^{17}0.1072
23	DAHUA-002	^{26}0.0035	^{23}0.0047	^{23}0.0058	^{22}0.0067	^{23}0.0074	^{22}0.0082	^{24}0.0100	^{24}0.0108	^{25}0.0169	^{27}0.0294	^{26}0.0449	^{25}0.0635	^{25}0.0817	^{26}0.1013	^{24}0.1291	^{23}0.1638
24	DAHUA-003	^{16}0.0026	^{16}0.0036	^{16}0.0043	^{16}0.0050	^{16}0.0055	^{15}0.0062	^{18}0.0080	^{16}0.0073	^{24}0.0160	^{25}0.0280	^{24}0.0432	^{24}0.0615	^{24}0.0794	^{24}0.0987	^{23}0.1270	^{22}0.1587
25	DEEPGLINT-001	^{14}0.0024	^{13}0.0032	^{11}0.0037	^{10}0.0040	^{10}0.0043	^{11}0.0049	^{11}0.0060	^{11}0.0052	^{9}0.0058	^{7}0.0087	^{8}0.0119	^{8}0.0155	^{8}0.0199	^{9}0.0249	^{8}0.0338	^{8}0.0463
26	DEEPSEA-001	^{65}0.0081	^{65}0.0116	^{68}0.0149	^{71}0.0182	^{71}0.0216	^{74}0.0260	^{76}0.0332	^{76}0.0432	^{61}0.0458	^{61}0.0752	^{59}0.1086	^{58}0.1460	^{58}0.1812	^{58}0.2186	^{58}0.2663	^{57}0.3213
27	DERMALOG-006	^{77}0.0113	^{77}0.0142	^{73}0.0163	^{72}0.0183	^{69}0.0200	^{68}0.0218	^{66}0.0251	^{64}0.0329	^{70}0.0545	^{68}0.0889	^{68}0.1271	^{67}0.1697	^{65}0.2090	^{65}0.2498	^{64}0.3028	^{64}0.3670
28	DERMALOG-007	^{83}0.0125	^{83}0.0170	^{83}0.0214	^{83}0.0264	^{82}0.0309	^{81}0.0356	^{82}0.0432	^{82}0.0579	^{87}0.0910	^{87}0.1453	^{87}0.2009	^{87}0.2602	^{87}0.3134	^{87}0.3649	^{86}0.4289	^{87}0.5007
29	DERMALOG-008	^{47}0.0057	^{47}0.0077	^{49}0.0095	^{49}0.0110	^{48}0.0128	^{50}0.0148	^{49}0.0180	^{50}0.0223	^{65}0.0501	^{64}0.0850	^{65}0.1247	^{66}0.1692	^{67}0.2105	^{66}0.2541	^{66}0.3102	^{66}0.3762
30	GORILLA-002	^{95}0.0213	^{95}0.0359	^{96}0.0528	^{97}0.0716	^{98}0.0895	^{98}0.1088	^{98}0.1367	^{98}0.1765	^{98}0.1828	^{99}0.2787	^{99}0.3654	^{99}0.4485	^{99}0.5168	^{97}0.5823	^{97}0.6508	^{97}0.7180
31	GORILLA-005	^{33}0.0044	^{42}0.0070	^{53}0.0102	^{57}0.0136	^{62}0.0170	^{66}0.0204	^{69}0.0272	^{71}0.0373	^{74}0.0566	^{76}0.0973	^{77}0.1432	^{76}0.1937	^{76}0.2398	^{78}0.2862	^{77}0.3437	^{77}0.4150
32	IDEMIA-003	^{76}0.0110	^{81}0.0151	^{81}0.0196	^{80}0.0238	^{79}0.0281	^{79}0.0313	^{79}0.0368	^{78}0.0504	^{82}0.0717	^{81}0.1147	^{81}0.1614	^{81}0.2113	^{80}0.2553	^{80}0.2976	^{79}0.3537	^{80}0.4334
33	IDEMIA-004	^{75}0.0107	^{79}0.0148	^{80}0.0192	^{79}0.0233	^{78}0.0277	^{78}0.0312	^{78}0.0367	^{79}0.0512	^{53}0.0373	^{50}0.0587	^{49}0.0833	^{48}0.1100	^{47}0.1340	^{45}0.1580	^{42}0.1911	^{43}0.2482
34	IDEMIA-005	^{79}0.0118	^{82}0.0167	^{85}0.0218	^{84}0.0270	^{83}0.0317	^{82}0.0357	^{81}0.0425	^{81}0.0579	^{60}0.0440	^{59}0.0689	^{55}0.0964	^{54}0.1254	^{53}0.1513	^{51}0.1762	^{46}0.2113	^{47}0.2698
35	IDEMIA-006	^{82}0.0124	^{84}0.0171	^{84}0.0218	^{82}0.0263	^{81}0.0302	^{80}0.0321	^{77}0.0356	^{77}0.0471	^{57}0.0409	^{54}0.0620	^{52}0.0850	^{47}0.1097	^{44}0.1309	^{39}0.1486	^{37}0.1738	^{36}0.2200
36	IDEMIA-007	^{42}0.0050	^{43}0.0071	^{43}0.0089	^{45}0.0106	^{46}0.0124	^{46}0.0142	^{46}0.0171	^{48}0.0220	^{31}0.0202	^{31}0.0335	^{29}0.0491	^{28}0.0663	^{26}0.0825	^{25}0.0999	^{22}0.1240	^{24}0.1645
37	IDEMIA-008	^{3}0.0018	^{3}0.0024	^{3}0.0029	^{3}0.0032	^{5}0.0035	^{4}0.0039	^{4}0.0046	^{5}0.0033	^{2}0.0034	^{2}0.0051	^{3}0.0069	^{4}0.0087	^{4}0.0102	^{3}0.0123	^{2}0.0146	^{2}0.0186
38	IMAGUS-005	^{28}0.0039	^{28}0.0052	^{26}0.0061	^{24}0.0067	^{25}0.0077	^{25}0.0088	^{25}0.0103	^{25}0.0109	^{34}0.0212	^{34}0.0357	^{35}0.0539	^{35}0.0755	^{33}0.0967	^{33}0.1183	^{32}0.1485	^{30}0.1893
39	IMPERIAL-000	^{29}0.0040	^{30}0.0054	^{31}0.0067	^{33}0.0079	^{35}0.0093	^{36}0.0112	^{35}0.0139	^{37}0.0178	^{44}0.0286	^{46}0.0503	^{46}0.0779	^{49}0.1116	^{51}0.1455	^{53}0.1844	^{55}0.2341	^{54}0.2951
40	INCODE-003	^{89}0.0155	^{91}0.0247	^{91}0.0348	^{91}0.0463	^{91}0.0571	^{91}0.0674	^{91}0.0856	^{92}0.1114	^{97}0.1627	^{97}0.2507	^{97}0.3322	^{95}0.4122	^{95}0.4772	^{96}0.5368	^{96}0.6059	^{96}0.6766
41	INCODE-004	^{51}0.0061	^{54}0.0087	^{54}0.0110	^{56}0.0136	^{59}0.0161	^{59}0.0185	^{62}0.0236	^{60}0.0309	^{68}0.0532	^{69}0.0908	^{70}0.1334	^{70}0.1809	^{72}0.2245	^{71}0.2675	^{70}0.3249	^{69}0.3932
42	INNOVATRICS-004	^{109}0.3594	^{108}0.3629	^{108}0.3688	^{107}0.3754	^{107}0.3813	^{107}0.3870	^{107}0.3960	^{107}0.4135	^{102}0.4234	^{101}0.4642	^{101}0.5073	^{101}0.5522	^{100}0.5902	^{100}0.6274	^{98}0.6736	^{98}0.7253
43	INNOVATRICS-005	^{36}0.0046	^{36}0.0063	^{37}0.0078	^{40}0.0092	^{40}0.0106	^{38}0.0124	^{38}0.0149	^{38}0.0178	^{50}0.0343	^{51}0.0590	^{53}0.0886	^{53}0.1222	^{54}0.1544	^{55}0.1881	^{54}0.2321	^{52}0.2874
44	IREX-000	^{20}0.0031	^{20}0.0042	^{20}0.0051	^{21}0.0060	^{21}0.0068	^{21}0.0080	^{22}0.0095	^{23}0.0107	^{47}0.0313	^{47}0.0539	^{48}0.0815	^{51}0.1137	^{50}0.1442	^{50}0.1755	^{51}0.2181	^{48}0.2718

Table 5: **Accuracy for the FRVT 2018 mugshot sets under ageing**. *The second row shows the time lapse between gallery and subsequent probe images, in years. The first two columns identify the algorithm The next 8 values give rank-based FNIR with R = 1, T = 0 and FPIR = 1. All these are relevant to investigational uses where candidates from all searches would need human review. The second 8 values give threshold-based FNIR with T $\geq$ 0, FPIR = 0.001 and no rank criterion. The shaded cells indictate indicate the three most accurate algorithms for that elapsed time. The gallery size is 3068801. The total number of searches is 10951064.*

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MISS RATES		INVESTIGATION, FNIR(N, R = 1, T = 0)								IDENTIFICATION, FNIR(N, R = L, T $\geq$ 0) FOR FPIR = 0.001							
#	ALGORITHM	(0, 2]	(2, 4]	(4, 6]	(6, 8]	(8, 10]	(10, 12]	(12, 14]	(14, 18]	(0, 2]	(2, 4]	(4, 6]	(6, 8]	(8, 10]	(10, 12]	(12, 14]	(14, 18]
45	ISYSTEMS-002	^{71}0.0101	^{74}0.0135	^{75}0.0169	^{74}0.0197	^{75}0.0228	^{72}0.0256	^{72}0.0304	^{73}0.0398	^{85}0.0779	^{85}0.1258	^{86}0.1759	^{85}0.2299	^{85}0.2758	^{84}0.3204	^{84}0.3763	^{82}0.4401
46	ISYSTEMS-003	^{70}0.0089	^{64}0.0115	^{64}0.0139	^{64}0.0158	^{65}0.0177	^{65}0.0198	^{61}0.0234	^{58}0.0303	^{79}0.0647	^{79}0.1056	^{79}0.1502	^{79}0.1986	^{78}0.2402	^{74}0.2819	^{73}0.3351	^{71}0.3976
47	KEDACOM-001	^{78}0.0116	^{70}0.0130	^{62}0.0135	^{55}0.0133	^{52}0.0135	^{45}0.0141	^{39}0.0151	^{36}0.0176	^{36}0.0241	^{36}0.0360	^{34}0.0513	^{29}0.0689	^{29}0.0866	^{29}0.1060	^{25}0.1327	^{25}0.1694
48	LOOKMAN-003	^{81}0.0123	^{78}0.0144	^{72}0.0158	^{65}0.0168	^{66}0.0178	^{61}0.0188	^{54}0.0212	^{54}0.0260	^{59}0.0438	^{57}0.0687	^{56}0.0978	^{56}0.1296	^{55}0.1581	^{54}0.1879	^{53}0.2294	^{50}0.2756
49	LOOKMAN-005	^{80}0.0118	^{72}0.0134	^{65}0.0142	^{61}0.0144	^{56}0.0150	^{55}0.0160	^{47}0.0176	^{45}0.0213	^{46}0.0310	^{44}0.0480	^{41}0.0698	^{41}0.0954	^{41}0.1216	^{41}0.1491	^{41}0.1890	^{41}0.2381
50	MICROFOCUS-005	^{110}0.4269	^{110}0.5527	^{110}0.6355	^{111}0.7024	^{111}0.7503	^{111}0.7876	^{111}0.8234	^{112}0.8601	^{106}0.8338	^{107}0.9113	^{107}0.9468	^{107}0.9667	^{107}0.9771	^{106}0.9836	^{106}0.9880	^{106}0.9924
51	MICROSOFT-003	^{24}0.0034	^{27}0.0050	^{28}0.0064	^{31}0.0078	^{33}0.0092	^{33}0.0107	^{34}0.0135	^{35}0.0166	^{45}0.0288	^{45}0.0503	^{45}0.0763	^{45}0.1067	^{49}0.1359	^{48}0.1680	^{47}0.2116	^{45}0.2644
52	MICROSOFT-004	^{21}0.0032	^{22}0.0047	^{24}0.0060	^{27}0.0075	^{30}0.0087	^{30}0.0103	^{33}0.0131	^{33}0.0159	^{42}0.0268	^{43}0.0470	^{44}0.0716	^{43}0.1007	^{43}0.1291	^{47}0.1610	^{45}0.2052	^{44}0.2590
53	MICROSOFT-005	^{19}0.0031	^{24}0.0047	^{30}0.0066	^{38}0.0084	^{38}0.0103	^{42}0.0131	^{44}0.0164	^{40}0.0185	^{38}0.0243	^{39}0.0432	^{39}0.0658	^{39}0.0913	^{40}0.1172	^{38}0.1476	^{40}0.1874	^{38}0.2272
54	MICROSOFT-006	^{22}0.0032	^{26}0.0049	^{29}0.0065	^{37}0.0081	^{37}0.0096	^{37}0.0117	^{36}0.0144	^{34}0.0160	^{19}0.0134	^{19}0.0233	^{20}0.0346	^{18}0.0462	^{17}0.0578	^{18}0.0713	^{18}0.0903	^{18}0.1156
55	NEC-000	^{92}0.0195	^{94}0.0316	^{94}0.0445	^{94}0.0581	^{93}0.0699	^{93}0.0817	^{94}0.0998	^{94}0.1237	^{84}0.0759	^{84}0.1245	^{84}0.1729	^{84}0.2240	^{84}0.2671	^{83}0.3117	^{81}0.3639	^{81}0.4348
56	NEC-001	^{99}0.0246	^{97}0.0382	^{95}0.0524	^{95}0.0672	^{96}0.0793	^{96}0.0904	^{95}0.1076	^{95}0.1317	^{89}0.1019	^{89}0.1623	^{89}0.2214	^{89}0.2834	^{89}0.3341	^{89}0.3844	^{89}0.4440	^{88}0.5183
57	NEC-002	^{23}0.0033	^{19}0.0041	^{15}0.0043	^{13}0.0044	^{11}0.0045	^{10}0.0049	^{10}0.0056	^{7}0.0041	^{12}0.0066	^{8}0.0090	^{7}0.0111	^{7}0.0131	^{6}0.0149	^{6}0.0171	^{7}0.0207	^{7}0.0267
58	NEC-003	^{27}0.0036	^{21}0.0046	^{19}0.0051	^{19}0.0055	^{19}0.0059	^{16}0.0067	^{15}0.0077	^{17}0.0073	^{6}0.0056	^{6}0.0076	^{6}0.0091	^{5}0.0105	^{5}0.0119	^{5}0.0137	^{4}0.0162	^{4}0.0209
59	NEUROTECHNOLOGY-003	^{96}0.0234	^{96}0.0379	^{97}0.0549	^{96}0.0682	^{95}0.0720	^{93}0.0747	^{93}0.0886	^{91}0.1066	^{104}0.6802	^{104}0.8187	^{105}0.8920	^{105}0.9355	^{105}0.9594	^{105}0.9738	^{105}0.9828	^{105}0.9885
60	NEUROTECHNOLOGY-004	^{74}0.0104	^{73}0.0134	^{71}0.0156	^{68}0.0173	^{67}0.0195	^{67}0.0212	^{65}0.0245	^{62}0.0320	^{78}0.0642	^{77}0.1015	^{76}0.1426	^{74}0.1881	^{73}0.2299	^{72}0.2722	^{71}0.3269	^{70}0.3943
61	NEUROTECHNOLOGY-005	^{69}0.0089	^{66}0.0116	^{63}0.0136	^{63}0.0152	^{64}0.0173	^{64}0.0196	^{60}0.0233	^{59}0.0306	^{71}0.0556	^{71}0.0913	^{69}0.1315	^{69}0.1766	^{69}0.2192	^{68}0.2617	^{67}0.3174	^{67}0.3843
62	NEUROTECHNOLOGY-007	^{61}0.0078	^{60}0.0103	^{59}0.0124	^{60}0.0140	^{58}0.0161	^{58}0.0185	^{57}0.0225	^{56}0.0290	^{77}0.0641	^{80}0.1069	^{80}0.1546	^{80}0.2075	^{81}0.2572	^{82}0.3081	^{83}0.3713	^{83}0.4421
63	NOBLIS-002	^{107}0.1520	^{107}0.2419	^{107}0.3296	^{108}0.4114	^{108}0.4856	^{108}0.5528	^{108}0.6061	^{108}0.6532	^{108}0.9984	^{108}0.9996	^{108}0.9998	^{108}0.9999	^{108}0.9999	^{108}1.0000	^{109}1.0000	^{108}1.0000
64	NTECHLAB-003	^{60}0.0078	^{71}0.0131	^{82}0.0202	^{85}0.0295	^{86}0.0405	^{88}0.0543	^{89}0.0761	^{90}0.1035	^{63}0.0491	^{67}0.0881	^{74}0.1384	^{78}0.1985	^{82}0.2594	^{85}0.3270	^{85}0.4065	^{85}0.4891
65	NTECHLAB-004	^{57}0.0068	^{63}0.0110	^{74}0.0167	^{81}0.0239	^{84}0.0330	^{85}0.0447	^{87}0.0641	^{88}0.0891	^{55}0.0379	^{58}0.0688	^{61}0.1108	^{61}0.1629	^{68}0.2192	^{77}0.2846	^{82}0.3657	^{84}0.4524
66	NTECHLAB-006	^{46}0.0056	^{57}0.0095	^{67}0.0148	^{78}0.0218	^{80}0.0301	^{83}0.0413	^{84}0.0591	^{87}0.0814	^{51}0.0349	^{55}0.0636	^{58}0.1023	^{59}0.1506	^{61}0.2024	^{67}0.2617	^{74}0.3374	^{78}0.4185
67	NTECHLAB-007	^{32}0.0044	^{38}0.0066	^{44}0.0089	^{52}0.0118	^{55}0.0150	^{62}0.0189	^{67}0.0255	^{67}0.0342	^{40}0.0256	^{41}0.0450	^{43}0.0705	^{44}0.1012	^{46}0.1334	^{49}0.1692	^{48}0.2170	^{49}0.2752
68	NTECHLAB-008	^{15}0.0025	^{18}0.0038	^{21}0.0052	^{26}0.0074	^{39}0.0104	^{47}0.0146	^{63}0.0236	^{68}0.0348	^{21}0.0143	^{23}0.0267	^{27}0.0459	^{32}0.0733	^{35}0.1062	^{37}0.1469	^{44}0.2044	^{46}0.2698
69	NTECHLAB-009	^{10}0.0022	^{12}0.0031	^{13}0.0038	^{14}0.0045	^{15}0.0055	^{18}0.0067	^{20}0.0088	^{22}0.0100	^{14}0.0073	^{14}0.0117	^{14}0.0170	^{14}0.0238	^{15}0.0319	^{15}0.0419	^{15}0.0577	^{15}0.0833
70	PARAVISION-002	^{48}0.0058	^{53}0.0083	^{55}0.0111	^{58}0.0137	^{60}0.0162	^{60}0.0187	^{59}0.0229	^{57}0.0295								
71	PARAVISION-003	^{39}0.0048	^{39}0.0067	^{46}0.0090	^{47}0.0109	^{49}0.0128	^{48}0.0148	^{48}0.0178	^{46}0.0219	^{52}0.0354	^{53}0.0618	^{54}0.0931	^{55}0.1290	^{56}0.1625	^{56}0.1964	^{56}0.2408	^{53}0.2924
72	PARAVISION-004	^{13}0.0024	^{14}0.0032	^{14}0.0040	^{15}0.0047	^{14}0.0053	^{14}0.0061	^{14}0.0073	^{15}0.0072	^{16}0.0118	^{18}0.0209	^{19}0.0327	^{19}0.0465	^{19}0.0613	^{19}0.0779	^{19}0.1008	^{19}0.1285
73	PARAVISION-005	^{9}0.0021	^{10}0.0028	^{10}0.0035	^{11}0.0041	^{12}0.0046	^{12}0.0054	^{12}0.0067	^{14}0.0070	^{8}0.0057	^{9}0.0093	^{9}0.0144	^{11}0.0207	^{12}0.0278	^{12}0.0368	^{13}0.0508	^{13}0.0715
74	PARAVISION-007	^{4}0.0019	^{5}0.0025	^{4}0.0029	^{6}0.0033	^{6}0.0036	^{6}0.0042	^{6}0.0049	^{4}0.0030	^{7}0.0057	^{10}0.0094	^{11}0.0144	^{10}0.0206	^{11}0.0275	^{11}0.0357	^{11}0.0485	^{11}0.0652
75	PIXELALL-002	^{67}0.0085	^{68}0.0119	^{66}0.0147	^{67}0.0172	^{68}0.0198	^{69}0.0225	^{68}0.0270	^{69}0.0349	^{92}0.1193	^{92}0.1900	^{92}0.2601	^{92}0.3332	^{92}0.3955	^{92}0.4565	^{92}0.5268	^{93}0.6030
76	PIXELALL-003	^{41}0.0050	^{37}0.0063	^{34}0.0072	^{29}0.0077	^{28}0.0085	^{28}0.0095	^{29}0.0113	^{27}0.0119	^{39}0.0248	^{38}0.0418	^{38}0.0622	^{38}0.0861	^{38}0.1104	^{35}0.1364	^{35}0.1723	^{34}0.2167
77	PIXELALL-004	^{40}0.0049	^{35}0.0063	^{35}0.0072	^{32}0.0079	^{31}0.0089	^{32}0.0103	^{32}0.0127	^{31}0.0146	^{33}0.0211	^{35}0.0360	^{37}0.0553	^{37}0.0792	^{34}0.1045	^{34}0.1317	^{34}0.1700	^{37}0.2246
78	PTAKURATSATU-000	^{49}0.0061	^{50}0.0082	^{50}0.0097	^{48}0.0109	^{44}0.0120	^{41}0.0131	^{37}0.0146	^{39}0.0180	^{54}0.0375	^{52}0.0596	^{50}0.0842	^{50}0.1116	^{48}0.1357	^{44}0.1553	^{38}0.1820	^{40}0.2326
79	RANKONE-002	^{94}0.0212	^{93}0.0313	^{93}0.0431	^{93}0.0562	^{94}0.0712	^{95}0.0881	^{96}0.1130	^{97}0.1543	^{90}0.1111	^{90}0.1707	^{90}0.2305	^{90}0.2968	^{91}0.3646	^{91}0.4345	^{91}0.5172	^{94}0.6110
80	RANKONE-004	^{103}0.0424	^{102}0.0643	^{102}0.0875	^{102}0.1127	^{102}0.1364	^{100}0.1579	^{100}0.1914	^{100}0.2378	^{99}0.1855	^{98}0.2681	^{98}0.3431	^{96}0.4155	^{96}0.4785	^{95}0.5350	^{95}0.5980	^{95}0.6722
81	RANKONE-005	^{87}0.0136	^{88}0.0192	^{86}0.0246	^{86}0.0303	^{85}0.0362	^{84}0.0422	^{83}0.0521	^{83}0.0694	^{76}0.0582	^{70}0.0910	^{66}0.1260	^{63}0.1645	^{60}0.2005	^{59}0.2353	^{59}0.2816	^{60}0.3522
82	RANKONE-007	^{62}0.0078	^{59}0.0099	^{56}0.0113	^{53}0.0123	^{53}0.0139	^{54}0.0156	^{53}0.0191	^{52}0.0242	^{37}0.0242	^{37}0.0376	^{36}0.0542	^{33}0.0737	^{32}0.0935	^{31}0.1130	^{29}0.1416	^{29}0.1811
83	RANKONE-009	^{43}0.0054	^{44}0.0072	^{41}0.0085	^{42}0.0098	^{42}0.0113	^{40}0.0130	^{45}0.0169	^{49}0.0220	^{32}0.0208	^{33}0.0345	^{32}0.0504	^{31}0.0706	^{31}0.0930	^{32}0.1174	^{33}0.1504	^{32}0.2002
84	RANKONE-010	^{37}0.0047	^{33}0.0061	^{33}0.0070	^{28}0.0076	^{29}0.0087	^{29}0.0098	^{30}0.0113	^{28}0.0120	^{26}0.0177	^{24}0.0269	^{21}0.0368	^{21}0.0479	^{18}0.0590	^{17}0.0688	^{17}0.0803	^{16}0.0991
85	REALNETWORKS-002	^{102}0.0381	^{103}0.0687	^{103}0.1062	^{103}0.1495	^{104}0.1963	^{104}0.2513	^{106}0.3206	^{106}0.3927	^{100}0.2153	^{100}0.3323	^{100}0.4444	^{100}0.5485	^{101}0.6355	^{101}0.7132	^{102}0.7855	^{102}0.8437
86	REALNETWORKS-003	^{98}0.0245	^{100}0.0437	^{100}0.0686	^{101}0.0975	^{101}0.1312	^{102}0.1719	^{102}0.2294	^{103}0.2907	^{93}0.1468	^{95}0.2370	^{96}0.3313	^{98}0.4269	^{98}0.5142	^{99}0.5979	^{100}0.6815	^{100}0.7567
87	REALNETWORKS-004	^{97}0.0244	^{99}0.0428	^{99}0.0663	^{100}0.0939	^{100}0.1251	^{101}0.1634	^{101}0.2170	^{102}0.2785	^{94}0.1484	^{96}0.2377	^{95}0.3303	^{97}0.4249	^{97}0.5106	^{98}0.5924	^{99}0.6758	^{99}0.7534
88	SCANOVATE-001	^{63}0.0079	^{67}0.0117	^{70}0.0151	^{73}0.0185	^{73}0.0221	^{73}0.0259	^{75}0.0321	^{75}0.0427	^{83}0.0727	^{83}0.1169	^{82}0.1650	^{82}0.2115	^{79}0.2528	^{79}0.2925	^{76}0.3437	^{75}0.4084

Table 6: **Accuracy for the FRVT 2018 mugshot sets under ageing**. *The second row shows the time lapse between gallery and subsequent probe images, in years. The first two columns identify the algorithm The next 8 values give rank-based FNIR with R = 1, T = 0 and FPIR = 1. All these are relevant to investigational uses where candidates from all searches would need human review. The second 8 values give threshold-based FNIR with T $\geq$ 0, FPIR = 0.001 and no rank criterion. The shaded cells indictate indicate the three most accurate algorithms for that elapsed time. The gallery size is 3068801. The total number of searches is 10951064.*

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MISS RATES		INVESTIGATION, FNIR(N, R = 1, T = 0)								IDENTIFICATION, FNIR(N, R = L, T $\geq$ 0) FOR FPIR = 0.001							
#	ALGORITHM	(0, 2]	(2, 4]	(4, 6]	(6, 8]	(8, 10]	(10, 12]	(12, 14]	(14, 18]	(0, 2]	(2, 4]	(4, 6]	(6, 8]	(8, 10]	(10, 12]	(12, 14]	(14, 18]
89	SENSETIME-002	^{91}0.0186	^{87}0.0191	^{79}0.0183	^{70}0.0179	^{63}0.0173	^{43}0.0133	^{21}0.0089	^{12}0.0059	^{35}0.0220	^{20}0.0236	^{15}0.0237	^{15}0.0240	^{9}0.0245	^{7}0.0219	^{6}0.0195	^{5}0.0222
90	SENSETIME-003	^{8}0.0021	^{9}0.0028	^{8}0.0031	^{5}0.0033	^{4}0.0035	^{5}0.0040	^{5}0.0047	^{6}0.0033	^{5}0.0046	^{5}0.0064	^{4}0.0076	^{3}0.0086	^{3}0.0101	^{2}0.0122	^{3}0.0155	^{3}0.0196
91	SENSETIME-004	^{2}0.0016	^{2}0.0022	^{2}0.0025	^{2}0.0028	^{2}0.0030	^{2}0.0035	^{3}0.0043	^{2}0.0025	^{3}0.0036	^{3}0.0052	^{2}0.0066	^{2}0.0081	^{2}0.0099	^{4}0.0126	^{5}0.0169	^{6}0.0230
92	SENSETIME-005	^{1}0.0015	^{1}0.0020	^{1}0.0024	^{1}0.0026	^{1}0.0029	^{1}0.0035	^{2}0.0043	^{3}0.0028	^{4}0.0036	^{4}0.0059	^{5}0.0089	^{6}0.0128	^{7}0.0177	^{8}0.0240	^{9}0.0345	^{9}0.0493
93	SIAT-002	^{112}0.8309	^{112}0.8310	^{112}0.8311	^{112}0.8306	^{112}0.8296	^{112}0.8302	^{112}0.8300	^{111}0.8301	^{107}0.8340	^{105}0.8368	^{104}0.8404	^{104}0.8445	^{104}0.8480	^{104}0.8532	^{104}0.8595	^{103}0.8691
94	SYNESIS-003	^{84}0.0125	^{80}0.0151	^{78}0.0174	^{75}0.0199	^{74}0.0223	^{70}0.0240	^{70}0.0279	^{65}0.0331	^{80}0.0658	^{78}0.1052	^{78}0.1483	^{77}0.1968	^{77}0.2399	^{75}0.2834	^{75}0.3405	^{74}0.4046
95	SYNESIS-005	^{35}0.0044	^{32}0.0058	^{32}0.0070	^{35}0.0080	^{32}0.0091	^{31}0.0103	^{31}0.0125	^{32}0.0152	^{41}0.0262	^{40}0.0444	^{40}0.0666	^{40}0.0923	^{39}0.1156	^{36}0.1399	^{36}0.1736	^{35}0.2185
96	TECH5-001	^{52}0.0061	^{56}0.0093	^{61}0.0128	^{66}0.0171	^{72}0.0221	^{77}0.0289	^{80}0.0412	^{80}0.0560	^{81}0.0660	^{82}0.1156	^{85}0.1733	^{86}0.2385	^{86}0.2998	^{86}0.3629	^{88}0.4424	^{89}0.5284
97	TOSHIBA-001	^{68}0.0086	^{69}0.0119	^{69}0.0150	^{69}0.0178	^{70}0.0209	^{71}0.0241	^{71}0.0292	^{70}0.0365								
98	TRUEFACE-000	^{31}0.0043	^{31}0.0057	^{25}0.0061	^{23}0.0067	^{22}0.0073	^{23}0.0084	^{23}0.0097	^{21}0.0099	^{30}0.0200	^{32}0.0338	^{33}0.0504	^{30}0.0705	^{30}0.0904	^{30}0.1112	^{28}0.1401	^{28}0.1792
99	VERIDAS-001	^{53}0.0063	^{51}0.0083	^{51}0.0099	^{51}0.0113	^{51}0.0132	^{49}0.0148	^{50}0.0184	^{47}0.0219	^{56}0.0403	^{56}0.0684	^{57}0.1012	^{57}0.1386	^{57}0.1741	^{57}0.2113	^{57}0.2611	^{58}0.3233
100	VISIONLABS-004	^{38}0.0048	^{41}0.0069	^{47}0.0091	^{50}0.0111	^{50}0.0130	^{52}0.0152	^{51}0.0187	^{53}0.0242	^{69}0.0540	^{72}0.0916	^{73}0.1358	^{73}0.1855	^{74}0.2303	^{73}0.2745	^{72}0.3312	^{68}0.3913
101	VISIONLABS-005	^{34}0.0044	^{34}0.0063	^{38}0.0081	^{41}0.0095	^{41}0.0109	^{39}0.0125	^{40}0.0151	^{41}0.0187	^{62}0.0479	^{62}0.0812	^{63}0.1212	^{65}0.1664	^{64}0.2078	^{64}0.2473	^{63}0.2999	^{62}0.3577
102	VISIONLABS-006	^{25}0.0035	^{25}0.0048	^{27}0.0061	^{25}0.0069	^{24}0.0077	^{24}0.0087	^{26}0.0105	^{29}0.0120	^{43}0.0273	^{42}0.0465	^{42}0.0702	^{42}0.0970	^{42}0.1228	^{40}0.1486	^{39}0.1847	^{39}0.2295
103	VISIONLABS-008	^{18}0.0028	^{17}0.0037	^{18}0.0047	^{18}0.0053	^{18}0.0058	^{17}0.0067	^{19}0.0081	^{20}0.0085	^{22}0.0143	^{22}0.0241	^{23}0.0373	^{22}0.0519	^{22}0.0677	^{20}0.0850	^{20}0.1104	^{20}0.1444
104	VISIONLABS-009	^{7}0.0020	^{7}0.0026	^{7}0.0030	^{7}0.0034	^{8}0.0038	^{8}0.0044	^{9}0.0052	^{9}0.0046	^{11}0.0065	^{12}0.0105	^{12}0.0156	^{12}0.0217	^{13}0.0289	^{13}0.0368	^{12}0.0499	^{12}0.0681
105	VISIONLABS-010	^{6}0.0020	^{6}0.0025	^{6}0.0030	^{8}0.0034	^{7}0.0036	^{7}0.0043	^{7}0.0051	^{10}0.0047	^{13}0.0069	^{13}0.0113	^{13}0.0170	^{13}0.0238	^{14}0.0316	^{14}0.0411	^{14}0.0557	^{14}0.0740
106	VTS-000	^{111}0.5878	^{111}0.6312	^{111}0.6602	^{110}0.6863	^{110}0.7073	^{110}0.7246	^{110}0.7458	^{109}0.7747	^{103}0.5929	^{103}0.6397	^{103}0.6729	^{103}0.7034	^{102}0.7279	^{102}0.7493	^{101}0.7739	^{101}0.8076
107	XFORWARDAI-000	^{17}0.0027	^{15}0.0034	^{17}0.0044	^{17}0.0052	^{17}0.0058	^{19}0.0067	^{17}0.0079	^{18}0.0076	^{23}0.0157	^{26}0.0281	^{25}0.0443	^{26}0.0635	^{27}0.0834	^{27}0.1050	^{26}0.1330	^{26}0.1714
108	XFORWARDAI-001	^{12}0.0023	^{8}0.0028	^{9}0.0034	^{9}0.0037	^{9}0.0039	^{9}0.0045	^{8}0.0052	^{8}0.0043	^{10}0.0060	^{11}0.0096	^{10}0.0144	^{9}0.0200	^{10}0.0260	^{10}0.0334	^{10}0.0435	^{10}0.0586
109	YITU-002	^{55}0.0066	^{52}0.0083	^{48}0.0094	^{43}0.0101	^{45}0.0121	^{51}0.0150	^{56}0.0223	^{63}0.0328	^{28}0.0189	^{29}0.0317	^{30}0.0494	^{34}0.0750	^{36}0.1066	^{42}0.1494	^{49}0.2171	^{55}0.2958
110	YITU-003	^{58}0.0072	^{55}0.0089	^{52}0.0100	^{46}0.0107	^{47}0.0125	^{53}0.0153	^{58}0.0226	^{66}0.0334	^{29}0.0194	^{30}0.0321	^{31}0.0500	^{36}0.0756	^{37}0.1071	^{43}0.1500	^{50}0.2177	^{56}0.2964
111	YITU-004	^{50}0.0061	^{46}0.0075	^{39}0.0081	^{36}0.0081	^{34}0.0092	^{34}0.0107	^{42}0.0154	^{44}0.0207	^{18}0.0125	^{17}0.0204	^{18}0.0314	^{20}0.0469	^{21}0.0671	^{23}0.0955	^{31}0.1421	^{33}0.2006
112	YITU-005	^{56}0.0067	^{49}0.0080	^{42}0.0087	^{39}0.0085	^{36}0.0094	^{35}0.0108	^{41}0.0151	^{43}0.0204	^{17}0.0124	^{16}0.0198	^{17}0.0308	^{17}0.0462	^{20}0.0667	^{22}0.0953	^{30}0.1418	^{31}0.1930

Table 7: **Accuracy for the FRVT 2018 mugshot sets under ageing**. *The second row shows the time lapse between gallery and subsequent probe images, in years. The first two columns identify the algorithm The next 8 values give rank-based FNIR with R = 1, T = 0 and FPIR = 1. All these are relevant to investigational uses where candidates from all searches would need human review. The second 8 values give threshold-based FNIR with T $\geq$ 0, FPIR = 0.001 and no rank criterion. The shaded cells indictate indicate the three most accurate algorithms for that elapsed time. The gallery size is 3068801. The total number of searches is 10951064.*

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		INVESTIGATION MODE						IDENTIFICATION MODE						FAILURE TO EXTRACT				
		RANK ONE MISS RATE, FNIR(N, 0, 1)						HIGH T ⟶ FPIR = 0.001, FNIR(N, T, L)						FEATURES				
		N=1.6M						N=1.6M										
#	ALGORITHM	MUGSHOT	WEBCAM	PROFILE	BORDER	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK
1	3DIVI-003	^{191}0.083	^{187}0.206		^{119}0.141		^{125}0.474	^{187}0.400	^{185}0.626		^{121}0.605		^{100}0.821	0.002	0.005			
2	3DIVI-004	^{152}0.018	^{161}0.062		^{102}0.035		^{106}0.279	^{161}0.169	^{166}0.343		^{104}0.277		^{80}0.607	0.002	0.005			
3	3DIVI-005	^{153}0.018	^{160}0.062	^{129}0.930	^{137}0.821		^{107}0.279	^{158}0.166	^{164}0.339	^{98}0.996	^{126}0.864		^{79}0.597	0.002	0.005	0.442		
4	3DIVI-006	^{163}0.024	^{168}0.074		^{104}0.047		^{115}0.312	^{160}0.168	^{165}0.342		^{105}0.283		^{83}0.615	0.002	0.005			
5	ACER-000	^{132}0.011	^{125}0.036	^{111}0.827	^{90}0.025		^{91}0.209	^{151}0.146	^{144}0.246	^{62}0.981	^{99}0.201		^{69}0.490	0.000	0.000	0.042		
6	ALCHERA-000	^{148}0.016	^{148}0.047	^{118}0.870	^{103}0.046		^{112}0.292	^{148}0.138	^{132}0.216	^{112}0.999	^{96}0.176		^{96}0.803	0.006	0.014	0.328		
7	ALCHERA-001	^{217}0.987	^{213}1.000		^{139}1.000		^{150}1.000	^{214}0.999	^{218}1.000		^{209}1.000		^{155}1.000	0.006	0.013	0.324		
8	ALCHERA-002	^{192}0.095	^{184}0.166	^{142}0.954	^{134}0.668		^{123}0.446	^{194}0.486	^{182}0.591	^{133}1.000	^{125}0.827		^{97}0.811	0.001	0.002	0.106		
9	ALCHERA-003	^{129}0.010	^{123}0.035	^{88}0.741	^{83}0.016		^{89}0.206	^{152}0.155	^{141}0.239	^{120}0.999	^{95}0.172		^{66}0.464	0.001	0.002	0.106		
10	ALLGOVISION-000	^{135}0.011	^{120}0.033	^{121}0.894	^{87}0.021		^{109}0.282	^{128}0.088	^{121}0.166	^{76}0.990	^{80}0.117		^{74}0.526	0.002	0.003	0.122		
11	ALLGOVISION-001	^{120}0.009	^{133}0.038	^{78}0.661	^{86}0.021		^{101}0.241	^{133}0.102	^{135}0.221	^{68}0.986	^{90}0.150		^{70}0.491	0.001	0.001	0.042		
12	ANKE-000	^{143}0.013	^{129}0.038	^{132}0.931	^{142}1.000		^{188}1.000	^{138}0.117	^{134}0.220	^{81}0.994	^{177}1.000		^{198}1.000	0.000	0.001	0.080		
13	ANKE-001	^{144}0.013	^{128}0.038	^{137}0.946	^{157}1.000		^{193}1.000	^{142}0.119	^{133}0.220	^{85}0.994	^{160}1.000		^{217}1.000	0.000	0.001	0.080		
14	ANKE-002	^{59}0.003	^{61}0.016	^{60}0.522	^{39}0.005		^{52}0.119	^{63}0.032	^{52}0.079	^{40}0.948	^{40}0.034		^{31}0.245	0.001	0.001	0.049		
15	AWARE-003	^{170}0.031	^{173}0.090	^{154}0.966	^{125}0.316		^{111}0.290	^{146}0.128	^{158}0.298	^{66}0.984	^{113}0.428		^{75}0.530	0.004	0.003	0.874		
16	AWARE-004	^{186}0.068	^{186}0.176	^{161}0.976	^{117}0.122		^{121}0.414	^{174}0.269	^{178}0.509	^{135}1.000	^{110}0.397		^{98}0.816	0.003	0.003	0.776		
17	AWARE-005	^{171}0.031	^{162}0.067	^{162}0.978	^{106}0.048		^{114}0.308	^{182}0.364	^{145}0.253	^{137}1.000	^{103}0.255		^{107}0.916	0.001	0.002	0.189		
18	AWARE-006	^{188}0.070	^{180}0.128	^{164}0.983	^{116}0.111		^{122}0.421	^{175}0.276	^{169}0.398	^{129}0.999	^{108}0.368		^{90}0.749	0.001	0.002	0.189		
19	AYONIX-000	^{211}0.450	^{208}0.685	^{173}0.996	^{133}0.607		^{136}0.867	^{203}0.811	^{200}0.939	^{103}0.998	^{130}0.954		^{116}0.982	0.010	0.031	0.939		
20	AYONIX-001	^{207}0.341	^{201}0.527	^{168}0.993	^{138}0.994		^{134}0.778	^{205}0.824	^{195}0.920	^{125}0.999	^{134}0.999		^{113}0.969	0.010	0.031	0.939		
21	AYONIX-002	^{206}0.341	^{202}0.527	^{169}0.993	^{129}0.464		^{133}0.778	^{204}0.824	^{196}0.920	^{127}0.999	^{127}0.915		^{114}0.969	0.010	0.031	0.939		
22	CAMVI-003	^{182}0.052	^{174}0.090	^{123}0.911	^{113}0.093		^{118}0.360	^{112}0.071	^{99}0.132	^{48}0.970	^{79}0.114		^{58}0.402	0.006	0.013	0.675		
23	CAMVI-004	^{180}0.047	^{169}0.077	^{90}0.744	^{112}0.072		^{113}0.296	^{113}0.072	^{101}0.136	^{123}0.999	^{78}0.100		^{94}0.787	0.000	0.000	0.000		
24	CAMVI-005	^{185}0.065	^{178}0.103	^{92}0.746	^{114}0.098		^{117}0.341	^{132}0.099	^{128}0.179	^{132}1.000	^{91}0.156		^{123}0.999	0.000	0.000	0.000		
25	CIB-000	^{17}0.002	^{9}0.008	^{12}0.100	^{6}0.002	^{8}0.011	^{2}0.069	^{24}0.012	^{24}0.045	^{141}1.000	^{21}0.017	^{14}0.141	^{105}0.894	0.000	0.000	0.000		0.000
26	CLOUDWALK-HR-000	^{14}0.001	^{18}0.010	^{3}0.064	^{4}0.002	^{2}0.006	^{1}0.057	^{4}0.002	^{4}0.013	^{1}0.133	^{2}0.005	^{1}0.033	^{2}0.099	0.001	0.000	0.042		0.000
27	COGENT-000	^{131}0.010	^{146}0.046	^{153}0.965				^{90}0.053	^{102}0.140	^{91}0.995				0.000	0.000	0.000		
28	COGENT-001	^{130}0.010	^{145}0.046	^{152}0.965				^{91}0.053	^{103}0.140	^{90}0.995				0.000	0.000	0.000		
29	COGENT-002	^{72}0.004	^{84}0.020	^{127}0.925				^{78}0.044	^{73}0.098	^{102}0.998				0.000	0.000	0.000		
30	COGENT-003	^{74}0.004	^{88}0.021	^{136}0.939				^{82}0.046	^{68}0.095	^{104}0.998				0.000	0.000	0.000		
31	COGENT-004	^{34}0.002	^{38}0.013	^{126}0.922	^{33}0.004	^{13}0.019	^{48}0.113	^{64}0.033	^{29}0.051	^{100}0.997	^{25}0.022	^{13}0.126	^{65}0.456	0.000	0.000	0.000		0.000
32	COGNITEC-000	^{165}0.025	^{157}0.059	^{150}0.964				^{156}0.161	^{159}0.303	^{78}0.992				0.003	0.002	0.924		
33	COGNITEC-001	^{136}0.012	^{122}0.034	^{145}0.958				^{134}0.102	^{139}0.230	^{218}1.000				0.003	0.002	0.924		
34	COGNITEC-002	^{97}0.006	^{108}0.025	^{139}0.949				^{93}0.053	^{127}0.178	^{142}1.000				0.003	0.002	0.924		
35	COGNITEC-003	^{101}0.006	^{107}0.025	^{131}0.930				^{89}0.053	^{119}0.162	^{143}1.000				0.004	0.002	0.878		
36	COGNITEC-004	^{65}0.003	^{60}0.016	^{108}0.813	^{78}0.013	^{22}0.057	^{69}0.143	^{62}0.031	^{71}0.097	^{73}0.990	^{67}0.068	^{29}0.316	^{39}0.288	0.002	0.001	0.635		0.006
37	CYBERLINK-000	^{76}0.004	^{83}0.020	^{86}0.717	^{61}0.007		^{63}0.134	^{99}0.056	^{84}0.116	^{93}0.995	^{65}0.063		^{51}0.339	0.001	0.001	0.063		
38	CYBERLINK-001	^{70}0.004	^{72}0.018	^{87}0.731	^{56}0.007		^{62}0.133	^{94}0.054	^{81}0.109	^{89}0.995	^{62}0.062		^{84}0.652	0.000	0.000	0.040		
39	CYBERLINK-002	^{54}0.003	^{29}0.012	^{71}0.577	^{31}0.004		^{41}0.107	^{30}0.015	^{32}0.053	^{72}0.988	^{26}0.024		^{40}0.288	0.001	0.000	0.042		
40	CYBERLINK-003	^{19}0.002	^{13}0.009	^{53}0.474	^{17}0.003	^{9}0.012	^{15}0.082	^{16}0.008	^{20}0.035	^{50}0.972	^{15}0.012	^{10}0.100	^{53}0.368	0.000	0.000	0.039		0.000
41	DAHUA-000	^{124}0.009	^{110}0.026					^{124}0.086	^{100}0.135					0.004	0.003			
42	DAHUA-001	^{105}0.007	^{102}0.024	^{85}0.703				^{115}0.073	^{92}0.122	^{60}0.980				0.002	0.002	0.346		
43	DAHUA-002	^{26}0.002	^{28}0.012	^{34}0.304	^{14}0.003		^{16}0.084	^{31}0.015	^{26}0.046	^{16}0.638	^{20}0.017		^{15}0.159	0.001	0.000	0.099		
44	DAHUA-003	^{8}0.001	^{6}0.007	^{22}0.206	^{5}0.002	^{6}0.009	^{6}0.073	^{27}0.014	^{23}0.041	^{14}0.579	^{16}0.013	^{8}0.081	^{11}0.134	0.000	0.000	0.000		0.000
45	DEEPGLINT-001	^{13}0.001	^{5}0.007	^{21}0.200	^{12}0.002		^{7}0.073	^{9}0.003	^{5}0.014	^{130}1.000	^{5}0.006		^{14}0.159	0.000	0.000	0.038		
46	DEEPSEA-001	^{81}0.004	^{58}0.016	^{109}0.814	^{67}0.010		^{68}0.140	^{81}0.046	^{75}0.101	^{67}0.985	^{71}0.077		^{49}0.326	0.000	0.001	0.047		

Table 8: **Miss rates by dataset:** *At left, rank 1 miss rates relevant to investigations; at right, with threshold set to target FPIR = 0.01 for higher volume, low prior, uses. Yellow indicates most accurate algorithm. Throughout blue superscripts indicate the rank of the algorithm for that column.*

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		INVESTIGATION MODE						IDENTIFICATION MODE						FAILURE TO EXTRACT				
		RANK ONE MISS RATE, FNIR(N, 0, 1)						HIGH T → FPIR = 0.001, FNIR(N, T, L)						FEATURES				
		N=1.6M						N=1.6M										
#	ALGORITHM	MUGSHOT	WEBCAM	PROFILE	BORDER	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK
47	DERMALOG-003	^{196}0.126	^{189}0.217		^{124}0.296		^{128}0.560	^{193}0.482	^{187}0.655		^{124}0.677		^{103}0.870	0.002	0.002	0.103		
48	DERMALOG-004	^{195}0.125	^{188}0.215	^{130}0.930	^{118}0.135		^{124}0.467	^{192}0.480	^{188}0.657	^{94}0.995	^{120}0.603		^{102}0.856	0.001	0.002	0.107		
49	DERMALOG-005	^{147}0.015	^{127}0.037	^{84}0.701	^{123}0.242		^{120}0.384	^{127}0.088	^{112}0.154	^{75}0.990	^{106}0.300		^{82}0.614	0.001	0.002	0.102		
50	DERMALOG-006	^{115}0.008	^{106}0.024	^{76}0.619	^{68}0.010		^{76}0.155	^{88}0.052	^{77}0.105	^{61}0.981	^{60}0.059		^{48}0.318	0.003	0.006	0.181		
51	DERMALOG-007	^{123}0.009	^{111}0.027	^{80}0.675	^{80}0.014		^{79}0.170	^{125}0.086	^{110}0.152	^{74}0.990	^{77}0.099		^{78}0.557	0.001	0.002	0.102		
52	DERMALOG-008	^{60}0.003	^{50}0.015	^{59}0.516	^{54}0.007	^{21}0.029	^{67}0.139	^{80}0.045	^{65}0.094	^{157}1.000	^{57}0.057	^{32}0.382	^{111}0.940	0.000	0.000	0.002		0.000
53	EYEDEA-003	^{190}0.080	^{182}0.148	^{148}0.960	^{115}0.101		^{119}0.379	^{184}0.388	^{180}0.543	^{86}0.994	^{118}0.570		^{95}0.792	0.001	0.003	0.161		
54	F8-001	^{140}0.012		^{79}0.669	^{212}1.000		^{175}1.000	^{157}0.166		^{111}0.998				0.004	1.000	0.158		
55	GLORY-000	^{200}0.178	^{195}0.320	^{172}0.994	^{122}0.228		^{130}0.678	^{183}0.367	^{181}0.547	^{88}0.995	^{115}0.453		^{101}0.839	0.011	0.013	0.985		
56	GLORY-001	^{197}0.127	^{192}0.267	^{167}0.992	^{121}0.178		^{129}0.594	^{176}0.305	^{179}0.537	^{79}0.993	^{112}0.408		^{99}0.819	0.011	0.013	0.988		
57	GORILLA-001	^{183}0.060	^{175}0.095	^{134}0.936	^{110}0.069		^{116}0.329	^{188}0.406	^{174}0.453	^{152}1.000	^{116}0.468		^{152}1.000	0.001	0.001	0.069		
58	GORILLA-002	^{159}0.020	^{142}0.044	^{93}0.753	^{91}0.027		^{96}0.214	^{164}0.188	^{152}0.268	^{156}1.000	^{102}0.250		^{126}1.000	0.001	0.001	0.069		
59	GORILLA-003	^{172}0.036	^{164}0.070	^{110}0.821	^{105}0.048		^{104}0.265	^{178}0.318	^{173}0.434	^{196}1.000	^{111}0.407		^{194}1.000	0.001	0.001	0.069		
60	GORILLA-004	^{102}0.006	^{103}0.024	^{83}0.697	^{71}0.012		^{77}0.162	^{130}0.089	^{118}0.160	^{42}0.959	^{85}0.135		^{62}0.438	0.000	0.001	0.042		
61	GORILLA-005	^{64}0.003	^{73}0.018	^{23}0.209	^{49}0.006		^{54}0.124	^{103}0.058	^{105}0.142	^{19}0.700	^{75}0.088		^{47}0.315	0.000	0.000	0.040		
62	HIK-003	^{137}0.012	^{114}0.027	^{82}0.689	^{74}0.012		^{73}0.151	^{135}0.103	^{114}0.158	^{46}0.969	^{88}0.142		^{64}0.445	0.000	0.000	0.048		
63	HIK-004	^{134}0.011	^{112}0.027	^{89}0.743	^{72}0.012		^{75}0.152	^{131}0.099	^{111}0.153	^{52}0.976	^{86}0.137		^{61}0.434	0.000	0.000	0.048		
64	HIK-005	^{86}0.005	^{63}0.017	^{64}0.535	^{58}0.007		^{45}0.111	^{75}0.044	^{51}0.077	^{128}0.999	^{66}0.068		^{76}0.541	0.000	0.000	0.000		
65	HIK-006	^{85}0.005	^{62}0.017	^{65}0.535				^{83}0.047	^{57}0.086	^{147}1.000				0.000	0.000	0.000		
66	IDEMIA-003	^{108}0.007	^{121}0.034	^{143}0.958	^{85}0.018		^{92}0.210	^{84}0.047	^{120}0.165		^{82}0.123		^{92}0.766	0.000	0.000	0.041		
67	IDEMIA-004	^{104}0.007	^{119}0.032	^{138}0.947	^{84}0.018		^{93}0.210	^{71}0.037	^{88}0.118	^{51}0.973	^{81}0.123		^{93}0.766	0.000	0.000	0.041		
68	IDEMIA-005	^{114}0.008	^{134}0.039	^{141}0.954	^{88}0.021		^{97}0.217	^{77}0.044	^{109}0.150	^{55}0.978	^{83}0.130		^{104}0.879	0.000	0.000	0.041		
69	IDEMIA-006	^{127}0.010	^{166}0.072	^{156}0.969	^{93}0.030		^{103}0.253	^{74}0.043	^{137}0.226	^{63}0.982	^{89}0.144		^{88}0.733	0.000	0.000	0.041		
70	IDEMIA-007	^{53}0.003	^{55}0.015	^{207}1.000	^{50}0.006	^{31}1.000	^{59}0.131	^{36}0.018	^{34}0.055	^{198}1.000	^{53}0.052	^{18}0.182	^{174}1.000	0.000	0.000	0.040		0.000
71	IDEMIA-008	^{5}0.001	^{2}0.007	^{9}0.079	^{3}0.001	^{3}0.007	^{9}0.075	^{3}0.002	^{3}0.013	^{3}0.204	^{1}0.005	^{2}0.036	^{4}0.106	0.000	0.000	0.040		0.000
72	IMAGUS-002	^{203}0.220	^{193}0.301	^{166}0.988				^{201}0.749	^{192}0.816	^{149}1.000				0.004	0.008	0.550		
73	IMAGUS-003	^{208}0.356	^{190}0.513	^{170}0.993				^{202}0.807	^{194}0.909	^{145}1.000				0.004	0.008	0.550		
74	IMAGUS-005	^{31}0.002	^{30}0.012	^{36}0.319	^{48}0.006	^{14}0.022	^{61}0.132	^{39}0.018	^{41}0.066	^{29}0.838	^{30}0.029	^{17}0.161	^{28}0.231	0.000	0.000	0.000		0.000
75	IMAGUS-006	^{36}0.002	^{41}0.014	^{33}0.293	^{34}0.004	^{29}1.000	^{46}0.112	^{41}0.019	^{44}0.069	^{36}0.897	^{29}0.028	^{16}0.161	^{35}0.260	0.000	0.000	0.000		0.000
76	IMPERIAL-000	^{52}0.002	^{52}0.015	^{32}0.280	^{37}0.004		^{28}0.097	^{51}0.026	^{43}0.068	^{115}0.999	^{45}0.042		^{32}0.245	0.000	0.000	0.000		
77	INCODE-000	^{181}0.049	^{177}0.100	^{140}0.951				^{177}0.310	^{171}0.420	^{108}0.998				0.001	0.004	0.173		
78	INCODE-001	^{150}0.017	^{147}0.046	^{94}0.762				^{167}0.212	^{155}0.296	^{160}1.000				0.001	0.004	0.173		
79	INCODE-002	^{154}0.018	^{149}0.048	^{113}0.843				^{163}0.184	^{153}0.269	^{80}0.993				0.000	0.001	0.066		
80	INCODE-003	^{142}0.013	^{136}0.040	^{95}0.764				^{159}0.167	^{149}0.264	^{126}0.999				0.000	0.001	0.066		
81	INCODE-004	^{71}0.004	^{70}0.017	^{54}0.475	^{65}0.008		^{65}0.135	^{96}0.054	^{91}0.120	^{87}0.995	^{64}0.063		^{45}0.313	0.000	0.001	0.066		
82	INNOVATRICS-002	^{179}0.045	^{167}0.074	^{116}0.853				^{172}0.234	^{160}0.310	^{158}1.000				0.000	0.001	0.046		
83	INNOVATRICS-003	^{166}0.026	^{152}0.055	^{115}0.845				^{168}0.221	^{156}0.297	^{134}1.000				0.000	0.001	0.046		
84	INNOVATRICS-004	^{141}0.012	^{138}0.040	^{144}0.958				^{147}0.132	^{136}0.222	^{58}0.980				0.000	0.001	0.046		
85	INNOVATRICS-005	^{51}0.002	^{47}0.014	^{48}0.407	^{38}0.005		^{42}0.109	^{65}0.034	^{60}0.089	^{30}0.846	^{50}0.047		^{33}0.251	0.000	0.001	0.041		
86	INTSYSMSU-000	^{198}0.146	^{101}0.023	^{70}0.562	^{111}0.072		^{60}0.132	^{212}0.998	^{205}1.000	^{136}1.000	^{133}0.999		^{124}0.999	0.000	0.000	0.050		
87	IREX-000	^{82}0.004	^{14}0.010	^{81}0.681	^{11}0.002	^{10}0.012	^{13}0.082	^{58}0.028	^{37}0.060	^{41}0.957	^{47}0.044	^{28}0.302	^{18}0.170	0.000	0.000	0.042		0.000
88	ISYSTEMS-002	^{103}0.006	^{109}0.026	^{114}0.844				^{118}0.078	^{95}0.126	^{101}0.998				0.002	0.002	0.142		
89	ISYSTEMS-003	^{92}0.005	^{98}0.023	^{98}0.791				^{104}0.059	^{80}0.107	^{138}1.000				0.002	0.002	0.142		
90	KEDACOM-001	^{111}0.008	^{124}0.036	^{158}0.972	^{98}0.034		^{98}0.237	^{47}0.023	^{48}0.072	^{70}0.986	^{56}0.055		^{43}0.305	0.000	0.000	0.000		
91	KNERON-000	^{98}0.006	^{113}0.027	^{68}0.552	^{92}0.028		^{87}0.195							0.000	0.000	0.000		
92	KNERON-001	^{169}0.030	^{207}0.621	^{28}0.237	^{120}0.144	^{34}1.000	^{108}0.280							0.000	0.000	0.000		0.000

Table 9: **Miss rates by dataset:** *At left, rank 1 miss rates relevant to investigations; at right, with threshold set to target FPIR = 0.01 for higher volume, low prior, uses. Yellow indicates most accurate algorithm. Throughout blue superscripts indicate the rank of the algorithm for that column.*

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		INVESTIGATION MODE						IDENTIFICATION MODE						FAILURE TO EXTRACT				
		RANK ONE MISS RATE, FNIR(N, 0, 1)						HIGH T → FPIR = 0.001, FNIR(N, T, L)						FEATURES				
		N=1.6M						N=1.6M										
#	ALGORITHM	MUGSHOT	WEBCAM	PROFILE	BORDER	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK
93	LINE-000	^{41}0.002	^{43}0.014	^{26}0.223	^{42}0.005	^{33}1.000	^{39}0.107	^{61}0.031			^{48}0.046	^{26}0.278	^{208}1.000	0.000	0.000	0.000		0.000
94	LOOKMAN-003	^{119}0.009	^{132}0.038		^{101}0.035		^{100}0.239	^{76}0.044	^{83}0.112		^{74}0.084		^{52}0.355	0.000	0.000			
95	LOOKMAN-004	^{121}0.009	^{135}0.039	^{160}0.973				^{79}0.045	^{79}0.105	^{53}0.977				0.000	0.000	0.000		
96	LOOKMAN-005	^{113}0.008	^{126}0.036	^{159}0.972	^{100}0.035		^{99}0.237	^{60}0.030	^{56}0.086	^{56}0.978	^{63}0.062		^{44}0.308	0.000	0.000	0.000		
97	MEGVII-001	^{138}0.012	^{69}0.017		^{209}1.000			^{114}0.072	^{72}0.097					0.002	0.000			
98	MEGVII-002	^{139}0.012	^{71}0.017	^{50}0.450	^{198}1.000			^{117}0.077	^{70}0.096	^{110}0.998				0.002	0.000	0.033		
99	MICROFOCUS-003	^{215}0.594	^{211}0.781		^{136}0.708		^{138}0.907	^{208}0.931	^{204}0.979		^{132}0.982		^{120}0.991	0.001	0.005			
100	MICROFOCUS-004	^{213}0.576	^{210}0.758		^{135}0.701		^{137}0.904	^{213}0.999	^{202}0.975		^{131}0.974		^{118}0.989	0.001	0.005			
101	MICROFOCUS-005	^{209}0.424	^{205}0.601		^{131}0.494		^{132}0.777	^{206}0.835	^{198}0.928		^{129}0.935		^{117}0.985	0.001	0.005			
102	MICROFOCUS-006	^{210}0.427	^{204}0.583		^{130}0.490		^{135}0.782	^{210}0.978	^{197}0.923		^{128}0.923		^{115}0.971	0.001	0.005			
103	MICROSOFT-003	^{20}0.002	^{33}0.012		^{30}0.004		^{43}0.109	^{56}0.028	^{63}0.091		^{42}0.036		^{30}0.233	0.000	0.001			
104	MICROSOFT-004	^{15}0.001	^{32}0.012		^{24}0.004		^{44}0.109	^{52}0.026	^{58}0.087		^{38}0.033		^{26}0.222	0.000	0.001			
105	MICROSOFT-005	^{29}0.002	^{25}0.011	^{17}0.144	^{19}0.003		^{29}0.099	^{50}0.026	^{46}0.070	^{15}0.587	^{27}0.027		^{20}0.180	0.000	0.001	0.049		
106	MICROSOFT-006	^{33}0.002	^{27}0.011	^{19}0.150	^{27}0.004		^{31}0.100	^{21}0.012	^{21}0.037	^{5}0.386	^{35}0.032		^{19}0.178	0.000	0.001	0.049		
107	NEC-000	^{151}0.017	^{140}0.041	^{147}0.959	^{89}0.025		^{102}0.243	^{120}0.079	^{104}0.140	^{57}0.979			^{68}0.474	0.001	0.002	0.890		
108	NEC-001	^{160}0.021	^{153}0.056	^{155}0.967	^{97}0.033		^{105}0.277	^{137}0.106	^{130}0.197	^{69}0.986	^{84}0.133		^{67}0.468	0.005	0.003	0.934		
109	NEC-002	^{4}0.001	^{12}0.009	^{44}0.363	^{23}0.003		^{50}0.117	^{7}0.003	^{9}0.020	^{124}0.999	^{8}0.008		^{86}0.676	0.000	0.001	0.041		
110	NEC-003	^{11}0.001	^{19}0.010	^{43}0.352	^{26}0.004	^{11}0.013	^{53}0.120	^{6}0.002	^{8}0.017	^{26}0.824	^{11}0.008	^{3}0.036	^{85}0.668	0.000	0.001	0.041		0.001
111	NEUROTECHNOLOGY-003	^{161}0.022	^{141}0.042	^{149}0.961				^{199}0.636	^{151}0.266	^{214}1.000				0.000	0.001	0.131		
112	NEUROTECHNOLOGY-004	^{94}0.006	^{82}0.020	^{157}0.970				^{108}0.063	^{85}0.117	^{83}0.994				0.000	0.001	0.131		
113	NEUROTECHNOLOGY-005	^{80}0.004	^{105}0.024	^{120}0.893				^{97}0.054	^{97}0.130	^{105}0.998				0.000	0.000	0.030		
114	NEUROTECHNOLOGY-006	^{155}0.018	^{144}0.045	^{75}0.606				^{173}0.249	^{170}0.418					0.000	0.000			
115	NEUROTECHNOLOGY-007	^{75}0.004	^{87}0.021	^{101}0.796	^{66}0.009		^{84}0.180	^{107}0.062	^{124}0.173	^{139}1.000	^{107}0.339		^{168}1.000	0.001	0.001	0.041		
116	NEUROTECHNOLOGY-008	^{40}0.002	^{46}0.014	^{51}0.457	^{32}0.004	^{15}0.023	^{33}0.101	^{92}0.053	^{54}0.080	^{159}1.000	^{41}0.035	^{27}0.293	^{24}0.203	0.000	0.001	0.052		0.001
117	NEWLAND-002	^{189}0.079	^{179}0.117	^{133}0.936				^{190}0.438	^{175}0.466	^{117}0.999				0.007	0.012	0.200		
118	NOBLIS-001	^{205}0.249	^{200}0.522	^{171}0.993				^{215}1.000	^{217}1.000	^{148}1.000				0.000	0.000	0.000		
119	NOBLIS-002	^{201}0.179	^{197}0.392	^{163}0.982				^{211}0.997	^{207}1.000	^{154}1.000				0.000	0.000	0.000		
120	NTECHLAB-003	^{99}0.006	^{95}0.023	^{55}0.504				^{95}0.054	^{86}0.118	^{28}0.837				0.000	0.000	0.040		
121	NTECHLAB-004	^{89}0.005	^{78}0.019	^{56}0.506	^{63}0.008		^{57}0.129	^{72}0.041	^{78}0.105	^{27}0.833	^{55}0.053		^{37}0.263	0.000	0.000	0.040		
122	NTECHLAB-005	^{87}0.005	^{74}0.018	^{45}0.367	^{64}0.008		^{51}0.118	^{73}0.042	^{76}0.102	^{22}0.771	^{69}0.073		^{41}0.294	0.000	0.000	0.040		
123	NTECHLAB-006	^{79}0.004	^{67}0.017	^{42}0.347	^{60}0.007		^{49}0.113	^{68}0.037	^{66}0.094	^{21}0.754	^{58}0.057		^{36}0.260	0.000	0.000	0.040		
124	NTECHLAB-007	^{55}0.003	^{34}0.012	^{37}0.326	^{36}0.004		^{38}0.107	^{49}0.026	^{42}0.067	^{20}0.750	^{36}0.032		^{27}0.223	0.000	0.000	0.042		
125	NTECHLAB-008	^{22}0.002	^{15}0.010	^{20}0.157	^{22}0.003		^{17}0.084	^{28}0.014	^{25}0.045	^{13}0.529	^{39}0.033		^{21}0.183	0.000	0.000	0.044		
126	NTECHLAB-009	^{9}0.001	^{7}0.008	^{15}0.138	^{7}0.002	^{12}0.013	^{8}0.074	^{14}0.005	^{10}0.022	^{7}0.430	^{17}0.015	^{11}0.109	^{12}0.142	0.000	0.000	0.041		0.001
127	PARAVISION-000	^{156}0.019	^{131}0.038	^{63}0.534	^{128}0.423		^{127}0.529	^{129}0.089	^{122}0.170	^{119}0.999	^{117}0.470		^{110}0.926	0.000	0.000	0.000		
128	PARAVISION-001	^{73}0.004	^{85}0.020	^{38}0.329	^{127}0.414		^{126}0.484	^{85}0.049	^{96}0.128	^{113}0.999	^{114}0.444		^{89}0.739	0.000	0.000	0.000		
129	PARAVISION-002	^{78}0.004	^{90}0.022	^{40}0.335	^{81}0.015		^{81}0.175	^{86}0.050	^{89}0.119	^{64}0.983	^{72}0.080		^{71}0.497	0.000	0.000	0.032		
130	PARAVISION-003	^{63}0.003	^{79}0.019	^{29}0.252	^{82}0.015		^{78}0.167	^{66}0.035	^{69}0.096	^{84}0.994	^{59}0.058		^{42}0.296	0.000	0.000	0.032		
131	PARAVISION-004	^{21}0.002	^{21}0.010	^{13}0.104	^{47}0.006		^{49}0.112	^{20}0.010	^{22}0.038	^{153}1.000	^{22}0.018		^{106}0.908	0.000	0.000	0.032		
132	PARAVISION-005	^{16}0.002	^{16}0.010	^{8}0.079	^{57}0.007		^{37}0.106	^{11}0.004	^{11}0.024	^{59}0.980	^{14}0.011		^{9}0.132	0.000	0.000	0.038		
133	PARAVISION-007	^{7}0.001	^{8}0.008	^{4}0.066	^{41}0.005	^{7}0.010	^{32}0.101	^{10}0.004	^{12}0.025	^{161}1.000	^{13}0.009	^{12}0.113	^{203}1.000	0.000	0.000	0.000		0.000
134	PIXELALL-002	^{84}0.005	^{92}0.022	^{106}0.810	^{70}0.011		^{85}0.187	^{136}0.105	^{168}0.388	^{150}1.000	^{119}0.602		^{146}1.000	0.000	0.000	0.000		
135	PIXELALL-003	^{39}0.002	^{45}0.014	^{58}0.515	^{53}0.006		^{72}0.151	^{44}0.022	^{49}0.073	^{131}1.000	^{43}0.037		^{77}0.554	0.000	0.000	0.000		
136	PIXELALL-004	^{37}0.002	^{49}0.015	^{61}0.523	^{44}0.005		^{74}0.152	^{38}0.018	^{53}0.079	^{144}1.000	^{52}0.051		^{121}0.994	0.000	0.000	0.000		
137	PIXELALL-005	^{30}0.002	^{24}0.011	^{31}0.264	^{73}0.012	^{25}1.000	^{70}0.146	^{23}0.012	^{28}0.050	^{146}1.000	^{28}0.027	^{21}0.203	^{125}1.000	0.000	0.000	0.000		0.000
138	PTAKURATSATU-000	^{62}0.003	^{66}0.017	^{74}0.605	^{43}0.005	^{18}0.027	^{36}0.105	^{67}0.037	^{94}0.124	^{38}0.924	^{49}0.046	^{23}0.206	^{29}0.232	0.000	0.001	0.039		0.000

Table 10: **Miss rates by dataset:** *At left, rank 1 miss rates relevant to investigations; at right, with threshold set to target FPIR = 0.01 for higher volume, low prior, uses. Yellow indicates most accurate algorithm. Throughout blue superscripts indicate the rank of the algorithm for that column.*

FNIR(N, R, T) = False neg. identification rate
FPIR(N, T) = False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

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		INVESTIGATION MODE						IDENTIFICATION MODE						FAILURE TO EXTRACT				
		RANK ONE MISS RATE, FNIR(N, 0, 1)						HIGH T ⟶ FPIR = 0.001, FNIR(N, T, L)						FEATURES				
		N=1.6M						N=1.6M										
#	ALGORITHM	MUGSHOT	WEBCAM	PROFILE	BORDER	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK
139	QUANTASOFT-001	^{202}0.218	^{209}0.727					^{200}0.639						0.000	0.000			
140	RANKONE-002	^{157}0.019	^{163}0.071					^{140}0.118	^{147}0.261					0.000	0.000			
141	RANKONE-003	^{158}0.019	^{163}0.068					^{141}0.118	^{146}0.255					0.000	0.000			
142	RANKONE-004	^{178}0.041	^{181}0.141					^{165}0.193	^{172}0.426					0.000	0.000			
143	RANKONE-005	^{125}0.009	^{139}0.041	^{165}0.986				^{105}0.059	^{125}0.173	^{106}0.998				0.000	0.000	0.489		
144	RANKONE-006	^{91}0.005		^{103}0.797				^{69}0.037		^{54}0.977				0.002		0.167		
145	RANKONE-007	^{67}0.003	^{76}0.019	^{100}0.796				^{46}0.022	^{67}0.095	^{45}0.967				0.001	0.001	0.102		
146	RANKONE-009	^{47}0.002	^{36}0.013	^{66}0.549	^{46}0.006		^{64}0.134	^{35}0.018	^{50}0.076	^{47}0.969	^{61}0.062		^{50}0.328	0.000	0.000	0.000		
147	RANKONE-010	^{42}0.002	^{17}0.010	^{46}0.374	^{40}0.005	^{17}0.027	^{55}0.126	^{26}0.014	^{35}0.058	^{24}0.802	^{54}0.052	^{24}0.208	^{34}0.259	0.000	0.000	0.000		0.000
148	REALNETWORKS-000	^{176}0.040	^{171}0.078					^{171}0.234	^{163}0.319					0.001	0.000			
149	REALNETWORKS-001	^{177}0.040	^{172}0.078					^{170}0.234	^{162}0.319					0.001	0.000			
150	REALNETWORKS-002	^{173}0.039	^{170}0.078					^{169}0.231	^{161}0.315					0.001	0.000			
151	REALNETWORKS-003	^{164}0.024	^{159}0.062	^{97}0.771	^{96}0.031		^{90}0.209	^{155}0.159	^{150}0.266	^{109}0.998	^{93}0.164		^{72}0.500	0.001	0.000	0.009		
152	REALNETWORKS-004	^{162}0.024	^{156}0.059	^{102}0.797	^{95}0.031		^{95}0.213	^{154}0.158	^{148}0.263	^{121}0.999	^{94}0.170		^{81}0.613	0.001	0.000	0.009		
153	REMARKAI-000	^{69}0.003	^{75}0.018	^{77}0.660	^{62}0.008		^{71}0.148	^{98}0.055	^{90}0.120	^{118}0.999	^{68}0.069		^{87}0.717	0.000	0.000	0.000		
154	REMARKAI-000	^{118}0.009	^{118}0.030					^{145}0.128	^{131}0.203					0.000	0.001			
155	REMARKAI-002	^{116}0.008	^{117}0.029	^{104}0.802				^{144}0.124	^{129}0.196	^{77}0.991				0.000	0.001	0.017		
156	RENDIP-000	^{18}0.002	^{51}0.015	^{49}0.424	^{51}0.006	^{35}1.000	^{18}0.084	^{22}0.012	^{36}0.059	^{35}0.894	^{24}0.022	^{19}0.185	^{16}0.167	0.000	0.000	0.041		0.000
157	S1-000	^{49}0.002	^{65}0.017	^{30}0.258	^{45}0.005	^{28}1.000	^{21}0.090	^{57}0.028		^{163}1.000	^{51}0.047	^{135}1.000	^{182}1.000	0.000	0.000	0.040		0.000
158	SCANOVATE-000	^{90}0.005	^{143}0.045	^{69}0.560	^{99}0.035		^{94}0.211	^{111}0.067	^{143}0.240	^{34}0.893	^{100}0.215		^{57}0.400	0.000	0.001	0.057		
159	SCANOVATE-001	^{93}0.005	^{137}0.040	^{73}0.585	^{94}0.031		^{83}0.178	^{121}0.081	^{138}0.227	^{37}0.911	^{97}0.192		^{60}0.404	0.000	0.001	0.044		
160	SENSETIME-000	^{45}0.002	^{57}0.016	^{62}0.528				^{42}0.021	^{39}0.063	^{178}1.000				0.004	0.000	0.042		
161	SENSETIME-001	^{46}0.002	^{56}0.016					^{45}0.022	^{40}0.064					0.004	0.000			
162	SENSETIME-002	^{145}0.014	^{80}0.020	^{47}0.384	^{69}0.011		^{35}0.104	^{29}0.015	^{16}0.028	^{82}0.994	^{34}0.032		^{73}0.523	0.009	0.000	0.040		
163	SENSETIME-003	^{3}0.001	^{3}0.007	^{18}0.150	^{15}0.003		^{22}0.091	^{2}0.002	^{1}0.012	^{10}0.477	^{9}0.008		^{10}0.133	0.000	0.000	0.041		
164	SENSETIME-004	^{2}0.001	^{4}0.007	^{7}0.072	^{10}0.002		^{19}0.084	^{1}0.002	^{2}0.013	^{4}0.229	^{4}0.006		^{7}0.113	0.000	0.000	0.041		
165	SENSETIME-005	^{1}0.001	^{1}0.006	^{2}0.059	^{9}0.002	^{4}0.007	^{12}0.082	^{5}0.002	^{6}0.014	^{2}0.173	^{6}0.007	^{5}0.051	^{3}0.104	0.000	0.000	0.041		0.000
166	SHAMAN-003	^{193}0.124	^{185}0.172					^{191}0.451	^{183}0.597					0.020	0.011			
167	SHAMAN-004	^{204}0.222	^{194}0.319					^{198}0.615	^{190}0.754					0.020	0.011			
168	SHAMAN-006	^{175}0.040	^{155}0.058	^{135}0.938				^{149}0.141	^{140}0.237	^{49}0.972				0.020	0.011	0.869		
169	SHAMAN-007	^{174}0.040	^{154}0.057					^{150}0.141	^{142}0.240					0.020	0.010			
170	SIAT-001	^{24}0.002	^{196}0.333		^{35}0.004		^{30}0.099	^{33}0.018	^{167}0.365		^{32}0.031			0.000	0.000			
171	SIAT-002	^{25}0.002	^{198}0.446		^{128}0.348		^{34}0.102	^{43}0.022	^{176}0.478		^{109}0.372		^{109}0.923	0.000	0.000			
172	SMILART-004	^{216}0.965	^{212}0.974					^{209}0.968	^{203}0.976					0.011	0.013			
173	SMILART-005													0.011	0.013			
174	SYNESIS-003	^{149}0.016	^{99}0.023	^{112}0.827	^{76}0.013		^{66}0.136	^{109}0.065	^{93}0.123	^{43}0.960	^{70}0.075		^{46}0.314	0.000	0.001	0.063		
175	SYNESIS-003	^{199}0.170	^{190}0.235					^{196}0.582	^{186}0.646					0.006	0.015			
176	SYNESIS-005	^{117}0.009	^{37}0.013	^{91}0.744	^{21}0.003		^{23}0.092	^{48}0.025	^{47}0.072	^{65}0.984	^{37}0.032		^{25}0.214	0.001	0.000	0.135		
177	TECH5-001	^{77}0.004	^{64}0.017	^{72}0.584	^{55}0.007		^{40}0.107	^{100}0.057	^{199}0.935	^{162}1.000	^{101}0.244		^{122}0.994	0.000	0.000	0.006		
178	TECH5-002	^{56}0.003	^{23}0.011	^{35}0.312	^{20}0.003	^{20}0.029	^{20}0.089	^{55}0.027	^{45}0.070	^{25}0.805	^{44}0.039	^{22}0.205	^{63}0.440	0.001	0.000	0.041		0.000
179	TEVIAN-003	^{146}0.015	^{150}0.052					^{162}0.177	^{157}0.298					0.001	0.002			
180	TEVIAN-004	^{133}0.011	^{130}0.038					^{139}0.117	^{126}0.176					0.001	0.002			
181	TEVIAN-005	^{110}0.007	^{116}0.028	^{52}0.467				^{126}0.087	^{106}0.144	^{44}0.962				0.001	0.002	0.116		
182	TEVIAN-006	^{50}0.002	^{26}0.011	^{14}0.123	^{16}0.003	^{26}1.000	^{5}0.071	^{18}0.010	^{18}0.032	^{6}0.425	^{18}0.016	^{9}0.093	^{112}0.951	0.001	0.000	0.062		0.000
183	TIGER-000	^{184}0.062	^{176}0.095					^{186}0.390	^{177}0.500					0.000	0.000			
184	TIGER-002	^{96}0.006	^{97}0.023	^{57}0.514				^{123}0.086	^{116}0.158	^{116}0.999				0.000	0.000	0.056		

Table 11: **Miss rates by dataset:** *At left, rank 1 miss rates relevant to investigations; at right, with threshold set to target FPIR = 0.01 for higher volume, low prior, uses. Yellow indicates most accurate algorithm. Throughout blue superscripts indicate the rank of the algorithm for that column.*

		INVESTIGATION MODE						IDENTIFICATION MODE						FAILURE TO EXTRACT				
		RANK ONE MISS RATE, FNIR(N, 0, 1)						HIGH T → FPIR = 0.001, FNIR(N, T, L)						FEATURES				
		N=1.6M						N=1.6M										
#	ALGORITHM	MUGSHOT	WEBCAM	PROFILE	BORDER	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	BORDER	KIOSK	MUGSHOT	WEBCAM	PROFILE	BORDER	KIOSK
185	TIGER-003	^{95}0.006	^{96}0.023					^{122}0.086	^{115}0.158					0.000	0.000			
186	TONGYITRANS-000	^{106}0.007	^{93}0.022					^{116}0.074	^{82}0.112					0.003	0.001			
187	TONGYITRANS-001	^{107}0.007	^{94}0.022					^{110}0.066	^{74}0.101					0.003	0.001			
188	TOSHIBA-000	^{83}0.004	^{89}0.022	^{96}0.766				^{106}0.062	^{87}0.118	^{92}0.995				0.000	0.000	0.070		
189	TOSHIBA-001	^{88}0.005	^{91}0.022					^{102}0.058	^{64}0.092					0.000	0.000			
190	TRUEFACE-000	^{66}0.003	^{39}0.014	^{27}0.230	^{59}0.007	^{16}0.024	^{24}0.092	^{37}0.018	^{38}0.062	^{31}0.882	^{31}0.030	^{20}0.194	^{23}0.188	0.001	0.001	0.047		0.003
191	VD-000	^{212}0.474	^{203}0.551					^{207}0.917	^{201}0.946					0.011	0.013			
192	VD-001	^{168}0.028	^{151}0.053					^{160}0.201	^{154}0.281					0.005	0.001			
193	VD-002	^{126}0.010	^{115}0.027	^{119}0.893	^{79}0.013	^{30}1.000	^{82}0.176	^{119}0.079	^{108}0.148	^{95}0.996	^{76}0.095	^{30}0.367	^{54}0.372	0.004	0.003	0.156		0.002
194	VERIDAS-001	^{58}0.003	^{44}0.014	^{67}0.550	^{52}0.006	^{19}0.028	^{58}0.131	^{70}0.037	^{55}0.082	^{71}0.987	^{46}0.044	^{25}0.266	^{38}0.264	0.000	0.002	0.093		0.001
195	VIGILANTSOLUTIONS-003	^{187}0.069	^{183}0.151	^{146}0.958				^{189}0.408	^{189}0.660	^{114}0.999				0.000	0.001	0.127		
196	VIGILANTSOLUTIONS-004	^{194}0.125	^{191}0.244	^{151}0.965				^{195}0.549	^{193}0.817	^{97}0.996				0.000	0.001	0.127		
197	VIGILANTSOLUTIONS-005	^{122}0.009		^{124}0.920				^{185}0.388		^{155}1.000				0.000	0.001	0.127		
198	VIGILANTSOLUTIONS-006	^{128}0.010		^{125}0.921				^{180}0.353		^{151}1.000				0.000	0.001	0.127		
199	VIGILANTSOLUTIONS-007	^{68}0.003	^{68}0.017	^{128}0.925	^{77}0.013	^{23}0.068	^{80}0.175	^{59}0.028	^{59}0.088	^{96}0.996	^{73}0.081	^{31}0.371	^{56}0.391	0.000	0.001	0.127		0.001
200	VISIONLABS-004	^{57}0.003	^{81}0.020	^{41}0.343				^{101}0.058	^{117}0.159	^{33}0.890				0.001	0.001	0.046		
201	VISIONLABS-005	^{48}0.002	^{77}0.019	^{39}0.334				^{87}0.050	^{107}0.147	^{32}0.888				0.001	0.001	0.046		
202	VISIONLABS-006	^{27}0.002	^{54}0.015	^{25}0.211	^{28}0.004		^{27}0.096	^{54}0.027	^{62}0.090	^{17}0.672				0.001	0.001	0.051		
203	VISIONLABS-007	^{23}0.002	^{53}0.015	^{24}0.211	^{25}0.004		^{26}0.095	^{53}0.027	^{61}0.090	^{18}0.672	^{33}0.031		^{22}0.185	0.001	0.001	0.051		
204	VISIONLABS-008	^{35}0.002	^{40}0.014	^{16}0.141	^{8}0.002		^{11}0.081	^{25}0.013	^{30}0.051	^{11}0.481	^{19}0.017		^{13}0.151	0.001	0.000	0.075		
205	VISIONLABS-009	^{6}0.001	^{11}0.008	^{11}0.091	^{2}0.001		^{4}0.071	^{12}0.005	^{13}0.025	^{23}0.799	^{12}0.008		^{6}0.113	0.000	0.000	0.060		
206	VISIONLABS-010	^{12}0.001	^{22}0.010	^{6}0.069	^{1}0.001	^{1}0.006	^{3}0.069	^{15}0.005	^{15}0.027		^{7}0.008	^{6}0.055	^{5}0.109	0.000	0.000	0.040		0.000
207	VOCORD-003	^{100}0.006	^{104}0.024	^{105}0.804	^{109}0.061		^{86}0.188	^{143}0.122	^{113}0.155	^{107}0.998	^{92}0.157		^{59}0.404	0.001	0.011	0.425		
208	VOCORD-004	^{112}0.008	^{86}0.021	^{99}0.792	^{75}0.012		^{56}0.127	^{181}0.355	^{123}0.173	^{140}1.000	^{98}0.193		^{119}0.991	0.000	0.000	0.000		
209	VOCORD-005	^{109}0.007	^{100}0.023	^{107}0.812	^{107}0.055		^{88}0.206	^{153}0.158	^{98}0.130	^{99}0.997	^{87}0.138		^{55}0.381	0.001	0.009	0.554		
210	VOCORD-006	^{218}1.000	^{215}1.000	^{177}1.000	^{214}1.000		^{173}1.000	^{219}1.000	^{215}1.000	^{164}1.000	^{188}1.000		^{139}1.000	0.001	0.009	0.554		
211	VTS-000	^{214}0.594	^{206}0.608	^{122}0.909	^{132}0.607	^{32}1.000	^{131}0.739	^{197}0.598	^{184}0.619	^{122}0.999	^{122}0.613	^{33}0.760	^{91}0.761	0.000	0.001	0.047		0.000
212	XFORWARDAI-000	^{43}0.002	^{42}0.014	^{10}0.089	^{29}0.004	^{27}1.000	^{25}0.094	^{32}0.015	^{33}0.053	^{8}0.440	^{23}0.021	^{15}0.159	^{17}0.169	0.000	0.000	0.000		0.000
213	XFORWARDAI-001	^{38}0.002	^{35}0.013	^{5}0.067	^{18}0.003	^{5}0.009	^{14}0.082	^{13}0.005	^{17}0.028	^{9}0.448	^{10}0.008	^{7}0.062	^{8}0.123	0.000	0.000	0.000		0.000
214	XFORWARDAI-002	^{32}0.002	^{31}0.012	^{1}0.059	^{13}0.002	^{24}1.000	^{10}0.077	^{8}0.003	^{7}0.016	^{12}0.525	^{3}0.005	^{4}0.041	^{1}0.099	0.000	0.000	0.000		0.000
215	YISHENG-001	^{167}0.027	^{158}0.060		^{108}0.058		^{110}0.287	^{179}0.346	^{191}0.808		^{123}0.666		^{108}0.919	0.002	0.005			
216	YITU-002	^{28}0.002	^{20}0.010					^{34}0.018	^{27}0.049					0.000	0.000			
217	YITU-003	^{61}0.003	^{59}0.016					^{40}0.019	^{31}0.052					0.003	0.001			
218	YITU-004	^{10}0.001	^{10}0.008	^{117}0.866				^{17}0.010	^{14}0.027	^{39}0.936				0.000	0.000	0.000		
219	YITU-005	^{44}0.002	^{48}0.014					^{19}0.010	^{19}0.032					0.003	0.001			

Table 12: **Miss rates by dataset:** *At left, rank 1 miss rates relevant to investigations; at right, with threshold set to target FPIR = 0.01 for higher volume, low prior, uses. Yellow indicates most accurate algorithm. Throughout blue superscripts indicate the rank of the algorithm for that column.*

FNIR(N, R, T) = False neg. identification rate
FPIR(N, T) = False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

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MISSES BELOW THRESHOLD, T		ENROL MOST RECENT				
FNIR(N, T> 0, R >L)		DATASET: FRVT 2018				
#	ALGORITHM	N=0.64M	N=1.6M	N=3.0M	N=6.0M	N=12.0M
1	3DIVI-005	^{158}0.1358	^{158}0.1664	^{137}0.1915	^{129}0.2370	^{124}0.3054
2	ACER-000	^{152}0.1185	^{151}0.1455	^{132}0.1714	^{123}0.2074	^{117}0.2537
3	ALCHERA-003	^{150}0.1176	^{152}0.1553	^{133}0.1853	^{130}0.2409	^{132}0.3553
4	ALLGOVISION-000	^{127}0.0688	^{128}0.0881	^{115}0.1084	^{108}0.1389	^{97}0.2129
5	ALLGOVISION-001	^{133}0.0785	^{133}0.1017	^{122}0.1218	^{115}0.1584	^{104}0.2273
6	ANKE-000	^{139}0.0942	^{138}0.1169	^{127}0.1404	^{120}0.1776	^{118}0.2559
7	ANKE-002	^{63}0.0229	^{63}0.0318	^{63}0.0406	^{59}0.0605	^{52}0.1466
8	AWARE-003	^{147}0.1098	^{146}0.1283	^{128}0.1447	^{118}0.1768	^{109}0.2364
9	AWARE-005	^{183}0.3389	^{182}0.3643	^{144}0.3993	^{138}0.4526	^{116}0.2531
10	AYONIX-002	^{204}0.7862	^{204}0.8242	^{150}0.8508	^{143}0.8704	^{140}0.8939
11	CAMVI-004	^{87}0.0367	^{113}0.0716	^{110}0.0983	^{132}0.2508	^{121}0.2701
12	CIB-000	^{22}0.0086	^{24}0.0125	^{23}0.0160	^{30}0.0303	^{40}0.1251
13	CLOUDWALK-HR-000	^{5}0.0019	^{4}0.0020	^{3}0.0023	^{5}0.0072	^{9}0.0701
14	COGENT-000	^{104}0.0430	^{90}0.0527	^{91}0.0695	^{94}0.1133	^{86}0.1960
15	COGENT-001	^{103}0.0430	^{91}0.0527	^{92}0.0695	^{93}0.1133	^{87}0.1960
16	COGENT-002	^{74}0.0322	^{78}0.0444	^{78}0.0610	^{91}0.1116	^{99}0.2180
17	COGENT-003	^{75}0.0328	^{82}0.0463	^{89}0.0683	^{101}0.1294	^{111}0.2445
18	COGENT-004	^{60}0.0210	^{64}0.0331	^{73}0.0527	^{96}0.1138	^{96}0.2119
19	COGNITEC-000	^{160}0.1377	^{156}0.1606	^{136}0.1870	^{125}0.2176	^{123}0.2831
20	COGNITEC-001	^{135}0.0807	^{134}0.1017	^{121}0.1214	^{111}0.1513	^{102}0.2238
21	COGNITEC-002	^{97}0.0406	^{93}0.0531	^{85}0.0666	^{79}0.0935	^{82}0.1874
22	COGNITEC-003	^{95}0.0400	^{89}0.0526	^{81}0.0650	^{75}0.0895	^{75}0.1772
23	COGNITEC-004	^{62}0.0222	^{62}0.0313	^{59}0.0388	^{56}0.0540	^{27}0.1103
24	CYBERLINK-000	^{99}0.0414	^{99}0.0565	^{96}0.0707	^{87}0.1031	^{93}0.2050
25	CYBERLINK-001	^{91}0.0392	^{94}0.0536	^{90}0.0695	^{84}0.0973	^{76}0.1794
26	CYBERLINK-002	^{27}0.0105	^{30}0.0148	^{32}0.0202	^{43}0.0399	^{41}0.1255
27	CYBERLINK-003	^{16}0.0056	^{16}0.0077	^{16}0.0100	^{18}0.0235	^{38}0.1237
28	DAHUA-001	^{116}0.0569	^{115}0.0727	^{104}0.0878	^{97}0.1148	^{81}0.1867
29	DAHUA-002	^{31}0.0108	^{31}0.0151	^{30}0.0191	^{27}0.0291	^{34}0.1153
30	DAHUA-003	^{26}0.0100	^{27}0.0139	^{28}0.0180	^{28}0.0296	^{29}0.1130
31	DEEPGLINT-001	^{9}0.0027	^{9}0.0033	^{9}0.0043	^{9}0.0121	^{17}0.0922
32	DEEPSEA-001	^{83}0.0347	^{81}0.0462	^{77}0.0586	^{73}0.0802	^{73}0.1708
33	DERMALOG-005	^{131}0.0700	^{127}0.0880	^{117}0.1144	^{114}0.1578	^{112}0.2451
34	DERMALOG-006	^{92}0.0395	^{88}0.0517	^{82}0.0659	^{83}0.0973	^{74}0.1745
35	DERMALOG-007	^{128}0.0691	^{125}0.0863	^{116}0.1107	^{110}0.1504	^{107}0.2299
36	DERMALOG-008	^{79}0.0338	^{80}0.0455	^{80}0.0626	^{88}0.1060	^{105}0.2276
37	GORILLA-002	^{164}0.1539	^{164}0.1880	^{140}0.2184	^{133}0.2596	^{131}0.3398
38	GORILLA-004	^{130}0.0699	^{130}0.0892	^{113}0.1048	^{106}0.1370	^{90}0.1969
39	GORILLA-005	^{107}0.0453	^{103}0.0583	^{95}0.0704	^{85}0.0974	^{53}0.1474
40	HIK-003	^{136}0.0828	^{135}0.1028	^{120}0.1202	^{113}0.1525	^{114}0.2480
41	HIK-004	^{134}0.0796	^{131}0.0988	^{118}0.1147	^{109}0.1474	^{115}0.2483
42	HIK-005	^{72}0.0312	^{75}0.0436	^{76}0.0560	^{77}0.0911	^{98}0.2129
43	IDEMIA-003	^{81}0.0346	^{84}0.0471	^{105}0.0892	^{135}0.2789	^{135}0.4311
44	IDEMIA-004	^{71}0.0300	^{71}0.0373	^{65}0.0447	^{60}0.0617	^{71}0.1635
45	IDEMIA-005	^{86}0.0360	^{77}0.0440	^{74}0.0537	^{72}0.0764	^{83}0.1915
46	IDEMIA-006	^{84}0.0351	^{74}0.0433	^{72}0.0525	^{69}0.0734	^{100}0.2201
47	IDEMIA-007	^{37}0.0136	^{36}0.0181	^{33}0.0228	^{36}0.0357	^{51}0.1402
48	IDEMIA-008	^{4}0.0016	^{3}0.0019	^{4}0.0024	^{2}0.0053	^{4}0.0470
49	IMAGUS-005	^{38}0.0137	^{39}0.0185	^{38}0.0237	^{37}0.0368	^{25}0.1067
50	IMAGUS-006	^{39}0.0137	^{41}0.0190	^{40}0.0244	^{41}0.0396	^{35}0.1159
51	IMPERIAL-000	^{51}0.0187	^{51}0.0259	^{57}0.0358	^{68}0.0733	^{77}0.1794
52	INCODE-003	^{157}0.1324	^{159}0.1672	^{138}0.1961	^{128}0.2345	^{126}0.3123
53	INCODE-004	^{96}0.0403	^{96}0.0538	^{84}0.0662	^{78}0.0917	^{68}0.1619
54	INTSYSMSU-000	^{214}0.9982	^{212}0.9984	^{154}0.9985	^{146}0.9987	^{142}0.9988
55	IREX-000	^{55}0.0190	^{58}0.0280	^{60}0.0391	^{64}0.0677	^{56}0.1479
56	ISYSTEMS-002	^{118}0.0584	^{118}0.0783	^{109}0.0973	^{107}0.1373	^{106}0.2295
57	ISYSTEMS-003	^{106}0.0438	^{104}0.0590	^{102}0.0807	^{99}0.1259	^{108}0.2357
58	KEDACOM-001	^{48}0.0181	^{47}0.0227	^{42}0.0265	^{46}0.0422	^{48}0.1340
59	LOOKMAN-003	^{82}0.0346	^{76}0.0437	^{70}0.0514	^{67}0.0724	^{69}0.1620
60	LOOKMAN-005	^{64}0.0240	^{60}0.0301	^{56}0.0356	^{50}0.0512	^{47}0.1334
61	MEGVII-001	^{114}0.0562	^{114}0.0722	^{103}0.0872	^{103}0.1309	^{122}0.2713
62	MICROFOCUS-005	^{211}0.9732	^{206}0.8354	^{151}0.8555	^{144}0.8755	^{141}0.8954
63	MICROSOFT-003	^{57}0.0198	^{56}0.0278	^{55}0.0356	^{55}0.0538	^{62}0.1539
64	MICROSOFT-004	^{50}0.0185	^{52}0.0259	^{51}0.0333	^{51}0.0517	^{60}0.1510
65	MICROSOFT-005	^{49}0.0181	^{50}0.0256	^{50}0.0320	^{49}0.0512	^{58}0.1491
66	MICROSOFT-006	^{24}0.0091	^{21}0.0120	^{24}0.0162	^{29}0.0301	^{57}0.1482
67	NEC-000	^{122}0.0637	^{120}0.0789	^{108}0.0933	^{98}0.1163	^{85}0.1941
68	NEC-001	^{137}0.0863	^{137}0.1055	^{123}0.1249	^{112}0.1519	^{103}0.2253
69	NEC-002	^{6}0.0020	^{7}0.0026	^{7}0.0033	^{11}0.0135	^{7}0.0653
70	NEC-003	^{7}0.0021	^{6}0.0024	^{5}0.0028	^{4}0.0059	^{6}0.0540
71	NEUROTECHNOLOGY-003	^{198}0.5698	^{199}0.6362	^{149}0.7035	^{142}0.7602	^{139}0.8224
72	NEUROTECHNOLOGY-004	^{109}0.0466	^{108}0.0629	^{97}0.0779	^{95}0.1135	^{95}0.2102

Table 13: **Identification-mode: Effect of N on FNIR at high threshold.** *Values are threshold-based miss rates i.e.* FNIR *at* FPIR = *0.001 for five enrollment population sizes, N. The right six columns apply for enrollment of one image. Missing entries usually apply because another algorithm from the same developer was run instead. Some developers are missing because less accurate algorithms were not run on galleries with $N \geq 3\,000\,000$. Throughout blue superscripts indicate the rank of the algorithm for that column.*

MISSES BELOW THRESHOLD, T		ENROL MOST RECENT				
FNIR(N, T> 0, R >L)		DATASET: FRVT 2018				
#	ALGORITHM	N=0.64M	N=1.6M	N=3.0M	N=6.0M	N=12.0M
73	NEUROTECHNOLOGY-005	[93] 0.0396	[97] 0.0538	[87] 0.0675	[82] 0.0950	[89] 0.1966
74	NEUROTECHNOLOGY-007	[105] 0.0436	[107] 0.0623	[99] 0.0802	[104] 0.1320	[110] 0.2393
75	NEUROTECHNOLOGY-008	[80] 0.0339	[92] 0.0530	[106] 0.0893	[119] 0.1769	[129] 0.3288
76	NTECHLAB-003	[101] 0.0421	[95] 0.0537	[86] 0.0674	[76] 0.0907	[66] 0.1582
77	NTECHLAB-004	[73] 0.0312	[72] 0.0405	[71] 0.0519	[66] 0.0722	[59] 0.1503
78	NTECHLAB-005	[77] 0.0334	[73] 0.0424	[75] 0.0537	[71] 0.0760	[64] 0.1543
79	NTECHLAB-006	[69] 0.0288	[68] 0.0367	[68] 0.0471	[63] 0.0670	[61] 0.1523
80	NTECHLAB-007	[52] 0.0188	[49] 0.0256	[48] 0.0317	[48] 0.0495	[46] 0.1306
81	NTECHLAB-008	[30] 0.0107	[28] 0.0145	[29] 0.0187	[25] 0.0286	[18] 0.0995
82	NTECHLAB-009	[14] 0.0037	[14] 0.0049	[14] 0.0062	[10] 0.0125	[11] 0.0735
83	PARAVISION-003	[66] 0.0260	[66] 0.0351	[66] 0.0447	[62] 0.0657	[70] 0.1630
84	PARAVISION-004	[18] 0.0074	[20] 0.0101	[20] 0.0136	[23] 0.0267	[42] 0.1256
85	PARAVISION-005	[11] 0.0032	[11] 0.0041	[11] 0.0057	[14] 0.0174	[20] 0.1037
86	PARAVISION-007	[10] 0.0030	[10] 0.0040	[10] 0.0055	[15] 0.0211	[26] 0.1097
87	PIXELALL-002	[132] 0.0716	[136] 0.1052	[130] 0.1475	[131] 0.2489	[134] 0.3904
88	PIXELALL-003	[44] 0.0158	[44] 0.0218	[47] 0.0288	[47] 0.0474	[32] 0.1138
89	PIXELALL-004	[33] 0.0129	[38] 0.0183	[41] 0.0245	[38] 0.0378	[49] 0.1375
90	PIXELALL-005	[23] 0.0087	[23] 0.0121	[26] 0.0171	[19] 0.0250	[22] 0.1052
91	PTAKURATSATU-000	[67] 0.0275	[67] 0.0366	[67] 0.0458	[53] 0.0523	[5] 0.0523
92	QUANTASOFT-001	[200] 0.6387	[200] 0.6387	[148] 0.6387		[137] 0.6387
93	RANKONE-002	[145] 0.0973	[140] 0.1175	[124] 0.1359	[116] 0.1718	[119] 0.2613
94	RANKONE-003	[144] 0.0973	[141] 0.1175	[125] 0.1359	[117] 0.1718	[120] 0.2613
95	RANKONE-005	[110] 0.0473	[105] 0.0592	[93] 0.0700	[80] 0.0944	[91] 0.1998
96	RANKONE-007	[46] 0.0168	[46] 0.0222	[43] 0.0266	[40] 0.0381	[30] 0.1132
97	RANKONE-009	[34] 0.0132	[35] 0.0177	[35] 0.0230	[33] 0.0344	[16] 0.0921
98	RANKONE-010	[28] 0.0106	[26] 0.0136	[27] 0.0174	[22] 0.0265	[12] 0.0785
99	REALNETWORKS-002	[170] 0.1943	[169] 0.2314	[143] 0.2656	[137] 0.3134	[128] 0.3208
100	REALNETWORKS-003	[156] 0.1300	[155] 0.1594	[135] 0.1858	[126] 0.2246	[125] 0.3076
101	REALNETWORKS-004	[155] 0.1279	[154] 0.1581	[134] 0.1857	[127] 0.2329	[127] 0.3179
102	REMARKAI-000	[98] 0.0406	[98] 0.0552	[88] 0.0676	[86] 0.1028	[92] 0.2003
103	RENDIP-000	[21] 0.0085	[22] 0.0121	[22] 0.0156	[24] 0.0277	[36] 0.1182
104	S1-000	[59] 0.0204	[57] 0.0279	[58] 0.0382	[61] 0.0630	[72] 0.1707
105	SCANOVATE-000	[111] 0.0498	[111] 0.0667	[100] 0.0804	[90] 0.1097	[28] 0.1109
106	SCANOVATE-001	[121] 0.0630	[121] 0.0815	[111] 0.0993	[100] 0.1292	[88] 0.1960
107	SENSETIME-000	[43] 0.0158	[42] 0.0208	[44] 0.0270	[42] 0.0398	[37] 0.1232
108	SENSETIME-001	[45] 0.0161	[45] 0.0219	[46] 0.0277	[45] 0.0420	[44] 0.1304
109	SENSETIME-002	[41] 0.0146	[29] 0.0148	[21] 0.0153	[17] 0.0234	[8] 0.0657
110	SENSETIME-003	[2] 0.0016	[2] 0.0018	[2] 0.0021	[3] 0.0054	[2] 0.0451
111	SENSETIME-004	[1] 0.0015	[1] 0.0018	[1] 0.0021	[1] 0.0040	[1] 0.0354
112	SENSETIME-005	[3] 0.0016	[5] 0.0022	[6] 0.0031	[7] 0.0089	[3] 0.0454
113	SHAMAN-007	[154] 0.1212	[150] 0.1413	[131] 0.1587	[121] 0.1879	[113] 0.2460
114	SIAT-001	[36] 0.0136	[33] 0.0176	[36] 0.0230	[32] 0.0344	[19] 0.1035
115	SIAT-002	[42] 0.0154	[43] 0.0216	[45] 0.0273	[44] 0.0404	[43] 0.1283
116	SYNESIS-003	[112] 0.0499	[109] 0.0652	[101] 0.0804	[89] 0.1095	[84] 0.1916
117	SYNESIS-003	[196] 0.5341	[196] 0.5821	[147] 0.6113	[141] 0.6479	[138] 0.6822
118	SYNESIS-005	[47] 0.0181	[48] 0.0248	[49] 0.0319	[52] 0.0518	[65] 0.1580
119	TECH5-001	[100] 0.0420	[100] 0.0574	[107] 0.0911	[124] 0.2106	[133] 0.3725
120	TECH5-002	[56] 0.0194	[55] 0.0269	[54] 0.0346	[54] 0.0537	[67] 0.1607
121	TEVIAN-005	[129] 0.0692	[126] 0.0873	[114] 0.1066	[102] 0.1301	[79] 0.1840
122	TEVIAN-006	[20] 0.0078	[18] 0.0098	[18] 0.0130	[21] 0.0261	[45] 0.1305
123	TIGER-002	[124] 0.0647	[123] 0.0861	[112] 0.1036	[105] 0.1332	[101] 0.2231
124	TOSHIBA-000	[108] 0.0460	[106] 0.0620	[98] 0.0780	[92] 0.1117	[94] 0.2082
125	TRUEFACE-000	[35] 0.0134	[37] 0.0182	[39] 0.0238	[39] 0.0380	[50] 0.1385
126	VD-001	[166] 0.1642	[166] 0.2015	[142] 0.2351	[134] 0.2736	[130] 0.3293
127	VERIDAS-001	[68] 0.0278	[70] 0.0373	[69] 0.0491	[70] 0.0753	[63] 0.1541
128	VISIONLABS-004	[102] 0.0427	[101] 0.0578	[94] 0.0703	[81] 0.0949	[80] 0.1853
129	VISIONLABS-005	[89] 0.0369	[87] 0.0502	[79] 0.0626	[74] 0.0847	[78] 0.1815
130	VISIONLABS-006	[53] 0.0188	[54] 0.0267	[53] 0.0336	[58] 0.0542	[54] 0.1478
131	VISIONLABS-007	[54] 0.0188	[53] 0.0266	[52] 0.0335	[57] 0.0540	[55] 0.1479
132	VISIONLABS-008	[25] 0.0096	[25] 0.0131	[25] 0.0166	[26] 0.0291	[39] 0.1247
133	VISIONLABS-009	[12] 0.0034	[12] 0.0046	[12] 0.0060	[12] 0.0140	[14] 0.0881
134	VISIONLABS-010	[15] 0.0038	[15] 0.0051	[15] 0.0070	[13] 0.0149	[15] 0.0920
135	VOCORD-005	[151] 0.1179	[153] 0.1577	[139] 0.2183	[136] 0.3122	[136] 0.4490
136	XFORWARDAI-000	[29] 0.0107	[32] 0.0151	[31] 0.0195	[31] 0.0324	[23] 0.1057
137	XFORWARDAI-001	[13] 0.0037	[13] 0.0049	[13] 0.0060	[8] 0.0120	[13] 0.0800
138	XFORWARDAI-002	[8] 0.0026	[8] 0.0030	[8] 0.0035	[6] 0.0078	[10] 0.0706
139	YITU-002	[32] 0.0129	[34] 0.0177	[34] 0.0228	[34] 0.0345	[31] 0.1133
140	YITU-003	[40] 0.0138	[40] 0.0185	[37] 0.0236	[35] 0.0353	[33] 0.1148
141	YITU-004	[17] 0.0067	[17] 0.0096	[17] 0.0129	[16] 0.0232	[21] 0.1046
142	YITU-005	[19] 0.0074	[19] 0.0101	[19] 0.0135	[20] 0.0255	[24] 0.1057

Table 14: **Identification-mode: Effect of N on FNIR at high threshold.** *Values are threshold-based miss rates i.e.* FNIR *at* FPIR = *0.001 for five enrollment population sizes, N. The right six columns apply for enrollment of one image. Missing entries usually apply because another algorithm from the same developer was run instead. Some developers are missing because less accurate algorithms were not run on galleries with $N \geq 3\,000\,000$. Throughout blue superscripts indicate the rank of the algorithm for that column.*

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MISSES AT GIVEN RANK		ENROL MOST RECENT											
FNIR(N, T= 0, R)		RANK 1						RANK 50					
#	ALGORITHM	N=0.64M	N=1.6M	N=3.0M	N=6.0M	N=12.0M	aN^b	N=0.64M	N=1.6M	N=3.0M	N=6.0M	N=12.0M	aN^b
1	3DIVI-005	^{155}0.0137	^{153}0.0176	^{130}0.0210	^{125}0.0253	^{123}0.0302	^{100}0.0004 N$^{0.271\ 105}$	^{139}0.0040	^{138}0.0049	^{120}0.0057	^{117}0.0068	^{115}0.0081	^{46}0.0002 N$^{0.240\ 110}$
2	ACER-000	^{126}0.0081	^{132}0.0106	^{118}0.0128	^{117}0.0157	^{115}0.0195	^{47}0.0001 N$^{0.299\ 129}$	^{94}0.0020	^{108}0.0026	^{99}0.0031	^{100}0.0037	^{97}0.0045	^{17}0.0000 N$^{0.284\ 123}$
3	ALCHERA-003	^{123}0.0079	^{129}0.0104	^{116}0.0123	^{116}0.0147	^{114}0.0180	^{67}0.0002 N$^{0.278\ 116}$	^{121}0.0027	^{119}0.0032	^{105}0.0035	^{103}0.0042	^{98}0.0048	^{50}0.0002 N$^{0.199\ 100}$
4	ALLGOVISION-000	^{138}0.0101	^{135}0.0114	^{117}0.0127	^{115}0.0145	^{113}0.0166	^{121}0.0010 N$^{0.171\ 54}$	^{158}0.0063	^{152}0.0067	^{125}0.0071	^{120}0.0075	^{114}0.0081	^{128}0.0020 N$^{0.086\ 60}$
5	ALLGOVISION-001	^{116}0.0069	^{120}0.0090	^{111}0.0107	^{110}0.0128	^{110}0.0157	^{58}0.0002 N$^{0.277\ 114}$	^{110}0.0023	^{110}0.0027	^{100}0.0031	^{96}0.0036	^{94}0.0043	^{39}0.0001 N$^{0.211\ 105}$
6	ANKE-000	^{141}0.0102	^{143}0.0132	^{126}0.0155	^{122}0.0188	^{119}0.0225	^{88}0.0003 N$^{0.270\ 104}$	^{130}0.0032	^{131}0.0040	^{116}0.0046	^{111}0.0056	^{106}0.0066	^{38}0.0001 N$^{0.247\ 112}$
7	ANKE-002	^{60}0.0024	^{59}0.0028	^{59}0.0032	^{56}0.0037	^{52}0.0043	^{52}0.0002 N$^{0.203\ 63}$	^{71}0.0016	^{70}0.0017	^{64}0.0017	^{55}0.0018	^{50}0.0019	^{88}0.0006 N$^{0.067\ 52}$
8	AWARE-003	^{172}0.0238	^{170}0.0306	^{141}0.0361	^{136}0.0431	^{136}0.0506	^{119}0.0008 N$^{0.258\ 99}$	^{152}0.0055	^{158}0.0075	^{135}0.0092	^{131}0.0113	^{133}0.0143	^{28}0.0001 N$^{0.323\ 133}$
9	AWARE-005	^{173}0.0245	^{171}0.0311	^{142}0.0366	^{137}0.0434	^{127}0.0312	^{135}0.0056 N$^{0.118\ 31}$	^{156}0.0062	^{164}0.0082	^{137}0.0101	^{134}0.0128	^{117}0.0089	^{99}0.0007 N$^{0.169\ 95}$
10	AYONIX-002	^{206}0.2935	^{206}0.3414	^{152}0.3736	^{145}0.4101	^{142}0.4465	^{140}0.0440 N$^{0.143\ 40}$	^{205}0.0950	^{207}0.1274	^{152}0.1524	^{144}0.1828	^{141}0.2150	^{128}0.0023 N$^{0.279\ 121}$
11	CAMVI-004	^{148}0.0124	^{180}0.0468	^{146}0.0719	^{144}0.2363	^{141}0.2367	^{1}0.0000 N$^{1.055\ 143}$	^{176}0.0117	^{193}0.0464	^{148}0.0715	^{145}0.2361	^{142}0.2364	^{1}0.0000 N$^{1.071\ 143}$
12	CIB-000	^{17}0.0014	^{17}0.0015	^{16}0.0017	^{18}0.0019	^{104}0.0131	^{2}0.0000 N$^{0.635\ 142}$	^{27}0.0012	^{23}0.0012	^{21}0.0012	^{21}0.0012	^{129}0.0122	^{2}0.0000 N$^{0.647\ 142}$
13	CLOUDWALK-HR-000	^{21}0.0015	^{14}0.0015	^{14}0.0015	^{11}0.0016	^{8}0.0017	^{115}0.0007 N$^{0.054\ 9}$	^{58}0.0014	^{46}0.0014	^{39}0.0014	^{36}0.0014	^{25}0.0014	^{116}0.0012 N$^{0.012\ 9}$
14	COGENT-000	^{140}0.0101	^{131}0.0105	^{112}0.0109	^{105}0.0115	^{102}0.0125	^{132}0.0038 N$^{0.071\ 11}$	^{103}0.0021	^{102}0.0024	^{94}0.0028	^{99}0.0036	^{120}0.0095	^{6}0.0000 N$^{0.466\ 138}$
15	COGENT-001	^{139}0.0101	^{130}0.0105	^{113}0.0109	^{106}0.0115	^{101}0.0125	^{133}0.0038 N$^{0.071\ 12}$	^{102}0.0021	^{101}0.0024	^{95}0.0028	^{98}0.0036	^{121}0.0095	^{7}0.0000 N$^{0.466\ 139}$
16	COGENT-002	^{69}0.0029	^{72}0.0036	^{70}0.0041	^{69}0.0049	^{66}0.0059	^{37}0.0001 N$^{0.244\ 91}$	^{57}0.0014	^{61}0.0015	^{58}0.0017	^{59}0.0019	^{61}0.0021	^{51}0.0002 N$^{0.144\ 89}$
17	COGENT-003	^{75}0.0031	^{74}0.0038	^{74}0.0043	^{72}0.0051	^{69}0.0060	^{45}0.0001 N$^{0.230\ 81}$	^{65}0.0015	^{73}0.0017	^{74}0.0018	^{71}0.0020	^{66}0.0022	^{54}0.0002 N$^{0.143\ 88}$
18	COGENT-004	^{34}0.0018	^{34}0.0020	^{34}0.0022	^{33}0.0025	^{28}0.0028	^{73}0.0002 N$^{0.159\ 48}$	^{52}0.0013	^{44}0.0014	^{40}0.0014	^{37}0.0015	^{30}0.0015	^{91}0.0007 N$^{0.050\ 40}$
19	COGNITEC-000	^{166}0.0195	^{165}0.0252	^{138}0.0297	^{134}0.0352	^{131}0.0417	^{113}0.0006 N$^{0.259\ 100}$	^{148}0.0050	^{151}0.0065	^{132}0.0077	^{130}0.0097	^{128}0.0122	^{35}0.0001 N$^{0.305\ 127}$
20	COGNITEC-001	^{134}0.0090	^{136}0.0117	^{123}0.0139	^{120}0.0166	^{117}0.0199	^{81}0.0002 N$^{0.271\ 107}$	^{126}0.0030	^{125}0.0034	^{113}0.0040	^{110}0.0046	^{102}0.0054	^{49}0.0002 N$^{0.207\ 104}$
21	COGNITEC-002	^{99}0.0048	^{97}0.0057	^{91}0.0067	^{87}0.0079	^{88}0.0094	^{74}0.0002 N$^{0.232\ 83}$	^{112}0.0024	^{109}0.0026	^{97}0.0028	^{91}0.0030	^{83}0.0034	^{77}0.0005 N$^{0.117\ 76}$
22	COGNITEC-003	^{102}0.0053	^{101}0.0062	^{94}0.0072	^{92}0.0085	^{91}0.0100	^{87}0.0003 N$^{0.222\ 74}$	^{123}0.0028	^{117}0.0030	^{102}0.0032	^{94}0.0035	^{88}0.0037	^{102}0.0008 N$^{0.097\ 68}$
23	COGNITEC-004	^{65}0.0027	^{65}0.0032	^{65}0.0037	^{64}0.0045	^{63}0.0056	^{29}0.0001 N$^{0.253\ 97}$	^{50}0.0013	^{48}0.0014	^{46}0.0015	^{48}0.0017	^{45}0.0019	^{58}0.0002 N$^{0.123\ 81}$
24	CYBERLINK-000	^{80}0.0034	^{76}0.0040	^{77}0.0046	^{74}0.0054	^{71}0.0063	^{69}0.0002 N$^{0.209\ 68}$	^{100}0.0021	^{96}0.0022	^{88}0.0023	^{85}0.0025	^{78}0.0027	^{85}0.0006 N$^{0.092\ 65}$
25	CYBERLINK-001	^{72}0.0030	^{70}0.0035	^{72}0.0042	^{71}0.0050	^{68}0.0060	^{38}0.0001 N$^{0.243\ 90}$	^{74}0.0016	^{77}0.0017	^{68}0.0018	^{67}0.0020	^{64}0.0022	^{70}0.0004 N$^{0.109\ 72}$
26	CYBERLINK-002	^{59}0.0024	^{54}0.0026	^{51}0.0028	^{48}0.0031	^{41}0.0035	^{110}0.0005 N$^{0.121\ 32}$	^{96}0.0020	^{91}0.0021	^{84}0.0021	^{79}0.0022	^{67}0.0022	^{118}0.0012 N$^{0.036\ 27}$
27	CYBERLINK-003	^{19}0.0015	^{19}0.0016	^{17}0.0017	^{16}0.0018	^{14}0.0020	^{95}0.0003 N$^{0.110\ 25}$	^{23}0.0011	^{21}0.0012	^{20}0.0012	^{20}0.0012	^{17}0.0013	^{82}0.0006 N$^{0.047\ 37}$
28	DAHUA-001	^{104}0.0053	^{105}0.0067	^{98}0.0079	^{97}0.0093	^{95}0.0112	^{60}0.0002 N$^{0.256\ 98}$	^{120}0.0027	^{112}0.0029	^{101}0.0031	^{93}0.0034	^{90}0.0038	^{80}0.0005 N$^{0.121\ 79}$
29	DAHUA-002	^{30}0.0017	^{26}0.0018	^{28}0.0021	^{25}0.0023	^{22}0.0027	^{68}0.0002 N$^{0.156\ 43}$	^{44}0.0013	^{41}0.0013	^{36}0.0014	^{31}0.0014	^{27}0.0015	^{96}0.0007 N$^{0.043\ 34}$
30	DAHUA-003	^{6}0.0010	^{8}0.0012	^{9}0.0014	^{10}0.0016	^{12}0.0018	^{20}0.0001 N$^{0.199\ 62}$	^{11}0.0009	^{9}0.0009	^{8}0.0009	^{9}0.0009	^{8}0.0009	^{83}0.0006 N$^{0.027\ 24}$
31	DEEPGLINT-001	^{15}0.0014	^{13}0.0014	^{13}0.0015	^{12}0.0016	^{11}0.0018	^{104}0.0004 N$^{0.089\ 19}$	^{43}0.0013	^{32}0.0013	^{31}0.0013	^{26}0.0013	^{20}0.0013	^{114}0.0010 N$^{0.017\ 15}$
32	DEEPSEA-001	^{79}0.0033	^{81}0.0043	^{81}0.0052	^{81}0.0065	^{80}0.0081	^{16}0.0001 N$^{0.311\ 132}$	^{38}0.0012	^{43}0.0014	^{50}0.0015	^{51}0.0017	^{52}0.0020	^{42}0.0001 N$^{0.157\ 93}$
33	DERMALOG-005	^{147}0.0114	^{147}0.0149	^{128}0.0201	^{130}0.0289	^{134}0.0447	^{6}0.0000 N$^{0.470\ 141}$	^{172}0.0094	^{173}0.0122	^{143}0.0171	^{138}0.0254	^{137}0.0406	^{8}0.0000 N$^{0.505\ 140}$
34	DERMALOG-006	^{118}0.0075	^{115}0.0081	^{106}0.0086	^{98}0.0093	^{92}0.0104	^{127}0.0017 N$^{0.109\ 24}$	^{157}0.0062	^{150}0.0063	^{122}0.0064	^{116}0.0065	^{107}0.0068	^{133}0.0043 N$^{0.028\ 25}$
35	DERMALOG-007	^{124}0.0080	^{123}0.0092	^{110}0.0102	^{108}0.0118	^{106}0.0140	^{112}0.0006 N$^{0.190\ 60}$	^{150}0.0051	^{144}0.0054	^{119}0.0056	^{112}0.0058	^{105}0.0063	^{127}0.0020 N$^{0.068\ 53}$
36	DERMALOG-008	^{58}0.0024	^{60}0.0029	^{61}0.0034	^{60}0.0040	^{59}0.0048	^{32}0.0001 N$^{0.239\ 88}$	^{64}0.0015	^{59}0.0015	^{56}0.0016	^{50}0.0017	^{46}0.0019	^{73}0.0004 N$^{0.088\ 61}$
37	GORILLA-002	^{157}0.0147	^{159}0.0197	^{134}0.0238	^{129}0.0288	^{128}0.0351	^{90}0.0003 N$^{0.295\ 125}$	^{129}0.0032	^{133}0.0041	^{118}0.0049	^{115}0.0062	^{113}0.0080	^{18}0.0000 N$^{0.315\ 130}$
38	GORILLA-004	^{100}0.0048	^{102}0.0063	^{96}0.0075	^{96}0.0091	^{97}0.0114	^{33}0.0001 N$^{0.292\ 123}$	^{69}0.0015	^{78}0.0018	^{85}0.0021	^{83}0.0025	^{82}0.0029	^{30}0.0001 N$^{0.222\ 107}$
39	GORILLA-005	^{62}0.0026	^{64}0.0032	^{67}0.0038	^{66}0.0046	^{64}0.0056	^{18}0.0001 N$^{0.271\ 109}$	^{36}0.0012	^{33}0.0013	^{38}0.0014	^{43}0.0016	^{41}0.0018	^{56}0.0002 N$^{0.127\ 83}$
40	HIK-003	^{135}0.0091	^{137}0.0117	^{124}0.0140	^{121}0.0169	^{118}0.0203	^{77}0.0002 N$^{0.274\ 112}$	^{111}0.0024	^{116}0.0030	^{109}0.0036	^{107}0.0044	^{101}0.0053	^{23}0.0001 N$^{0.278\ 120}$
41	HIK-004	^{133}0.0088	^{134}0.0113	^{121}0.0134	^{119}0.0163	^{116}0.0195	^{79}0.0002 N$^{0.271\ 110}$	^{114}0.0024	^{113}0.0030	^{106}0.0035	^{104}0.0042	^{100}0.0052	^{29}0.0001 N$^{0.259\ 117}$
42	HIK-005	^{85}0.0036	^{86}0.0046	^{84}0.0053	^{80}0.0065	^{79}0.0081	^{31}0.0001 N$^{0.274\ 111}$	^{34}0.0012	^{55}0.0015	^{55}0.0016	^{60}0.0019	^{63}0.0022	^{33}0.0001 N$^{0.202\ 102}$
43	IDEMIA-003	^{105}0.0054	^{108}0.0069	^{103}0.0084	^{103}0.0101	^{100}0.0122	^{41}0.0001 N$^{0.281\ 118}$	^{107}0.0023	^{111}0.0027	^{98}0.0031	^{97}0.0036	^{92}0.0041	^{43}0.0002 N$^{0.201\ 101}$
44	IDEMIA-004	^{108}0.0054	^{104}0.0066	^{99}0.0079	^{102}0.0097	^{99}0.0117	^{46}0.0001 N$^{0.270\ 103}$	^{88}0.0018	^{92}0.0021	^{91}0.0025	^{90}0.0030	^{87}0.0036	^{27}0.0001 N$^{0.241\ 111}$
45	IDEMIA-005	^{112}0.0064	^{114}0.0081	^{108}0.0097	^{107}0.0118	^{107}0.0143	^{49}0.0002 N$^{0.277\ 115}$	^{106}0.0022	^{115}0.0030	^{108}0.0036	^{108}0.0044	^{103}0.0055	^{15}0.0000 N$^{0.300\ 126}$
46	IDEMIA-006	^{121}0.0076	^{127}0.0096	^{115}0.0113	^{112}0.0135	^{112}0.0161	^{80}0.0002 N$^{0.259\ 101}$	^{122}0.0028	^{128}0.0037	^{115}0.0046	^{113}0.0059	^{111}0.0076	^{13}0.0000 N$^{0.341\ 135}$
47	IDEMIA-007	^{47}0.0021	^{53}0.0026	^{54}0.0030	^{52}0.0036	^{53}0.0044	^{21}0.0001 N$^{0.250\ 95}$	^{21}0.0011	^{25}0.0012	^{26}0.0012	^{29}0.0014	^{29}0.0015	^{59}0.0002 N$^{0.110\ 74}$
48	IDEMIA-008	^{5}0.0010	^{5}0.0011	^{5}0.0011	^{5}0.0013	^{5}0.0014	^{65}0.0002 N$^{0.121\ 33}$	^{12}0.0009	^{10}0.0009	^{10}0.0009	^{10}0.0009	^{7}0.0009	^{95}0.0007 N$^{0.016\ 14}$
49	IMAGUS-005	^{33}0.0018	^{31}0.0019	^{33}0.0022	^{32}0.0025	^{26}0.0028	^{72}0.0002 N$^{0.158\ 47}$	^{40}0.0013	^{42}0.0013	^{35}0.0014	^{35}0.0014	^{32}0.0016	^{79}0.0005 N$^{0.066\ 51}$
50	IMAGUS-006	^{35}0.0018	^{36}0.0020	^{32}0.0022	^{31}0.0025	^{29}0.0029	^{75}0.0002 N$^{0.156\ 42}$	^{56}0.0014	^{51}0.0014	^{45}0.0015	^{39}0.0015	^{35}0.0016	^{94}0.0007 N$^{0.049\ 39}$
51	IMPERIAL-000	^{54}0.0022	^{52}0.0024	^{49}0.0027	^{47}0.0030	^{42}0.0035	^{86}0.0003 N$^{0.157\ 44}$	^{77}0.0016	^{71}0.0017	^{66}0.0017	^{54}0.0018	^{44}0.0018	^{109}0.0009 N$^{0.041\ 32}$
52	INCODE-003	^{137}0.0098	^{142}0.0129	^{125}0.0154	^{123}0.0191	^{120}0.0233	^{64}0.0002 N$^{0.296\ 126}$	^{113}0.0024	^{118}0.0031	^{111}0.0036	^{109}0.0046	^{104}0.0056	^{21}0.0001 N$^{0.285\ 124}$
53	INCODE-004	^{70}0.0029	^{71}0.0035	^{71}0.0041	^{70}0.0049	^{67}0.0060	^{36}0.0001 N$^{0.244\ 92}$	^{85}0.0018	^{81}0.0019	^{80}0.0020	^{76}0.0021	^{65}0.0022	^{87}0.0006 N$^{0.077\ 57}$
54	INTSYSMSU-000	^{198}0.1395	^{198}0.1457	^{148}0.1498	^{141}0.1544	^{138}0.1591	^{142}0.0768 N$^{0.045\ 6}$	^{207}0.1098	^{205}0.1163	^{151}0.1206	^{143}0.1252	^{140}0.1296	^{142}0.0519 N$^{0.056\ 44}$
55	IREX-000	^{92}0.0043	^{82}0.0044	^{75}0.0044	^{65}0.0046	^{58}0.0048	^{129}0.0028 N$^{0.032\ 4}$	^{143}0.0043	^{134}0.0043	^{114}0.0043	^{105}0.0043	^{93}0.0043	^{132}0.0042 N$^{0.002\ 4}$
56	ISYSTEMS-002	^{103}0.0053	^{103}0.0064	^{95}0.0072	^{91}0.0083	^{89}0.0096	^{98}0.0003 N$^{0.204\ 65}$	^{132}0.0033	^{126}0.0034	^{107}0.0036	^{101}0.0038	^{91}0.0041	^{119}0.0013 N$^{0.071\ 54}$
57	ISYSTEMS-003	^{95}0.0046	^{92}0.0052	^{85}0.0057	^{82}0.0066	^{77}0.0076	^{105}0.0004 N$^{0.174\ 56}$	^{128}0.0031	^{122}0.0033	^{103}0.0034	^{95}0.0035	^{89}0.0037	^{120}0.0013 N$^{0.063\ 49}$
58	KEDACOM-001	^{120}0.0076	^{111}0.0077	^{100}0.0079	^{90}0.0083	^{82}0.0087	^{134}0.0040 N$^{0.047\ 7}$	^{160}0.0071	^{154}0.0072	^{129}0.0072	^{118}0.0073	^{108}0.0073	^{137}0.0063 N$^{0.009\ 8}$
59	KNERON-000	^{98}0.0048	^{98}0.0059	^{92}0.0067	^{88}0.0079	^{87}0.0093	^{78}0.0002 N$^{0.226\ 78}$	^{145}0.0048	^{146}0.0059	^{124}0.0067	^{123}0.0079	^{119}0.0093	^{57}0.0002 N$^{0.226\ 108}$
60	LOOKMAN-003	^{128}0.0083	^{119}0.0088	^{107}0.0091	^{100}0.0096	^{93}0.0104	^{130}0.0030 N$^{0.076\ 13}$	^{163}0.0072	^{157}0.0074	^{131}0.0075	^{121}0.0076	^{112}0.0077	^{135}0.0054 N$^{0.022\ 22}$
61	LOOKMAN-005	^{122}0.0078	^{113}0.0080	^{102}0.0083	^{93}0.0086	^{85}0.0092	^{131}0.0038 N$^{0.053\ 8}$	^{161}0.0072	^{155}0.0072	^{130}0.0073	^{119}0.0073	^{109}0.0074	^{136}0.0060 N$^{0.013\ 12}$
62	MEGVII-001	^{143}0.0105	^{138}0.0118	^{119}0.0128	^{114}0.0142	^{111}0.0161	^{125}0.0015 N$^{0.143\ 41}$	^{165}0.0077	^{163}0.0080	^{133}0.0082	^{128}0.0086	^{118}0.0089	^{131}0.0040 N$^{0.048\ 38}$
63	MICROFOCUS-005	^{209}0.3700	^{209}0.4242	^{153}0.4610	^{146}0.5000	^{143}0.5391	^{141}0.0674 N$^{0.128\ 35}$	^{210}0.1300	^{210}0.1724	^{153}0.2046	^{146}0.2425	^{143}0.2810	^{130}0.0040 N$^{0.263\ 118}$
64	MICROSOFT-003	^{12}0.0013	^{20}0.0016	^{21}0.0018	^{24}0.0022	^{27}0.0028	^{12}0.0000 N$^{0.271\ 108}$	^{2}0.0006	^{2}0.0006	^{4}0.0007	^{5}0.0008	^{6}0.0009	^{26}0.0001 N$^{0.158\ 94}$
65	MICROSOFT-004	^{11}0.0012	^{15}0.0015	^{20}0.0018	^{22}0.0021	^{25}0.0028	^{11}0.0000 N$^{0.281\ 117}$	^{1}0.0006	^{1}0.0006	^{1}0.0007	^{1}0.0007	^{3}0.0009	^{36}0.0001 N$^{0.139\ 86}$
66	MICROSOFT-005	^{22}0.0015	^{29}0.0019	^{37}0.0023	^{45}0.0030	^{44}0.0037	^{7}0.0000 N$^{0.320\ 134}$	^{3}0.0006	^{3}0.0006	^{2}0.0007	^{2}0.0008	^{4}0.0009	^{37}0.0001 N$^{0.136\ 85}$
67	MICROSOFT-006	^{24}0.0016	^{33}0.0020	^{43}0.0025	^{46}0.0030	^{47}0.0038	^{10}0.0000 N$^{0.305\ 130}$	^{4}0.0006	^{4}0.0007	^{3}0.0007	^{7}0.0009	^{10}0.0010	^{20}0.0000 N$^{0.184\ 97}$
68	NEC-000	^{151}0.0131	^{151}0.0170	^{129}0.0203	^{124}0.0244	^{122}0.0294	^{94}0.0003 N$^{0.276\ 113}$	^{125}0.0029	^{130}0.0038	^{117}0.0048	^{114}0.0059	^{110}0.0074	^{14}0.0000 N$^{0.319\ 131}$
69	NEC-001	^{163}0.0180	^{160}0.0209	^{133}0.0233	^{128}0.0266	^{124}0.0304	^{126}0.0016 N$^{0.179\ 58}$	^{176}0.0109	^{169}0.0113	^{138}0.0116	^{132}0.0121	^{130}0.0129	^{134}0.0051 N$^{0.056\ 43}$
70	NEC-002	^{2}0.0009	^{4}0.0010	^{4}0.0011	^{4}0.0012	^{4}0.0013	^{71}0.0002 N$^{0.113\ 29}$	^{5}0.0008	^{5}0.0008	^{5}0.0008	^{4}0.0008	^{2}0.0008	^{75}0.0005 N$^{0.038\ 28}$
71	NEC-003	^{13}0.0013	^{11}0.0014	^{10}0.0015	^{9}0.0016	^{7}0.0016	^{106}0.0005 N$^{0.079\ 14}$	^{30}0.0012	^{24}0.0012	^{22}0.0012	^{18}0.0012	^{15}0.0012	^{107}0.0009 N$^{0.019\ 20}$
72	NEUROTECHNOLOGY-003	^{162}0.0179	^{161}0.0225	^{135}0.0263	^{131}0.0306	^{129}0.0361	^{118}0.0007 N$^{0.239\ 89}$	^{142}0.0042	^{145}0.0057	^{128}0.0072	^{129}0.0090	^{127}0.0112	^{19}0.0000 N$^{0.334\ 134}$

Table 15: **Investigation-mode: Effect of N on FNIR on recent images** *For five enrollment population sizes, N, with T = 0 and FPIR = 1. The left five columns are rank 1 miss rates The right five columns are rank 50 miss rates Missing entries usually apply because another algorithm from the same developer was run instead. Some developers are missing because less accurate algorithms were not run on galleries with $N > 1\,600\,000$. Throughout blue superscripts indicate the rank of the algorithm for that column, and yellow highlighting indicates the most accurate value. Caution: The Power-low models are mostly intended to draw attention to the kind of behavior, not as a model to be used for prediction.*

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MISSES AT GIVEN RANK		ENROL MOST RECENT											
FNIR(N, T= 0, R)		RANK 1						RANK 50					
#	ALGORITHM	N=0.64M	N=1.6M	N=3.0M	N=6.0M	N=12.0M	aN^b	N=0.64M	N=1.6M	N=3.0M	N=6.0M	N=12.0M	aN^b
73	NEUROTECHNOLOGY-004	^{96}0.0046	^{94}0.0056	^{90}0.0064	^{86}0.0074	^{83}0.0088	^{82}0.0002 N$^{0.220}$ ^{73}	^{104}0.0022	^{103}0.0025	^{96}0.0028	^{92}0.0031	^{85}0.0034	^{61}0.0003 N$^{0.154}$ ^{91}
74	NEUROTECHNOLOGY-005	^{83}0.0035	^{80}0.0043	^{79}0.0049	^{76}0.0057	^{72}0.0068	^{62}0.0002 N$^{0.223}$ ^{76}	^{101}0.0021	^{99}0.0023	^{89}0.0024	^{86}0.0025	^{79}0.0028	^{86}0.0006 N$^{0.092}$ ^{66}
75	NEUROTECHNOLOGY-007	^{77}0.0032	^{75}0.0039	^{76}0.0044	^{73}0.0052	^{70}0.0062	^{54}0.0002 N$^{0.222}$ ^{75}	^{97}0.0020	^{94}0.0022	^{87}0.0023	^{81}0.0024	^{73}0.0026	^{98}0.0007 N$^{0.076}$ ^{56}
76	NEUROTECHNOLOGY-008	^{37}0.0019	^{40}0.0022	^{40}0.0025	^{43}0.0029	^{39}0.0034	^{39}0.0001 N$^{0.205}$ ^{67}	^{49}0.0013	^{37}0.0013	^{34}0.0013	^{30}0.0014	^{26}0.0015	^{97}0.0007 N$^{0.043}$ ^{33}
77	NTECHLAB-003	^{97}0.0046	^{99}0.0062	^{97}0.0076	^{99}0.0094	^{96}0.0114	^{22}0.0001 N$^{0.310}$ ^{131}	^{46}0.0013	^{65}0.0016	^{73}0.0018	^{78}0.0022	^{74}0.0026	^{22}0.0001 N$^{0.237}$ ^{109}
78	NTECHLAB-004	^{86}0.0037	^{89}0.0048	^{86}0.0058	^{83}0.0071	^{81}0.0085	^{24}0.0001 N$^{0.291}$ ^{122}	^{25}0.0011	^{39}0.0013	^{49}0.0015	^{49}0.0017	^{59}0.0021	^{32}0.0001 N$^{0.198}$ ^{99}
79	NTECHLAB-005	^{81}0.0035	^{87}0.0047	^{87}0.0058	^{84}0.0073	^{86}0.0092	^{14}0.0000 N$^{0.334}$ ^{137}	^{8}0.0008	^{19}0.0011	^{24}0.0012	^{41}0.0015	^{48}0.0019	^{9}0.0000 N$^{0.283}$ ^{122}
80	NTECHLAB-006	^{71}0.0030	^{79}0.0041	^{80}0.0050	^{78}0.0062	^{78}0.0078	^{13}0.0000 N$^{0.326}$ ^{136}	^{6}0.0008	^{11}0.0009	^{18}0.0011	^{23}0.0013	^{36}0.0016	^{11}0.0000 N$^{0.253}$ ^{113}
81	NTECHLAB-007	^{52}0.0022	^{55}0.0027	^{55}0.0031	^{55}0.0037	^{54}0.0044	^{26}0.0001 N$^{0.245}$ ^{93}	^{24}0.0011	^{27}0.0012	^{29}0.0013	^{32}0.0014	^{31}0.0015	^{60}0.0003 N$^{0.109}$ ^{73}
82	NTECHLAB-008	^{18}0.0014	^{22}0.0017	^{22}0.0020	^{29}0.0024	^{23}0.0027	^{19}0.0001 N$^{0.224}$ ^{77}	^{18}0.0010	^{18}0.0010	^{16}0.0011	^{16}0.0011	^{14}0.0012	^{71}0.0004 N$^{0.065}$ ^{50}
83	NTECHLAB-009	^{10}0.0012	^{9}0.0013	^{8}0.0014	^{8}0.0015	^{10}0.0018	^{61}0.0002 N$^{0.140}$ ^{38}	^{15}0.0009	^{13}0.0009	^{12}0.0010	^{12}0.0010	^{11}0.0010	^{81}0.0005 N$^{0.041}$ ^{30}
84	PARAVISION-003	^{64}0.0026	^{63}0.0031	^{63}0.0035	^{61}0.0042	^{60}0.0048	^{50}0.0002 N$^{0.210}$ ^{69}	^{76}0.0016	^{74}0.0017	^{72}0.0018	^{68}0.0020	^{60}0.0021	^{76}0.0005 N$^{0.089}$ ^{62}
85	PARAVISION-004	^{23}0.0015	^{21}0.0016	^{19}0.0017	^{17}0.0019	^{16}0.0021	^{96}0.0003 N$^{0.111}$ ^{26}	^{45}0.0013	^{35}0.0013	^{30}0.0013	^{27}0.0013	^{23}0.0014	^{113}0.0010 N$^{0.020}$ ^{21}
86	PARAVISION-005	^{20}0.0015	^{16}0.0015	^{15}0.0016	^{15}0.0018	^{13}0.0019	^{103}0.0004 N$^{0.094}$ ^{21}	^{48}0.0013	^{38}0.0013	^{33}0.0013	^{28}0.0013	^{21}0.0014	^{115}0.0011 N$^{0.015}$ ^{13}
87	PARAVISION-007	^{8}0.0011	^{7}0.0012	^{7}0.0012	^{6}0.0013	^{6}0.0015	^{93}0.0003 N$^{0.091}$ ^{20}	^{19}0.0010	^{15}0.0010	^{13}0.0010	^{13}0.0010	^{12}0.0011	^{104}0.0008 N$^{0.018}$ ^{18}
88	PIXELALL-002	^{88}0.0037	^{84}0.0045	^{82}0.0052	^{79}0.0062	^{76}0.0075	^{48}0.0002 N$^{0.238}$ ^{87}	^{81}0.0017	^{87}0.0019	^{83}0.0021	^{82}0.0024	^{76}0.0027	^{53}0.0002 N$^{0.154}$ ^{92}
89	PIXELALL-003	^{39}0.0019	^{39}0.0021	^{39}0.0024	^{38}0.0028	^{37}0.0032	^{55}0.0002 N$^{0.182}$ ^{59}	^{55}0.0014	^{49}0.0014	^{41}0.0014	^{38}0.0015	^{33}0.0016	^{101}0.0007 N$^{0.045}$ ^{35}
90	PIXELALL-004	^{31}0.0017	^{37}0.0020	^{36}0.0023	^{35}0.0026	^{32}0.0030	^{43}0.0001 N$^{0.192}$ ^{61}	^{47}0.0013	^{40}0.0013	^{37}0.0014	^{33}0.0014	^{28}0.0015	^{93}0.0007 N$^{0.046}$ ^{36}
91	PIXELALL-005	^{32}0.0018	^{30}0.0019	^{24}0.0020	^{21}0.0021	^{19}0.0024	^{108}0.0005 N$^{0.098}$ ^{22}	^{68}0.0015	^{64}0.0016	^{54}0.0016	^{44}0.0016	^{37}0.0016	^{117}0.0012 N$^{0.018}$ ^{16}
92	PTAKURATSATU-000	^{61}0.0025	^{62}0.0030	^{64}0.0036	^{59}0.0040	^{49}0.0040	^{89}0.0003 N$^{0.167}$ ^{51}	^{67}0.0015	^{66}0.0016	^{75}0.0018	^{65}0.0020	^{54}0.0020	^{72}0.0004 N$^{0.096}$ ^{67}
93	QUANTASOFT-001	^{205}0.2177	^{202}0.2177	^{151}0.2177		^{139}0.2177	^{143}0.2177 N$^{0.000}$ ^{1}	^{208}0.1116	^{204}0.1116	^{150}0.1116		^{139}0.1116	^{143}0.1116 N$^{-0.000}$ ^{1}
94	RANKONE-002	^{158}0.0155	^{157}0.0194	^{131}0.0224	^{126}0.0262	^{126}0.0304	^{116}0.0007 N$^{0.230}$ ^{79}	^{147}0.0048	^{149}0.0060	^{127}0.0071	^{127}0.0085	^{125}0.0102	^{44}0.0002 N$^{0.254}$ ^{116}
95	RANKONE-003	^{159}0.0155	^{158}0.0194	^{132}0.0224	^{127}0.0262	^{125}0.0304	^{117}0.0007 N$^{0.230}$ ^{80}	^{146}0.0048	^{148}0.0060	^{126}0.0071	^{126}0.0085	^{124}0.0102	^{45}0.0002 N$^{0.254}$ ^{115}
96	RANKONE-005	^{119}0.0075	^{125}0.0094	^{114}0.0110	^{111}0.0132	^{109}0.0156	^{84}0.0003 N$^{0.251}$ ^{96}	^{119}0.0026	^{120}0.0032	^{110}0.0036	^{106}0.0043	^{99}0.0050	^{40}0.0001 N$^{0.221}$ ^{106}
97	RANKONE-007	^{68}0.0028	^{67}0.0034	^{66}0.0038	^{63}0.0045	^{62}0.0053	^{57}0.0002 N$^{0.211}$ ^{70}	^{66}0.0015	^{69}0.0017	^{69}0.0018	^{63}0.0019	^{62}0.0021	^{63}0.0003 N$^{0.123}$ ^{80}
98	RANKONE-009	^{42}0.0020	^{47}0.0024	^{48}0.0027	^{49}0.0032	^{46}0.0038	^{35}0.0001 N$^{0.219}$ ^{72}	^{53}0.0013	^{47}0.0014	^{43}0.0015	^{40}0.0015	^{34}0.0016	^{84}0.0006 N$^{0.059}$ ^{46}
99	RANKONE-010	^{45}0.0020	^{42}0.0022	^{42}0.0025	^{42}0.0029	^{38}0.0032	^{76}0.0002 N$^{0.164}$ ^{50}	^{61}0.0014	^{52}0.0015	^{48}0.0015	^{42}0.0016	^{39}0.0017	^{89}0.0006 N$^{0.058}$ ^{45}
100	REALNETWORKS-002	^{177}0.0299	^{173}0.0393	^{144}0.0470	^{139}0.0562	^{137}0.0580	^{123}0.0013 N$^{0.236}$ ^{86}	^{151}0.0054	^{159}0.0076	^{136}0.0097	^{133}0.0126	^{131}0.0132	^{31}0.0001 N$^{0.320}$ ^{132}
101	REALNETWORKS-003	^{164}0.0183	^{164}0.0242	^{137}0.0291	^{133}0.0352	^{133}0.0423	^{102}0.0004 N$^{0.287}$ ^{121}	^{141}0.0041	^{141}0.0054	^{123}0.0064	^{124}0.0080	^{123}0.0101	^{25}0.0001 N$^{0.307}$ ^{128}
102	REALNETWORKS-004	^{161}0.0175	^{162}0.0236	^{136}0.0284	^{132}0.0347	^{130}0.0416	^{97}0.0003 N$^{0.295}$ ^{124}	^{138}0.0040	^{139}0.0050	^{121}0.0061	^{122}0.0078	^{122}0.0099	^{24}0.0001 N$^{0.315}$ ^{129}
103	REMARKAI-000	^{67}0.0027	^{69}0.0034	^{69}0.0040	^{68}0.0048	^{65}0.0058	^{28}0.0001 N$^{0.260}$ ^{102}	^{62}0.0014	^{62}0.0015	^{57}0.0016	^{53}0.0018	^{51}0.0020	^{65}0.0003 N$^{0.108}$ ^{70}
104	RENDIP-000	^{16}0.0014	^{18}0.0015	^{18}0.0017	^{19}0.0019	^{18}0.0022	^{56}0.0002 N$^{0.158}$ ^{45}	^{28}0.0012	^{26}0.0012	^{23}0.0012	^{19}0.0012	^{16}0.0013	^{106}0.0008 N$^{0.025}$ ^{23}
105	S1-000	^{46}0.0021	^{49}0.0024	^{50}0.0028	^{50}0.0032	^{45}0.0037	^{44}0.0001 N$^{0.203}$ ^{64}	^{63}0.0014	^{58}0.0015	^{51}0.0015	^{46}0.0016	^{40}0.0017	^{92}0.0007 N$^{0.055}$ ^{42}
106	SCANOVATE-000	^{89}0.0038	^{90}0.0050	^{88}0.0059	^{85}0.0073	^{75}0.0073	^{59}0.0002 N$^{0.235}$ ^{85}	^{59}0.0014	^{63}0.0015	^{62}0.0017	^{73}0.0020	^{57}0.0020	^{52}0.0002 N$^{0.142}$ ^{87}
107	SCANOVATE-001	^{91}0.0041	^{93}0.0053	^{89}0.0064	^{89}0.0079	^{90}0.0098	^{23}0.0001 N$^{0.299}$ ^{127}	^{54}0.0013	^{60}0.0015	^{63}0.0017	^{74}0.0021	^{72}0.0024	^{34}0.0001 N$^{0.207}$ ^{103}
108	SENSETIME-000	^{51}0.0022	^{45}0.0023	^{46}0.0026	^{41}0.0028	^{36}0.0032	^{99}0.0003 N$^{0.135}$ ^{36}	^{78}0.0016	^{75}0.0017	^{70}0.0018	^{57}0.0018	^{55}0.0020	^{100}0.0007 N$^{0.060}$ ^{47}
109	SENSETIME-001	^{50}0.0022	^{46}0.0023	^{44}0.0025	^{44}0.0029	^{43}0.0037	^{66}0.0002 N$^{0.177}$ ^{57}	^{75}0.0016	^{67}0.0016	^{61}0.0017	^{56}0.0018	^{70}0.0024	^{62}0.0003 N$^{0.125}$ ^{82}
110	SENSETIME-002	^{154}0.0136	^{145}0.0137	^{122}0.0137	^{113}0.0138	^{105}0.0139	^{138}0.0124 N$^{0.007}$ ^{2}	^{182}0.0136	^{175}0.0136	^{140}0.0136	^{135}0.0136	^{132}0.0136	^{139}0.0135 N$^{0.001}$ ^{3}
111	SENSETIME-003	^{4}0.0010	^{3}0.0010	^{3}0.0010	^{3}0.0011	^{3}0.0012	^{91}0.0003 N$^{0.085}$ ^{18}	^{14}0.0009	^{12}0.0009	^{11}0.0009	^{11}0.0010	^{9}0.0010	^{103}0.0008 N$^{0.013}$ ^{11}
112	SENSETIME-004	^{3}0.0010	^{2}0.0010	^{2}0.0010	^{2}0.0011	^{2}0.0012	^{92}0.0003 N$^{0.081}$ ^{15}	^{9}0.0008	^{7}0.0009	^{7}0.0009	^{6}0.0009	^{5}0.0009	^{90}0.0007 N$^{0.018}$ ^{19}
113	SENSETIME-005	^{1}0.0008	^{1}0.0009	^{1}0.0009	^{1}0.0010	^{1}0.0011	^{85}0.0003 N$^{0.085}$ ^{17}	^{7}0.0008	^{6}0.0008	^{6}0.0008	^{3}0.0008	^{1}0.0008	^{105}0.0008 N$^{0.002}$ ^{5}
114	SHAMAN-007	^{181}0.0371	^{174}0.0396	^{143}0.0416	^{138}0.0443	^{135}0.0473	^{137}0.0122 N$^{0.083}$ ^{16}	^{194}0.0308	^{189}0.0314	^{146}0.0319	^{139}0.0326	^{136}0.0337	^{140}0.0207 N$^{0.029}$ ^{26}
115	SIAT-001	^{29}0.0017	^{24}0.0018	^{25}0.0020	^{27}0.0023	^{24}0.0027	^{51}0.0002 N$^{0.173}$ ^{55}	^{20}0.0010	^{20}0.0011	^{19}0.0012	^{22}0.0013	^{19}0.0013	^{66}0.0003 N$^{0.085}$ ^{59}
116	SIAT-002	^{28}0.0016	^{25}0.0018	^{27}0.0020	^{26}0.0023	^{21}0.0027	^{53}0.0002 N$^{0.171}$ ^{53}	^{26}0.0011	^{28}0.0012	^{28}0.0013	^{25}0.0013	^{22}0.0014	^{78}0.0005 N$^{0.062}$ ^{48}
117	SYNESIS-003	^{160}0.0161	^{149}0.0162	^{127}0.0163	^{119}0.0165	^{121}0.0254	^{128}0.0027 N$^{0.127}$ ^{34}	^{185}0.0160	^{180}0.0160	^{142}0.0160	^{137}0.0160	^{135}0.0245	^{110}0.0009 N$^{0.192}$ ^{98}
118	SYNESIS-003	^{199}0.1456	^{199}0.1700	^{149}0.1876	^{142}0.2088	^{140}0.2317	^{139}0.0177 N$^{0.158}$ ^{46}	^{201}0.0828	^{201}0.0869	^{149}0.0920	^{142}0.0998	^{138}0.1104	^{141}0.0218 N$^{0.098}$ ^{69}
119	SYNESIS-005	^{130}0.0085	^{117}0.0085	^{105}0.0085	^{94}0.0086	^{84}0.0088	^{136}0.0072 N$^{0.012}$ ^{3}	^{169}0.0085	^{165}0.0085	^{134}0.0085	^{125}0.0085	^{116}0.0085	^{138}0.0085 N$^{0.000}$ ^{2}
120	TECH5-001	^{76}0.0032	^{77}0.0040	^{78}0.0047	^{75}0.0057	^{74}0.0071	^{27}0.0001 N$^{0.271}$ ^{106}	^{70}0.0016	^{72}0.0017	^{71}0.0018	^{66}0.0020	^{68}0.0023	^{64}0.0003 N$^{0.119}$ ^{77}
121	TECH5-002	^{43}0.0020	^{56}0.0027	^{57}0.0031	^{54}0.0037	^{57}0.0047	^{15}0.0000 N$^{0.285}$ ^{120}	^{13}0.0009	^{16}0.0010	^{17}0.0011	^{17}0.0012	^{18}0.0013	^{47}0.0002 N$^{0.127}$ ^{84}
122	TEVIAN-005	^{109}0.0056	^{110}0.0073	^{104}0.0084	^{104}0.0105	^{103}0.0130	^{42}0.0001 N$^{0.283}$ ^{119}	^{95}0.0020	^{98}0.0023	^{92}0.0025	^{88}0.0028	^{84}0.0034	^{48}0.0002 N$^{0.178}$ ^{96}
123	TEVIAN-006	^{56}0.0023	^{50}0.0024	^{47}0.0026	^{39}0.0028	^{35}0.0031	^{111}0.0005 N$^{0.106}$ ^{23}	^{72}0.0016	^{68}0.0017	^{60}0.0017	^{52}0.0017	^{43}0.0018	^{108}0.0009 N$^{0.041}$ ^{31}
124	TIGER-002	^{93}0.0044	^{96}0.0056	^{93}0.0068	^{95}0.0086	^{94}0.0105	^{25}0.0001 N$^{0.299}$ ^{128}	^{41}0.0013	^{56}0.0015	^{69}0.0018	^{75}0.0021	^{75}0.0027	^{16}0.0000 N$^{0.253}$ ^{114}
125	TOSHIBA-000	^{82}0.0035	^{83}0.0045	^{83}0.0052	^{77}0.0061	^{108}0.0154	^{4}0.0000 N$^{0.449}$ ^{140}	^{73}0.0016	^{79}0.0018	^{78}0.0019	^{77}0.0021	^{126}0.0105	^{3}0.0000 N$^{0.539}$ ^{141}
126	TRUEFACE-000	^{74}0.0031	^{66}0.0033	^{62}0.0035	^{58}0.0039	^{51}0.0043	^{114}0.0006 N$^{0.115}$ ^{30}	^{116}0.0025	^{105}0.0026	^{93}0.0026	^{87}0.0027	^{80}0.0028	^{122}0.0015 N$^{0.038}$ ^{29}
127	VD-001	^{171}0.0230	^{168}0.0276	^{139}0.0315	^{135}0.0363	^{132}0.0418	^{124}0.0015 N$^{0.204}$ ^{66}	^{179}0.0120	^{174}0.0130	^{141}0.0140	^{136}0.0154	^{134}0.0170	^{129}0.0024 N$^{0.120}$ ^{78}
128	VERIDAS-001	^{57}0.0023	^{58}0.0028	^{58}0.0032	^{57}0.0037	^{55}0.0045	^{34}0.0001 N$^{0.231}$ ^{82}	^{60}0.0014	^{53}0.0015	^{47}0.0015	^{47}0.0016	^{42}0.0018	^{74}0.0005 N$^{0.083}$ ^{58}
129	VISIONLABS-004	^{53}0.0022	^{57}0.0027	^{60}0.0032	^{62}0.0044	^{73}0.0070	^{5}0.0000 N$^{0.387}$ ^{138}	^{37}0.0012	^{45}0.0014	^{59}0.0017	^{84}0.0025	^{96}0.0045	^{4}0.0000 N$^{0.435}$ ^{137}
130	VISIONLABS-005	^{41}0.0020	^{48}0.0024	^{53}0.0029	^{53}0.0037	^{61}0.0051	^{9}0.0000 N$^{0.322}$ ^{135}	^{35}0.0012	^{34}0.0013	^{53}0.0016	^{64}0.0019	^{81}0.0029	^{10}0.0000 N$^{0.298}$ ^{125}
131	VISIONLABS-006	^{27}0.0016	^{27}0.0018	^{35}0.0022	^{40}0.0028	^{50}0.0041	^{8}0.0000 N$^{0.314}$ ^{133}	^{32}0.0012	^{31}0.0013	^{44}0.0015	^{58}0.0019	^{77}0.0027	^{12}0.0000 N$^{0.275}$ ^{119}
132	VISIONLABS-007	^{26}0.0016	^{23}0.0018	^{23}0.0020	^{28}0.0023	^{40}0.0034	^{17}0.0001 N$^{0.248}$ ^{94}	^{31}0.0012	^{29}0.0012	^{27}0.0013	^{24}0.0013	^{53}0.0020	^{41}0.0001 N$^{0.152}$ ^{90}
133	VISIONLABS-008	^{36}0.0019	^{35}0.0020	^{31}0.0021	^{34}0.0025	^{33}0.0030	^{63}0.0002 N$^{0.169}$ ^{52}	^{79}0.0016	^{76}0.0017	^{65}0.0017	^{69}0.0020	^{69}0.0023	^{67}0.0003 N$^{0.114}$ ^{75}
134	VISIONLABS-009	^{7}0.0011	^{6}0.0011	^{6}0.0012	^{7}0.0014	^{9}0.0017	^{40}0.0001 N$^{0.160}$ ^{49}	^{17}0.0010	^{14}0.0010	^{14}0.0010	^{15}0.0011	^{24}0.0014	^{55}0.0002 N$^{0.109}$ ^{71}
135	VISIONLABS-010	^{14}0.0014	^{12}0.0014	^{11}0.0015	^{13}0.0017	^{15}0.0021	^{70}0.0002 N$^{0.137}$ ^{37}	^{39}0.0013	^{30}0.0013	^{32}0.0013	^{34}0.0014	^{38}0.0017	^{69}0.0004 N$^{0.090}$ ^{64}
136	VOCORD-005	^{110}0.0060	^{109}0.0070	^{101}0.0082	^{101}0.0097	^{98}0.0117	^{83}0.0003 N$^{0.232}$ ^{84}	^{133}0.0033	^{127}0.0035	^{112}0.0037	^{102}0.0040	^{95}0.0043	^{111}0.0010 N$^{0.090}$ ^{63}
137	XFORWARDAI-000	^{49}0.0021	^{43}0.0023	^{38}0.0024	^{36}0.0027	^{30}0.0029	^{107}0.0005 N$^{0.111}$ ^{27}	^{92}0.0019	^{86}0.0019	^{79}0.0019	^{70}0.0020	^{56}0.0020	^{121}0.0015 N$^{0.018}$ ^{17}
138	XFORWARDAI-001	^{44}0.0020	^{38}0.0020	^{29}0.0021	^{23}0.0022	^{20}0.0024	^{120}0.0009 N$^{0.055}$ ^{10}	^{91}0.0019	^{85}0.0019	^{77}0.0019	^{62}0.0019	^{49}0.0019	^{125}0.0018 N$^{0.004}$ ^{7}
139	XFORWARDAI-002	^{40}0.0019	^{32}0.0020	^{26}0.0020	^{20}0.0021	^{17}0.0022	^{122}0.0011 N$^{0.038}$ ^{5}	^{90}0.0019	^{83}0.0019	^{76}0.0019	^{61}0.0019	^{47}0.0019	^{124}0.0018 N$^{0.003}$ ^{6}
140	YITU-002	^{25}0.0016	^{28}0.0018	^{30}0.0021	^{30}0.0024	^{31}0.0029	^{30}0.0001 N$^{0.213}$ ^{71}	^{16}0.0009	^{17}0.0010	^{15}0.0010	^{14}0.0011	^{13}0.0012	^{68}0.0004 N$^{0.073}$ ^{55}
141	YITU-003	^{63}0.0026	^{61}0.0029	^{56}0.0031	^{51}0.0035	^{48}0.0039	^{101}0.0004 N$^{0.141}$ ^{39}	^{98}0.0020	^{93}0.0021	^{86}0.0022	^{80}0.0023	^{71}0.0024	^{112}0.0010 N$^{0.054}$ ^{41}
142	YITU-004	^{9}0.0011	^{10}0.0013	^{12}0.0015	^{14}0.0017	^{56}0.0047	^{3}0.0000 N$^{0.438}$ ^{139}	^{10}0.0008	^{8}0.0009	^{9}0.0009	^{8}0.0009	^{86}0.0036	^{5}0.0000 N$^{0.395}$ ^{136}
143	YITU-005	^{55}0.0022	^{44}0.0023	^{41}0.0025	^{37}0.0027	^{34}0.0031	^{109}0.0005 N$^{0.113}$ ^{28}	^{93}0.0020	^{88}0.0020	^{82}0.0020	^{72}0.0020	^{58}0.0020	^{123}0.0017 N$^{0.012}$ ^{10}

Table 16: **Investigation-mode: Effect of N on FNIR on recent images** *For five enrollment population sizes, N, with T = 0 and FPIR = 1. The left five columns are rank 1 miss rates The right five columns are rank 50 miss rates Missing entries usually apply because another algorithm from the same developer was run instead. Some developers are missing because less accurate algorithms were not run on galleries with $N > 1\,600\,000$. Throughout blue superscripts indicate the rank of the algorithm for that column, and yellow highlighting indicates the most accurate value. Caution: The Power-low models are mostly intended to draw attention to the kind of behavior, not as a model to be used for prediction.*

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MISSES OUTSIDE RANK R		RESOURCE USAGE		ENROL MOST RECENT, N = 1.6M					
FNIR(N, T=0, R)		TEMPLATE		FRVT 2018 MUGSHOTS					
#	ALGORITHM	BYTES	MSEC	R=1	R=5	R=10	R=20	R=50	WORK-10
1	3DIVI-003	^{38}512	^{118}625	^{191}0.0833	^{186}0.0444	^{186}0.0349	^{182}0.0270	^{182}0.0191	^{187}1.447
2	3DIVI-004	^{203}4096	^{119}628	^{152}0.0175	^{145}0.0091	^{143}0.0075	^{141}0.0061	^{137}0.0049	^{149}1.092
3	3DIVI-005	^{199}4096	^{126}653	^{153}0.0176	^{146}0.0091	^{141}0.0074	^{140}0.0061	^{138}0.0049	^{150}1.092
4	3DIVI-006	^{47}528	^{127}653	^{163}0.0240	^{170}0.0171	^{172}0.0160	^{173}0.0154	^{178}0.0148	^{168}1.162
5	ACER-000	^{35}512	^{29}201	^{132}0.0106	^{117}0.0051	^{114}0.0041	^{113}0.0034	^{108}0.0026	^{118}1.053
6	ALCHERA-000	^{129}2048	^{42}263	^{148}0.0161	^{157}0.0124	^{162}0.0117	^{167}0.0111	^{168}0.0105	^{156}1.116
7	ALCHERA-001	^{115}2048	^{6}66	^{217}0.9869	^{217}0.9782	^{217}0.9735	^{217}0.9679	^{216}0.9590	^{217}9.811
8	ALCHERA-002	^{137}2048	^{14}115	^{192}0.0949	^{191}0.0555	^{189}0.0443	^{189}0.0354	^{184}0.0254	^{191}1.544
9	ALCHERA-003	^{119}2048	^{107}548	^{129}0.0104	^{119}0.0054	^{119}0.0045	^{119}0.0038	^{119}0.0032	^{121}1.055
10	ALLGOVISION-000	^{114}2048	^{79}425	^{135}0.0114	^{140}0.0084	^{146}0.0078	^{147}0.0073	^{152}0.0067	^{140}1.079
11	ALLGOVISION-001	^{142}2048	^{176}792	^{120}0.0090	^{115}0.0048	^{113}0.0040	^{112}0.0033	^{110}0.0027	^{115}1.048
12	ANKE-000	^{178}2072	^{81}431	^{143}0.0132	^{131}0.0073	^{131}0.0060	^{131}0.0050	^{131}0.0040	^{136}1.072
13	ANKE-001	^{177}2072	^{83}433	^{144}0.0132	^{132}0.0073	^{133}0.0061	^{132}0.0050	^{132}0.0040	^{137}1.073
14	ANKE-002	^{169}2056	^{121}641	^{59}0.0028	^{59}0.0020	^{59}0.0018	^{66}0.0018	^{70}0.0017	^{60}1.019
15	AWARE-003	^{179}2076	^{159}716	^{170}0.0306	^{167}0.0162	^{164}0.0127	^{161}0.0100	^{158}0.0075	^{169}1.163
16	AWARE-004	^{2}92	^{156}712	^{186}0.0679	^{183}0.0348	^{180}0.0274	^{180}0.0208	^{177}0.0145	^{183}1.354
17	AWARE-005	^{190}3100	^{182}827	^{171}0.0311	^{168}0.0167	^{166}0.0134	^{163}0.0107	^{164}0.0082	^{170}1.167
18	AWARE-006	^{3}124	^{179}818	^{188}0.0697	^{185}0.0369	^{181}0.0288	^{181}0.0223	^{179}0.0158	^{185}1.371
19	AYONIX-000	^{70}1036	^{1}10	^{211}0.4505	^{212}0.3540	^{212}0.3176	^{212}0.2834	^{212}0.2381	^{212}4.288
20	AYONIX-001	^{72}1036	^{3}12	^{207}0.3414	^{206}0.2338	^{206}0.1977	^{207}0.1652	^{206}0.1274	^{206}3.226
21	AYONIX-002	^{73}1036	^{2}11	^{206}0.3414	^{207}0.2338	^{207}0.1977	^{206}0.1652	^{207}0.1274	^{207}3.226
22	CAMVI-003	^{63}1024	^{152}707	^{182}0.0520	^{190}0.0517	^{191}0.0517	^{194}0.0517	^{194}0.0517	^{189}1.466
23	CAMVI-004	^{61}1024	^{161}718	^{180}0.0468	^{188}0.0465	^{190}0.0465	^{191}0.0464	^{193}0.0464	^{186}1.419
24	CAMVI-005	^{64}1024	^{170}769	^{185}0.0652	^{192}0.0648	^{195}0.0648	^{196}0.0648	^{198}0.0647	^{192}1.584
25	CIB-000	^{218}8196	^{133}674	^{17}0.0015	^{19}0.0013	^{20}0.0012	^{22}0.0012	^{23}0.0012	^{19}1.012
26	CLOUDWALK-HR-000	^{103}2048	^{206}908	^{14}0.0015	^{29}0.0014	^{32}0.0014	^{40}0.0014	^{46}0.0014	^{26}1.013
27	COGENT-000	^{45}525	^{108}551	^{131}0.0105	^{150}0.0096	^{153}0.0095	^{108}0.0032	^{102}0.0024	^{147}1.088
28	COGENT-001	^{44}525	^{109}552	^{130}0.0105	^{151}0.0096	^{156}0.0095	^{107}0.0032	^{101}0.0024	^{146}1.088
29	COGENT-002	^{75}1043	^{217}987	^{72}0.0036	^{68}0.0022	^{67}0.0020	^{64}0.0018	^{61}0.0015	^{69}1.021
30	COGENT-003	^{74}1043	^{216}960	^{74}0.0038	^{78}0.0024	^{74}0.0021	^{78}0.0019	^{73}0.0017	^{75}1.023
31	COGENT-004	^{168}2053	^{215}952	^{34}0.0020	^{35}0.0016	^{38}0.0015	^{42}0.0015	^{44}0.0014	^{35}1.015
32	COGNITEC-000	^{166}2052	^{19}176	^{165}0.0252	^{163}0.0136	^{161}0.0107	^{160}0.0085	^{151}0.0065	^{164}1.136
33	COGNITEC-001	^{167}2052	^{30}202	^{136}0.0117	^{125}0.0062	^{125}0.0051	^{127}0.0042	^{125}0.0034	^{125}1.062
34	COGNITEC-002	^{164}2052	^{35}227	^{97}0.0057	^{98}0.0037	^{99}0.0032	^{100}0.0029	^{109}0.0026	^{98}1.035
35	COGNITEC-003	^{155}2052	^{52}297	^{101}0.0062	^{105}0.0040	^{107}0.0036	^{111}0.0033	^{117}0.0030	^{104}1.039
36	COGNITEC-004	^{157}2052	^{26}192	^{65}0.0032	^{62}0.0020	^{54}0.0018	^{48}0.0015	^{48}0.0014	^{63}1.020
37	CYBERLINK-000	^{160}2052	^{147}699	^{76}0.0040	^{87}0.0028	^{91}0.0026	^{94}0.0024	^{96}0.0022	^{86}1.027
38	CYBERLINK-001	^{163}2052	^{82}433	^{70}0.0035	^{74}0.0023	^{73}0.0021	^{69}0.0018	^{77}0.0017	^{71}1.022
39	CYBERLINK-002	^{214}4140	^{167}738	^{54}0.0026	^{70}0.0023	^{81}0.0022	^{87}0.0021	^{91}0.0021	^{67}1.021
40	CYBERLINK-003	^{216}6212	^{145}696	^{19}0.0016	^{21}0.0013	^{21}0.0013	^{20}0.0012	^{21}0.0012	^{21}1.012
41	DAHUA-000	^{105}2048	^{68}378	^{124}0.0093	^{128}0.0066	^{132}0.0061	^{138}0.0057	^{142}0.0054	^{126}1.062
42	DAHUA-001	^{138}2048	^{64}371	^{105}0.0067	^{106}0.0040	^{106}0.0036	^{110}0.0033	^{112}0.0029	^{106}1.040
43	DAHUA-002	^{109}2048	^{146}699	^{26}0.0018	^{31}0.0015	^{35}0.0014	^{38}0.0014	^{41}0.0013	^{30}1.014
44	DAHUA-003	^{127}2048	^{164}725	^{8}0.0012	^{7}0.0010	^{9}0.0009	^{9}0.0009	^{9}0.0009	^{6}1.009
45	DEEPGLINT-001	^{195}4096	^{137}687	^{13}0.0014	^{22}0.0014	^{25}0.0013	^{29}0.0013	^{32}0.0013	^{22}1.012
46	DEEPSEA-001	^{150}2048	^{174}780	^{81}0.0043	^{69}0.0022	^{57}0.0018	^{53}0.0016	^{43}0.0014	^{72}1.022
47	DERMALOG-003	^{5}128	^{32}211	^{196}0.1259	^{195}0.0744	^{194}0.0603	^{193}0.0480	^{192}0.0347	^{195}1.731
48	DERMALOG-004	^{6}128	^{31}208	^{195}0.1251	^{194}0.0739	^{193}0.0598	^{192}0.0475	^{191}0.0343	^{194}1.727
49	DERMALOG-005	^{7}128	^{101}532	^{147}0.0149	^{160}0.0129	^{163}0.0125	^{169}0.0123	^{173}0.0122	^{157}1.118
50	DERMALOG-006	^{19}256	^{99}514	^{115}0.0081	^{130}0.0069	^{134}0.0066	^{142}0.0065	^{150}0.0063	^{128}1.063
51	DERMALOG-007	^{4}128	^{77}413	^{123}0.0092	^{129}0.0066	^{130}0.0060	^{137}0.0057	^{144}0.0054	^{127}1.062
52	DERMALOG-008	^{36}512	^{63}370	^{60}0.0029	^{58}0.0020	^{56}0.0018	^{56}0.0017	^{59}0.0015	^{59}1.019
53	EYEDEA-003	^{71}1036	^{69}385	^{190}0.0800	^{182}0.0451	^{187}0.0362	^{183}0.0289	^{183}0.0211	^{188}1.448
54	F8-001	^{99}2048	^{192}851	^{140}0.0120	^{152}0.0105	^{159}0.0102	^{162}0.0100	^{166}0.0099	^{152}1.096
55	GLORY-000	^{29}418	^{15}160	^{200}0.1781	^{202}0.1391	^{202}0.1266	^{202}0.1154	^{202}0.1007	^{201}2.298
56	GLORY-001	^{93}1726	^{74}405	^{197}0.1268	^{197}0.0967	^{197}0.0869	^{198}0.0778	^{199}0.0673	^{197}1.903
57	GORILLA-001	^{180}2156	^{17}169	^{183}0.0603	^{178}0.0304	^{177}0.0230	^{177}0.0174	^{170}0.0117	^{178}1.309
58	GORILLA-002	^{77}1132	^{60}341	^{159}0.0197	^{147}0.0092	^{137}0.0070	^{134}0.0054	^{133}0.0041	^{151}1.096
59	GORILLA-003	^{181}2156	^{111}563	^{172}0.0361	^{165}0.0146	^{160}0.0106	^{154}0.0078	^{143}0.0054	^{167}1.158
60	GORILLA-004	^{182}2192	^{71}395	^{102}0.0063	^{95}0.0032	^{92}0.0026	^{90}0.0023	^{78}0.0018	^{95}1.033
61	GORILLA-005	^{217}6288	^{93}483	^{64}0.0032	^{50}0.0019	^{48}0.0017	^{43}0.0015	^{33}0.0013	^{57}1.018
62	HIK-003	^{83}1408	^{120}633	^{137}0.0117	^{124}0.0060	^{123}0.0048	^{124}0.0039	^{116}0.0030	^{124}1.061
63	HIK-004	^{78}1152	^{97}510	^{134}0.0113	^{123}0.0059	^{122}0.0047	^{117}0.0037	^{113}0.0030	^{123}1.060
64	HIK-005	^{82}1408	^{117}619	^{86}0.0046	^{79}0.0025	^{70}0.0020	^{60}0.0017	^{53}0.0015	^{81}1.025
65	HIK-006	^{81}1408	^{114}610	^{85}0.0046	^{80}0.0025	^{71}0.0020	^{59}0.0017	^{54}0.0015	^{80}1.025
66	IDEMIA-003	^{46}528	^{138}689	^{108}0.0069	^{111}0.0045	^{111}0.0039	^{114}0.0034	^{111}0.0027	^{109}1.043
67	IDEMIA-004	^{48}528	^{131}669	^{104}0.0066	^{102}0.0038	^{100}0.0032	^{99}0.0027	^{92}0.0021	^{100}1.038
68	IDEMIA-005	^{27}352	^{66}374	^{114}0.0081	^{109}0.0044	^{108}0.0036	^{109}0.0032	^{115}0.0030	^{111}1.044
69	IDEMIA-006	^{28}352	^{63}373	^{127}0.0096	^{118}0.0052	^{116}0.0042	^{123}0.0039	^{128}0.0037	^{117}1.052
70	IDEMIA-007	^{56}860	^{178}807	^{53}0.0026	^{36}0.0016	^{31}0.0014	^{27}0.0013	^{25}0.0012	^{40}1.015
71	IDEMIA-008	^{26}300	^{86}451	^{5}0.0011	^{5}0.0009	^{8}0.0009	^{10}0.0009	^{10}0.0009	^{4}1.009
72	IMAGUS-002	^{31}512	^{7}76	^{203}0.2203	^{201}0.1342	^{200}0.1090	^{199}0.0871	^{197}0.0632	^{202}2.308

Table 17: **Rank-based accuracy for the FRVT 2018 mugshot sets**. *In columns 3 and 4 are template size and template generation duration. Thereafter values are rank-based FNIR with T = 0 and FPIR = 1. This is appropriate to investigational uses but not those with higher volumes where candidates from all searches would need review. The next column is a workload statistic, a small value shows an algorithm front-loads mates into the first 10 candidates. Throughout, blue superscripts indicate the rank of the algorithm for that column, and the best value is highlighted in yellow.*

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MISSES OUTSIDE RANK R		RESOURCE USAGE		ENROL MOST RECENT, N = 1.6M					
FNIR(N, T=0, R)		TEMPLATE		FRVT 2018 MUGSHOTS					
#	ALGORITHM	BYTES	MSEC	R=1	R=5	R=10	R=20	R=50	WORK-10
73	IMAGUS-003	^{37}512	^{5}57	^{208}0.3559	^{208}0.2491	^{208}0.2132	^{208}0.1791	^{208}0.1397	^{208}3.363
74	IMAGUS-005	^{128}2048	^{175}788	^{31}0.0019	^{37}0.0016	^{37}0.0015	^{37}0.0014	^{42}0.0013	^{36}1.015
75	IMAGUS-006	^{135}2048	^{204}905	^{36}0.0020	^{40}0.0016	^{43}0.0015	^{44}0.0015	^{51}0.0014	^{37}1.015
76	IMPERIAL-000	^{107}2048	^{128}654	^{52}0.0024	^{52}0.0019	^{58}0.0018	^{65}0.0018	^{71}0.0017	^{52}1.018
77	INCODE-000	^{62}1024	^{24}190	^{181}0.0489	^{176}0.0261	^{176}0.0204	^{174}0.0160	^{171}0.0117	^{176}1.262
78	INCODE-001	^{144}2048	^{140}690	^{150}0.0166	^{141}0.0084	^{136}0.0067	^{135}0.0055	^{135}0.0043	^{142}1.086
79	INCODE-002	^{100}2048	^{49}291	^{154}0.0178	^{144}0.0090	^{138}0.0070	^{136}0.0056	^{136}0.0043	^{148}1.092
80	INCODE-003	^{133}2048	^{149}704	^{142}0.0129	^{127}0.0064	^{128}0.0051	^{125}0.0040	^{118}0.0031	^{130}1.066
81	INCODE-004	^{121}2048	^{96}508	^{71}0.0035	^{75}0.0024	^{77}0.0021	^{81}0.0020	^{81}0.0019	^{73}1.023
82	INNOVATRICS-002	^{50}530	^{40}255	^{179}0.0451	^{180}0.0342	^{183}0.0322	^{185}0.0308	^{187}0.0297	^{182}1.321
83	INNOVATRICS-003	^{49}530	^{39}255	^{166}0.0263	^{158}0.0126	^{154}0.0095	^{149}0.0074	^{140}0.0053	^{161}1.129
84	INNOVATRICS-004	^{76}1076	^{75}406	^{141}0.0123	^{126}0.0063	^{124}0.0050	^{126}0.0040	^{121}0.0032	^{129}1.064
85	INNOVATRICS-005	^{52}538	^{190}842	^{51}0.0024	^{47}0.0018	^{49}0.0017	^{51}0.0016	^{50}0.0014	^{47}1.017
86	INTSYSMSU-000	^{145}2048	^{135}675	^{198}0.1457	^{200}0.1320	^{203}0.1272	^{203}0.1225	^{205}0.1163	^{200}2.203
87	IREX-000	^{189}3080	^{219}2379	^{82}0.0044	^{107}0.0043	^{118}0.0043	^{128}0.0043	^{134}0.0043	^{105}1.039
88	ISYSTEMS-002	^{153}2048	^{57}316	^{103}0.0064	^{108}0.0043	^{112}0.0039	^{116}0.0037	^{126}0.0034	^{108}1.041
89	ISYSTEMS-003	^{124}2048	^{193}856	^{92}0.0052	^{103}0.0039	^{109}0.0036	^{115}0.0034	^{122}0.0033	^{99}1.037
90	KEDACOM-001	^{24}292	^{103}537	^{111}0.0077	^{133}0.0074	^{139}0.0073	^{146}0.0072	^{154}0.0072	^{131}1.067
91	KNERON-000	^{130}2048	^{100}530	^{98}0.0059	^{122}0.0059	^{129}0.0059	^{139}0.0059	^{146}0.0059	^{119}1.053
92	KNERON-001	^{143}2048	^{91}468	^{169}0.0295	^{177}0.0295	^{182}0.0295	^{184}0.0295	^{186}0.0295	^{177}1.266
93	LINE-000	^{152}2048	^{92}482	^{41}0.0022	^{34}0.0015	^{30}0.0014	^{24}0.0013	^{22}0.0012	^{34}1.015
94	LOOKMAN-003	^{25}292	^{61}342	^{119}0.0088	^{137}0.0078	^{145}0.0076	^{151}0.0075	^{157}0.0074	^{134}1.071
95	LOOKMAN-004	^{54}548	^{58}325	^{121}0.0091	^{138}0.0079	^{144}0.0076	^{150}0.0075	^{156}0.0073	^{135}1.072
96	LOOKMAN-005	^{53}548	^{98}514	^{113}0.0080	^{135}0.0075	^{142}0.0074	^{148}0.0073	^{155}0.0072	^{132}1.068
97	MEGVII-001	^{198}4096	^{124}652	^{138}0.0118	^{148}0.0093	^{148}0.0087	^{158}0.0084	^{163}0.0080	^{143}1.086
98	MEGVII-002	^{200}4096	^{129}656	^{139}0.0118	^{149}0.0093	^{150}0.0088	^{157}0.0084	^{162}0.0080	^{144}1.087
99	MICROFOCUS-003	^{13}256	^{45}269	^{215}0.5942	^{214}0.4692	^{214}0.4204	^{214}0.3724	^{214}0.3095	^{214}5.361
100	MICROFOCUS-004	^{18}256	^{46}270	^{213}0.5763	^{213}0.4519	^{213}0.4026	^{213}0.3560	^{213}0.2957	^{213}5.199
101	MICROFOCUS-005	^{20}256	^{44}266	^{209}0.4242	^{209}0.3028	^{209}0.2606	^{209}0.2209	^{210}0.1724	^{209}3.861
102	MICROFOCUS-006	^{15}256	^{43}265	^{210}0.4268	^{210}0.3049	^{210}0.2623	^{211}0.2233	^{211}0.1746	^{210}3.880
103	MICROSOFT-003	^{59}1024	^{73}404	^{20}0.0016	^{10}0.0010	^{5}0.0009	^{3}0.0008	^{2}0.0006	^{9}1.009
104	MICROSOFT-004	^{149}2048	^{172}773	^{15}0.0015	^{6}0.0009	^{1}0.0008	^{1}0.0007	^{1}0.0006	^{8}1.009
105	MICROSOFT-005	^{60}1024	^{132}673	^{29}0.0019	^{8}0.0010	^{4}0.0008	^{2}0.0008	^{3}0.0006	^{12}1.010
106	MICROSOFT-006	^{65}1024	^{144}695	^{33}0.0020	^{14}0.0011	^{10}0.0010	^{4}0.0008	^{4}0.0007	^{14}1.011
107	NEC-000	^{188}2592	^{8}82	^{151}0.0170	^{143}0.0086	^{135}0.0066	^{133}0.0052	^{130}0.0038	^{145}1.087
108	NEC-001	^{187}2592	^{9}88	^{160}0.0209	^{164}0.0141	^{165}0.0128	^{168}0.0119	^{169}0.0113	^{163}1.135
109	NEC-002	^{91}1616	^{125}653	^{4}0.0010	^{3}0.0009	^{3}0.0008	^{5}0.0008	^{5}0.0008	^{2}1.008
110	NEC-003	^{92}1712	^{141}690	^{11}0.0014	^{17}0.0012	^{17}0.0012	^{23}0.0012	^{24}0.0012	^{15}1.011
111	NEUROTECHNOLOGY-003	^{148}2048	^{106}547	^{161}0.0225	^{159}0.0126	^{157}0.0100	^{155}0.0078	^{145}0.0057	^{160}1.125
112	NEUROTECHNOLOGY-004	^{108}2048	^{105}543	^{94}0.0056	^{97}0.0036	^{103}0.0032	^{104}0.0029	^{103}0.0025	^{97}1.035
113	NEUROTECHNOLOGY-005	^{21}256	^{76}412	^{80}0.0043	^{89}0.0029	^{93}0.0027	^{93}0.0024	^{99}0.0023	^{89}1.028
114	NEUROTECHNOLOGY-006	^{14}256	^{168}746	^{155}0.0180	^{139}0.0079	^{128}0.0059	^{129}0.0046	^{123}0.0033	^{141}1.083
115	NEUROTECHNOLOGY-007	^{16}256	^{18}169	^{75}0.0039	^{84}0.0027	^{89}0.0025	^{91}0.0023	^{94}0.0022	^{82}1.026
116	NEUROTECHNOLOGY-008	^{43}514	^{177}804	^{40}0.0022	^{32}0.0015	^{34}0.0014	^{35}0.0014	^{37}0.0013	^{33}1.015
117	NEWLAND-002	^{151}2048	^{197}868	^{189}0.0786	^{189}0.0480	^{188}0.0397	^{188}0.0332	^{185}0.0263	^{190}1.468
118	NOBLIS-001	^{111}2048	^{33}211	^{205}0.2492	^{205}0.1772	^{205}0.1542	^{205}0.1339	^{203}0.1112	^{205}2.679
119	NOBLIS-002	^{215}6144	^{102}535	^{201}0.1794	^{198}0.1108	^{198}0.0903	^{197}0.0722	^{196}0.0535	^{198}2.077
120	NTECHLAB-003	^{193}3484	^{184}831	^{99}0.0062	^{91}0.0029	^{86}0.0023	^{79}0.0019	^{65}0.0016	^{94}1.030
121	NTECHLAB-004	^{192}3484	^{209}929	^{89}0.0048	^{72}0.0023	^{62}0.0019	^{55}0.0016	^{39}0.0013	^{78}1.024
122	NTECHLAB-005	^{97}1940	^{160}717	^{87}0.0047	^{67}0.0022	^{52}0.0017	^{31}0.0013	^{19}0.0011	^{74}1.023
123	NTECHLAB-006	^{96}1940	^{188}841	^{79}0.0041	^{51}0.0019	^{39}0.0015	^{19}0.0012	^{11}0.0009	^{62}1.019
124	NTECHLAB-007	^{191}3348	^{187}834	^{55}0.0027	^{41}0.0017	^{33}0.0014	^{34}0.0013	^{27}0.0012	^{43}1.016
125	NTECHLAB-008	^{80}1300	^{110}562	^{22}0.0017	^{15}0.0012	^{16}0.0012	^{16}0.0011	^{18}0.0010	^{16}1.012
126	NTECHLAB-009	^{79}1300	^{203}900	^{9}0.0013	^{12}0.0011	^{13}0.0010	^{12}0.0010	^{13}0.0009	^{13}1.010
127	PARAVISION-000	^{125}2048	^{85}438	^{156}0.0188	^{169}0.0171	^{174}0.0167	^{176}0.0165	^{181}0.0164	^{166}1.156
128	PARAVISION-001	^{117}2048	^{112}590	^{73}0.0038	^{77}0.0024	^{78}0.0022	^{84}0.0020	^{82}0.0019	^{76}1.023
129	PARAVISION-002	^{118}2048	^{67}377	^{78}0.0040	^{81}0.0025	^{84}0.0022	^{86}0.0021	^{84}0.0019	^{79}1.025
130	PARAVISION-003	^{101}2048	^{166}735	^{63}0.0031	^{66}0.0022	^{72}0.0020	^{74}0.0019	^{74}0.0017	^{66}1.021
131	PARAVISION-004	^{201}4096	^{163}720	^{21}0.0016	^{25}0.0014	^{26}0.0013	^{32}0.0013	^{35}0.0013	^{24}1.013
132	PARAVISION-005	^{197}4096	^{194}858	^{16}0.0015	^{23}0.0014	^{28}0.0013	^{33}0.0013	^{38}0.0013	^{23}1.013
133	PARAVISION-007	^{205}4096	^{151}706	^{7}0.0012	^{13}0.0011	^{14}0.0010	^{14}0.0010	^{15}0.0010	^{11}1.010
134	PIXELALL-002	^{186}2560	^{27}198	^{84}0.0045	^{90}0.0029	^{90}0.0025	^{89}0.0022	^{87}0.0019	^{90}1.028
135	PIXELALL-003	^{184}2560	^{162}719	^{39}0.0021	^{38}0.0016	^{41}0.0015	^{41}0.0014	^{49}0.0014	^{39}1.015
136	PIXELALL-004	^{185}2560	^{87}453	^{37}0.0020	^{33}0.0015	^{36}0.0015	^{39}0.0014	^{40}0.0013	^{32}1.014
137	PIXELALL-005	^{183}2560	^{191}845	^{30}0.0019	^{42}0.0017	^{44}0.0016	^{54}0.0016	^{64}0.0016	^{38}1.015
138	PTAKURATSATU-000	^{51}538	^{207}910	^{62}0.0030	^{65}0.0021	^{66}0.0019	^{62}0.0018	^{66}0.0016	^{64}1.020
139	QUANTASOFT-001	^{102}2048	^{72}396	^{202}0.2177	^{204}0.1643	^{204}0.1468	^{204}0.1312	^{204}0.1116	^{204}2.539
140	RANKONE-002	^{9}133	^{12}113	^{157}0.0194	^{154}0.0112	^{152}0.0093	^{152}0.0077	^{149}0.0060	^{154}1.111
141	RANKONE-003	^{8}133	^{13}114	^{158}0.0194	^{153}0.0112	^{153}0.0093	^{153}0.0077	^{148}0.0060	^{153}1.111
142	RANKONE-004	^{1}85	^{4}36	^{178}0.0415	^{175}0.0226	^{175}0.0177	^{171}0.0141	^{167}0.0102	^{175}1.225
143	RANKONE-005	^{10}133	^{10}94	^{125}0.0094	^{120}0.0054	^{120}0.0046	^{122}0.0039	^{120}0.0032	^{120}1.054
144	RANKONE-006	^{12}165	^{41}261	^{91}0.0050	^{94}0.0030	^{94}0.0027	^{92}0.0024	^{90}0.0021	^{93}1.030

Table 18: **Rank-based accuracy for the FRVT 2018 mugshot sets**. *In columns 3 and 4 are template size and template generation duration. Thereafter values are rank-based FNIR with T = 0 and FPIR = 1. This is appropriate to investigational uses but not those with higher volumes where candidates from all searches would need review. The next column is a workload statistic, a small value shows an algorithm front-loads mates into the first 10 candidates. Throughout, blue superscripts indicate the rank of the algorithm for that column, and the best value is highlighted in yellow.*

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MISSES OUTSIDE RANK R		RESOURCE USAGE		ENROL MOST RECENT, N = 1.6M					
FNIR(N, T=0, R)		TEMPLATE		FRVT 2018 MUGSHOTS					
#	ALGORITHM	BYTES	MSEC	R=1	R=5	R=10	R=20	R=50	WORK-10
145	RANKONE-007	^{11}165	^{48}278	^{67}0.0034	^{73}0.0023	^{75}0.0021	^{71}0.0018	^{69}0.0017	^{70}1.022
146	RANKONE-009	^{22}260	^{25}191	^{47}0.0024	^{39}0.0016	^{42}0.0015	^{45}0.0015	^{47}0.0014	^{41}1.015
147	RANKONE-010	^{23}261	^{28}200	^{42}0.0022	^{45}0.0018	^{46}0.0016	^{49}0.0015	^{52}0.0015	^{44}1.016
148	REALNETWORKS-000	^{206}4100	^{37}244	^{176}0.0402	^{174}0.0195	^{170}0.0149	^{165}0.0111	^{160}0.0077	^{173}1.201
149	REALNETWORKS-001	^{210}4104	^{36}243	^{177}0.0402	^{173}0.0195	^{169}0.0149	^{166}0.0111	^{161}0.0077	^{174}1.201
150	REALNETWORKS-002	^{211}4104	^{38}245	^{173}0.0393	^{172}0.0189	^{168}0.0142	^{164}0.0108	^{159}0.0076	^{172}1.195
151	REALNETWORKS-003	^{94}1848	^{20}178	^{164}0.0242	^{156}0.0117	^{151}0.0090	^{145}0.0070	^{141}0.0054	^{158}1.120
152	REALNETWORKS-004	^{95}1848	^{21}185	^{162}0.0236	^{155}0.0112	^{149}0.0087	^{143}0.0068	^{139}0.0050	^{155}1.116
153	REMARKAI-000	^{131}2048	^{142}691	^{69}0.0034	^{64}0.0021	^{60}0.0019	^{57}0.0017	^{62}0.0015	^{63}1.020
154	REMARKAI-000	^{134}2048	^{115}615	^{118}0.0086	^{110}0.0044	^{105}0.0036	^{106}0.0031	^{104}0.0025	^{112}1.045
155	REMARKAI-002	^{104}2048	^{84}434	^{116}0.0081	^{104}0.0040	^{98}0.0031	^{95}0.0026	^{89}0.0021	^{107}1.041
156	RENDIP-000	^{140}2048	^{201}894	^{18}0.0015	^{20}0.0013	^{19}0.0012	^{21}0.0012	^{26}0.0012	^{20}1.012
157	S1-000	^{202}4096	^{196}865	^{49}0.0024	^{44}0.0018	^{47}0.0017	^{52}0.0016	^{58}0.0015	^{46}1.017
158	SCANOVATE-000	^{147}2048	^{155}712	^{90}0.0050	^{83}0.0026	^{79}0.0022	^{68}0.0018	^{63}0.0015	^{85}1.026
159	SCANOVATE-001	^{113}2048	^{134}675	^{93}0.0053	^{85}0.0027	^{83}0.0022	^{70}0.0018	^{60}0.0015	^{88}1.028
160	SENSETIME-000	^{209}4104	^{158}715	^{45}0.0023	^{60}0.0020	^{64}0.0019	^{67}0.0018	^{75}0.0017	^{55}1.018
161	SENSETIME-001	^{208}4104	^{130}656	^{46}0.0023	^{57}0.0020	^{61}0.0019	^{61}0.0017	^{67}0.0016	^{53}1.018
162	SENSETIME-002	^{171}2056	^{123}650	^{145}0.0137	^{162}0.0136	^{167}0.0136	^{170}0.0136	^{175}0.0136	^{159}1.122
163	SENSETIME-003	^{170}2056	^{213}940	^{3}0.0010	^{9}0.0010	^{11}0.0010	^{11}0.0009	^{12}0.0009	^{5}1.009
164	SENSETIME-004	^{69}1032	^{154}710	^{2}0.0010	^{2}0.0009	^{6}0.0009	^{7}0.0009	^{7}0.0009	^{3}1.008
165	SENSETIME-005	^{67}1032	^{218}1007	^{1}0.0009	^{1}0.0008	^{2}0.0008	^{6}0.0008	^{6}0.0008	^{1}1.008
166	SHAMAN-003	^{136}2048	^{148}704	^{193}0.1243	^{196}0.0823	^{196}0.0708	^{195}0.0616	^{195}0.0518	^{196}1.789
167	SHAMAN-004	^{139}2048	^{122}642	^{204}0.2221	^{203}0.1473	^{201}0.1241	^{201}0.1049	^{200}0.0825	^{203}2.411
168	SHAMAN-006	^{116}2048	^{150}706	^{175}0.0398	^{182}0.0344	^{185}0.0332	^{187}0.0323	^{190}0.0315	^{181}1.316
169	SHAMAN-007	^{120}2048	^{153}709	^{174}0.0396	^{181}0.0342	^{184}0.0331	^{186}0.0322	^{189}0.0314	^{179}1.315
170	SIAT-001	^{159}2052	^{189}842	^{24}0.0018	^{26}0.0014	^{22}0.0013	^{18}0.0012	^{20}0.0011	^{25}1.013
171	SIAT-002	^{162}2052	^{205}906	^{25}0.0018	^{24}0.0014	^{27}0.0013	^{28}0.0013	^{28}0.0012	^{28}1.013
172	SMILART-004	^{40}512	^{16}167	^{216}0.9648	^{216}0.9641	^{216}0.9640	^{216}0.9639	^{217}0.9638	^{216}9.678
173	SMILART-005	^{123}2048	^{90}464						^{219}10.000
174	SYNESIS-003	^{122}2048	^{34}215	^{149}0.0162	^{166}0.0160	^{171}0.0160	^{175}0.0160	^{180}0.0160	^{165}1.144
175	SYNESIS-003	^{204}4096	^{11}103	^{199}0.1700	^{199}0.1172	^{199}0.1047	^{200}0.0953	^{201}0.0869	^{199}2.120
176	SYNESIS-005	^{207}4104	^{171}772	^{117}0.0085	^{142}0.0085	^{147}0.0085	^{159}0.0085	^{165}0.0085	^{139}1.076
177	TECH5-001	^{84}1536	^{202}898	^{77}0.0040	^{76}0.0024	^{76}0.0021	^{72}0.0018	^{72}0.0017	^{77}1.024
178	TECH5-002	^{42}513	^{214}941	^{56}0.0027	^{28}0.0014	^{18}0.0012	^{17}0.0011	^{16}0.0010	^{31}1.014
179	TEVIAN-003	^{110}2048	^{55}300	^{146}0.0147	^{134}0.0074	^{127}0.0059	^{130}0.0047	^{129}0.0037	^{138}1.075
180	TEVIAN-004	^{106}2048	^{53}299	^{133}0.0113	^{121}0.0057	^{121}0.0047	^{118}0.0037	^{114}0.0030	^{122}1.058
181	TEVIAN-005	^{146}2048	^{78}416	^{110}0.0073	^{101}0.0038	^{97}0.0031	^{98}0.0027	^{98}0.0023	^{103}1.038
182	TEVIAN-006	^{68}1032	^{113}599	^{50}0.0024	^{48}0.0018	^{53}0.0018	^{58}0.0017	^{65}0.0017	^{48}1.017
183	TIGER-000	^{158}2052	^{80}428	^{184}0.0616	^{179}0.0310	^{178}0.0236	^{178}0.0178	^{172}0.0120	^{180}1.315
184	TIGER-002	^{156}2052	^{88}464	^{96}0.0056	^{92}0.0029	^{88}0.0024	^{73}0.0019	^{56}0.0015	^{91}1.030
185	TIGER-003	^{154}2052	^{89}464	^{95}0.0056	^{93}0.0029	^{87}0.0024	^{75}0.0019	^{57}0.0015	^{92}1.030
186	TONGYITRANS-000	^{173}2070	^{23}190	^{106}0.0069	^{99}0.0038	^{102}0.0032	^{102}0.0029	^{106}0.0026	^{101}1.038
187	TONGYITRANS-001	^{175}2070	^{22}189	^{107}0.0069	^{100}0.0038	^{101}0.0032	^{103}0.0029	^{107}0.0026	^{102}1.038
188	TOSHIBA-000	^{90}1548	^{210}930	^{83}0.0045	^{82}0.0026	^{82}0.0022	^{83}0.0020	^{79}0.0018	^{83}1.026
189	TOSHIBA-001	^{172}2060	^{211}931	^{88}0.0048	^{86}0.0027	^{85}0.0023	^{85}0.0020	^{80}0.0018	^{87}1.027
190	TRUEFACE-000	^{98}2000	^{62}365	^{66}0.0033	^{88}0.0028	^{95}0.0028	^{97}0.0026	^{105}0.0026	^{84}1.026
191	VD-000	^{66}1028	^{59}337	^{212}0.4737	^{211}0.3204	^{211}0.2695	^{210}0.2215	^{209}0.1678	^{211}4.058
192	VD-001	^{161}2052	^{143}695	^{168}0.0276	^{171}0.0181	^{173}0.0162	^{172}0.0146	^{174}0.0130	^{171}1.174
193	VD-002	^{163}2052	^{139}689	^{126}0.0095	^{136}0.0077	^{140}0.0073	^{144}0.0070	^{153}0.0068	^{133}1.071
194	VERIDAS-001	^{141}2048	^{200}885	^{58}0.0028	^{54}0.0019	^{50}0.0017	^{50}0.0015	^{53}0.0015	^{54}1.018
195	VIGILANTSOLUTIONS-003	^{89}1544	^{185}832	^{187}0.0694	^{184}0.0349	^{179}0.0262	^{179}0.0201	^{176}0.0140	^{184}1.355
196	VIGILANTSOLUTIONS-004	^{86}1544	^{183}830	^{194}0.1249	^{193}0.0706	^{192}0.0557	^{190}0.0434	^{188}0.0305	^{193}1.699
197	VIGILANTSOLUTIONS-005	^{88}1544	^{173}778	^{122}0.0092	^{112}0.0045	^{104}0.0036	^{101}0.0029	^{95}0.0022	^{113}1.046
198	VIGILANTSOLUTIONS-006	^{87}1544	^{186}834	^{128}0.0099	^{114}0.0048	^{110}0.0038	^{105}0.0030	^{97}0.0022	^{116}1.049
199	VIGILANTSOLUTIONS-007	^{85}1544	^{116}618	^{68}0.0034	^{56}0.0020	^{51}0.0017	^{47}0.0015	^{36}0.0013	^{61}1.019
200	VISIONLABS-004	^{17}256	^{56}315	^{57}0.0027	^{46}0.0018	^{43}0.0016	^{46}0.0015	^{45}0.0014	^{50}1.017
201	VISIONLABS-005	^{32}512	^{54}300	^{48}0.0024	^{43}0.0017	^{40}0.0015	^{36}0.0014	^{34}0.0013	^{42}1.016
202	VISIONLABS-006	^{33}512	^{50}292	^{27}0.0018	^{30}0.0015	^{29}0.0014	^{30}0.0013	^{31}0.0013	^{29}1.014
203	VISIONLABS-007	^{39}512	^{51}293	^{23}0.0018	^{27}0.0014	^{24}0.0013	^{25}0.0013	^{29}0.0012	^{27}1.013
204	VISIONLABS-008	^{41}512	^{47}277	^{35}0.0020	^{49}0.0018	^{55}0.0018	^{63}0.0018	^{76}0.0017	^{45}1.017
205	VISIONLABS-009	^{30}512	^{95}494	^{6}0.0011	^{11}0.0011	^{12}0.0010	^{13}0.0010	^{14}0.0010	^{10}1.010
206	VISIONLABS-010	^{34}512	^{165}732	^{12}0.0014	^{18}0.0013	^{23}0.0013	^{26}0.0013	^{30}0.0013	^{18}1.012
207	VOCORD-003	^{58}896	^{157}714	^{100}0.0062	^{96}0.0035	^{96}0.0030	^{96}0.0026	^{100}0.0023	^{96}1.035
208	VOCORD-004	^{57}896	^{104}538	^{112}0.0079	^{116}0.0049	^{117}0.0043	^{121}0.0038	^{124}0.0034	^{114}1.048
209	VOCORD-005	^{53}768	^{180}822	^{109}0.0070	^{113}0.0046	^{115}0.0041	^{120}0.0038	^{127}0.0035	^{110}1.044
210	VOCORD-006	^{219}10240	^{181}825	^{218}1.0000	^{219}1.0000	^{219}1.0000	^{218}1.0000	^{218}1.0000	^{218}10.000
211	VTS-000	^{126}2048	^{94}492	^{214}0.5937	^{215}0.5936	^{215}0.5936	^{215}0.5936	^{215}0.5936	^{215}6.343
212	XFORWARDAI-000	^{112}2048	^{169}768	^{43}0.0023	^{61}0.0020	^{68}0.0020	^{80}0.0019	^{86}0.0019	^{56}1.018
213	XFORWARDAI-001	^{132}2048	^{136}681	^{38}0.0020	^{55}0.0019	^{65}0.0019	^{77}0.0019	^{85}0.0019	^{51}1.018
214	XFORWARDAI-002	^{196}4096	^{212}935	^{32}0.0020	^{53}0.0019	^{63}0.0019	^{76}0.0019	^{83}0.0019	^{49}1.017
215	YISHENG-001	^{194}3704	^{70}387	^{167}0.0265	^{161}0.0130	^{158}0.0102	^{156}0.0080	^{147}0.0059	^{162}1.134
216	YITU-002	^{212}4138	^{198}870	^{28}0.0018	^{16}0.0012	^{15}0.0011	^{15}0.0011	^{17}0.0010	^{17}1.012

Table 19: **Rank-based accuracy for the FRVT 2018 mugshot sets**. *In columns 3 and 4 are template size and template generation duration. Thereafter values are rank-based FNIR with T = 0 and FPIR = 1. This is appropriate to investigational uses but not those with higher volumes where candidates from all searches would need review. The next column is a workload statistic, a small value shows an algorithm front-loads mates into the first 10 candidates. Throughout, blue superscripts indicate the rank of the algorithm for that column, and the best value is highlighted in yellow.*

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MISSES OUTSIDE RANK R		RESOURCE USAGE		ENROL MOST RECENT, N = 1.6M					
FNIR(N, T=0, R)		TEMPLATE		FRVT 2018 MUGSHOTS					
#	ALGORITHM	BYTES	MSEC	R=1	R=5	R=10	R=20	R=50	WORK-10
217	YITU-003	^{213}4138	^{199}871	^{61}0.0029	^{71}0.0023	^{80}0.0022	^{88}0.0021	^{93}0.0021	^{68}1.021
218	YITU-004	^{174}2070	^{208}910	^{10}0.0013	^{4}0.0009	^{7}0.0009	^{8}0.0009	^{8}0.0009	^{7}1.009
219	YITU-005	^{176}2070	^{195}861	^{44}0.0023	^{63}0.0021	^{69}0.0020	^{82}0.0020	^{88}0.0020	^{58}1.019

Table 20: **Rank-based accuracy for the FRVT 2018 mugshot sets**. *In columns 3 and 4 are template size and template generation duration. Thereafter values are rank-based FNIR with T = 0 and FPIR = 1. This is appropriate to investigational uses but not those with higher volumes where candidates from all searches would need review. The next column is a workload statistic, a small value shows an algorithm front-loads mates into the first 10 candidates. Throughout, blue superscripts indicate the rank of the algorithm for that column, and the best value is highlighted in yellow.*

MISSES BELOW THRESHOLD, T		ENROL RECENT MUGSHOT, N = 1.6M									ENROL APPLICATION PORTRAIT, N = 1.6M				
ENROL		DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: VISA		DATASET: BORDER		DATASET: VISA
PROBE		DATASET: MUGSHOT			DATASET: WEBCAM			DATASET: PROFILE			DATASET: BORDER		DATASET: BORDER 10+YR		DATASET: KIOSK
#	ALGORITHM	FPIR=0.0003	FPIR=0.001	FPIR=0.0003	FPIR=0.001	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01		
1	3DIVI-003	^{175}0.482	^{187}0.400	^{176}0.685	^{185}0.626	^{187}0.497			^{121}0.605	^{121}0.445			^{100}0.821	^{110}0.717	
2	3DIVI-004	^{149}0.256	^{161}0.169	^{149}0.400	^{166}0.343	^{169}0.237			^{104}0.277	^{106}0.172			^{80}0.607	^{92}0.485	
3	3DIVI-005	^{148}0.255	^{158}0.166	^{148}0.395	^{164}0.339	^{168}0.234	^{98}0.996	^{103}0.990	^{126}0.864	^{128}0.846			^{79}0.597	^{91}0.484	
4	3DIVI-006	^{147}0.253	^{160}0.168	^{152}0.403	^{165}0.342	^{170}0.238			^{105}0.283	^{107}0.174			^{83}0.615	^{93}0.490	
5	ACER-000	^{137}0.208	^{151}0.146	^{134}0.300	^{144}0.246	^{144}0.157	^{62}0.981	^{70}0.955	^{99}0.201	^{102}0.114			^{69}0.490	^{79}0.363	
6	ALCHERA-000	^{142}0.231	^{148}0.138	^{124}0.259	^{132}0.216	^{138}0.146	^{112}0.999	^{128}0.996	^{96}0.176	^{100}0.111			^{96}0.803	^{88}0.456	
7	ALCHERA-001	^{214}1.000	^{214}0.999	^{206}1.000	^{218}1.000	^{218}1.000			^{209}1.000	^{154}1.000			^{155}1.000	^{191}1.000	
8	ALCHERA-002	^{194}0.807	^{194}0.486	^{175}0.685	^{182}0.591	^{182}0.442	^{133}1.000	^{147}0.999	^{125}0.827	^{125}0.770			^{97}0.811	^{107}0.705	
9	ALCHERA-003	^{170}0.450	^{152}0.155	^{135}0.304	^{141}0.239	^{143}0.152	^{120}0.999	^{133}0.997	^{95}0.172	^{94}0.097			^{66}0.464	^{78}0.362	
10	ALLGOVISION-000	^{105}0.138	^{128}0.088	^{112}0.202	^{121}0.166	^{127}0.106	^{76}0.990	^{93}0.982	^{80}0.117	^{84}0.066			^{74}0.526	^{86}0.396	
11	ALLGOVISION-001	^{114}0.155	^{133}0.102	^{128}0.275	^{135}0.221	^{137}0.141	^{68}0.986	^{60}0.933	^{90}0.150	^{90}0.081			^{70}0.491	^{85}0.389	
12	ANKE-000	^{125}0.184	^{138}0.117	^{123}0.256	^{134}0.220	^{141}0.151	^{81}0.994	^{101}0.990	^{177}1.000	^{186}1.000			^{198}1.000	^{137}1.000	
13	ANKE-001	^{123}0.183	^{142}0.119	^{122}0.256	^{133}0.220	^{142}0.151	^{85}0.994	^{111}0.992	^{160}1.000	^{190}1.000			^{217}1.000	^{153}1.000	
14	ANKE-002	^{59}0.062	^{63}0.032	^{49}0.103	^{52}0.079	^{53}0.050	^{40}0.948	^{43}0.795	^{40}0.034	^{41}0.018			^{31}0.245	^{41}0.190	
15	AWARE-003	^{122}0.174	^{146}0.128	^{144}0.351	^{158}0.298	^{162}0.204	^{66}0.984	^{88}0.977	^{113}0.428	^{115}0.378			^{75}0.530	^{87}0.443	
16	AWARE-004	^{162}0.355	^{174}0.269	^{169}0.619	^{176}0.509	^{180}0.375	^{135}1.000	^{148}0.999	^{110}0.397	^{111}0.279			^{98}0.816	^{102}0.631	
17	AWARE-005	^{184}0.608	^{182}0.364	^{139}0.342	^{145}0.253	^{146}0.163	^{137}1.000	^{149}0.999	^{103}0.255	^{104}0.122			^{107}0.916	^{109}0.714	
18	AWARE-006	^{174}0.475	^{175}0.276	^{160}0.466	^{169}0.398	^{173}0.283	^{129}0.999	^{144}0.999	^{108}0.368	^{109}0.254			^{90}0.749	^{99}0.623	
19	AYONIX-000	^{197}0.846	^{203}0.811	^{192}0.956	^{200}0.939	^{202}0.892	^{103}0.998	^{125}0.995	^{130}0.954	^{130}0.891			^{116}0.982	^{124}0.959	
20	AYONIX-001	^{198}0.875	^{205}0.824	^{187}0.946	^{195}0.920	^{198}0.845	^{125}0.999	^{130}0.996	^{134}0.999	^{134}0.998			^{113}0.969	^{121}0.926	
21	AYONIX-002	^{199}0.876	^{204}0.824	^{188}0.946	^{196}0.920	^{197}0.845	^{127}0.999	^{129}0.996	^{127}0.915	^{126}0.821			^{114}0.969	^{120}0.926	
22	CAMVI-003	^{78}0.094	^{112}0.071	^{84}0.152	^{99}0.132	^{128}0.108	^{48}0.970	^{65}0.940	^{79}0.114	^{95}0.100			^{58}0.402	^{82}0.377	
23	CAMVI-004	^{87}0.107	^{113}0.072	^{119}0.240	^{101}0.136	^{117}0.100	^{123}0.999	^{136}0.998	^{78}0.100	^{89}0.081			^{94}0.787	^{94}0.507	
24	CAMVI-005	^{106}0.139	^{132}0.099	^{158}0.451	^{128}0.179	^{133}0.132	^{132}1.000	^{142}0.998	^{91}0.156	^{101}0.112			^{123}0.999	^{130}0.983	
25	CIB-000	^{40}0.044	^{24}0.012	^{31}0.077	^{24}0.045	^{24}0.025	^{141}1.000	^{154}1.000	^{21}0.017	^{16}0.008	^{14}0.141	^{14}0.068	^{105}0.894	^{95}0.521	
26	CLOUDWALK-HR-000	^{4}0.004	^{4}0.002	^{3}0.015	^{4}0.013	^{6}0.012	^{1}0.133	^{2}0.095	^{2}0.005	^{2}0.003	^{1}0.033	^{1}0.018	^{2}0.099	^{1}0.075	
27	COGENT-000	^{110}0.143	^{90}0.053	^{95}0.175	^{102}0.140	^{120}0.100	^{91}0.995	^{106}0.991							
28	COGENT-001	^{109}0.143	^{91}0.053	^{94}0.175	^{103}0.140	^{121}0.100	^{90}0.995	^{107}0.991							
29	COGENT-002	^{119}0.159	^{78}0.044	^{65}0.124	^{73}0.098	^{75}0.063	^{102}0.998	^{116}0.994							
30	COGENT-003	^{135}0.203	^{82}0.046	^{63}0.121	^{68}0.095	^{73}0.061	^{104}0.998	^{124}0.995							
31	COGENT-004	^{138}0.209	^{64}0.033	^{26}0.067	^{29}0.051	^{29}0.031	^{100}0.997	^{126}0.995	^{25}0.022	^{25}0.012	^{13}0.126	^{16}0.072	^{65}0.456	^{35}0.178	
32	COGNITEC-000	^{141}0.226	^{156}0.161	^{156}0.439	^{159}0.303	^{160}0.200	^{78}0.992	^{78}0.971							
33	COGNITEC-001	^{133}0.192	^{134}0.102	^{202}0.997	^{139}0.230	^{135}0.135	^{218}1.000	^{74}0.965							
34	COGNITEC-002	^{94}0.122	^{93}0.053	^{199}0.990	^{127}0.178	^{124}0.101	^{142}1.000	^{71}0.956							
35	COGNITEC-003	^{82}0.099	^{89}0.053	^{116}0.222	^{119}0.162	^{118}0.100	^{143}1.000	^{66}0.946							
36	COGNITEC-004	^{54}0.055	^{62}0.031	^{68}0.127	^{71}0.097	^{66}0.058	^{73}0.990	^{56}0.919	^{67}0.068	^{68}0.038	^{29}0.316	^{31}0.196	^{39}0.288	^{48}0.218	
37	CYBERLINK-000	^{104}0.137	^{99}0.056	^{89}0.162	^{84}0.116	^{85}0.070	^{93}0.995	^{92}0.981	^{65}0.063	^{63}0.032			^{51}0.339	^{54}0.232	
38	CYBERLINK-001	^{79}0.096	^{94}0.054	^{77}0.138	^{81}0.109	^{80}0.067	^{89}0.995	^{94}0.984	^{62}0.062	^{59}0.031			^{84}0.652	^{56}0.239	
39	CYBERLINK-002	^{36}0.038	^{30}0.015	^{28}0.068	^{32}0.053	^{32}0.032	^{72}0.988	^{72}0.957	^{26}0.024	^{26}0.013			^{40}0.288	^{27}0.157	
40	CYBERLINK-003	^{43}0.045	^{16}0.008	^{18}0.045	^{20}0.035	^{17}0.021	^{50}0.972	^{48}0.845	^{15}0.012	^{15}0.007	^{10}0.100	^{11}0.051	^{53}0.368	^{16}0.120	
41	DAHUA-000	^{99}0.128	^{124}0.086	^{97}0.179	^{100}0.135	^{103}0.083									
42	DAHUA-001	^{86}0.106	^{115}0.073	^{83}0.151	^{92}0.122	^{94}0.075	^{60}0.980	^{61}0.933							
43	DAHUA-002	^{24}0.026	^{31}0.015	^{23}0.060	^{26}0.046	^{27}0.029	^{16}0.638	^{23}0.522	^{20}0.017	^{20}0.008			^{15}0.159	^{17}0.125	
44	DAHUA-003	^{23}0.025	^{27}0.014	^{21}0.054	^{23}0.041	^{22}0.024	^{14}0.579	^{18}0.447	^{16}0.013	^{14}0.006	^{8}0.081	^{9}0.043	^{11}0.134	^{10}0.109	
45	DEEPGLINT-001	^{8}0.010	^{9}0.003	^{5}0.018	^{3}0.014	^{4}0.010	^{130}1.000	^{20}0.503	^{3}0.006	^{7}0.004			^{14}0.159	^{7}0.097	
46	DEEPSEA-001	^{68}0.073	^{81}0.046	^{70}0.129	^{75}0.101	^{69}0.059	^{67}0.985	^{83}0.973	^{71}0.077	^{72}0.041			^{49}0.326	^{57}0.251	

Table 21: **Threshold-based accuracy**. *Values are FNIR(N, T, L) with N = 1.6 million with thresholds set to produce FPIR = 0.0003, 0.001, and 0.01 in non-mate searches. Throughout blue superscripts indicate the rank of the algorithm for that column. Caution: The Power-low models are mostly intended to draw attention to the kind of behavior, not as a model to be used for prediction.*

FNIR(N, R, T) = False neg. identification rate
FPIR(N, T) = False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

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MISSES BELOW THRESHOLD, T		ENROL RECENT MUGSHOT, N = 1.6M									ENROL APPLICATION PORTRAIT, N = 1.6M				
ENROL		DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: VISA		DATASET: BORDER		DATASET: VISA
PROBE		DATASET: MUGSHOT			DATASET: WEBCAM			DATASET: PROFILE			DATASET: BORDER		DATASET: BORDER 10+YR		DATASET: KIOSK
#	ALGORITHM	FPIR=0.0003	FPIR=0.001	FPIR=0.0003	FPIR=0.001	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01		
47	DERMALOG-003	^{180}0.550	^{193}0.482	^{179}0.715	^{187}0.655	^{191}0.526			^{124}0.677	^{123}0.554			^{103}0.870	^{117}0.791	
48	DERMALOG-004	^{182}0.554	^{192}0.480	^{178}0.711	^{188}0.657	^{189}0.526	^{94}0.995	^{110}0.991	^{120}0.603	^{122}0.458			^{102}0.856	^{113}0.751	
49	DERMALOG-005	^{132}0.189	^{127}0.088	^{108}0.201	^{112}0.154	^{114}0.096	^{75}0.990	^{69}0.950	^{106}0.300	^{110}0.267			^{82}0.614	^{89}0.459	
50	DERMALOG-006	^{81}0.098	^{88}0.052	^{76}0.137	^{77}0.105	^{79}0.067	^{61}0.981	^{62}0.933	^{60}0.059	^{61}0.031			^{48}0.318	^{52}0.230	
51	DERMALOG-007	^{130}0.188	^{125}0.086	^{107}0.200	^{110}0.152	^{111}0.093	^{74}0.990	^{68}0.950	^{77}0.099	^{79}0.052			^{78}0.557	^{72}0.299	
52	DERMALOG-008	^{152}0.268	^{80}0.045	^{117}0.231	^{65}0.094	^{62}0.054	^{157}1.000	^{155}1.000	^{57}0.057	^{54}0.025	^{32}0.382	^{30}0.158	^{111}0.940	^{105}0.678	
53	EYEDEA-003	^{178}0.509	^{184}0.388	^{171}0.625	^{180}0.543	^{181}0.404	^{86}0.994	^{100}0.990	^{118}0.570	^{117}0.392			^{95}0.792	^{104}0.658	
54	F8-001	^{172}0.458	^{157}0.166				^{111}0.998	^{127}0.995							
55	GLORY-000	^{169}0.441	^{183}0.367	^{167}0.586	^{181}0.547	^{185}0.470	^{88}0.995	^{114}0.993	^{115}0.453	^{116}0.381			^{101}0.839	^{118}0.795	
56	GLORY-001	^{161}0.355	^{176}0.305	^{166}0.582	^{179}0.537	^{183}0.448	^{79}0.993	^{105}0.991	^{112}0.408	^{113}0.336			^{99}0.819	^{114}0.753	
57	GORILLA-001	^{192}0.747	^{188}0.406	^{168}0.590	^{174}0.453	^{175}0.314	^{152}1.000	^{166}1.000	^{116}0.468	^{112}0.299			^{152}1.000	^{108}0.710	
58	GORILLA-002	^{151}0.266	^{164}0.188	^{141}0.342	^{152}0.268	^{152}0.170	^{156}1.000	^{115}0.993	^{102}0.250	^{105}0.137			^{126}1.000	^{90}0.466	
59	GORILLA-003	^{190}0.694	^{178}0.318	^{174}0.684	^{173}0.434	^{171}0.247	^{196}1.000	^{158}1.000	^{111}0.407	^{108}0.213			^{194}1.000	^{97}0.562	
60	GORILLA-004	^{102}0.135	^{130}0.089	^{109}0.202	^{118}0.160	^{122}0.101	^{42}0.959	^{53}0.903	^{85}0.135	^{86}0.072			^{62}0.438	^{74}0.309	
61	GORILLA-005	^{76}0.086	^{103}0.058	^{96}0.179	^{105}0.142	^{105}0.088	^{19}0.700	^{24}0.553	^{75}0.088	^{71}0.040			^{47}0.315	^{49}0.223	
62	HIK-003	^{120}0.159	^{135}0.103	^{104}0.190	^{114}0.158	^{126}0.105	^{46}0.969	^{58}0.925	^{88}0.142	^{88}0.080			^{64}0.445	^{77}0.359	
63	HIK-004	^{116}0.156	^{131}0.099	^{100}0.182	^{111}0.153	^{123}0.101	^{52}0.976	^{67}0.947	^{86}0.137	^{87}0.077			^{61}0.434	^{76}0.353	
64	HIK-005	^{84}0.102	^{75}0.044	^{45}0.098	^{51}0.077	^{52}0.048	^{128}0.999	^{138}0.998	^{66}0.068	^{66}0.036			^{76}0.541	^{59}0.258	
65	HIK-006	^{108}0.142	^{83}0.047	^{52}0.111	^{57}0.086	^{57}0.052	^{147}1.000	^{150}0.999							
66	IDEMIA-003	^{181}0.552	^{84}0.047	^{208}1.000	^{120}0.165	^{98}0.079		^{219}1.000	^{82}0.123	^{80}0.061			^{92}0.766	^{101}0.630	
67	IDEMIA-004	^{53}0.055	^{71}0.037	^{79}0.144	^{88}0.118	^{97}0.079	^{51}0.973	^{75}0.968	^{81}0.123	^{81}0.061			^{93}0.766	^{100}0.630	
68	IDEMIA-005	^{66}0.066	^{77}0.044	^{99}0.181	^{109}0.150	^{125}0.102	^{55}0.978	^{82}0.973	^{83}0.130	^{85}0.070			^{104}0.879	^{111}0.743	
69	IDEMIA-006	^{64}0.065	^{74}0.043	^{127}0.266	^{137}0.226	^{145}0.161	^{63}0.982	^{91}0.980	^{89}0.144	^{92}0.090			^{88}0.733	^{96}0.531	
70	IDEMIA-007	^{32}0.035	^{36}0.018	^{30}0.073	^{34}0.055	^{33}0.033	^{198}1.000	^{183}1.000	^{53}0.052	^{52}0.022	^{18}0.182	^{21}0.109	^{174}1.000	^{128}0.982	
71	IDEMIA-008	^{2}0.004	^{3}0.002	^{4}0.016	^{3}0.013	^{2}0.009	^{3}0.204	^{4}0.136	^{1}0.005	^{1}0.003	^{2}0.036	^{3}0.019	^{4}0.106	^{4}0.092	
72	IMAGUS-002	^{202}0.908	^{201}0.749	^{186}0.944	^{192}0.816	^{194}0.645	^{149}1.000	^{160}1.000							
73	IMAGUS-003	^{201}0.898	^{202}0.807	^{191}0.954	^{194}0.909	^{196}0.809	^{145}1.000	^{150}1.000							
74	IMAGUS-005	^{31}0.034	^{39}0.018	^{37}0.088	^{41}0.066	^{40}0.040	^{29}0.838	^{31}0.647	^{30}0.029	^{35}0.016	^{17}0.161	^{20}0.094	^{28}0.231	^{40}0.189	
75	IMAGUS-006	^{37}0.039	^{41}0.019	^{41}0.093	^{44}0.069	^{47}0.042	^{36}0.897	^{26}0.621	^{29}0.028	^{31}0.015	^{16}0.161	^{19}0.092	^{35}0.260	^{37}0.181	
76	IMPERIAL-000	^{113}0.154	^{51}0.026	^{39}0.089	^{43}0.068	^{44}0.041	^{115}0.999	^{120}0.995	^{45}0.042	^{48}0.020			^{32}0.245	^{30}0.168	
77	INCODE-000	^{168}0.423	^{177}0.310	^{162}0.486	^{171}0.420	^{174}0.304	^{108}0.998	^{117}0.994							
78	INCODE-001	^{159}0.319	^{167}0.212	^{143}0.348	^{155}0.296	^{158}0.198	^{160}1.000	^{153}1.000							
79	INCODE-002	^{156}0.285	^{163}0.184	^{138}0.333	^{153}0.269	^{154}0.176	^{80}0.993	^{87}0.976							
80	INCODE-003	^{157}0.286	^{159}0.167	^{147}0.372	^{149}0.264	^{148}0.164	^{126}0.999	^{131}0.996							
81	INCODE-004	^{83}0.099	^{96}0.054	^{91}0.167	^{91}0.120	^{86}0.070	^{87}0.995	^{59}0.929	^{64}0.063	^{60}0.031			^{45}0.313	^{50}0.226	
82	INNOVATRICS-002	^{166}0.379	^{172}0.234	^{151}0.403	^{160}0.310	^{164}0.209	^{158}1.000	^{151}0.999							
83	INNOVATRICS-003	^{158}0.297	^{168}0.221	^{145}0.351	^{156}0.297	^{161}0.203	^{134}1.000	^{141}0.998							
84	INNOVATRICS-004	^{128}0.184	^{147}0.132	^{125}0.262	^{136}0.222	^{139}0.149	^{58}0.980	^{80}0.973							
85	INNOVATRICS-005	^{56}0.057	^{65}0.034	^{55}0.114	^{60}0.089	^{58}0.052	^{30}0.846	^{35}0.723	^{50}0.047	^{51}0.022			^{33}0.251	^{38}0.182	
86	INTSYSMSU-000	^{210}0.999	^{212}0.998	^{203}1.000	^{205}1.000	^{206}0.998	^{136}1.000	^{130}0.998	^{133}0.999	^{133}0.989			^{124}0.999	^{131}0.988	
87	IREX-000	^{67}0.068	^{58}0.028	^{46}0.099	^{37}0.060	^{30}0.032	^{41}0.957	^{34}0.680	^{47}0.044	^{24}0.011	^{28}0.302	^{13}0.062	^{18}0.170	^{21}0.135	
88	ISYSTEMS-002	^{115}0.155	^{118}0.078	^{87}0.161	^{95}0.126	^{100}0.080	^{101}0.998	^{113}0.993							
89	ISYSTEMS-003	^{136}0.204	^{104}0.059	^{75}0.135	^{80}0.107	^{82}0.068	^{138}1.000	^{135}0.997							
90	KEDACOM-001	^{39}0.041	^{47}0.023	^{43}0.096	^{48}0.072	^{61}0.054	^{70}0.986	^{84}0.973	^{56}0.055	^{73}0.043			^{43}0.305	^{61}0.264	
91	KNERON-000					^{116}0.099									
92	KNERON-001														

Table 22: **Threshold-based accuracy**. *Values are FNIR(N, T, L) with N = 1.6 million with thresholds set to produce FPIR = 0.0003, 0.001, and 0.01 in non-mate searches. Throughout blue superscripts indicate the rank of the algorithm for that column. Caution: The Power-low models are mostly intended to draw attention to the kind of behavior, not as a model to be used for prediction.*

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MISSES BELOW THRESHOLD, T		ENROL RECENT MUGSHOT, N = 1.6M									ENROL APPLICATION PORTRAIT, N = 1.6M				
ENROL		DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: VISA		DATASET: BORDER		DATASET: VISA
PROBE		DATASET: MUGSHOT			DATASET: WEBCAM			DATASET: PROFILE			DATASET: BORDER		DATASET: BORDER 10+YR		DATASET: KIOSK
#	ALGORITHM	FPIR=0.0003	FPIR=0.001	FPIR=0.0003	FPIR=0.001	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01		
93	LINE-000	^{60}0.062	^{61}0.031					^{162}1.000	^{48}0.046	^{49}0.021	^{26}0.278	^{29}0.151	^{208}1.000	^{62}0.268	
94	LOOKMAN-003	^{65}0.066	^{76}0.044	^{73}0.131	^{83}0.112	^{101}0.082			^{74}0.084	^{82}0.061			^{52}0.355	^{73}0.304	
95	LOOKMAN-004	^{69}0.074	^{79}0.045	^{64}0.123	^{79}0.105	^{92}0.075	^{53}0.977	^{85}0.974							
96	LOOKMAN-005	^{51}0.050	^{60}0.030	^{47}0.102	^{56}0.086	^{76}0.063	^{56}0.978	^{81}0.973	^{63}0.062	^{75}0.047			^{44}0.308	^{64}0.273	
97	MEGVII-001	^{139}0.210	^{114}0.072	^{60}0.119	^{72}0.097	^{71}0.061									
98	MEGVII-002	^{150}0.258	^{117}0.077	^{61}0.120	^{70}0.096	^{68}0.059	^{110}0.998	^{52}0.872							
99	MICROFOCUS-003	^{205}0.958	^{208}0.931	^{198}0.988	^{204}0.979	^{204}0.948			^{132}0.982	^{132}0.945			^{120}0.991	^{127}0.977	
100	MICROFOCUS-004	^{212}0.999	^{213}0.999	^{197}0.984	^{202}0.975	^{203}0.940			^{131}0.974	^{131}0.935			^{118}0.989	^{126}0.976	
101	MICROFOCUS-005	^{200}0.883	^{206}0.835	^{190}0.951	^{198}0.928	^{200}0.865			^{129}0.935	^{129}0.848			^{117}0.985	^{125}0.965	
102	MICROFOCUS-006	^{208}0.983	^{210}0.978	^{189}0.950	^{197}0.923	^{199}0.858			^{128}0.923	^{127}0.843			^{115}0.971	^{122}0.939	
103	MICROSOFT-003	^{49}0.049	^{56}0.028	^{56}0.117	^{63}0.091	^{65}0.056			^{42}0.036	^{46}0.019			^{30}0.233	^{34}0.176	
104	MICROSOFT-004	^{45}0.046	^{52}0.026	^{53}0.111	^{58}0.087	^{60}0.053			^{38}0.033	^{42}0.018			^{26}0.222	^{32}0.170	
105	MICROSOFT-005	^{46}0.047	^{50}0.026	^{40}0.090	^{46}0.070	^{45}0.041	^{15}0.587	^{16}0.354	^{27}0.027	^{28}0.013			^{20}0.180	^{20}0.134	
106	MICROSOFT-006	^{22}0.025	^{21}0.012	^{19}0.048	^{21}0.037	^{23}0.024	^{5}0.386	^{11}0.281	^{35}0.032	^{32}0.015			^{19}0.178	^{22}0.138	
107	NEC-000	^{90}0.113	^{120}0.079	^{92}0.171	^{104}0.140	^{109}0.093	^{57}0.979	^{77}0.969					^{68}0.474	^{83}0.377	
108	NEC-001	^{112}0.148	^{137}0.106	^{118}0.238	^{130}0.197	^{134}0.133	^{69}0.986	^{79}0.972	^{84}0.133	^{91}0.082			^{67}0.468	^{84}0.378	
109	NEC-002	^{14}0.018	^{7}0.003	^{10}0.029	^{9}0.020	^{8}0.013	^{124}0.999	^{122}0.995	^{8}0.008	^{11}0.005			^{86}0.676	^{69}0.292	
110	NEC-003	^{5}0.005	^{6}0.002	^{8}0.021	^{8}0.017	^{7}0.013	^{26}0.824	^{28}0.628	^{11}0.008	^{12}0.006	^{3}0.036	^{4}0.023	^{85}0.668	^{60}0.261	
111	NEUROTECHNOLOGY-003	^{211}0.999	^{199}0.636	^{181}0.773	^{151}0.266	^{147}0.164	^{214}1.000	^{169}1.000							
112	NEUROTECHNOLOGY-004	^{92}0.120	^{108}0.063	^{80}0.146	^{85}0.117	^{88}0.073	^{83}0.994	^{102}0.990							
113	NEUROTECHNOLOGY-005	^{91}0.117	^{97}0.054	^{121}0.252	^{97}0.130	^{91}0.074	^{105}0.998	^{99}0.989							
114	NEUROTECHNOLOGY-006	^{209}0.987	^{173}0.249	^{205}1.000	^{170}0.418	^{163}0.206									
115	NEUROTECHNOLOGY-007	^{146}0.252	^{107}0.062	^{201}0.996	^{124}0.173	^{81}0.068	^{139}1.000	^{134}0.997	^{107}0.339	^{67}0.036			^{168}1.000	^{132}0.989	
116	NEUROTECHNOLOGY-008	^{193}0.797	^{92}0.053	^{51}0.110	^{54}0.080	^{51}0.047	^{159}1.000	^{163}1.000	^{41}0.035	^{39}0.017	^{27}0.293	^{28}0.149	^{24}0.203	^{26}0.152	
117	NEWLAND-002	^{179}0.523	^{190}0.438	^{163}0.535	^{175}0.466	^{177}0.335	^{117}0.999	^{140}0.998							
118	NOBLIS-001	^{215}1.000	^{215}1.000	^{204}1.000	^{217}1.000	^{217}1.000	^{148}1.000	^{168}1.000							
119	NOBLIS-002	^{213}1.000	^{211}0.997	^{214}1.000	^{207}1.000	^{207}1.000	^{154}1.000	^{165}1.000							
120	NTECHLAB-003	^{72}0.080	^{95}0.054	^{81}0.148	^{86}0.118	^{93}0.075	^{28}0.837	^{42}0.752							
121	NTECHLAB-004	^{62}0.063	^{72}0.041	^{72}0.131	^{78}0.105	^{78}0.065	^{27}0.833	^{40}0.746	^{55}0.053	^{58}0.030			^{37}0.263	^{47}0.214	
122	NTECHLAB-005	^{61}0.062	^{73}0.042	^{71}0.130	^{76}0.102	^{77}0.063	^{22}0.771	^{33}0.661	^{69}0.073	^{70}0.039			^{41}0.294	^{51}0.227	
123	NTECHLAB-006	^{55}0.056	^{68}0.037	^{62}0.121	^{66}0.094	^{67}0.059	^{21}0.754	^{29}0.635	^{58}0.057	^{62}0.032			^{36}0.260	^{45}0.207	
124	NTECHLAB-007	^{38}0.040	^{49}0.026	^{36}0.085	^{42}0.067	^{43}0.041	^{20}0.750	^{30}0.642	^{36}0.032	^{40}0.017			^{27}0.223	^{33}0.176	
125	NTECHLAB-008	^{20}0.024	^{28}0.014	^{22}0.057	^{25}0.045	^{28}0.029	^{13}0.529	^{17}0.391	^{39}0.033	^{43}0.018			^{21}0.183	^{23}0.140	
126	NTECHLAB-009	^{7}0.010	^{14}0.005	^{9}0.028	^{10}0.022	^{10}0.014	^{7}0.430	^{13}0.311	^{17}0.015	^{18}0.008	^{11}0.109	^{12}0.061	^{12}0.142	^{11}0.114	
127	PARAVISION-000	^{155}0.278	^{129}0.089	^{157}0.447	^{122}0.170	^{119}0.100	^{119}0.999	^{132}0.997	^{117}0.470	^{120}0.443			^{110}0.926	^{116}0.779	
128	PARAVISION-001	^{107}0.140	^{85}0.049	^{113}0.207	^{96}0.128	^{90}0.074	^{113}0.999	^{118}0.994	^{114}0.444	^{119}0.428			^{89}0.739	^{98}0.573	
129	PARAVISION-002	^{75}0.085	^{86}0.050	^{85}0.152	^{89}0.119	^{95}0.076	^{64}0.983	^{41}0.748	^{72}0.080	^{74}0.043			^{71}0.497	^{63}0.268	
130	PARAVISION-003	^{63}0.063	^{66}0.035	^{67}0.124	^{69}0.096	^{70}0.060	^{84}0.994	^{36}0.733	^{59}0.058	^{65}0.034			^{42}0.296	^{53}0.232	
131	PARAVISION-004	^{21}0.025	^{20}0.010	^{20}0.049	^{22}0.038	^{21}0.024	^{153}1.000	^{46}0.797	^{22}0.018	^{23}0.011			^{106}0.908	^{46}0.211	
132	PARAVISION-005	^{13}0.014	^{11}0.004	^{11}0.031	^{11}0.024	^{12}0.016	^{59}0.980	^{8}0.181	^{14}0.011	^{19}0.008			^{9}0.132	^{15}0.120	
133	PARAVISION-007	^{47}0.048	^{10}0.004	^{164}0.560	^{12}0.025	^{11}0.015	^{161}1.000	^{161}1.000	^{13}0.009	^{13}0.006	^{12}0.113	^{6}0.024	^{203}1.000	^{139}1.000	
134	PIXELALL-002	^{187}0.664	^{136}0.105	^{194}0.974	^{168}0.388	^{102}0.083	^{150}1.000	^{159}1.000	^{119}0.602	^{77}0.047			^{146}1.000	^{133}1.000	
135	PIXELALL-003	^{48}0.049	^{44}0.022	^{48}0.102	^{49}0.073	^{48}0.043	^{131}1.000	^{139}0.998	^{43}0.037	^{47}0.020			^{77}0.554	^{58}0.255	
136	PIXELALL-004	^{93}0.120	^{38}0.018	^{182}0.783	^{53}0.079	^{38}0.037	^{144}1.000	^{146}0.999	^{52}0.051	^{33}0.015			^{121}0.994	^{123}0.942	
137	PIXELALL-005	^{71}0.079	^{23}0.012	^{159}0.456	^{28}0.050	^{25}0.027	^{146}1.000	^{152}0.999	^{28}0.027	^{37}0.017	^{21}0.203	^{15}0.071	^{125}1.000	^{129}0.983	
138	PTAKURATSATU-000	^{57}0.057	^{67}0.037	^{90}0.165	^{94}0.124	^{87}0.071	^{38}0.924	^{51}0.868	^{49}0.046	^{50}0.022	^{23}0.206	^{25}0.120	^{29}0.232	^{36}0.179	

Table 23: **Threshold-based accuracy**. *Values are FNIR(N, T, L) with N = 1.6 million with thresholds set to produce FPIR = 0.0003, 0.001, and 0.01 in non-mate searches. Throughout blue superscripts indicate the rank of the algorithm for that column. Caution: The Power-low models are mostly intended to draw attention to the kind of behavior, not as a model to be used for prediction.*

FNIR(N, R, T) = False neg. identification rate
FPIR(N, T) = False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

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MISSES BELOW THRESHOLD, T		ENROL RECENT MUGSHOT, N = 1.6M									ENROL APPLICATION PORTRAIT, N = 1.6M				
ENROL		DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: VISA		DATASET: BORDER		DATASET: VISA
PROBE		DATASET: MUGSHOT			DATASET: WEBCAM			DATASET: PROFILE			DATASET: BORDER		DATASET: BORDER 10+YR		DATASET: KIOSK
#	ALGORITHM	FPIR=0.0003	FPIR=0.001	FPIR=0.0003	FPIR=0.001	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01		
139	QUANTASOFT-001	^{191}0.713	^{200}0.639												
140	RANKONE-002	^{129}0.184	^{140}0.118	^{136}0.308	^{149}0.261	^{157}0.190									
141	RANKONE-003	^{126}0.184	^{141}0.118	^{133}0.300	^{146}0.255	^{155}0.187									
142	RANKONE-004	^{145}0.250	^{165}0.193	^{161}0.482	^{172}0.426	^{176}0.324									
143	RANKONE-005	^{80}0.096	^{105}0.059	^{114}0.212	^{125}0.173	^{130}0.119	^{106}0.998	^{119}0.994							
144	RANKONE-006	^{58}0.061	^{69}0.037				^{54}0.977	^{63}0.937							
145	RANKONE-007	^{30}0.034	^{46}0.022	^{59}0.118	^{67}0.095	^{72}0.061	^{45}0.967	^{57}0.924							
146	RANKONE-009	^{27}0.031	^{35}0.018	^{44}0.098	^{50}0.076	^{50}0.045	^{47}0.969	^{50}0.859	^{61}0.062	^{57}0.029			^{50}0.328	^{44}0.206	
147	RANKONE-010	^{17}0.023	^{26}0.014	^{32}0.077	^{35}0.058	^{37}0.036	^{24}0.802	^{32}0.652	^{54}0.052	^{55}0.027	^{24}0.208	^{24}0.119	^{34}0.259	^{42}0.194	
148	REALNETWORKS-000	^{164}0.374	^{171}0.234	^{154}0.433	^{163}0.319	^{166}0.209									
149	REALNETWORKS-001	^{165}0.374	^{170}0.234	^{155}0.433	^{162}0.319	^{165}0.209									
150	REALNETWORKS-002	^{163}0.370	^{169}0.231	^{153}0.416	^{161}0.315	^{167}0.209									
151	REALNETWORKS-003	^{153}0.273	^{155}0.159	^{140}0.342	^{150}0.266	^{153}0.172	^{109}0.998	^{96}0.987	^{93}0.164	^{96}0.103			^{72}0.500	^{80}0.364	
152	REALNETWORKS-004	^{144}0.242	^{154}0.158	^{146}0.353	^{148}0.263	^{150}0.169	^{121}0.999	^{112}0.992	^{94}0.170	^{97}0.103			^{81}0.613	^{81}0.370	
153	REMARKAI-000	^{97}0.125	^{98}0.055	^{93}0.173	^{90}0.120	^{84}0.070	^{118}0.999	^{121}0.995	^{68}0.069	^{64}0.033			^{87}0.717	^{75}0.315	
154	REMARKAI-000	^{134}0.197	^{145}0.128	^{126}0.263	^{131}0.203	^{132}0.123									
155	REMARKAI-002	^{131}0.188	^{144}0.124	^{120}0.248	^{129}0.196	^{131}0.122	^{77}0.991	^{90}0.980							
156	RENDIP-000	^{18}0.023	^{22}0.012	^{103}0.189	^{36}0.059	^{35}0.034	^{35}0.894	^{39}0.744	^{24}0.022	^{27}0.013	^{19}0.185	^{18}0.089	^{16}0.167	^{18}0.130	
157	S1-000	^{103}0.137	^{57}0.028				^{163}1.000	^{25}0.596	^{51}0.047	^{44}0.018	^{135}1.000	^{26}0.123	^{182}1.000	^{103}0.632	
158	SCANOVATE-000	^{85}0.103	^{111}0.067	^{132}0.296	^{143}0.240	^{140}0.150	^{34}0.893	^{47}0.803	^{100}0.215	^{103}0.118			^{57}0.400	^{71}0.299	
159	SCANOVATE-001	^{98}0.128	^{121}0.081	^{131}0.281	^{138}0.227	^{136}0.140	^{37}0.911	^{48}0.834	^{97}0.192	^{98}0.103			^{60}0.404	^{68}0.290	
160	SENSETIME-000	^{33}0.036	^{42}0.021	^{33}0.078	^{39}0.063	^{41}0.040	^{178}1.000	^{97}0.988							
161	SENSETIME-001	^{34}0.036	^{45}0.022	^{35}0.080	^{40}0.064	^{46}0.041									
162	SENSETIME-002	^{35}0.037	^{29}0.015	^{66}0.124	^{16}0.028	^{20}0.023	^{82}0.994	^{89}0.979	^{34}0.032	^{38}0.017			^{73}0.523	^{29}0.160	
163	SENSETIME-003	^{3}0.004	^{2}0.002	^{1}0.014	^{1}0.012	^{1}0.009	^{10}0.477	^{14}0.311	^{9}0.008	^{10}0.005			^{10}0.133	^{12}0.115	
164	SENSETIME-004	^{1}0.003	^{1}0.002	^{2}0.015	^{2}0.013	^{5}0.010	^{4}0.229	^{6}0.149	^{4}0.006	^{4}0.004			^{7}0.113	^{8}0.100	
165	SENSETIME-005	^{10}0.011	^{5}0.002	^{6}0.018	^{6}0.014	^{3}0.010	^{2}0.173	^{3}0.103	^{6}0.007	^{5}0.004	^{5}0.051	^{5}0.023	^{3}0.104	^{5}0.093	
166	SHAMAN-003	^{177}0.506	^{191}0.451	^{173}0.650	^{183}0.597	^{186}0.472									
167	SHAMAN-004	^{188}0.679	^{198}0.615	^{183}0.812	^{190}0.754	^{193}0.639									
168	SHAMAN-006	^{129}0.185	^{149}0.141	^{129}0.278	^{140}0.237	^{149}0.168	^{49}0.972	^{73}0.960							
169	SHAMAN-007	^{124}0.183	^{150}0.141	^{130}0.280	^{142}0.240	^{151}0.169									
170	SIAT-001	^{101}0.132	^{33}0.018	^{172}0.641	^{167}0.365	^{178}0.348			^{32}0.031	^{29}0.014					
171	SIAT-002	^{167}0.417	^{43}0.022	^{185}0.942	^{176}0.478	^{184}0.460			^{109}0.372	^{114}0.356			^{109}0.923	^{31}0.169	
172	SMILART-004	^{207}0.970	^{209}0.968	^{195}0.977	^{203}0.976	^{205}0.973									
173	SMILART-005														
174	SYNESIS-003	^{89}0.111	^{109}0.065	^{86}0.155	^{93}0.123	^{96}0.078	^{43}0.960	^{54}0.911	^{70}0.075	^{69}0.039			^{46}0.314	^{55}0.235	
175	SYNESIS-003	^{186}0.648	^{196}0.582	^{177}0.708	^{186}0.646	^{188}0.524									
176	SYNESIS-005	^{50}0.050	^{48}0.025	^{38}0.088	^{47}0.072	^{49}0.043	^{65}0.984	^{44}0.795	^{37}0.032	^{34}0.016			^{25}0.214	^{28}0.158	
177	TECH5-001	^{195}0.807	^{100}0.057	^{200}0.994	^{199}0.935	^{64}0.055	^{162}1.000	^{157}1.000	^{101}0.244	^{56}0.028			^{122}0.994	^{119}0.817	
178	TECH5-002	^{52}0.053	^{55}0.027	^{42}0.094	^{45}0.070	^{42}0.040	^{25}0.805	^{27}0.627	^{44}0.039	^{45}0.019	^{22}0.205	^{22}0.111	^{63}0.440	^{39}0.182	
179	TEVIAN-003	^{143}0.239	^{162}0.177	^{142}0.346	^{157}0.298	^{159}0.198									
180	TEVIAN-004	^{121}0.170	^{139}0.117	^{115}0.216	^{126}0.176	^{129}0.115									
181	TEVIAN-005	^{100}0.129	^{126}0.087	^{98}0.180	^{106}0.144	^{106}0.089	^{44}0.962	^{45}0.796							
182	TEVIAN-006	^{19}0.024	^{18}0.010	^{17}0.041	^{18}0.032	^{18}0.021	^{6}0.425	^{12}0.291	^{18}0.016	^{21}0.009	^{9}0.093	^{10}0.050	^{112}0.951	^{13}0.117	
183	TIGER-000	^{173}0.462	^{186}0.390	^{165}0.565	^{177}0.500	^{179}0.366									
184	TIGER-002	^{117}0.158	^{123}0.086	^{111}0.202	^{116}0.158	^{113}0.095	^{116}0.999	^{86}0.975							

Table 24: **Threshold-based accuracy**. *Values are FNIR(N, T, L) with N = 1.6 million with thresholds set to produce FPIR = 0.0003, 0.001, and 0.01 in non-mate searches. Throughout blue superscripts indicate the rank of the algorithm for that column. Caution: The Power-low models are mostly intended to draw attention to the kind of behavior, not as a model to be used for prediction.*

FNIR(N, R, T) = False neg. identification rate
FPIR(N, T) = False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

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MISSES BELOW THRESHOLD, T		ENROL RECENT MUGSHOT, N = 1.6M									ENROL APPLICATION PORTRAIT, N = 1.6M				
ENROL		DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: MUGSHOT			DATASET: VISA		DATASET: BORDER		DATASET: VISA
PROBE		DATASET: MUGSHOT			DATASET: WEBCAM			DATASET: PROFILE			DATASET: BORDER		DATASET: BORDER 10+YR		DATASET: KIOSK
#	ALGORITHM	FPIR=0.0003	FPIR=0.001	FPIR=0.0003	FPIR=0.001	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01	FPIR=0.001	FPIR=0.01		
185	TIGER-003	^{118}0.158	^{122}0.086	^{110}0.202	^{115}0.158	^{112}0.095									
186	TONGYITRANS-000	^{88}0.107	^{116}0.074	^{78}0.141	^{82}0.112	^{83}0.069									
187	TONGYITRANS-001	^{96}0.124	^{110}0.066	^{69}0.128	^{74}0.101	^{74}0.062									
188	TOSHIBA-000	^{95}0.123	^{106}0.062	^{82}0.150	^{87}0.118	^{89}0.074	^{92}0.995	^{98}0.988							
189	TOSHIBA-001	^{140}0.225	^{102}0.058	^{74}0.133	^{64}0.092	^{63}0.054									
190	TRUEFACE-000	^{44}0.046	^{37}0.018	^{34}0.079	^{38}0.062	^{39}0.039	^{31}0.882	^{19}0.499	^{31}0.030	^{36}0.016	^{20}0.194	^{23}0.111	^{23}0.188	^{24}0.145	
191	VD-000	^{204}0.950	^{207}0.917	^{193}0.968	^{201}0.946	^{201}0.871									
192	VD-001	^{154}0.278	^{166}0.201	^{137}0.331	^{154}0.281	^{156}0.188									
193	VD-002	^{111}0.144	^{119}0.079	^{102}0.188	^{108}0.148	^{107}0.092	^{95}0.996	^{95}0.987	^{76}0.095	^{78}0.048	^{30}0.367	^{32}0.220	^{54}0.372	^{65}0.280	
194	VERIDAS-001	^{73}0.080	^{70}0.037	^{50}0.106	^{55}0.082	^{54}0.051	^{71}0.987	^{64}0.938	^{46}0.044	^{53}0.023	^{25}0.266	^{27}0.146	^{38}0.264	^{43}0.204	
195	VIGILANTSOLUTIONS-003	^{176}0.482	^{189}0.408	^{180}0.730	^{189}0.660	^{190}0.526	^{114}0.999	^{123}0.995							
196	VIGILANTSOLUTIONS-004	^{185}0.624	^{195}0.549	^{184}0.858	^{193}0.817	^{195}0.709	^{97}0.996	^{108}0.991							
197	VIGILANTSOLUTIONS-005	^{203}0.936	^{185}0.388				^{155}1.000	^{164}1.000							
198	VIGILANTSOLUTIONS-006	^{206}0.959	^{180}0.353				^{151}1.000	^{167}1.000							
199	VIGILANTSOLUTIONS-007	^{70}0.076	^{59}0.028	^{54}0.113	^{59}0.088	^{59}0.053	^{96}0.996	^{109}0.991	^{73}0.081	^{76}0.047	^{31}0.371	^{33}0.242	^{56}0.391	^{70}0.295	
200	VISIONLABS-004	^{77}0.091	^{101}0.058	^{106}0.199	^{117}0.159	^{115}0.097	^{33}0.890	^{38}0.742							
201	VISIONLABS-005	^{74}0.080	^{87}0.050	^{101}0.183	^{107}0.147	^{104}0.087	^{32}0.888	^{37}0.736							
202	VISIONLABS-006	^{42}0.044	^{54}0.027	^{58}0.117	^{62}0.090	^{56}0.051	^{17}0.672	^{22}0.511							
203	VISIONLABS-007	^{41}0.044	^{53}0.027	^{57}0.117	^{61}0.090	^{55}0.051	^{18}0.672	^{21}0.511	^{33}0.031	^{30}0.014			^{22}0.185	^{25}0.145	
204	VISIONLABS-008	^{25}0.028	^{25}0.013	^{27}0.068	^{30}0.051	^{31}0.032	^{11}0.481	^{15}0.317	^{19}0.017	^{17}0.008			^{13}0.151	^{14}0.119	
205	VISIONLABS-009	^{11}0.012	^{12}0.005	^{12}0.032	^{13}0.025	^{13}0.017	^{23}0.799	^{9}0.196	^{12}0.008	^{8}0.004			^{6}0.113	^{6}0.093	
206	VISIONLABS-010	^{12}0.014	^{15}0.005	^{13}0.034	^{15}0.027	^{15}0.019		^{7}0.169	^{7}0.008	^{6}0.004	^{6}0.055	^{7}0.027	^{5}0.109	^{3}0.089	
207	VOCORD-003	^{160}0.354	^{143}0.122	^{105}0.195	^{113}0.155	^{110}0.093	^{107}0.998	^{104}0.991	^{92}0.157	^{99}0.105			^{59}0.404	^{67}0.289	
208	VOCORD-004	^{196}0.826	^{181}0.355	^{150}0.401	^{123}0.173	^{108}0.093	^{140}1.000	^{145}0.999	^{98}0.193	^{83}0.065			^{119}0.991	^{115}0.776	
209	VOCORD-005	^{189}0.689	^{153}0.158	^{88}0.161	^{98}0.130	^{99}0.080	^{99}0.997	^{76}0.968	^{87}0.138	^{93}0.090			^{55}0.381	^{66}0.287	
210	VOCORD-006	^{216}1.000	^{219}1.000	^{211}1.000	^{215}1.000	^{216}1.000	^{164}1.000	^{215}1.000	^{188}1.000	^{172}1.000			^{139}1.000	^{212}1.000	
211	VTS-000	^{183}0.605	^{197}0.598	^{170}0.624	^{184}0.619	^{192}0.613	^{122}0.999	^{143}0.998	^{122}0.613	^{124}0.609	^{33}0.760	^{34}0.739	^{91}0.761	^{112}0.749	
212	XFORWARDAI-000	^{26}0.029	^{32}0.015	^{29}0.070	^{33}0.053	^{36}0.034	^{8}0.440	^{10}0.250	^{23}0.021	^{22}0.011	^{15}0.159	^{17}0.082	^{17}0.169	^{19}0.134	
213	XFORWARDAI-001	^{9}0.010	^{13}0.005	^{15}0.036	^{17}0.028	^{16}0.020	^{9}0.448	^{5}0.143	^{10}0.008	^{9}0.005	^{7}0.062	^{8}0.030	^{8}0.123	^{9}0.102	
214	XFORWARDAI-002	^{6}0.007	^{8}0.003	^{7}0.018	^{7}0.016	^{9}0.014	^{12}0.525	^{1}0.095	^{3}0.005	^{3}0.003	^{4}0.041	^{2}0.018	^{1}0.099	^{2}0.089	
215	YISHENG-001	^{171}0.452	^{179}0.346	^{196}0.983	^{191}0.808	^{172}0.269			^{123}0.666	^{118}0.396			^{108}0.919	^{106}0.695	
216	YITU-002	^{28}0.031	^{34}0.018	^{24}0.063	^{27}0.049	^{26}0.028									
217	YITU-003	^{29}0.032	^{40}0.019	^{25}0.067	^{31}0.052	^{34}0.033									
218	YITU-004	^{15}0.019	^{17}0.010	^{14}0.035	^{14}0.027	^{14}0.017	^{39}0.936	^{55}0.913							
219	YITU-005	^{16}0.022	^{19}0.010	^{16}0.039	^{19}0.032	^{19}0.023									

Table 25: **Threshold-based accuracy**. *Values are FNIR(N, T, L) with N = 1.6 million with thresholds set to produce FPIR = 0.0003, 0.001, and 0.01 in non-mate searches. Throughout blue superscripts indicate the rank of the algorithm for that column. Caution: The Power-low models are mostly intended to draw attention to the kind of behavior, not as a model to be used for prediction.*

Appendices

Appendix A Accuracy on large-population FRVT 2018 mugshots

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2021/06/22	FNIR(N, R, T) =	False neg. identification rate	N = Num. enrolled subjects	T = Threshold	$T = 0 \rightarrow$ Investigation
10:55:01	FPIR(N, T) =	False pos. identification rate	R = Num. candidates examined		$T > 0 \rightarrow$ Identification

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FPIR(N, T) = False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

Figure 20: **[FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects**. *The figure shows false negative identification rates, FNIR(N, R), across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means FPIR = 1, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.*

Figure 21: **[FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects**. *The figure shows false negative identification rates, FNIR(N, R), across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means FPIR = 1, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.*

Figure 22: **[FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects**. *The figure shows false negative identification rates, FNIR(N, R), across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means FPIR = 1, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.*

Figure 23: **[FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects**. *The figure shows false negative identification rates, FNIR(N, R), across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means FPIR = 1, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.*

Figure 24: **[FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects**. *The figure shows false negative identification rates, FNIR(N, R), across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means FPIR = 1, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.*

Figure 25: **[FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects**. *The figure shows false negative identification rates, FNIR(N, R), across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means FPIR = 1, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.*

Figure 26: **[FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects**. *The figure shows false negative identification rates, FNIR(N, R), across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means FPIR = 1, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.*

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Figure 27: **[FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. number of enrolled subjects**. *The figure shows false negative identification rates, FNIR(N, R), across various gallery sizes and ranks 1, 10 and 50. The threshold is set to zero, so this metric rewards even weak scoring rank 1 mates. This also means FPIR = 1, so any search without an enrolled mate will return non-mated candidates. For clarity, results are sorted and reported into tiers spanning multiple pages, the tiering criteria being rank 1 hit rate on a gallery size of 640 000.*

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Figure 28: **[FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. rank**. *The figure shows false negative identification rates (FNIR) for ranks up to 50. This metric is appropriate to investigational applications where human reviewers will adjudicate sorted candidate lists. Note that with threshold set to zero, FPIR = 1, i.e. any search without an enrolled mate will return non-mated candidates. Results are sorted and reported into tiers for clarity, with the tiering criteria being rank 1 hit rate on a gallery size of N = 640 000 subjects.*

Figure 29: **[FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. rank**. *The figure shows false negative identification rates (FNIR) for ranks up to 50. This metric is appropriate to investigational applications where human reviewers will adjudicate sorted candidate lists. Note that with threshold set to zero, FPIR = 1, i.e. any search without an enrolled mate will return non-mated candidates. Results are sorted and reported into tiers for clarity, with the tiering criteria being rank 1 hit rate on a gallery size of N = 640 000 subjects.*

Figure 30: **[FRVT-2018 Mugshot Dataset] Rank-based identification miss rates vs. rank**. *The figure shows false negative identification rates (FNIR) for ranks up to 50. This metric is appropriate to investigational applications where human reviewers will adjudicate sorted candidate lists. Note that with threshold set to zero, FPIR = 1, i.e. any search without an enrolled mate will return non-mated candidates. Results are sorted and reported into tiers for clarity, with the tiering criteria being rank 1 hit rate on a gallery size of N = 640 000 subjects.*

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Figure 36: **[FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects**. *The figure shows FNIR(N, T) across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N, so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by FNIR(N_b, 1, 0), then sorting by median FNIR(N_b, T), N_b = 640 000.*

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Figure 42: **[FRVT-2018 Mugshot Dataset] Threshold-based identification miss rates vs. number of enrolled subjects**. *The figure shows FNIR(N, T) across various gallery sizes when the threshold is set to achieve the given FPIRs. The rank criterion is irrelevant at high thresholds as mates are always at rank 1. The results are computed from the trials listed in rows 1-10 of Table 1. Less accurate algorithms were not run on large N, so results are missing. For clarity, results are sorted and reported into tiers spanning multiple pages. The tiering criteria is complicated: First paging by FNIR(N_b, 1, 0), then sorting by median FNIR(N_b, T), N_b = 640 000.*

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Figure 48: **[FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates**. *The figure shows miss rates FNIR(N, L, T) as a function of FPIR(N, T), with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, FPIR(T) rises with N, and mate scores are independent of N. Other algorithms adjust scores in an attempt to make FPIR independent of N.*

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Figure 49: **[FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates**. *The figure shows miss rates FNIR(N, L, T) as a function of FPIR(N, T), with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, FPIR(T) rises with N, and mate scores are independent of N. Other algorithms adjust scores in an attempt to make FPIR independent of N.*

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Figure 52: **[FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates**. *The figure shows miss rates FNIR(N, L, T) as a function of FPIR(N, T), with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, FPIR(T) rises with N, and mate scores are independent of N. Other algorithms adjust scores in an attempt to make FPIR independent of N.*

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Figure 53: **[FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates**. *The figure shows miss rates FNIR(N, L, T) as a function of FPIR(N, T), with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, FPIR(T) rises with N, and mate scores are independent of N. Other algorithms adjust scores in an attempt to make FPIR independent of N.*

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Figure 55: **[FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates**. *The figure shows miss rates FNIR(N, L, T) as a function of FPIR(N, T), with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, FPIR(T) rises with N, and mate scores are independent of N. Other algorithms adjust scores in an attempt to make FPIR independent of N.*

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Figure 57: **[FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates**. *The figure shows miss rates FNIR(N, L, T) as a function of FPIR(N, T), with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, FPIR(T) rises with N, and mate scores are independent of N. Other algorithms adjust scores in an attempt to make FPIR independent of N.*

FNIR(N, R, T) = False neg. identification rate
FPIR(N, T) = False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

Figure 58: **[FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates**. *The figure shows miss rates FNIR(N, L, T) as a function of FPIR(N, T), with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, FPIR(T) rises with N, and mate scores are independent of N. Other algorithms adjust scores in an attempt to make FPIR independent of N.*

Figure 59: **[FRVT-2018 Mugshot Dataset] Identification miss rates vs. false positive rates**. *The figure shows miss rates FNIR(N, L, T) as a function of FPIR(N, T), with N ranging from 640 000 to 12 000 000 as noted in rows 1-10 of Table 1. These error tradeoff characteristics are useful for applications where a threshold must be elevated to limit false positives, such as when human reviewer labor is not matched to the volume of searches. Dark lines join points of equal threshold: If horizontal, FPIR(T) rises with N, and mate scores are independent of N. Other algorithms adjust scores in an attempt to make FPIR independent of N.*

Appendix B Effect of time-lapse: Accuracy after face ageing

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Figure 60: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 61: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 62: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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N = Num. enrolled subjects
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Figure 63: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 64: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 65: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 66: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 67: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 68: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 69: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 70: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 71: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 72: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 73: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 74: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 75: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 76: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 77: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 78: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

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Figure 79: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. rank by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment.*

2021/06/22	FNIR(N, R, T) =	False neg. identification rate	N = Num. enrolled subjects	T = Threshold	$T = 0 \rightarrow$ Investigation
10:55:01	FPIR(N, T) =	False pos. identification rate	R = Num. candidates examined		$T > 0 \rightarrow$ Identification

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Figure 80: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with N = 3 000 000.*

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Figure 81: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with N = 3 000 000.*

Figure 82: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with N = 3 000 000.*

Figure 83: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with N = 3 000 000.*

Figure 84: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with N = 3 000 000.*

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Figure 85: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with N = 3 000 000.*

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Figure 86: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with N = 3 000 000.*

Figure 87: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with N = 3 000 000.*

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Figure 88: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with N = 3 000 000.*

Figure 89: **[FRVT-2018 Mugshot Ageing Dataset] Identification miss rates vs. FPIR by time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Miss rates are computed over all searches noted in row 17 of Table 1 and binned by number of years between search and initial enrollment. FPIR is computed from the same FRVT 2018 non-mates noted in row 3 of Table 1 with N = 3 000 000.*

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Figure 90: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 91: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 92: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 93: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 94: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 95: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 96: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 97: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 98: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 99: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 100: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 101: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 102: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 103: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 104: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 105: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 106: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 107: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 108: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 109: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 110: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 111: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 112: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 113: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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N = Num. enrolled subjects
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T = Threshold
T = 0 → Investigation
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Figure 114: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 115: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 116: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 117: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 118: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 119: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 120: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 121: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 122: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 123: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 124: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 125: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 126: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 127: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 128: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 129: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 130: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 131: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 132: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 133: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 134: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

FNIR(N, R, T) = False neg. identification rate
FPIR(N, T) = False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

Figure 135: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 136: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 137: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 138: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 139: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 140: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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FNIR(N, R, T) = False neg. identification rate
FPIR(N, T) = False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

Figure 141: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 142: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 143: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 144: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 145: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 146: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Figure 147: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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FNIR(N, R, T) = False neg. identification rate
FPIR(N, T) = False pos. identification rate
N = Num. enrolled subjects
R = Num. candidates examined
T = Threshold
T = 0 → Investigation
T > 0 → Identification

Figure 148: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

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Figure 149: **[FRVT-2018 Mugshot Ageing Dataset] Native mate scores vs. time-elapsed**. *The oldest image of each individual is enrolled. Thereafter, all more recent images are searched. Mated score distributions are computed over all searches noted in row 17 of Table 1 binned by number of years between search and initial enrollment.*

Appendix C Effect of enrolling multiple images

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Figure 150: **[FRVT-2018 Mugshot Dataset] Effect of enrolling multiple images for each identity**. *The plot shows an identification miss rates vs. false positive rates, at seven operating thresholds. The enrolled population size is fixed. The images are enrolled with lifetime-consolidation - see section 2.3.*

Figure 151: **[FRVT-2018 Mugshot Dataset] Effect of enrolling multiple images for each identity**. *The plot shows an identification miss rates vs. false positive rates, at seven operating thresholds. The enrolled population size is fixed. The images are enrolled with lifetime-consolidation - see section 2.3.*

Figure 152: **[FRVT-2018 Mugshot Dataset] Effect of enrolling multiple images for each identity**. *The plot shows an identification miss rates vs. false positive rates, at seven operating thresholds. The enrolled population size is fixed. The images are enrolled with lifetime-consolidation - see section 2.3.*

Figure 153: **[FRVT-2018 Mugshot Dataset] Effect of enrolling multiple images for each identity**. *The plot shows an identification miss rates vs. false positive rates, at seven operating thresholds. The enrolled population size is fixed. The images are enrolled with lifetime-consolidation - see section 2.3.*

Figure 154: **[FRVT-2018 Mugshot Dataset] Effect of enrolling multiple images for each identity**. *The plot shows an identification miss rates vs. false positive rates, at seven operating thresholds. The enrolled population size is fixed. The images are enrolled with lifetime-consolidation - see section 2.3.*

Figure 155: **[FRVT-2018 Mugshot Dataset] Effect of enrolling multiple images for each identity**. *The plot shows an identification miss rates vs. false positive rates, at seven operating thresholds. The enrolled population size is fixed. The images are enrolled with lifetime-consolidation - see section 2.3.*

Appendix D Accuracy with poor quality webcam images

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2021/06/22	FNIR(N, R, T) =	False neg. identification rate	N = Num. enrolled subjects	T = Threshold	$T = 0 \rightarrow$ Investigation
10:55:01	FPIR(N, T) =	False pos. identification rate	R = Num. candidates examined		$T > 0 \rightarrow$ Identification

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Figure 156: **[Webcam Dataset] Identification miss rates vs. rank**. *The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.*

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Figure 157: **[Webcam Dataset] Identification miss rates vs. rank**. *The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.*

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Figure 158: **[Webcam Dataset] Identification miss rates vs. rank**. *The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.*

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Figure 159: **[Webcam Dataset] Identification miss rates vs. rank**. *The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.*

2021/06/22	FNIR(N, R, T) =	False neg. identification rate	N = Num. enrolled subjects	T = Threshold	$T = 0 \rightarrow$ Investigation
10:55:01	FPIR(N, T) =	False pos. identification rate	R = Num. candidates examined		$T > 0 \rightarrow$ Identification

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Figure 160: **[Webcam Dataset] Identification miss rates vs. false positive rates**. *The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.*

Figure 161: **[Webcam Dataset] Identification miss rates vs. false positive rates**. *The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.*

Figure 162: **[Webcam Dataset] Identification miss rates vs. false positive rates**. *The results apply to cross-domain recognition in which webcams are searched against enrolled mugshots. The FNIR values are higher than those for mugshot-mugshot identification due to low image resolution, lighting and less constrained subject pose in webcam images - see Figure 6.*

Appendix E Accuracy for profile-view to frontal recognition

Figures 163 - 165 gives accuracy results for searching 100 000 mated and 100 000 non-mated profile-view images against the same FRVT 2018 frontal enrollment dataset, N = 1 600 000, used in the main mugshot trials. This experiment corresponds to row-13 of Table 1. An example of profile-view image is given in Figure 7.

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Figure 163: **[Mugshot and profile-view dataset] Rank-based accuracy**. *For some of the more accurate Phase 3 algorithms the figure plots error tradeoff characteristics for frontal and profile-view searches into an enrolled set of N = 1 600 000 frontal images. Note that some algorithms fail on profile-view images with FNIR → 1 - this evaluation did not ask developers to provide profile-view capability. Some algorithms, on the other hand, give FNIR approaching that for frontal-view searches using c. 2010 algorithms. The best result is that 91% of profile-view searches yield the correct mate at rank 1, and better than 94% in the top-50 candidates.*

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Figure 164: **[Mugshot and profile-view dataset] Threshold-based accuracy**. *For some of the more accurate Phase 3 algorithms the figure plots error tradeoff characteristics for frontal and profile-view searches into an enrolled set of N = 1 600 000 frontal images. Note that some algorithms fail on profile-view images with FNIR → 1 - this evaluation did not ask developers to provide profile-view capability. Some algorithms, on the other hand, give FNIR approaching that for frontal-view searches using c. 2010 algorithms.*

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Figure 165: **[Mugshot and profile-view dataset] Speed-accuracy tradeoff**. *For some of the more accurate Phase 3 algorithms the figure plots error tradeoff characteristics for frontal and profile-view searches into an enrolled set of N = 1 600 000 frontal images. Some algorithms fail on profile-view images with FNIR → 1 - this evaluation did not ask developers to provide profile-view capability. Some algorithms, on the other hand, give FNIR approaching that for frontal-view searches using c. 2010 algorithms. Blue lines connect points of equal threshold from which it is evident that some algorithms would give markedly higher false positive outcomes if profile-view images were searched in a system configured for frontal searches. This would be a vulnerability in an access control system.*

Appendix F Search duration

As in and prior tests, this section documents search speeds spanning three orders of magnitude. In applications where search volumes are high enough, this will have implications for hardware requirements especially for large N or when search duration is appreciably larger than the time it takes to prepare a template from the search image(s). Further, given very large (and growing) operational databases, the scalability of algorithms is important. It has been reported previously [8] that search duration can scale sublinearly with enrolled population size N. Further there has been considerable recent research on indexing, exact [13] and approximate nearest neighbor search [1,13] and fast-search [14,16].

Figure 166 charts the search duration measurements presented earlier in Tables 2 - 4.

- ▷ Most algorithms scale linearly. For those in that category, there is a wide range in speed with search durations ranging from 82 milliseconds for a 12 million gallery (for NEC-3) to more than 40 seconds (for Yitu-3, Toshiba-2) and even higher for less accurate algorithms.
- ▷ Some developers (Camvi, Dermalog, EverAI, Innovatrics, and Visionlabs) provide algorithms whose template search durations grow approimately logarithmically i.e. $T(N)\tilde{a}\log N$ with the constant a varying between implementations. In the figure this model is fit using the point $T(1) = 0$, and $T(640\,000)$. This very sublinear behaviour affords extremely fast search times in very large galleries. One caveat for the sublinear algorithms is that their fast-search data structures can require considerable computation time - on the order of hours - for N in the millions, and this scales mildy super-linearly, i.e. $O(N^b), b > 1$. There are exceptions: the Camvi algorithms take minutes; and Innvovatrics' scale sublinearly.

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10:55:01	FPIR(N, T) =	False pos. identification rate	R = Num. candidates examined		$T > 0 \rightarrow$ Identification

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Figure 166: **[Mugshot Dataset] Search duration vs. enrolled population size**. *In red are the actual point durations measured on a single c. 2016 core. The blue shows linear growth from $N = 640\,000$. The green line shows logathmic growth from that point to $N = 1\,600\,000$. Note the sublinear growth from algorithms from Camvi, Dermalog, EverAI, Innovatrics, and Visionlabs. The tiger_1 algorithm is also sublinear, but inaccurate and inoperable at $N \geq 3000000$. This capability sometimes comes at the additional expense of converting a linear gallery data structure into whatever fast-search data structure is used. Note that search times are sometimes dominated by the template generation times shown in Table 17.*

Figure 167: **[Mugshot Dataset] Search duration vs. enrolled population size**. *In red are the actual point durations measured on a single c. 2016 core. The blue shows linear growth from $N = 640\,000$. The green line shows logathmic growth from that point to $N = 1\,600\,000$. Note the sublinear growth from algorithms from Camvi, Dermalog, EverAI, Innovatrics, and Visionlabs. The tiger_1 algorithm is also sublinear, but inaccurate and inoperable at $N \geq 3000000$. This capability sometimes comes at the additional expense of converting a linear gallery data structure into whatever fast-search data structure is used. Note that search times are sometimes dominated by the template generation times shown in Table 17.*

Figure 168: **[Mugshot Dataset] Search duration vs. enrolled population size**. *In red are the actual point durations measured on a single c. 2016 core. The blue shows linear growth from $N = 640\,000$. The green line shows logathmic growth from that point to $N = 1\,600\,000$. Note the sublinear growth from algorithms from Camvi, Dermalog, EverAI, Innovatrics, and Visionlabs. The tiger_1 algorithm is also sublinear, but inaccurate and inoperable at $N \geq 3000000$. This capability sometimes comes at the additional expense of converting a linear gallery data structure into whatever fast-search data structure is used. Note that search times are sometimes dominated by the template generation times shown in Table 17.*

Figure 169: **[Mugshot Dataset] Search duration vs. enrolled population size**. *In red are the actual point durations measured on a single c. 2016 core. The blue shows linear growth from $N = 640\,000$. The green line shows logathmic growth from that point to $N = 1\,600\,000$. Note the sublinear growth from algorithms from Camvi, Dermalog, EverAI, Innovatrics, and Visionlabs. The tiger_1 algorithm is also sublinear, but inaccurate and inoperable at $N \geq 3000000$. This capability sometimes comes at the additional expense of converting a linear gallery data structure into whatever fast-search data structure is used. Note that search times are sometimes dominated by the template generation times shown in Table 17.*

Figure 170: **[Mugshot Dataset] Search duration vs. enrolled population size**. *In red are the actual point durations measured on a single c. 2016 core. The blue shows linear growth from $N = 640\,000$. The green line shows logathmic growth from that point to $N = 1\,600\,000$. Note the sublinear growth from algorithms from Camvi, Dermalog, EverAI, Innovatrics, and Visionlabs. The tiger_1 algorithm is also sublinear, but inaccurate and inoperable at $N \geq 3000000$. This capability sometimes comes at the additional expense of converting a linear gallery data structure into whatever fast-search data structure is used. Note that search times are sometimes dominated by the template generation times shown in Table 17.*

Appendix G Gallery Insertion Timing

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Figure 171: **[Mugshot Dataset] Gallery insertion duration vs. enrolled population size**. *This chart plots the time it takes to insert a single template into a finalized gallery, illustrated over increasing gallery sizes. For reference, search times on finalized galleries of corresponding sizes are plotted right underneath. Gallery insertion time plots were generated on algorithms that 1) successfully implemented gallery insertion with no errors and 2) that were run on galleries with N up to* 12 000 000*. Generally, only the more accurate algorithms were run on galleries with N up to* 12 000 000*.*

Figure 172: **[Mugshot Dataset] Gallery insertion duration vs. enrolled population size**. *This chart plots the time it takes to insert a single template into a finalized gallery, illustrated over increasing gallery sizes. For reference, search times on finalized galleries of corresponding sizes are plotted right underneath. Gallery insertion time plots were generated on algorithms that 1) successfully implemented gallery insertion with no errors and 2) that were run on galleries with N up to* 12 000 000*. Generally, only the more accurate algorithms were run on galleries with N up to* 12 000 000*.*

Figure 173: **[Mugshot Dataset] Gallery insertion duration vs. enrolled population size**. *This chart plots the time it takes to insert a single template into a finalized gallery, illustrated over increasing gallery sizes. For reference, search times on finalized galleries of corresponding sizes are plotted right underneath. Gallery insertion time plots were generated on algorithms that 1) successfully implemented gallery insertion with no errors and 2) that were run on galleries with N up to* 12 000 000. *Generally, only the more accurate algorithms were run on galleries with N up to* 12 000 000.

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Figure 174: **[Mugshot Dataset] Gallery insertion duration vs. enrolled population size**. *This chart plots the time it takes to insert a single template into a finalized gallery, illustrated over increasing gallery sizes. For reference, search times on finalized galleries of corresponding sizes are plotted right underneath. Gallery insertion time plots were generated on algorithms that 1) successfully implemented gallery insertion with no errors and 2) that were run on galleries with N up to* 12 000 000*. Generally, only the more accurate algorithms were run on galleries with N up to* 12 000 000*.*

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