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# High capacity clinical SARS-CoV-2 molecular testing using combinatorial pooling

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## 28 Abstract

29 The SARS-CoV-2 pandemic led to unprecedented testing demands, causing significant testing delays  
30 globally. One strategy used for increasing testing capacity was pooled-testing, using a two-stage  
31 technique first introduced during WWII. Here we report the development, validation and clinical  
32 application of P-BEST - a single-stage pooled-testing strategy that was approved for clinical use in  
33 Israel. P-BEST was clinically evaluated using 3,636 side-by-side tests and was able to correctly detect  
34 all positive samples and accurately estimate their Ct value. P-BEST was then used to clinically test  
35 837,138 samples using 270,095 PCR tests - a 3.1 fold reduction in the number of tests. Importantly, P-  
36 BEST was also used during the Alpha and Delta waves, when positivity rates exceeded 10%, rendering  
37 traditional pooling non-practical. We also describe a tablet-based solution that allows performing  
38 manual single-stage pooling in settings where liquid dispensing robots are not available. Our data  
39 provides a proof-of-concept for large-scale clinical implementation of single-stage pooled-testing for  
40 continuous surveillance of multiple pathogens with reduced test costs, and as an important tool for  
41 increasing testing efficiency during pandemic outbreaks.

## 42 Introduction

43 The SARS-CoV-2 pandemic spread rapidly worldwide leading to over 608 million documented  
44 infections and 6.5 million deaths<sup>1</sup>. A variety of different mitigation measures were used to control the  
45 spread of SARS-CoV-2, which included lockdowns, school closures, travel restrictions, quarantines,  
46 diagnostic testing, and vaccination. Until the rise of the Omicron BA.1 variant, community testing for  
47 SARS-CoV-2 was utilized by most countries around the world. To date, over  $1.5 \times 10^{10}$  PCR tests have  
48 been performed throughout the world, leading to continuous shortages of test reagents, and significant  
49 delays in test turnaround times<sup>2</sup>.

50 Israel was one of the first countries that offered government funded PCR-based testing to all its  
51 residents, rapidly building a network of HMO laboratories and private laboratories to increase testing  
52 capacity. To date, a total of 45.5 million PCR tests were conducted in Israel, making it one of the leading  
53 countries in COVID-19 tests per capita <sup>2</sup> (**Supplementary Fig. 1**). As part of Israel's strategy for  
54 COVID-19 testing, the Israeli ministry of health authorized the use of pooled testing methods, in the  
55 spring of 2020. This included the use of traditional Dorfman pooling<sup>3</sup>, which was also approved in other  
56 countries<sup>4</sup>, and also P-BEST - a combinatorial single-stage pooling method<sup>5</sup>.

57 In contrast to Dorfman pooling, which requires a second round of individual testing of samples that  
58 belong to positive pools (**Fig. 1A**), P-BEST provides diagnostic results within a single round of testing  
59 (**Fig. 1B**). Each pool contains multiple samples and each sample is included in multiple pools, such that

60 the set of measurements across all pools corresponds to a unique set of positive samples and is therefore  
61 sufficient to detect these positive samples and their corresponding Ct values after a single round of  
62 testing. The approach uses pooling designs that are optimized for detecting all positive samples up to a  
63 specific positivity rate, and as positivity rates change, the specific pooling design used changes  
64 accordingly.

65 Here we present the validation and clinical rollout of P-BEST - the first combinatorial single-stage  
66 pooling method used for mass testing during the SARS-CoV-2 pandemic. During the validation phase,  
67 a set of 3,636 samples were tested side-by-side with individual testing. We demonstrated that P-BEST  
68 correctly classified all samples with zero false positives and false negatives, and correctly estimated the  
69 Ct values of positive samples leading to regulatory approval for clinical diagnostic testing by the Israeli  
70 ministry of health (MOH). To facilitate clinical usage of P-BEST a software product (PoolDi) that  
71 provides a user-friendly interface of P-BEST was designed and developed by a startup company funded  
72 by a grant from the Israel Innovation authority. PoolDi was installed in 3 major diagnostic labs in Israel,  
73 and routinely used for clinical SARS-CoV-2 diagnostic testing starting in January 2021. Here we  
74 analyze the clinical use of P-BEST in these three labs during the period of January 2021 to January  
75 2022. Within this period, a total of 837,138 samples were clinically tested using P-BEST using 270,095  
76 PCR reactions, a reduction of 68% in the number of tests performed leading to savings of over 10  
77 million USD in testing reagents alone. Our analysis provides proof-of-concept for the feasibility of  
78 using combinatorial pooling solutions for mass testing in clinical settings.

79

80

# 81 Results

## 82 Clinical validation of P-BEST

83 To validate P-BEST and obtain regulatory approval for its use in clinical SARS-CoV-2 diagnostic  
84 testing in Israel, we followed guidelines outlined by the Israeli MOH, which required side-by-side  
85 validation studies to be conducted in each lab independently. We conducted a set of 35 side-by-side  
86 experiments comparing P-BEST to testing each sample individually. A total of 3,636 samples, collected  
87 between 24/11/2020 and 07/02/2021, were tested during the validation stage (**Supplementary Table**  
88 **1**). All samples were tested individually 24-48 hours prior to P-BEST pooling, and most positive  
89 samples were also individually re-tested in tandem with P-BEST to account for potential signal decay  
90 of stored samples.

## 91 Evaluation of P-BEST calls

92 Experiments were performed using three pooling designs, that were relevant to SARS-CoV-2  
93 prevalence levels in Israel during this period: (a) 96 samples pooled into 25 pools (x3.8 efficiency gain)  
94 suitable for up to 2% disease prevalence (19 experiments); (b) 96 samples pooled into 46 pools (x2.1  
95 efficiency gain) suitable for up to 6% disease prevalence (15 experiments); and (c) 372 samples pooled  
96 into 186 pools (x2 efficiency gain) suitable for up to 6% disease prevalence (1 experiment). In each  
97 experiment the number of positive samples matched or exceeded the maximal prevalence of the pooling  
98 design used (**Supplementary Table 2**). This allowed us to also assess the performance of P-BEST in  
99 situations where the actual prevalence may be higher than expected - a scenario which may occur in  
100 real-world clinical settings due to batch effects (e.g., an infected family), or to dynamic changes in  
101 disease prevalence caused by pandemic waves. Validation was performed following the MOH  
102 guidelines for clinical pooled testing, requiring correct detection of all samples with Ct values below  
103 35. A total of 141 positive samples whose Ct was lower than 35 were included in this set. P-BEST had  
104 zero false positive detections and a single false negative call based on MOH requirements (**Table 1**).

105 The P-BEST algorithm classifies each sample into one of three categories: (1) “Positive” - a sample  
106 from an infected individual; (2) “Negative” - a sample from an un-infected individual; and (3)  
107 “Suspected” - samples that require retesting individually due to several types of inconclusive or partial  
108 measurements, as detailed below. The suspected category was defined by the clinical laboratories to  
109 minimize the number of false positives. P-BEST classified 97 out of the 141 positive samples as  
110 “positive”. The remaining 44 positive samples were classified as “suspected”, due to one of the  
111 following reasons: (a) Invalidated pools - samples which were included in a pool that was classified as  
112 invalid due to technical PCR issues (n=6). (b) Weak pools - Samples that appeared in at least one pool

113 with high Ct values (n=16). (c) Overcrowding - Samples included in overcrowded experiments where  
114 the actual positivity rate exceeded the maximal positivity rate of the pooling design used (n=21).

115 Importantly, there were zero false positive calls, and a single case of a false negative call. This specific  
116 positive sample was included in five pools, three of which were negative, one had a Ct value of 39.9  
117 and a fifth pool contained an additional positive sample with a low Ct value. Although the initial Ct of  
118 the false negative sample was 32.2 it was not measured in tandem with the pooling experiment,  
119 performed 18 hours afterwards, and may have been missed due to sample deterioration. We also  
120 analyzed 13 weak positive samples (Ct > 35) which were not required to be detected by P-BEST per  
121 the Israeli MOH guidelines. We found that P-BEST classified 8/13 (61%) of these samples as  
122 “suspected”.

### 123 **P-BEST provides accurate Ct estimates**

124 Another advantage of P-BEST is its ability to estimate the Ct value of positive samples. Using positive  
125 samples identified by individual testing, we compared the Ct values of the N-gene as measured using  
126 the Seegene COVID-19 PCR kit, to the ones estimated by P-BEST. We found that the correlation  
127 between the measured and estimated Ct values was  $r = 0.95$  (Pearson correlation, **Fig. 2A**). To further  
128 analyze the Ct estimates of P-BEST we stratified the Ct values of samples that were classified as  
129 “suspected” using the 3 categories defined above (i.e., invalidated pools, weak-pools and overcrowding)  
130 and plotted their individual Ct values as measured using the Seegene assay (**Fig. 2B**). As expected, we  
131 observed that the Ct values of samples classified due to weak pools were indeed significantly higher  
132 than those of the two other categories that lead to “suspected” classifications.

### 133 **Using P-BEST for clinical diagnostics**

134 Following the completion of the validation studies, P-BEST was approved for clinical use in Israel by  
135 the Israeli MOH. During the 13 months of clinical operation (January 2021 to January 2022), a total of  
136 837,138 samples were tested with P-BEST using 270,095 PCR reactions, corresponding to an average  
137 efficiency of 3.1 and a reduction of 68% in the number of tests performed. We executed a total of 4,874  
138 runs with the following efficiencies: 347 runs with 1.5x efficiency, 2287 runs with 2x efficiency, 700  
139 runs with 3x efficiency, 1458 runs with 4x efficiency and 82 runs with 8x efficiency (**Fig. 3A**). P-BEST  
140 was used during the Alpha and Delta waves in Israel when positivity rates approached 10% (**Fig. 3B**).  
141 The specific pooling designs used were selected based on the positivity rate per week (**Fig. 3C-D**).  
142 During the Alpha wave most of the tests performed used the 2% or 6% designs, even when positivity  
143 rates were higher, thanks to a pre-testing screening procedure performed by the clinical laboratories.  
144 Samples were classified into ‘high’ and ‘low’ risk of positivity, based on de-identified demographic  
145 information, and only ‘low’ risk samples were pooled using P-BEST. During the peak of the Delta

146 wave, a 10% pooling design was used in combination with the pre-screening testing approach, allowing  
147 labs to continue pooling samples even when de facto rates exceeded 10% (**Fig. 3C-D**)

### 148 **High capacity pooling during the tail of the Delta wave**

149 While positivity rates at the end of the Alpha wave in Israel were very low (< 0.8%, **Fig. 3B**), resulting  
150 in a sharp reduction in the total number of PCR tests performed (data not shown), the Delta wave  
151 declined more gradually with an average positivity rate of ~1% (**Fig. 3B**). During November to  
152 December 2021, the labs converted their entire testing pipeline into a pooling pipeline using P-BEST,  
153 and a total of 210,090 samples were tested using pooling designs of 1%-4%. The number of PCR  
154 reactions used to test these samples in total was 62,040 tests, a reduction of 70% in testing reagents  
155 used, which translated to significant financial savings for the labs.

### 156 **Samples requiring retest are mainly due to improper use of P-BEST**

157 During the Alpha wave, 6% of the samples tested were classified as “suspected” by P-BEST, thus  
158 requiring re-testing (see Methods). We found that “suspected” calls were not uniformly distributed  
159 across runs, with 60% of them appearing in only 7% of the runs. These runs were ‘overcrowded’ runs  
160 in which the effective positivity rate exceeded the recommended rate of the pooling design used for  
161 testing. This was mostly due to human error as samples whose pre-screening classification was ‘high-  
162 risk’ were tested using P-BEST, rather than being tested as individual samples. Excluding these runs,  
163 the empirical efficiency during the Alpha wave reached 3.1x corresponding to a reduction of 68% in  
164 the number of tests. We note that during the Delta wave, following additional training of lab personnel  
165 and sufficient hands-on experience of using the software, the number of “suspected” samples that  
166 required retesting was significantly reduced.

### 167 **Adapting combinatorial pooling to low-resource laboratories**

168 A key challenge in implementing combinatorial pooling is the need to obtain a costly liquid dispensing  
169 robot, which also requires continuous technical support. While such robots have become common in  
170 many western-world laboratories, they are not widely used in many low- and mid-income countries.  
171 We therefore sought to adapt our pooling method for use in such settings. Building upon a tablet-  
172 directed pooling solution<sup>6</sup> we developed a version of our pooling method for manual combinatorial  
173 pooling which requires minimal laboratory equipment (**Fig. 4A**). Since all pipetting operations are  
174 performed by a laboratory technician, we used small scale pooling designs that pool 96 samples into 25  
175 or 46 pools and take less than 25 minutes (**Fig. 4B**). To make pipetting more user-friendly, we re-  
176 ordered the pipetting operations such that the required movements are always from left to right, and  
177 dispensing is more regular (e.g., two dispensing operations per row of pools) (**Fig. 4C**). Decoding was



178 performed using an online cloud-based server onto which the technician could load a PCR result file.  
179 We also extended our decoding algorithm to identify manual pipetting errors (e.g., erroneous pipetting  
180 into a wrong well), usage of an incorrect pooling matrix, etc. Basically, such errors are identified by  
181 detecting significant discordance between the measured viral load of a pool and the estimated Ct values  
182 of its samples. We tested our manual pooling method with two SARS-CoV-2 PCR kits developed in  
183 India, in collaboration with a local lab. Pilot studies demonstrated that all positive samples were  
184 properly detected using our approach (data not shown).

## 185 **Discussion**

186 The SARS-CoV-2 pandemic led to a massive expansion of molecular testing capacity around the world.  
187 Despite this, in many countries turnaround times for PCR testing were very slow, both due to limited  
188 testing capacity and shortages of testing reagents. While some countries such as the USA, the UK, and  
189 Uganda authorized two-stage traditional pooled testing<sup>7-9</sup>, pooling was not widely used to increase  
190 testing capacity and reduce costs. To the best of our knowledge, Israel was the only country in the world  
191 to validate and authorize a combinatorial single-stage pooling method for clinical use, which among  
192 other factors allowed it to offer some of the highest testing capacity per-capita in the world<sup>2</sup>.

193 Several studies reported results using adaptive two-stage group testing, i.e., pooling methods for SARS-  
194 CoV-2 testing<sup>3,10,11</sup>. The clinical testing described here utilized the P-BEST (Pooling-Based Efficient  
195 SARS-CoV-2 Testing) method, which, as opposed to former methods, is a non-adaptive group testing  
196 approach that requires only a single round of testing<sup>5</sup>. Several other papers have since presented  
197 analogous non-adaptive approaches<sup>12-16</sup>, yet, to the best of our knowledge, none of these methods were  
198 utilized in clinical settings.

199 We summarized data from 13 months of clinical use of P-BEST for COVID-19 PCR testing. During  
200 this period, a total of 837,138 PCR results were processed using P-BEST in 3 large clinical diagnostic  
201 laboratories in Israel. Pooled testing was not only performed in periods of low disease prevalence, but  
202 also during the Alpha and Delta waves in Israel, including a period where positivity rates exceeded  
203 10%. The use of pooled testing resulted in a reduction of 68% in the number of PCR kits used, allowing  
204 labs to increase testing capacity even during infection peaks.

205 This rapid and effective clinical implementation of P-BEST was possible due to several important  
206 factors: first and foremost, the Israeli MOH actively sought innovative ideas for increasing testing  
207 capacity, and provided a well-defined and rapid regulatory pathway for clinical validation of new testing  
208 methods. Second, a startup company funded by a grant from the Israeli Innovation Authority was  
209 founded to develop a user-friendly software product that implemented P-BEST, allowing minimally

210 trained laboratory technicians to easily use the method, and also integrating in medical record systems.  
211 Finally, a close collaboration with Clalit Healthcare virology labs was critical for gaining hands-on  
212 experience of the lab testing workflows, and for obtaining critical feedback regarding the usability and  
213 requirements of the software product implementing P-BEST.

214 Another critical factor for clinical implementation was reducing overall test-time. Since pooling  
215 introduces an additional pre-processing step, it may increase testing time thereby increasing labs' time-  
216 to-result, which was an important performance measure utilized by the Israeli MOH during the  
217 pandemic. To reduce test turnaround time, we developed an optimization procedure that minimizes the  
218 number of pipetting steps by the liquid handling robot. This enabled testing more than 5000 samples  
219 per day on a single Tecan Freedom EVO 200 robot. In one of the labs, the overall pooled testing  
220 capacity was 15,000 samples per day.

221 P-BEST classification calls were tuned towards reducing false positive calls. For example, a sample of  
222 very low Ct would be called "suspected" if one of its pools was invalidated due to technical issues. In  
223 practice, 3.4% of samples were classified as "suspected", and most of these (56%) were due to 'weak  
224 pools', i.e., pools with Ct > 36 or even negative pools. An additional 41% were classified as "suspected"  
225 due to 'overcrowding'. It should be noted that these criteria are utilized as post-processing decisions  
226 and may be easily altered in different testing scenarios. In practice, 70% of the "suspected" calls  
227 (16,613) originated from 12.6% (n=613) of the total number of pooling runs (n=4874).

228 A key advantage of combinatorial pooling over two-stage Dorfman pooling is that each sample is added  
229 into multiple (3-5) pools and in essence is tested multiple times. Our clinical experience demonstrated  
230 that such repeated measurements can counteract the dilution effect due to sample pooling, allowing us  
231 to detect all samples with Ct value below 35. In general, the performance of P-BEST depends on the  
232 limit of detection (LoD) of the kit used for downstream analysis. For example, the LoD of the Seegene  
233 PCR kit used in this study, as stated by the FDA approved EUA, corresponds to a Ct of 33<sup>17</sup>, i.e., below  
234 which at least 19 of 20 technical repeats would yield a positive result. Clinical data from the validation  
235 study in the Soroka University Medical Center virology lab (one of the three labs using P-BEST  
236 clinically) demonstrated an effective LoD Ct of 35. This increased sensitivity may be due to the repeated  
237 measurements of each sample when using combinatorial pooling. Therefore, clinical use of P-BEST  
238 requires calibration to each individual testing kit used, using side-by-side testing of individual and  
239 pooled samples. Indeed, this was performed for multiple PCR kits which were in clinical use within  
240 these laboratories, and typically took less than a week for each new kit.

241 Another strategy used in Israel during the pandemic was pod-testing, in which each individual was  
242 sampled using two swabs - one that was added into a Pod, i.e., a pool consisting of multiple swabs in a  
243 single large tube, and another individual sample was stored in a standard UTM tube. Pods were tested,

244 and every positive pod was then deconvoluted by testing all of the individual tubes that were included  
245 in the pod. This strategy was widely used for testing nursing homes and schools, as well as individuals  
246 arriving at the airport. Pod sizes ranged from 5-25, depending on the positivity rate at a given time point.  
247 While this strategy was highly effective when positivity rates were very low, we found that when  
248 positivity rates exceeded 1% - labs effectively ceased testing the pods and resorted to individual sample  
249 testing. In contrast, during the Alpha and Delta waves in Israel, we demonstrated that our approach can  
250 be effectively used for positivity rates of up to 10% by high-capacity clinical labs. While from a  
251 theoretical perspective, optimal Dorfman pooling can reduce the number of tests comparable to the  
252 combinatorial pooling approach, in practice Dorfman pooling was not utilized for clinical testing when  
253 rates begin to rise, due to the additional labor involved in the large number of retests required using this  
254 approach (**Supplementary Fig. 2**). We note that one advantage of the pod testing approach used in  
255 Israel is that since each individual is sampled twice, labs can automatically decide if to use the two-  
256 stage pod-testing strategy, or switch to combinatorial pooling when positivity rates rise, without having  
257 to modify the sampling scheme used. This is done simply by ignoring the pods, and using combinatorial  
258 pooling on the individual sample tubes.

259 P-BEST can be easily adapted to diverse diagnostic tests, including multiplex testing of several  
260 pathogens. The latter case is highly important since it is unique to single-stage group testing and cannot  
261 be performed via Dorfman pooling. The de-facto prevalence when performing Dorfman pooling for  
262 screening multiple pathogens is the sum across the prevalence of each target in the multiplex test.  
263 Therefore, the number of pools whose samples need to be retested may be very large, rendering  
264 Dorfman pooling highly inefficient. In contrast, the de-facto prevalence for P-BEST is governed by the  
265 maximal prevalence across targets. Hence, P-BEST can be applied for simultaneous detection of carriers  
266 of multiple infectious agents, e.g., carriers of SARS-CoV-2 and Flu. Preliminary results demonstrated  
267 the ability of P-BEST to correctly identify positive samples of various respiratory viruses (Flu A, Flu  
268 B, MPV, PIV, RSV, HRV), using the Allplex™ RV7 Essential Assay (Seegene, data not shown).  
269 Correct identification of FluA, FluB and RSV was also achieved using the GeneXpert® Xpress  
270 Flu/RSV kit (data not shown). The P-BEST pooling method can be easily applied to other multiplex  
271 PCR assays being especially efficient for large scale screening, e.g., for urinary tract infections,  
272 gastrointestinal and sexually transmitted infections.

273 While our data demonstrates high-capacity combinatorial pooled testing, that requires liquid dispensing  
274 robots, we also showed that our method can be adapted for use in low-resource settings where robots  
275 are not available. Such a solution is important for future pandemics, since shortages in testing reagents  
276 would inevitably impact low and middle-income countries. The implementation of a manual  
277 combinatorial pooling solution only requires a tablet and a manual pipette, which are readily available  
278 worldwide.

279 In sum, here we report the first high-throughput application of combinatorial single-stage pooling in  
280 clinical settings. The large number of clinical tests performed using P-BEST during the pandemic  
281 demonstrates the feasibility of implementing combinatorial pooled testing in clinical settings, which  
282 may be critically important in future pandemics, and also for conducting large scale screening studies  
283 using multiplex PCR kits. As molecular diagnostic testing becomes more prevalent, P-BEST offers a  
284 strategy that may allow continuous surveillance for multiple common human pathogens with  
285 manageable test costs and using existing testing infrastructure.

286

## 287 **Material and methods**

### 288 **Clinical samples**

289 SARS-CoV-2 clinical Nasopharyngeal swab samples were collected at two public labs and one private  
290 lab in Israel. All labs were approved by the Israeli Ministry of Health (MOH) for SARS-CoV-2  
291 molecular diagnostic testing. Upon arrival at the labs, samples were neutralized by incubation at 70°C  
292 for 30 minutes per guidelines by the MOH.

293 **Side-by-side validation:** For P-BEST clinical validation 3636 samples were used in side-by-side  
294 experiments as follows. Each lab tested the samples individually using their standard diagnostic testing  
295 protocol, and leftover sample material was subsequently used by P-BEST. In general, P-BEST runs  
296 were performed 24-48 hours after standard testing, therefore, in most cases, positive samples were re-  
297 tested as singles to provide an accurate Ct value and also to account for viral RNA degradation over  
298 time.

299 **Clinical testing:** Following MOH approval, a total of 837,138 samples were tested with the P-BEST  
300 system. Samples classified “positive” or “negative” were reported to medical records, while undecided  
301 samples were classified as “suspected” and were individually retested and subsequently reported.

### 302 **Sample pooling**

303 Pools were prepared using a liquid-handling robot (a liquid handling Tecan Freedom Evo 200). To  
304 reduce contamination and increase testing efficiency pooling was performed using the original swab  
305 collection sample tubes (‘source tubes’) without removing the swabs. Pooling was performed into 5 ml  
306 empty tubes (‘pooling tubes’) or 96-well deepwell plates. Source and pooling tubes were placed onto  
307 racks, each containing up to 16 samples. The pooling process included automated barcode scanning of

308 the source and pooled samples, allowing automated decoding of the test results. Liquid dispensing  
309 parameters were optimized to prevent any sample carryover and to reduce pipetting time.

### 310 **Pooling designs**

311 A variety of pooling designs were used for clinical testing (**Table 2**). Pooling designs were based on  
312 pseudo random matrices shown to achieve optimal decoding (Shalem et al. in preparation). Each design  
313 was optimized for a specific sample set size ranging from 80 to 384 samples, and for a specific maximal  
314 disease prevalence (1%-10%). Designs were tailored per labs' requirements for small (80 or 96),  
315 medium (188) or large (~384) number of samples. Based on the prevalence of SARS-CoV-2 in Israel  
316 during this period several pooling designs were used for clinical testing offering efficiency gains  
317 ranging from x1.5-x8.

### 318 **Pooled sample testing pipeline**

319 To enable minimally trained lab operators to utilize P-BEST, we developed a user-friendly software  
320 product that automates the pooling process. The lab operator selects (a) a specific pooling design based  
321 on the current disease prevalence, (b) the specific diagnostic kits used, and (c) the number of samples  
322 tested. The user is provided with easy-to-use instructions on how to load source and pool tubes or plates  
323 onto the liquid handling robot worktable, after which sample pooling is automatically performed using  
324 the liquid handler. Following testing the pools, PCR results are decoded and results are sent to medical  
325 records.

### 326 **SARS-CoV-2 diagnostic testing**

327 Nucleic acids were extracted from 350ul of sample using the STARMag 2019-nCoV kit (Seegene, CA,  
328 USA) on a liquid-dispensing robot (STARlet Hamilton, USA). Elution volume was 100ul. 8 ul of the  
329 extracted nucleic acids were taken for cDNA preparation and quantitative reverse transcription PCR  
330 (qRT-PCR)-based amplification. qRT-PCR was performed using either of the following clinically  
331 approved kits: (a) Allplex 2019-nCoV detection kit (Seegene, CA, USA) which identifies three SARS-  
332 CoV-2 genes: E, RdRP, and N; (b) Allplex SARS-CoV-2 Assay (Seegene, CA, USA) which identifies  
333 four SARS-CoV-2 genes: E, RdRP, N and S. These assays were performed on a Biorad CFX real-time  
334 PCR detection system.

335 Some of the samples were analyzed on a Panther instrument (Hologic, Inc., San Diego, CA). 500 ul of  
336 the sample was taken for RNA isolation, purification, and qualitative detection of SARS-CoV-2, using  
337 the Aptima® SARS-CoV-2 assay (Hologic, Inc., San Diego, CA).

## 338 P-BEST decoding algorithm

339 **Decoding:** P-BEST finds a sparse solution that best fits the measured viral load across pools, thus  
340 providing an estimate for the Ct value of each detected sample. In brief, pools whose Ct values  $<40$  are  
341 converted to viral load counts as  $\lambda$ , where in case of the Seegene kit, was based on the kit's most sensitive  
342 gene, i.e., the N-gene. We then seek the sparsest set of samples that maximizes the likelihood of the  
343 pools' measurements, provided the pooling design and a measurements noise model. For the latter noise  
344 model we have experimentally estimated the probability of a false negative measurement as a function  
345 of Ct. The set of detected samples and those with zero viral load are provided to the classification  
346 module as explained below.

347 **Sample classification:** First, all samples whose estimated viral load is zero are classified as “negative”,  
348 i.e., are COVID-free and do not require retesting. All other non-negative samples are classified as  
349 “positive” or as “suspected”. To classify a sample as “positive”, i.e., reported as COVID-positive, a  
350 sample should meet the following two criteria: (a) All of its pools should be “strong positive” (i.e., N  
351 gene  $Ct \leq 36$ ). (b) There exists at least one such “strong positive” pool that contains this sample and  
352 does not contain any of the other detected non-negative samples. These criteria are quite stringent and  
353 were required to avoid false positive detections. Samples that do not meet these criteria are classified  
354 as “suspected” and require re-testing. Specifically, this happens in three cases: (a) The sample belongs  
355 to a pool that was invalidated (i.e., the internal control was negative). (b) The sample belongs to a pool  
356 which is negative, inconclusive (i.e., some of the genes are not detected) or “weak positive” (i.e., N  
357 gene  $Ct > 36$ ). (c) All of the pools of a specific sample contain other samples that were detected as non-  
358 negative.

359 **Fig. 5A** presents examples of classification scenarios. In the interest of clarity, we present the case of  
360 five samples ( $S_1$ - $S_5$ ) being measured in five pools, although in practice the number of pools is always  
361 much smaller than the number of samples. Gray shaded squares denote the samples in each pool, e.g.,  
362 pool #1 in **Fig. 5A** comprises  $S_3$  and  $S_4$ . The number inside a gray shaded square corresponds to the  
363 true, yet unknown, viral load of the sample. The measured viral loads of each pool should correspond  
364 to the sum of the viral loads of its samples, yet are subject to measurement noise. In this example, pools  
365 whose viral loads are lower than 20 are considered “weak positive”. The solution to the optimization  
366 problem would detect two “negative” samples ( $S_3$ ,  $S_4$ ), and would assign non-negative values to  $S_1$ ,  $S_2$   
367 and  $S_5$ . The latter samples are classified as detailed below.

368  $S_5$  is classified as “positive” since (a) both its pools have a high enough viral load, and (b) pool #5 is  
369 unique to  $S_5$  and does not contain the other detected samples,  $S_1$  and  $S_2$ .

370 Both pools containing  $S_1$  are “weak positive” pools, and, therefore, it is classified as “suspected”.  
 371 Similarly,  $S_2$  is classified as “suspected” since one of its pools (pool #4) is “weak positive”. Subsequent  
 372 re-testing of single samples is deemed to find  $S_2$  as “negative” in this case, yet a different scenario is  
 373 also plausible. **Fig. 5B** is identical to **Fig. 5A** except for the fact that  $S_2$  has a low viral load rather than  
 374 being negative, i.e., two different scenarios for  $S_2$  share the same pooling measurements. Hence, since  
 375 measurement noise cannot discern between a negative and a weak positive  $S_2$ , it is classified as  
 376 “suspected”.

377 **Tables:**

Single classification	#Samples	P-BEST classification				
		#"Positive"	#"Negative"	#"Suspected"		
				<i>Invalidated pool</i>	<i>Weak pool</i>	<i>Overcrowding</i>
Positive (Ct < 35)	141	97	1	6	16	21
Weak positive (Ct > 35)	13	0	5	-	8	-
Negative	3482	0	3383	4	75	20

378 **Table 1. Evaluating P-BEST classification performance using side-by-side testing.** Each sample was tested individually  
 379 and then using the P-BEST pooling. P-BEST’s classifications of samples as “positive”, “negative” or “suspected” (i.e.,  
 380 requiring retesting) are presented. “Suspected” calls are further classified into 3 categories: (i) *invalidated pool*: cases in which  
 381 the detected sample participated in a pool whose PCR measurement was invalidated. (ii) *weak pool*: corresponds to cases in  
 382 which the sample was part of a pool whose PCR was negative or of Ct>36. (iii) *overcrowding*: are cases in which a positive  
 383 sample shares all of its pools with other positive samples and thus cannot be decisively classified.

384

Pooling Design (samples to #pools)	Efficiency	Recommended positivity rate	samples per pool	pools per sample	Run time
80 to 10	8	1%	24	3	15
96 to 25	3.8	2%	19-20	5-6	24

384 to 94	4.1	2%	28-29	6-7	55
282 to 94	3	4%	12	4	45
96 to 46	2.1	6%	10-11	4-5	28
188 to 94	2	6%	8	4	25
372 to 186	2	6%	8	4	55
282 to 188	1.5	10%	6	4	50

385

386 **Table 2. P-BEST designs used in clinical settings.** The number of samples and pools in each applied design and  
387 their efficiency (i.e., the ratio between them). Recommended positivity rate corresponds to the rate below which  
388 the number of "suspected" samples reported by the method is negligible. The run time corresponds to total  
389 pipetting time for sample pooling using a Tecan robot.

390

### 391 **Figure legends:**

392 **Figure 1. Two-stage pooling vs. single-stage pooling. A.** In traditional two-stage Dorfman pooling,  
393 each sample is added to a single pool. Samples belonging to negative pools are classified as "negative"  
394 and results can be reported after a single round of testing. Positive pools indicate that one or more of  
395 the pooled samples are positive, thus all corresponding samples are re-tested individually and only  
396 then, results can be reported. **B.** In combinatorial single-stage pooling, each sample is added to several  
397 pools, according to a specific pooling design. A decoding algorithm is used to detect all positive  
398 samples and their Ct value after a single round of testing.

399 **Figure 2. Ct value estimates via P-BEST. A.** A scatter plot of the Ct value of positive samples as  
400 measured individually (x-axis) vs. their P-BEST estimated value (y-axis). Shown is the Pearson  
401 correlation coefficient. **B.** The Ct value (as measured individually) of samples classified by P-BEST  
402 as "suspected". Samples are divided into 3 groups according to the reason for their classification, i.e.,  
403 *invalidated pools* (blue), *weak pools* (orange), and *overcrowding* (green).  
404

405 **Figure 3. P-BEST in clinical diagnostics during 2022. A.** The number of P-BEST runs performed  
406 stratified by pooling design. **B.** The average weekly positivity rate in Israel in 2022 based on Israeli  
407 MOH published data. **C.** Weekly number of samples tested by P-BEST color-coded by pooling  
408 design. **D.** Weekly number of runs performed using P-BEST color-coded by pooling design. The same  
409 as C for the number of runs.  
410

411 **Figure 4. Tablet-directed pooling. A.** Description of the equipment required for manual pooling. **B.**  
412 The number of samples and pools in each manual design and their efficiency. Recommended  
413 positivity rate corresponds to the rate below which the number of "suspected" samples reported by the  
414 method is negligible. The run time corresponds to total pipetting time for sample pooling using a  
415 manual pipette. **C.** An illustration of the first three iPipet (6) pipetting operations using two 96-well



416 plates on top of a standard tablet.

417

418 **Figure 5. Classification example. A.** A schematic design of five samples and five pools, their viral  
419 load measurements, and the classification of each sample as “positive” (+), “negative” (-) or  
420 “suspected” (?). The numbers in gray shaded squares correspond to the true, although unknown viral  
421 load of each sample. **B.** The same case as in panel A, with S2 as a weak positive sample.

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479

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483 **Author contributions:**

484 Conceptualization: SZ, BS, JM, DR, AP, NS, TH

485 Study design: JM, DR, AN, YS, AB, DA, AP

486 Data analysis: SZ, BS, JM, DR, NS, TH

487 Project administration: RA

488 Writing – original draft: SZ, BS, JM, DR, NS, TH

489 Writing – review & editing: NS, TH

490 **Competing interests:** AP, NS and TH are co-founders and shareholders in Poold Diagnostics.

491 **Data and materials availability:** All data needed to evaluate the conclusions in the paper are  
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493 request.

# Figures

Figure 1

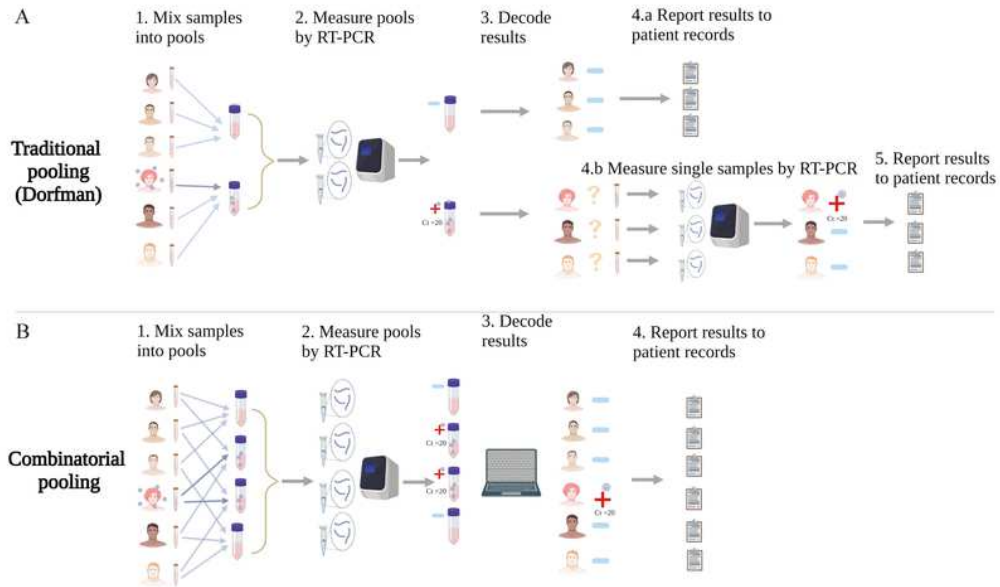


Figure 1

Two-stage pooling vs. single-stage pooling.



Figure 2

# Ct value estimates via P-BEST.

Figure 3

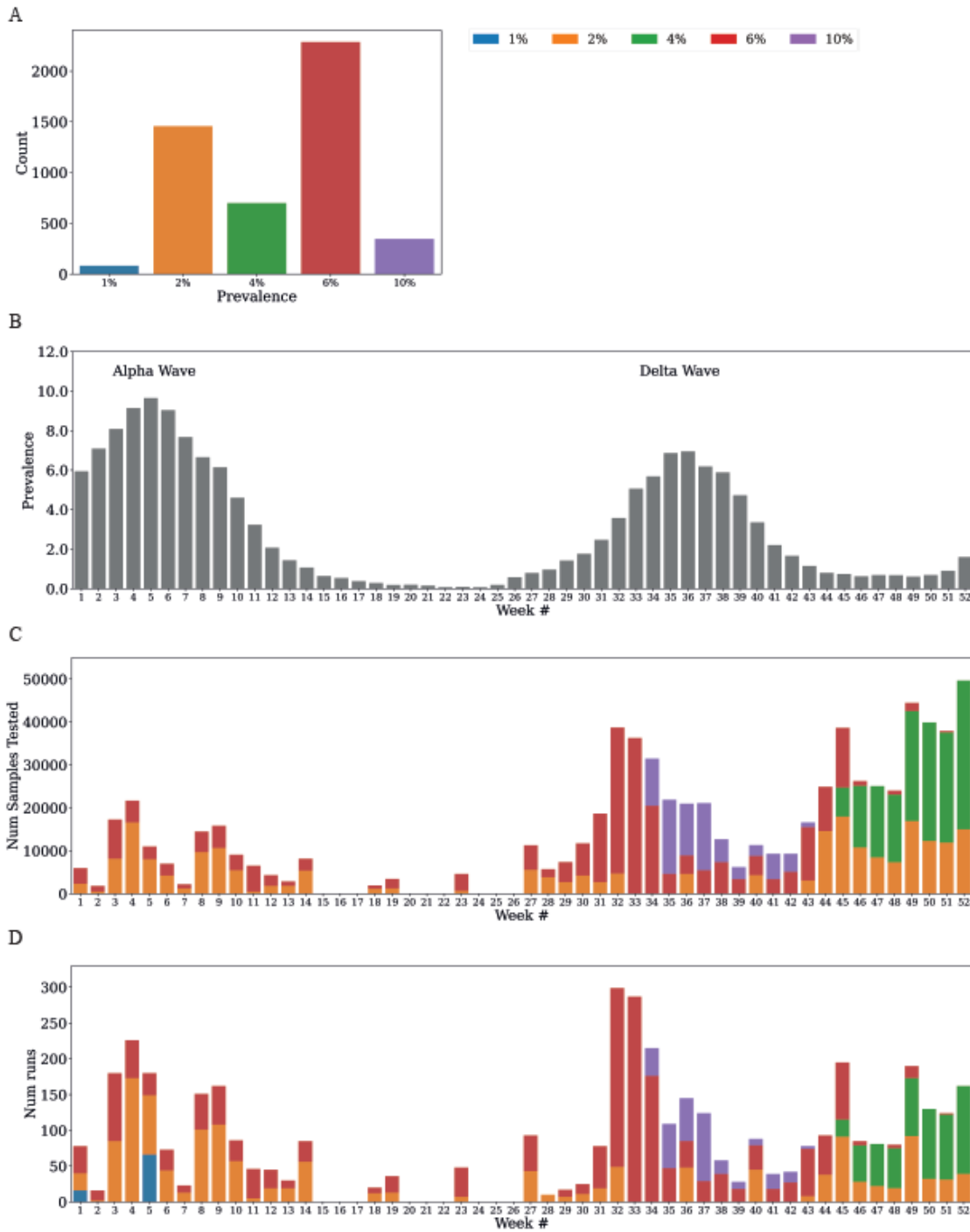


Figure 3

P-BEST in clinical diagnostics during 2022.

Figure 4

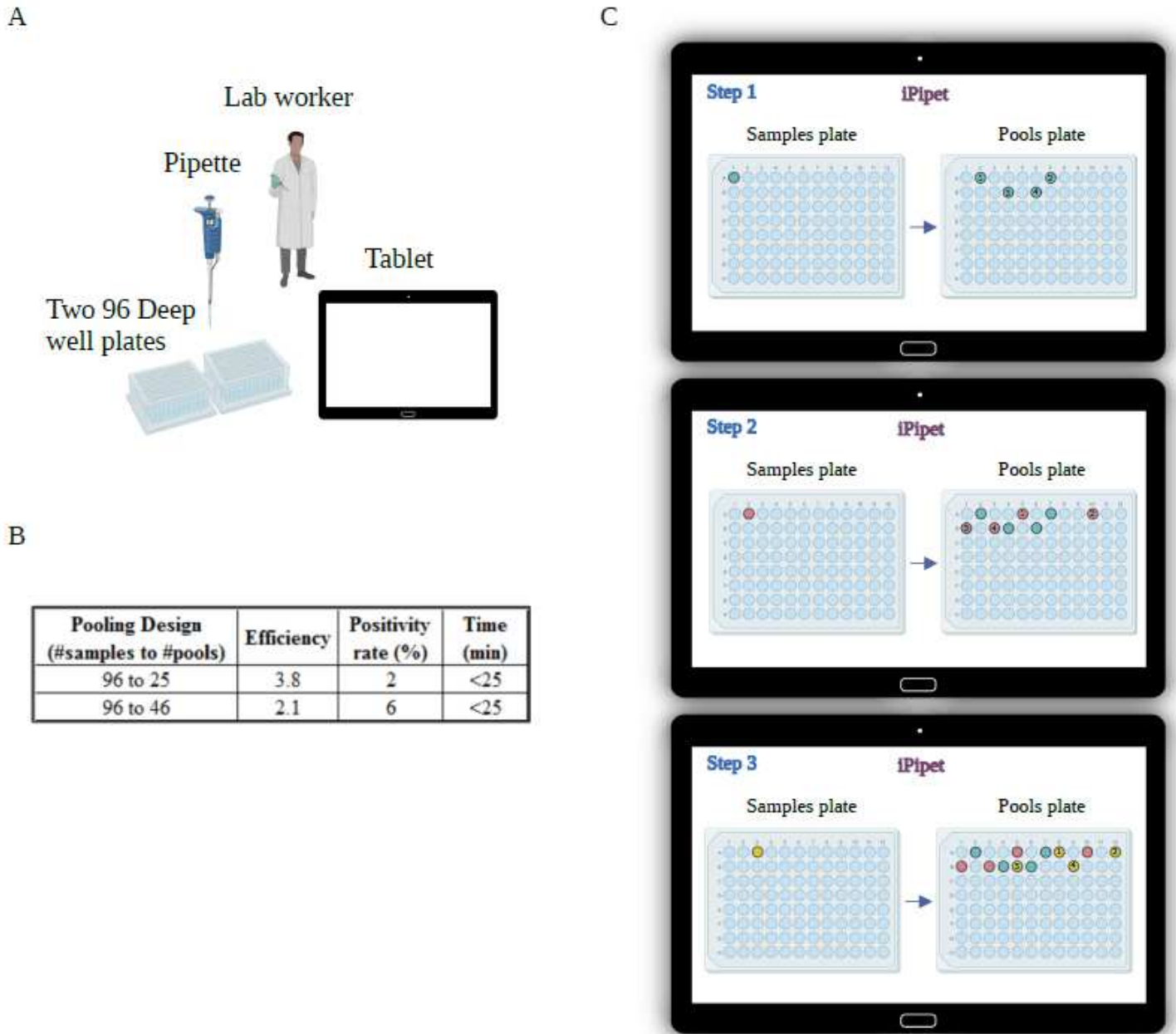


Figure 4

Tablet-directed pooling.

Figure 5

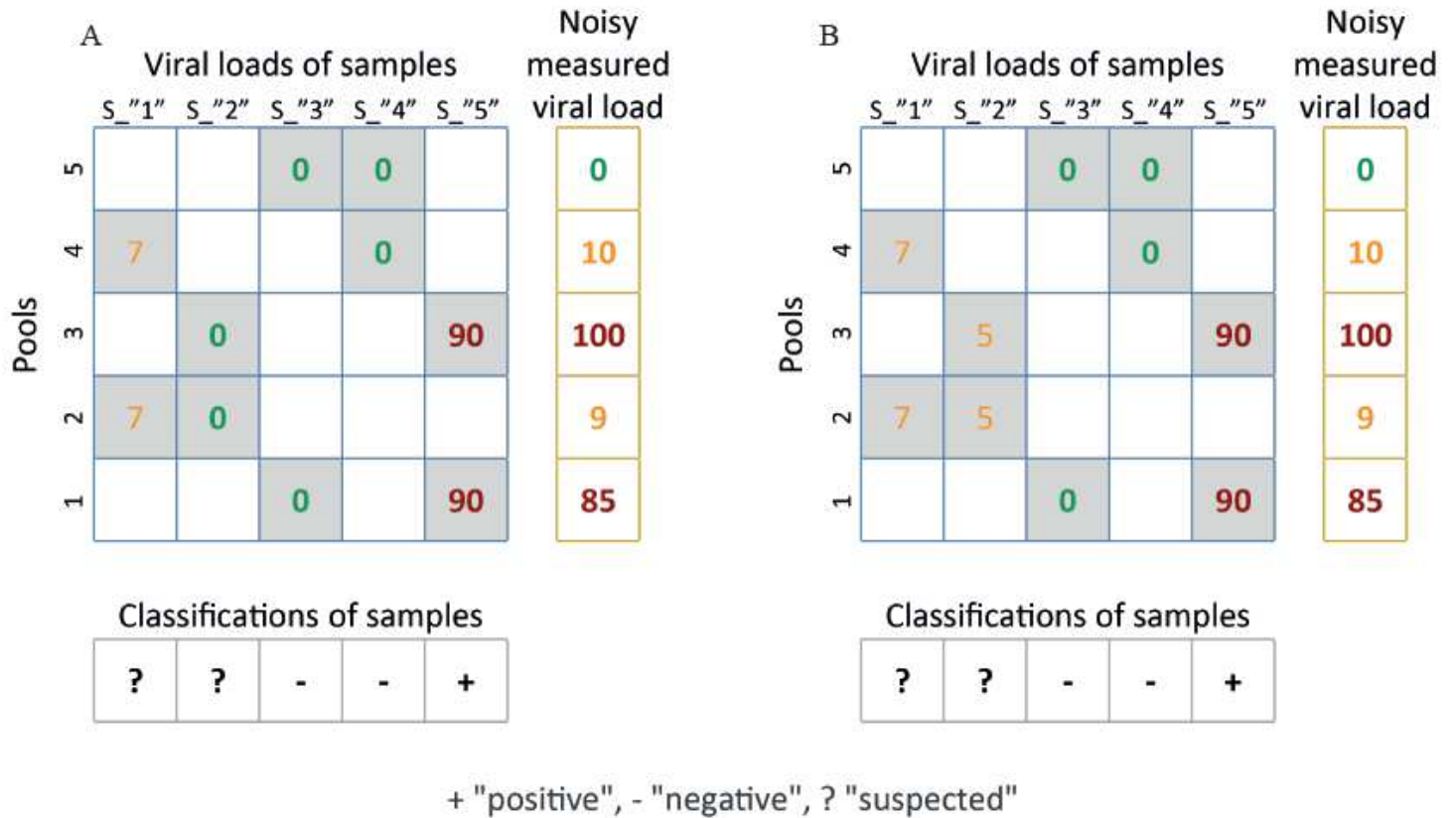


Figure 5

Classification example.

## Supplementary Files

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- [SupplementaryMaterialsHighcapacityclinicalSARSCoV2moleculartestingusingcombinatorialpooling.pdf](#)