

1 **Supplementary materials**

2 **Methods**

3 **Sample collection, gDNA extraction and sample preparation**

4 gDNA from patients genetically diagnosed with a chromosomal aneuploidy were purchased
5 from Coriell Institute (Table S5). Control gDNA from healthy subjects was extracted from swab
6 samples using Genomic Micro AX Swab Gravity Plus (A&A Biotechnology, Gdansk, Poland,
7 105-100P) according to the manufacturer's instructions. All gDNA samples were quantified
8 using Qubit® 1X dsDNA HS Assay Kit on Qubit Fluorometer (Life Technologies, CA, USA).
9 They were then normalized to approximately 1 ng/μL in UV-treated milli-q water and stored
10 at 5°C prior to analysis. Sample stocks were stored at -80°C. The DNA extraction step is
11 estimated to take between 2,5 to 3h for up to 24 samples.

12 **Detection of five chromosomal aneuploidies using two-step PCR system**

13 A two-step PCR system targets six chromosomes and incorporates patient specific barcodes.
14 PCR₁ includes a multiplex setup of primers targeting six chromosomes containing overhangs
15 for the second PCR (Table S6). Six specific primer pairs were designed to target chromosomes
16 associated with the most common chromosomal aneuploidies, namely chromosomes 13, 18, 21,
17 X, and Y. These primer pairs were optimized for high specificity to their target chromosomes
18 while minimizing the potential for self- and hetero-dimerization. In the multiplex setup, the
19 average sequence similarity between the generated amplicons was 37% (max = 47%, min =
20 32%, SD = 4%), ensuring high specificity in sequence classification. Chromosome 15 was
21 used as a reference in the assay. The PCR₁ reaction mix contained 12μL PCR BIO UltraMix
22 (PCR Biosystems Ltd, PA, USA PB10.32-05), 2μL of each primer set (5μM each), 1μL of DNA
23 (~ 5ng/μL), and nuclease-free water to a total volume of 25μL. The PCR₁ thermal conditions

24 were optimized as follows: denaturation at 95°C for 5 min; 15 cycles at 95°C for 30 sec, 63°C
25 for 30 sec, and 72°C for 45 sec, followed by the final elongation at 72°C for 5 min using a
26 thermocycler (PCRmax™Alpha Cycler 1, UK). PCR₁-product was cleaned using AMPure XP
27 Beads (Beckman Coulter Genomic, Brea, CA, USA) following manufacturer's instructions to
28 remove excess of primers and resuspended in 11µL of nuclease-free water. The PCR₂ reaction
29 mix included 10µL of the clean PCR₁-product, 12µL of PCR BIO UltraMix (PCR Biosystems
30 Ltd, PA, USA PB10.32-05) and 2µL of barcode primer (10µM). The sequence of the barcodes
31 used in PCR₂ is given in Table S7. The PCR₂ thermal conditions were as follows: 95°C for
32 2 min, followed by 30 cycles of 95°C for 20 sec, 55°C for 20 sec, and 72°C for 40 sec. The final
33 extension was set to 72°C for 4 min using thermocycler (PCRmax™Alpha Cycler 1, UK). The
34 quality control of the PCR₂-product was evaluated with gel electrophoresis on a 1,5% agarose
35 gel stained with Midori Green (Nippon Genetics Co., Ltd., MG04, Tokyo, Japan). The two-step
36 PCR protocol is estimated to take 2 to 2.5 h for up to 24 samples in four technical replicates.

37 **Sequencing Libraries Preparation**

38 PCR₂-products were pooled within each plate and cleaned with AMPure XP Beads (Beckman
39 Coulter Genomic, Brea, CA, USA) using 250µL of the pooled PCR₂ product and 80µL of beads.
40 The motor protein ligation was performed for each four pools individually using ligation proto-
41 col SQK-LSK110 by Oxford Nanopore Technologies (version: ACDE_9110_v110_revE_10Nov2020).
42 The libraries were sequenced on GridION (Oxford Nanopore Technologies, Oxford, UK) using
43 four R9.4.1 Flow Cells. The ligation protocol takes approximately 2.5 to 3 hours.

44 **Second level Multiplexing and Sequencing with Oxford Nanopore Tech-** 45 **nologies**

46 To test the performance of the analysis with second-level multiplexing, the four pooled li-
47 braries were subjected to barcoding using the native barcoding kit SQK-NBD112.24 by Oxford

48 Nanopore Technologies (version: NBA_9135_v112_revJ_01Dec2021). The final pool of 384
49 samples/replicates was sequenced together on a single R9.4.1 Flow Cell. The basecalling and
50 first level demultiplexing (NBD112.24) was performed live on GridIONx5 (Oxford Nanopore
51 Technologies, Oxford, United Kingdom) using MinKNOW GUI (version 23.03.3). The native
52 barcoding protocol is optional when loading more than 24 samples on a single GridION flow
53 cell and is estimated to take 3 to 3.5 hours.

54 **Basecalling, DNA reads processing and sample and chromosome classifica-** 55 **tion**

56 The basecalling is performed using Guppy, the production basecaller integrated within Min-
57 KNOW. The signal stored within the FAST5 files is processed in real time during the run and
58 the FASTQ files are generated one by one. Once a FASTQ file is generated, a quality check
59 and filtering (as a first processing step) of the reads that belong to that particular FASTQ file is
60 initiated.

61 Every read from the FASTQ file (one FASTQ file contains 4000 sequences) must meet
62 certain quality criteria. The length of the sequence must be between 900 and 1200 characters
63 and its average Phred quality score has to be higher than 8 (88% of base call accuracy). The
64 quality score is calculated based on the average quality values of each base. If the sequence is
65 longer than 1700 characters, the sequence is split and treated as two separate sequences. The
66 barcode assigned to the particular sample is used as a splitting point. If the barcode is not found
67 in the middle of the sequence (between the 100th character from left and the 100th character
68 from right of the middle character), then the sequence is rejected and it is not used for further
69 processing.

70 The processing of the qualified DNA reads continues with barcode classification or demul-
71 tiplexing of the DNA sequences. In particular, the barcode that encodes the information about

72 the person to which the sequence read is associated should be identified. The proposed algo-
73 rithm uses Levenshtein distance to find the location of the spacer (15 characters) and linker (15
74 characters) first, and then to identify the barcode (24 characters) located between the spacer and
75 the linker.

76 The algorithm performs the search on the first and the last 150 characters of the sequence.
77 First, we find the spacer/linker (Figure S1) by comparing a sliding window (with size 15 and
78 stride 1) to the known values with Levenshtein Distance less than 5. The barcode should follow
79 directly after the spacer and before the linker. Once the start and the end of the barcode are
80 identified we find the most similar barcode from the database and perform the sample classi-
81 fication. The barcode search is performed using a sliding window technique with size 24 and
82 stride 1. The distance between the window and the barcode is defined using the Levenshtein
83 distance and it should be less than 5. This phase has low computational complexity and can be
84 performed in real-time.

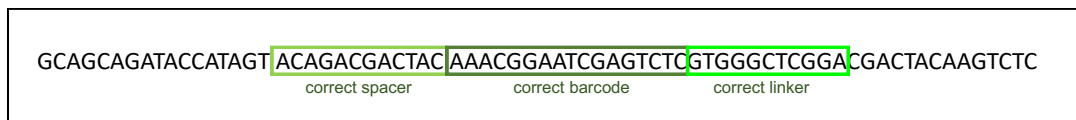


Figure S1: Correct barcode

85 Sometimes, the spacer or the linker could be corrupted (Figure S2), so the start and the end
86 of the barcode could not be identified precisely. In that case we take the 24 characters that
87 follow the spacer and try to match with the barcodes in the database. The same procedure is
88 repeated for the 24 characters that precede the linker. The sequence that has lower Levenshtein
89 Distance with the barcodes in the database is used for the sample classification. Again, the
90 maximum Levenshtein Distance which is acceptable for person classification is less than 5.

91 To identify the end of the human DNA sequence we use the same approach. We perform the
92 search on the last 150 characters taking into account that the linker is in opposite order with the

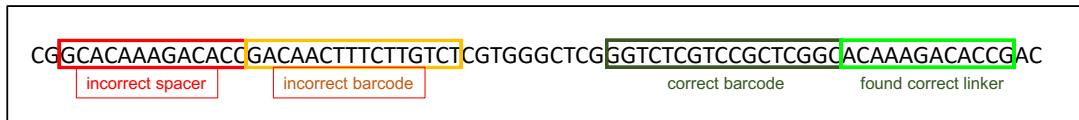


Figure S2: Corrupted barcode

93 replacement of characters T and G with A and C due to the reverse-complement representation.

94 After the demultiplexing of the sequences (sample classification), the process continues
 95 with the chromosome classification phase. In this phase, similarity scores between each demul-
 96 tiplexed sequence and the reference chromosome sequences are computed using the BLAST
 97 alignment method. The used scoring system awards 2 points for a base match, while penaliz-
 98 ing 3 points for a mismatch, 3 points for extending a gap, and 5 points for opening a gap. A
 99 sequence is classified as belonging to a specific chromosome only if its final alignment score
 100 with that chromosome exceeds 250. If multiple chromosomes have alignment scores higher
 101 than 250, the sequence is assigned to the chromosome with the highest score. Sequences with
 102 alignment scores below 250 for all chromosomes are rejected and not classified. Chromosome
 103 sequences and their number grouped by barcode and chromosome are the output of this phase.

104 **Statistical analysis**

105 To assess whether the difference between the samples' representations from the healthy donors
 106 and the different chromosomal aneuploidies are statistically significant, a Hotelling's t-squared
 107 statistic (t^2) was performed on first three principal components. P-values showed a signifi-
 108 cant difference for all samples. Hotelling's t-squared statistic is a generalization of Student's
 109 t-statistic that is used in multivariate hypothesis testing. It tests the differences between the
 110 (multivariate) means of different populations. The test is applied on the reads proportions ob-
 111 tained for each barcoded sample normalized using the means and standard deviation of the
 112 controls in the one vs the rest setup (measures the difference between the population of one

113 disease and the combined populations from the rest of the diseases).

114 **Performance for KS decision-supporting tool (EU IVD certification)**

115 EU IVD certification was performed solely on the Klinefelter syndrome. The machine learning
116 model that was built to discriminate against Klinefelter is a binary SVM classification model.
117 First, the model was trained and tuned on a separate set of samples that included healthy, Kline-
118 felter, Angelman (AMS), Prader–Willi syndromes (PWS) and trisomies (13, 18, and 21). After
119 the training and the tuning phase, the model was tested and evaluated on a different set of test
120 samples that also included cases from Klinefelter, healthy, trisomy, AMS and PWS. Details
121 about the training and evaluation phases are given in the following subsections.

122 **Model training and parameter tuning**

123 In this phase, we trained a classification model and performed parameter tuning by cross vali-
124 dation using 278 technical replicates representing respective aneuploidy or healthy subjects (68
125 KS, 198 healthy, 4 trisomy syndrome, 4 AMS and 4 PWS). All the samples were obtained from
126 10 different individuals, generated in 5 individual runs on the Oxford Nanopore Technologies
127 GridION x5 device. All the samples that did not meet the minimal number of reads per chromo-
128 some (100 reads per chromosome) from the 5 individual runs were filtered out and not used for
129 training the model. In each individual run we introduced 4 male and 4 female healthy control
130 samples, which are used to estimate the quality of the run and the variance between the different
131 runs. All Klinefelter syndrome samples (68 technical replicates from two patients) were labeled
132 as positive and all the other samples (including healthy and non Klinefelter syndrome samples)
133 as negative (210). The parameter tuning of the classifier was performed using stratified 5 fold
134 cross validation, where 80% of the data were used for training and the other 20% of the data for
135 classifier validation. In this experiment, SVM with RBF kernel was used as a classifier. Support

136 Vector Machine is a natural binary classifier that works well with small to moderately sized
137 datasets where the relationship between features and the target is not overly complex, achieving
138 high accuracy. SVMs can handle both linear and non-linear classification tasks (by applying
139 kernel functions like RBF, polynomial, and sigmoid, allowing it to transform the original data
140 into a higher-dimensional space where a linear separation is possible), while avoiding the risk of
141 overfitting, especially in scenarios with fewer data points. SVM focuses on finding the decision
142 hyperplane that maximizes the margin between the classes, which leads to better generalization
143 to unseen data. We have experimented with multiple different classification techniques, but the
144 best results were achieved using the SVM classifier (in terms of predictive performance and
145 model complexity).

146 The samples were represented with 8 continuous variables (features):

- 147 1. The normalized discrete probability distribution of chromosome occurrence (calculated as
148 the proportion or percentage of identified sequences for a specific chromosome relative
149 to the total number of sequences identified from all chromosomes in each sample) is
150 provided for that particular sample. This is represented by columns p-chY, p-chX, p-
151 ch21, p-ch18, p-ch13 and p-ch15 in Table S2.
- 152 2. The average Euclidean distance from the normalized discrete probability distribution of
153 the sample to the normalized discrete probability distributions of the 4 male healthy con-
154 trol samples from the corresponding run (column “distance” in Table S2).
- 155 3. The ratio between the chY and chX.

156 The features associated with the chromosomes’ representation were selected by a domain
157 expert. Additionally, the feature that represents the average Euclidean distance between the
158 normalized discrete probability distribution of the sample and that of the male healthy control

159 samples was included as a plate normalization measure. Samples closer to the healthy control
 160 distributions are more likely to be healthy compared to those farther from the control samples.

Table S1: Example of the classified reads grouped per chromosome and barcode for two KS cases

	chY	chX	ch21	ch18	ch13	ch15	total
KS02	4010	12936	7623	5242	1734	8047	37107
KS91	2048	5337	3996	3360	952	4082	19775

Table S2: Example of the dataset (after normalization and feature engineering) for the KS cases from Table S1

	p-chY	p-chX	p-ch21	p-ch18	p-ch13	p-ch15	distance	chY/chX
KS02	0.101	0.327	0.193	0.132	0.044	0.203	0.023	0.310
KS91	0.104	0.270	0.202	0.170	0.048	0.206	0.025	0.384

161 **Model testing and performance evaluation**

162 The evaluation of the binary SVM classifier is performed using new, unseen samples from 2
 163 KS patients in comparison to either negative samples from two healthy donors or samples from
 164 10 patients with other chromosomal abnormalities. Data from the healthy controls was used
 165 to calculate the analytical and the diagnostic sensitivity and data from patients with a chromo-
 166 somal abnormality different from KS were used to calculate the analytical and the diagnostic
 167 specificity. Each biological sample was evaluated in quadruplicates (one different barcode for
 168 each technical replicate).

169 The number of true positive (TP), true negative (TN), false positive (FP) and false negative
 170 (FN) from four different sequencing runs were calculated overall for each independent tech-
 171 nical replicate (that is, for each barcode independently) but also, per sample (that is, for each
 172 four replicates assuming that 75% of the results were coincident, either positive or negative).

173 Inconclusive results (either at barcode level or at patient level) were not taken into account for
174 TP, TN, FP or FN calculations.

175 Klinefelter positive samples were analyzed 10 times (that is, with 40 different barcodes).
176 Of the 40 replicates, 32 were classified by the model as "positive" for Klinefelter, that is 80%
177 TP, 1 was classified by as "negative", that is 2.5% FN and 7 were classified as "inconclusive"
178 (17.5%). The 32 TP allowed classifying as "positive" 7 samples (replicates of 4) and the FN
179 did not have an impact on analytical sensitivity as the three remaining replicates were classified
180 as "positive". Three of the 10 samples were classified as inconclusive (30%).

181 Healthy control samples were analyzed 8 times (that is, with 32 different barcodes). Of the
182 32 replicates, 30 were classified by the software as "negative" for Klinefelter, that is 94% TN,
183 and 2 were classified by the software as "inconclusive" (6%). These two inconclusive replicates
184 belonged to a same patient/run, impeding to correctly classify this sample as negative (and
185 leaving it as inconclusive); however, this did not have an impact on sensitivity or specificity
186 calculations. Samples from the other chromosomal abnormalities were analyzed 24 times (that
187 is, with 96 different barcodes). Of the 96 replicates, 84 were classified by the software as
188 "negative" for Klinefelter, that is 87.5% TN (that will be added to the 30 TN from healthy
189 donors for the calculations); 1 was classified by the software as "positive", that is 1% FP and
190 13 were classified by the model as "inconclusive" (all barcodes provided a results and thus
191 all were included in the analysis). In total, there were 27 samples (either patients from other
192 chromosomal abnormality or healthy controls) that were correctly classified as "negative" by
193 the system, that is 84% and 5 samples that could not be classified as they were reported as
194 "inconclusive" (16%).

195 **Analytical performance:** Analytical sensitivity (as a measurement of precision) was as-
196 sessed as the ratio of correctly positives out the total number of positives reported= $TP/(TP+FP)$.
197 At barcode level this value was = $32/(32+1) = 97.0\%$. At patient level, this value was = $7/(7+0)$

Table S3: Performance parameters

	Analytical sensitivity	Analytical specificity	Accuracy
Per replicate (per barcode)	97.0%	99.1%	98.6%
Per patient (group of 4 replicates)	100%	100%	100%

198 = 100%.

199 Analytical specificity was the ratio of correctly negatives out of the total number of negatives
 200 reported = $TN/(TN+FN)$. At barcode level this value was $=114/(114+1) = 99.1\%$. At patient
 201 level, this value was $= 27/(27+0) = 100\%$.

202 Accuracy was calculated as the proportion of correct predictions using the following for-
 203 mula = $(TP+TN)/(TP+TN+FP+FN)$ at both, barcode and patient levels, and data is showed in
 204 Table S3.

205 **Clinical performance:** Diagnostic sensitivity (True Positive Rate, TPR) was assessed as
 206 the number of individuals having a positive outcome of those who actually have the condition =
 207 $TP/(TP+FN)$. At barcode level, this value was $= 32/(32+1) = 97.0\%$. At patient level, this value
 208 was $= 7/(7+0) = 100\%$.

209 Diagnostic specificity (True Negative Rate, TNR) was assessed as the number of individuals
 210 having a negative outcome of those who actually do not have the condition = $TN/(TN+FP)$. At
 211 barcode level, this value was $=114/(114+1) = 99.1\%$. At patient level, this value was $= 27/$
 212 $(27+0) = 100\%$.

213 Positive likelihood ratio (LR+) was assessed as the TPR / FPR . As value of TPR, we used
 214 the diagnostic sensitivity and as value for the FPR we used $1-\text{diagnostic specificity} = 99.1$ for
 215 replicates and 0 per patient. Thus, we only could calculate LR+ for replicates $= 97.0/99.1 =$
 216 0.978 . Negative likelihood ratio (LR-) was assessed as FNR / TNR . As value of the FNR, we
 217 used $1-\text{diagnostic sensitivity}$ (3 for replicates and 0 per patient) and as value for the TNR we
 218 used the diagnostic specificity. We could only calculate LR- for replicates $= 3/97.0 = 0.031$.

219 The diagnostic odds ratio (DOR) was calculated as a ratio $LR+/LR- = 0.978/0.031 = 31.30$.

220 The clinical performance described above are summarized and presented in Table S4.

Table S4: Diagnostic utility

	Diagnostic sensitivity (TPR=1-FNR)	Diagnostic specificity (TNR=1-FPR)	Positive likelihood ratio $LR+=TPR/FPR$	Negative likelihood ratio $LR-=FNR/TNR$	Diagnostic odds ratio $DOR=LR+/LR-$
Per replicate (per barcode)	97.0%	99.1%	0.978	0.031	32
Per patient (group of 4 replicates)	100%	100%	N/A*	N/A*	N/A*

*N/A states for not applicable as FPR for patient was 0, thus it LR+ cannot be calculated

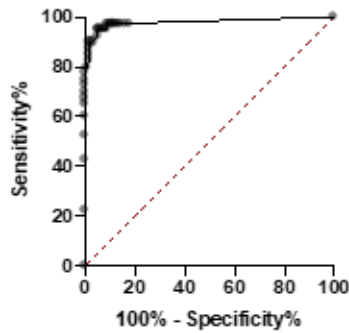
221 Finally, for statistical analysis of the sensitivity/specificity, ROC analysis was done either
222 considering the values of "probability of being diagnosed as Klinefelter" or the outcome values
223 of the model as follows: "negative"=0; "inconclusive"=1; "positive"=2. Both analysis were
224 performed for barcode and for sample and are visualized using the ROC curves in Figure S3

225 **Limit of Detection:** In order to evaluate the limit of detection (LOD) of the method, we
226 simulated a KS positive sample in a mosaic configuration with decreasing ratios of 47,XXY
227 mixed with 46,XY healthy control. The details of the assay design are in Supplementary Table
228 2, Plate004.

229 IVD certification

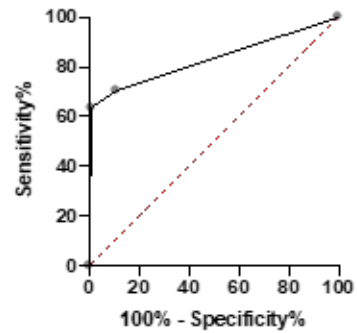
230 The device used in the study complies with the **ISO 13485:2016** and **ISO 14971:2019** stan-
231 dards for medical devices, as certified by **LRQA Nederland B.V.**, with Single Registration
232 Number: **DK-MF-000018618**. The product Phivea® conforms to Directive 98/79/EC on in
233 vitro diagnostic medical devices.

VALIDATION RUN (probabilities per barcode)



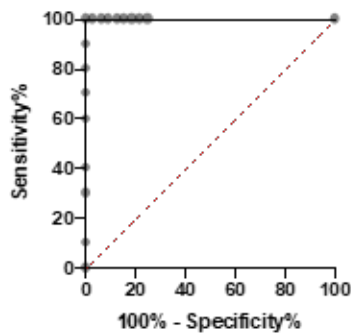
Area under the ROC curve	
Area	0.9794
Std. Error	0.01605
95% confidence interval	0.9479 to 1.000
P value	<0.0001

VALIDATION RUN (values per barcode)



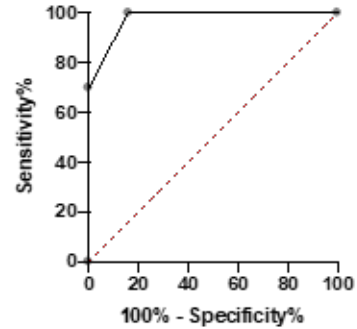
Area under the ROC curve	
Area	0.8296
Std. Error	0.04425
95% confidence interval	0.7429 to 0.9164
P value	<0.0001

VALIDATION RUN (probabilities per patient)



Area under the ROC curve	
Area	1.000
Std. Error	0.000
95% confidence interval	1.000 to 1.000
P value	<0.0001

VALIDATION RUN (values per patient)



Area under the ROC curve	
Area	0.9766
Std. Error	0.01927
95% confidence interval	0.9388 to 1.000
P value	<0.0001

Figure S3: ROC curves for each barcode independently and for each patient represented by quadruplicates.

234 **Supplementary tables**

Table S6: Primers sequence for the multiplex setup. Sequence marked in bold represents the overhang which is a target for barcoding primers during PCR₂

Chromosome Y	
Forward	5'-GTCTCGTGGGCTCGGGATCTCTTCAGCGTGGGAGG- '3
Revers	3'- GTCTCGTGGGCTCGGGCTGAGAGGGTGAGGACAGGA- '5
Chromosome X	
Forward	5'-GTCTCGTGGGCTCGGGAGAGGGAGGAACGCATAGC- '3
Revers	3'- GTCTCGTGGGCTCGGAGGGAGCAGAATTGAGGCAC- '5
Chromosome 21	
Forward	5'-GTCTCGTGGGCTCGGGTCCCCAGGTAACATCCACG-'3
Revers	3'-GTCTCGTGGGCTCGGAGCTATAAGCCAAGGGACGC-'5
Chromosome 18	
Forward	5'-GTCTCGTGGGCTCGGGTCTAGAGTGGGAGGGGCTA- '3
Revers	3'- GTCTCGTGGGCTCGGCCAGCTGGCTGAAATGAAGAA- '5
Chromosome 13	
Forward	5'-GTCTCGTGGGCTCGGTAGTTGAGGGGTGGCTTTGC- '3
Revers	3'- GTCTCGTGGGCTCGGCCTACCTCCCTGTTCTCTGC- '5
Chromosome 15	
Forward	5'-GTCTCGTGGGCTCGGGTGGGCAGCTTCCAGTAGTT- '3
Revers	3'- GTCTCGTGGGCTCGGGCTGAGACTCGGGGTTTGCAT- '5

PCR₁ targets the gene of interest during unsaturated PCR and incorporates “linker” sequence that will become a primer binding site for PCR₂. The linker sequence is palindromic, hence only one barcode primer is needed in PCR₂. Each primer includes 15 bp spacer separating ONT motor protein adapter from the barcode sequence. The spacer was added to ensure higher tolerance for the low quality at the beginning of the sequence entering the pore and thus higher recovery of barcode sequence. The barcoded DNA constructs are subsequently pooled and motor protein is added using the ligation protocol.

Table S7: Sequence of oligonucleotides used for barcoding with PCR₂

barcode name	spacer	barcode sequence	linker
BRK01	GTCCTGCTCCGCTCGG	CACAAAGACACCGACAACTTCTT	GTCCTGCTGGGCCTCGG
BRK02	GTTAGTTGATGTAGT	ACAGACGACTACAAACGSAATCGA	GTCCTGCTGGGCCTCGG
BRK03	GTCCTGCTCCGCTCGG	CCTGTGAACGGGACACAAGACTC	GTCCTGCTGGGCCTCGG
BRK04	GTTAGTTGATGTAGT	TAGGGAAACACGATAGAATCCGAA	GTCCTGCTGGGCCTCGG
BRK05	GTCCTGCTCCGCTCGG	AAGGTTACACAACCCCTGGACAAAG	GTCCTGCTGGGCCTCGG
BRK06	GTTAGTTGATGTAGT	GACTACTTTCTGCCTTTGCAGAA	GTCCTGCTGGGCCTCGG
BRK07	GATTGATATAGATA	AAGGATTCATTTCCACGGTAACAC	GTCCTGCTGGGCCTCGG
BRK08	GTTAGTTGATGTAGT	ACGTAACTTGGTTTCTCCCTGAA	GTCCTGCTGGGCCTCGG
BRK09	GTCCTGCTCCGCTCGG	AACCAAGACTCGCTGCCTAGTT	GTCCTGCTGGGCCTCGG
BRK10	GTTAGTTGATGTAGT	GAGAGGACAAAGGTTCAACGCTT	GTCCTGCTGGGCCTCGG
BRK11	GTTAGTTGATGTAGT	TCCATTCCCTCCGATAGATGAAC	GTCCTGCTGGGCCTCGG
BRK12	GTCCTGCTCCGCTCGG	TCCGATTCTGCTCTTTCTACCTG	GTCCTGCTGGGCCTCGG
BRK13	GTCCTGCTCCGCTCGG	TCACACGAGTATGGAAGCTGTTCT	GTCCTGCTGGGCCTCGG
BRK14	TACATTGATGCATGG	TCTATGGTCCCAAGAGACTCGTT	GTCCTGCTGGGCCTCGG
BRK15	GTTAGTTGATGTAGT	CAGTGGTGTAGCAGGATAGACCT	GTCCTGCTGGGCCTCGG
BRK16	TACATTGATGCATGG	AGTACGAACCACTGTCAGTTGACG	GTCCTGCTGGGCCTCGG
BRK17	GTCCTGCTCCGCTCGG	ATCCAGGACTACTTCTCGAGGGT	GTCCTGCTGGGCCTCGG
BRK18	GTTAGTTGATGTAGT	GCCATGATAGTGTGGCTTTGG	GTCCTGCTGGGCCTCGG
BRK19	GTTAGTTGATGTAGT	ATCTCTGACACTGCACGAGGAAC	GTCCTGCTGGGCCTCGG
BRK20	GTTAGTTGATGTAGT	ATGAGTTCTGTAACAGGACCGAA	GTCCTGCTGGGCCTCGG
BRK21	GTTAGTTGATGTAGT	TAGAGAACGGACAATGAGAGGCTC	GTCCTGCTGGGCCTCGG
BRK22	GTTAGTTGATGTAGT	GCTACTTTGATACATGGCAGTGGT	GTCCTGCTGGGCCTCGG
BRK23	GTCCTGCTCCGCTCGG	CGAGGAGGTTCACTGGTAGTAAG	GTCCTGCTGGGCCTCGG
BRK24	GTTAGTTGATGTAGT	CTAACCCATCATGCAAGCAATGTC	GTCCTGCTGGGCCTCGG
BRK25	GTCCTGCTCCGCTCGG	CATTGGTTCATACCCAACTTAC	GTCCTGCTGGGCCTCGG
BRK26	TACATTGATGCATGG	ATGAGAATGCGTAGTCCGCTGATG	GTCCTGCTGGGCCTCGG
BRK27	GTCCTGCTCCGCTCGG	TGTAAAGGTGAATCTAACCGTCTG	GTCCTGCTGGGCCTCGG
BRK28	GTTAGTTGATGTAGT	GATACGGTCCCTTTAAGTTTCA	GTCCTGCTGGGCCTCGG
BRK29	GTTAGTTGATGTAGT	GGTCTGCAACCAAGGCTCTAG	GTCCTGCTGGGCCTCGG
BRK30	GTTAGTTGATGTAGT	TGGGTGAACTAGATCTCTCACTGA	GTCCTGCTGGGCCTCGG
BRK31	GTCCTGCTCCGCTCGG	CAATGAACTGATTGCTGTACGCA	GTCCTGCTGGGCCTCGG
BRK32	GTTAGTTGATGTAGT	ATGACGTTGTCGGACTTCTACTGG	GTCCTGCTGGGCCTCGG
BRK33	GTCCTGCTCCGCTCGG	AGTAAACCAACCGTACCAAGTCTG	GTCCTGCTGGGCCTCGG
BRK34	GTTAGTTGATGTAGT	GCCTTTGACTTGAAGTCTTCTGTC	GTCCTGCTGGGCCTCGG
BRK35	GTCCTGCTCCGCTCGG	CGACTCCCTCAGCTTCTGAACTAG	GTCCTGCTGGGCCTCGG
BRK36	GTTAGTTGATGTAGT	TGTTTCTCCTCTAACTGGGACAT	GTCCTGCTGGGCCTCGG
BRK37	GTCCTGCTCCGCTCGG	TGATACTAAGCATCAATCGCAAGC	GTCCTGCTGGGCCTCGG
BRK38	GTTAGTTGATGTAGT	TTCTCTATCTGCTCTCTGTTGGT	GTCCTGCTGGGCCTCGG
BRK39	GTTAGTTGATGTAGT	GAGAGGCTCTAAGTGGACCTGTGG	GTCCTGCTGGGCCTCGG
BRK40	GTTAGTTGATGTAGT	GGCTATCCTTGGTCACTCAAACTA	GTCCTGCTGGGCCTCGG
BRK41	GTTAGTTGATGTAGT	CGTGTACTTCTGGACGAACTCC	GTCCTGCTGGGCCTCGG
BRK42	GTCCTGCTCCGCTCGG	CTGGCAGGTATGCTTACACGTAG	GTCCTGCTGGGCCTCGG
BRK43	GTTAGTTGATGTAGT	CTACCGTCCAGTCAACACGAAAG	GTCCTGCTGGGCCTCGG
BRK44	GTTAGTTGATGTAGT	GAGTGGAGAGGAAAGCCTTTCTACT	GTCCTGCTGGGCCTCGG
BRK45	GTCCTGCTCCGCTCGG	CACTGAAGGCATCTCTGTTGGATC	GTCCTGCTGGGCCTCGG
BRK46	GTTAGTTGATGTAGT	CAGGAGAATGAAGTGGAAACACAGC	GTCCTGCTGGGCCTCGG
BRK47	GTCCTGCTCCGCTCGG	GAACTACCTGTGGGAAAGTTGCAC	GTCCTGCTGGGCCTCGG
BRK48	GTTAGTTGATGTAGT	TACAGGTGTACCAAGTCCAGATG	GTCCTGCTGGGCCTCGG
BRK49	GTCCTGCTCCGCTCGG	CTAGATGTTCAAAGCTGCACAGT	GTCCTGCTGGGCCTCGG
BRK50	GTTAGTTGATGTAGT	ACCGAGGAAGTTACCAAGTCCAT	GTCCTGCTGGGCCTCGG
BRK51	GTCCTGCTCCGCTCGG	GAGGACCCAGTAGGCTCATTCAAC	GTCCTGCTGGGCCTCGG
BRK52	TACATTGATGCATGG	GTCCACGAACAATCTTGTCTCTCA	GTCCTGCTGGGCCTCGG
BRK53	GTCCTGCTCCGCTCGG	CTTTGCATGAGACGGTCTGAATCT	GTCCTGCTGGGCCTCGG
BRK54	GTTAGTTGATGTAGT	CATGCTCTTAACTCAAAGCTCTTG	GTCCTGCTGGGCCTCGG
BRK55	GTCCTGCTCCGCTCGG	CGTAGATCAAGGCTCATCTTCTGA	GTCCTGCTGGGCCTCGG
BRK56	GTCCTGCTCCGCTCGG	TTCTATGCCACCTGTTGAGTAGTGA	GTCCTGCTGGGCCTCGG
BRK57	TACATTGATGCATGG	ACTTCCGAAGGAGATTGACCTAGC	GTCCTGCTGGGCCTCGG
BRK58	GTTAGTTGATGTAGT	TCAGACTCACGGAGAGTAACTGTG	GTCCTGCTGGGCCTCGG
BRK59	GTTAGTTGATGTAGT	ACCTTCTCTTCCCTTCTTGAATGA	GTCCTGCTGGGCCTCGG
BRK60	GTTAGTTGATGTAGT	CCATAGAACCCTTTCGTTGAGATG	GTCCTGCTGGGCCTCGG
BRK61	TACATTGATGCATGG	GTGCTGAGGCACATAGTACCCTCT	GTCCTGCTGGGCCTCGG
BRK62	GTTAGTTGATGTAGT	TACGTCTGAAGTAAAGTGGGTG	GTCCTGCTGGGCCTCGG
BRK63	GTTAGTTGATGTAGT	GTTCAAAGACCCAGAACTTCAGAA	GTCCTGCTGGGCCTCGG
BRK64	GTTAGTTGATGTAGT	GAAAGTCGATGAACGGTGTCTGTCT	GTCCTGCTGGGCCTCGG
BRK65	GTCCTGCTCCGCTCGG	CCTTGTCTGGAGAAAGACTGASAA	GTCCTGCTGGGCCTCGG
BRK66	GTCCTGCTCCGCTCGG	GAAAGTTAGAAGCCCAAGGATCGG	GTCCTGCTGGGCCTCGG
BRK67	TACATTGATGCATGG	GGTGAACACACAGATGACAAAC	GTCCTGCTGGGCCTCGG
BRK68	GTCCTGCTCCGCTCGG	CCACCCTTCTGTTTCTTGAATTC	GTCCTGCTGGGCCTCGG
BRK69	GTTAGTTGATGTAGT	AGATCACATGAGGCTCGGACTGTA	GTCCTGCTGGGCCTCGG
BRK70	GTTAGTTGATGTAGT	AGACTCCATTCTGAGGATCTGGT	GTCCTGCTGGGCCTCGG
BRK71	GTCCTGCTCCGCTCGG	CTGTTACTACTGATGCTCCAGG	GTCCTGCTGGGCCTCGG
BRK72	GTTAGTTGATGTAGT	GTCGGTATGGAAGACAGTCAAGTA	GTCCTGCTGGGCCTCGG
BRK73	GTCCTGCTCCGCTCGG	GAGGGTTCTGTCTCTCTGTTTCTT	GTCCTGCTGGGCCTCGG
BRK74	GTTAGTTGATGTAGT	AGTGGAAAGTGGGATGCTTTGTA	GTCCTGCTGGGCCTCGG
BRK75	GTCCTGCTCCGCTCGG	ACAAACAGGGTTTCACTCAATGGTC	GTCCTGCTGGGCCTCGG
BRK76	GTTAGTTGATGTAGT	GTCAGGGTGTATTAACAGCAAT	GTCCTGCTGGGCCTCGG
BRK77	GTCCTGCTCCGCTCGG	GTTGTATCCCTGAGAAACAGGTCG	GTCCTGCTGGGCCTCGG
BRK78	GTTAGTTGATGTAGT	TTCTGATTCAAAGGTTCCGTTGTT	GTCCTGCTGGGCCTCGG
BRK79	GTCCTGCTCCGCTCGG	CAGCAGTGAGAATATCTCCGAGA	GTCCTGCTGGGCCTCGG
BRK80	GTTAGTTGATGTAGT	GAATCGCTATCCTATGTTCTATCCG	GTCCTGCTGGGCCTCGG
BRK81	GTCCTGCTCCGCTCGG	CCSAAACCAACTCACAAAGTAGGG	GTCCTGCTGGGCCTCGG
BRK82	GTTAGTTGATGTAGT	TAGTCCCTGAACTCGACATACCGT	GTCCTGCTGGGCCTCGG
BRK83	GTCCTGCTCCGCTCGG	TTCCACCTTACCTAGATCAAGCCA	GTCCTGCTGGGCCTCGG
BRK84	GTTAGTTGATGTAGT	TGGCACAGGTTCTAGGTCACACTAC	GTCCTGCTGGGCCTCGG
BRK85	GTCCTGCTCCGCTCGG	GATCATCCAACTAACTCCTCCGTT	GTCCTGCTGGGCCTCGG
BRK86	GTCCTGCTCCGCTCGG	TACTTACGCTTGTGGGATCACTCT	GTCCTGCTGGGCCTCGG
BRK87	GTCCTGCTCCGCTCGG	CCTCCCTAAACACAGGAGCATGTA	GTCCTGCTGGGCCTCGG
BRK88	GTTAGTTGATGTAGT	CTGCTTCGGATCGGTAGTGAAGA	GTCCTGCTGGGCCTCGG
BRK89	GTCCTGCTCCGCTCGG	CAACTAGCCAAACATTGATGCTGT	GTCCTGCTGGGCCTCGG
BRK90	GTTAGTTGATGTAGT	GCCTCAAACCCTGACCTCTACATC	GTCCTGCTGGGCCTCGG
BRK91	TACATTGATGCATGG	AGTACCCCTGAGTCTATGGAGCC	GTCCTGCTGGGCCTCGG
BRK92	GTCCTGCTCCGCTCGG	GCTGCTGCTTCTGCTCACTCACA	GTCCTGCTGGGCCTCGG
BRK93	GTCCTGCTCCGCTCGG	CCCAAGTCTGAAGTGTGAAACT	GTCCTGCTGGGCCTCGG
BRK94	GTTAGTTGATGTAGT	GTAGGTGCAAGTGTGAGGACAATC	GTCCTGCTGGGCCTCGG
BRK95	GTCCTGCTCCGCTCGG	AAGTCCATTCTTCCAGACAGG	GTCCTGCTGGGCCTCGG
BRK96	TACATTGATGCATGG	ATGGTGAAGTCTATGACCCTTCAG	GTCCTGCTGGGCCTCGG

Barcodes sequence for PCR₂ (5'-3' orientation)