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Supplementary Data

Cancer signature ensemble integrating cfDNA methylation, copy number, and fragmentation facilitates multi-cancer early detection

Su Yeon Kim *et al.*

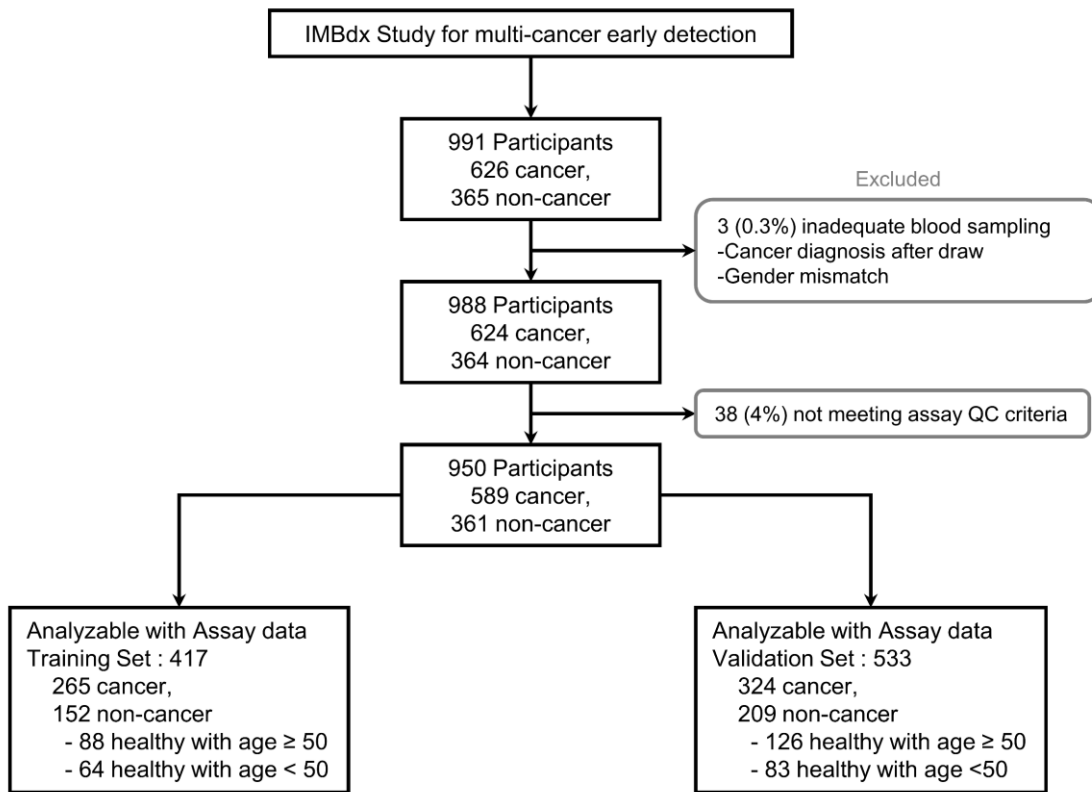
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This PDF file includes:

Supplementary Figs. 1 to 20

Other Supplementary Data for this manuscript include the following:

Supplementary Tables 1 to 3



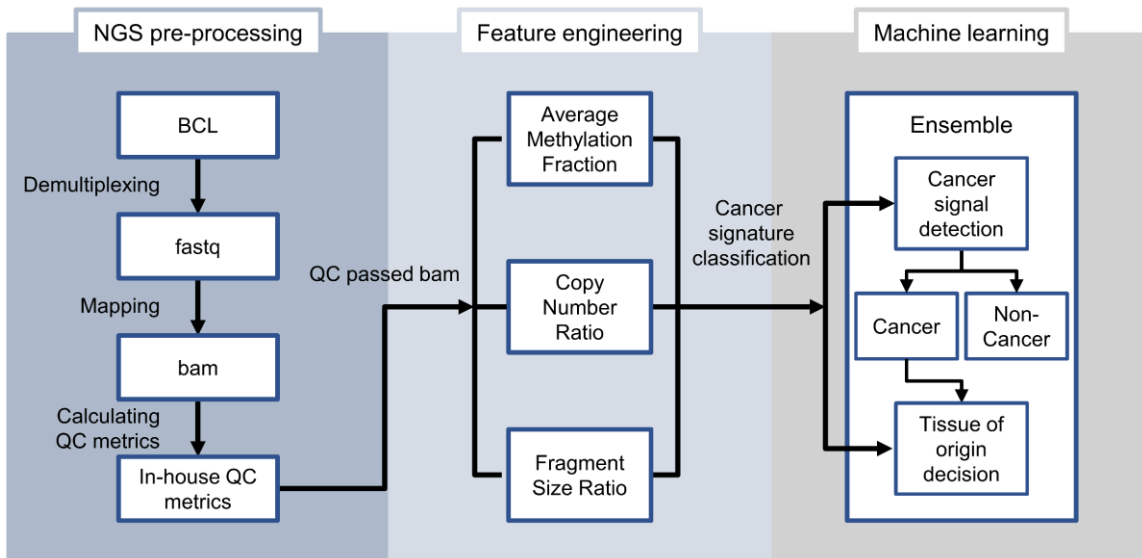
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25 **Supplementary Fig. 1. AlphaLiquid® Screening study.**

26 Data from 991 participants were collected, including 626 cancer patients and 365 healthy
 27 controls. Three participants were excluded due to inadequate blood sampling and an additional 38
 28 samples were filtered out by assay quality control (QC) criteria. The remaining participants were
 29 divided into training (n=417) and test (n=533) sets for machine learning.

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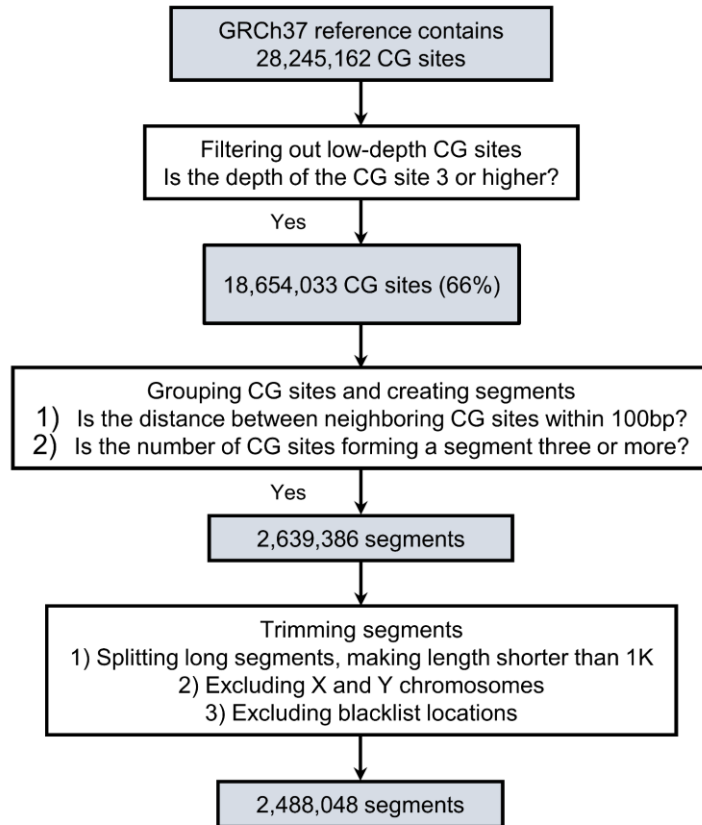
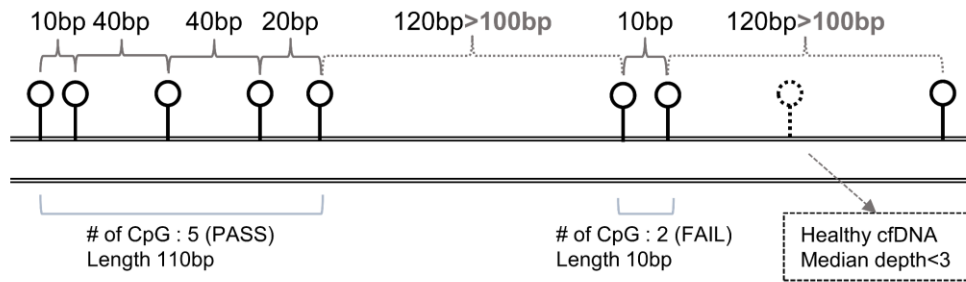
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33 **Supplementary Fig. 2. AlphaLiquid® Screening analysis workflow.**

34 The workflow consisted of three procedures: next-generation sequencing (NGS) pre-processing,
 35 feature engineering, and machine learning application. NGS pre-processing started with
 36 demultiplexing, converting a bcl file to a fastq file, and then performing read mapping onto the
 37 GRCh37 reference genome creating a bam file. Subsequently, in-house quality control (QC)
 38 metrics were calculated. Next, the average methylation fraction, copy number ratio, and fragment
 39 size ratio features were extracted from the bam file and fed to the cancer signature ensemble
 40 model for cancer signal detection and to search for the tissue of origin.

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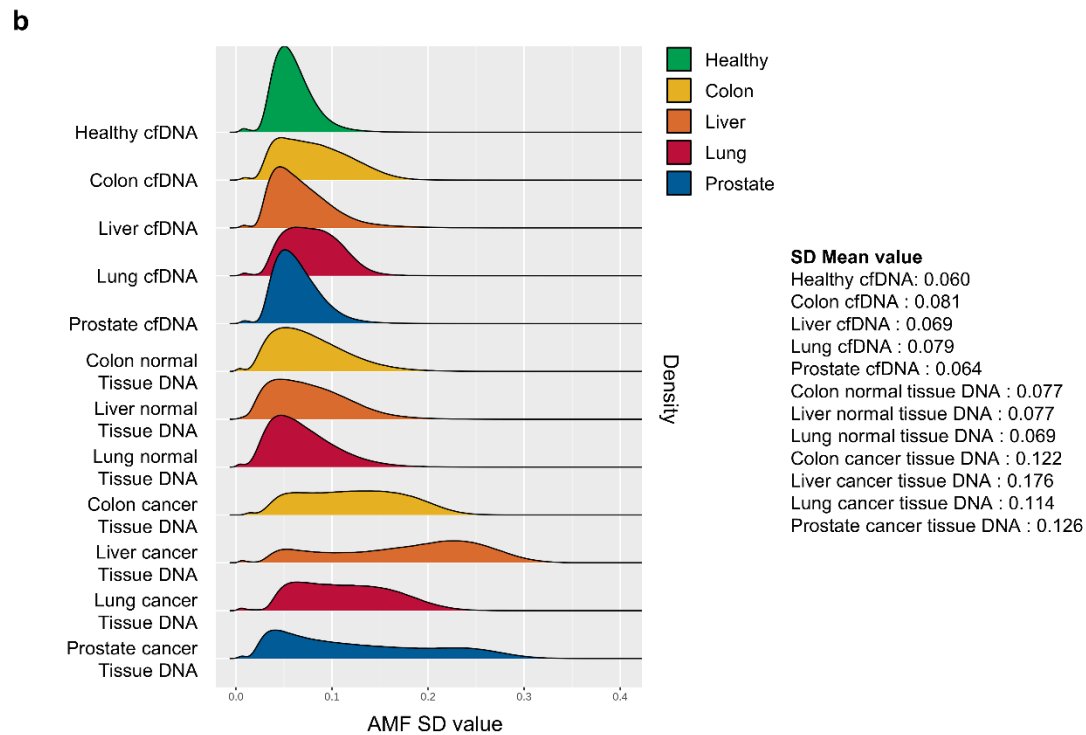
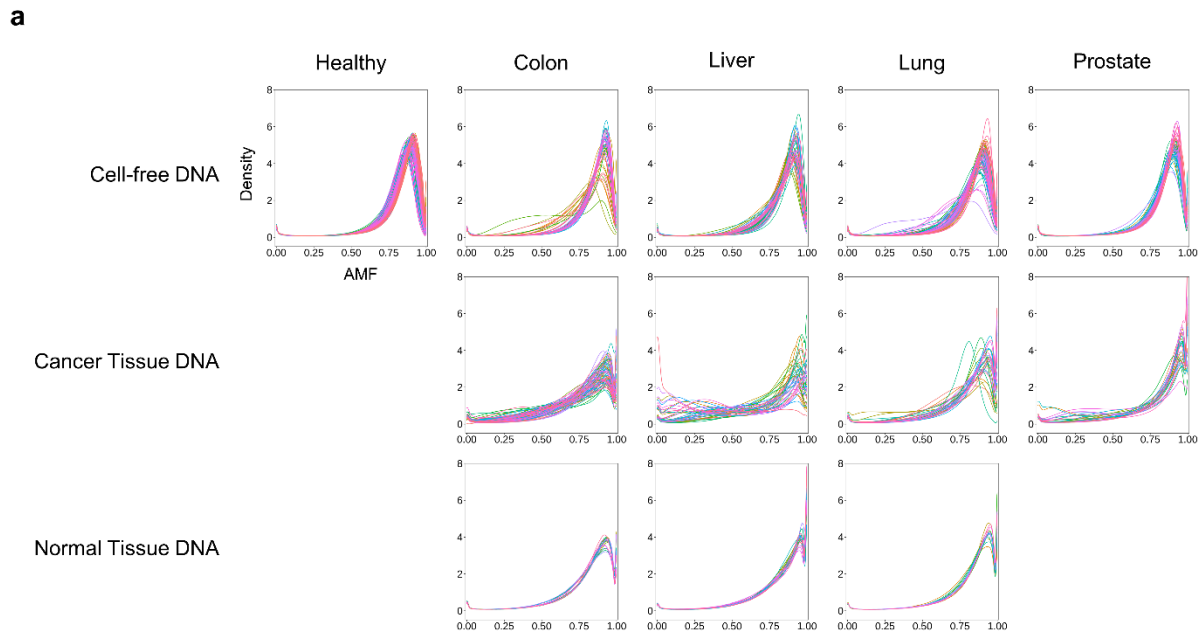
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44 **Supplementary Fig. 3. Definition of methylation regions analyzed in this study.**

45 Starting from the ~30 million CpG sites in the GRCh37 reference genome, 2,488,048 methylation
 46 regions were obtained for downstream analyses following the steps described in the flow chart.

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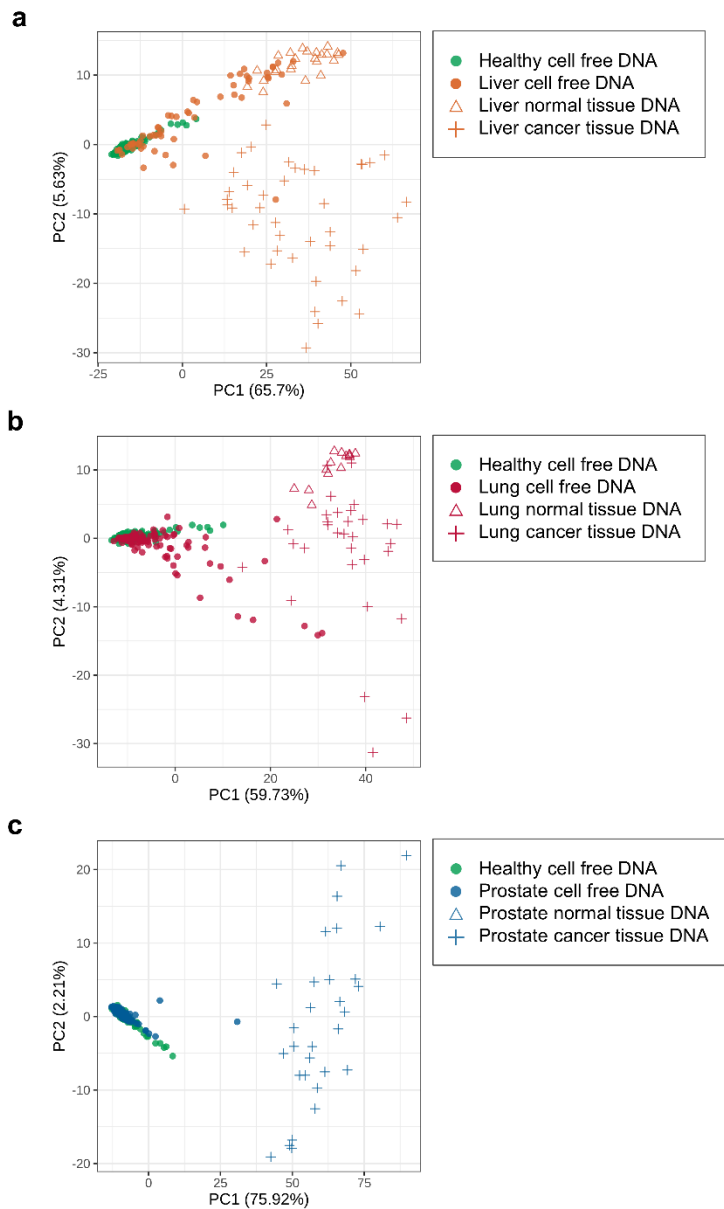


49

Supplementary Fig. 4. Genome-wide distribution of the regional methylation level.

(a) Density plot of the average methylation fraction (AMF) collected from ~2.4 million methylation regions per each sample (colored lines). Samples were grouped by sample type (row) and cohort type (column). (b) Genome-wide distribution of the standard deviation (SD) of the AMF value calculated at each methylation region. The mean of the SD of each group is listed on the right side.

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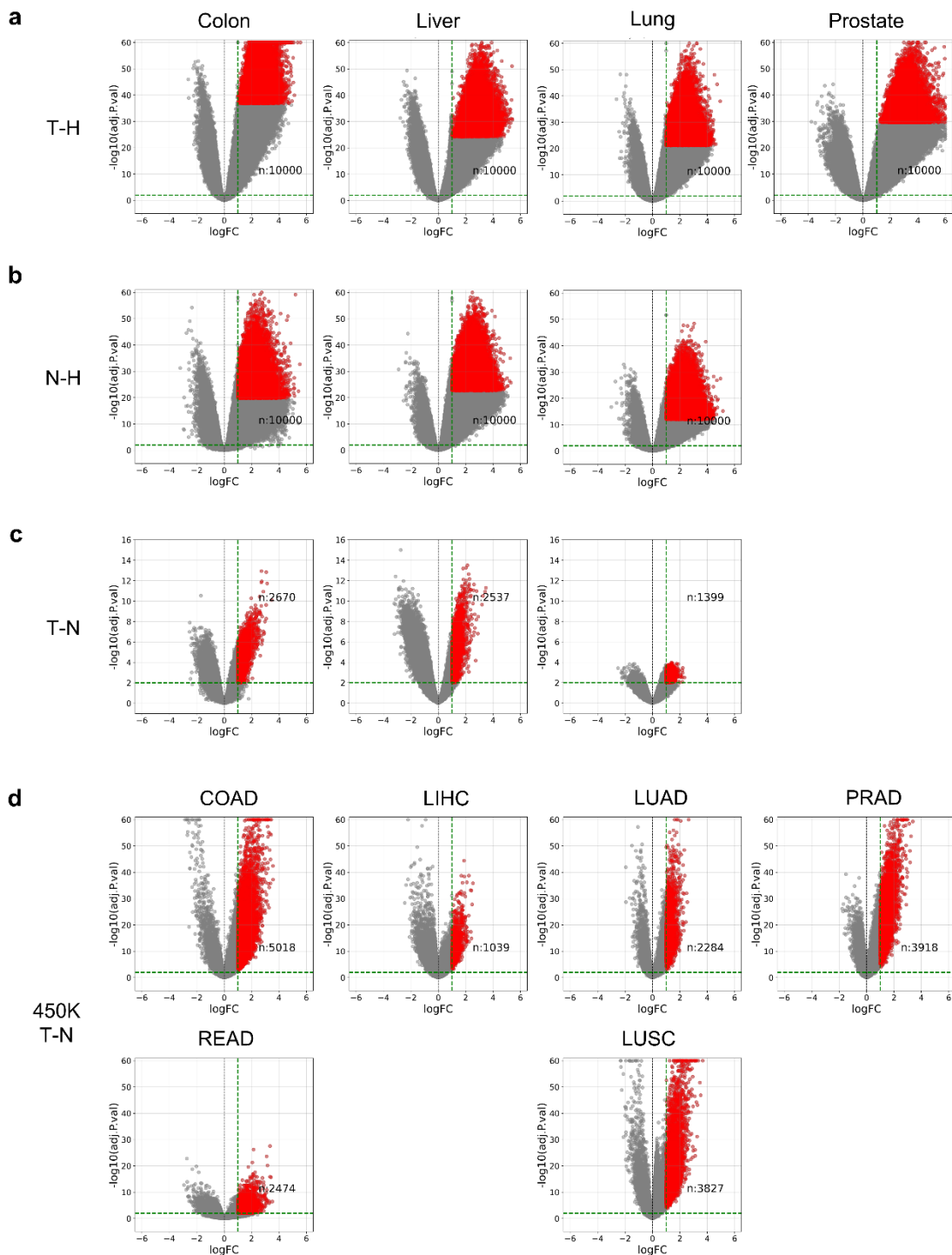
56

57 **Supplementary Fig. 5. Variation in the methylation level by sample type.**

58 Principal component analysis was performed on healthy cfDNA samples (green-filled circles) and
 59 all sample types from hepatocellular carcinoma (a), lung cancer (b), and prostate cancer (c). The
 60 average methylation fractions of ~67,000 regions with low methylation levels in the healthy
 61 training set were used for the analysis.

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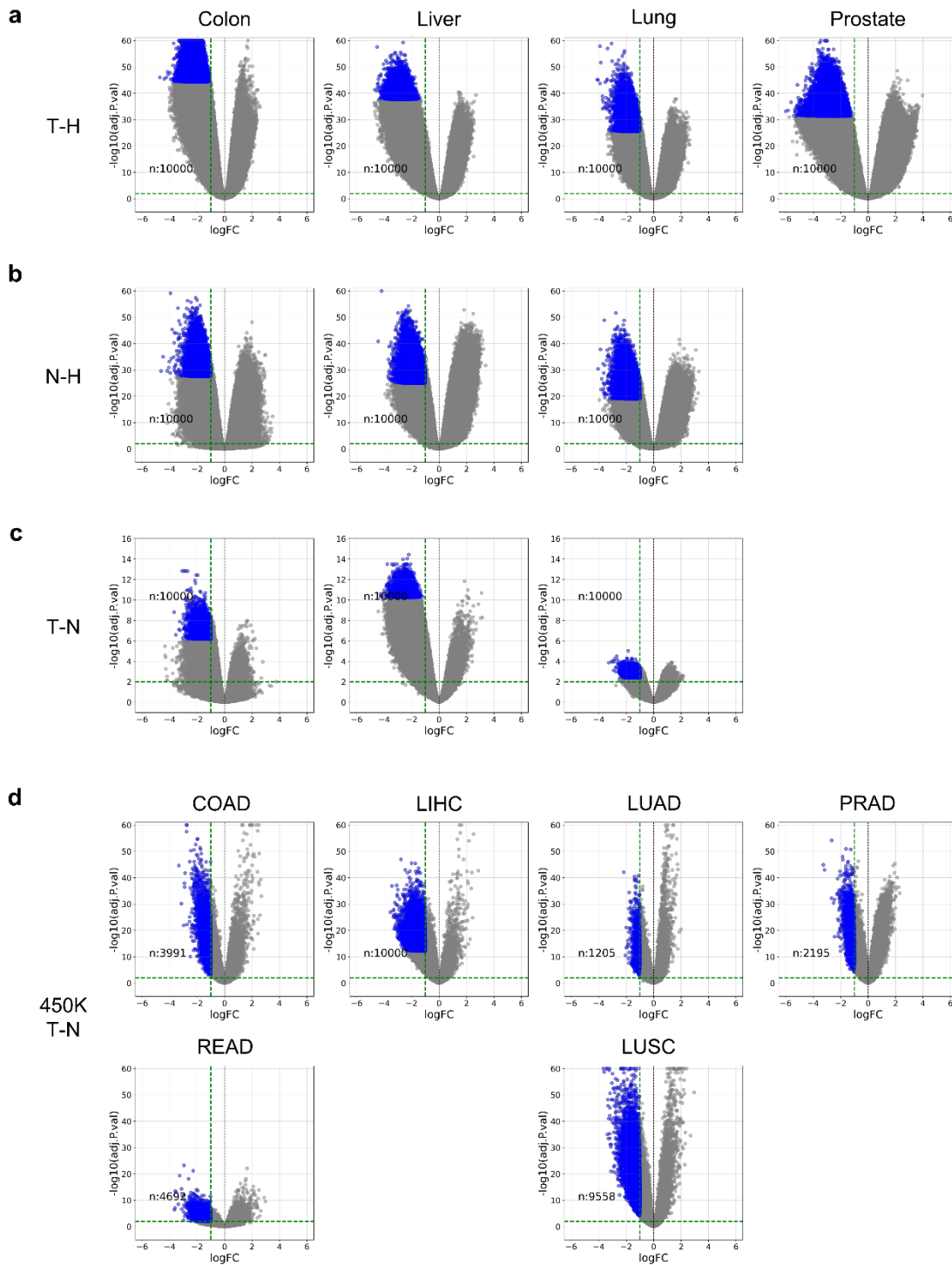
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65 **Supplementary Fig. 6. Volcano plots indicating differentially methylated markers among**
 66 **regions with low methylation in the healthy cohort.**

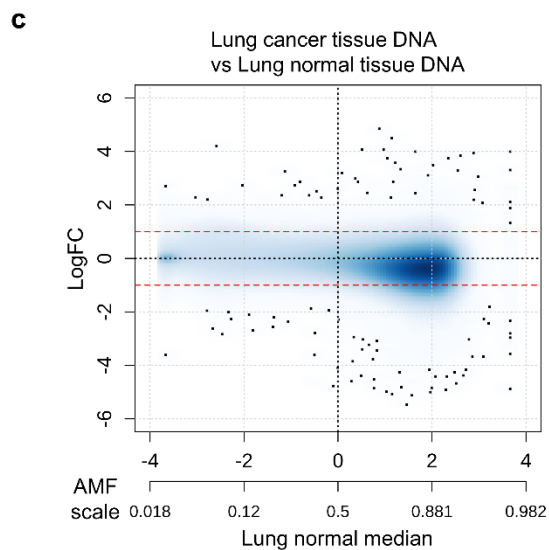
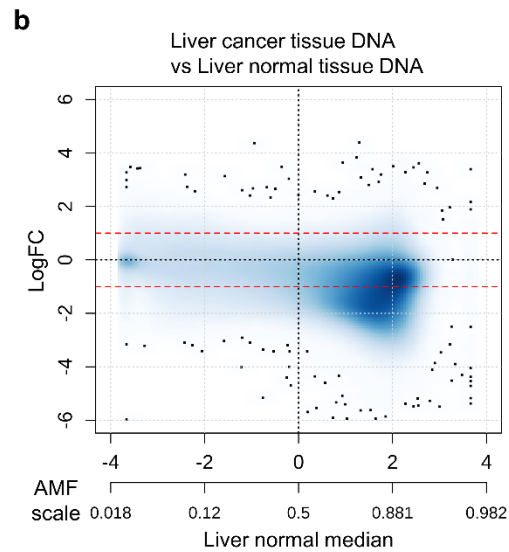
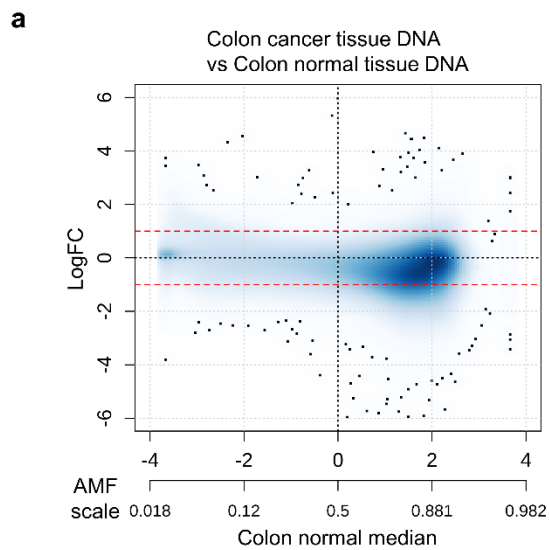
67 Differential methylation analyses were carried out using sequencing data and The Cancer
 68 Genome Atlas 450K data for markers in the ‘healthy-unmethylated’ regions (for details, see
 69 Materials and Methods). For the sequencing data, comparisons were performed between (a)
 70 cancer tissue and healthy cfDNA (‘T-H’), (b) normal tissue and healthy cell-free DNA (‘N-H’),
 71 and (c) cancer tissue and normal tissue (‘T-N’). For the 450K data (d), comparisons between
 72 tumor and normal tissues (‘T-N’) were performed using the related cancer cohorts.



73

74 **Supplementary Fig. 7. Volcano plots indicating differentially methylated markers among**
 75 **methylated regions in the healthy cohort.**

76 Differential methylation analyses were carried out using sequencing data and The Cancer
 77 Genome Atlas 450K data for markers in the ‘healthy-methylated’ regions (for details, see
 78 Materials and Methods). Other details are similar to those in Supplementary Fig. 6.
 79



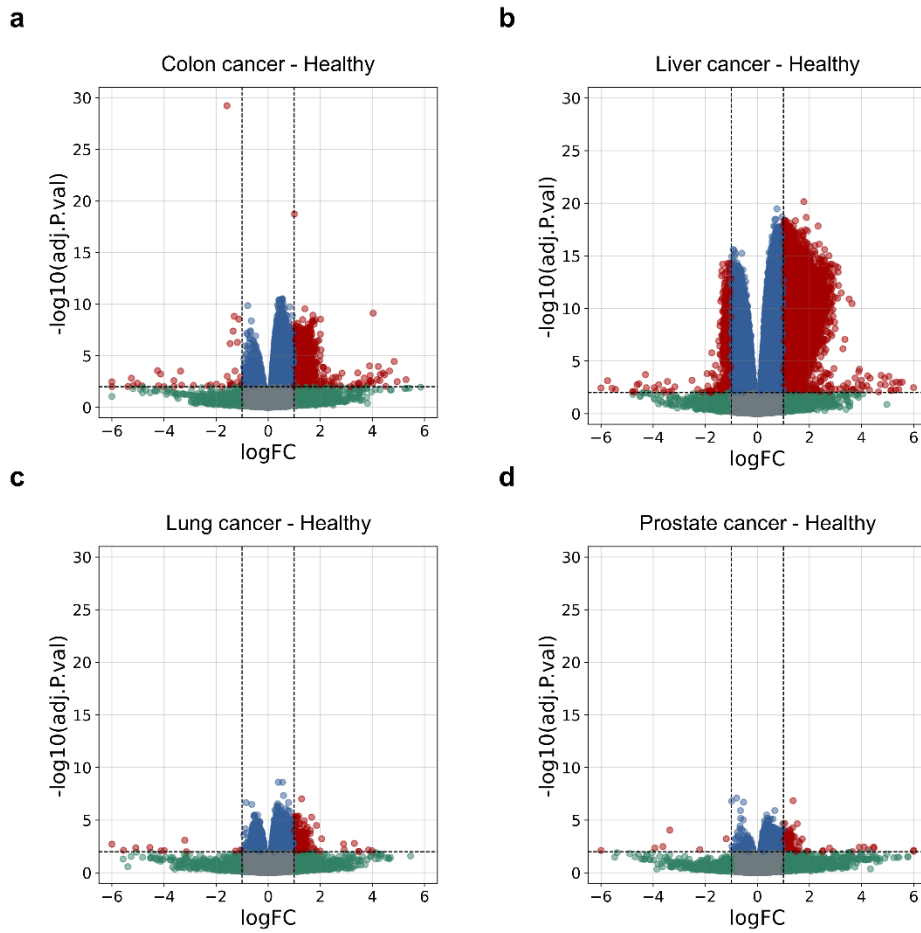
80

81 **Supplementary Fig. 8. Magnitude of differential methylation levels between cancer and**
 82 **normal tissues.**

83 For each colon **(a)**, liver **(b)**, and lung **(c)** cancer type, a smoothed scatter plot shows the log fold
 84 change according to the differential methylation analysis between the cancer tissues and the
 85 normal tissues, along with the median methylation level in the normal cohort.

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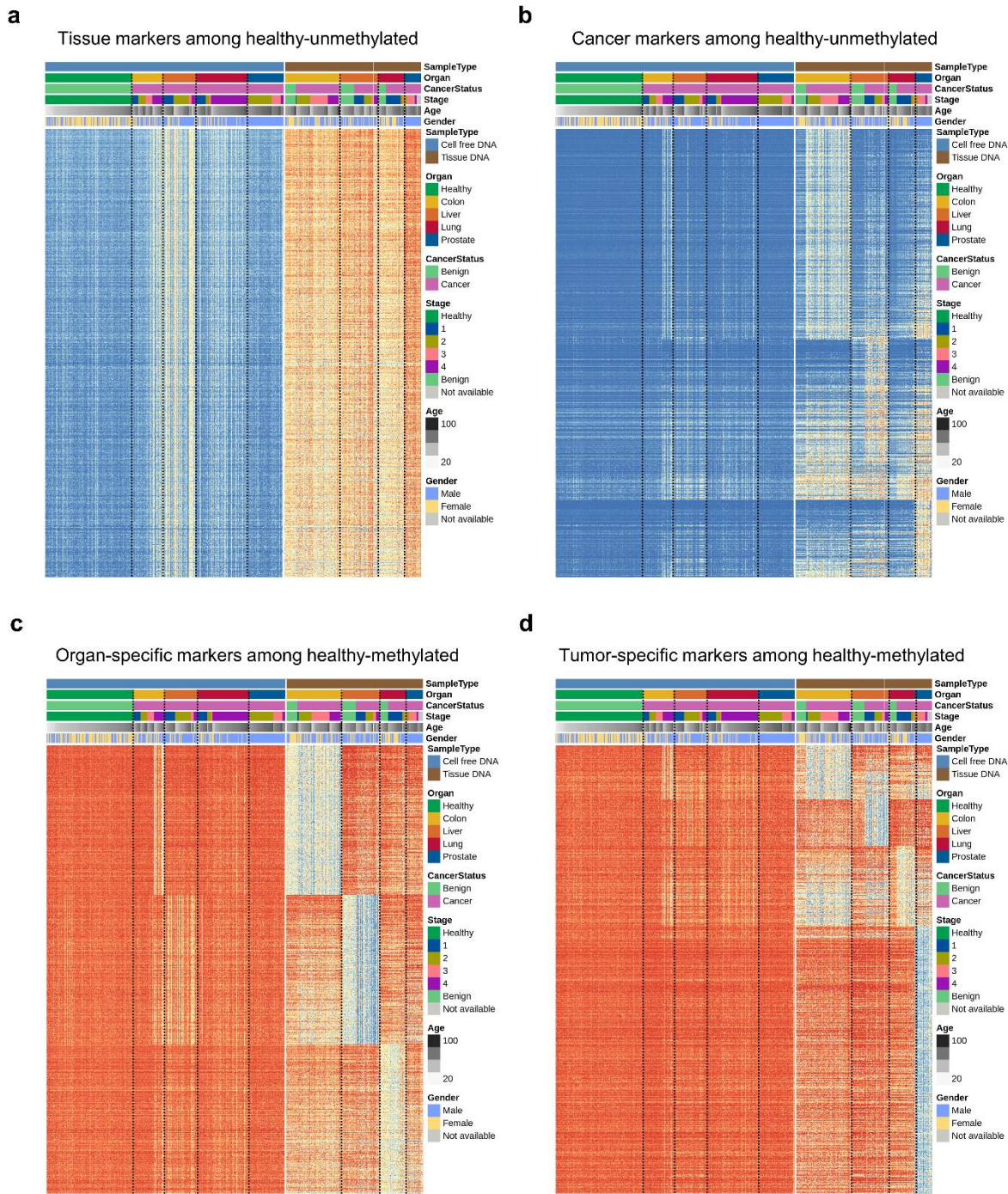
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89 **Supplementary Fig. 9. Differential methylation analysis using cell-free DNA (cfDNA) only.**

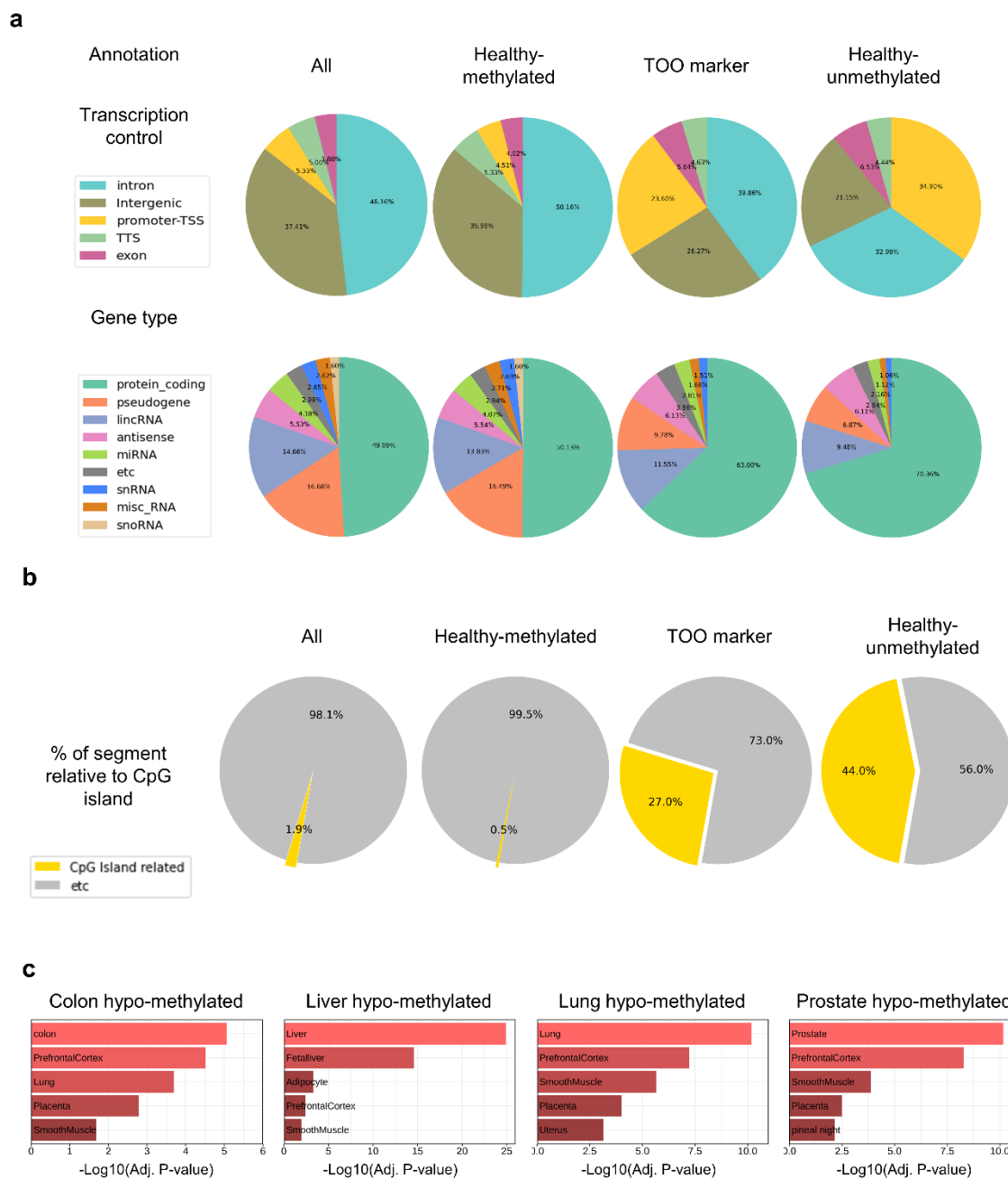
90 For each colon (**a**), liver (**b**), lung (**c**), and prostate (**d**) cancer type, a differential methylation
 91 analysis was conducted comparing the associated cancer cfDNA samples with the healthy
 92 cfDNAs. Each volcano plot demonstrates the $-\log_{10}$ (false discovery rate-adjusted p -value)
 93 against the log fold change.
 94



95

96 **Supplementary Fig. 10. Heatmap visualizing methylation markers that reveal cancer**
 97 **signatures or tissue signatures.**

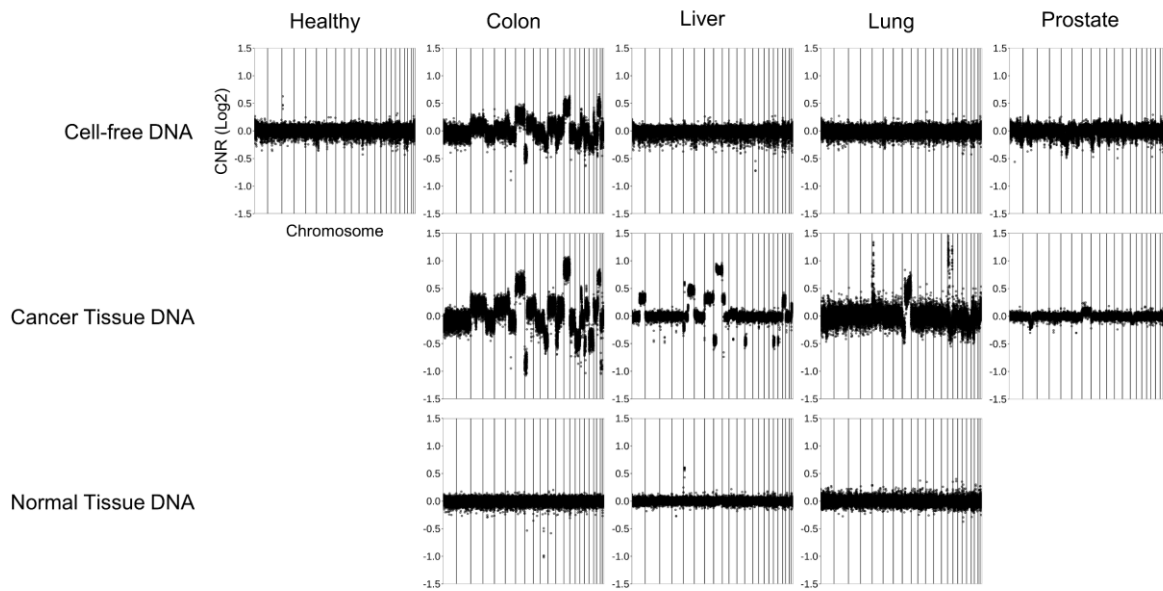
98 **(a)** and **(b)** Differentially methylated markers between cell-free DNA and tissues **(a)** and between
 99 normal tissue and cancer tissues **(b)** among those in the ‘healthy-unmethylated’ regions. **(c)** and
 100 **(d)** Differentially methylated markers across organ-specific tissues **(c)** and between normal tissue
 101 and cancer tissue within each organ type **(d)** among those in the ‘healthy-methylated’ regions. For
 102 more details on marker selection, see Materials and Methods. The graphical details are similar to
 103 those of Fig. 3c.



104

105 **Supplementary Fig. 11. Characterization of biological functions of the methylation markers**
 106 **used for cancer detection and localization.**

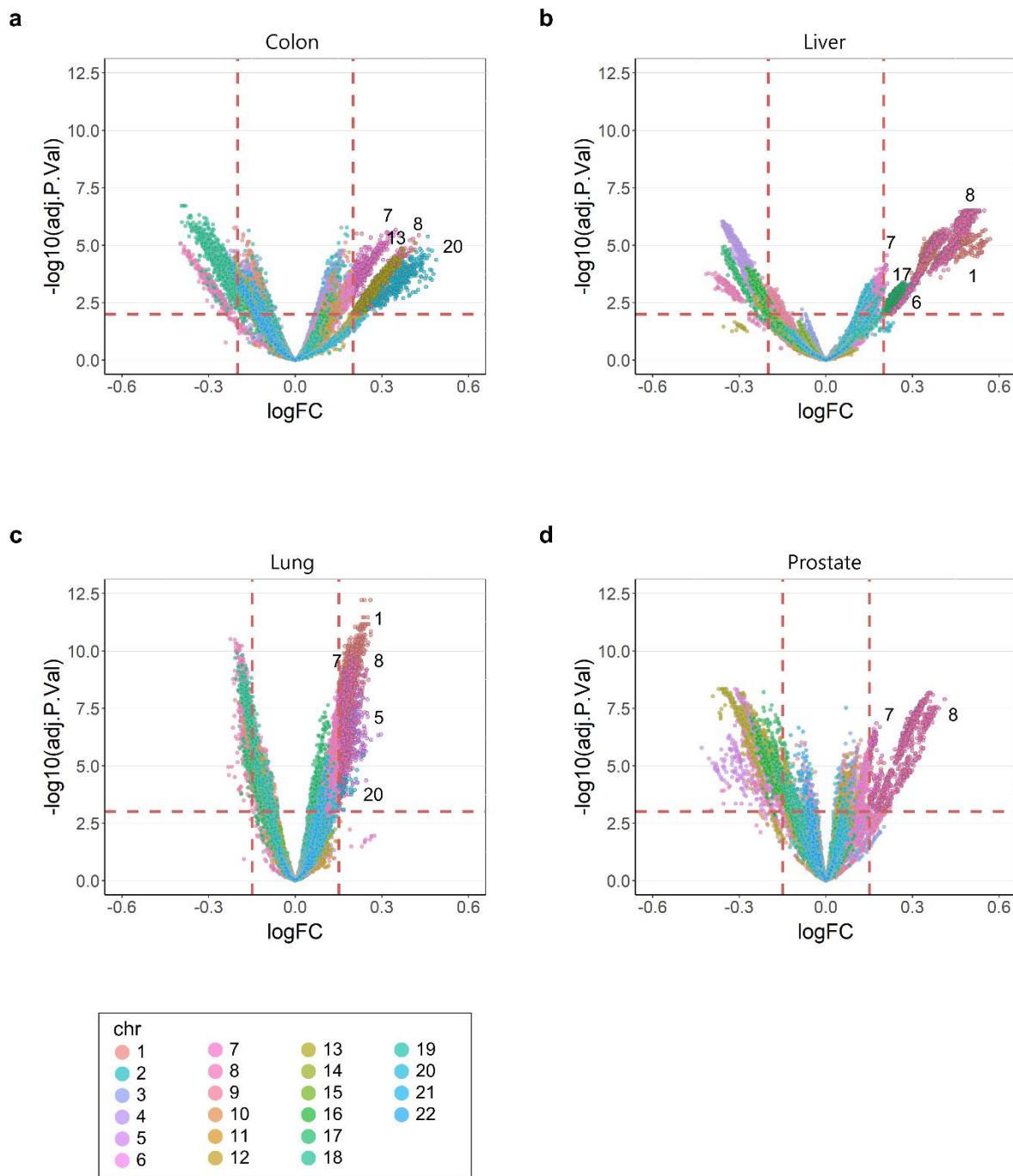
107 **(a)** Transcriptional (upper) or gene type (lower) categories were annotated and are shown as pie
 108 charts for all ~2.5 million methylation regions ('All'), 'healthy-methylated' regions, regions used
 109 for tissue of origin classification, and 'healthy-unmethylated' regions. For details of the region
 110 definition, see Materials and Methods. **(b)** Percentage of overlapping base pairs with CpG islands
 111 for the four regions analyzed in **(a)**. **(c)** Gene set analysis of the 'cell type' category for the
 112 cancer-hypo markers specific to each organ (y-axis).
 113



114

115 **Supplementary Fig. 12. Genome-wide copy number patterns at the individual sample level.**

116 The copy number ratio (CNR) profile is shown along the genomic coordinates for cell-free DNA
 117 (cfDNA) or tissue samples. Each black point indicates the log₂-transformed CNR value computed
 118 for a 100-kb bin. The gray vertical lines separate chromosomes. For colon, liver, and lung
 119 samples, the cfDNA, cancer tissue DNA, and normal tissue DNA samples were obtained from a
 120 matched donor.
 121

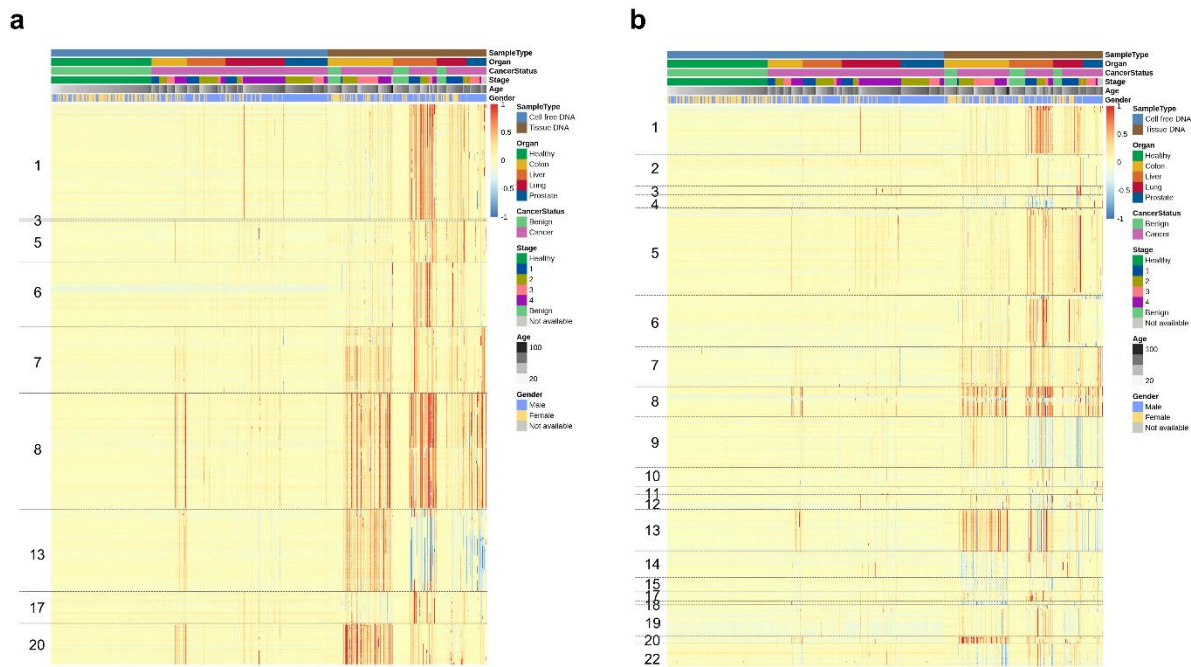


122

123 **Supplementary Fig. 13. Differential copy number ratio analysis between cancer tissues and**
 124 **normal tissues using whole-genome methylation sequencing data.**

125 For each colon **(a)**, liver **(b)**, lung **(c)**, and prostate **(d)** cancer, a volcano plot shows the results of
 126 differential copy number ratio (CNR) analysis (performed in log₂ scale) comparing cancer tissues
 127 with normal tissues. Each CNR value calculated per 100-kb bin (one point) is colored according
 128 to the associated chromosome. Because large copy number events are often much longer than 100
 129 kb, clusters of neighboring bins were observed. The chromosome numbers of repeated copy
 130 number gain events are indicated with black text.

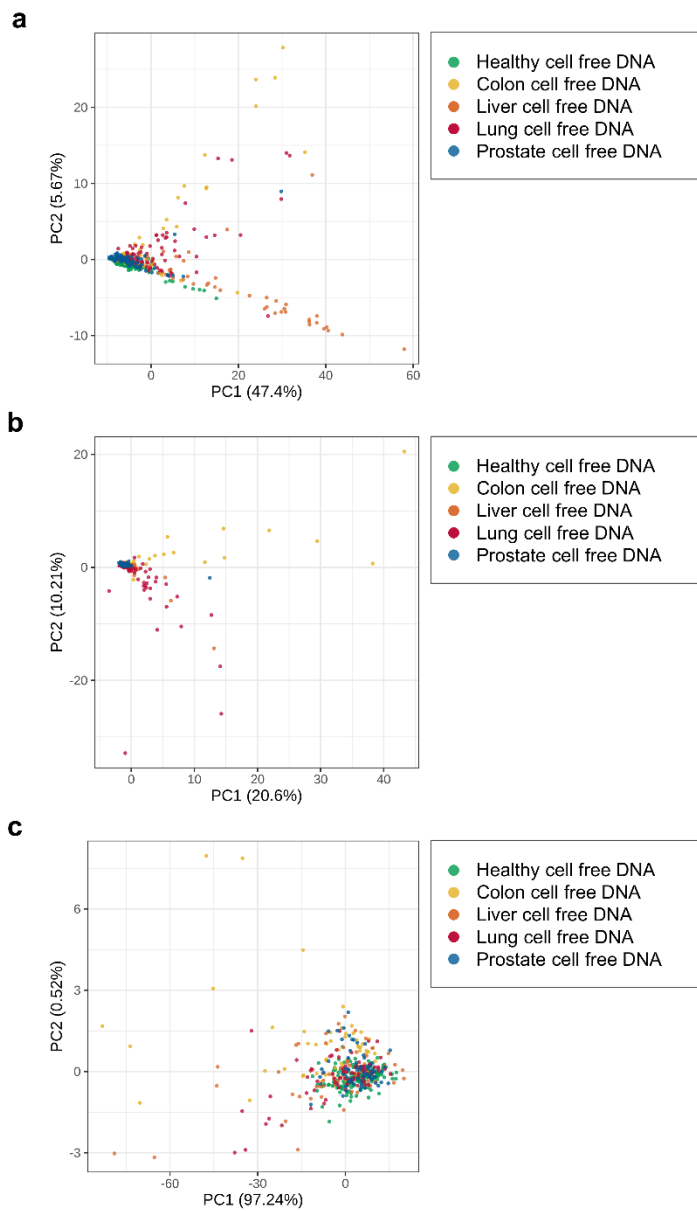
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132

133 **Supplementary Fig. 14. Heatmap visualizing log₂-scale copy number ratio (CNR) values of**
 134 **our data for the copy number gain regions found by whole-genome methylation sequencing**
 135 **(WGMS) data and by a pan-cancer study of The Cancer Genome Atlas (TCGA).**

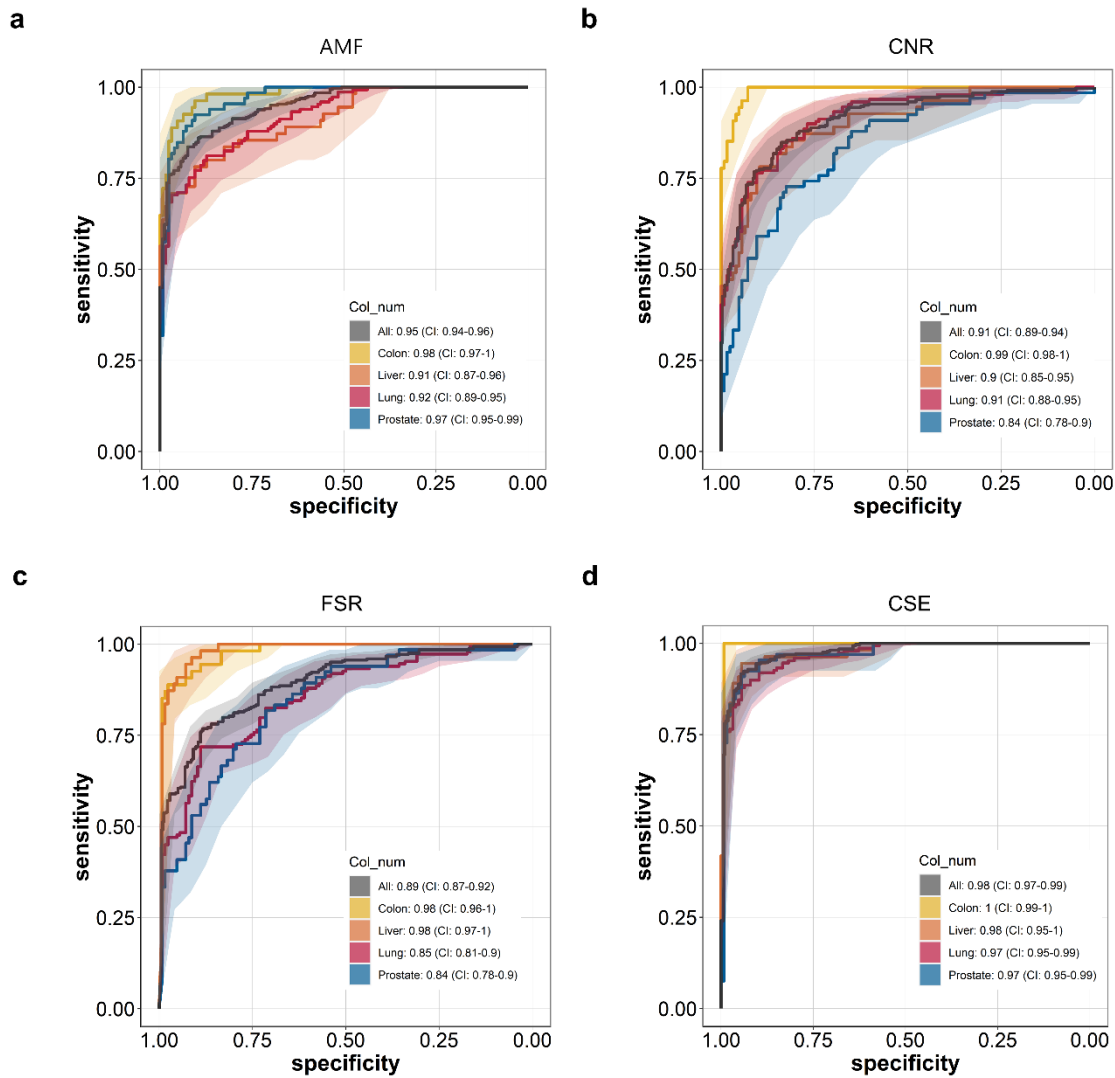
136 The heatmap shows all training cell-free DNA and tissue samples for (a) the regions that showed
 137 a significant increase in the CNR values in our WGMS cancer tissues compared with normal
 138 tissues by any cancer type and (b) the regions that were reported by a pan-cancer study of TCGA
 139 as having a frequent copy number gain event. The log₂-scale CNR value is plotted for each
 140 sample (columns) and genomic bin (rows). Sample annotations are shown on the upper part,
 141 similar to those in Fig. 3c, and the horizontal gray lines indicate separate chromosomes.



142

143 **Supplementary Fig. 15. Unsupervised clustering analysis using cell-free DNA (cfDNA)**
 144 **samples only.**

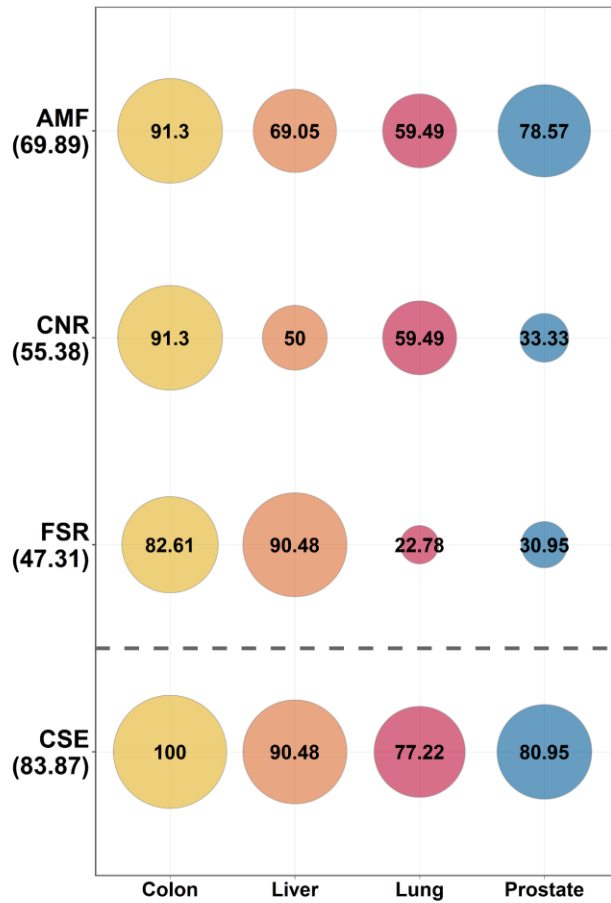
145 Principal component analysis of all cfDNA samples using the average methylated fraction (AMF)
 146 **(a)**, copy number ratio (CNR) **(b)**, and fragment size ratio (FSR) **(c)** features. For the AMF,
 147 ~67,000 regions with low methylation levels in the healthy training set were used. For the CNR
 148 and FSR, values were computed over non-overlapping 100-kb bins.
 149



150

151 **Supplementary Fig. 16. Receiver operating characteristic (ROC) curves for cancer detection**
 152 **classifiers.**

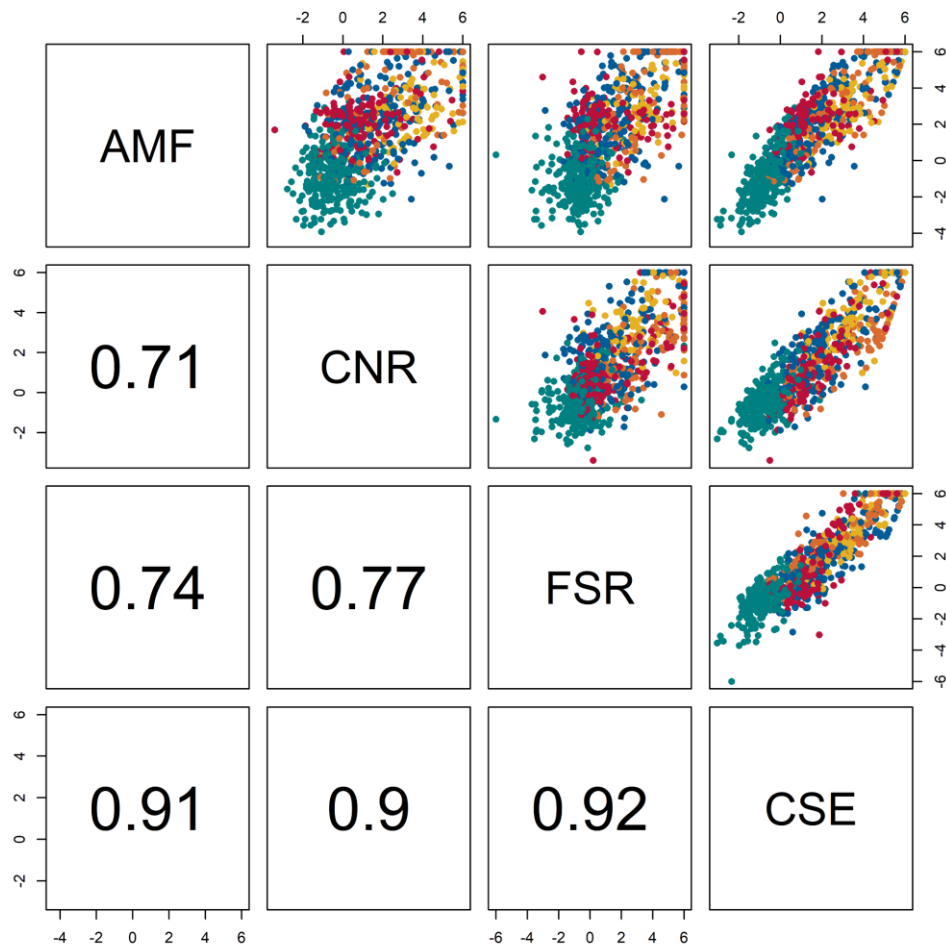
153 ROC curves are shown for each cancer detection classifier, including the average methylated
 154 fraction (AMF) (a), copy number ratio (CNR) (b), fragment size ratio (FSR) (c), and cancer
 155 signature ensemble (CSE) (d), computed using all samples (black line) or including one cancer
 156 type at a time with healthy controls (colored line). The area under the curve and 95% confidence
 157 interval (CI) are shown in the lower right part of each panel.
 158



159

160 **Supplementary Fig. 17. Sensitivity of cancer detection classifiers at 95.2% specificity for**
 161 **stage 1 and 2 cancer patients.**

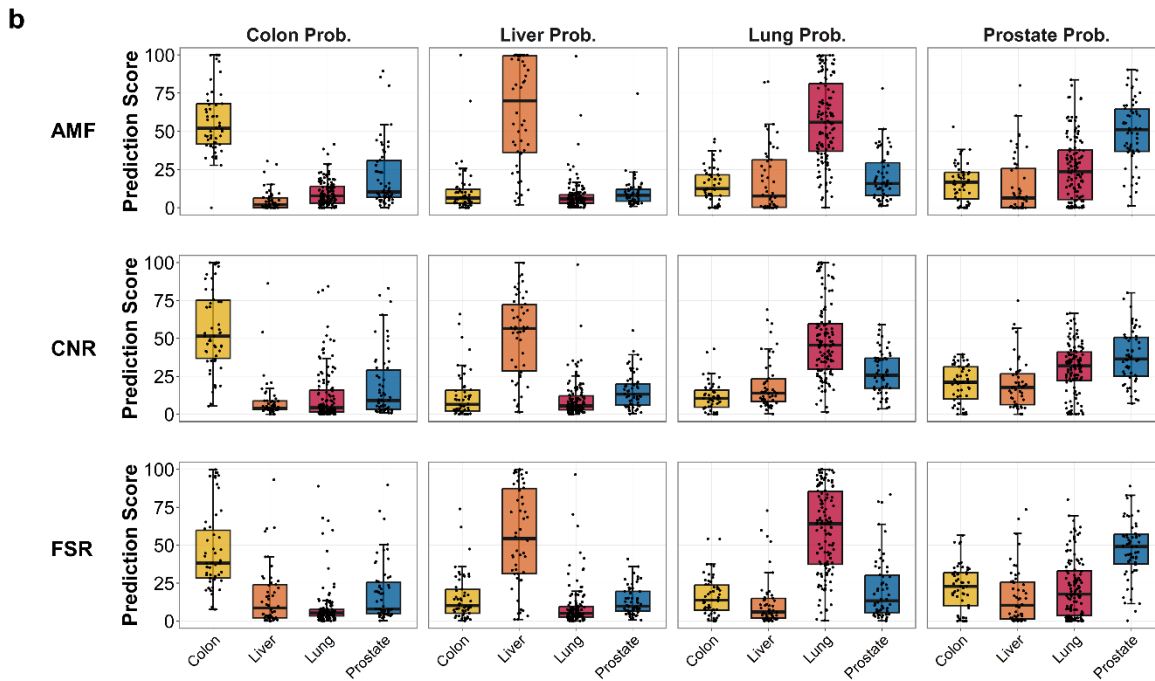
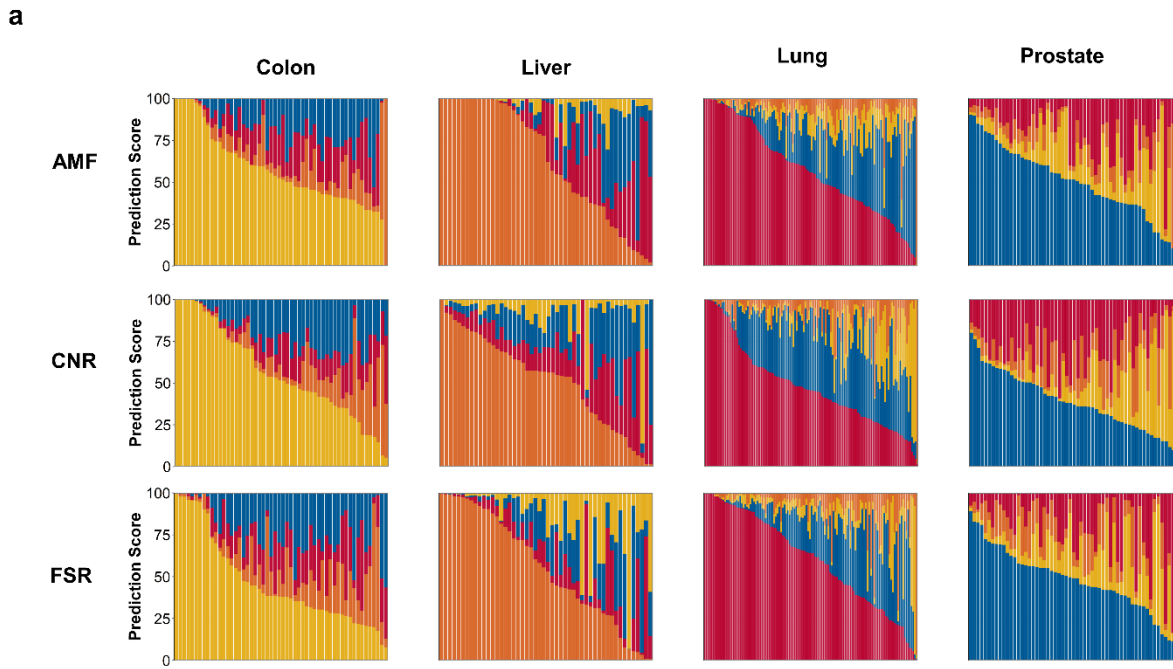
162 The sensitivity for stage 1 and stage 2 cancer patients was calculated for each cancer type
 163 (columns) by each classifier (rows). The other graphical details are similar to those in Fig. 6.
 164



165

166 **Supplementary Fig. 18. Correlation among the cancer detection classifier scores.**

167 A pairwise correlation plot between cancer detection classifiers was constructed. The classifier
 168 name is shown in diagonal blocks; the upper part includes the scatterplot, and the lower part
 169 shows the Pearson correlation coefficient. Each sample is colored according to the cohort type:
 170 green, healthy; yellow, colon; orange, liver; red, lung; and blue, prostate cancer.
 171



Supplementary Fig. 19. Distribution of the tissue of origin (TOO) conditional probability.

(a) Stacked bar plot visualizing the conditional probability decomposition in each sample by average methylated fraction (AMF), copy number ratio (CNR), and fragment size ratio (FSR) TOO classifiers (rows) across the four cancer types (columns). (b) Boxplots showing each organ-supporting probability (titled in each panel) across the four cancer cohorts (x-axis).

a

ID		Name	
Specimen	Specimen	Institution	
Collector Date		Department	
Receipt Date		Phone number	

Positive

The CancerFind test detected genetic/epigenetic alteration signals associated with cancer in the analyzed cfDNA acquired from the patient's blood sample. **[Positive]**

Based on the features of the genetic alterations, the predicted probabilities for the primary site of cancer origin are 80% and 10% for the colon and lungs, respectively.

❖ Results Interpretation and recommendation

- The CancerFind is a precise multi-cancer screening assay that utilizes next-generation sequencing to detect trace amount of cancer related genes derived from cancer cell into bloodstream. This assay identifies cancer associated methylation patterns, copy number variant(CNV) patterns, and fragmentomic patterns.
- Based on the observed methylation, CNV, and fragmentomics patterns, CancerFind provides conditional probabilities for the primary origin of cancer among eight possible sites.
- This assay has shown results with 95% specificity, 82% sensitivity, and 78% accuracy in predicting the primary site of origin, as demonstrated in clinical trials. All results should be interpreted and consulted with a clinician.

b

ID		Name	
Specimen	Specimen	Institution	
Collector Date		Department	
Receipt Date		Phone number	

Negative

The CancerFind test do not detected genetic/epigenetic alteration signals associated with cancer in the analyzed cfDNA acquired from the patient's blood sample. **[Negative]**

❖ Results Interpretation and recommendation

- The CancerFind is a precise multi-cancer screening assay that utilizes next-generation sequencing to detect trace amount of cancer related genes derived from cancer cell into bloodstream. This assay identifies cancer associated methylation patterns, copy number variant(CNV) patterns, and fragmentomic patterns.
- Based on the observed methylation, CNV, and fragmentomics patterns, CancerFind provides conditional probabilities for the primary origin of cancer among eight possible sites.
- This assay has shown results with 95% specificity, 82% sensitivity, and 78% accuracy in predicting the primary site of origin, as demonstrated in clinical trials. All results should be interpreted and consulted with a clinician.

180

181 **Supplementary Fig. 20. Draft version of AlphaLiquid® Screening platform report example.**
 182 The report presents the positive/negative outcomes determined by the CSE model and the tissue-
 183 of-origin. Additionally, it encompasses a comprehensive interpretation of these findings
 184 accompanied by pertinent recommendations. (a) and (b) illustrate examples of a positive case and
 185 a negative case, respectively.

186

187