

**Supplementary Fig. 1. Supporting data for genome model development. (A)** The ratio of single nucleotide variants detected in cancer versus normal cfDNA samples before and after a pplying our variant filtering pipeline. Variant calling was performed at differing read depths. E ach box indicates IQR and median, whiskers indicates 1.5 x IQR, black dots indicates outlier. **(B)** Heatmaps showing the average LMD values in high LMD regions (left) and low LMD regio ns (right), specifically identified for each cancer type. The color intensity is scaled to show th e degree of relative mutation enrichment (left) or mutation depletion (left). A total of 2,754 PCAWG samples were used for this analysis. **(C)** Distribution of the LVD in cfDNA in the abo ve identified high or low LMD regions in the matching cancer type before and after applying our variant filtering pipeline. Source data are provided as a Source Data file.





**Supplementary Fig. 2. Supporting data for epigenome model development. (A)** Illustration of peak call process for typical peak caller (MACS2) and NDR peak caller (HMMRATAC). **(B)** V-plot image constructed for the NDRs identified by ATAC-seq peak calling by MACS2 (left) and HMMRATAC (right). Data from the GM12878 cell line are shown. **(C)** ChIP-seq signals of histone modification (H3K27ac, H3K9ac, H3K4me1, H3K4me2, and H3K4me3) centered on the NDRs identified by HMMRATAC (red) and MACS2 (gray). **(D)** Nucleosome occupancy at GM12878-specific (left) and K562-specific (right) NDRs in GM12878 cell line (red) and in K562 cell line (blue). **(E)** The number of the NDRs identified by HMMRATAC in 431 samples grouped into 23 tumor tissues, 2 normal tissues, or PBMCs. The red horizontal dashed line indicates the peak count threshold for sample filtering. The filtered and total number of samples is denoted in parentheses. **(F)** Heatmap showing the average peak scores of the NDRs specific to each tissue group. The color intensity is proportional to the peak score. Source data are provided as a Source Data file.



Kernel size : [min=1, max=50, step=1] Node number : [min=10, max=100, step=5] Dropout rate : [min=0, max=0.5, step=0.05]

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MGI models Illumina models **Supplementary Fig. 3. Schematic of the training and prediction of genome and epigeno me models. (A)** Illustration of the genome and epigenome model structure and hyperparamet er space. **(B)** Schematic of the model training process using the training cohorts. Stratified fiv e-fold cross-validation method was used to train and evaluate the models for each training c ohort. At each split, the best hyperparameter that minimizes the validation loss was selected. Using the fixed hyperparameter, the model was trained 30 times and the model with lowest v alidation loss was chosen as the final model. **(C)** Schematic of the external prediction using t he validation cohorts. The validation cohorts were predicted using the five models trained wit h the training cohort. The average of five prediction values was used as the final prediction s core.



Supplementary Fig. 4. Validation performance of the cancer detection models trained wit h fixed hyperparameter in 30 different random states. (A-D) Validation loss and ROC-AUC of (A) the genome model of the MGI training cohort, (B) the epigenome model of the MGI t raining cohort, (C) the genome model of the Illumina training cohort, (D) the epigenome mo del of the Illumina training cohort. Bar plots (gray) represent ROC AUC of the validation set. Line plot (yellow) represent loss of the validation set. The red arrows indicate the final mode l with the minimum loss at the validation set. AUC, area under the curve; CV, cross validatio n. Source data are provided as a Source Data file.



Supplementary Fig. 5. Validation performance of the cancer localization models trained with fixed hyperparameter in 30 different random states. (A-D) Validation accuracy and lo ss of (A) the genome model of the MGI training cohort, (B) the epigenome model of the MG I training cohort, (C) the genome model of the Illumina training cohort and (D) the epigeno me model of the Illumina training cohort. Bar plots (gray) represent accuracy of the validatio n set. Line plot (yellow) represent loss of the validation set. The red arrows indicate the final model with the minimum loss at the validation set. ACC, accuracy; CV, cross-validation. Sour ce data are provided as a Source Data file.





**Supplementary Fig. 6. Performance of cancer detection on an external cohort. (A)** ROC c urve and **(B)** ROC-AUC table providing the 95% confidence interval for different models on th e DELFI dataset<sup>9</sup>. A total of 208 cacner and 214 normal control samples were used. **(C)** Sensit ivity values with the 95% confidence interval at 95%, 98%, and 99% specificity broken down by the tumor stage (left) and cancer type (right) for the DELFI dataset<sup>9</sup>. Confidence interval f or sensitivity value was calculated from 1,000 bootstraping samplings. **(A-C)** Our genome, epig enome, and combined models were compared with predictions based on fragmentation pattern s<sup>9</sup> (fragpattern), fragment size profiles<sup>8</sup> (fragsize), and copy number variations<sup>3</sup> (cnv). The gray ROC curve and bar graphs marked as DELFI correspond to the score provided by the authors<sup>9</sup> combining fragmentation with other features. auc, area under the curve; NA, stage informati on not available; CI, Confidence interval. Source data are provided as a Source Data file.



Supplementary Fig. 7. Sensitivity of cancer detection. (A-B) Sensitivity values with the 95% confidence interval at (A) 98% and (B) 99% specificity broken down by the tumor stage (left) and cancer type (right) on the MGI training cohort. (C-D) Sensitivity values with the 95% c onfidence interval at (C) 98% and (D) 99% specificity broken down by the tumor stage (left) and cancer type (right) on the Illumina training cohort. Confidence interval for sensitivity value was calculated from 1,000 bootstraping samplings. Our genome, epigenome, and combined models were compared with predictions based on fragmentation patterns<sup>9</sup> (fragpattern), fragme nt size profiles<sup>8</sup> (fragsize), and copy number variations<sup>3</sup> (cnv). NA, stage information not avail able. Source data are provided as a Source Data file.







fragsize model colon - 0.29 0.02 0.22 0.16 0.1 0.2 lung - 0.32 0.04 0.13 0.15 0.31 0.06 Besophagus - 0.26 0.04 0.24 0.21 0.18 0.07 ovary - 0.17 0.03 0.52 0.1 0.12 0.06 pancreas - 0.08 0.82 0.07 0.01 0.02 0 liver = 0.65 0.03 0.14 0.07 0.1 0.02

liver creas ovary sophagus

Predicted tissue

lung



Predicted tissue

genome model

lung = 0 0.02 0.08 0.08 0.04 0.79

pancreas = 0.06 0.11 0.02 0 0.76 0.05

t resophagus = 0.03 0.04 0.85 0.03 0.01 0.05

ovary = 0.05 0.01 0.01 0.92 0 0.01

liver = 0.08 0.81 0.03 0.04 0.03 0

breast - 0.93 0.03 0.02 0.01 0.01 0.01

liver sophagus ovary pancreas

1 I I I

Bung







Α

Supplementary Fig. 8. Confusion matrix for tissue-of-origin localization on the (A) MGI training cohort and (B) Illumina training cohort. The y-axis represents the actual site, and the x-axis represents the predicted site. The numbers in the cells of the matrix represent th e proportion of samples of each cancer type localized to respective tumor sites. Our genome, epigenome, and combined models were compared with predictions based on fragmentation pat terns<sup>9</sup> (fragpattern), fragment size profiles<sup>8</sup> (fragsize), and copy number variations<sup>3</sup> (cnv). Sourc e data are provided as a Source Data file.































fragsize model



epigenome model



fragsize model



Supplementary Fig. 9. Performance of tissue-of-origin localization using samples predicte d as cancer. (A) Average accuracy (left) and accuracy (right) on each cancer type for different t models on the MGI training cohort. (B) Average accuracy (left) and accuracy (right) on each cancer type for different models on the Illumina training cohort. (C-D) Confusion matrix for localization using the combined model on the (C) MGI training cohort and (D) Illumina training cohort. The y-axis represents the actual site, and the x-axis represents the predicted site. The numbers in the cells of the matrix represent the proportion of samples of each cancer type localized to respective tumor sites. (A-D) Our genome, epigenome, and combined models were compared with predictions based on fragmentation patterns<sup>9</sup> (fragpattern), fragment size profiles<sup>8</sup> (fragsize), and copy number variations<sup>3</sup> (cnv). Source data are provided as a Source D ata file.



Supplementary Fig. 10. Additional analyses of our model. (A-B) Correlation between cfDN A tumor fraction and prediction score of combined, genome and epigenome model of the (A) MGI training cohort and (B) Illumina training cohort. (C-D) Combined models of the MGI trai ning cohort and Illumina training cohort were used to predict the external cohort dataset. (C) ROC curve for the external cohort prediction. The combined model of the MGI training coho rt was used to predict the Illumina training cohort, Illumina validation cohort and DELFI coh ort (left). The combined model of the Illumina training cohort was used to predict the MGI t raining cohort, MGI validation cohort and DELFI cohort (right). (D) Density scatter plots whic h represent the relationship between the prediction score of the MGI trained model and the I llumina trained model on the MGI training cohort (left) and Illumina training cohort (right). The red dots indicate the density of cancer patient samples. The blue dots indicate the densit y of normal control samples. (E-F) Downsampled cfDNA WGS (3x, 1x) were compared with th e original cfDNA WGS (5x) of the MGI training cohort. (E) ROC curve and (F) Sensitivity valu es with the 95% confidence Interval at 95%, 98%, 99% specificity for the different depth mod els of the MGI training cohort. Confidence interval for sensitivity value was calculated from 1 ,000 bootstraping samplings. Illu train, Illumina training cohort; Illu vali, Illumina validation c ohort; MGI train, MGI training cohort; MGI vali, MGI validation cohort. Source data are provi ded as a Source Data file.





**Supplementary Fig. 11. Additional interpretation of the genome model. (A)** LMD values o btained from tumor tissues in the LVD regions with positive or negative attribution for cance r samples in the genome model for cancer detection on the Illumina training cohort. *P* values from the Wilcoxon test are indicated (two-sided). Each box indicates IQR and median, whisk ers indicates 1.5 x IQR, black dots indicates outlier. **(B)** Distribution of the attribution values assigned by the cancer localization genome model of the Illumina training cohort to high or low LMD regions in comparison to other regions of the PCAWG cancer type matching the giv en prediction label. **(C)** The same plot as Fig. 5B and Supplementary Fig. 11B, broken down b y cancer types for the MGI training cohort (left) and Illumina training cohort (right). Box ele ments are same as (A). **(D)** Comparison of the attribution values assigned by the cancer local to high (upper) or low (lower) LMD regions of the PCAWG cancer type s matching with the given prediction label. Source data are provided as a Source Data file.





**Supplementary Fig. 12. Additional interpretation of the epigenome model. (A)** Attribution values of the tissue-specific V-plots of the epigenome model for cancer detection on the Illu mina training cohort. The average attribution values across the tissue-specific V-plots are com pared for cancer samples (left) and normal samples (right). (B) Distribution of the normalized attribution values according to fragment size. (C) Attribution values mapped to the tissue-specific V-plots of the epigenome model for tissue-of origin localization on the Illumina training cohort. The average attribution values across the tissue-specific V-plots are shown for each ca ncer type. (D) Attribution values of the epigenome model for cancer localization on the Illumina training (bl ue) cancer types, and plotted according to the distance from the NDR midpoints. Attribution values were smoothed using lowess regression. (E) The sample plot as (D) broken down by ca ncer types. Source data are provided as a Source Data file.