Supplemental Online Content

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This supplemental material has been provided by the authors to give readers additional information about their work.

eMethods

Patient cohorts and genomic data collection

Germline whole-exome sequencing (WES) data of a convenience cohort of 1072 patients with prostate cancer were used for the initial performance evaluation of Genome Analysis ToolKit (GATK) and DeepVariant (DV) (Figure 1 and eFigure 1). These patients were sequenced as part of large cancer genomics sequencing projects including the Cancer Genome Atlas (TCGA) and the Stand Up 2 Cancer-Prostate Cancer Foundation (SU2C-PCF) studies [1-3]. Details of the clinical and molecular data of these patients have been previously described [3]. Raw sequencing data of these patients are accessible through dbGAP (https://www.ncbi.nlm.nih.gov/gap/). Tumor WES data of 268 PC patients were available for somatic validation of the detected germline putative loss-of-function (pLOF) variants in the OMIM genes as well as the 12 multi-gene panels.

To evaluate if variant detection performance findings of GATK and DV, on the prostate cancer cohort, extends to other histopathological and clinical phenotypes, we used germline WES data of an independent convenience cohort of 1295 patients with primary or metastatic melanoma from 10 previously published studies including the Cancer Genome Atlas [4], Hodis et al., 2012 [5], Hayward et al., 2017 [6], Krauthammer et al., 2015 [7], Van Allen et al., 2014 [8], Snyder et al., 2014 [9], Wagle et al., 2014 [10], Van Allen et al., 2015 [11], Johnson et al. 2017 [12], and Miao et al., 2018b [13] (Figure 1 and eFigure 1). Germline data of these patients were generated by sequencing circulating lymphocytes or adjacent normal tissue which had a normal histopathological examination. In addition to the germline genomic data of these patients, paired tumor WES data from 286 patients with prostate cancer and all patients with melanoma were used for secondary analyses to validate the presence of germline pLOF variants that were detected in the germline samples. All cohorts had institutional review board (IRB) approval for access from the original studies. All germline WES data were generated by the original studies using paired-end, short-read Illumina platforms (Illumina, Inc, San Diego, USA).

Data harmonization and quality control

Raw genomic data of all samples were obtained from the respective data repository, as previously described [3]. All "FASTQ" and binary alignment map (BAM) files aligned to GRCh37 were realigned to hg19 using "Picard tool kits (https://github.com/broadinstitute/picard). GATK (version 3.7) DepthOfCoverage [14] was used to determine the mean target coverage of germline and tumor samples, and deTiN [15] was used to estimate the degree of tumor-in-normal contamination. A genetic relatedness method was run on the germline samples of the prostate cancer and melanoma cohorts to exclude potential duplicates. The final sample sets (PC: 1072 patients, melanoma: 1295 patients) of this study only included unique unrelated samples. For the discovery analysis, we applied stringent quality control (QC) steps. Germline WES with a sample-wide mean depth of coverage under 20X or those with significant tumor-in-normal (TiN) contamination were excluded from all analyses. All germline WES of 1072 PC patients used for the discovery analysis passed all QC metrics (eFigure 2 A-C). To mimic challenging genomic analysis scenarios, we validated our findings using a heterogenous germline WES dataset of 1295 patients with melanoma who were sequenced at multiple time

points using different sequencing platforms with variable quality and depth of sequencing (eFigure 2 D-F).

Detection of germline variants

To evaluate the performance of GATK, the standard germline variant detection method, against the deep learning-based method, DeepVariant (DV), we ran both algorithms on the germline WES data of the prostate cancer and melanoma cohorts (Figure 1 and eFigure 1). For each sample, the same BAM file was used to run GATK and DV without any further preprocessing. 1- GATK:

Genome Analysis Toolkit (GATK) HaplotypeCaller (HC) pipeline (version 3.7) was used to call germline variants according to the GATK "Best Practices" [16]. More specifically, we ran GATK HC on each sample individually to call single nucleotide variants (SNVs) and short indels via the de-novo assembly of haplotypes of the examined regions. This per sample analysis generates an intermediate file called genomic variant calling format (gVCF) file that has a record for every position of the examined genomic intervals. We then aggregated the generated single sample gVCFs and performed joint genotyping using GATK "GenotypeGVCFs" as recommended by the current germline variant calling Best Practices [14,16]. At each position of the input gVCFs, GATK "GenotypeGVCFs" module evaluates the genotype likelihood across all the samples and produce one quality score for each unique genomic alteration across the cohort (n=1072 for the prostate cancer cohort and n=1295 for the melanoma cohort), which is then used by the GATK "Variant Quality Score Recalibration (VQSR)" module to assign a "Quality Tranche to each variant and perform variant filtering. To filter low-quality calls, VQSR uses highly validated variant callsets (such as dbSNP and the 1000 Genomes) to build a model that can be then applied to calculate the probability of each variant being real. As recommended by the GATK Best Practices, the SNVs VQSR model was trained using HapMap3.3 and 1KG Omni 2.5 SNP sites, and a 99.6% sensitivity threshold was applied to filter variants. In addition, Mills et. al. 1KG gold standard and Axiom Exome Plus sites were used for VQSR indel recalibration using a 99% sensitivity threshold [17]. Specific commands and parameters used for the GATK pipeline are summarized in the Supplementary Note.

2- DeepVariant:

Germline variants of the prostate cancer and melanoma cohorts were also independently called using DeepVariant version 0.6.0 (eFigure 1). DeepVariant is a deep convolutional neural network, based on the inception framework, trained to identify inherited variants from read pileup pseudo-images. We ran DeepVariant using recommended settings for the analysis of exomes (https://github.com/google/deepvariant). First, candidate variants were identified within the targeted sequencing region using "make examples." Next, candidate variants were classified through the "call variants" module, using the saved Exome checkpoint for version 0.6.0, and "postprocess_variants" was run to format the VCF file. All computation was performed on the Google Cloud Platform, and Nvidia K80 GPUs were used to perform inference. Specific commands used for the DV and its parameters are summarized in the Supplementary Note.

Selection of Mendelian gene sets

In this study, we analyzed disease-causing variants in three gene sets, the germline cancer predisposition genes, the American College of Medical Genetics (ACMG) genes, and the Online Mendelian Inheritance in Men (OMIM) genes. The germline cancer predisposition genes were selected based on the level of evidence supporting their Mendelian disease susceptibility. This is composed of the well-curated COSMIC germline cancer census gene set (v86; http://cancer.sanger.ac.uk/census) and the germline cancer gene set listed in Huang et al. 2018 [18] and Rahman 2014 [19]. Cancer genes with preliminary evidence of cancer association or those with no established inheritance pattern were removed. In total, 118 cancer predisposition genes were examined in the prostate cancer and melanoma cohorts (eTable 1). In addition to cancer genes, we also examined 59 Mendelian high-penetrance genes associated with severe life-threatening diseases that have been deemed clinically actionable by the American College of Medical Genetics (ACMG) (eTable 1). Given the well-established clinical utility, pathogenic variants in the ACMG genes are highly recommended to be disclosed to patients, even if discovered incidentally, regardless of the patient's phenotype [20]. Finally, we also expanded our head-to-head comparison of the examined methods by performing an exome-wide analysis of the clinically relevant genes by evaluating putative loss-of-function (pLOF) variants in 5197 Mendelian disease-causing genes in the OMIM database (collectively called the OMIM genes) (eTable 1) (https://www.omim.org/). In addition to these three gene sets, we also evaluated the number of validated pathogenic variants detected by each method in 12 multi-gene panels clinically used to evaluate cardiovascular disorders, ciliopathies, dermatological disorders, hearing loss, hematological disorders, mitochondrial disorders, neurological disorders, neuromuscular disorders, pulmonary disorders, renal disorders, retinal disorders, and expanded prenatal screening (eTable 2).

Functional annotation

Germline variant annotation of all variants was performed using Variant Effect Predictor (VEP) (version 92.0) from Ensembl [21]. Only variants impacting the canonical transcript of the examined genes were included.

Ancestry inference

To infer the genetic ancestry of the prostate cancer and melanoma samples, we first performed principal-component analysis (using hail v0.2- https://hail.is/docs/0.2/index.html) and uniform manifold approximation and projection (using umap v0.4.3- https://pypi.org/project/umap-learn/) on these samples and 1000G reference samples. Next, we trained a Random Forest classifier (using sklean v0.20.0- https://scikit-learn.org/stable/whats_new/v0.20.html#version-0-20-0) on the first 10 principal components and UMAP values from 2504 participants in the 1000 Genome cohort that have self-reported ancestry information. We then used the trained random forest classifier to assign one of the five 1000 Genome defined super populations - European, African American, Admixed American, East Asian, and South Asian - to each of our prostate cancer and melanoma samples. A more detailed description of subpopulations included in 1000 Genome continental ancestries be found here. can https://www.internationalgenome.org/category/population/.

Germline variant pathogenicity evaluation

Pathogenicity of the detected germline variants in the cancer predisposition and ACMG gene sets across all cohorts was evaluated using the American College of Medical Genetics and Genomics (ACMG) and the Association for Molecular Pathology (AMP) clinically-oriented guidelines [22]. Germline variants detected by GATK and DV in the prostate cancer and melanoma cohorts were independently evaluated for pathogenicity, by two clinical geneticists, against the published literature and publicly-available databases such as ClinVar and gene-specific databases. Population minor allele frequencies were extracted from publicly-available databases such as the Exome Aggregation Consortium (ExAC) and the Genome Aggregation Database (gnomAD) [23]. Based on the available evidence, germline variants were classified into five categories: benign, likely benign, variants of unknown significance, likely pathogenic, and pathogenic [22]. Only germline variants that had sufficient evidence of pathogenicity to be classified as pathogenic or likely pathogenic variants were included in this study (hereafter collectively referred to as pathogenic variants). Variants of unknown significance (VUSs) were excluded from all analyses. For the expanded analysis using 5197 OMIM genes, we analyzed the performance of each germline variant detection tool by examining putative LOF (pLOF) variants in this expanded gene set. Putative LOF variants were defined as 1) rare variants with minor allele frequency (MAF) <1% in all reference populations in gnomAD that are expected to produce a truncated gene product (i.e., stop codon, frameshift, and canonical splice site variants) and 2) rare missense variants (MAF<1%) that are annotated as pathogenic or likely pathogenic in the Clinical Variation database (ClinVar) (https://www.ncbi.nlm.nih.gov/clinvar/).

Validation of detected germline variants

1- Manual review of the variants using a genome browser:

Pathogenic germline variants in the germline cancer predisposition and ACMG gene sets, that were detected by the standard variant detection method and deep learning, were validated by examining the Binary Alignment Map (BAM) file using the integrative Genomics Viewer (IGV; v2.3.81) (Figure 1) [24]. IGV snapshots of pathogenic variants were generated using the IGV Snapshot Generator (https://github.com/stevekm/IGV-snapshot-automator). IGV snapshots of each called pathogenic variants (in the cancer predisposition and ACMG gene sets) were independently manually evaluated, in a blind fashion, by three computational biologists with expertise in next-generation sequencing analysis. Variants were marked as "True Positive" or "False Positive," depending on the depth of sequencing, the number of alternative allele reads, the variant allelic fraction (VAF), and the presence of artifacts at or around the examined variant site. Variants that were called "True Positive" by at least two examiners were considered real variants. Otherwise, the variant was labeled as an artifactual call.

2- Tumor-profiling:

Although the manual review of the IGV snapshot of detected variants is considered the standard protocol for variant review [24], this method is not easily scalable to validate detected pLOF variants in 5197 clinically-relevant protein-coding genes. To examine the validity of variants across the clinically relevant OMIM genes, germline pLOF variants exclusively called by a single method (i.e. only GATK or DV) were validated using the matched tumor samples (Figure 1). We followed the following process to validate candidate germline variants using tumor sequencing $data:$

- 1. Collected tumor base-pair counts using Samtools [25].
- 2. Determined if the tumor sequencing depth is sufficient to identify three or more alternate reads given the observed reads in the normal tissue sample.
	- a. For sites without a somatic copy number alteration event, this power was computed using the beta-binomial distribution; a site was considered powered if $p(X > 3 | N,a,b) > 0.95$. Where a and b are the normal alternate and reference counts, respectively, and N is the sequencing depth in the tumor.
	- b. For sites with somatic copy number alterations, power was computed using the binomial distribution were sites were considered powered if $p(X>=3 | N, p) > 0.95$ where N is the sequencing depth of the tumor and p is the minor allele fraction of the overlapping copy number segment.
- 3. If the tumor is sequenced sufficiently deeply, the site is considered validated if 3 or more alternate reads supporting the variant were found in the tumor; otherwise, the site is called a "False Positive".

For the prostate cancer cohort (n=1072), only 286 tumor WES data were available for tumor-based validation, while all matched tumor samples of the melanoma cohort (n=1295) were available for this analysis.

Performance metrics

We evaluated the ability of the standard variant detection method. GATK, and deep learning. DV, to detect clinically relevant variants in the cancer predisposition genes, the ACMG genes, and the OMIM genes. For each gene set, we looked at the absolute number of manually validated pathogenic germline or computationally validated pLOF variants called by each method. We also evaluated the sensitivity (also known as the true positive rate or recall) of each method by looking at the proportion of validated variants detected by that method to the total number of real pathogenic variants detected by the combined approaches in that gene set (eTable 3). Similarly, the specificity (also known as the true negative rate) of GATK and DV were calculated as the proportion of validated negative calls (i.e. correctly identifying the reference allele as such) by each method relative to the total number of true reference (non-variant) alleles in that gene set. The reference variant set that was used to compare GATK and DV performance in this study was created through manual review of IGV snapshots (see Validation of detected germline variants). In addition, we looked at precision, defined as the proportion of correctly called variants to the total number of called variants, and accuracy, which is defined as the ratio of the total number of correct assignments (i.e., true positive and true negative) to the total number of all evaluated variants [26]. In addition, for each method, we evaluated the positive predictive value (PPV), defined as the probability of a called variant being a validated "real" variant, and negative predictive value (NPV), defined as the probability of a called reference allele being a truly reference allele (i.e., not an alternative variant). Finally, we looked at the absolute number of validated variants that were detected by the standard approach and deep learning in 12 commonly used multi-gene panels (eTable 2).

Characteristics of variants exclusively detected by DV or GATK

To evaluate the properties of variants exclusively detected by deep learning and the standard method, the sequencing depth of true positive and false positive variants exclusively called by DV and GATK was compared using the non parametric Mann–Whitney tests. In addition, we calculated the likelihood of each variant category (frameshift, stop codon, and splice variants) to be correctly identified by deep learning and standard methods by generating odds ratios (ORs), 95% CI and P values using two-sided Fisher's exact test.

Post hoc analysis for adopting a more stringent criterion (3 of 3 examiners) for "true-positive" variants

To evaluate the effect of defining "True-Positive" variants as variants that were judged to be valid variants by all three examiners on the primary outcomes of this study (see Validation of detected germline variants), the absolute number and fraction of manually validated pathogenic variants in the cancer-predisposition genes were calculated. The sensitivity of each method was calculated by assessing the fraction of true-positive variants to the total number of detected variants (true-positives and false-positives). The sensitivity values of both methods were compared using two-sided Chi-square tests.

Calculation of the Receiver Operating Characteristics (ROC) curve

For both models, DV and GATK, a set of potential thresholds of the quality scores (QUAL for GATK, and GQ for DV) are calculated for the called variants. For each threshold (th) in the thresholds set, a new model prediction is calculated (a variant is called if QUAL>th). The new predictions are compared to the ground truth (present in the BAM file or not) and the True positive (TP), True Negatives (TN), False Positive (FP), and False Negative (FN) rates are calculated. The true positive rate is calculated as the number of true positives divided by the sum of the number of true positives and the number of false negatives:

True Positive Rate (TPR) = True Positives (TP) / (True Positives (TP) + False Negatives (FN))

The false-positive rate is calculated as the number of false positives divided by the sum of the number of false positives and the number of true negatives:

 $(FPR) =$ False Positive Rate False Positives (FP) / (False Positives (FP) + True Negatives (TN))

The Receiver Operator Curve (ROC) is reported by plotting the false positive rate (FPR) on the X-axis and the true positive rate (TPR) on the Y-axis. The area under the ROC curve (AUC) is calculated for both DV and GATK models.

eFigures:

eFigure 1: Technical overview of the preprocessing, variant calling, and variant analysis steps.

^a Binary Alignment Map (BAM) files are highly compressed files that are used to represent aligned sequencing reads. They are the most commonly used input format for variant detection and other downstream analyses

 b Variant Quality Score Recalibration (VQSR) is a step in GATK, the standard germline variant detection pipeline, that determines the quality of each identified variant. The generated quality scores are subsequently used for downstream variant filtration

 \degree Variant Call Format (VCF) files are the most widely used files to store variants and their functional annotations for sequenced individual samples and cohorts of samples

 d Ensemble Variant Effect Predictor (VEP) is an annotation tool that provides the functional impact, the conservation scores, and the population level minor allele frequency of each identified germline variant

eFigure 2: Sequencing and quality control (QC) metrics of the prostate cancer (A, B, and C) and melanoma (D, E, and F) cohorts. A; The exome-wide depth of coverage for germline WES of the prostate cancer cohort was 105.78X (interquartile range: 78.00-162.64). B; The average coverage of the cancer predisposition genes in patients with prostate cancer was 122.78X. C: The mean tumor-in-normal contamination of the prostate cancer germline data was 0.7%. D&E; The sample-wide and cancer gene average depth of coverage in the melanoma cohort were 86.85X (interquartile range: 70.55-115.90) and 92.07X, respectively. F; The mean tumor-in-normal contamination of the melanoma cohort samples was 1.0%.

eFigure 3: Exome-wide germline variant detection in 1072 germline samples of patients with prostate cancer. A; only 92.1% of all detected germline variants were called by both the standard (GATK) and deep learning (DV) methods, while 2,953,059 variants were exclusively detected by one of these approaches. B; Of 559,011 unique genomic sites with potential variants that were detected by one or both methods, only 475,124 (85.0%; 95% CI:84.9-85.1) of these genomic sites were concordant between both variant detection tools. C; Number of genomic sites evaluated by the high-sensitivity initial variant detection step of each algorithm ("HaplotypeCaller" for GATK and "Call Variants" for DV). Although both tools aim to flag any site suspected of having a non-reference variant for downstream analysis, most of the sites included for further analysis by DV were not flagged by GATK HaplotypeCaller for further assessment, suggesting multiple modes for variant underdetection. D; Compared to 7,651 unique genetic variant sites exclusively detected by the standard method, nearly 40,000 unique genetic variant sites were exclusively detected by deep learning.

eFigure 4: Pathogenic cancer-predisposition variants discovered in 1295 patients with melanoma. A: A total of 209 pathogenic cancer-risk variants were only identified by the standard method, GATK, in 118 cancer predisposition genes in the melanoma dataset. However, only 32 of these were validated true positive variants. B; A total of 171 pathogenic variants were identified exclusively by deep learning in the cancer-predisposition genes, 51 of which were validated true positive variants.

eFigure 5: A representative pathogenic predisposition variant in the succinate dehydrogenase complex, subunit A (SDHA) gene that was only detected by deep learning but not standard variant calling methodology. A; An IGV snapshot of the variant showed adequate sequencing coverage and a balanced variant allelic fraction (VAF) in both the germline sample (top panel) and the tumor sample (bottom panel). B; This truncating variant in SDHA (c.1534C>T; p. Arg512Ter) introduces a stop codon leading to the termination of the gene transcript at codon 512 and is known to be pathogenic in the ClinVar database (https://www.ncbi.nlm.nih.gov/clinvar/variation/VCV000371805.3 [accessed Sept. 3, 2019]). In addition, this variant has been frequently seen in patients with paraganglioma, pheochromocytoma, and gastrointestinal stromal tumors (PMIDs: 22955521, 371805, 25720320).

eFigure 6: Effect of considering true positive variants as variants that were considered "valid" by all three examiners. This post hoc analysis showed that although the absolute number and fraction of true positive variants dropped when adopting a more stringent criterion for true positive calls, DV still detected more "true-positive" variants compared to GATK across all cohorts.

E Figure 7: Performance of GATK and DV models to detect pathogenic variants in 151 cancer predisposition and ACMG genes in 1072 patients with prostate cancer. (AUC: Area under the curve, AuPR: Area under precision-recall)

eFigure 8: Performance of GATK and DV models to detect pathogenic variants in 151 cancer predisposition and ACMG genes in 1295 patients with melanoma. (AUC: Area under the curve, AuPR: Area under precision-recall)

eFigure 9: Performance of the deep learning and standard methods to detect pLOF variants that were judged to be valid in 12 clinically oriented multi-gene panels. A; Analysis of 286 patients with prostate cancer using the deep learning method, DV, identified more pLOF variants that were judged valid (Method) in 11 (91.7%; 95% CI: 61.5-99.8) of the 12 phenotype-targeted multi-gene panels that were evaluated. DV and GATK, the standard method, detected the same number of pLOF variants in one multi-gene panel $(8.3\%; 95\% \text{ Cl:})$ 0.21 -38.5). B; Similarly, analysis of these multi-gene panels in 1295 patients with melanoma showed that the deep learning method identified more pLOF variants, that were judged valid, in 9 panels $(75.0\%; 95\% \text{ Cl}: 42.8-94.5)$ compared with 2 $(16.7\%; 95\% \text{ Cl}: 2.1-48.4)$ panels where the standard method detected more pLOF variants that were judged valid while both methods had equal performance in one panel $(8.3\%; 95\% \text{ Cl: } 0.21\text{-}38.5)$. Full names of these clinical multi-gene panels are listed in eTable 2. (DV: DeepVariant, GATK: The Genome Analysis Toolkit, and pLOF: putative loss-of-function)

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eFigure 11: Characteristics of validated germline pathogenic variants in 151 ACMG and cancer predisposition genes. Regardless of the functional class of the germline pathogenic variants in these genes, DV identified more manually validated pathogenic variants in patients with prostate cancer (A) and those with melanoma (B). C; Validated pathogenic frameshifts and splice variants, exclusively detected by deep learning in both cohorts, were more likely to be deemed "valid" variants upon manual evaluation compared to those exclusively called by the standard method (OR=2.79; 95%Cl:1.47-5.29; P=0.001 and OR=3.04; 95%Cl:1.39-6.73; P=0.004 for frameshifts and splice variants respectively; two-sided Fisher's exact).

eFigure 12: Depth of sequencing coverage of pathogenic variants exclusively called by deep learning and the gold-standard method in 151 cancer predisposition and ACMG genes. False-positive variants exclusively called by deep learning were in significantly lower coverage genomic regions compared with DV-only validated true positive variants (A & B). However, false-positive variants exclusively called by the standard method had sufficient sequencing coverage which was comparable to the sequencing coverage of the GATK-only true positive calls (C & D), raising concern about additional sources of false-positive calls. E & F; Comparison of the sequencing depth of coverage of false-positive variants exclusively called by deep learning and those exclusively called by the standard method.

eFigure 13: Performance of the standard method, GATK, and deep learning, DV, for detecting common, uncommon, and rare variants (minor allele frequency (MAF) of >5%, 1-5%, and <1% respectively). A; Our analysis shows that deep learning called 1.3% and 2.1% more common (MAF>5%) and uncommon variants (MAF:1-5%), respectively, than the standard method in 1072 germline prostate cancer exomes. However, deep learning identified 53,161 (12.7%) more rare variants (MAF<1%) than the standard approach in this dataset, suggesting a substantially higher performance of deep learning towards detecting this variant subset which is highly enriched for Mendelian disease-causing variants. B; A similar pattern of substantially higher detection rate of rare variants was also seen when analyzing germline WES data of 1295 patients with melanoma.

Supplementary Tables:

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eTable4: Pathogenic and likely pathogenic variants exclusively detected by deep learning in the cancer predisposition genes in 1072 prostate

eTable5: Pathogenic and likely pathogenic variants exclusively detected by the standard method, GATK, in the cancer predisposition genes in 1072 prostate cancer patients.

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eTable6: Pathogenic and likely pathogenic variants exclusively detected by the standard method in the cancer predisposition genes in 1295 melanoma patients.

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eTable10: Pathogenic and likely pathogenic variants exclusively detected by the standard method in the ACMG genes in 1295 melanoma

eTable11: Pathogenic and likely pathogenic variants exclusively detected by deep learning in the ACMG genes in 1295 melanoma patients.

eTable12: Performance of the standard and deep learning models in 1072 and 1295 patients with prostate cancer and melanoma using the ACMG and the cancer predisposition gene sets.

eNotes:

1- Genome Analysis Toolkit (GATK) pipeline

Genome Analysis Toolkit (GATK) HaplotypeCaller (HC) pipeline (version 3.7) was used to call germline variants according to the GATK Best Practices. The following steps and commands were followed:

1. HaplotypeCaller (HC): this command is run on each sample individually:

```
java -Xmx12G -jar ~/GenomeAnalysisTK.jar \
-nct 8 \
-T HaplotypeCaller \
-R ~/Homo sapiens assembly19.fasta \
-I [single.sample.bam] \
--dbsnp ~/dbsnp 138.hq19.vcf.qz \
--genotyping mode DISCOVERY \
-variant index type LINEAR \
-variant index parameter 128000 \
--emitRefConfidence GVCF \
--max alternate alleles 6 \
--minPruning 2-stand call conf 30.0 \
-A DepthPerSampleHC \
-A StrandBiasBySample \
-A Coverage \setminus-A StrandBiasBySample \
-o ~/[single.sample].gvcf.gz
```
2. Joint genotyping (GenotypeGVCFs): this step combines all the gVCFs that were generated by the previous step to do cohort-wide genotyping:

```
java -jar -Xmx32G ~/GenomeAnalysisTK.jar \
-R ~/Homo sapiens assembly19.fasta -T GenotypeGVCFs \
--variant ~/[list of all qVCFs].list \
-L \sim / [capture region]. interval list \
-o ~/[cohort].gvcf.gz
```
3. VariantRecalibration (SNPs):

```
java -Xmx24G -jar ~/GenomeAnalysisTK.jar \
-T VariantRecalibrator \
-R ~/Homo sapiens assembly19.fasta \
-input \sim/[cohort].qvcf.qz \
-resource: hapmap, known=false, training=true, truth=true, prior=15.
0 \sim/hapmap 3.3.b37.vcf \
-resource: omni, known=false, training=true, truth=true, prior=12.0
\sim/1000G omni2.5.b37.vcf \
```

```
-resource: 1000G, known=false, training=true, truth=false, prior=10.
0 ~/1000G phase1.snps.high confidence.b37.vcf \
-resource: dbsnp, known=true, training=false, truth=false, prior=2.0
\sim/dbsnp 138.b37.vcf \
-an QD -an MQRankSum -an ReadPosRankSum -an FS -an MQ -an
InbreedingCoeff \
-mode SNP \
-tranche 100.0 \
-tranche 99.9 -tranche 99.9 -tranche 99.8 -tranche 99.7
-tranche 99.6 -tranche 99.5 \
-tranche 99.4 -tranche 99.3 -tranche 99.2 -tranche
                                                          99.1
-tranche 99.0-tranche 98.9 -tranche 98.8 -tranche 98.6 -tranche 98.5
-tranche 98.3-tranche 98.2
              -tranche 98.1 -tranche 98.0 -tranche 97.9
-tranche 97.8-tranche 97.5 -tranche 97.0 -tranche 95.0 -tranche 90.0 \
-recalFile ~/[cohort].SNP.recal \
-tranchesFile ~/[cohort].SNP.tranches \
-rscriptFile ~/[cohort].SNP.R \
-nt 4
```
4. Apply recalibration (SNP):

```
java -jar -Xmx24G ~/GenomeAnalysisTK.jar \
-T ApplyRecalibration \
-R ~/Homo sapiens assembly19.fasta \
-input \sim/[cohort].qvcf.qz \
--ts filter level 99.6 \
-tranchesFile ~/[cohort].SNP.tranches \
-recalFile ~/[cohort].SNP.recal \
-mode SNP \
-o ~/[cohort].snp.recalibrated.vcf.gz
```
5. VariantRecalibration (INDELs):

```
java -jar -Xmx24G ~/GenomeAnalysisTK.jar \
-T VariantRecalibrator \
-R ~/Homo sapiens assembly19.fasta \
-input ~/[cohort].gvcf.gz \
-tranche 100.0 \setminus-tranche 99.9 -tranche 99.9 -tranche 99.8 -tranche
                                                            99.7
-tranche 99.6 -tranche 99.5 \
-tranche 99.4 -tranche 99.3 -tranche 99.2 -tranche
                                                            99.1
-tranche 99.0 \setminus
```

```
-tranche  98.9 -tranche  98.8 -tranche  98.6 -tranche  98.5
-tranche 98.3-tranche 98.2 -tranche 98.1 -tranche 98.0 -tranche 97.9-tranche 97.8 \
-tranche 97.5 -tranche 97.0 -tranche 95.0 -tranche 90.0 \
-resource: mills, known=false, training=true, truth=true, prior=12.0
\sim/Mills and 1000G gold standard.indels.b37.vcf \
-resource:dbsnp, known=true, training=false, truth=false, prior=2.0
\sim/dbsnp 138.b37.vcf \
-an FS -an QD -an MQRankSum -an ReadPosRankSum -an
InbreedingCoeff \setminus-mode INDEL \
-recalFile ~/[cohort].INDEL.recal \
-tranchesFile \sim/ [cohort]. INDEL. tranches \
-rscriptFile \sim/[cohort] .INDEL.R \setminus-nt 4
```
6. Apply recalibration (INDELS):

```
java -jar -Xmx24G ~/GenomeAnalysisTK.jar \
-T ApplyRecalibration \
-R \sim/Homo sapiens assembly19.fasta \
-input \sim[cohort].snp.recalibrated.vcf.gz \
--ts filter level 99.0 \
-tranchesFile ~/[cohort].INDEL.tranches \
-recalFile ~/[cohort].INDEL.recal \
-mode INDEL \
-o ~/[cohort].snp.recalibrated.indel.recalibrated.vcf.qz
```
2- DeepVariant Pipeline

DeepVariant version 0.6.0 was used to call variants on the same sample cohorts as follows:

1. Make examples:

```
\sim/deepvariant/bin/make examples \
--mode calling \
--ref ~/Homo sapiens assembly19.fasta \
--reads \sim [single.sample].bam \
--examples ~/[single.sample].examples.tfrecord \
--regions ~/[capture region].interval list
```
2. Call variants:

```
\sim/deepvariant/bin/call variants \
--outfile call variants output.tfrecord \
--examples ~/[single.sample].examples.tfrecord \
```
--checkpoint models/model.ckpt

3. Postprocess variants:

 \sim /deepvariant/bin/postprocess_variants \ --ref ~/Homo_sapiens_assembly19.fasta \ --infile call_variants_output.tfrecord \ --outfile [single.sample].vcf

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