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Ultrafast WGS protocol

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We use this protocol and it's working

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Abstract

Ultra-Fast Whole Genome Sequencing (UF-WGS) offers rapid, comprehensive molecular profiling in paediatric haematology-oncology, enabling critical improvements in diagnosis and patient management. In a prospective study of 54 children with suspected or confirmed cancer, UF-WGS reduced turnaround time from 37 to 3 days versus standard NHS practice and captured 95% of all clinically actionable variants found by conventional methods. UF-WGS also identified 19 additional actionable variants, leading to demonstrable improvements in care for 51% of prospective patients, including avoidance of over-medicalisation and support for timely precision therapy. UF-WGS was feasible across diverse tumour types and sample sources, with additional technical advantages in variant detection and workflow simplicity. These results support UF-WGS as a transformative single-test approach in paediatric oncology, facilitating safer, more rapid allocation of targeted treatment and precise risk stratification.

Materials

QIAmp Blood DNA Mini kit, MagAttract® HMW DNA kit (Qiagen, Germany), Qubit dsDNA BR Assay kit (ThermoFisher Scientific), genomic DNA ScreenTape assay (Agilent Technologies)

KEY RESOURCES TABLE

RESOURCE	SOURCE	IDENTIFIER
Deposited Data		
Raw 26 Processed Data	This study	Available upon request

Software and Algorithms		
R	R-Core Team	v4.5.0
RStudio	Posit	v2025.05.0+496
readxl	CRAN	v1.4.5
dplyr	CRAN	v1.1.4
ggplot2	CRAN	v3.5.2
ComplexHeatmap	Bioconductor	v2.24.0
circlize	CRAN	v0.4.16
stringr	CRAN	v1.5.1
rvest	CRAN	v1.0.4
reshape2	CRAN	v1.4.4
grDevices	R-Core Package	v4.5.0
grid	R-Core Package	v4.5.0
Analysis Scripts	This study	See METHOD

DNA extraction		
QIAmp Blood DNA Mini kit	Qiagen	
MagAttract® HMW DNA kit	Qiagen	
Qubit dsDNA BR Assay kit	Thermofisher	
DNA ScreenTape assay	Agilent Technologies	

Sequencing data alignment and variant calling		
DRAGEN somatic pipeline	version 4.0	
DRAGEN somatic pipeline	version 4.2	
DRAGEN germline pipeline	4.2	
Nirvana	version 3.9.0	

Annotation and Variant Filtering

- 1 Germline and somatic variants were annotated by Nirvana version 3.9.0 using the Ensembl 91 transcript reference database. Pertinent variants, other than pharmacogenomic variants, were triaged via consequence annotations (SO terms): feature elongation, non-synonymous coding sequence variant, unidirectional gene fusion, bidirectional gene fusion, transcript ablation, canonical splice acceptor/donor variants, stop gained, transcript truncation, frameshift variant, stop lost, start lost, transcript amplification, in-frame insertion, in-frame deletion, missense variant, protein altering variant, splice region variant, incomplete terminal codon variant, copy number increase, copy number decrease, copy number change, transcript variant. Somatic and germline structural variants, other than inter-chromosomal translocations, were considered only if they would disrupt the exons of one of the genes or were located within its promoter region.
Pertinent germline and somatic variants were triaged further using gene and genomic region of interest list provided for each cancer and/or variant type. In the case of no findings, the list was extended to COSMIC cancer gene census v83 (<https://www.sanger.ac.uk/data/cancer-gene-census/>).

These analyses focused primarily on data aggregation and visualization rather than formal statistical testing. The core of the method involved transforming data from a long format into wide-format matrices suitable for heatmaps. This was achieved using functions like dcast or by transposing the data frame. The resulting matrices contained values indicating the detection of a variant in an assay or platform (1 for presence, 0 for absence in Analysis 1, and 1 for UF and GMS concordance, 0.5 for UF additional variants and 0 for GMS additional variants in Analyses 2).

No statistical clustering was performed. Instead, the rows and columns of the heatmaps were explicitly ordered based on predefined factors such as Variant type and Diagnosis Subgroup to facilitate qualitative comparisons between groups and platforms.

Variant Allele Frequency (VAF) Analysis

- 2 This analysis was performed using an Excel file containing patient data, diagnostic subgroups, and genetic variant data – including variant type and variant allele frequency (VAF) – for both Solid and Haematological cancer types across the GMS WGS and UF WGS platforms. - Software and Libraries: The scatter plot was generated using R script with the following libraries: readxl, dplyr, and ggplot2. - Data Processing and Visualisation: The dataset was imported and filtered to include only somatic single nucleotide variants (SNVs) and insertions/deletions (Indels), based on the "Origin" and "Variant type" columns for both solid and haematological cancer types. VAF values were

converted to numeric format and visualized as a scatter plot using ggplot2, with points coloured by concordance between GMS WGS and UF WGS platforms.

Comparative Analysis of WGS and Other Assays

- 3 This analysis was performed using an Excel File contains patient data, diagnostic subgroups, and detection across different genomic assays.
 - Environment Setup: The analysis was conducted in R using the readxl, dplyr, ComplexHeatmap, circlize, and grid packages.
 - Data Structuring for Visualization: Data was loaded and converted to a numerical matrix, with patient IDs as row names, the assays detection as columns and missing values imputed to 0. The matrix was transposed so that assays detection were rows and patients were columns. The data was then partitioned into three matrices (Ultrafast WGS data, Routine NHS WGS and all other assays). The top two heatmaps display the detection in Ultrafast WGS and Routine NHS WGS, respectively. The larger heatmap displays all other assays performed in GMS, with rows grouped by assay type. All heatmaps share the same column order, which is determined by the Diagnosis Subgroup and are annotated accordingly. The final figure is a composite of three vertically concatenated heatmaps and was saved as a high-resolution SVG file.

Turnaround Time (TAT) Analysis

- 4 This analysis was performed using an Excel file containing turnaround time (TAT) data for Solid and Haematological cancer types and for GMS WGS and UF WGS platforms.
 - Software and Libraries: The analysis used R with the readxl, dplyr, and ggplot2 packages.
 - Data Processing and Visualization: Data was imported and grouped by Sample Type (Solid and Haem), Platform, and sample processing stage. Summary statistics, including the number of observations, mean TAT, and standard deviation were calculated for each Sample Type. A bar chart was generated using ggplot2 to represent the mean TAT, with error bars indicating the 95% confidence intervals. To visually separate each sample processing stage, the mean values for the "Samples 3e Sendout" stage were negated on the plot. The final plot was faceted by Sample Type and saved as an SVG file.
- 5 For the TAT analysis, 95% confidence intervals (CI) for the mean TAT were calculated for each group using the t-distribution. The formula used was: $CI = \text{mean_TAT} \pm t_{0.975, n-1} \times \text{sd_TAT} / \sqrt{n}$

where $t_{0.975, n-1}$ is the critical value from the t-distribution for a 95% confidence level

with $n-1$ degrees of freedom. The calculated means and confidence intervals were then visualized as bar plots with error bars.

Genetic Variant Detection by GMS and UF Platforms

- 6 This analysis was performed using two independent Tables in an Excel File (Solid and Haematological cancer types) contains patient data, genetic variants, diagnostic subgroups, and detection across GMS and UF WGS platforms.
- Environment Setup: The heatmaps were generated in R script using libraries readxl, stringr, rvest, ggplot2, ComplexHeatmap, reshape2, dplyr, grDevices, and circlize.
 - Data Loading and Preprocessing: The dataset was loaded from an Excel file. Data was aggregated to create unique entries for each genetic variant per patient. A custom function converted protein change notations in the Variant column from three-letter to one-letter amino acid codes. "Yes"/"No" values in the GMS and UF WGS columns were converted to numeric 1/0.
 - Heatmap Visualization: Two data matrices were created to represent the presence or absence of each variant for each patient on GMS and UF WGS platforms, respectively. A primary heatmap was built using ComplexHeatmap with a custom cell function to render each cell as a rectangle split by a diagonal line. The upper triangle was coloured based on the GMS value, and the lower triangle by the UF value. A second heatmap was created to display the presence of mutational signatures (MMRD/Hypermethylated, AID/APOBEC, UV-light, Signature 6). The two heatmaps were combined vertically and the final figure was exported as an SVG file.

Calculation of Tumour Mutational Burden (TMB) and Mutational Signatures

- 7 TMB was calculated as the sum of somatic SNVs and indels divided by the size of the GRCh38 genome reference in megabases. Variants with a population frequency $3e1\%$ in the 1000 Genomes Project were excluded on the basis that they likely represent germline variants.
- Mutational signature analysis was performed by calculating the fraction of each somatic mutation type in a specific class and then applying non-negative least squares to decompose the fraction data from each sample into the operative mutational signatures. To calculate fractions, single base substitutions were divided into 96 classes, double base substitutions into 78 classes, and indels into 83 classes using SigProfilerMatrixGenerator [7, 8]. Reference mutational signatures used for decomposition were from the COSMIC 3.3 release [9]. Only signatures supported by $3e1000$ single-base substitutions or $3e200$ indels were considered significant.

DUX4r calling

- 8 DUX4 rearrangements were called using the customized caller Pelops (feature available in DRAGEN version 4.4+). SRPB threshold of 10 was used to call samples positive for DUX4::IGH, while a threshold of 15 was used for DUX4-other. False positive regions were filtered using a blacklist as described in Grobecker et al [10].

Method Details

- 9 Data Processing and Visualisation: The dataset was imported and filtered to include only somatic single nucleotide variants (SNVs) and insertions/deletions (Indels), based on the "Origin" and "Variant type" columns for both solid and haematological cancer types. VAF values were converted to numeric format and visualized as a scatter plot using ggplot2, with points coloured by concordance between GMS WGS and UF WGS platforms.
- 10 Genetic Variant Detection by GMS and UF Platforms: This analysis was performed using two independent Tables in an Excel File (Solid and Haematological cancer types) contains patient data, genetic variants, diagnostic subgroups, and detection across GMS and UF WGS platforms.
- 11 Environment Setup: The heatmaps were generated in R script using libraries readxl, stringr, rvest, ggplot2, ComplexHeatmap, reshape2, dplyr, grDevices, and circlize.
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Environment Setup: The analysis was conducted in R using the readxl, dplyr, ComplexHeatmap, circlize, and grid packages.
- 15 Turnaround Time (TAT) Analysis: This analysis was performed using an Excel file containing turnaround time (TAT) data for Solid and Haematological cancer types and for GMS WGS and UF WGS platforms.

Software and Libraries: The analysis used R with the readxl, dplyr, and ggplot2 packages.

Data Processing and Visualization: Data was imported and grouped by Sample Type (Solid and Haem), Platform, and sample processing stage. Summary statistics, including the number of observations, mean TAT, and standard deviation were calculated for each Sample Type. A bar chart was generated using ggplot2 to represent the mean TAT, with error bars indicating the 95% confidence intervals. To visually separate each sample processing stage, the mean values for the "Samples 3e Sendout" stage were negated on the plot. The final plot was faceted by Sample Type and saved as an SVG file.

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Software and Libraries: The scatter plot was generated using R script with the following libraries: readxl, dplyr, and ggplot2.

Quantification and Statistical Analysis

- 16 Heatmap-Based Visual Analysis (Analyses 1 26 2): These analyses focused primarily on data aggregation and visualization rather than formal statistical testing. The core of the method involved transforming data from a long format into wide-format matrices suitable for heatmaps. This was achieved using functions like dcast or by transposing the data frame. The resulting matrices contained values indicating the detection of a variant in an assay or platform (1 for presence, 0 for absence in Analysis 1, and 1 for UF and GMS concordance, 0.5 for UF additional variants and 0 for GMS additional variants in Analyses 2).

No statistical clustering was performed. Instead, the rows and columns of the heatmaps were explicitly ordered based on predefined factors such as Variant type and Diagnosis Subgroup to facilitate qualitative comparisons between groups and platforms.

Statistical Analysis of Turnaround Times (Analysis 3): For the TAT analysis, 95% confidence intervals (CI) for the mean TAT were calculated for each group using the t-distribution. The formula used was: $CI = \text{meanTAT} \pm t_{0.975, n-1} \times \text{sdTAT} / \sqrt{n}$ where $t_{0.975, n-1}$ is the critical value from the t-distribution for a 95% confidence level with $n-1$ degrees of freedom. The calculated means and confidence intervals were then visualized as bar plots with error bars.

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Acknowledgements

DATA AND CODE AVAILABILITY

The original data files and the R scripts used for analysis and visualization are available from the corresponding author upon reasonable request. All software packages used are publicly available from the CRAN or Bioconductor.