



Máster de Tecnologías de Telecomunicación

Trabajo Fin de Máster

Implementation of Hyperspectral Image Classification Algorithms for Brain Tumour Detection using Graphical Processing Units (GPUs)

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Abstract:

Graphic Processing Units are suitable platforms to accelerate the classification of hyperspectral images tasks which are an emerging technology for medical diagnosis. Random Forest has proved to be a great candidate in order to classify hyperspectral images. The goal of this paper is focused in the Random Forest training phase acceleration using GPUs, starting from an efficiently CPU implementation of this algorithm. We present multiple bottlenecks identified in the training phase and their solution in order to accelerate them. The different bottleneck solutions achieved in this research study have demonstrated that GPU acceleration is promising in order to generate models in a shorter time, giving the possibility to perform this process in real-time in the not too distant future.

Keywords - Hyperspectral imaging; Supervised Learning; High Performance Computing; Graphical Processing Units; Random Forest

Materials

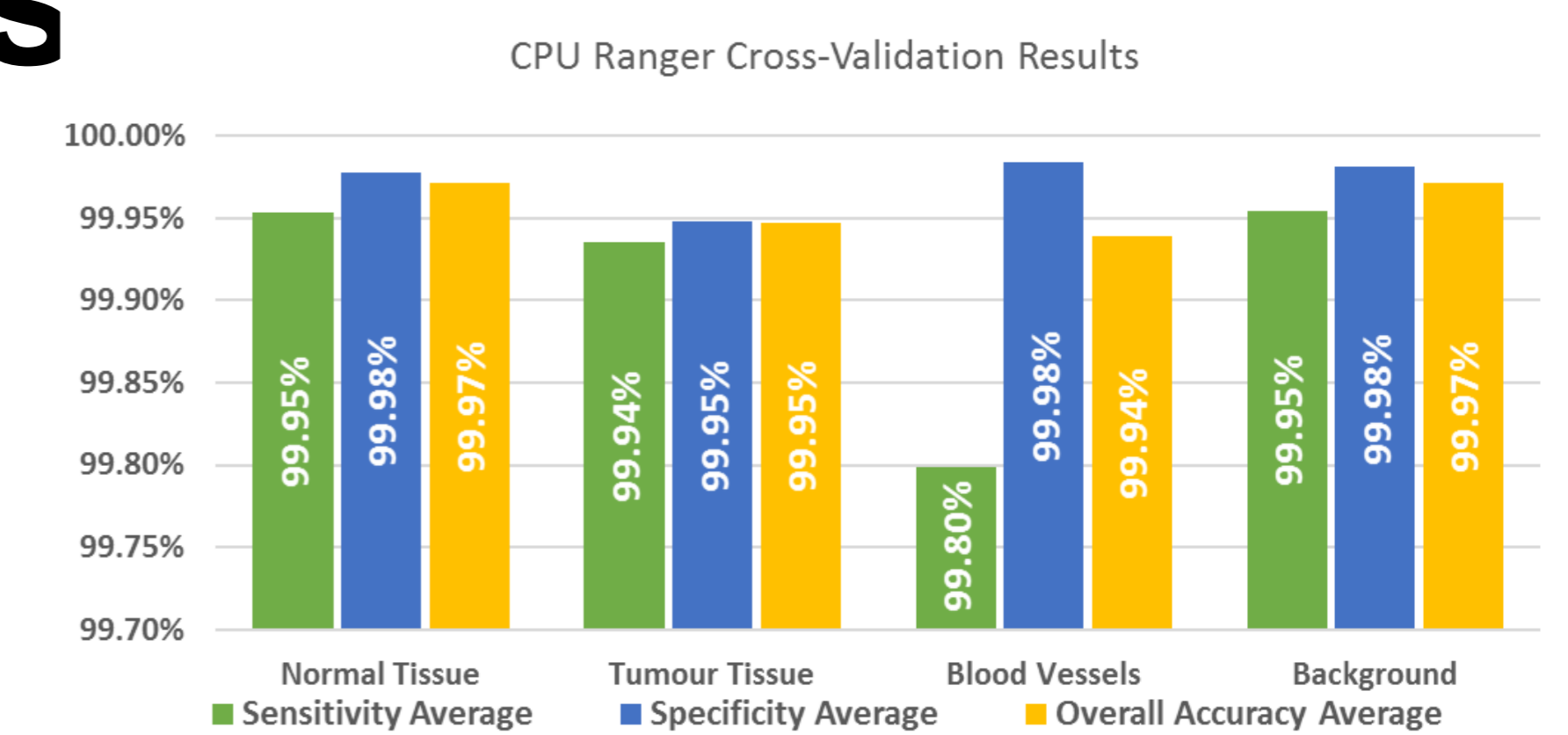
- This study uses the hyperspectral labelled samples of in-vivo human brain acquired within the HELICoiD project at the University Hospital Doctor Negrín of Las Palmas de Gran Canaria. A total of 87,722 in-vivo human brain samples.
- The equipment used for multiple test are a laptop composed by Intel Processor i7-6700HQ and a NVIDIA GPU GTX 960M and a IUMA's equipment rack with and Intel Xeon Processor E3-1225 v3 and two NVIDIA GPU Tesla K40.

Feature	GTX 960M	Tesla K40
CUDA Capability	5.0	3.5
Global Memory (GB)	2	12
Multiprocessors (MP)	5	15
CUDA Cores per MP	128	192

Methods

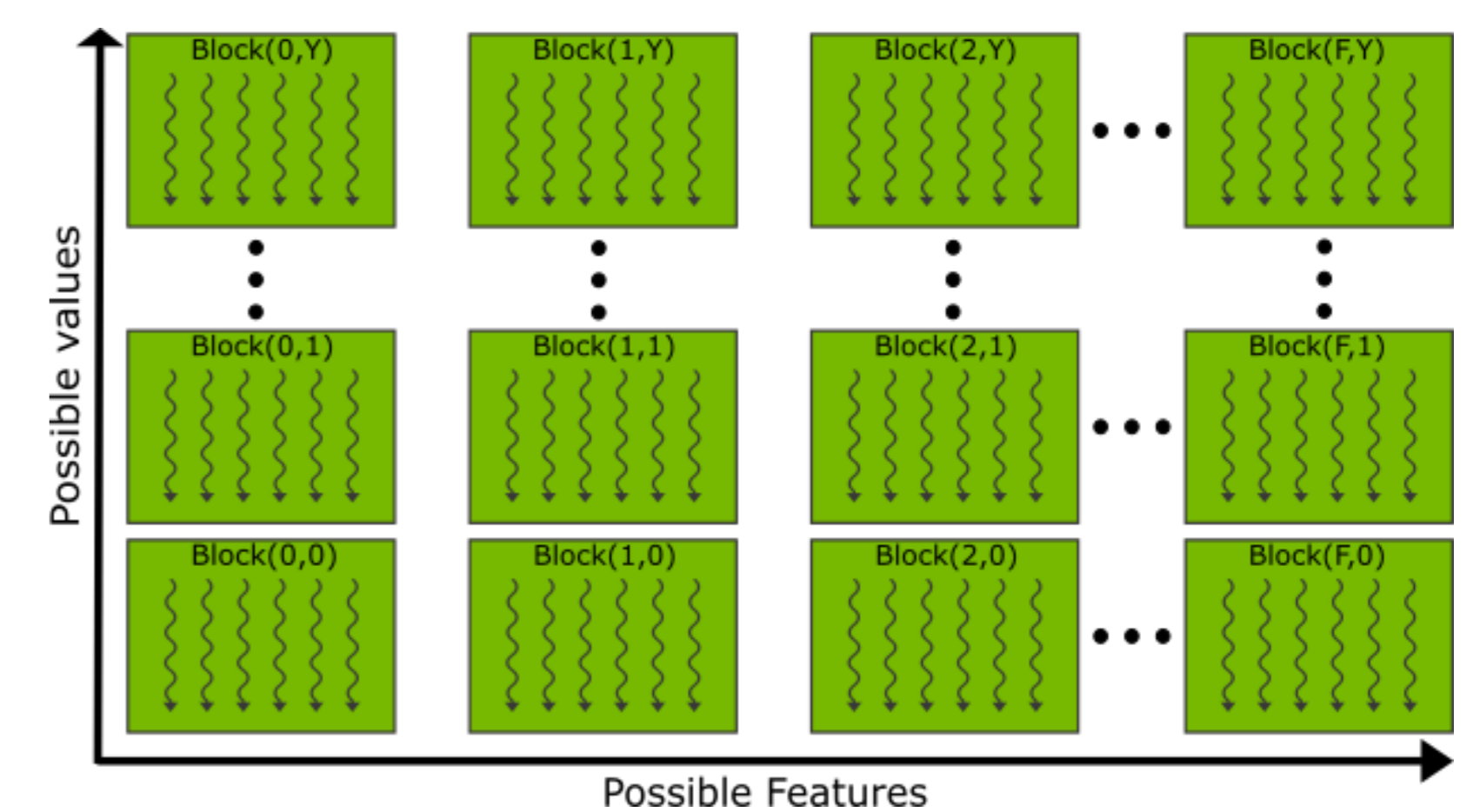
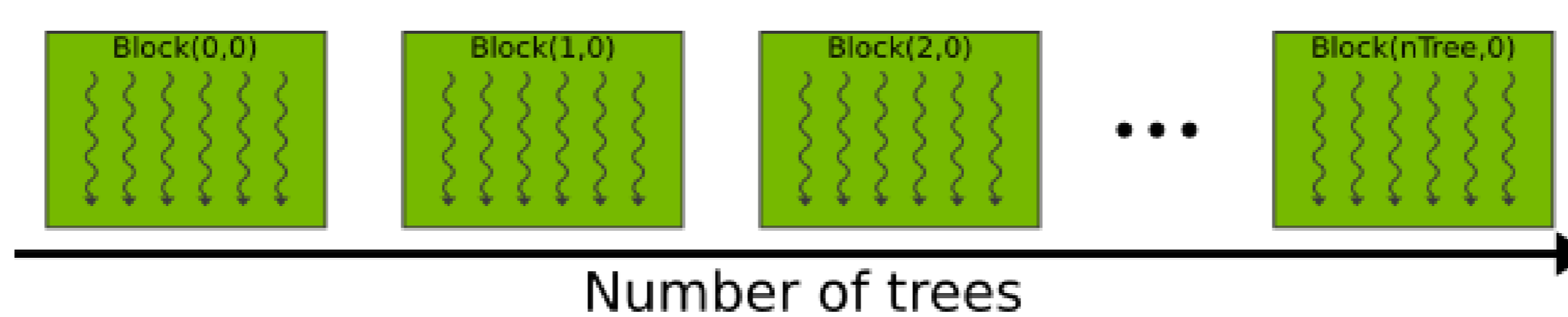
Random Forest for Tumour Detection

The RF CPU implementation has been based on an existent implementation called Ranger (RANDOM Forest GeneRator). Ranger has been verified using the previously described database. K-Fold Cross-Validation method has been employed for the evaluation with 10 folds.



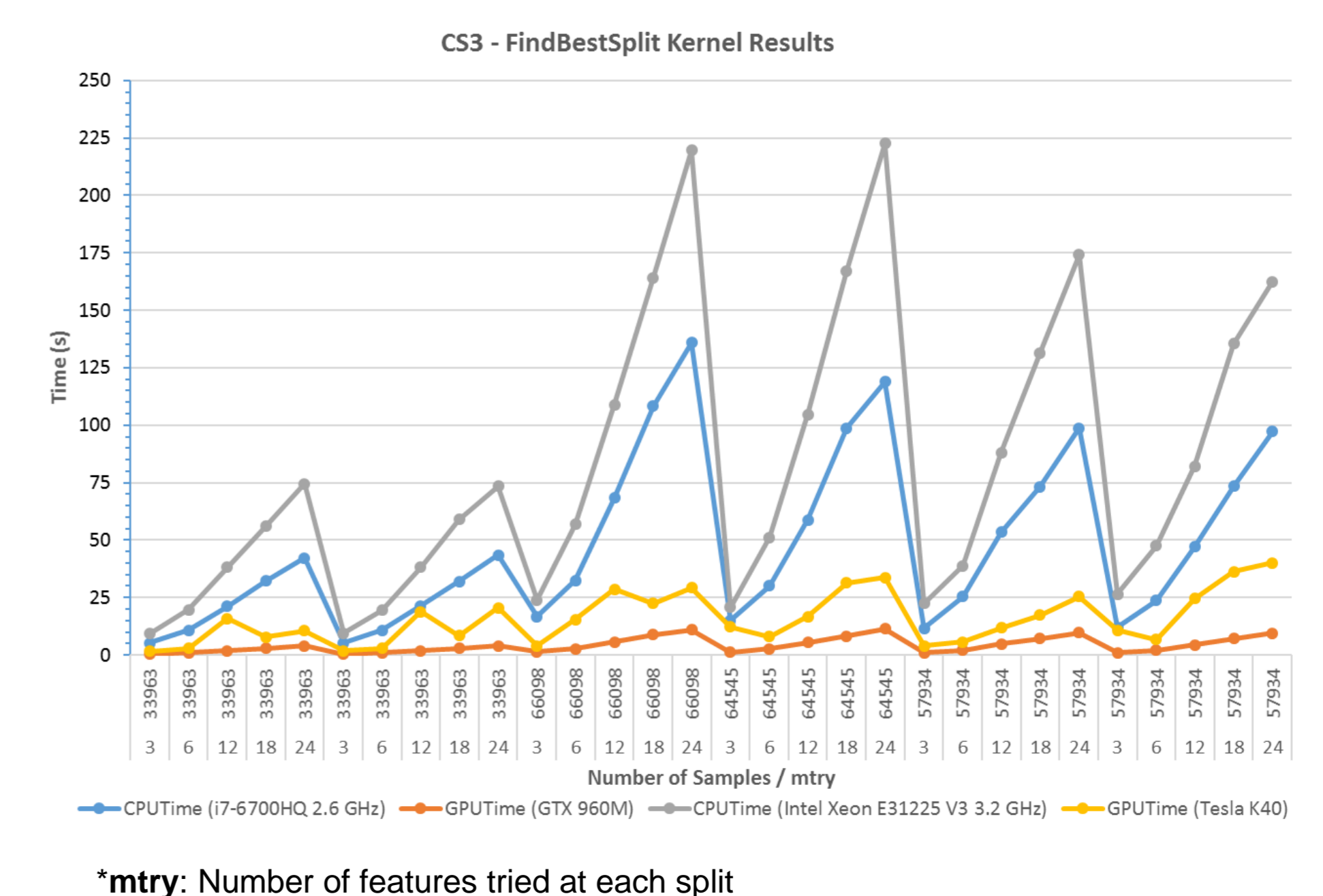
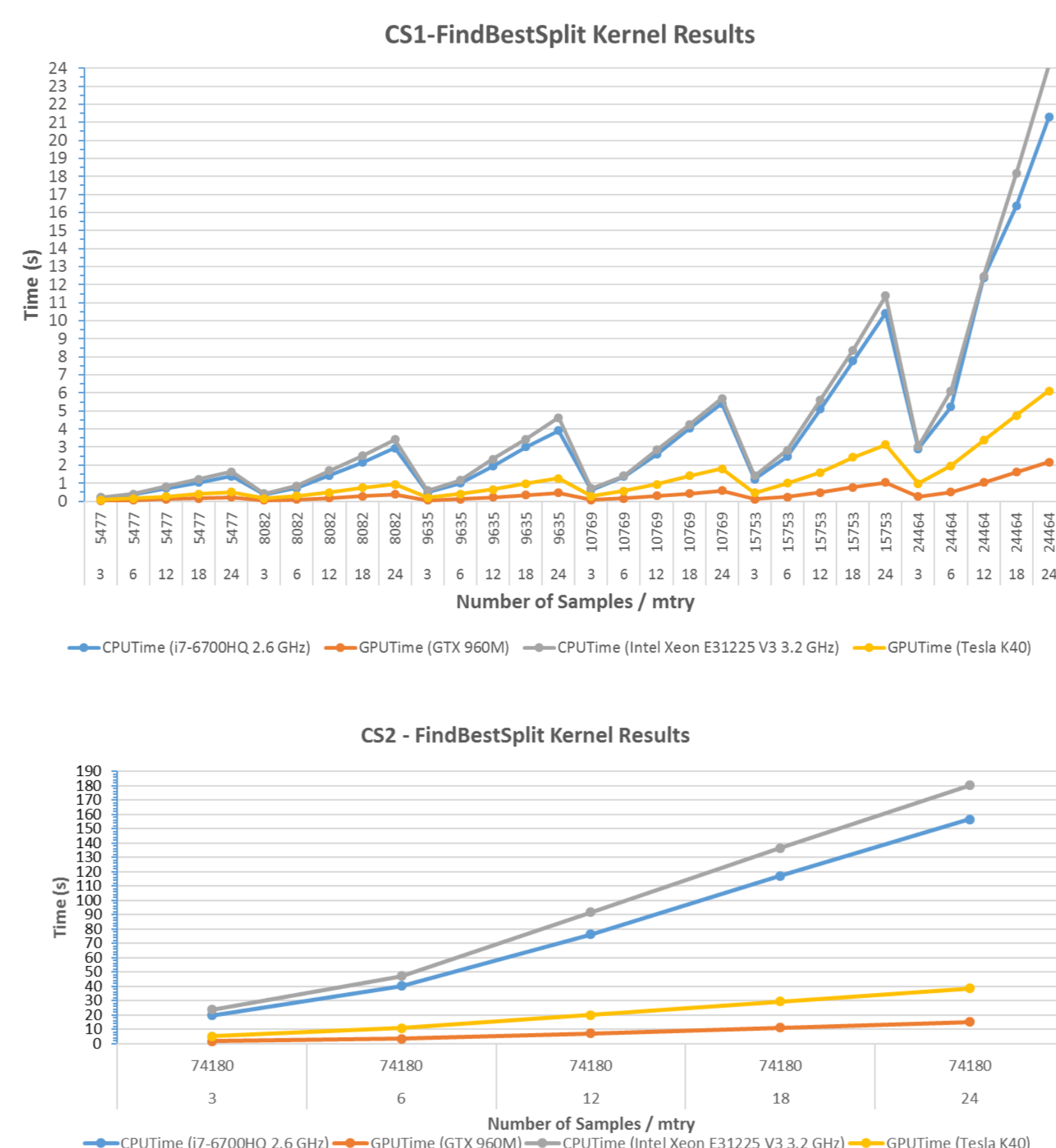
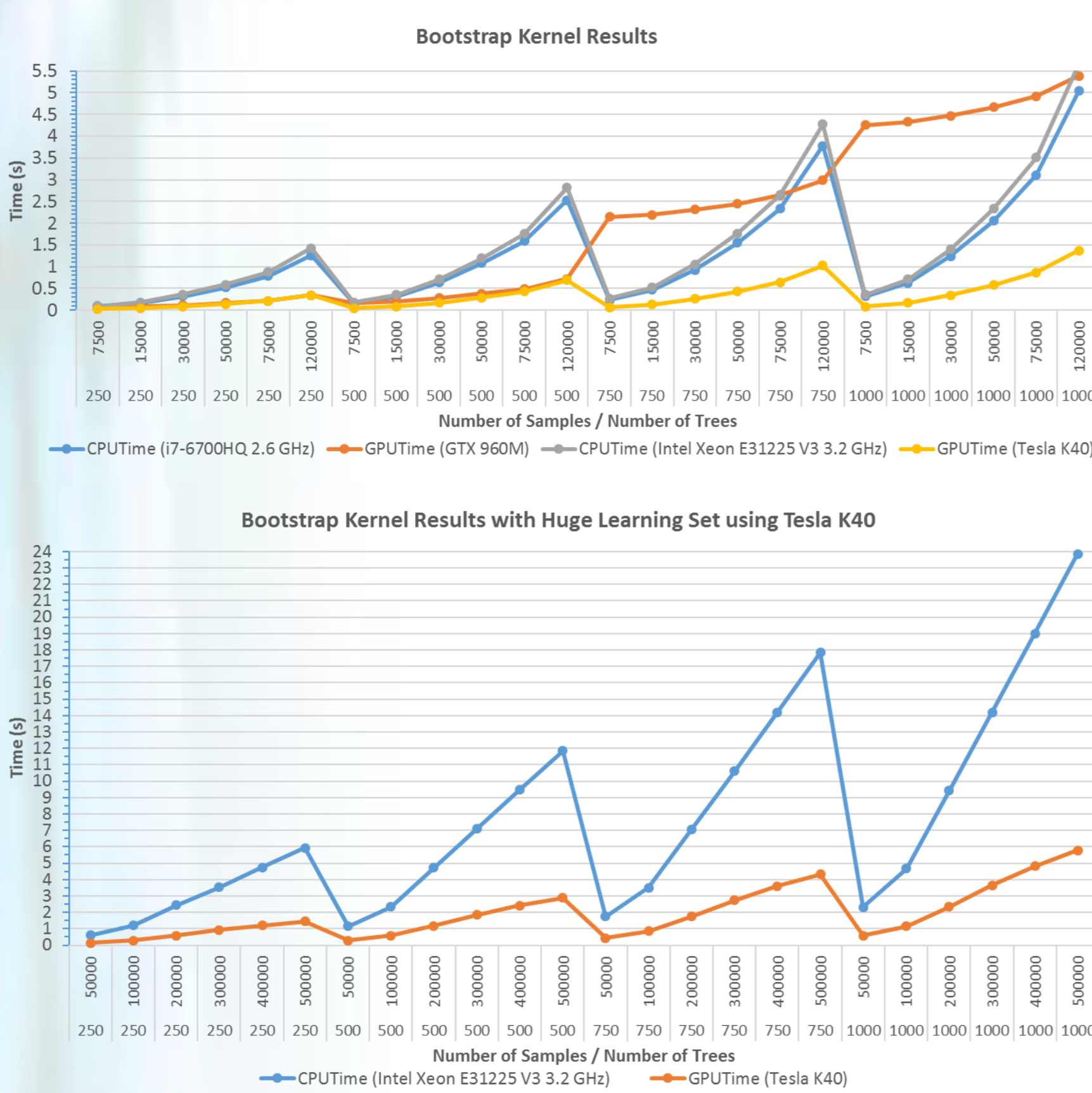
Random Forest Parallelization Analysis

- Bootstrap() kernel:** First bottleneck solution will accelerate the forest initialization generating the learning set of different trees during the initialization of the forest in order to construct multiple trees by setting the learning set.
- FindBestSplit() kernel:** Second bottleneck is found in the splitting process, during the grow phase of a tree, to compute node impurity. Non-terminal nodes need to splitting and is necessary to identify which feature is better, between all possible candidate, and what value to use for threshold.



Experimental Results

In order to obtain the experimental results of the different kernels comparing both platforms, the datasets of each Case Study (CS) of the HELICoiD project have been used. The elapsed time of this graphics are an average result from 10 consecutive tests varying the input data.



Conclusions

The Ranger implementation was studied and verified in order to detect bottlenecks. The bottleneck solutions are implemented in CUDA kernels getting a better performances than sequential implementation in both kernels. *Bootstrap kernel* presents a higher difference between GTX 960M and Tesla K40 from 750 trees onwards due to the number of SMX and synchronization time of multiple blocks. *findBestSplit kernel* exhibits a better performance in GTX 960M than Tesla K40 because of this kernel has a grid with less variability that benefits to GTX 960M with its higher clock frequency but fewer resources.

