

Performance Evaluation of Al Algorithms on Heterogeneous Edge Devices for Manufacturing

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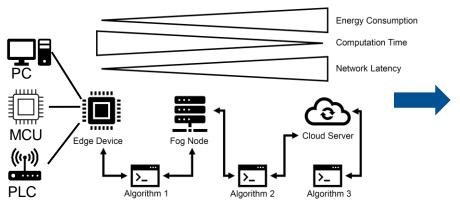






Edge Computing in Smart Manufacturing

- Limited Network Bandwidth Real-time Requirements
- **Edge Computing Approaches**
- Challenge of Software/Hardware Co-Design: "Where to run which Algorithm?"



This paper examines algorithm behavior on heterogeneous hardware in order to assist SW/HW-codesign of CPPS











Contributions of this Paper



C1: Overview of properties of ML Algorithms -> well-conceived deployment



C2: Examination of ML Algorithms on heterogeneous hardware platforms -> chose appropriate ML inference hardware



C3: Introduction of metrics tailored to the manufacturing domain -> supports assessment of ML Algorithms



C4: Examination ML Algorithms on heterogeneous hardware platforms -> reveals unexpected behavior and specialties.







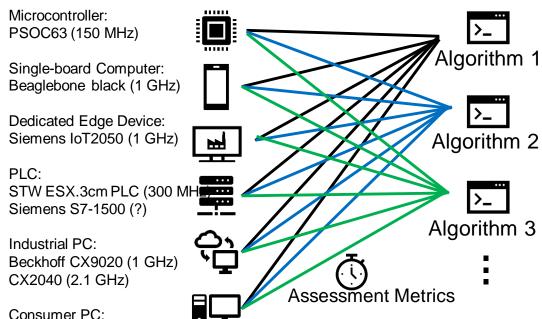




Concept of this Paper

HP Spectre (2.5 GHz)

Heterogeneous Hardware



- Execute various ML Algorithms on different hardware
- Examine behavior using assessment metrics:



Performance Metrics: Execution Time, Memory Consumption



Numerical Accuracy: Double- vs. Single-Precision



Energy Consumption











Selected Algorithms

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Algorithm	Domain	Applications	Time Complexity	Space Complexity	
Standard Matrix Multiplication	Basis Operation	ML, MPC	$\mathcal{O}(N^3)$	$\mathcal{O}(N^2)$	_
Gauss Jordan Matrix Inversion	Basis Operation	ML, MPC	$\mathcal{O}(N^3)$	$\mathcal{O}(N^2)$	
Grubbs Test	Statistic	Outlier Detection	$\mathcal{O}(n)$	$\mathcal{O}(n)$	
Butterworth Filter	Signal processing	Preprocessing	$\mathcal{O}(n)$	$\mathcal{O}(n)$	Example: Matrix
DBSCAN	Clustering	Outlier Detection	$\mathcal{O}(n^2)$	$\mathcal{O}(n)$	Multiplication
Random Forest (Prediction)	Classification	Fault detection	$\mathcal{O}(k * D(n))$	$\mathcal{O}(k*\#nodes)$	
SVM (Prediction)	Classification	Fault detection	$\mathcal{O}(f)$	$\mathcal{O}(f)$	
N: Matrix Dimension n: Number of Datapoints k: Number of trees in the forest D(n): Average tree depth in the forest f: Number of features		120 Windows Beagle 100 - 10172050 10172050		800 PSOC STW CX9020 ST ST ST ST ST ST ST S	











Findings of this Paper- Summary



Conclusions-Excerpt:

- All algorithms except the RF depth show their expected theoretical time complexity on all devices
- Single-precision execution is not always faster than double-precision
- Behavior of the algorithms can differ dependent on the considered hardware, compiler and runtime
- Energy consumption directly depends on the execution time of the algorithm (except RF algorithm)



Identified relevant aspects of SW/HW Codesign for the creation of CPPS