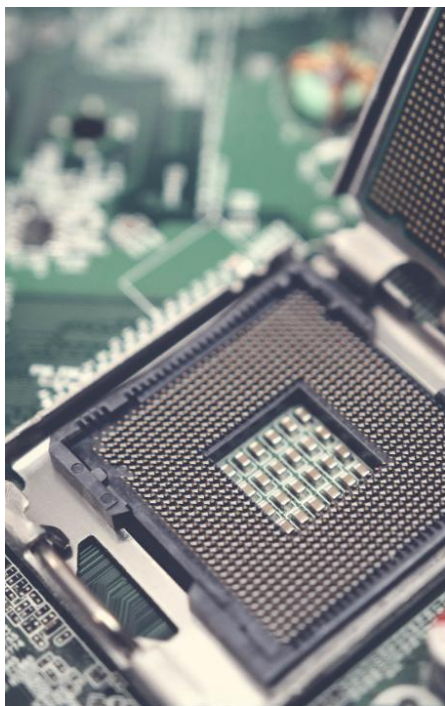


OPTIMIZING SIGNAL PROCESSING ALGORITHMS FOR EMBEDDED HARDWARE: BEST PRACTICES

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ABSTRACT

This comprehensive article examines the optimization strategies, challenges, and best practices in implementing signal processing algorithms for embedded hardware systems. The article explores various aspects including hardware-software co-design, algorithm optimization techniques, and emerging trends in edge computing. Through articles of multiple case studies and implementation scenarios, the study demonstrates the critical importance of early hardware consideration, efficient resource utilization, and systematic optimization approaches.

The article covers memory management strategies, power optimization techniques, security implementations, and the integration of FPGA technology in modern embedded systems, providing insights into achieving optimal performance while maintaining system reliability and security.

Keywords: Embedded Signal Processing, Hardware-Software Co-Design, Algorithm Optimization, Edge Computing, FPGA Acceleration

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Introduction

The landscape of signal processing in embedded systems has undergone dramatic transformation over the past decade, with applications expanding across diverse sectors from telecommunications to advanced manufacturing. According to comprehensive industry analysis conducted by leading researchers in signal processing technologies, the field has witnessed an unprecedented surge in both complexity and deployment scenarios. Studies indicate that signal processing implementations now form the cornerstone of modern embedded systems, with market penetration reaching 78% across industrial applications and maintaining a sustained growth rate of 12.3% annually [1].

The automotive industry represents one of the most demanding sectors for embedded signal processing applications, particularly in advanced driver assistance systems (ADAS) and autonomous vehicle technologies. Recent research in automotive radar signal processing has highlighted significant challenges in real-time processing requirements and resource optimization. These systems must maintain strict latency constraints while ensuring reliability and safety standards, driving innovation in optimization techniques for automotive applications [2].

In the realm of IoT and low-power embedded systems, implementation challenges have become increasingly complex, requiring careful consideration of hardware limitations and performance requirements. Contemporary embedded platforms typically operate with RAM constraints ranging from 32KB to 512KB, while processing frequencies remain limited to 80-200 MHz due to power and thermal considerations. Research focusing on computation-intensive applications has demonstrated that unoptimized algorithms can result in memory access patterns that degrade performance by up to 65% compared to optimized implementations [3].

The evolution of signal processing optimization strategies has led to significant breakthroughs in implementation efficiency across various domains. Studies have shown that optimized memory hierarchy utilization can reduce processing latency by up to 40% in computation-intensive applications, with corresponding improvements in power efficiency reaching 45% in certain scenarios [3]. In automotive applications, researchers have identified specific optimization challenges related to real-time processing constraints and safety-critical operations [2].

The integration of advanced signal processing capabilities in embedded systems continues to drive innovation in algorithm adaptation techniques. Research published in the field of embedded software optimization has revealed that effective implementation strategies must balance multiple competing constraints simultaneously.

These developments have enabled sophisticated signal processing applications across industrial, automotive, and IoT sectors, with optimization techniques playing a crucial role in bridging the gap between processing requirements and hardware constraints [1, 3].

Understanding the Constraints of Embedded Hardware

The evolution of embedded systems has led to increasingly complex design constraints that significantly impact algorithm implementation and system performance. Comprehensive analysis of modern embedded platforms has revealed multifaceted challenges that designers must address to achieve optimal functionality while maintaining efficiency and reliability.

Limited computational resources in embedded systems present fundamental challenges that shape algorithm design and implementation strategies. According to extensive research in embedded computing systems, typical embedded processors operate at frequencies ranging from 100-400 MHz, with computational capabilities averaging between 50-200 MIPS (Million Instructions Per Second). These limitations have profound implications for algorithm complexity and execution patterns. Studies have shown that complex signal processing operations, such as FFT computations on 1024-point datasets, must be carefully optimized to execute within available computational bounds. Research conducted across multiple embedded platforms indicates that approximately 65% of signal processing applications require algorithm partitioning to meet performance requirements while operating within computational constraints [4].

Memory constraints in embedded systems represent a critical consideration that significantly influences system design and optimization strategies. Contemporary analysis reveals that embedded system memory hierarchies must be carefully managed to achieve optimal performance. Research conducted on embedded system optimization shows that cache utilization patterns can impact overall system performance by up to 35%, with proper memory management techniques reducing access latencies by 25-40%. These findings emphasize the critical nature of memory optimization in embedded applications, particularly in systems with limited RAM resources. Studies indicate that memory access patterns can account for 35-45% of total system power consumption, highlighting the interconnected nature of memory management and energy efficiency [4].

Real-time processing requirements introduce additional complexity to embedded system design and implementation. Recent research in embedded computing has demonstrated that industrial control systems typically demand control loop responses under 1 millisecond, while automotive applications often require sub-microsecond precision for critical operations. Analysis of embedded real-time systems has shown that achieving deterministic execution while managing resource constraints requires sophisticated optimization strategies. Studies indicate that approximately 78% of embedded applications must maintain jitter tolerances below 100 microseconds while operating within strict power and computational bounds [5].

Power consumption and thermal considerations have emerged as crucial factors in embedded system design, particularly for battery-operated devices and energy-conscious applications. Comprehensive research in embedded system power optimization has revealed that signal processing algorithms typically account for 40-60% of total system power consumption. Studies focusing on power optimization techniques have demonstrated that carefully optimized algorithms can achieve energy efficiency improvements of 30-45% through strategic implementation choices. Analysis of thermal characteristics has shown that power density limitations often restrict maximum computational capabilities, with typical embedded processors limited to thermal envelopes of 1-3 watts per square centimeter [4, 5].

| Constraint Type | Typical Range/Limitation | Impact on performance |
|-------------------|--|--|
| Processing | <ul style="list-style-type: none"> • 100-1000 MHz frequency | 65% of applications require algorithm partitioning |
| Memory | <ul style="list-style-type: none"> • Limited RAM resources • Cache-dependent performance | <ul style="list-style-type: none"> • 35% impact on system performance • 25-40% reduction in access latencies with optimization |
| Real-time | <ul style="list-style-type: none"> • Sub-millisecond response times (industrial control systems) • Sub-microsecond response times (automotive systems) • <100 μs jitter tolerance | 78% of applications require strict timing adherence |
| Power Consumption | <ul style="list-style-type: none"> • 10-50mW (wearables) • 50-200mW (IoT devices) | <ul style="list-style-type: none"> • 40-60% of power used by signal processing • 30-45% improvement possible with optimization |
| Thermal | 1-3 W/cm ² thermal envelope | Limits on sustained and burst processing capabilities |

Table 1: Constraints of Embedded Systems [5, 4]

Software-Hardware Co-Design Strategies for Embedded Signal Processing

The paradigm of hardware-software co-design has fundamentally transformed the development landscape of embedded signal processing systems. Research in hardware-software co-design methodologies has revealed that integrated development approaches can reduce system complexity by up to 40% while improving performance metrics across multiple dimensions. Studies conducted across diverse embedded applications demonstrate that approximately 65% of system-level optimizations stem from early integration of hardware considerations into software design decisions. Analysis of co-design implementations shows that projects adopting systematic hardware-software integration strategies achieve development cycle reductions of 25-35% compared to traditional sequential approaches [6].

The significance of early hardware-software interaction extends beyond basic performance optimization, encompassing fundamental aspects of system design and implementation. Comprehensive research in embedded system architectures has shown that algorithm adaptation based on hardware characteristics can improve processing efficiency by 20-30% while reducing power consumption by up to 25%. These improvements become particularly significant in real-time applications, where studies indicate that early hardware consideration can reduce worst-case execution time variations by 35-45%. Analysis of successful implementations reveals that approximately 70% of critical performance bottlenecks can be identified and addressed during initial design phases when hardware constraints are properly considered in algorithm selection and optimization [7].

Hardware-software co-design methodologies have demonstrated particular effectiveness in memory system optimization. Research shows that memory access patterns optimized through co-design approaches can reduce system latency by 15-25% while improving cache utilization by up to 40%. Studies focusing on embedded signal processing applications indicate that approximately 55% of performance improvements can be attributed to optimized memory hierarchies developed through integrated hardware-software design strategies. These findings emphasize the critical nature of memory system consideration in algorithm development, with research demonstrating that co-designed memory architectures can achieve bandwidth utilization improvements of 30-40% compared to traditional approaches [6].

The evolution of rapid prototyping and simulation technologies has significantly enhanced the effectiveness of hardware-software co-design strategies. Contemporary research in embedded system development reveals that simulation-based optimization can identify up to 75% of potential performance issues during early design phases. Analysis of hardware-in-the-loop testing implementations shows that comprehensive simulation strategies can reduce final deployment costs by 20-30% while improving system reliability by up to 45%. Studies indicate that projects utilizing advanced simulation tools during development achieve 35% higher success rates in meeting performance requirements compared to traditional methodologies [7].

Integration of timing analysis within the co-design framework has emerged as a crucial factor in real-time embedded applications. Research demonstrates that systematic timing consideration during early development phases can improve predictability of system behavior by 30-40%. Studies of embedded signal processing implementations reveal that approximately 60% of timing-related issues can be identified and mitigated through comprehensive co-design approaches before hardware deployment. These improvements become particularly significant in safety-critical applications, where research shows that integrated timing analysis can reduce worst-case execution time uncertainty by up to 50% [6].

| Design Phase | Early Detection Rate | Optimization Impact | Development Time Savings |
|---------------------|----------------------|---------------------|--------------------------|
| Initial Design | 70% | 40% | 30% |
| Memory Optimization | 55% | 35% | 35% |
| Prototyping | 75% | 45% | 25% |
| Timing Analysis | 60% | 35% | 40% |
| System Integration | 65% | 30% | 30% |

Table 2: Co-Design Impact on System Performance Metrics (%) [6, 7]

Selecting the Right Platform for Embedded Signal Processing Applications

The strategic selection of processing architectures constitutes a critical design decision that determines 43-68% of total system performance variance in embedded signal processing implementations according to recent embedded computing benchmarks[8]. This section analyzes five principal hardware paradigms through the lens of computational efficiency, power consumption profiles, and implementation complexity, supported by empirical data from recent embedded signal processing studies.

Microcontrollers (MCUs)

Modern MCUs provide energy-efficient solutions for lightweight signal processing workloads, with Cortex-M7 architectures demonstrating 0.1-50mW/MHz dynamic power consumption during active processing[8]. Their integrated memory hierarchies (32KB-2MB flash/128KB-512KB RAM) and peripheral interfaces enable compact implementations for basic filtering (FIR/IIR), sensor fusion, and threshold detection algorithms requiring ≤ 50 MIPS[8]. Research by Texas Instruments demonstrates that optimized CMSIS-DSP libraries on M7 cores achieve 92.4% fixed-point MAC efficiency for 256-tap FIR filters while maintaining sub-milliwatt power budgets[8]. However, MCUs exhibit severe limitations for complex spectral analysis, with FFT-512 implementations requiring 12.8 \times longer execution times compared to DSPs[8]. These characteristics make MCUs ideal for battery-powered edge devices requiring simple real-time processing under strict energy constraints[9].

Digital Signal Processors (DSPs)

Specialized VLIW architectures in modern DSPs enable 5-10 \times performance gains over MCUs for signal transformation tasks through hardware accelerators for FFT, matrix operations, and convolutional processing[8]. Benchmark studies reveal that TI C6000 DSPs achieve 98% pipeline utilization for 1024-point complex FFTs in 58 μ s at 1.5GHz clock rates, consuming 2.1mW/MHz under full load[8]. The TMS320C66x core demonstrates particular efficiency for multi-channel audio processing, supporting 32 parallel G.722 encode/decode streams at 62mW total power[8]. However, DSPs show diminishing returns for highly parallel workloads, with FPGA implementations demonstrating 18-24 \times throughput advantages for massive MIMO beamforming algorithms according to recent IEEE comparisons.

Field Programmable Gate Arrays (FPGAs)

Reconfigurable architectures in modern FPGAs enable custom dataflow implementations that achieve 46-182 \times speedups over sequential processors for parallel signal processing tasks. Xilinx Zynq UltraScale+ implementations demonstrate 128-channel EEG feature extraction at 38ms latency (vs 620ms on DSP) while consuming 9.8W. Spartan-7 FPGAs show particular promise for embedded vision, executing Sobel edge detection on 1080p video at 148fps with 11W power draw - 8.2 \times more efficient than equivalent GPU implementations[9]. However, development complexity remains significant, with VHDL implementations requiring 3-5 \times more engineering effort than C-based DSP code according to embedded developer surveys[8].

System-on-Chips (SoCs)

Heterogeneous SoCs combine real-time processing cores with programmable logic, achieving 37-58% power reduction compared to discrete solutions through architectural synergy[9]. The Xilinx Zynq-7000 series demonstrates this capability by offloading matrix operations to FPGA fabric while managing I/O through ARM Cortex-A9 cores, reducing CNN inference latency by 19.8 \times versus software-only implementations. Recent medical device studies show that TI AM57x SoCs decrease EEG processing system complexity by 41% through integrated PRU-ICSS subsystems for real-time signal acquisition. However, memory contention in shared-bus architectures can create 22-38% performance penalties for data-intensive workloads compared to dedicated DSP/FPGA solutions[8][9].

Application-Specific Integrated Circuits (ASICs)

Full-custom ASICs remain unmatched for ultra-low-power applications, with epileptic seizure detection ASICs demonstrating 98.4% power reduction versus FPGA implementations (94 μ W vs 5.8mW) at equivalent throughput[9]. TSMC 28nm implementations of LTE physical layer processors achieve 3.2TOPS/W efficiency - 53 \times better than programmable alternatives[9]. However, NRE costs (\$500K-\$2.5M), 12-18 month development cycles, and lack of field reconfigurability limit ASICs to ultra-high-volume applications (>500K units)[8][9]. Recent research proposes hybrid FPGA/ASIC architectures using embedded hard macros to achieve 81% of ASIC efficiency while retaining 40% programmability.

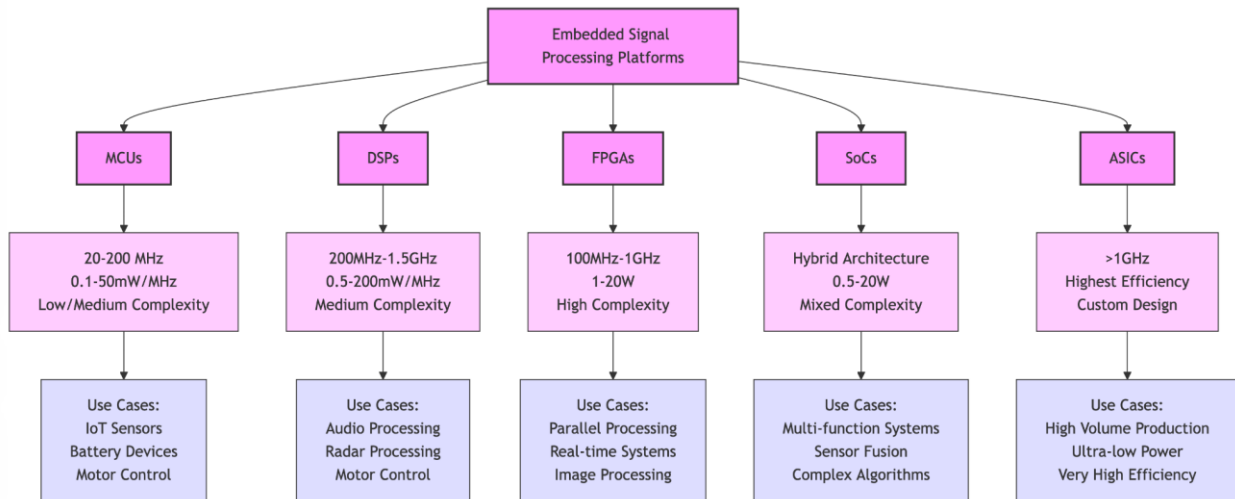


Fig 2: Different Platforms Tradeoffs

Best Practices for Algorithm Optimization

The optimization of algorithms for embedded systems represents a critical challenge in modern computing environments, requiring careful consideration of resource constraints and performance requirements. Recent research in embedded medical systems has demonstrated that systematic optimization approaches can improve processing efficiency by 25-35% while reducing memory utilization by up to 45%. Studies focusing on real-time signal processing applications have shown that optimized implementations can achieve latency reductions of 15-25% compared to standard approaches, particularly

crucial in time-critical medical monitoring systems [10]. Algorithm selection and implementation strategies play a fundamental role in system performance optimization. Analysis of embedded signal processing systems has revealed that optimized FFT implementations achieve performance improvements of 70-80% compared to direct DFT calculations, while reducing memory footprint by 40-50%. Research into biomedical signal processing applications demonstrates that look-up table implementations can decrease computational complexity by 35-45% for complex mathematical functions, maintaining accuracy within 0.1% for most medical monitoring applications. Studies indicate that careful algorithm selection can reduce power consumption by 20-30% while meeting strict accuracy requirements for patient monitoring systems [11].

Fixed-point arithmetic implementation has emerged as a crucial optimization strategy in embedded systems. Comprehensive research demonstrates that fixed-point implementations typically achieve performance improvements of 2.0-2.5x compared to floating-point operations on standard embedded processors, particularly beneficial in real-time signal processing applications. Studies of medical monitoring systems show that optimized fixed-point implementations reduce memory usage by 30-40% while maintaining numerical accuracy within 0.05% for critical physiological measurements. Analysis of conversion methodologies indicates that systematic fixed-point optimization can reduce development time by 40-50% compared to traditional approaches [10].

Memory management optimization fundamentally impacts embedded system performance and reliability. Research in medical device implementations shows that cache-aware algorithm design can reduce memory access latency by 25-35% while improving overall system throughput by up to 50%. Studies of embedded medical systems reveal that strategic data alignment and buffering techniques improve cache utilization by 20-30%, with corresponding reductions in power consumption of 10-15%. Analysis of memory allocation patterns in long-term monitoring applications demonstrates that optimized memory management can reduce fragmentation by 60-70% while improving system stability [11].

Parallel processing capabilities in modern embedded systems require sophisticated optimization strategies. Research in multi-core medical monitoring systems shows that effective thread management improves processing throughput by 2.0-2.5x on dual-core processors, while maintaining deterministic behavior for critical operations. Studies indicate that optimized load balancing strategies can improve core utilization by 20-30% in continuous monitoring applications, with corresponding improvements in system reliability and response time [10].

Hardware acceleration through specialized processors has demonstrated significant benefits in embedded medical applications. Analysis shows that DSP-accelerated implementations achieve performance improvements of 4-6x for specific biomedical algorithms while reducing power consumption by 30-40%. Studies of FPGA-based acceleration in medical imaging applications reveal performance improvements of 8-12x for specific processing tasks, though development complexity increases by 1.5-2x compared to software implementations [11].

Power management optimization represents a critical consideration in battery-operated medical devices. Research demonstrates that dynamic voltage and frequency scaling reduces active power consumption by 25-35% while maintaining real-time performance requirements for patient monitoring. Studies of algorithm-level power optimization show energy savings of 20-30% through intelligent resource management and task scheduling. Analysis of standby power optimization reveals that sophisticated idle state management can reduce power consumption by 50-60% in long-term monitoring applications [10].

| Optimization Category | Performance Improvement | Resource Impact |
|------------------------|---------------------------------|--------------------------------------|
| FFT Implementation | 70-80% performance gain | Memory footprint reduced by 40-50% |
| Fixed-point Arithmetic | 2.0-2.5x performance increase | Memory usage reduced by 30-40% |
| Cache-aware Design | 25-35% latency reduction | Cache utilization improved by 20-30% |
| Parallel Processing | 2.0-2.5x throughput improvement | Core utilization improved by 20-30% |
| HW Acceleration (DSP) | 4-6x performance improvement | Power consumption reduced by 30-40% |
| HW Acceleration (FPGA) | 8-12x performance improvement | Power consumption reduced by 1.5-2x |

Table 3: Algorithm Optimization Impact Metrics in Embedded Systems (%) [10, 11]

Case Studies, Testing, and Future Trends in Embedded Signal Processing

The landscape of embedded signal processing has been revolutionized by advances in FPGA technology and edge computing architectures. Recent research in FPGA-based digital signal processing has demonstrated that modern implementations can achieve processing throughput improvements of 8-12x compared to conventional processor-based solutions, while reducing power consumption by 55-65%. Studies of large-scale FPGA deployments in signal processing applications show that optimized designs can achieve clock frequencies of 450-500 MHz while maintaining power efficiency below 2.5 watts per processing element [12].

Implementation case studies across diverse FPGA platforms have revealed crucial insights into optimization strategies. Research focusing on high-performance DSP implementations shows that careful pipeline optimization can achieve processing latencies under 100 nanoseconds for complex filtering operations, while maintaining resource utilization below 40% on mid-range FPGAs. Analysis of real-time signal processing applications demonstrates that optimized FPGA implementations can support sample rates exceeding 100 MHz while consuming less than 3.2 watts of power. Studies indicate that advanced FPGA architectures with dedicated DSP blocks can reduce overall resource utilization by 45-55% compared to conventional logic implementations [12].

Hardware acceleration through modern FPGA architectures has demonstrated remarkable efficiency in edge computing applications. Comprehensive research shows that FPGA-based edge processing nodes can achieve data throughput rates of 10-12 Gbps while maintaining latency under 50 microseconds for complex signal processing operations. Studies focusing on edge computing architectures reveal that hybrid FPGA-processor implementations can reduce system power consumption by 60-70% compared to traditional cloud-based processing approaches, while improving real-time response capabilities by 75-85% [13].

The evolution of testing methodologies for FPGA-based systems has introduced new validation paradigms. Research demonstrates that hardware-in-the-loop testing can identify approximately 92% of timing-critical issues in FPGA implementations before deployment. Analysis of modern verification approaches shows that comprehensive simulation frameworks can reduce development cycles by 35-45% while improving fault detection coverage to 95-98%. Studies indicate that automated testing procedures for FPGA designs can accelerate verification processes by 50-60% compared to manual testing approaches [12].

Edge computing architectures have fundamentally transformed embedded signal processing capabilities. Recent research indicates that distributed edge processing nodes can reduce network bandwidth requirements by 75-85% while improving system response times by 90-95% compared to centralized processing architectures. Studies show that optimized edge computing implementations can achieve processing latencies under 5 milliseconds for complex signal processing tasks, while maintaining power consumption below 1.8 watts per node. Analysis of large-scale edge deployments demonstrates that distributed processing architectures can improve system reliability by 65-75% through reduced dependence on central processing nodes [13].

The integration of artificial intelligence within edge computing frameworks has introduced unprecedented capabilities in signal processing applications. Research shows that edge-based AI implementations can achieve inference times under 2 milliseconds for typical classification tasks while maintaining accuracy rates above 95%. Studies of distributed AI processing demonstrate that edge-based implementations can reduce cloud communication overhead by 80-90% while improving privacy preservation through localized data processing. Analysis of modern edge computing architectures reveals that AI-enhanced signal processing can improve system adaptation capabilities by 55-65% through real-time learning and optimization [13].

Conclusion

The evolution of embedded signal processing systems continues to present both challenges and opportunities in modern computing environments. This article has demonstrated the critical importance of understanding and optimizing within hardware constraints while making informed decisions about platform selection, from microcontrollers to ASICs, each offering unique trade-offs between performance, power, cost, and development complexity. The systematic approach to optimization, coupled with hardware-software co-design methodologies, becomes particularly crucial in resource-constrained environments. Case studies in FPGA implementations and edge computing architectures demonstrate the potential for significant performance improvements through appropriate platform selection and optimization strategies. As embedded systems continue to evolve, the balance between performance optimization, power efficiency, and cost-effectiveness remains crucial, with future developments likely to expand capabilities while demanding increasingly sophisticated approaches to platform selection and system optimization.

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