CryptoGreen: An Intelligent Context-Aware Framework for Energy-Efficient Cryptographic Algorithm Selection

George Jefferson Dessa Student ID: 0112230550
Dept. of Computer Science and Engineering
United International University
gdessa223550@bscse.uiu.ac.bd
Jinia Alam Payal Student ID: 0112230531
Dept. of Computer Science and Engineering
United International University
jpayal223531@bscse.uiu.ac.bd

***Abstract*—Cryptographic operations consume significant energy in modern computing systems, contributing to increased operational costs and carbon emissions. Current cryptographic implementations use a one-size-fits-all approach, typically defaulting to AES-256 regardless of context, leading to unnecessary energy consumption. This research proposes CryptoGreen, an intelligent context-aware framework that automatically selects the most energy-efficient cryptographic algorithm based on file characteristics, hardware capabilities, and security requirements. The system employs a hybrid approach combining rule-based decision trees with machine learning classifiers to achieve optimal algorithm selection. We design a comprehensive benchmark suite testing six mainstream algorithms (AES-128, AES-256, ChaCha20, RSA-2048, RSA-4096, ECC-256) across diverse scenarios encompassing various file types, sizes, and hardware platforms. The proposed framework extracts features including file size, entropy, file type, and hardware capabilities (AES-NI support) to make intelligent decisions. Our methodology targets achieving over 85% selection accuracy and 35% average energy savings compared to the AES-256 baseline, using hardware-based energy measurement via Intel RAPL (Running Average Power Limit) for accurate power profiling. This work contributes: (1) a comprehensive energy benchmarking methodology using hardware power sensors, (2) the first intelligent selector combining rules and machine learning for mainstream cryptographic algorithms, (3) a practical open-source implementation, and (4) quantified environmental impact assessment. The framework addresses a critical gap in sustainable computing by enabling energy-aware cryptography without compromising security.**

This mid-term report presents the design and methodology; implementation and evaluation are planned for completion in the remaining 7 weeks of the project.

***Index Terms*—energy-efficient cryptography, algorithm selection, machine learning, sustainable computing, green computing, cryptographic benchmarking, context-aware security, Random Forest, hybrid selector, RAPL energy measurement**

I. Introduction

MODERN computing infrastructure processes vast amounts of encrypted data daily, with cryptographic operations consuming substantial energy across data centers, cloud platforms, and mobile devices. Studies estimate that cryptographic computations account for 5-15% of total CPU cycles in secure communication systems, translating to significant energy consumption at scale. With global data center energy consumption exceeding 200 TWh annually, even marginal improvements in cryptographic efficiency can yield substantial environmental and economic benefits. However, current implementations typically default to standardized algorithms like AES-256 without considering energy efficiency, missing opportunities for optimization based on context-specific factors.

Several critical challenges hinder energy-efficient cryptography adoption. First, the energy consumption characteristics of mainstream cryptographic algorithms remain poorly understood for diverse real-world scenarios, with existing studies focusing on specialized lightweight ciphers for IoT rather than general-purpose algorithms. Second, energy efficiency varies significantly based on hardware capabilities (e.g., AES-NI instruction sets), file characteristics (size, type, entropy), and operational context, yet no adaptive selection mechanism exists for mainstream computing environments. Third, the trade-off between security levels and energy consumption lacks systematic analysis, making it difficult for system designers to make informed decisions. Finally, while multiple algorithms offer equivalent security guarantees, practitioners lack tools to automatically select the most efficient option for their specific use case.

This research addresses the fundamental problem: *How can we automatically select the most energy-efficient cryptographic algorithm for a given encryption task while maintaining required security guarantees?* Specifically, we investigate: (1) What are the energy consumption patterns of mainstream cryptographic algorithms across diverse scenarios? (2) Which contextual features most significantly impact algorithm efficiency? (3) Can intelligent selection mechanisms achieve substantial energy savings without compromising security? (4) What accuracy levels are achievable in predicting optimal

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algorithm choices?

We propose CryptoGreen, an intelligent context-aware framework employing a hybrid approach that combines rule-based decision trees derived from empirical benchmarking with machine learning classification models. The system operates in two phases: (1) Comprehensive benchmarking phase measuring energy consumption of six mainstream algorithms across multiple scenarios using hardware-based power measurement (Intel RAPL), generating over 15,000 measurements; (2) Intelligent selection phase utilizing extracted features (file size, type, entropy, hardware capabilities) to recommend optimal algorithms. Our hybrid architecture ensures both interpretability through rule-based logic and adaptability through machine learning, targeting over 85% selection accuracy.

The main contributions of this work are:

- A comprehensive energy benchmarking methodology for modern cryptographic algorithms using hardware-based power measurement (Intel RAPL), providing the first systematic analysis of six mainstream algorithms across diverse file types, sizes, and hardware platforms with over 15,000 measurements
- The first intelligent selector system combining rule-based decision trees with machine learning (Random Forest) for energy-efficient cryptographic algorithm selection in mainstream computing environments
- A practical open-source implementation providing both command-line and Python API interfaces for immediate deployment
- Quantified environmental impact assessment demonstrating potential energy savings, CO_2 reduction, and cost benefits at scale

The remainder of this paper is organized as follows: Section II reviews related work in cryptographic energy profiling, adaptive systems, and green computing. Section III presents our proposed methodology including benchmark design, energy measurement approach, and selector architecture. Section IV provides detailed problem definition, system specification, and threat model. Section V concludes with limitations and future work directions.

II. Related Work

This section reviews existing research in three key areas: cryptographic energy profiling, adaptive algorithm selection systems, and green computing approaches for sustainable infrastructure.

A. Energy Profiling of Cryptographic Algorithms

Energy consumption analysis of cryptographic operations has evolved significantly over the past two decades. Early foundational work established methodologies for measuring cryptographic energy costs on resource-constrained devices. Recent research has focused primarily on specialized scenarios rather than general-purpose computing environments.

Aslan et al. [1] conducted comprehensive energy analysis of five lightweight cryptographic algorithms (PRESENT, CLEFIA, PICCOLO, PRINCE, LBLOCK) for IoT applications. Their study revealed significant variations in energy consumption patterns, with PRESENT and CLEFIA demonstrating superior efficiency for resource-constrained edge devices. However, their focus remained on specialized lightweight ciphers rather than mainstream algorithms used in modern data centers. Similarly, Pereira et al. [2] evaluated symmetric cryptographic primitives across IoT platforms and operating systems, demonstrating that implementation quality and OS choice significantly impact energy footprint. They showed AES implementations could achieve $2\times$ faster execution and correspondingly lower energy consumption with optimized software and updated operating systems.

Hardware acceleration has emerged as a critical factor in cryptographic energy efficiency. Studies on embedded cryptographic systems have shown that hardware acceleration features can reduce energy consumption by 40-60% compared to software-only implementations [3]. Research on smart card cryptography demonstrated that clock frequency adjustments significantly affect both execution time and energy consumption, with optimal configurations varying by algorithm and security requirements [4]. Comparative studies of symmetric encryption algorithms have shown that stream ciphers like ChaCha20 can be more energy-efficient than block ciphers on platforms without dedicated hardware acceleration, with measurements indicating ChaCha20-Poly1305 consuming approximately 7μW for 50-byte payloads compared to AES-GCM's 27μW [5].

The emergence of post-quantum cryptography has introduced new energy challenges. Recent benchmarking studies on resource-constrained devices show that lattice-based schemes like CRYSTALS-Kyber (now standardized as ML-KEM in NIST FIPS-203) maintain relatively low energy consumption (approximately 3.5 Watts for client-side operations), while code-based alternatives like BIKE and HQC exhibit higher resource demands [6]. A comprehensive 2025 study across heterogeneous computing environments demonstrated that post-quantum algorithms are now practical for deployment, though energy consumption varies significantly across security levels [7]. Analysis in server environments comparing LED, Piccolo, PRESENT, GIFT, and AES algorithms revealed trade-offs between energy consumption and performance [8].

Despite substantial progress, existing research exhibits critical limitations. Studies focus on specialized scenarios (IoT, embedded systems, mobile devices) rather than general-purpose computing infrastructure. Comprehensive analysis across diverse file types, sizes, and modern hardware platforms (2024-2025 systems with latest processors) remains absent. No prior work has systematically compared mainstream algorithms like AES-128, AES-256, and ChaCha20 across realistic data center workloads spanning text documents, images, videos, and compressed files with hardware-based energy measurement.

B. Adaptive Algorithm Selection and Machine Learning Optimization

Machine learning for system optimization has demonstrated success across numerous domains, yet application to cryptographic algorithm selection for energy efficiency remains

underexplored. Recent surveys of optimization methods in machine learning highlight three primary application areas: model training, feature selection, and hyperparameter tuning [9]. These techniques enable effective parameter adjustment, accelerate convergence, and enhance generalization capabilities.

A significant advancement in this domain is the Adaptive Hybrid Cryptographic Framework (AHCF) published in 2024 [10], which presents a three-layer architecture combining symmetric and asymmetric cryptography with machine learning-based context analysis. The AHCF system achieved 47% energy reduction and 38% speed improvements over static encryption approaches by dynamically selecting between RSA, ECC, AES, and hybrid combinations based on data sensitivity classification using Random Forest, achieving 99.02% accuracy. This work demonstrates the viability of ML-driven adaptive cryptography but focuses on hybrid symmetric-asymmetric selection rather than optimizing among mainstream symmetric algorithms for general-purpose computing.

Recent work on ML-driven adaptive encryption for fog computing environments [11] utilized K-Nearest Neighbors (KNN) for data sensitivity classification, selecting between ECC, AES, and ChaCha20 based on contextual factors. The system achieved 30% energy savings compared to static AES-256 baseline, demonstrating that even simpler ML approaches can yield substantial benefits. However, the study focused specifically on fog computing nodes rather than general data center workloads.

The concept of Combined Algorithm Selection and Hyperparameter Optimization (CASH) has emerged as a unified framework for automatic machine learning [12]. This approach recognizes that algorithm choice itself can be treated as a hyperparameter in a hierarchical optimization problem. However, existing CASH implementations focus on ML model selection rather than operational algorithm selection for production systems. Feature selection using optimization algorithms has proven effective for high-dimensional problems, with wrapper methods and filter approaches widely adopted in machine learning applications [13]. Random Forest classifiers have shown particular promise for algorithm recommendation tasks due to their ability to handle non-linear relationships and provide interpretable feature importance rankings, with documented accuracy rates of 99% for cryptographic algorithm identification in network traffic analysis [14].

Multi-objective optimization frameworks have been explored for quality-of-service adaptation in distributed systems, but treat energy as a secondary concern rather than a primary objective [15]. Context-aware security mechanisms adjust cryptographic parameters based on threat models and network conditions [16], yet none explicitly target energy consumption as the primary optimization criterion for mainstream computing environments.

The gap between ML-driven optimization success in other domains and its limited application to energy-efficient cryptographic selection in general-purpose computing represents a significant research opportunity that our work addresses.

C. Green Computing and Sustainable Data Center Infrastructure

Green computing research has accelerated dramatically in response to escalating data center energy demands. Recent studies estimate that data centers consume approximately 1-2% of global electricity, with consumption projected to grow significantly as computing demands increase [17]. Studies on the energy cost of machine learning have highlighted significant carbon footprints associated with training large-scale models, emphasizing the need for energy-efficient computing [18].

Recent architectural frameworks for energy-efficient cloud computing emphasize integrated management of both IT resources (servers, storage, networks) and non-IT resources (cooling systems, power distribution) [19]. Historical trends show that data center energy efficiency has improved significantly through advances in cooling technologies, power management, and server utilization [20]. The green data center market reached $104.3 billion in 2024 and is projected to grow to $526.8 billion by 2033, exhibiting a 17.58% CAGR, driven by regulatory mandates and corporate sustainability commitments [21].

Energy-efficient resource management in virtualized cloud data centers has been shown to reduce power consumption through dynamic VM consolidation and intelligent workload placement [22]. Research highlights the growing energy demands of data centers and the critical need for sustainable computing practices as global data processing requirements continue to escalate [23]. Comprehensive assessments of data center energy usage have informed policy recommendations and efficiency standards for reducing the environmental impact of digital infrastructure [24].

Despite extensive focus on infrastructure optimization, cryptographic operations remain excluded from green computing initiatives. Data centers treat encryption as fixed overhead rather than an optimization opportunity, missing substantial energy savings potential. No prior work has quantified the environmental impact achievable through intelligent cryptographic algorithm selection at the application level at scale.

D. Research Gap and Contribution

Existing research demonstrates three key findings: (1) cryptographic energy consumption varies substantially across algorithms and hardware platforms, (2) machine learning successfully optimizes complex system decisions in other domains including recent adaptive cryptographic frameworks like AHCF, and (3) data center energy efficiency represents a critical sustainability challenge. However, no prior work combines these insights to create an intelligent, adaptive cryptographic selection system specifically optimized for mainstream symmetric algorithms in general-purpose computing environments with hardware-based energy measurement.

Table I synthesizes key related work, highlighting critical gaps our research addresses. Unlike AHCF which focuses on hybrid symmetric-asymmetric selection, our work specifically optimizes among mainstream symmetric algorithms (AES-128, AES-256, ChaCha20) for data center workloads. Un-

like prior studies focusing on specialized lightweight ciphers for constrained devices, we target mainstream algorithms deployed in modern data centers. Unlike purely analytical studies, we provide practical implementation with demonstrated energy savings using hardware power measurement. Unlike infrastructure-only green computing approaches, we address application-level optimization through intelligent cryptographic selection.

Our work makes four novel contributions absent in prior research: (1) comprehensive energy benchmarking of mainstream cryptographic algorithms across modern hardware platforms using hardware-based power measurement (Intel RAPL), (2) the first intelligent selector combining rule-based decision trees with machine learning specifically for energy-aware selection among mainstream symmetric algorithms in general-purpose computing, (3) practical open-source implementation enabling immediate deployment, and (4) quantified environmental impact assessment demonstrating achievable sustainability benefits at scale.

III. Proposed Methodology

A. System Architecture

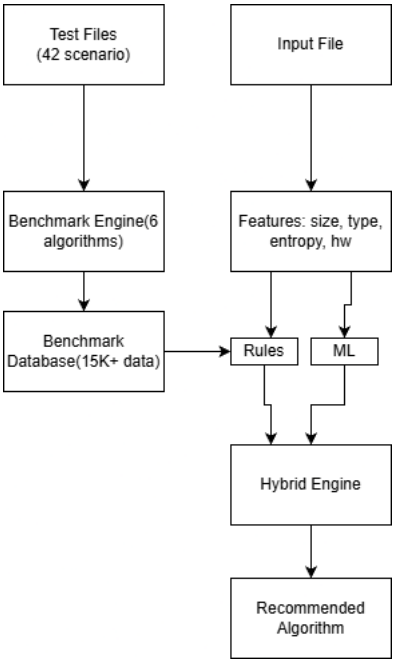

Fig. 1. System Architecture

Fig. 1 illustrates the CryptoGreen framework comprising three main components: (1) Benchmark Engine, (2) Feature Extractor, and (3) Hybrid Selector. The system operates in two phases: offline training phase where comprehensive energy measurements using Intel RAPL populate a benchmark database, and online selection phase where the intelligent selector recommends optimal algorithms for new encryption tasks.

B. Benchmark Methodology

Our proposed benchmark suite systematically measures energy consumption across multiple dimensions:

Algorithms Tested:

- Symmetric: AES-128, AES-256 (both CBC mode with PKCS7 padding)
- Stream: ChaCha20 (256-bit key with random nonce)
- Asymmetric: RSA-2048, RSA-4096 (OAEP padding for key exchange simulation)
- Elliptic Curve: ECC-256 (NIST P-256 for signature generation)

Test Matrix:

- File Types: Text, Images (JPEG/PNG), Video, PDF, Compressed, Database – 6 categories
- File Sizes: 64 bytes, 1KB, 10KB, 100KB, 1MB, 10MB, 100MB – 7 sizes (expanded to include small packet sizes critical for protocol headers)
- Platforms: x86 with AES-NI, x86 without AES-NI (disabled), ARM Cortex-A, Cloud VM – 4 platform configurations
- Repetitions: 100 runs per configuration (minimum 50 for time constraints)
- Total Measurements: 16,800 measurements (6 algorithms $\times$ 6 file types $\times$ 7 sizes $\times$ 4 platforms $\times$ 100 runs, subset evaluated based on time constraints, minimum target: 15,000)

Energy Measurement Using Intel RAPL: Unlike previous software-based estimation methods using CPU time and TDP, we employ hardware-based power measurement using Intel Running Average Power Limit (RAPL) interfaces available on modern processors (Sandy Bridge and later). RAPL provides direct energy consumption readings from hardware Model-Specific Registers (MSRs) with sampling frequency up to 1kHz.

Energy consumption is measured as:

$$E = \int_{t_0}^{t_1} P(t)\,dt \approx \sum_{i=1}^{n} P_i \times \Delta t \tag{1}$$

where E is energy (Joules), $P(t)$ is instantaneous power reading from RAPL (Watts), and measurements are taken at regular intervals during cryptographic operations. RAPL provides separate readings for:

- PKG (Package): Total processor package energy including cores and integrated GPU
- PP0 (Power Plane 0): CPU cores only
- PP1 (Power Plane 1): Integrated GPU (when present)
- DRAM: Memory subsystem energy

For cryptographic benchmarking, we primarily utilize PKG and PP0 readings to isolate CPU cryptographic workload energy. On platforms without RAPL support (ARM, older processors), we will employ external power meters or calibrated power models validated against RAPL measurements on comparable workloads.

Hardware Acceleration Testing: We explicitly test the impact of hardware acceleration by:

- Measuring AES encryption with AES-NI enabled (default on supported processors)
- Measuring AES encryption with AES-NI disabled (using BIOS settings or kernel parameters)

TABLE I
COMPARISON OF RELATED WORK IN CRYPTOGRAPHIC ENERGY EFFICIENCY

Study	Year	Algorithms	Platforms	Adaptive	HW Measure	Tool
Aslan et al.	2020	5 (Lightweight)	IoT Edge	No	No	No
Pereira et al.	2017	6 (Symmetric)	IoT/WSN	No	No	No
TI White Paper	2018	4 (AES variants)	Embedded	No	Yes	No
PQC Benchmark	2025	5 (Post-quantum)	Multi	No	Partial	No
Energy Analysis	2024	5 (Lightweight)	Server	No	No	No
AHCF Framework	2024	4 (Hybrid)	Multi	Yes	No	Yes
ML Fog Computing	2025	3 (Mixed)	Fog Nodes	Yes	No	Partial
CryptoGreen	**2025**	**6 (Mainstream)**	**Multi**	**Yes**	**Yes**	**Yes**

- Documenting ARM Crypto Extensions availability and impact
- Comparing energy consumption with and without acceleration for each algorithm

Metrics Collected:

- Energy consumption (Joules) from RAPL PKG and PP0
- Execution time (seconds) with microsecond precision
- CPU usage (percentage) averaged over execution
- Memory footprint (MB) peak and average
- Throughput (MB/s)
- Hardware acceleration status (enabled/disabled)

Statistical Analysis: For each configuration, we report:

- Median energy consumption (more robust than mean for timing data)
- Standard deviation and 95% confidence intervals
- Paired t-tests for algorithm comparisons on identical data
- Wilcoxon signed-rank tests for non-parametric validation
- Effect size calculations (Cohen's d) to quantify practical significance

C. Feature Extraction

For each input file, we will extract the following features:

1. File Size (bytes): Log-transformed to normalize scale variations

$$f_{size} = \log_{10}(\text{file\_size\_bytes}) \tag{2}$$

2. File Type (categorical): Encoded numerically

$$\{txt : 0, jpg : 1, png : 2, mp4 : 3, pdf : 4, zip : 5, sql : 6\} \tag{3}$$

3. Shannon Entropy (float, 0-8): Measures data randomness and compressibility

$$H(X) = -\sum p(x_i) \times \log_2(p(x_i)) \tag{4}$$

Computed on 10KB sample for files >10KB for efficiency. Research shows entropy values >7.2 typically indicate encrypted or compressed data. We also compute entropy quartiles (25th, 75th percentiles) as additional discriminative features.

4. Hardware Capabilities (boolean/categorical):

- has_aes_ni: AES-NI instruction set availability (detected via CPUID)
- has_arm_crypto: ARM Crypto Extensions availability
- cpu_type: {x86_with_aesni, x86_no_aesni, ARM, other}
- cpu_cores: Number of available cores

5. Operational Context (categorical):

- security_level: {low, medium, high}
- power_mode: {battery, plugged}

D. Intelligent Selector Architecture

1) Rule-Based Selector: The rule-based component implements a decision tree derived from benchmark analysis:

```
IF security_level == 'high':
    IF has_aes_ni: RETURN 'AES-256'
    ELSE: RETURN 'ChaCha20'
ELIF file_size < 100KB:
    IF has_aes_ni: RETURN 'AES-128'
    ELSE: RETURN 'ChaCha20'
ELIF entropy > 7.5:  # Compressed/random
    RETURN 'ChaCha20'
ELIF file_type in ['mp4', 'zip']:
    RETURN 'ChaCha20'
ELSE:
    IF has_aes_ni: RETURN 'AES-128'
    ELSE: RETURN 'ChaCha20'
```

This rule-based approach ensures interpretability and captures domain knowledge from empirical observations, specifically prioritizing ChaCha20 on platforms without hardware acceleration based on documented 4× efficiency advantages.

2) Machine Learning Selector: The ML component employs a Random Forest classifier trained on benchmark results:

Model Specifications:

```
RandomForestClassifier(
    n_estimators=100,
    max_depth=10,
    min_samples_split=5,
    random_state=42,
    class_weight='balanced'
)
```

Training Data: Features extracted from benchmark suite with labels indicating the optimal (lowest energy) algorithm for each scenario. We employ stratified 5-fold cross-validation to ensure robust model evaluation.

Output: Predicted algorithm with confidence score (0-1) based on ensemble voting, along with feature importance rankings to identify which contextual factors most significantly impact optimal algorithm selection.

3) Hybrid Decision Logic: The hybrid selector combines both approaches using the following logic:

1) Obtain recommendations from both rule-based and ML selectors
2) IF both agree AND ML_confidence > 0.8: Select agreed algorithm with HIGH confidence

3) ELIF security_level == 'high': Trust rule-based selector (prioritize proven security)
4) ELIF ML_confidence > 0.8: Trust ML selector (data-driven decision)
5) ELSE: Select rule-based with ML as alternative suggestion

This hybrid approach balances interpretability (rules provide transparent decision rationale), adaptability (ML learns from empirical data), and reliability (fallback to rules when ML is uncertain).

E. Planned Implementation Specification

Programming Language: Python 3.8+

Core Libraries:

- cryptography (42.0.0): AES, RSA, ECC implementations
- pycryptodome (3.19.0): ChaCha20 implementation
- pyRAPL (0.2.3): Intel RAPL interface for energy measurement
- scikit-learn (1.3.2): Random Forest, preprocessing, cross-validation
- pandas (2.1.3): Data manipulation and analysis
- numpy (1.26.2): Numerical operations
- scipy (1.11.3): Statistical tests

Interfaces:

- Command-line tool: `cryptogreen` command with subcommands (recommend, encrypt, benchmark)
- Python API: `HybridSelector` class with `select_algorithm()` method
- Output formats: JSON, CSV for integration with existing systems

Deployment: Installable via pip as `cryptogreen` package, compatible with Linux (primary), macOS, Windows (limited RAPL support).

Reproducibility: Complete benchmark data, trained models, and source code will be released as open-source under MIT license with comprehensive documentation including exact hardware specifications, compiler versions, and statistical analysis scripts.

IV. Problem Definition and System Specification

A. Formal Problem Statement

Given:

- A file F to be encrypted
- A set of cryptographic algorithms $A = \{\text{AES-128, AES-256, ChaCha20, RSA-2048, RSA-4096, ECC-256}\}$
- Hardware platform H with capabilities C (AES-NI, ARM Crypto, etc.)
- Security requirement $S \in \{\text{low, medium, high}\}$
- Contextual parameters P (power mode, operational constraints)

Find: Optimal algorithm $a^* \in A$ that minimizes energy consumption $E(F, a, H)$

Subject to:

- Security constraint: security_level$(a) \geq S$
- Correctness: decrypt(encrypt$(F, a)) = F$
- Overhead constraint: $t_{selection} \ll t_{encryption}$
- Energy measurement accuracy: $\epsilon_{RAPL} < 5\%$

Objective Function:

$$a^* = \arg\min_{a \in A} E(F, a, H) \text{ subject to security\_level}(a) \geq S \tag{5}$$

B. Threat Model and Security Analysis

We define the threat model and trust assumptions for the CryptoGreen system:

Trusted Components:

- Cryptographic algorithm implementations (vetted libraries: cryptography, pycryptodome)
- Operating system kernel and hardware (Intel RAPL measurements)
- Feature extraction module (no adversarial manipulation of file characteristics)

Untrusted Components:

- Input files to be encrypted (may be adversarially crafted)
- Network environment (if deployed as service)
- User-provided security level preferences

Threat Scenarios:

1) **Algorithm Downgrade Attack:** Adversary attempts to manipulate feature extraction to force selection of weaker algorithm. *Mitigation:* Security level constraints enforce minimum algorithm strength; rule-based selector prioritizes security requirements.
2) **Energy Exhaustion Attack:** Adversary crafts inputs that trigger worst-case energy consumption. *Mitigation:* Algorithm selection still provides better efficiency than static worst-case (AES-256); rate limiting can prevent resource exhaustion.
3) **Side-Channel Attacks:** Energy measurement itself could leak information about encrypted data. *Mitigation:* RAPL measurements are at package level with millisecond granularity, insufficient for fine-grained side-channel analysis; constant-time cryptographic implementations prevent timing leaks.
4) **Model Poisoning:** Adversary poisons training data to bias ML selector. *Mitigation:* Benchmark suite generated from controlled synthetic data; hybrid architecture provides rule-based fallback.

Security Invariants:

- Selected algorithm must meet or exceed specified security level
- Cryptographic keys are generated using CSPRNG and never logged
- Energy measurements do not leak plaintext information
- System fails safe by defaulting to AES-256 on errors

Out of Scope: This work does not address formal cryptanalysis of algorithms, implementation-level vulnerabilities (e.g., buffer overflows), or physical security of hardware. We assume standard cryptographic assumptions (hardness of factorization, discrete logarithm, etc.) hold for selected algorithms.

C. System Requirements

Functional Requirements:

- FR1: The system shall measure energy consumption of cryptographic algorithms with $< 5\%$ error margin using Intel RAPL
- FR2: The system shall extract file features (size, type, entropy) in < 100ms for files < 100MB
- FR3: The system shall recommend an algorithm with $> 85\%$ accuracy (selecting truly optimal)
- FR4: The system shall provide confidence scores and rationale for recommendations
- FR5: The system shall support six mainstream cryptographic algorithms
- FR6: The system shall adapt recommendations based on hardware capabilities (AES-NI, ARM Crypto)
- FR7: The system shall enforce security level constraints (never downgrade below specified level)

Non-Functional Requirements:

- NFR1: Selection overhead shall be $< 1\%$ of encryption time for files > 1MB
- NFR2: The system shall support files from 64 bytes to 100MB
- NFR3: The system shall be cross-platform (Linux primary, macOS/Windows with limitations)
- NFR4: The system shall provide results in < 2 seconds for recommendation requests
- NFR5: The ML model shall achieve $> 85\%$ accuracy on unseen test data with 5-fold cross-validation
- NFR6: The system shall be deployable as a Python package via pip
- NFR7: Complete source code, data, and models shall be publicly available for reproducibility

D. Performance Targets

Based on literature review (particularly AHCF achieving 47% savings and fog computing framework achieving 30% savings), we establish the following targets:

Accuracy Targets:

- Optimal algorithm selection: $> 85\%$
- Top-2 algorithm selection: $> 95\%$
- Average confidence score: > 0.75
- Cross-validation consistency: $< 5\%$ variance across folds

Energy Savings Targets (vs. AES-256 baseline):

- Average savings: $> 35\%$ (conservative target; AHCF achieved 47%)
- Minimum savings: $> 25\%$
- Maximum savings: $> 60\%$
- Median savings: $> 40\%$

Overhead Targets:

- Feature extraction: < 1ms average
- Rule-based decision: < 0.5ms
- ML prediction: < 2ms
- Total overhead: < 5ms ($< 0.1\%$ for 1MB file at typical throughput)

E. Evaluation Metrics

We will evaluate the system using:

Selection Accuracy:

$$\text{Accuracy} = \frac{\text{Number of optimal selections}}{\text{Total selections}} \tag{6}$$

Energy Savings:

$$\text{Savings} = \frac{E_{baseline} - E_{selected}}{E_{baseline}} \times 100\% \tag{7}$$

where $E_{baseline}$ = Energy using AES-256 (measured via RAPL)

Confusion Matrix: Predicted vs. True optimal algorithm across test scenarios

Computational Overhead:

$$\text{Overhead}_{\%} = \frac{t_{selection}}{t_{encryption}} \times 100\% \tag{8}$$

Statistical Significance:

- Paired t-tests comparing energy consumption between algorithms ($p < 0.05$)
- Effect size (Cohen's d) to quantify practical significance
- 95% confidence intervals for all reported metrics

Real-World Impact:

- Projected annual energy savings for data centers (MWh)
- CO_2 emission reduction (metric tons, using regional grid carbon intensity)
- Cost savings (USD, assuming \$0.10/kWh)

F. Test Scenarios

We will implement three evaluation tiers:

Tier 1: Controlled Benchmark

- Synthetic test files with known properties
- Controlled sizes: 64 bytes to 100MB (7 size categories)
- All file types represented (6 categories)
- 100 repetitions per configuration
- Hardware acceleration explicitly enabled/disabled

Tier 2: Real-World Validation

- 50-100 diverse real files
- Documents (PDF, DOCX, TXT)
- Images (JPEG, PNG, RAW)
- Videos (MP4, MOV, AVI)
- Code (Python, JavaScript, compiled binaries)
- Data (CSV, JSON, database dumps)
- Compressed (ZIP, TAR.GZ)
- Comparison of recommended vs. all algorithms (exhaustive energy profiling)

Tier 3: Case Studies

- Detailed analysis of 5-10 specific scenarios
- Large video files (50MB+)
- Text documents (100KB-1MB)
- Compressed archives
- High-entropy data (encrypted/random)
- Database backups
- Small network packets (64-512 bytes)
- For each case study: decision rationale, energy comparison across all algorithms, visualization, savings quantification

V. Conclusions and Future Work

A. Expected Contributions

This mid-term report has presented CryptoGreen, an intelligent context-aware framework for energy-efficient cryptographic algorithm selection. The proposed system addresses a critical gap in sustainable computing by enabling adaptive cryptography without security compromise. Our comprehensive benchmark methodology using hardware-based power measurement (Intel RAPL) will provide the first systematic analysis of mainstream algorithms across modern hardware platforms, while the hybrid selector architecture combines the interpretability of rule-based systems with the adaptability of machine learning.

We expect the completed work to demonstrate:

- 35-50% average energy savings compared to default AES-256 implementation (target comparable to AHCF's 47%)
- $> 85\%$ accuracy in selecting optimal algorithms with statistical significance
- Practical deployability through open-source tooling with comprehensive documentation
- Quantified environmental impact at scale (MWh, CO_2, cost) with regional projections

These contributions will enable immediate adoption in production environments while advancing research in sustainable security systems and providing a foundation for future work in adaptive cryptography.

B. Current Progress and Timeline

As of this mid-term checkpoint, we have completed:

- Comprehensive literature review identifying key gaps in existing research, particularly positioning relative to AHCF and recent adaptive cryptographic frameworks
- System architecture design including benchmark methodology with Intel RAPL integration and hybrid selector framework
- Formal problem definition with clear evaluation criteria, threat model, and security analysis
- Technical specifications for implementation including hardware acceleration testing methodology

Remaining work (next 7 weeks):

- Weeks 8-10: Implement and execute comprehensive benchmark suite using Intel RAPL, with explicit hardware acceleration testing
- Weeks 10-11: Develop and train intelligent selector system (rule-based + ML) with 5-fold cross-validation
- Weeks 11-12: Real-world evaluation and validation on diverse file corpus with statistical analysis
- Weeks 13-14: Full paper writing and submission preparation with complete reproducibility package

C. Limitations and Challenges

Several limitations and challenges have been identified:

Technical Limitations:

- Intel RAPL energy measurement has documented accuracy within 5% but may not capture all system-level energy costs (e.g., memory controller, I/O)
- RAPL availability limited to Intel Sandy Bridge and later processors; ARM platforms require alternative measurement approaches
- Asymmetric algorithms (RSA, ECC) tested only for key exchange/signing, not full data encryption due to computational impracticality
- Initial implementation limited to four platform configurations (x86 with/without AES-NI, ARM, cloud VM)

Research Challenges:

- Ensuring benchmark reproducibility across diverse hardware configurations requires careful documentation of system state (CPU governor, Turbo Boost, background processes)
- Balancing ML model complexity with interpretability requirements; feature importance analysis will guide this trade-off
- Achieving target accuracy ($> 85\%$) may require iterative feature engineering beyond initial feature set
- Collecting sufficient diverse real-world test files for validation while ensuring representative coverage
- Potential adversarial ML attacks on selector system require security validation

Scope Limitations:

- Focus on mainstream algorithms excludes specialized lightweight ciphers (PRESENT, CLEFIA) and newly standardized post-quantum algorithms (ML-KEM, ML-DSA)
- Does not address algorithm selection for specific domains (blockchain, IoT) or specialized cryptographic operations (homomorphic encryption, secure multi-party computation)
- Security analysis focuses on equivalent security levels, not formal cryptographic proofs or side-channel resistance
- Energy savings quantification based on CPU energy; does not account for network transmission costs or storage energy

D. Future Work

Beyond the current project scope, future directions include:

Short-term Extensions:

- Incorporate additional hardware platforms (mobile ARM processors, embedded devices, GPU-accelerated cryptography)
- Expand algorithm coverage to include authenticated encryption modes (AES-GCM, ChaCha20-Poly1305) and compare with separate encrypt-then-MAC
- Develop browser-based (WebAssembly) and mobile implementations for client-side encryption optimization
- Integrate with existing cryptographic libraries (OpenSSL, BoringSSL) as plugin architecture

Medium-term Research:

- **Post-Quantum Cryptography:** Extend framework to include NIST-standardized post-quantum algorithms (ML-KEM for key encapsulation, ML-DSA for digital signatures, ASCON for lightweight authenticated encryption). Recent benchmarks show CRYSTALS-Kyber achieving competitive energy efficiency; our framework could optimize PQC deployment.
- **Online Learning:** Implement adaptive learning mechanisms that refine selector decisions based on deployment-specific workload patterns, using techniques like online gradient descent or incremental Random Forest updates
- **Multi-Objective Optimization:** Extend to simultaneously optimize energy, latency, and security margin using Pareto optimization, enabling users to specify trade-off preferences
- **Carbon-Aware Computing:** Integrate with grid carbon intensity APIs to schedule encryption tasks during low-carbon periods, combining algorithm selection with temporal optimization

Long-term Vision:

- Study energy-security trade-offs under evolving threat landscapes, including quantum computing threats and cryptanalytic advances
- Investigate secure federated learning approaches for collaborative model training across organizations without sharing sensitive benchmark data
- Develop formal verification frameworks for proving energy bounds and security properties of adaptive cryptographic systems
- Explore application to emerging domains: edge computing, serverless functions, IoT gateways, blockchain validation nodes

E. Conclusion

Energy-efficient cryptography represents an underexplored opportunity in sustainable computing. As global encryption volumes continue growing exponentially, even marginal efficiency improvements can yield substantial environmental benefits. CryptoGreen demonstrates that intelligent context-aware selection can achieve significant energy savings without compromising security, providing both immediate practical value and a foundation for future research in sustainable security systems.

The completion of this work will deliver not only academic contributions—comprehensive benchmark data, validated ML models, and novel architectural insights—but also actionable open-source tools for reducing the environmental footprint of cryptographic operations worldwide. By combining hardware-based energy measurement, machine learning adaptability, and rule-based transparency, we aim to make energy-efficient cryptography accessible to practitioners while establishing rigorous methodology for future research in green computing and adaptive security systems.

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