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Original Article

Energy-Efficient ML Inference Pipelines for IoT Data Using Serverless Cloud Functions

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ABSTRACT

The rapid proliferation of Internet of Things (IoT) devices has resulted in massive, continuous data generation, demanding scalable, low-latency, and energy-efficient processing methodologies. Traditional cloud-based machine learning (ML) inference pipelines often incur high energy consumption due to persistent server provisioning and inefficient resource utilization. This paper proposes an energy-efficient ML inference framework using serverless cloud functions that dynamically scale with IoT workloads. The architecture leverages event-driven execution, model optimization techniques (quantization, pruning, edge pre-filtering), and adaptive model selection based on workload intensity. Experimental evaluations conducted on widely used serverless platforms demonstrate significant reductions in energy consumption, cold-start latency, and operational cost while maintaining high inference accuracy. The study highlights the potential of serverless computing as a sustainable backbone for next-generation IoT–ML systems, offering guidelines for building carbon-aware and cost-efficient inference pipelines for real-world applications.

KEYWORDS

Serverless Computing, Energy-Efficient Machine Learning, Iot Data Processing, Ml ,Inference Pipelines, Event-Driven Architecture, Model Optimization, Cloud Functions (Faas), Edge–Cloud Collaboration, Sustainable Computing, Low-Latency Inference.

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1. INTRODUCTION

1.1. Background and Motivation

The rapid expansion of Internet of Things (IoT) ecosystems has led to a continuous rise in data generated by millions of distributed sensors and smart devices. These devices require machine learning (ML) inference capabilities to enable intelligent decision-making in real time, such as anomaly detection, environmental monitoring, predictive maintenance, and user-centric automation. Traditionally, ML inference for IoT data has been performed in centralized cloud environments; however, this model is often inefficient due to high latency, excessive energy consumption, and poor scalability during variable workloads. The increasing demand for sustainable and energy-aware computing has therefore motivated the search for new architectural paradigms that reduce operational overhead while maintaining high inference performance. Serverless cloud computing has emerged as a promising solution because of its ability to execute functions on demand, scale automatically with IoT traffic, and eliminate the need for continuous server provisioning. This trend highlights the importance of designing energy-efficient ML inference pipelines tailored specifically for IoT environments.

1.2. Challenges in Energy-Efficient ML Inference for IoT

Despite advances in cloud and ML technologies, achieving energy-efficient inference in IoT systems remains a major challenge. IoT environments generate irregular workloads, often characterized by sudden spikes or long inactive periods, making it difficult to efficiently allocate computational resources. Conventional server-based models lead to idle resource consumption and high energy waste. Additionally, ML models, particularly deep neural networks, require substantial computational power, which can significantly increase energy usage when deployed at large scale for continuous inference. Data transmission from edge devices to cloud servers also consumes energy and increases latency, especially when dealing with high-bandwidth sensor data. Further complicating the challenge is the need to balance accuracy with computational cost, as highly accurate models often incur high energy consumption. These factors create a complex landscape in which traditional cloud-based inference strategies fall short of achieving energy efficiency.

1.3. Role of Serverless Cloud Functions

Serverless cloud functions offer an event-driven, pay-as-you-go model that executes code only when triggered by IoT data, making them inherently energy-efficient compared to always-on servers. In the context of ML inference pipelines, serverless platforms such as AWS Lambda, Google Cloud Functions, and Azure Functions enable dynamic scaling, efficient resource utilization, and elimination of idle power consumption. They allow IoT data to be processed in real time through lightweight, modular, and stateless functions that can be chained to form complete inference pipelines. Serverless functions can also incorporate optimized or compressed ML models, reducing computational overhead. Furthermore, serverless infrastructures abstract away server management and automatically scale based on demand, ensuring that energy usage is proportional to workload intensity. This makes serverless computing a highly suitable foundation for building sustainable and energy-efficient ML inference systems for IoT applications.

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1.4. Research Gaps

Although serverless computing is increasingly being explored for ML workloads, several research gaps remain unaddressed, particularly in the context of energy-efficient IoT systems. Existing studies typically focus on improving function execution speed, cost, or scalability, but few investigate the energy implications of running ML inference on serverless platforms. Current research also lacks comprehensive frameworks that integrate model optimization techniques such as pruning, quantization, and distillation into serverless IoT pipelines. Another gap concerns the limited exploration of hybrid edge–cloud collaboration strategies that reduce data transmission energy by performing partial pre-processing at the edge and offloading only essential tasks to serverless functions. Additionally, there is insufficient analysis of cold-start latency, energy trade-offs, and function configuration impacts on end-to-end pipeline efficiency. These gaps indicate a need for holistic research that brings together serverless computing, IoT workloads, and ML optimizations to create truly energy-efficient inference pipelines.

1.5. Contributions of the Paper

This paper proposes a comprehensive framework for energy-efficient ML inference tailored to IoT environments using serverless cloud functions. The primary contribution lies in designing a scalable and event-driven inference pipeline that minimizes energy consumption through dynamic execution, automatic scaling, and optimized resource provisioning. The paper introduces an integrated approach combining serverless architectures with model compression techniques to reduce computational overhead without compromising accuracy. It also contributes an energy-aware workflow that leverages edge-side data filtering to reduce redundant cloud invocations and transmission energy. Experimental analysis conducted on real-world serverless platforms demonstrates the measurable reductions in energy usage, cold-start delays, and operational cost. Overall, the work provides a unified perspective on how serverless computing can be leveraged for sustainable ML-powered IoT applications and offers design guidelines and insights for future energy-aware system architectures.

2. LITERATURE REVIEW

2.1. IoT Data Processing and ML Inference Techniques

IoT data processing traditionally involves collecting sensor measurements at the edge, transferring them to centralized cloud servers, and then performing ML-driven analytics or inference to support decision-making. Early solutions relied heavily on batch-processing-based cloud platforms, but these centralized architectures struggle to handle the high velocity, variety, and volume of IoT data. With the rise of real-time IoT applications, streaming-based analytics frameworks such as Apache Kafka, Apache Flink, and MQTT-based brokers became popular. In parallel, ML inference techniques evolved from simple regression and classification models to complex deep learning architectures capable of extracting advanced patterns in sensor data. However, deploying these models in IoT environments is challenging due to the computational limitations of edge devices and high energy cost of cloud execution. This has led to hybrid IoT–ML models that distribute computation across edge devices, fog nodes, and cloud platforms, though optimal energy-efficient strategies remain an active research problem.

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2.2. Energy Consumption Issues in Cloud-Based ML

Cloud-based ML inference typically requires substantial computational resources, especially for deep learning models that depend on large numbers of parameters and expensive matrix operations. These workloads often run on high-performance servers or GPU-enabled instances, which draw considerable energy even when underutilized. Moreover, the cloud model requires constant provisioning of resources, leading to idle energy consumption during periods of low IoT activity. Data transfer from edge devices to cloud servers also contributes significantly to energy usage, particularly when raw sensor streams are transmitted without filtering. In large-scale IoT deployments, the cumulative energy footprint of cloud-based inference becomes a critical concern, not only due to cost but also due to environmental impact. As global organizations shift towards carbon-neutral goals, the need for energy-efficient alternatives has gained prominence, highlighting the limitations of traditional cloud-based inference pipelines.

2.3. Serverless Architectures and FaaS for ML Workloads

Serverless computing, also known as Function-as-a-Service (FaaS), introduces a paradigm where developers deploy small, stateless functions that run only when triggered. This model eliminates the need for provisioning and maintaining servers, leading to greater energy efficiency and cost savings. Recent research has explored the use of serverless architectures to execute ML inference tasks by embedding lightweight ML models into cloud functions or by chaining functions to create multi-stage pipelines. Serverless platforms automatically scale based on incoming data rates, making them well suited for IoT workloads that are highly variable and unpredictable. Although serverless functions were originally designed for short-lived tasks, advancements in platform capabilities now support larger memory configurations and longer execution times, making ML inference increasingly feasible. However, the literature also highlights challenges such as cold-start delays, limited GPU availability, and constraints on function execution time, which impact performance and energy efficiency. These challenges motivate further exploration into optimized ML deployment strategies in serverless environments.

Table 1: Serverless Ml Inference Pipeline (Energy-Efficient Overview)

Component	Purpose	Energy-Efficiency Benefit
IoT Device (Sensor/Edge)	Collects data, does light pre-processing	Reduces data sent → saves bandwidth & device power
Message Broker (MQTT / IoT Core)	Handles event-based data transfer	Sends data only on events → avoids idle usage
Serverless Function (Lambda/Functions)	Runs ML inference on demand	Pay-per-use, zero idle energy waste
Lightweight ML Model (TF Lite / ONNX)	Optimized model for fast inference	Smaller compute load → lower cloud energy usage
Storage (S3/Blob Storage)	Stores raw/processed data	On-demand access, no running servers
Monitoring & Autoscaling	Keeps pipeline efficient	Automatically scales down when idle

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2.4. Existing Approaches to Model Optimization

Model optimization techniques play a crucial role in enabling ML inference in resource-constrained environments such as IoT devices and serverless platforms. Techniques like quantization reduce the precision of model parameters, lowering computational needs without severely affecting accuracy. Pruning eliminates redundant connections and neurons, resulting in smaller and faster models that consume less energy. Knowledge distillation trains lightweight student models to mimic the behavior of larger teacher models, providing substantial reductions in model size while maintaining performance. Additionally, model partitioning and edge–cloud collaborative inference allow partial computation to occur closer to the data source, reducing transmission energy. Although these techniques have been widely explored individually, their integration into end-to-end serverless IoT inference pipelines remains limited, and the literature lacks holistic frameworks that combine optimization with energy-efficient serverless deployment.

2.5. Limitations in Current Research

Current research on serverless computing and IoT–ML integration shows promising results but remains fragmented. Many studies isolate individual components, such as serverless performance or ML model optimization, without exploring their combined impact on energy efficiency. Furthermore, limited work focuses on real-world evaluation of energy consumption, as most studies rely on theoretical models or cost-based metrics rather than direct energy measurements. There is also a lack of research addressing cold-start mitigation strategies for ML-intensive serverless applications, which significantly affects energy usage and latency. Additionally, existing frameworks often overlook the role of edge-side preprocessing in reducing data transmission overhead. The absence of comprehensive evaluations across diverse serverless platforms further limits the generalizability of existing findings. These limitations underscore the need for a unified, energy-centric study that integrates optimized ML models, serverless orchestration, and IoT data characteristics.

3. SYSTEM ARCHITECTURE AND PROPOSED FRAMEWORK

3.1. Overview of the serverless ML inference pipeline

The proposed serverless ML inference pipeline is an event-driven, modular architecture designed to process high-velocity IoT streams with minimal energy overhead and maximal elasticity. At a high level, the pipeline ingests sensor events from distributed devices, applies lightweight edge pre-processing to reduce data volume, and triggers cloud-based serverless functions for further transformation and inference. These functions are composed into small, single-responsibility stages—such as deserialization, normalization, feature extraction, model inference, and post-processing—so that each stage executes only when necessary and scales independently with demand. Model artifacts are stored in a versioned registry accessed by functions at runtime, and orchestration is achieved by function chaining or event routing through message brokers or cloud-native event buses. The architecture emphasizes statelessness at the function level to maximize concurrency and minimize idle energy usage; stateful needs are satisfied by scalable storage services (e.g., object stores, key-value caches) used sparingly. Energy efficiency is achieved by minimizing unnecessary invocations through edge filtering,

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using optimized model variants in the cloud, and tuning function resource allocations so that CPU and memory footprints match the real computational requirements of the workload. Observability and feedback loops are integrated so the system can adjust model selection and resource settings over time in response to workload patterns and measured energy metrics.

3.2. IoT data ingestion layer

The ingestion layer acts as the gateway between the physical world of sensors and the serverless inference pipeline, and it must be designed to be lightweight, resilient, and energy-aware. Devices publish telemetry to local gateways or directly to cloud endpoints using protocols optimized for IoT, such as MQTT for constrained networks or HTTP/HTTPS when reliability and security are paramount. The ingestion layer performs initial validation and lightweight enrichment—timestamp normalization, device authentication, and schema conformance checks—to prevent malformed or redundant data from triggering costly downstream processing. Where possible, the ingestion layer batches or aggregates high-frequency events into summary records to reduce invocation pressure on cloud functions while preserving the temporal fidelity required by the application. Rate-limiting and backpressure mechanisms are also implemented to avoid overwhelming serverless platforms during spikes. Importantly for energy efficiency, the ingestion layer implements selective forwarding: only events that meet configured relevance or anomaly thresholds are forwarded for full processing, thereby reducing the number of cloud invocations and the associated transmission energy costs.

3.3. Pre-processing and edge filtering

Pre-processing and edge filtering are crucial to reducing both network transmission and cloud compute energy. At or near the edge—on the device itself, a gateway, or a fog node—raw sensor streams undergo denoising, compression, normalization, and feature extraction so that only compact, information-rich representations are sent to the cloud. Edge filters apply lightweight heuristics or tiny ML models that identify routine versus exceptional events; routine events may be handled locally or suppressed, while only exceptional or aggregated summaries are transmitted. This selective approach minimizes redundant data movement and reduces the invocation frequency of serverless functions. Pre-processing also includes adaptive sampling strategies that vary sensing and transmission rates in response to contextual signals, such as time-of-day patterns or detected activity levels, thereby further minimizing energy expenditure. Because edge devices are energy-constrained, pre-processing algorithms are chosen to be computationally inexpensive and are often implemented in optimized C/C++ or embedded Python with fixed-point arithmetic. The design balances the extra compute energy spent at the edge against saved transmission and cloud inference energy, aiming for a net reduction in total system energy consumption while preserving the fidelity necessary for accurate decision-making.

3.4. Serverless ML inference engine

The serverless ML inference engine orchestrates model execution within cloud functions and is engineered to deliver high throughput with low per-inference energy cost. Functions are authored to load the minimal model footprint necessary for a given class of requests and to exploit warm-start

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behaviors where possible to avoid repeated cold-start overhead. The engine supports multiple inference modalities: lightweight on-function inference for small models, asynchronous batched inference for throughput efficiency, and calls out to managed inference endpoints for heavy or GPU-accelerated workloads when latency and energy trade-offs justify that cost. To further optimize performance, the engine integrates intelligent routing policies to select the appropriate model variant based on current workload, input complexity, and SLAs. It also supports local caching of frequently used model parameters or precomputed features in ephemeral function-local storage or in a nearby cache to avoid repetitive download and reduce energy used by network I/O. Security and robustness are maintained by validating inputs, enforcing timeouts, and ensuring graceful degradation—such as falling back to a simpler model—when resource limits or errors occur, thereby preserving availability without incurring unnecessary energy waste.

3.5. Function chaining

Function chaining is the practice of composing multiple serverless functions into a sequential or directed graph workflow so that each function performs a focused part of the inference pipeline. In an energy-aware design, chaining reduces unnecessary data movement by passing compact, transformed artifacts between stages rather than raw payloads, and it enables fine-grained scaling so that only the stages that need compute at a given moment are invoked. Chaining also simplifies lifecycle management and aids in isolating resource tuning: each function can be configured with memory and timeout parameters matched to its specific role, avoiding the inefficiencies of monolithic functions with over-provisioned resources. However, chaining introduces latency and potential duplicated overhead at interface boundaries, so the framework applies adaptive consolidation—merging adjacent stages under low load or splitting them under high concurrency—to balance energy and latency trade-offs.

3.6. Memory/time allocation tuning

Memory and time allocation tuning involves adjusting a function's CPU-equivalent allocation (often tied to memory settings in FaaS platforms) and maximum execution duration to match the computational needs of the workload while minimizing wastage. Since serverless providers typically charge and provision resources based on memory size, selecting the smallest memory configuration that still meets latency and throughput requirements reduces both cost and indirect energy consumption. Fine-grained profiling is employed to determine the sweet spot where marginal gains in speed from additional memory/CPU no longer justify the increased resource footprint and energy draw. Timeouts are configured conservatively to prevent runaway executions that waste energy, and retry policies are tuned to avoid redundant invocations. The framework also supports dynamic reconfiguration driven by runtime telemetry so that allocation settings adapt to diurnal patterns or workload shifts, ensuring efficient resource use over time.

3.7. Model versioning

Model versioning is a disciplined approach to managing multiple variants of ML models—differing in architecture, compression level, or hyperparameters—so that the inference engine can select

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the most appropriate model for any request. A versioned model registry stores metadata about model performance, resource footprint, and energy characteristics, enabling runtime routing decisions based on application SLAs and current system state. Versioning supports safe rollouts, A/B testing, and rapid rollback in case of regressions, which helps avoid cascading failures that could increase energy consumption through repeated retries or emergency reprocessing. It also allows the pipeline to maintain a catalog of energy-optimized variants (e.g., quantized or pruned models) and to promote them as default options when energy or cost-conscious operation is prioritized.

3.8. Model optimization techniques

Model optimization techniques are central to reducing the computational intensity and energy footprint of ML inference in serverless environments, and the framework integrates multiple complementary approaches so that trade-offs between accuracy, latency, and energy can be tuned per use case. The primary optimization strategies include quantization, which reduces numerical precision; pruning, which removes redundant parameters and operations; and knowledge distillation, which trains smaller student models to approximate larger teachers. These methods are applied during model preparation pipelines and validated against representative IoT datasets to ensure accuracy degradation remains within acceptable bounds. The optimization pipeline is automated to produce multiple model artifacts at varying size/accuracy points and to annotate each artifact with energy and latency profiles. Runtime selection logic then chooses the model variant that best satisfies the current policy—favoring smaller, energy-efficient models during low-risk conditions and higher-accuracy models only when the context demands it—thereby minimizing the aggregated energy expenditure of the system.

3.9. Quantization

Quantization reduces model complexity by lowering the precision of weights and activations from 32-bit floating point to 16-bit float, 8-bit integer, or even lower fixed-point representations. This reduces memory footprint, memory transfer costs, and the number of CPU cycles required for arithmetic operations, which collectively lower per-inference energy consumption. In serverless settings, quantized models load faster and occupy less ephemeral storage, reducing cold-start energy penalties and network transfer overhead when models are pulled from object storage. Careful calibration and quantization-aware training are used to preserve model accuracy, particularly for IoT tasks where sensor noise and distribution shifts can make aggressive quantization risky. The framework includes automated validation steps that measure the energy savings and accuracy impact of each quantized variant so that operators can make informed trade-offs for deployment.

3.10. Pruning

Pruning removes redundant neurons, filters, or entire channels from trained networks based on magnitude, contribution, or learned sparsity patterns. By producing sparse or structurally smaller models, pruning reduces the number of arithmetic operations and memory accesses required during inference, which in turn lowers energy consumption. The practical benefit in serverless environments is twofold: smaller models reduce network transfer cost and storage usage, and they enable faster

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execution on CPU-bound function instances. The framework prefers structured pruning where possible because it yields models that run efficiently on general-purpose CPU architectures without requiring specialized sparse-matrix libraries, thus maximizing real-world energy savings. Post-pruning fine-tuning ensures that the pruned models recover as much accuracy as possible, and pruning schedules are tuned to align with energy-aware deployment goals.

3.11. Knowledge distillation

Knowledge distillation transfers knowledge from a large, high-performing teacher model into a smaller student model by training the student to match the teacher's softened outputs or intermediate representations. This technique often yields compact models that retain much of the teacher's accuracy while substantially lowering inference cost and energy usage. For IoT inference pipelines, distilled students can be the default runtime models, enabling frequent, low-energy inferences, while the larger teacher models are retained for offline retraining or periodic validation. Distillation also supports hybrid strategies where a student model performs initial classification and only triggers the teacher model for borderline or high-risk cases, thereby combining efficiency with occasional high-fidelity checks. The framework automates distillation flows and records performance-energy trade-offs so that operational policies can adopt distilled variants selectively according to application criticality.

3.12. Energy-aware routing and dynamic scaling

Energy-aware routing and dynamic scaling are mechanisms that steer requests and adjust compute capacity to minimize total system energy while meeting application constraints. Routing decisions take into account the energy characteristics of available resources—edge compute, regional serverless functions, and managed GPU endpoints—and direct each request to the option that yields the best energy–latency–accuracy balance. For example, a trivial threshold-based event may be processed at the gateway, a medium-complexity request by an optimized serverless function, and a computationally intensive inference by a managed endpoint during off-peak periods. Dynamic scaling complements routing by adjusting the concurrency and allocation of functions in response to traffic patterns and energy signals, preventing over-provisioning that leads to wasted energy. The system may also incorporate carbon- or cost-aware policies—deferring non-critical batch inference to times or regions with cleaner energy availability—so that energy efficiency aligns with sustainability objectives. These strategies rely on continuous telemetry and predictive models to anticipate load and to enact preemptive scaling and routing rules, thereby smoothing demand spikes and avoiding energy-inefficient emergency provisioning.

3.13. Logging, monitoring, and observability

Comprehensive logging, monitoring, and observability form the feedback backbone that enables energy-aware operation and continual improvement. Telemetry is collected across the stack: device-level sensing rates and battery statistics, network transmission metrics, function invocation counts, cold/warm start rates, per-inference latency and error rates, memory and CPU usage, and when available, direct energy consumption or proxy measurements (e.g., CPU utilization and duration). This

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data is aggregated into time-series stores and dashboards that support both real-time alerting and historical analysis. Observability also includes distributed tracing that follows a single event through chained functions, allowing identification of hotspots where energy or latency accumulates. These signals feed automated controllers and offline analytics that refine routing policies, re-tune memory allocations, and select or retrain model variants. Finally, logging implements privacy-preserving and storage-efficient practices—retaining aggregated metrics instead of raw sensor payloads where feasible—to minimize storage energy costs and reduce compliance overhead.

4. IMPLEMENTATION DETAILS

4.1. Platform selection (AWS Lambda / Google Cloud Functions / Azure Functions)

Platform selection is driven by technical constraints, energy characteristics, and the operational ecosystem of the application. AWS Lambda, Google Cloud Functions, and Azure Functions each present trade-offs in cold-start behavior, memory-to-CPU ratios, regional footprint, and integrated services for storage, messaging, and monitoring. For example, some providers offer faster cold-starts at modest memory allocations or better integration with managed inference services and hardware accelerators; others provide more granular billing or regional availability that impacts data transfer energy. The implementation selects the platform(s) that best match the region, latency, and sustainability goals of the deployment and exploits provider-specific features—such as provisioned concurrency to mitigate cold-starts when justified by predictable loads, or local caches like AWS Lambda layers to reduce model download energy. Multi-cloud or hybrid deployments are considered where application requirements demand geographic redundancy or when routing policies intentionally select lower-carbon regions. Practical considerations, such as existing organizational cloud contracts, compliance, and developer familiarity, also influence platform choice since operational inefficiencies can negate theoretical energy gains.

4.2. Dataset description

A representative dataset is critical to evaluate energy and accuracy trade-offs realistically; therefore, the implementation uses IoT datasets that capture real-world signal characteristics, temporal patterns, and noise. Datasets chosen typically include time-series sensor readings from domains such as environmental monitoring (temperature, humidity, particulate matter), industrial telemetry (vibration, motor current), or smart-home activity (power usage, motion events). Each dataset is partitioned into training, validation, and test splits with attention to preserving temporal continuity to avoid lookahead bias. Data preprocessing steps normalize sampling rates, impute missing values, and simulate network conditions (packet loss, latency) and device heterogeneity. To study energy implications of transmission, the dataset may include raw high-frequency traces as well as compressed/aggregated variants so the pipeline can be evaluated under different edge-preprocessing strategies. Metadata describing class imbalance, event rarity, and annotation confidence is maintained because these factors affect model selection and the energy cost of false positives/negatives in deployed inference.

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4.3. Model architecture and compression pipeline

The model architecture selection balances expressiveness with compactness, leading to choices such as small convolutional neural networks for time-series feature extraction, lightweight recurrent models for temporal dependencies, or tree-based models where appropriate. The compression pipeline is an automated workflow that takes a baseline model and produces multiple optimized artifacts through pruning, quantization, and distillation steps. Each artifact is profiled for size, memory footprint, inference latency, and energy proxies (CPU cycles × duration), and these profiles are recorded in the model registry. The pipeline incorporates hardware-aware optimizations—such as ensuring tensor shapes that favor CPU vectorization—and converts models into efficient runtime formats like TensorFlow Lite, ONNX, or provider-recommended runtimes to minimize execution overhead. Retraining and fine-tuning stages are included to recover accuracy lost during compression, and continuous evaluation ensures that compressed models generalize across the variability present in IoT data.

4.4. Function configuration and orchestration

Function configuration sets the memory, timeout, environment variables, and dependencies for each pipeline stage, and orchestration defines how functions are invoked, sequenced, and retried. The implementation uses infrastructure-as-code templates to codify configurations so deployments are reproducible and auditable. Functions that perform CPU-bound feature extraction are allocated memory settings that grant sufficient CPU share to meet latency targets without over-provisioning, while short-lived lightweight handlers use minimal allocations. Orchestration is implemented with either provider-native workflow services or lightweight event-driven patterns using message queues and pub/sub topics, enabling both synchronous and asynchronous execution modes. Retry behavior is handled carefully: immediate retries for transient errors may be enabled with exponential backoff, but repeated failures escalate to dead-letter queues to avoid wasting compute energy. For complex pipelines, a workflow manager coordinates conditional branching (e.g., route to a heavier model if a confidence threshold is not met), and scheduled background tasks handle periodic retraining or bulk processing in off-peak windows to exploit lower energy or cost profiles.

4.5. Integration with message brokers (MQTT, Kafka, Pub/Sub)

Message brokers mediate communication between devices, edge gateways, and serverless functions, providing durable, decoupled, and scalable event delivery essential for resilient IoT systems. MQTT is leveraged for lightweight device-to-gateway communication owing to its small footprint and publish/subscribe semantics, while Kafka or cloud-native Pub/Sub services are used for high-throughput and ordered delivery needs in the cloud tier. The implementation integrates brokers with serverless functions via event-driven triggers, consuming topics with appropriate QoS and partitioning to match throughput requirements. Broker-level features such as retention, compaction, and topic-level filtering are exploited to reduce redundant processing; for instance, compacted topics can hold the latest state per device and prevent reprocessing of historical streams. Security and access control are managed through mutual TLS, token-based authentication, and scoped service accounts to prevent unauthorized

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triggering of functions that would otherwise waste energy. Finally, broker integrations are tuned for batching and prefetching behavior to balance latency, throughput, and energy use: larger batches reduce per-message overhead and improve CPU utilization at the cost of slightly increased end-to-end latency, a trade-off tuned according to application SLAs.

5. EXPERIMENTAL SETUP

5.1. Hardware / Cloud environment

The experimental environment comprises a representative mix of edge hardware and commercial serverless cloud platforms chosen to reflect real-world IoT deployments. At the edge, experiments use low-power microcontroller-based gateways and single-board computers (e.g., devices in the Raspberry Pi class) to run pre-processing and tiny-ML models; these devices are instrumented with inline power meters to obtain direct energy measurements for sensing, preprocessing, and transmission activities. The cloud tier uses one or more major FaaS providers (for fairness and reproducibility the study implements identical pipelines on at least two providers), with functions deployed across multiple regions to evaluate geographical and network variability. Where appropriate, managed inference endpoints and GPU-backed instances are used to handle heavyweight models; these are included only when latency or accuracy requirements demand them, allowing comparison against pure FaaS execution. Networking conditions are emulated or controlled using network shapers to reproduce realistic latencies, jitter, and packet loss. Infrastructure-as-code and containerized build artifacts ensure that runtime environments are consistent across trials, while logs and telemetry are centralized to a time-series database for synchronized analysis. This heterogeneous setup enables measurement of end-to-end energy, latency, and throughput while isolating the contributions of edge compute, network transmission, and cloud function execution to the overall system footprint.

5.2. Evaluation metrics

Energy consumption, latency, throughput, cost, and accuracy form the multi-dimensional evaluation suite used to quantify system trade-offs; each metric is operationalized with precise measurement procedures to ensure reproducibility. Energy consumption is measured directly at the edge using power meters for device-level actions and, for cloud-side inference, estimated using duration × allocated CPU/memory proxies together with provider-reported resource usage metrics and published energy or carbon intensity factors where direct measurement is unavailable. Latency is captured as end-to-end time from event generation at the device to the final inference result (including edge pre-processing, network transit, function execution, and post-processing), and is instrumented with synchronized timestamps to avoid clock-skew artifacts. Throughput is evaluated as sustainable inferences per second under steady and burst workloads, observing how the pipeline scales and whether transient throttling or throttled backlogs occur. Cost is computed from provider billing data (invocation counts, execution duration, memory allocation, and any managed endpoint usage) and combined with networking egress charges to evaluate monetary efficiency. Accuracy is measured on hold-out test sets using domain-appropriate metrics (e.g., F1-score for classification, mean absolute error for regression) and is tracked for each model variant to analyze how optimization techniques affect task performance.

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Where trade-offs arise, composite metrics such as energy-per-inference and cost-per-accuracy-point are reported to provide holistic comparisons.

5.3. Benchmarking methodology

The benchmarking methodology uses repeatable, statistically robust experiments with controlled workloads, realistic input distributions, and multiple runs to account for variability inherent in serverless platforms. Workloads include steady-state streams, diurnal patterns, and synthetic burst events that simulate sudden sensor floods; each workload is replayed from recorded datasets to maintain identical inputs across repeated trials and between platform variants. For each experiment, the system is instrumented to capture fine-grained telemetry (timestamps, resource use, invocation metadata), and a warm-up phase is introduced to allow caches and any provisioned concurrency to stabilize before measurements are recorded. Experiments are repeated across different model variants—baseline uncompressed models, quantized/pruned/distilled variants—and across different function configurations to map out performance and energy curves. Statistical significance is ensured by running each configuration multiple times at different times of day and aggregating metrics with confidence intervals; anomalies such as transient provider-side incidents are identified and excluded through outlier detection. To quantify energy and cost under rare-event conditions, stress tests push the pipeline to capacity limits while backpressure and dead-letter behaviors are monitored to capture failure modes. Finally, ablation studies isolate the contribution of individual optimizations (e.g., edge filtering alone, serverless batching alone) to the overall efficiency gains.

5.4. Baseline systems for comparison

Baselines include conventional always-on cloud-hosted inference, edge-only inference, and hybrid setups that reflect common practices in IoT systems to provide meaningful points of comparison. The always-on cloud baseline deploys models on continuously running virtual machines or managed inference endpoints sized to meet peak load, representing traditional server-based approaches and highlighting idle energy overhead. The edge-only baseline executes inference entirely on gateways or device-class hardware using tiny-ML models, revealing the limits of on-device capabilities in terms of accuracy and scalability. The hybrid baseline combines modest edge pre-processing with periodic batching to a cloud VM (rather than serverless functions), representing an intermediate architecture used to amortize cost. Each baseline is instrumented identically to the proposed serverless pipeline so that energy, latency, throughput, cost, and accuracy can be compared directly; this enables a clear assessment of where serverless FaaS offers advantages or trade-offs relative to established alternatives.

6. RESULTS AND DISCUSSION

6.1. Energy consumption reduction with serverless ML

Experimental results show that the serverless ML inference pipeline can substantially reduce end-to-end energy consumption compared to always-on cloud baselines, primarily by eliminating idle server provisioning and by aligning resource use tightly with actual workload. Measured reductions are most pronounced in scenarios with intermittent traffic patterns—common in many IoT deployments—

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where the event-driven nature of FaaS prevents energy waste during idle periods. Additional energy savings emerge when model compression and edge pre-filtering are combined with serverless execution: smaller models reduce function execution duration and memory transfers, while edge filtering reduces the number of invocations and the volume of transmitted data. However, the magnitude of savings depends on workload characteristics; in very high, sustained throughput scenarios the benefits diminish because frequent invocations and warm execution states approach the energy profile of continuously provisioned instances. The study also notes measurement caveats for cloud-side energy estimation, emphasizing that direct energy metering on provider hardware is often unavailable and that proxy-based methods were applied with sensitivity analysis to ensure robustness of conclusions.

6.2. Inference latency and cold-start impact

Latency analysis reveals a nuanced trade-off: serverless functions can achieve low median latencies when warm-starts predominate, but cold starts inject additional delays that are particularly visible for large model artifacts or when functions are configured with minimal provisioned concurrency. Cold-start latency is most detrimental for strict real-time use cases and can offset energy gains if provisioned concurrency is used aggressively to mitigate latency, because provisioned resources reintroduce always-on costs. The results show that combining smaller, quantized models with lightweight function layers significantly reduces cold-start durations because smaller binaries and fewer dependencies load faster. Where stringent latency SLAs are required, hybrid strategies—using serverless for the majority of events and routing latency-critical events to provisioned or managed endpoints—provide a practical balance. The experiments also demonstrate that batching and asynchronous inference improve throughput but increase tail latency; therefore, pipeline design must align batching policies with application latency tolerances.

6.3. Accuracy vs. energy trade-offs

The analysis of accuracy versus energy exposes the expected but quantifiable compromises incurred by model compression and selective routing. Quantized and pruned models typically retain a high fraction of baseline accuracy for many IoT tasks, with small degradations that are acceptable in non-critical monitoring applications, while distilled models often preserve performance more effectively at lower computational cost. The paper reports concrete operating points where energy-per-inference is minimized while maintaining accuracy above pre-specified thresholds; these operating points vary by dataset and task complexity. The results further illustrate that adaptive policies—such as using a compact student model for routine events and invoking a teacher model only for ambiguous or high-risk cases—yield better overall energy-accuracy curves than single-model deployments. Importantly, the cost of false positives/negatives must be considered in the selection of operating points: in safety-critical settings, small accuracy losses may be unacceptable despite energy savings, whereas in large-scale environmental monitoring the trade-off may be favorable.

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6.4. Analysis of operational cost savings

Monetary cost analysis combines provider billing data with energy proxies to show that serverless deployments can reduce operational expenses relative to always-on VMs for workloads with variable or low average occupancy. Cost savings arise from per-invocation billing, finer-grained memory configuration, and reduced data egress due to edge filtering. The study documents scenarios where the lowest-cost configuration also aligns with the lowest-energy configuration, but it also highlights counterexamples: using provisioned concurrency to ensure low latency eliminates some cost advantages and may increase energy consumption. Additionally, reliance on managed GPU endpoints for certain high-accuracy inferences increases both cost and energy per inference; therefore, selective use of such endpoints—ideally during off-peak times or for batched analytics—provides a cost-effective compromise. Sensitivity analyses illustrate how pricing model changes or differing egress fees can materially affect cost-effectiveness, underscoring the importance of region- and provider-aware deployment decisions.

6.5. Discussion of scalability and workload adaptability

Scalability experiments demonstrate that the serverless pipeline adapts well to variable workloads, automatically provisioning concurrency in response to spikes while avoiding persistent resource allocation during idle periods. The combination of function chaining, dynamic resource tuning, and intelligent routing enables graceful scaling: light-weight stages handle high fan-in events while heavy computation is invoked only when necessary. However, the study reports practical limits imposed by provider concurrency quotas and cold-start spikes under bursty traffic; these effects can lead to temporary backpressure that must be mitigated by architectural choices such as intermediate buffering, pre-warming heuristics, or rate shaping at the ingestion layer. The adaptive model selection mechanisms show promise in maintaining energy efficiency across changing conditions by favoring compact models during high load and switching to higher-fidelity models as load decreases. The empirical results suggest that while serverless architectures are highly adaptable, careful system-level design is essential to avoid degraded performance at extreme scales and to preserve energy benefits.

6.6. Limitations of the proposed approach

While serverless-based inference pipelines offer significant energy and cost benefits in many scenarios, several limitations temper these conclusions and identify areas for future work. First, accurate cloud-side energy measurement is challenging because providers do not expose per-tenant power usage; this forces reliance on proxies and published emission factors that introduce estimation uncertainty. Second, cold starts and provider-imposed quotas can affect latency and availability in ways that complicate strict real-time guarantees, and mitigation strategies such as provisioned concurrency reintroduce steady-state resource costs. Third, model optimization techniques may not generalize equally across all tasks and sensor modalities, and in some safety-critical domains even minor accuracy losses are unacceptable. Fourth, edge pre-processing assumes sufficient edge compute and power budget; for severely constrained devices, the cost of edge computation may outweigh transmission savings. Finally, multi-cloud or cross-region routing to exploit lower-carbon electricity mixes raises

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complexity, regulatory, and data-governance concerns. These limitations indicate that while the proposed framework is broadly applicable, deployment decisions must be made with awareness of measurement constraints, application-criticality, and operational trade-offs.

7. USE CASES AND APPLICATIONS

7.1. Smart agriculture

In smart agriculture, distributed sensor networks monitor soil moisture, temperature, humidity, nutrient levels, pest activity, and crop health to enable precision farming and resource-efficient irrigation and fertilization. An energy-efficient serverless ML inference pipeline for this domain can dramatically reduce operational cost and carbon footprint by performing lightweight filtering at field gateways—such as event consolidation when conditions are within normal ranges—and invoking serverless inference only for anomalies or threshold crossings that require agronomic action. Compact, distilled models embedded in serverless functions can classify disease symptoms from imagery or predict irrigation needs from multi-sensor time series while quantized and pruned variants minimize energy use during bursts of harvest-time monitoring. The event-driven nature of FaaS also supports seasonal workloads: compute is nearly zero during fallow periods and scales automatically during planting, growth, and harvest peaks. Furthermore, the ability to route compute to regions with cleaner energy or to defer non-urgent batch analytics to off-peak hours aligns precision agriculture with sustainability goals, enabling farmers to optimize yield while reducing both costs and environmental impact.

7.2. Smart healthcare monitoring

Smart healthcare monitoring relies on continuous streams of physiological and activity data from wearable devices, in-home sensors, and remote diagnostic equipment to provide early warning of health deterioration, support chronic disease management, and enable telemedicine. In this sensitive domain, energy-efficient serverless inference pipelines must balance strict privacy, latency, and accuracy requirements with the need to conserve device and system energy. Edge pre-processing and tiny-ML models on wearables can perform initial screening—filtering routine readings and forwarding only clinically relevant anomalies—while serverless functions execute more sophisticated inference or aggregate multi-device contexts for clinician review. Model versioning and A/B testing ensure that updates meet clinical validation before rollout, and knowledge-distilled models provide near-teacher accuracy at far lower energy cost. Because patient safety may demand rapid responses, the pipeline can combine fast, low-energy student models for triage with conditional escalation to heavier, higher-fidelity models when uncertainty is high, thereby minimizing unnecessary high-energy computation while preserving clinical effectiveness.

7.3. Industrial IoT (IIoT) anomaly detection

Industrial IoT environments generate high-frequency telemetry from machinery, motors, and control systems, and anomaly detection is critical to prevent costly downtime and catastrophic failures. The proposed energy-efficient serverless pipeline suits IIoT by enabling continuous monitoring without the overhead of permanently provisioned compute and by reducing false alarm rates through edge-

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based filtering and context-aware routing. Lightweight anomaly detectors deployed on fog nodes can capture early deviations and only forward suspicious windows to serverless functions that run more sophisticated predictive maintenance models. Model compression techniques allow complex vibration- or waveform-analysis models to be executed efficiently within FaaS constraints, while function chaining supports staged decision-making—initial scoring followed by root-cause analysis—minimizing the number of heavy invocations. In high-stakes industrial settings, the pipeline can be further tuned to meet real-time constraints by selectively using provisioned concurrency or dedicated inference endpoints for critical assets, while still realizing energy savings across the broader fleet through adaptive hybrid strategies.

7.4. Smart home automation

Smart home automation systems integrate a variety of sensors and actuators to manage energy use, security, and occupant comfort. Energy-efficient ML inference in this context reduces latency for interactive automation while limiting cloud energy and bandwidth use through intelligent edge pre-processing. Routine behaviors—thermostat adjustments, lighting cycles, or known occupancy patterns—can be handled locally, while serverless functions process aggregated or anomalous events such as security alerts, unusual appliance energy usage, or health-related incidents. The serverless model is particularly attractive for homeowners because it provides pay-as-you-go economics: during vacations or prolonged inactivity the cloud cost and energy footprint drops to near-zero. Additionally, model versioning enables privacy-preserving A/B testing and gradual rollouts of new automation policies, and distilled models ensure that common inference tasks remain lightweight. By combining local responsiveness with cloud-level analytics only when necessary, smart homes can deliver convenience and safety while minimizing overall energy consumption.

7.5. Environmental IoT sensing

Environmental monitoring initiatives—ranging from air and water quality surveillance to wildfire detection and biodiversity tracking—often deploy large numbers of low-power sensors across remote or wide geographic areas, making energy efficiency paramount. In such deployments, the serverless ML inference pipeline provides a scalable way to analyze infrequent but critical events without maintaining always-on cloud infrastructure. Edge filtering compresses continuous sensor streams into salient events, such as pollutant threshold exceedances or acoustic signatures of targeted species, and serverless functions perform classification, aggregation, and geospatial correlation at scale when needed. Because environmental applications often tolerate modest processing delays for non-critical analytics, the system can defer batch analyses to periods of lower electricity grid carbon intensity or to regions with cleaner energy, thereby reducing the overall environmental impact of the monitoring program. The pipeline's modularity and model versioning also facilitate collaborative, multi-stakeholder deployments where different agencies can deploy and update models independently while sharing a common energy-optimized processing backbone.

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8. CONCLUSION AND FUTURE WORK

8.1. Summary of findings

This paper has presented an integrated framework for energy-efficient ML inference pipelines targeted at IoT applications by leveraging serverless cloud functions, edge pre-processing, and model optimization techniques. Through architectural design that emphasizes event-driven execution, function-level resource tuning, and selective use of compressed model variants, the approach reduces idle compute waste, lowers per-inference energy consumption, and maintains acceptable accuracy across a variety of IoT workloads. Experimental methodology and benchmarking reveal that the greatest gains occur for intermittent workloads typical of many IoT deployments, where FaaS's pay-per-invocation model and automatic scaling align resource consumption with actual demand. The combined use of edge filtering, quantization, pruning, and knowledge distillation further improves energy profiles while enabling practical trade-offs between latency, cost, and predictive performance. Overall, the findings indicate that serverless architectures, when thoughtfully integrated with edge intelligence and optimized model artifacts, can form a sustainable backbone for large-scale, real-time IoT inference.

8.2. Contributions to sustainable IoT systems

The work contributes to sustainable IoT systems by demonstrating how architectural choices and model-level optimizations translate into measurable energy and cost savings without wholesale sacrifice of accuracy. By framing ML inference as an elastic, event-driven workload and by introducing energy-aware routing, adaptive model selection, and observability-driven feedback loops, the paper provides actionable design patterns and operational guidelines that practitioners can apply to reduce the environmental footprint of IoT analytics. The model registry and profiling approach gives operators the tools to reason about energy–accuracy trade-offs and to select deployment points appropriate for application criticality. In sum, the contributions bridge the gap between theoretical model compression techniques and practical, deployable serverless pipelines suited to real-world sustainability objectives.

8.3. Future improvements

Future work will explore several avenues to make serverless ML inference even more energy- and carbon-aware, to improve real-time guarantees, and to broaden applicability across constrained-device ecosystems. First, Green FaaS investigations will examine provider-level and cross-region orchestration strategies that explicitly minimize carbon intensity by preferring regions or time windows with lower grid emissions and by dynamically routing or deferring non-urgent inference. Second, on-device tinyML integration will be deepened so that a greater fraction of routine inference and pre-filtering can be performed on battery-powered sensors while maintaining lifecycle provisioning and seamless model updates. Third, adaptive hybrid inference models will be developed that automatically choose between on-device, fog, serverless, and managed endpoint executions on a per-request basis using learned policies that factor in energy, latency, accuracy, and cost. Finally, carbon-aware scheduling mechanisms will be integrated into the orchestration layer so that batch retraining, heavy inference, and non-urgent analytics can be scheduled in response to real-time grid carbon signals, electricity price

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signals, or renewable availability, enabling IoT analytics to be both performant and environmentally responsible.

REFERENCES

[1] S. Han, H. Mao, and W. J. Dally, "Deep compression: Compressing deep neural networks with pruning, trained quantization, and Huffman coding," *Proc. ICLR*, 2016.
[2] G. Hinton, O. Vinyals, and J. Dean, "Distilling the knowledge in a neural network," *arXiv preprint arXiv:1503.02531*, 2015.
[3] Satyanarayanan, M. (2017). The emergence of edge computing. *Computer*, 50(1), 30–39.
[4] Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016). Edge computing: Vision and challenges. *IEEE Internet of Things Journal*, 3(5), 637–646.
[5] Mao, Y., Zhang, J., & Letaief, K. B. (2017). Dynamic computation offloading for mobile-edge computing with energy harvesting devices. *IEEE Journal on Selected Areas in Communications*, 34(12), 3590–3605.
[6] Sardellitti, S., Scutari, G., & Barbarossa, S. (2015). Joint optimization of radio and computational resources for multicell mobile-edge computing. *IEEE Transactions on Signal and Information Processing over Networks*, 1(2), 89–103.
[7] Deng, R., Lu, R., Lai, C., Luan, T. H., & Liang, H. (2016). Optimal workload allocation in fog-cloud computing toward balanced delay and power consumption. *IEEE Internet of Things Journal*, 3(6), 1171–1181.
[8] Hellerstein, J. M., Faleiro, J., Gonzalez, J., Schleier-Smith, J., Sreekanti, V., Tumanov, A., & Wu, C. (2018). Serverless computing: One step forward, two steps back. *CIDR*.
[9] Jonas, E., Schleier-Smith, J., Sreekanti, V., Tsai, C.-C., Khandelwal, A., Pu, Q., … Stoica, I. (2017). Cloud programming simplified: A Berkeley view on serverless computing. *arXiv preprint arXiv:1902.03383*.
[10] McGrath, G., & Brenner, P. R. (2017). Serverless computing: Design, implementation, and performance. *2017 IEEE 37th International Conference on Distributed Computing Systems Workshops (ICDCSW)*, 405–410.
[11] Ao, L., Izhikevich, L., Voelker, G. M., & Porter, G. (2018). Sprocket: A serverless video processing framework. *Proceedings of the ACM Symposium on Cloud Computing*, 263–274.
[12] Ishakian, V., Muthusamy, V., & Slominski, A. (2018). Serving deep learning models in a serverless platform. *IEEE International Conference on Cloud Engineering (IC2E)*, 257–262.
[13] Carreira, J., Fonseca, P., Tumanov, A., Zhang, A., & Katz, R. (2018). A case for serverless machine learning. *Workshop on Systems for ML (SysML)*.
[14] Zhang, Q., Chen, M., & Li, L. (2017). Deep learning-based energy-efficient resource management for IoT systems. *IEEE Network*, 31(5), 70–76.
[15] Xu, X., Chen, Y., Li, Q., Liu, Y., & Zhang, W. (2018). Efficient multi-user computation offloading for mobile-edge cloud computing. *IEEE/ACM Transactions on Networking*, 26(3), 1485–1498.