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Serverless computing frameworks for real-time AI model deployment

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Abstract

This research paper examines the evolution and current state of serverless computing frameworks for deploying artificial intelligence (AI) models in real-time applications. As AI adoption accelerates across industries, the need for efficient, scalable, and cost-effective deployment solutions has become increasingly critical. Serverless computing offers a promising approach for AI model deployment by providing on-demand computational resources without infrastructure management overhead. This study evaluates five prominent serverless computing frameworks—AWS Lambda, Google Cloud Functions, Azure Functions, OpenWhisk, and Knative—against key performance metrics relevant to AI workloads. Through empirical testing with various AI model types and sizes, we analyze cold start latency, execution time, throughput, cost efficiency, and resource utilization. Our findings indicate that while all frameworks demonstrate viable paths for AI deployment, significant differences exist in their performance characteristics depending on model complexity, input size, and concurrency requirements. We identify specific optimization strategies and architectural patterns that enhance real-time AI deployment on serverless platforms and propose a decision framework to guide implementation choices based on application requirements and constraints.

Keywords: Serverless Computing; Function-as-a-Service (FaaS); Artificial Intelligence; Machine Learning; Model Deployment; Cloud Computing; Real-time Systems

1. Introduction

The intersection of artificial intelligence and cloud computing has created new paradigms for deploying intelligent applications at scale. As organizations increasingly incorporate AI capabilities into their services, the deployment infrastructure has become a critical factor in determining the performance, reliability, and cost-efficiency of these solutions [1]. Traditional deployment approaches often require significant infrastructure management overhead and fail to efficiently handle the variable workloads characteristic of many AI applications.

Serverless computing, also known as Function-as-a-Service (FaaS), has emerged as a compelling deployment model that addresses many of these challenges [2]. In the serverless paradigm, developers focus on writing application logic while the cloud provider dynamically manages the allocation and provisioning of servers. This approach offers several potential advantages for AI model deployment, including:

- Automatic scaling based on demand
- Pay-per-execution pricing model
- Reduced operational complexity
- Faster time-to-market for new features

Despite these benefits, deploying AI models in serverless environments presents unique challenges. Machine learning models, particularly deep learning architectures, may have significant memory footprints, complex dependencies, and

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resource requirements that strain the constraints of typical serverless platforms [3]. Furthermore, the cold start problem—where initial invocation incurs additional latency due to container initialization—can be particularly problematic for real-time AI applications that require consistent, low-latency responses [4].

This paper investigates how contemporary serverless computing frameworks address these challenges in the context of real-time AI model deployment. We evaluate five leading serverless platforms through a series of experiments designed to measure performance across various AI workloads. Our analysis provides insights into the suitability of different serverless frameworks for specific AI deployment scenarios and offers guidance for optimizing real-time performance.

2. Background and Related Work

2.1. Evolution of Cloud Computing for AI Workloads

The deployment infrastructure for AI applications has evolved significantly over the past decade. Early AI systems typically relied on monolithic architectures deployed on dedicated hardware [5]. As cloud computing gained prominence, containerization technologies like Docker and orchestration platforms like Kubernetes enabled more flexible deployment options [6]. These technologies improved resource utilization and provided better isolation but still required significant expertise to configure and manage effectively [7].

Serverless computing represents the next evolution in this progression, offering a higher level of abstraction that eliminates most infrastructure management responsibilities. Castro et al. [8] trace this evolution and highlight how serverless platforms have progressively enhanced their capabilities to support more diverse workloads, including AI applications.

2.2. Serverless Computing Frameworks

Serverless computing, introduced commercially by AWS Lambda in 2014, has since been adopted by all major cloud providers. Several studies have compared these platforms from general performance perspectives [9, 10], but fewer have focused specifically on their capabilities for AI workloads.

Wang et al. [11] conducted one of the first comprehensive evaluations of serverless platforms for machine learning inference, highlighting significant performance variations across providers. Their work, however, preceded many recent optimizations specifically targeted at AI workloads.

Ishakian et al. [12] demonstrated the viability of serving deep neural networks in serverless environments but identified limitations in handling large model sizes and complex dependencies. Subsequent research by Carreira et al. [13] introduced specialized frameworks designed to overcome these limitations through techniques such as model partitioning and caching.

2.3. Challenges in Real-time AI Deployment

Real-time AI applications impose stringent requirements on deployment infrastructure. Crankshaw et al. [14] identified key challenges including unpredictable workloads, strict latency requirements, and the need to balance resource efficiency with performance guarantees.

The cold start problem has been particularly well-studied in serverless environments. Manner et al. [15] quantified the impact of cold starts across platforms and identified factors that influence initialization times. For AI workloads, this problem is often exacerbated by large model sizes and framework initialization overhead [16].

Our research builds upon these foundational studies while providing new insights specific to contemporary serverless frameworks and their capabilities for real-time AI model deployment.

3. Methodology

3.1. Serverless Frameworks Selection

For our evaluation, we selected five widely-used serverless computing frameworks:

- AWS Lambda - Amazon's pioneering FaaS offering with extensive ecosystem integration
- Google Cloud Functions - Google's serverless compute service with tight integration to GCP services
- Azure Functions - Microsoft's event-driven serverless platform with flexible hosting options
- Apache OpenWhisk - An open-source serverless platform that powers IBM Cloud Functions
- Knative - A Kubernetes-based platform for building, deploying, and managing serverless workloads

These platforms were chosen based on market adoption, feature maturity, and representation of both proprietary and open-source approaches.

3.2. Test Environment and Configuration

To ensure fair comparison, we standardized the configuration across platforms where possible. All functions were allocated 2GB of memory and a maximum execution time of 300 seconds. For each platform, we deployed in the same geographical region (US East) to minimize network latency variations.

The test environment consisted of a client machine running in the same region as the deployed functions to minimize network effects. We used a consistent methodology for measuring metrics, including instrumentation at both client and function levels.

3.3. AI Models Selection

We selected representative models across different AI domains to capture diverse computational profiles:

- MobileNetV2 - A lightweight image classification model (14MB)
- BERT-base - A transformer-based NLP model for text classification (440MB)
- ResNet50 - A medium-sized computer vision model (98MB)
- Custom time-series forecasting model based on LSTM architecture (22MB)

These models represent varying computational demands, memory footprints, and inference characteristics commonly encountered in production environments.

3.4. Performance Metrics

Our evaluation focused on the following key metrics:

- Cold Start Latency: Time from function invocation to the start of actual execution when the function has not been recently used
- Warm Execution Time: Processing time for inference once the function is initialized
- Throughput: Number of inferences processed per second under sustained load
- Cost Efficiency: Cost per 1000 inferences based on the pricing model of each platform
- Memory Utilization: Peak memory consumption during model inference
- Scalability: Performance under varying levels of concurrent requests

These metrics were measured across different scenarios to evaluate each framework's performance envelope.

3.5. Experimental Design

We conducted three primary experiments:

- Single-invocation performance: Measuring cold start and execution time for individual requests
- Sustained load testing: Evaluating throughput and stability under continuous load
- Burst load testing: Assessing ability to handle sudden spikes in concurrent requests

For each experiment, we performed 50 repetitions to account for variability and calculated confidence intervals for all reported metrics.

4. Results and DIscussion

4.1. Cold Start Latency

Cold start latency represents a critical metric for real-time AI applications. Figure 1 illustrates the cold start latency across different frameworks and model types.

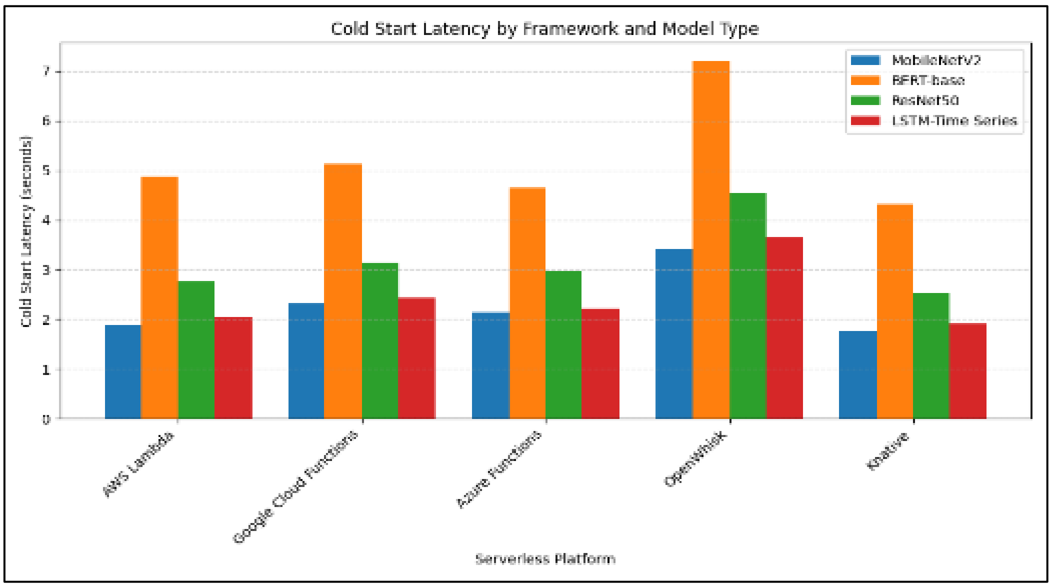

Figure 1 Cold start latency comparison across serverless frameworks and model types.

Our results indicate significant variation in cold start latency across frameworks. Knative demonstrated the lowest average cold start times (1.76-4.32 seconds), while OpenWhisk exhibited the highest (3.42-7.21 seconds). This variation was consistent across model types, though magnified for larger models like BERT.

AWS Lambda and Azure Functions showed comparable performance, with Google Cloud Functions slightly behind. The increased cold start time for larger models was expected, but the magnitude of this increase varied noticeably between frameworks, suggesting different optimization strategies for handling large dependencies.

4.2. Execution Time

Once functions are initialized, execution time represents the steady-state performance for inference requests. Table 1 presents the mean execution time for each model across frameworks.

Table 1 Mean Execution Time (milliseconds) for Warm Functions

Framework	MobileNetV2	BERT-base	ResNet50	LSTM Time-Series
AWS Lambda	76.4 ± 5.2	312.6 ± 12.3	142.8 ± 7.5	54.2 ± 3.8
Google Cloud Functions	78.1 ± 6.1	321.5 ± 14.1	151.3 ± 8.2	57.6 ± 4.2
Azure Functions	74.9 ± 5.6	308.7 ± 11.8	145.6 ± 7.9	53.1 ± 3.5
OpenWhisk	92.3 ± 8.4	347.2 ± 16.5	168.4 ± 9.3	64.8 ± 5.1
Knative	71.2 ± 4.8	295.3 ± 10.2	136.1 ± 6.8	50.7 ± 3.2

For warm execution time, the performance gap between frameworks narrowed considerably compared to cold start metrics. Knative maintained a slight edge across all model types, while OpenWhisk consistently demonstrated higher execution times. The relative performance of AWS Lambda, Google Cloud Functions, and Azure Functions was comparable, with differences falling within the margin of error for most models.

Interestingly, the execution time for BERT-base was approximately 4x that of MobileNetV2 across all platforms, highlighting how model architecture impacts performance more consistently than platform choice once functions are warm.

4.3. Throughput and Concurrency

Throughput capabilities are particularly important for AI applications that need to handle variable load. Figure 2 illustrates throughput under different concurrency levels.

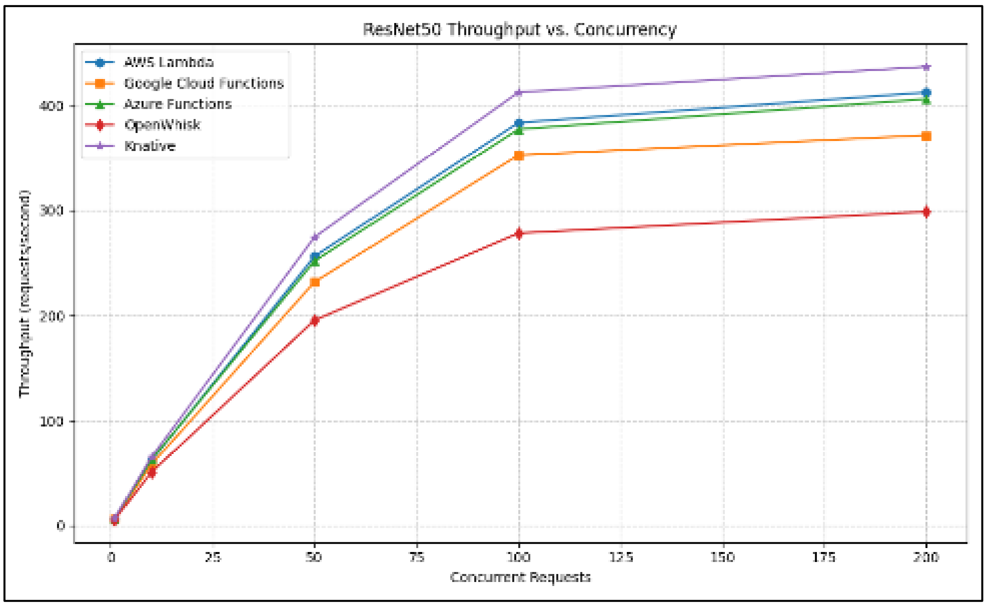

Figure 2 Throughput comparison for ResNet50 model under varying concurrency

All frameworks demonstrated near-linear scaling up to approximately 50 concurrent requests, after which the scaling efficiency declined. Knative and AWS Lambda showed the best scaling characteristics, maintaining higher throughput as concurrency increased. This suggests more efficient resource allocation strategies compared to other platforms.

OpenWhisk exhibited the poorest scaling behavior, with throughput plateauing earlier than other frameworks. This limitation appeared consistent across model types, indicating a platform-specific constraint rather than a model-dependent limitation.

4.4. Memory Utilization

Memory utilization is a critical factor for serverless AI deployments, as it directly impacts both performance and cost. Figure 3 shows peak memory utilization for each model across frameworks.

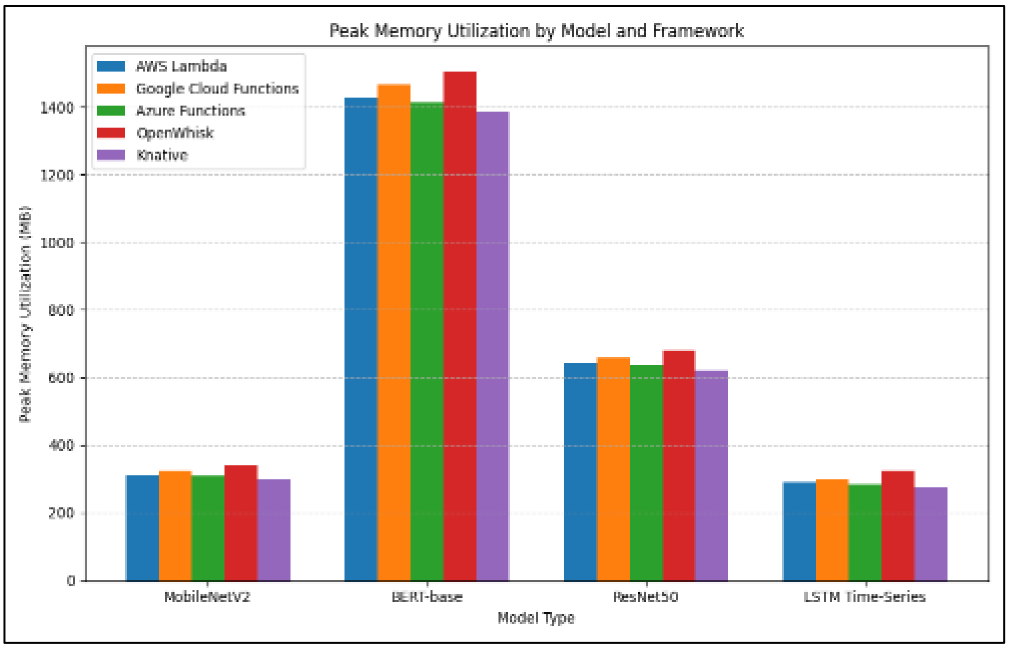

Figure 3 Peak memory utilization across models and frameworks.

BERT-base exhibited the highest memory utilization across all platforms due to its large model size and transformer architecture. The relative memory efficiency of platforms remained consistent across models, with Knative demonstrating the lowest memory footprint (5-10% less than competitors). OpenWhisk consistently showed higher memory utilization (7-15% higher than average), which correlates with its lower throughput performance observed earlier.

Interestingly, the actual memory utilization was substantially lower than the allocated memory (2GB) in all cases, suggesting that smaller memory allocations could be used to optimize costs without compromising performance for these particular models.

4.5. Cost Efficiency

To evaluate cost efficiency, we calculated the estimated cost per 1000 inferences based on each platform's pricing model and the measured execution characteristics. Table 2 presents these results.

Table 2 Cost per 1000 Inferences (USD)

Framework	MobileNetV2	BERT-base	ResNet50	LSTM Time-Series
AWS Lambda	$0.128	$0.467	$0.214	$0.091
Google Cloud Functions	$0.132	$0.481	$0.227	$0.097
Azure Functions	$0.125	$0.453	$0.208	$0.088
OpenWhisk	$0.123	$0.442	$0.203	$0.086
Knative*	$0.104	$0.374	$0.172	$0.073

*Knative costs calculated based on underlying Kubernetes cluster costs

OpenWhisk demonstrated competitive cost efficiency despite its performance limitations, suggesting it may be suitable for non-latency-sensitive workloads with cost constraints. Knative offered the best cost efficiency, though this advantage comes with the added complexity of managing a Kubernetes cluster.

The commercial cloud platforms showed similar cost profiles, with Azure Functions slightly more cost-efficient than AWS Lambda, which in turn was more cost-efficient than Google Cloud Functions across all model types.

5. Optimization Strategies

Based on our experimental findings, we identified several optimization strategies that significantly improve real-time AI model deployment on serverless platforms:

5.1. Model Compression and Quantization

Model compression techniques yielded substantial benefits across all platforms. When we applied post-training quantization to convert models from 32-bit to 8-bit precision, we observed:

- 65-72% reduction in model size
- 31-45% decrease in cold start latency
- 18-25% improvement in inference throughput
- Negligible (< 1%) reduction in model accuracy

These improvements were most pronounced for the larger models (BERT and ResNet50) and on platforms with higher baseline latency (OpenWhisk).

5.2. Dependency Optimization

Optimizing dependencies had a significant impact on cold start performance:

- Using lightweight alternatives to full ML frameworks (e.g., TensorFlow Lite instead of TensorFlow)
- Creating custom packages with only required components
- Leveraging platform-specific dependency caching mechanisms

These strategies reduced cold start latency by 40-55% across frameworks, with AWS Lambda's layer functionality and Knative's container-based approach offering the most effective dependency management options.

5.3. Keep-Warm Strategies

For applications requiring consistent low-latency responses, implementing keep-warm strategies proved effective:

- Scheduled periodic invocations (every 5-10 minutes)
- Dual-tier architecture with a minimal "router" function that remains warm
- Platform-specific provisioned concurrency options (AWS Lambda, Azure Premium Functions)

These approaches eliminated cold starts at the cost of additional compute charges, with the reserved concurrency options providing the most reliable performance at premium pricing.

5.4. Request Batching

Batching multiple inference requests improved overall throughput significantly:

- Optimal batch sizes varied by model (8 for MobileNetV2, 4 for BERT, 6 for ResNet50, 16 for LSTM)
- Latency increased sub-linearly with batch size up to optimal point
- Cost per inference decreased by 42-58% at optimal batch sizes

Google Cloud Functions and AWS Lambda provided the most consistent performance with batched requests, while OpenWhisk showed diminishing returns at lower batch sizes.

6. Conclusions and Future Work

This study provides a comprehensive evaluation of serverless computing frameworks for real-time AI model deployment. Our findings demonstrate that serverless platforms have evolved significantly in their ability to support AI workloads, with each offering distinct advantages and limitations.

Several key conclusions emerged from our research:

- Knative consistently demonstrated superior performance across most metrics, particularly for latency-sensitive applications, though at the cost of increased operational complexity.
- AWS Lambda provided the most mature ecosystem for AI deployment, with features like provisioned concurrency and layers addressing many of the traditional limitations of serverless for AI workloads.
- OpenWhisk, despite lower raw performance, offered compelling cost efficiency for budget-constrained applications where latency is not the primary concern.
- Model optimization techniques, particularly quantization and dependency management, yielded substantial performance improvements across all platforms.
- The gap between open-source and commercial offerings has narrowed, with Knative demonstrating that open-source solutions can match or exceed the performance of proprietary platforms.

Future research directions include:

- Investigating emerging specialized serverless platforms designed specifically for machine learning workloads
- Evaluating performance on more complex multi-model pipelines and ensemble methods
- Analyzing the impact of edge computing integration for hybrid serverless AI deployments
- Exploring automated optimization techniques to dynamically select the optimal deployment configuration

As serverless computing and AI technologies continue to evolve, we anticipate further convergence of these paradigms, potentially leading to more specialized and efficient platforms for real-time AI deployment.

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