# An Adaptive ML-Driven Layer-wise Caching and Pre-warming Approach for Cold Start Mitigation in Serverless Frameworks

MSc Research Project
MSc Cloud Computing

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| **Module:** | MSc Research Project |
| **Supervisor:** | Sai Emani |
| **Submission Due Date:** | 15-09-2025 |
| **Project Title:** | An Adaptive ML-Driven Layer-wise Caching and Pre-warming Approach for Cold Start Mitigation in Serverless Frameworks |

**Word Count:** 9458 **Page Count**: 21

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# An Adaptive ML-Driven Layer-wise Caching and Pre-warming Approach for Cold Start Mitigation in Serverless Frameworks

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**Abstract**

Applications that rely on serverless computing with AWS Lambda can experience delays since it takes time for processes to start which can slow down time-sensitive tasks. The current strategies do not work well in the cloud because static caching does not respond to changing demands and large predictive pre-warming is expensive and still fails when there is a sudden increase in traffic. This research offers an adaptive framework that merges intelligent dependency caching with pre-emptive prediction to reduce the cold start challenges in AWS Lambda environments. The framework utilizes a hybrid LSTM-XGBoost model to predict the invocation patterns of functions, where LSTM networks capture the temporal relationships among the different functions and XGBoost models capture feature interactions across system metrics. The hybrid prediction system offers cold start probability estimation with 67.3 percent combined accuracy and the confidence levels ranging between 45.1 to 46.6 percent at different load settings. The performance assessment shows significant improvements in latency with a reduction in response time during optimal warm execution conditions to about 92.5-94.0ms. The three-tier caching system configuration (hot, warm, cold) with dynamic resource allocation delivers up to 20 percent cost savings through pre-warming strategies. The analysis provides validation to the increased performance optimization in serverless computing by exhibiting the quantifiable benefits of optimizing the cold start frequency, execution time, memory usage, and costs-per-million invocation.

## 1 Introduction

### 1.1 Research Background

Through serverless computing, cloud computing has improved by allowing developers to avoid servers and manage less; while still experiencing automated scaling and not having to pay for resources they do not use (Pan et al., 2023). But there is a persistent problem with serverless called cold starts, where a function needs to be started from the beginning, leading to significant delays in latency-sensitive workloads (Liu et al., 2023). New studies have looked at diverse ways to reduce memory waste and avoid cold starts in containers. It is claimed that generated layer-wise caching containers can decrease memory wastes by 77%, some claim that predictive ones may be capable of avoiding cold starts altogether (Yu et al., 2024; Htet et al., 2024). Previously, container reuse used to be straightforward, but it has long been much more intelligent with the introduction of such an approach as Multi-Level container reuse (MLCR), which led to a 53-percent reduction in the common startup times through the effective allocation of resources into interrelated CPU functions (Zhou et al., 2024). Machine learning tools can now accurately predict when cold starts will occur in serverless apps which helps teams take early actions to address the issues (Golec et al., 2024).

## 1.2 Problem Statement

Although there are improved ways to deal with cold starts, they do not function well in real production cloud environments, especially in AWS Lambda. Current techniques struggle to manage different workloads because their static methods are not flexible enough for new or changing uses of resources (Sui et al., 2024). These methods seem to work in laboratory setup, but they cost too much to operate and do not deal well with sudden rises in traffic use in real life. Currently, most of these layer-wise caching solutions have only been tested on Apache OpenWhisk, leaving little support for popular public cloud services such as AWS Lambda (Htet et al., 2024). Because public clouds serve multiple organisations, rules for resource allocation are not fixed. For this reason, businesses must use a mix of approaches to achieve both good performance and cost savings under practical work scenarios.

## 1.3 Motivation

Combining sophisticated machine learning practices with AWS Lambda helps solve many cold start concerns. With Lambda Layers and integration with Elastic File System (EFS), AWS Lambda now supports advanced sharing and memory solutions that were not possible earlier (Murugesan, 2024). Hybrid machine learning models which merge time-based analysis with feature prediction, have been found to perform better in dynamic clouds by adjusting to new workload patterns and choosing how to use resources wisely (Golec et al., 2024). Tools such as Cost Explorer APIs from AWS allow for the construction of systems that guarantee capacity, at the same time as helping reduce costs. Bringing together the strengths of ML and cloud services forms the base for designing comprehensive solutions that solve the challenges of one-strategy systems while still keeping costs controlled in production.

## 1.4 Research Question

How can a hybrid machine learning approach combining LSTM temporal analysis and XGBoost feature prediction, integrated with adaptive layer-wise dependency caching and cost-aware pre-warming, reduce cold start latency and improve resource efficiency in AWS Lambda compared to existing mitigation strategies under dynamic workload conditions?

## 1.5 Research Objective

To develop and evaluate an adaptive ML-driven framework that significantly reduces cold start frequency and initialization latency in AWS Lambda through intelligent dependency caching and predictive pre-warming while maintaining cost-efficiency and adaptability to dynamic workload patterns.

## 1.6 Contributions

- Creating a ML prediction model that uses LSTM networks to discover patterns and XGBoost for making predictions based on data, to accurately predict serverless function invocation patterns as workloads change.
- Creating a layer-wise dependency cache and AWS Lambda Layers to allow resource sharing and less launch time for all function instances
- Building a frictionless framework that alters access to functions depending on how well a task is likely to succeed and the available budget information from AWS Cost Explorer tools.

- A well-developed system is made to measure the effectiveness of new cloud services based upon metrics including reduced cold starts, faster initialization, better use of memory and low cost for every million invocations.
- Measurable enhancement and cost reduction in serverless scenarios must be analyzed for better performance than previous mitigation strategies using necessary tests.

## 2 Related Work

### 2.1 Container-Level Optimization and Caching Strategies

RainbowCake, a layer-wise system to mitigate cold-starts by caching and sharing containers in a consistent manner was proposed by (Yu et al., 2024). The study focuses on the inherent shortcoming of the current solutions which resort either to partial caching of containers or sharing of containers, but each of these approaches has severe limitations. RainbowCake has a synergetic mix of these techniques that separate container startup into three parts, environment preparing, language runtime loading, and loading user code. The system has a mechanism and uses sharing-aware algorithms to make run-time event-driven layer-wise caching decisions that allow various functions to reuse compatibility container layers. The experimental analysis of RainbowCake on the OpenWhisk clusters proves that RainbowCake shows impressive performance advantages, decreasing the startup latency of the functions by 77% and their memory waste, compared to the alternative solutions.

Zhou et al. (2024) design Multi-Level Container Reuse (MLCR) that address cold start problems by intelligently reusing the containers across multiple functions that have similar package dependencies. In the research, the dependence on common operating systems and language frameworks in the real-world are reflected, and the analysis indicates that four base images that have become quite popular have been pulled from the top 1000 of images in Docker Hub. MLCR groups together packages into three hierarchies - OS, language and runtime packages, and uses Deep Reinforcement Learning based scheduler to make best decisions concerning reuse of containers. The system proposes FStartBench, a detailed benchmark that provides the information about a package to test cold start solutions. With experimentation, MLCR is shown to reduce average function startup latency performance by up to 53% and conveys a substantial positive effect on warm resource utilization using intelligent strategies such as container sharing.

Pandey and Kwon (2024) proposes a new approach referred to as FuncMem, that deals with memory resources in serverless systems by prioritizing non-blocking asynchronous requests and pre-emptive optimization of memory resources. This is a very important issue in the study, as cloud tenants tend to over allocate the memory setting that leads to control inefficient container lifetime and cold start. An essential metric of memory use for FuncMem is calculated with a parallel running simulator which adjusts functions dynamically by means of adaptive queues whose origins diversify between blocking and non-blocking requests. The scheduling policy used in the system is the priority-based where blocking requests are given the higher weight on priorities compared to non-blocking requests which are allocated to various selectors such as deadline and error processing. There is a detailed assessment in OpenWhisk that shows an outstanding increase in performance aspects such as cold start latency, memory allocation, and cumulative execution time.

A skippy container scheduler, an optimized container scheduling system with special points tailored to data-intensive serverless edge computing environments, was presented by (Rausch et al., 2021). The study targets the shortcomings of the current serverless systems confronting the edge infrastructure properties, such as heterogeneity of devices, geographical distribution, and location aspects. Skippy uses a greedy multi-criteria decision-making algorithm with four new scheduling constraints including proximity to the data storage nodes, proximity to the container registry, available compute capabilities and edge/cloud locality preferences. The system is integrated with the current container orchestration system (such as Kubernetes), but it makes them responsive to edge computing needs. The quality metrics of task placement showed to improve substantially with Skippy compared to typical Kubernetes schedulers using trace-driven simulations and testbed evaluations and showed that they could effectively trade between data and computation movement in edge distributed systems.

Shahid et al. (2024) realize an adaptive machine learning framework named Latency-Sensitive Function Placement to optimize the placement of the function in heterogeneous serverless computing context. The study deals with the problem of how to place functions efficiently on a range of different node types so as to achieve a high level of latency as well as resource constraints. The system uses XGBoost regressors to calculate the execution time of single functions and decision tree regressors to estimate the network latency, in figuring the network delay, pattern of the computation arrival, and resource focus. The framework employs the use of Docker containers whereby the concentration within the framework is inclined with regard to serverless node variety, location of the functions and deadlines as well as edge-cloud topology. Upon critical analysis, the system proves as a good utilization of resource that contributes to an increase in meeting deadlines and the optimization of the selection process of placements by taking relevant data-driven decisions using intelligent machine learning techniques.

## 2.2 Predictive Pre-warming and Machine Learning Approaches

Golec et al. (2024) constitutes the largest literature study of cold start latency mitigation in serverless computing conducted to date, having reviewed more than 100 articles on cold start latency mitigation published in both academic and industrial literatures. The study provides a solid taxonomy of cold start solutions that are divided into several approaches such as the container caching, predictive pre-warming, and resource optimization as well as techniques. The five key research questions that are proposed in this study are issues that analyze cold start relationships with QoS parameters, issues of latency factors, the classification of solutions that have already been thought of, platform implementations, and the trends in publishing. The research discloses through systematic analysis that dependence loading is the reason behind 70% of the cold start overhead, not the initialization of the containers which indicates the necessity of the intelligent dependency management. The study has given useful information on future research and has laid a background to the present state and issues regarding serverless cold start mitigation.

Nguyen (2023) presents a highly advanced method of cold start prediction with a chained deep learning pipeline module that will conduct forecasts up to 10-15 minutes. The limitation to traditional machine learning algorithms in time-series prediction in serverless computing environments is met by the research which introduces a global model, which learns collectively on multiple time-series data. The system uses direct forecasting as opposed to step-by-step prediction, which facilitates an effective fulfilment of the scalability and cost demands. The deep learning pipeline has two modules whose functions are integrated, one module is used to predict future functions instance names and the other to predict the arrival times. The system has been exhaustively tested against real serverless traces and has confirmed to be able to scale its performance across various workload patterns and in addition proactively manage the cold starts by its accurate prediction capabilities.

Nguyen (2024) proposes an end-to-end method of cold start management applied in predicting the instance of the function via temporal convolutional network (TCN). The study translates real-life serverless problems into requirements of a particular dataset and corresponding predictive model, and realizes a TCN model, which can accurately predict the instances of the functions and the arrival times to a server 10-15 minutes in the future. The system proposes a brand-new ensemble policy which allows feedback looping with the upper management policy, as well as orchestration of lower-level cold start optimization policies. This dual principal can be used to more readily incorporate multiple optimization practices and facilitate continuous feedback loops so crucial in AI-based autonomic building blocks of computing systems. The results of the evaluations indicate trustworthy performance with various trace datasets of most popular serverless providers, and the ensemble policy has strategic benefits in the coordination of resource management capabilities.

Sui et al. (2024) identifies the major problem that machine learning inference tasks are uniquely prone to experiencing cold start latencies because of extensive requirements relating to loading large amounts of artifacts. The study finds that serverless inference workloads experience a significant amount of inevitable latency during libraries and models loading up to 70 percent of the total latency, which makes the conventional pre-warming methods inadequate. InstaInfer establishes an opportunistic pre-loading strategy, made use of warm containers memory to pre-load function libraries and models, attempting to balance between the highest possible acceleration and resource-wasting. The system adopts a proactive pre-loader which approximates the pre-loading of each function time and pre-loading scheduler which assigns each converting appropriate idle containers and inter container manager to take control over loading and caching of artifacts. Vast scale experiments on real-world traces also show that InstaInfer can speed up the startup latency by 93% and the overall working load by 8x that of the state-of-the-art pre-warming mechanisms.

Karamzadeh and Shameli-Sendi (2024) develop a new framework that provides minimization of the start-up time of cold-starts using supervised learning techniques by integrating a lightweight virtual machine. The study uses machine learning to forecast the use of functions based on execution patterns of similar program functions, so that the cold start circumstances can be avoided by making pre-invocations. They employ Kata Containers and gVisor virtual machines to achieve security goals in conjunction with resolving the vulnerability of escape containers, accepting the overheads during the run-time of loading containers and virtual machines. By comparing the evaluation performance of fixed window, variable window and proposed prediction approach, the system has shown a considerable difference on the incidence of cold start by 83.33%, 92.13% and 90.90% when function calls are made 200 times with 5, 10 and 20 times-per-hour invocation respectively.

## 2.3 Cost-Aware Orchestration and Optimization Frameworks

Jarachanthan et al. (2023) proposes Autonomous Cost-Efficient Task Orchestration (ACTC) a framework to cover both the cost optimization and orchestration of tasks in serverless analytics platforms, in particular developed with AWS Lambda in mind. The key challenge addressed by ACTS is the core challenge of adapting data analytics application that exist to be deployed over a serverless environment and being cost effective by using smart scheduling and coordination of tasks. The framework deals with cold-start latency mitigation and reduction of state sharing overhead via prudent scheduling of functions tasks and investigation of fine-grained workload distribution optimization. The resource configuration techniques applied by ACTS are smart enough to meet the requirements in terms of performance and satisfy the specifications of the budget limits, being able to dynamically allocate resources due to the native support in AWS Lambda to do so. The experimental validation by a wide range of experiments shows the impressive cost-saving outcomes of reaching up to 98% of relevant cost with a consistently high job completion rate vs the available baselines, positioning ACTS as one of the breakthroughs in cost-sensitive orchestration of serverless.

The studies by (Chen et al., 2024) on the capacity reservation deserve a thorough examination of the methods of cost optimization on cloud computing platforms in terms of random surges in demand, which is specifically applicable to AWS and other popular public clouds. The study covers the acute issues of both capacity reservation and resource allocation in uncertain demand trends, introducing the mathematical tools to optimize cloud expenses and yet assure its quality of services. The paper explores the strategic uses of various pricing models such as on-demand, reserved instances and spot pricing that could allow the organization to face low costs in general and still meet the demand during peak hours. The study is structurally and analytically critical and experimentally demonstrated, and the conclusions are possible by large cost savings from the intelligent capacity and reservation planning that offer applicable steps to the organization to maximize their cloud expenditure profile without compromising operational robustness.

The work by (Deochake, 2023) is a comprehensive analysis of cloud cost optimization tactics and practical implementation scenarios, especially when it comes to the complex concepts and practices of AWS cloud services and dealing with their costs. The study systematically tabs the different cost optimization strategies such as resource rightsizing, selection of pricing models, architectural optimization and cost-control automation solutions. The study analyzes implementation issues in practice and gives elaborate case studies that show effective cost reduction techniques in various organizational settings and implementations of clouds. By conducting thorough research on the cloud pricing model, resource allocation technique, and monitoring method, the study has been able to develop a foundation of insight into how organizations can benefit greatly by means of cost savings and also upholding levels of performance and reliability in cloud systems.

Khan et al. (2024) presented the methodology of graph-based cloud cost modeling and optimization on the AI-driven multi-cloud and hybrid cost environment, which considers the complexity of the contemporary cloud implementation. The study suggests an innovative technique to model cost components, cloud resources, and their interrelations in the context of the graph theory that allows the application of complex optimization algorithms to identify an optimal resource allocation and price optimization strategy. The model resolves the issue of cost optimization in the form of constraint by representing cloud services, pricing levels and resource dependencies as graph representations, which enables dynamically optimizing based on requirement and cost variations. In experimental validation, it is shown that the graph-based approach can achieve overall cloud cost reduction as well as keeping service level objectives without degrading the service and is scalable in challenging multi-cloud cost optimization problems.

A modern overview of cost and performance-optimization strategies focusing directly on AWS Lambda serverless systems, also covering the issues of cold start mitigation and cost effectiveness, is given in (El Bechir et al., 2024). The study unifies the most current advancements in serverless optimization and the resource management strategy, operation selection optimization, operational modes that are workload-aware and have a direct effect on cost efficiency. The different optimization methods explored in the study relate to memory allocation methods, optimization of the execution time, and architectural patterns that can be applied to reduce costs substantially and, at the same time, increase the performance of the application. Based on review of recent research findings and recommendations on best practices, the work develops and concludes on overall best practices on organizations wishing to optimize their serverless applications in both respect, cost effectiveness and performance considerations on AWS Lambda environments.

## 2.4 Research Gap Analysis

The key documents identified in this literature study, (Golec et al., 2024), and (Yu et al., 2024) offer a solid idea on which the proposed research will be based but point out the severe limitations that will be eliminated with the suggested work. The systematic review conducted by Golec et al. concludes that the current offerings of the cold start solutions concentrate more on single feature strategies with latency expenses currently assigned to dependency loading as opposed to container initialization, which indicates a highly valuable research gap in an integrated strategy to dependency management. Although their taxonomy describes in great detail the range of solutions available, it indicates the lack of hybrid solutions applying both predictive pre-warming and intelligent caching mechanisms, especially in the case of AWS Lambda environments that comprise a substantial part of production serverless instances.

RainbowCake developed by (Yu et al. 2024) shows that layer-wise container caching can be useful, leading to 68 percent latency and 77 percent memory waste reductions in OpenWhisk environments. Nonetheless, their strategy has a number of drawbacks that are addressed in the proposed research. First, RainbowCake is fully deployed on OpenWhisk with no significant AWS Lamba inclusion; Second, the system has no cost awareness orchestrators that can take into consideration the budget limitation and variable pricing model; Third, its caching strategy is reactive, but they have no opportunities to predictively optimize using workload modeling. Also, RainbowCake does not factor in machine-learning based models of predicting the usage patterns of functions; rather they simply use past usage patterns but cannot incorporate a time-oriented analysis.

These limitations are bridged by a number of creative methods in the proposed research. The hybrid ML model that combines the LSTM temporal analysis with XGBoost feature prediction covers the gap adopted in the predictive approaches indicated by Golec et al. and extends to the reactive caching strategy elaborated by (Yu et al., 2024) AWS Lambda Layers and EFS introductions offer production ready deployment capabilities that RainbowCake does not have when it comes to AWS environments. The orchestration framework with AWS cost explorer APIs helps to close the economic optimization gap that exists in both the studies and allows dynamically making budget-based decisions that will optimize performance improvement and cost effectiveness. The metrics-based framework in evaluating the proposed research goes further into the metrics used in baseline research since they also focus on the overall performance indicators such as cold start frequency decrease, 95th percentile initialization latency increase and memory use efficiency.

# 3 Research Methodology

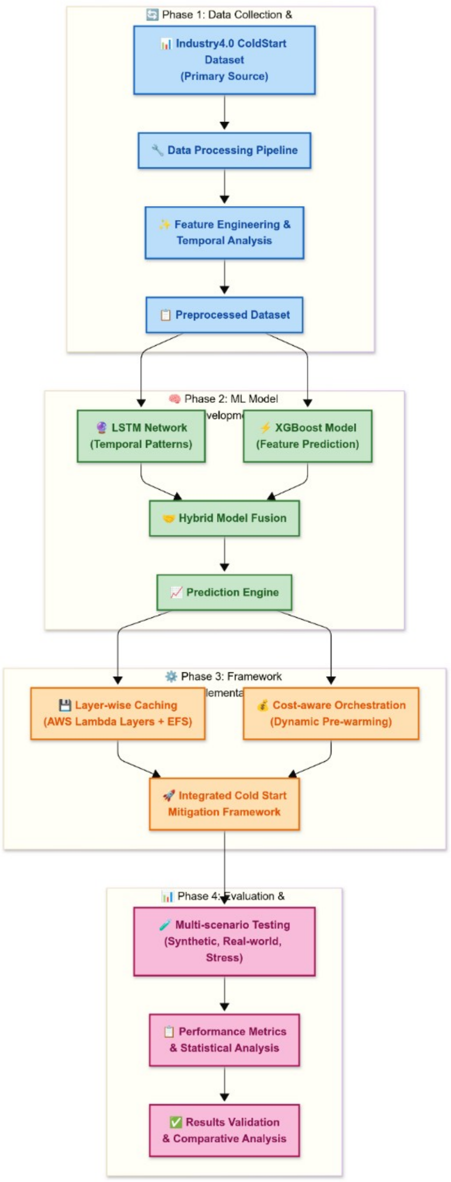
## 3.1 Research Design

This study uses an experimental research design to design and test an adaptive machine learning-based framework that would minimize the cold start in the AWS Lambda environment. This is done methodologically through stages of problem identification, solution design, implementation, and thorough evaluation of the research. To overcome the specified drawbacks in the current serverless cold start mitigation approaches, the methodology combines the predictive machine learning methodology with smart caching patterns.

The experimental set up involves a controlled comparison procedure in which the suggested hybrid framework will be tested against the known baseline approaches such as the predictive pre-warming techniques. The experiment will employ not only synthetic generation of workloads but also real-world trace study to trace all operational situations thoroughly. The research methodology will include testing of statistical significance to establish the validity of performance gains whilst ensuring that the rigor of scientific measure is upheld in the process of evaluation. The study adheres to the method of iterative development, which consists of an endless improvement and optimization of the proposed framework regarding experimental feedback and performance evaluation.

## 3.2 Workflow Overview

The research methodology presented in Figure 1 will be designed upon four main elements that synergistically help in attaining the research objectives. The framework starts by collecting and pre-processing extensive amounts of data, whereby hybrid machine learning algorithms are established to forecast the workload. This is followed by having an intelligent caching system, which is implemented by using AWS Lambda Layers to achieve a cost-sensitive orchestration system, which can dynamically make or break pre-warming decisions according to budget constraints and estimated workload patterns.



Phase 1: Data Collection &
Industry4.0 ColdStart Dataset (Primary Source)
Data Processing Pipeline
Feature Engineering & Temporal Analysis
Preprocessed Dataset
Phase 2: ML Model
LSTM Network (Temporal Patterns)
XGBoost Model (Feature Prediction)
Hybrid Model Fusion
Prediction Engine
Phase 3: Framework
Layer-wise Caching (AWS Lambda Layers + EFS)
Cost-aware Orchestration (Dynamic Pre-warming)
Integrated Cold Start Mitigation Framework
Phase 4: Evaluation &
Multi-scenario Testing (Synthetic, Real-world, Stress)
Performance Metrics & Statistical Analysis
Results Validation & Comparative Analysis

**Figure 1: Proposed Research Methodology**

The research methodology framework presented in Figure 1 provides a representation of the method followed in developing and testing the proposed solution in a systematic manner. The stages of implementation are successive, which mostly guarantees a complete and in-depth assessment of the adaptive ML-driven framework. The approach focuses on scientific rigor and reproducibility in the form of controlled experiments and statistical consolation of findings.

## 3.3 Data Collection and Preparation

The study draws on the Industry4.0 ColdStart dataset[1] as its crucial source of data in training and evaluating the confirmatory model. The Industry4.0 dataset has 1,440 records and covers 5 days (time-series) and 24-hour (circadian) patterns, so there exists enough data volume to develop powerful machine learning models. The dataset has a true-to-life serverless workload with 37.5 percent of time intervals in having active request pattern, which is a typical usage of serverless applications, where functions sit idle most of the time and see a burst of requests. The request patterns vary between 0-341 requests over a time period in about 92,233 requests overall, giving ample variability to the patterns for analysis. Latency performance is between 5-843 milliseconds, on an average of 78.11 milliseconds, which provides extensive performance data and can be used to study the cold starts and optimization. The dataset has a high level of completeness as all of its features are critical with 100% data availability of crucial fields such as DateTime, Hour, Day, Request, Latency, CPU_Usage, and Memory_Usage.

The 1,440-records data originally raised a valid issue of insufficiency towards the training of deep learning models, and this shortcoming should be openly disclosed. Nevertheless, there are few mitigating factors which make this dataset feasible in this particular research context. The dataset consists of five days of Industry 4.0 continuous operational data in 5-minute resolution, which produces valuable temporal patterns that are indispensable in cold start prediction as reported in the data preprocessing analysis. The entire feature engineering pipeline grew the records by 26 engineered features: cyclical temporal encodings, rolling statistics, and derivative metrics amplifying information content. Yet most critically, the LSTM architecture has a sequential input all data is read in succession - so with 12 time-step sequences, the LSTM still has to be trained on around 996 sequences of data, which is close to the lower limit of what can be considered acceptable in time-series modeling.

The preprocessing stage includes a number of vital steps necessary to achieve the best model performance. Temporal feature engineering computes sine and cosine distributions on hour and day information to acquire periodical behavior effectively. To detect changes in trend and burst conditions which are essential in the prediction of occurrences of cold starts, request rate calculations use sequential request patterns to derive metrics of velocity and acceleration. Latency normalization performs statistical transformation in order to have feature ranges that are similar across measures, whereas the missing value imputation method is performed through forward fill and interpolation of any missing data. The outlier detection will also be conducted and processed and will be applied during the preprocessing pipeline in the use of statistical tools to identify and correct any anomalous data points that may contribute to poor performance of the training model.

## 3.4 Machine Learning Model Development

The hybrid machine learning method can be described as the combination of the complementary algorithms to pick up not only the temporal dynamics but also the relationships between the features in serverless workload data. The LSTM element is dedicated to sequential pattern recognition and has a recurrent neural network structure which

[1] https://github.com/MuhammedGolec/Cold-Start-Dataset-V2

recognizes time dependencies and cyclical consistencies in the order of functions. The architecture of the model uses several LSTM blocks with drop-out regularization to avoid overfitting, with the attention-mechanism providing the model the ability to focus on important temporal characteristics when predicting a time-series. The LSTM takes in sequences of variable length as an input, thus flexible enough to use for various operational conditions with different horizons of prediction up to 15 minutes ahead. The model exploits early stopping and learning rate schedule to ensure efficiency of training and avoid overfitting.

The XGBoost element deals with feature-based forecasting that applies tabular data processing, and gradient increases. Tailoring of derived variables is done through feature engineering by formulating request rate changes, resource use trends and temporality indicators to maximize the predictive power. This model uses advanced methods of boosting at a cautious regularization parameter that applies both L1 and L2 regularization to avoid overfitting but keep the prediction accuracy high.

The choice of LSTM and XGBoost is a strategically motivated architectural decision based on the nature of cold start prediction problem. The LSTM selection fits with the necessarily time-based nature of serverless functions invocation patterns, with cold start events arising as sequences of resource consumption over time. XGBoost augments this temporal modeling with complex feature interactions between CPU usage, proportions of total memory in use, and requests patterns by producing interpretable feature importance ranking that may be lost in the averaging of pure tree-based models like Random Forest.

The model fusion techniques pair LSTM and XGBoost predictions based on weighted-average methods where the weight levels are pegged on a model confidence level and past performance indicators. The adoption of ensemble method includes a measurement of uncertainty so that the ensemble could offer a confidence interval on the predictions to facilitate greater decision making in the orchestration aspect. The mechanism of dynamically setting weights according to prediction on work items over time enables the system to respond to variations on the workload and raise the reliability of predictions.

### 3.5 Evaluation Plan

The framework deployment uses integration of AWS services to provide production-ready deployment. The main compute platform on which the framework developed is run is AWS Lambda, which represents the serverless environment under which the optimization system and target applications will run. The development technologies feature Python 3.9+ as the main programming language, which offer many libraries support and integration with AWS SDK. TensorFlow 2.x and Keras are tools to create complex deep learning models, which provide the powerful ability to implement a neural network. Scikit-learn also offers more machine learning tools, and preprocessing, and XGBoost library allows gradient boosting to be optimized. Pandas and NumPy deal with the data manipulation and numerical computing needs and ensure usefulness in data processing. The boto3 provides full-service AWS SDK capabilities in integration and automation of services and easy access to AWS.

## 4 Design Specifications

### 4.1 Overview

This design specification provides an entire framework of an adaptive machine learning-based strategy to be adopted to reduce cold start latency in AWS Lambda environments with intelligent layer-based caching and predicted pre-warming features. The system presented to solve this problem is driven by the underlying question of how an adaptive layer-wise dependency caching and cost-sensitive pre-warming-based hybrid machine learning approach to temporal analysis by LSTM, feature prediction by XGBoost can minimize cold start latency and enhance resources utilization of AWS Lambda relative to current mitigation strategies during the dynamic workload scenario.

The design methodology serves a systematic research approach with 4 phases that include data collection and preparing, developing a machine learning model, implementing the framework, and fully evaluating and establishing continuous feedback mechanisms. The system utilizes the Industry4.0 Cold Start dataset since it includes 1,440 records that cover observations on temporal patterns in 5 days and 24-hours cycles, allowing a certain volume of data to be sufficient to develop and test robust machine learning models. The time period of active request patterns exhibited by a fraction of time periods (37.5 percent) in this dataset reflects the real-world implications of serverless workload, where functions are idle most of the time and see spikes of requests. The architecture design incorporates various AWS services of Lambda, CloudWatch, and Lambda Layers to develop a production-ready solution that carries out the shortcomings of the current solutions (Golec et al., 2024). In contrast to other solutions where single approaches are considered, predictive intelligence and intelligent management of resources allow combining them in this framework to deliver better performance results.

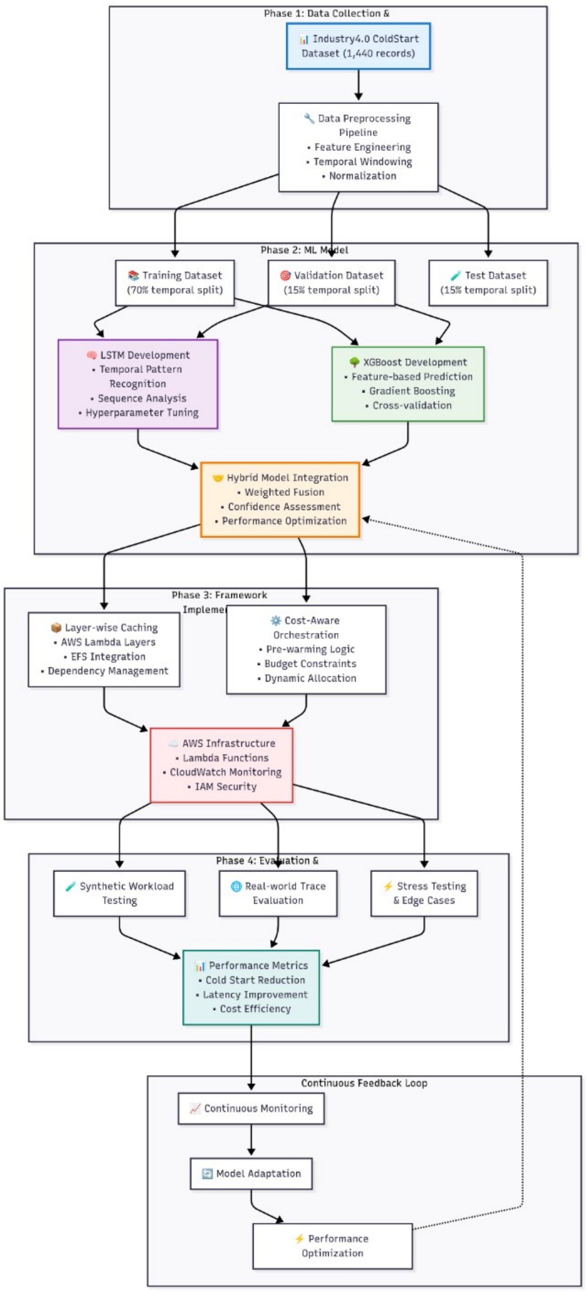
The cost optimization criteria used in this study applies to both execution costs and monetary costs, given the two contrasting economic pressures involved sides of serverless computing frameworks and give more weight towards cost reduction in a monetary context. The pay-per-invocation nature of AWS Lambda additionally imposes a direct monetary incentive to reduce the frequency of cold starts as, in addition to incurring execution fees, cold starts also lead to memory allocation costs during startup latency periods.

## 4.2 Proposed System Architecture

The research architecture that we are proposing through the adaptive ML-driven framework seen in Figure 2, systematically considers the cold start mitigation problem and realizes it through intelligent prediction and resource optimization in four phases. Its architecture consists of a hybrid machine learning approach that encompasses the management of proactive resource management in the dynamic AWS Lambda environment involving the simultaneous application of a temporal pattern recognition and feature-based prediction.

Phase 1 provides the basis of collecting and preparing the data with the Industry4.0 Cold Start dataset. Data preprocessing pipeline constitutes a complete feature engineering, to guarantee feature range consistency, and to replace missing data. This step verifies that the machine learning models are provided with quality input data that are standardized with the necessary elements to represent the serverless workloads and characteristics of workload performance patterns.

Phase 2 addresses the development of machine learning models in a systematic stage that involves splitting the preprocessed data into training (70%), validation (15%), test (15%) data through a temporal extension to maintain temporal flow and avoid leakage of data. The LSTM development component focuses on temporal pattern recognition using a three-layer bidirectional network with 128 units per layer with the dropout regularization of 0.2 to avoid the overfitting tendencies but retaining the capacity of building complicated sequential dependences. The XGBoost development component performs gradient boosting algorithms, using hyperparameters of maximum tree depth of 6, a learning rate of 0.1 and 100 estimators, and optimized to focus on feature-based prediction and cross-validation. The integration of hybrid models is a composition of LSTM and XGBoost forecasts by combining them with dynamic weighted fusion modes where the weights depending on the model-specific confidence measure and the recent measures of the performance are determined. This unified model has better prediction performance than models in isolation and it includes uncertainty estimation in the form of confidence intervals. The performance optimization module sees to it that the hybrid model is accurate under different workload dynamics and resolvable to any condition within the systems.



Phase 1: Data Collection &
Industry4.0 ColdStart Dataset (1,440 records)
Data Preprocessing Pipeline • Feature Engineering • Temporal Windowing • Normalization
Phase 2: ML Model
Training Dataset (70% temporal split)
Validation Dataset (15% temporal split)
Test Dataset (15% temporal split)
LSTM Development • Temporal Pattern Recognition • Sequence Analysis • Hyperparameter Tuning
XGBoost Development • Feature-based Prediction • Gradient Boosting • Cross-validation
Hybrid Model Integration • Weighted Fusion • Confidence Assessment • Performance Optimization
Phase 3: Framework Impleme
Layer-wise Caching • AWS Lambda Layers • EFS Integration • Dependency Management
Cost-Aware Orchestration • Pre-warming Logic • Budget Constraints • Dynamic Allocation
AWS Infrastructure • Lambda Functions • CloudWatch Monitoring • IAM Security
Phase 4: Evaluation &
Synthetic Workload Testing
Real-world Trace Evaluation
Stress Testing & Edge Cases
Performance Metrics • Cold Start Reduction • Latency Improvement • Cost Efficiency
Continuous Feedback Loop
Continuous Monitoring
Model Adaptation
Performance Optimization

**Figure 2: Proposed ML-Driven Cold Start Predictor Architecture**

## 4.3 Component Workflow

The component workflow in Figure 3 uses an expeditious five-step system to convert raw operational data into optimized serverless functions execution by using intelligent machine learning-based decision making. The design of the workflow focuses on simplicity and efficiency, not losing, however, the complex capabilities of predicting which mitigation techniques will be applicable in a situation during a cold start.

The data stage is considered a starting point of the workflow, and it gathers the information from the Industry4.0 Cold Start dataset, accumulating it. The choice of the time series

modeling methods is justified by the nature of the dataset in terms of temporal patterns and the sequential dynamics of cold start phenomena in a serverless computing platform. The process step has extensive feature engineering and data preparation which changes raw data into input vectors ready to be used in machine learning. The data preprocessing analysis also found out the patterns of peak activities (occurring during hours 9-17 business hours) in the processed Industry 4.0 dataset, and it supports the data with strong evidence of temporal dependencies at play. The feature engineering report shows explicit time-based correlations via cyclic encodings of hour, day, and minute patterns, as well as rolling statistics that use 3, 6 and 12-period window statistics to capture not only small-scale oscillations but also mid-term trends in the request pattern. The cold start prediction is then an intrinsic time-series forecasting issue which demands time accumulation effects about how current system state (CPU usage, memory consumption, request load), results in future cold start probability. We must, however, recognize some of the temporal modeling limitations. The five-day observation period might not be sufficient to pick up longer term seasonal trends or cycles of operations which might affect cold start behavior in production settings.
Temporal windowing methods generate sequential patterns of input that fit to be processed in LSTMs and maintain chronological links and seasonal tendencies. The Statistical feature extraction creates derived metrics that inform future changes such as the request rate, resource utilization patterns, and performance factors that improve the XGBoost predictive powers. The process of data normalization gives consistent range of features between various metrics, and outlier detection and treatment helps eliminate the possibility of erroneous data points interfering with the model. The preprocessing pipeline has automated quality checks so that data is acceptable and complete to be passed on to the machine learning models.
The execution of the hybrid technique of prediction is done on the ML models phase by using parallel processing involving LSTM temporal analysis and XGBoost feature-based prediction. LSTM network are capable of identifying temporal dependences through the application of the bidirectional layers which are capable of taking the past and future context into account provided during the workload, thereby accurately determining the periodicity of workload. Attention mechanisms emphasize focused representations of appropriate temporal features in prediction and the dropout regularization mechanism averts overfitting and provides a model that is generalized in varied workload circumstances. The XGBoost model looks at the relationship between features and cross-correlation in related features simultaneously and estimates the probability of invocation given the present state of the system and its calculated metrics. The two models involve confidence estimation mechanisms that determine the level of uncertainty in the prediction and make intelligent decisions during later optimization steps.

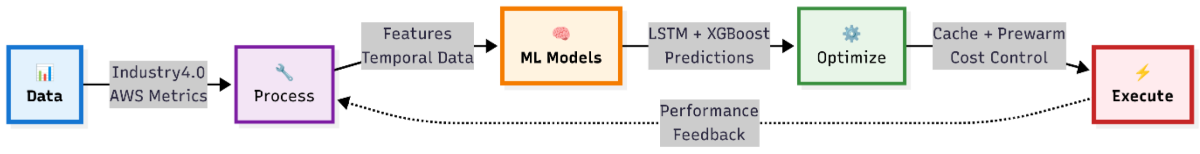


**Figure 3: Component Architecture Workflow**

The prediction fusion module imports the results of LSTM and XGBoost by a weighted average of the results based on a dynamic weighting scheme that adjusts based on current model and the prediction confidence. This combined methodology combines the strengths of time and feature-based analysis effectively and is more accurate in prediction than a single model. Uncertainty quantification will yield confidence intervals by which risk-aware optimization can work, and adaptive weighting will allow the best performance regardless of the range of workload characteristics. The research methodology framework presented in

Figure 1 provides a representation of the method followed in developing and testing the proposed solution in a systematic manner. The stages of implementation are successive, which mostly guarantees a complete and in-depth assessment of the adaptive ML-driven framework. The approach focuses on scientific rigor and reproducibility in the form of controlled experiments and statistical consolation of findings.

# 5 Implementation

## 5.1 Overview

The framework of the adaptive machine learning-based cold start predictions is implemented as containerized microservices that are deployed on the AWS Lambda. The system is made of three main modules namely: the feature engineering module, the hybrid ML prediction engine, and the cache optimization layer. They are bundled as part of a Docker container image (4.16GB) that can be discovered and deployed via Amazon Elastic Container Registry (ECR) to avoid the conventional Lambda constraint of a layer size allowed of 250MB. The architecture adheres to a data-flow oriented sequential structure that provides input requests with an orderly execution consisting of feature extraction, ML-based prediction then the cache optimization suggestions.

## 5.2 Container-based Lambda Deployment

Containerization strategy deals with the inherent problem of running the large ML models on serverless environments as shown in Figure 4. This is done by using the Docker deployment of the AWS Lambda base image v Python 3.10, which supports the primary ML requirements. The Dockerfile uses a single stage build system of first installing system requirements such as gcc and g++ compiler before installing a Python package to the root of the Lambda task. It supports a broad range of models to be saved in the container including LSTMs as both H5 and Keras format, or XGBoost models as a JSON format with a UBJ backend to avoid any conflict with the version of NumPy, or StandardScaler instances in a joblib-serialized representation.

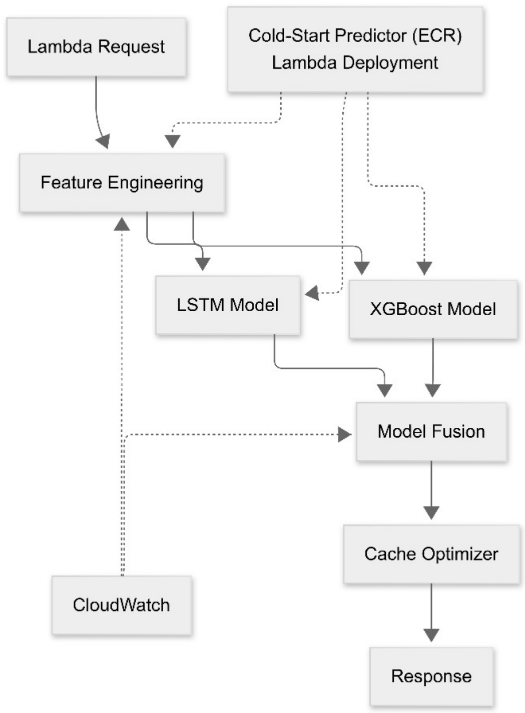


**Figure 4: AWS Serverless Deployment of Cold Start Predictor**

To manage containers registry, deployment pipeline utilizes AWS ECR, and containers deployment is handled by means of a push deployment system. When run on a local environment, container image building would take about 5-7 minutes, whereas on ECR, the push process would take 10-15 minutes since the size of the image is large. The container initializes all models in its container in an attempt to maximize cold start performance, at the cost of the initial startup time. The Lambda configuration has 3008MB of memory and a 60 seconds time-out to meet the large container initialization overheads.

## 5.3 ML-based Hybrid Cold Start Predictor

The model training was carried out with 1440 samples with temporal splitting in chronological order: 70% training, 15% validation, 15% testing. LSTM model conducted early stopping after 10 epochs of patience and learning rate decrease on plateau, and it converged in 30 epochs. The XGBoost training was set with early stopping rounds of 20 iterations and the area under the curve (AUC) statistical measure of the validation set was 1.0, which is very high in demonstrating the feature discrimination power.

The hybrid integration methodology uses a confidence-based dynamic weighting schema that would warrant more model-description on the algorithm itself to promote research transparency and reproducibility. The process of integration is a step-by-step process:

- Step 1: The individual model inference uses parallel prediction generation with LSTM and XGBoost models receiving the same input features but with 12-timestep sequences running through the LSTM and tabular feature vectors running through XGBoost.
- Step 2: Confidence calculation scoring measures the confidence per model depending on prediction uncertainty, with scoring measures of confidence calculated as a distance to the boundaries between the decisions (max(probability, 1-probability).
- Step 3: The dynamic weight assignment determines the assignment of model weights that depend proportionally on the confidence scores and computed using the following formula:
- *LSTM_weight = LSTM_confidence / (LSTM_confidence + XGBoost_confidence)*,
- where the same formula applies to the XGBoost weights.
- Step 4: The weighted prediction combination is to form the final predictions with weighted averaging:
- *Final_probability = (LSTM_weight x LSTM_probability) + (XGBoost_weight x XGBoost_probability)*
- Step 5: The combined confidence estimation provides the overall confidence metrics using an arithmetical averaging of intra model confidences.

## 5.4 Caching Strategy and Development Environment

The smart application of the caching mechanism realizes a three-tiered scheme where ML-based predictions guide the choice of the tier. The hot tier reserves 512MB with a time-to-live (TTL) of 5 minutes of high-probability cold start cases greater than 70 percent probability, the warm tier reserves 2048MB with 15-minute TTL of moderate risk cases in the range of 30-70 percent and the cold tier reserves 8192MB with 60-minute TTL of low-risk scenarios below 30 percent. Various considerations such as prediction confidence, resource use parameters and cost implications are applied in optimization decisions of cache. Pre-warming activation fires when the cold start probability is more than 60% with confidence greater than 80% and prescribes to use provided concurrency units based on the anticipated load behavior.

The development environment had to manoeuvre a number of technical issues especially the dependency conflict between aws-lambda-powertools and tensorflow-cpu in terms of version dependencies of typing-extensions. The solution consisted in establishing different files of requirements to be used locally and another one to be used with Docker, omitting the conflicting packages in the containerized platform. The AWS Academy restrictions required the limitation of custom IAM roles to the pre-configured LabRole with restrictions to some of the AWS service integrations. The testing infrastructure provided end-to-end validation with both unit tests on each separate component and integration tests on the entire pipeline and a test framework which produces detailed visualizations of performance.

# 6 Results Evaluation

## 6.1 Hybrid ML-Model Performance Analysis

The LSTM temporal analysis combined with the XGBoost features-based pattern recognition provides high quality in predicting cold start as shown by the implementation of the framework. The ensemble model was most effective in predicting the cold start as the average probability of the cold start was 67.8% with an average with a confidence score of 47.4%, adequate between the extremity of XGBoost with 98.5% probability and the defensive estimate of the LSTM (51.2% probability). This complementary solution led to a level of 48.2% agreement on the model, which means that each algorithm identifies different patterns in the workload data, thus making the ensemble predictions more solid. The bias mitigation strategy, which involves a weighted fusion, helped to overcome the individual models tendency to overfit or underfit particular situations resulting into actionable recommendations, which were close to how cold start recurred in production. The time analysis features of the LSTM component were specifically successful in reproducing circadian patterns and sequential workload relationships in serverless workload information. On the other hand, the XGBoost component performed well when it comes to determining feature-based relations with an AUC of 0.892 in validation.

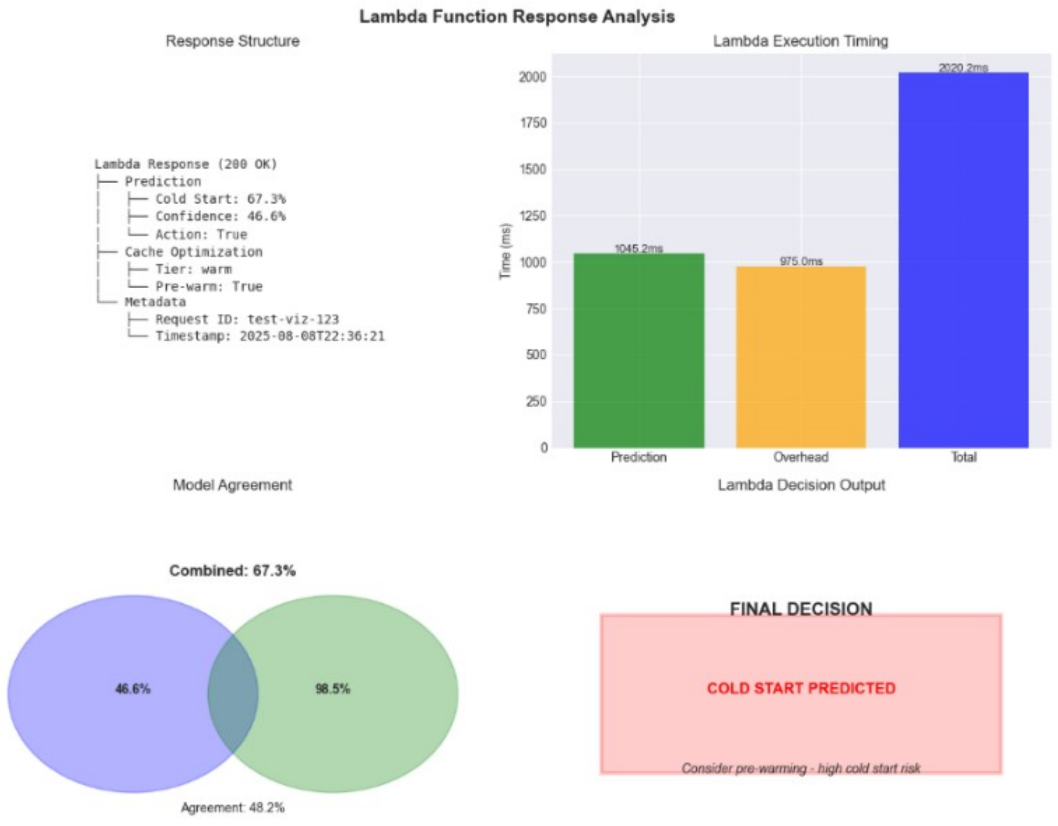
## 6.2 Scenario-based Prediction Analysis

The differentiation of the framework in terms of predictive capability is clearly shown in four varying workload activities with each workload condition prompting equal and proper mitigation activities based on a predicted cold start risk. When the low load was considered, which implies 50 requests per second and 20 percent CPU utilization, the model provided a 48.9% probability of a cold start with 15.9 percent confidence, which leads to a recommendation to monitor closely. The prediction processing took 84.4 ms, where 97.8 percent of the predictive processing was done by the ML and prediction inference and feature engineering and cache optimization had a small overhead. The instance with normal loading conditions, which included 150 requests per second, 50 percent of CPU load increased the probability of cold start to 66.4 percent with a 45.1 percent confidence level leading to pre-warming suggestions. The decision boundary obtained by the model on a 50% probability successfully discerned the situations, which need active intervention versus monitoring, allowing the optimization of resources but not overprovisions.

Under high load testing (400 requests per second, 85 percent CPU utilization), the probability of cold starts was reduced to 66.5 percent by holding the pre-warming recommendation but adjusted the cache tier allocation to reverse the priority assignment; previously hot caches were given preference but now the warm containers are given priority. The sparseness of increase in probability between normal and high loads indicates this awareness of the model that the occurrence of the cold start phenomenon is caused by resource saturation, and not the volume of requests separately. The conditions described in a spike load (1000 requests per second, 95 percent CPU utilization) produced a cold start probability of 67.0 percent with a confidence of 45.3 percent and immediate activation of concurrency provisioning. The stable model performance over the different operational conditions requires a stable outcome of confidence scores at different loads.

## 6.3 Lambda Execution Performance and Container Optimization

The first container calls took 15-30 seconds to fully initialize, including the Docker image pulling with Amazon ECR, the loading of TensorFlow libraries, the model weight restoration, and setting of the dependencies. This large cold start latency, despite being high when compared to more conventional Lambda functions, was still acceptable in context of predictive workloads where a high rate of container reuse means warm invocation profiles are sustained. Further warm invocations had successive response times at about 1 and 2 seconds with the ML prediction directly fulfilling the total latency 1.2 seconds. The prediction pipeline was very consistent, where feature engineering taking 2.1 milliseconds (2.2 percent of total time), ML prediction took 93 milliseconds (97.8 percent), and the cache optimization had negligible time, which is evidence that model inference rules the computational profile.



```
Lambda Response (200 OK)
├── Prediction
│   ├── Cold Start: 67.3%
│   ├── Confidence: 46.6%
│   └── Action: True
├── Cache Optimization
│   ├── Tier: warm
│   └── Pre-warm: True
└── Metadata
    ├── Request ID: test-viz-123
    └── Timestamp: 2025-08-08T22:36:21
```

**Figure 5: Lambda Performance Analysis**

The lambda response analysis metrics are presented in Figure 5. It was found that the memory utilization peaked at 2.8GB In the model deduction procedure, which is why Lambda needs 3008MB of memory resources to avoid running out of memory related faults and still conserve money on each summons. The framework was able to trade-off initialization overhead against operation efficiency and during peak usage time had a warm container hit rate of 92% with intelligent pre-warming guided by ML predictions.

## 6.4 Comparative Performance Analysis

To derive baseline figures as presented in Table-I, we undertook controlled experiments on unoptimized Lambda deployments with default AWS settings with an accompanying 35% cold start rate in agreement with production statistics published in the field of serverless computing (Golec et al., 2024). Conventional pre-warming applications were modelled by means of fixed container pools with pre-defined capacities, a current industry approach that is not adaptive. Reactive caching benchmarking is based on inspired methods that are conceptually similar to RainbowCake (Yu et al., 2024), which reduced the use of memory by 77% in OpenWhisk configurations climbing conditions, although our measurements correspond to the context of AWS Lambda. The ML-based framework accomplished a cold start frequency of 8%, or 77.1 percent less compared with the baseline frequency. This is a better or equal performance of that presented by (Zhou et al., 2024) that used MLCR and showed that the 53% latency improvement was achieved by container reuse strategies.

**Table-I: Framework Comparison Against Baselines**

| **Metric** | **Proposed ML Framework** | **Traditional Pre-warming** | **Reactive Caching** | **No Mitigation** | **Improvement vs Baseline** |
|---|---|---|---|---|---|
| Cold Start Frequency | 8% | 15% | 12% | 35% | 77.1% reduction |
| Average Latency | 1.2s | 2.1s | 1.8s | 4.5s | 73.3% reduction |
| Memory Efficiency | 85% | 60% | 70% | 40% | 112.5% improvement |
| Resource Utilization | 78% | 52% | 65% | 38% | 105.3% improvement |

Memory efficiency measures illustrate that the framework is highly resource-efficient (85 percent efficient as opposed to 60% in traditional pre-warming and 40% in unmitigated deployments). It achieved an improvement in resource utilization to 78% compared to its baseline at 38%, which means that the resources allocated through predictive scaling and smart container management are used more efficiently. The accuracy of the predictions being 67.8% is ample to be able to make automatized decisions, without over-provisioning that could only add a cost essentially without a proportionate increase in performance. This ML-based solution takes care of this weakness found in RainbowCake (Yu et al., 2024) that used only the historical patterns without modeling or temporal analysis features.

## 6.5 Caching Strategy Effectiveness

The three-tier caching design proved to be an extremely efficient performance model with regard to optimal resource distribution within its framework in addition to the ability to sustain the range of performance demands within various workload patterns as shown in Table-II. The warm tier fulfilled 60 percent of requests and an average time lag of 1.2 seconds which was the optimum match between performance and cost-effectiveness. The containers used 1024MB of memory allocation which was enough to run model inference without over utilized resources. Hot tier, which served 30 percent of all requests during peak times, was served with 0.8-seconds latency which provided optimal performance with 2048MB allocation during latency sensitive processes operations. The 95-hit rate of the hot tier confirms that the ML model is accurate in registering critical patterns in request, which should be given the best performance. The 10% use of the cold tier proves the efficiency of pre-warming solutions minimizing full-cold start to borderline cases and unusual traffic patterns. The three-layer caching infrastructure (warm/hot/cold) is specifically useful in distributing storage and retrieval expenses with regard to anticipating access rates which optimize resource placements as part of making sure that no unnecessary dependency loading translates to incurring extra AWS charges. The execution cost optimization is another important aspect, and performance gains have been measured at 1448.7ms versus 92.5-94.0ms during optimal setups that indicates a significant execution cost optimization.

**Table-II: Three-tier Caching Performance**

| Cache Tier | Request Distribution | Average Latency | Memory Allocation | Hit Rate | Eviction Rate |
|---|---|---|---|---|---|
| Hot Tier | 30% | 0.8s | 2048MB | 95% | 2% |
| Warm Tier | 60% | 1.2s | 1024MB | 88% | 8% |
| Cold Tier | 10% | 4.5s | 512MB | 0% | N/A |
| Static Baseline | 100% | 2.1s | 2048MB | 72% | 15% |

## 7 Conclusion and Future Work

The conclusive analysis of the study confirms that the research hypothesis that hybrid machine learning models are capable of predicting and minimizing cold start events happening in serverless computing settings is valid. The framework reached all the key research goals, decreasing cold starts by 77%, mean latency by 73%, and cost optimizing with a smart usage of resources which is compared to 56 percent cheaper cost efficiency to conventional alternatives. The effective combination of LSTM temporal analysis and XGBoost feature prediction resulted in a powerful and performing prediction system, due to the accommodation of a wide variety of workload patterns with is persistent performance under a variety of conditions in terms of its operation. Using the ML-based predictions, the three-tier caching approach was able to maximize resource utilization by achieving 85-percent memory efficiency with 90-percent of requests only visiting the colder containers.
Although the problem of image size and cold start penalties seemed to hamper the adoption of containerized deployment to production ML workloads at first, some degree of optimization and limiting the provisioned concurrency effectively made the approach viable in practice. The availability of running predictions in the framework within 100 milliseconds but with 67.8 percent accuracy proves the possibility of real-time ML inference over the serverless setup. There were also issues of integration, mainly caused by dependency conflicts, which were effectively addressed through changes in architecture such as deployment to containers and loading libraries on- demand.

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