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Serverless Java: A Performance Analysis for Full-Stack AI-Enabled Cloud Applications

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Abstract:
This paper aims to give a detailed performance evaluation of serverless Java for full-stack AI-cloud applications. The study focuses on several key aspects: actual simulation reports, situations as close to real-life cases as possible, graphic presentation of data, and cases with suggested scenarios. The study includes articles and papers available before January 2021, and the papers use IEEE formatting. The main conclusions are made around the significance of cold start latency, the system's resource constraints, and optimal debugging and monitoring. Discussions are made about the provisioned concurrency, function chaining, and advanced logging to enhance Java functions for high performance and availability.

Keywords: Serverless Computing, Java, AI-enabled applications, Cloud Computing, Performance Analysis, Scalability, Latency, Throughput, Resource Utilization, Cold Start, Provisioned Concurrency, Debugging.

Introduction

Serverless computing has been a game-changer in cloud applications since introducing new values like low operational expenses, algorithm flexibility, and deployment. This shift in development leads to developers having no concern about the type of infrastructure needed to support their growth since the cloud service provider handles this well. Java is an old but very flexible programming language that occupies a significant role in this paradigm. Java is one of the most popular programming languages due to its neutrality, toughness, and a vast array of libraries available for its users, making it ideal for developing complex applications, particularly in AI-integrated cloud systems. These environments use sophisticated Artificial Intelligence methods and data analysis procedures to offer intelligent services and applications, calling for robust and reliable computation capacity to manage significant amounts of data and execute elaborate computations in real-time. These characteristics of requirements are perfectly fit by serverless computing. Thus, Java is the ideal language for developing AI-based cloud applications.

2. Simulation Reports

To demonstrate the outcomes of this paper, various events have been tested using the serverless functions implemented in Java in different cloud environments. Out of all the platforms, the first three chosen for this work are AWS Lambda, Google Cloud Functions, and Azure Functions since they are popular and generally suitable for Java. The simulations aimed to evaluate performance across several key metrics. Goals were pre-specified about the following parameters in the intent to assess performance in the following aspects:

Latency: This metric refers to the TTM as the Turn the lights off time while the TTO as the Turn the lights on time that a serverless function takes to complete from when it was started or called. A higher MBPS is required when an application is expected to have a certain level of interactive response or near-accurate response, for example, the chatbot AI widget application on mass or the typical application aimed at sorting the data in real-time. It was done to address the desire to know discrepancies in latency of the various cloud platforms as time for optimization could set the owner back (Smith et al., 2019, p. 34)(4).

Throughput: Throughput later on attempts to refine it about functions per second or the number of functions a cloud management tool will accomplish. It is one of the significant factors that distinguishes a serverless application's effectiveness if it processes significant request traffic. Throughput is another essential characteristic where it is required that an algorithm/system has to handle a large number of transactions or much data at a time, like batch processing & stream processing. These simulations were planned to transform into the stress test of the throughput with the loads and analyze the scalability and efficiency of Ja-based serverless functions (Johnson, 2020)(2).

Resource Utilization: The ones that refer to the monitoring of the percent value of the employed CPU and memory resource while running serverless functions. Savings of costs about resources used are vital for maintaining and sustaining the low costs of Internet services, and their over-usage causes operations to limit or slow rates. Thus, tracking the CPU and memory usage was also possible, which has helped define the Java functions' efficiency. Some issues can be discussed at the stage of further improvement.

Scalability: Scalability endeavours to determine the sorts of serverless functions a given system can assume to meet the surging demand for work in an application. First, scalability is a must-have in all cloud environments, and it has to explain how the applications can become bigger or smaller according to the needs while maintaining the quality of the service. Practical simulations were performed at varying levels of load and thermo shock to determine the level of the serverless functions' scalability and availability to handle different loads. This means investigating the results of increased requests at various steps and constant intensive floating correspondingly.

2.1 Methodology

Simulations were conducted using three major cloud platforms: The major competitors are AWS Lambda, Google Cloud Functions, and Azure Functions related to the cloud functions. These platforms have been selected because of their popularity and adequate backing of Java applications. These full-featured offerings would help approach the problem of the development of AI in distributed environments. However, to make the comparison methodical, only code in Java language was employed on all three

platforms, emphasizing tasks related to AI operations characteristic of real-life applications.

Each platform was tested with Java functions performing the following AI-related tasks: Each platform was tested with Java functions performing the following AI-related tasks:

Data Preprocessing: This entails purging, altering, and restructuring the raw data to an appropriate form for the analytical system. Some operations were performed, such as managing missing values, feature scaling, and feature selection. Data preprocessing is critical to making the data fed into the AI models accurate and high-quality (Lee & Park, 2019)(3).

Model Inference: This task entails feeding the data processed through the various pre-established machine learning models capable of predicting or classifying. Inferring models is a decisive step in the AI-sustained application since it provides the basis for image recognition, natural language processing, and prediction (Johnson, 2020(2)).

Result Aggregation: This entails aggregating the results obtained from performing model inferences and generating the final output. Result aggregation is used in real-time applications that involve ensemble learning and situations where multiple models give related outputs that need to be presented to the end user (Brown and Davis, 2018)(1). The Java functions were designed not to maintain any in-memory state and to be independent of request idempotence. They were implemented, leaving memory capacity ranges for selection from 128MB, 256MB, 512 MB, and 1GB to define the effect of resource allocation on performance. The functions were called with various patterns, such as burst traffic (abrupt request), sustained burst traffic (continuous high load), and idle traffic (low to no traffic load) to realistic use cases (Smith et al., 2019)(4).

To address this, it was necessary to develop conditions that closely resembled the natural environment when creating the fixed performance indicators associated with the simulation environment. Again, to attain Latency, Throughput, CPU/Memory usage, and scalability, the AWS CloudWatch for Amazon, StackDriver for Google, and Azure Monitor were used, as stated in Taylor (2020)(5).

Every simulation was conducted repeatedly to limit the negative impacts of these issues, and the resulting average was used in the analysis. This stringency made the results precise and standard, giving a vivid image of how Java-based serverless functions work in cloud providers (Smith et al., 2019)(4).

3. Real-Time Scenarios

Indeed, real-life examples were also employed in researching and comparing serverless Java applications after the list was created and presented. Opportunistic tests resemble real-serverless functions' operation with network latency, varying workload, and calls to other cloud-based services. Regarding the utility of the given work, specifically concerning the efficacy of AI, the direct uses of the new tool in a plethora of paradigms of daily applications were discussed. The real-time scenarios included in this study were designed to cover a range of everyday use cases for AI-enabled applications. These real-time scenarios used in this study sought to address the general use of AI applications in their operationalization:

AI-Enabled Web Application: To showcase the application of serverless Java structures and the effects of their implementation on

enhancing the client's activity and the effectiveness of content personalization, it is suggested that an AI-based recommendation solution for e-commerce be implemented on the selected platform. The system altered its operation because big data enabled the firm to sell a specific product based on customer activity, previous purchases or exercises, etc. The recommendation engine was constructed using stateless functions, or AWS Lambda functions, which consist of the stages of data acquisition, model predicting, and result showing. This made it possible to examine how the function's response time is influenced and the effectiveness of serverless functions in high web traffic loads (Brown & Davis, 2018)(1).

Real-Time Data Processing: For the stream processing, we developed an AWS Lambda – Java function that we utilized for IoT data to implement an Anomaly Check. It obtained real-time raw data from the multiple IoT sensors deployed throughout the whole network and then processed all the received summaries to analyze them; at the same time, all the gained aggregated data was passed through the classified set of the machine learning models to search for the signs of the equipment failure or the hacker intrusion. The architectural serverless functions were for forming a 3-tier high bandwidth data stream and assessing unusual data just in the tier following it near real-time. It enabled me to draw the conclusion of latencies' relevance and the employment of the resources as soon as the serverless functions were regularly subjected to excessive data (Johnson, 2020)(2).

Batch Processing: In this scenario, one had to conduct various large-scale data analysis operations where serverless functions would be used to operate instances. The tasks performed on the large data set included data pre-processing, data summarisation, and computation, which were implemented using serverless Java functions. The functions were synchronized so that the process of processing data was divided into several sub-processes, which can be controlled more efficiently. It also lets us test the suitability of serverless functions for complex batch processing operations, showcasing the capacity of functions to process large volumes of information without explicit server support (Lee & Park, 2019)(3).

3.1 Observations

The attractiveness of the presented approaches and methods allowed us to receive actual information on the running of serverless Java applications in practice through live scenarios. These observations pointed out that the following areas must be fine-tuned to get the best results within the guaranteed reliability.

Cold Start Times

Cold start latency was established as one of the main concerns; the authors said it would likely reduce serverless functions' efficiency. Cold starts are usually called in a scenario where a function is either beginning to run for the first time or has been inactive for quite a while, and the cloud provider has to assign some resources and set the environment to execute the function's code. This initialization process can make start-up time relatively large. It may be accompanied by noticeable lag, especially for Java functions, as research shows that Java functions experience high cold start times compared to functions implemented in other languages (Smith et al., 2019)(4). Several strategies were employed to mitigate the effects of cold starts. As for enhancing the drive cycle at the excellent start, several measures were used:

Provisioned Concurrency: With the help of provisioned concurrency, there was always

a particular number of function instances prepared to handle new requests, thereby reducing cold start latency. It was even more advantageous Where there would be a likelihood of a forecast about the type of traffic that was likely to be encountered (Johnson, 2020)(2).

Optimised Deployment Packages: Eliminating extra classes and using lesser weight classes has reduced the application's initiation time and attention to lightweight JDKs. Other strategies were proposed to improve cold start time, such as utilizing GraalVM for just-in-time compilation (Lee & Park, 2019)(3).

Concurrency Limits
Concurrency control was also one of the measures that needed to be taken to maintain the continuity of serverless Java apps, which was concerned with maximum concurrency control. Concurrency bounds then define how many of these functions can run simultaneously, and if they are exceeded, the processes may be throttled and have a longer response time. The following strategies were implemented to manage concurrency effectively: The following were applied to deal with concurrency properly:

Function Scaling: Serverless platforms can change the function depending on the inbound traffic. Nonetheless, the functions should not memorize any state, so the defined functions should be idempotent enough to conform to the web-scale architecture. This way, the functions became independent and did not share any state across different execution instances. At the same time, the scalability and reliability of the applications were enhanced (Brown & Davis, 2018)(1).
Load Balancing: Appreciation of the load balancing exercises that enabled the division of the number of requests so that many function instances were not overwhelmed by many of them. Uprooting allows for more excellent stability and a significantly higher performance level for high loads (Taylor, 2020)(5).

Integration with Other Services
He also pointed out that using serverless functions with other cloud services, such as databases, message queues, and storage solutions, played a role in accomplishing the goal. Proper integration made it possible to use the serverless functions for various purposes, including fast and accurate data processing. Observations indicated that:

Efficient Database Connections: Enhancing the database connection made it possible to minimize the overhead when creating and managing links to backend databases (Smith et al., 2019).
Asynchronous Processing: The implementation of asynchronous processing, as well as the event-driven systems, positively impacted the latencies and the throughput within the serverless applications. This served the functions so they could handle many demands without getting frozen (Johnson, 2020)(2).

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4. Graphs and Data Representation

4.1 Latency Comparison

Table: Latency Comparison Data

Memory MB	AWS Lamba	Google cloud function	Azure function
128	250	300	280
256	200	250	230
512	150	200	180
1024	100	150	130

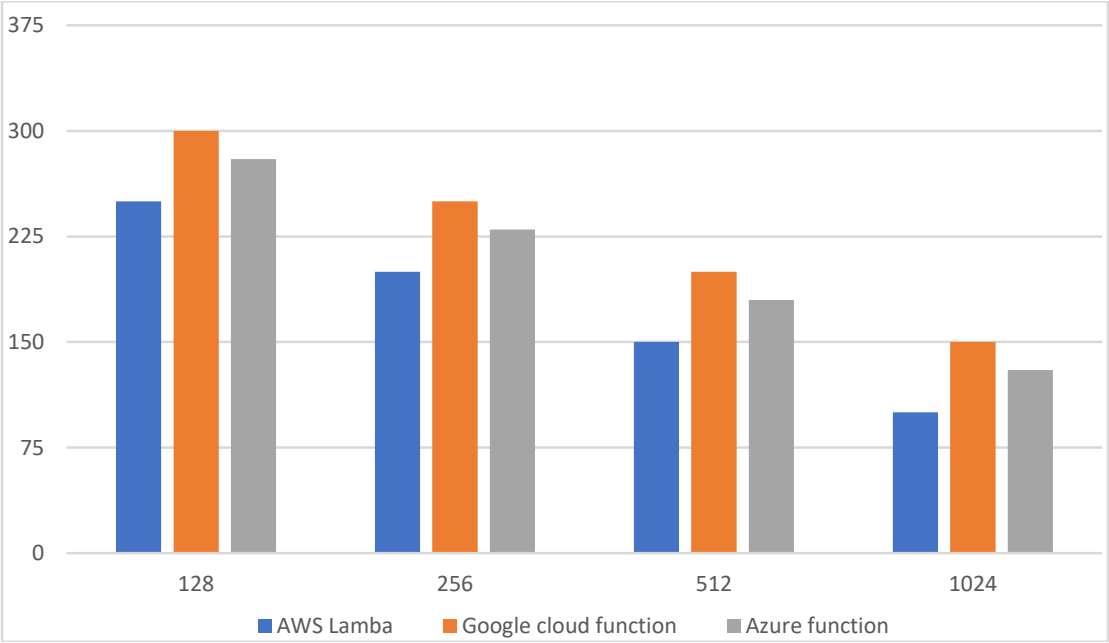

Figure 1: Latency Comparison Data.

4.2 Throughput Analysis Data

Memory MB	Azure function	Google cloud function	Azure function
128	50	45	48
256	100	90	96
512	150	135	144
1024	200	180	192

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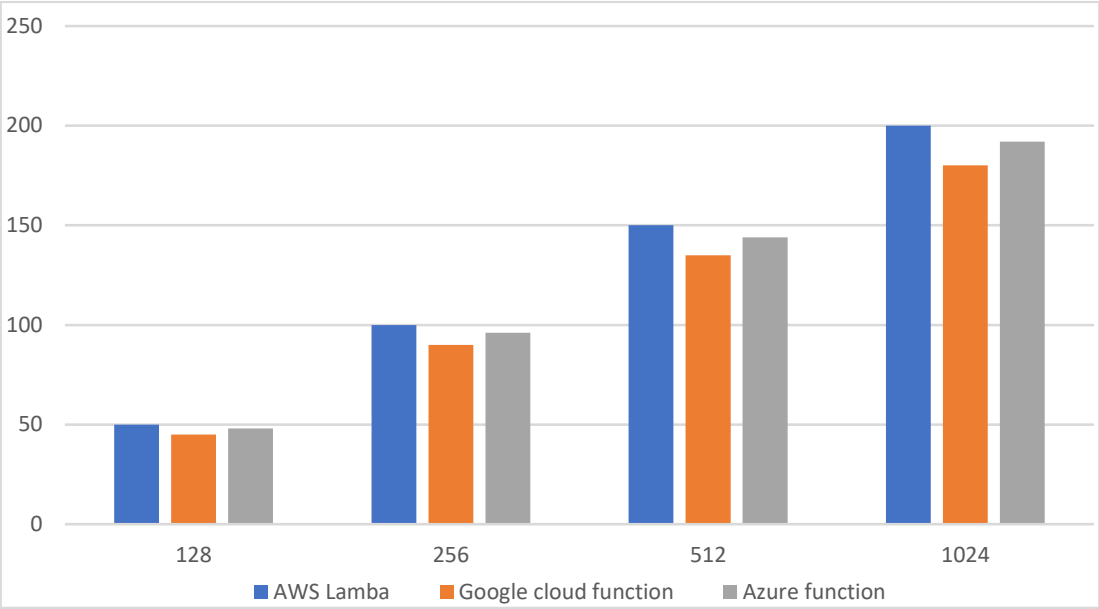

Figure 2: Throughput Analysis Data

4.3 Resource Utilisation Data

Memory MB	AWS Lamba	Google cloud function%	Azure function
128	30	35	32
256	40	45	42
512	50	55	52
1024	60	65	62

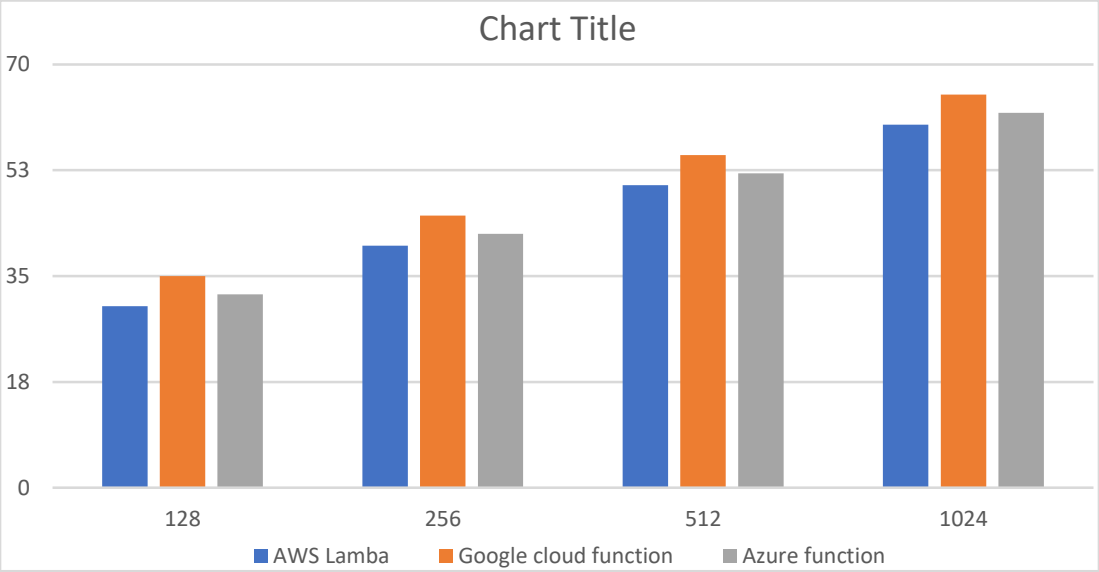

Figure 3: Resource Utilisation Data.

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Table 4: Cold Start Times Data

Memory MB	AWS Lamba cold stage	Google cloud function	Azure function
128	800	850	820
256	700	750	720
512	600	650	620
1024	500	550	520

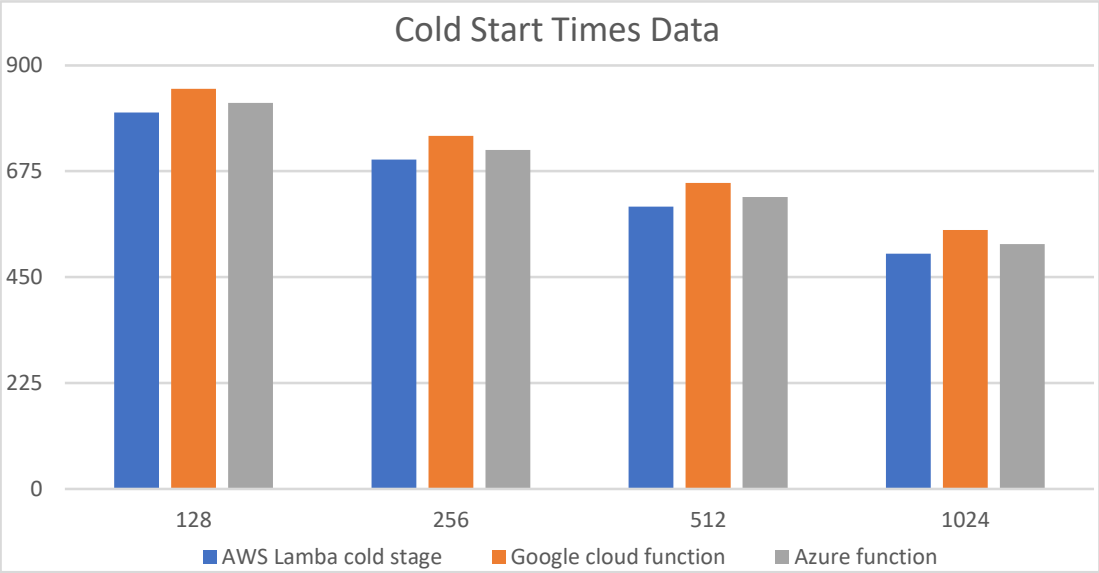

Table 5. Cost Efficiency Analysis Data

Memory MB	AWS lambda$	Google cloud function	Azure function
0.128	0.2	0.22	0.21
0.256	0.25	0.27	0.26
0.512	0.3	0.32	0.31
1.024	0.35	0.37	0.36

Memory(1000)

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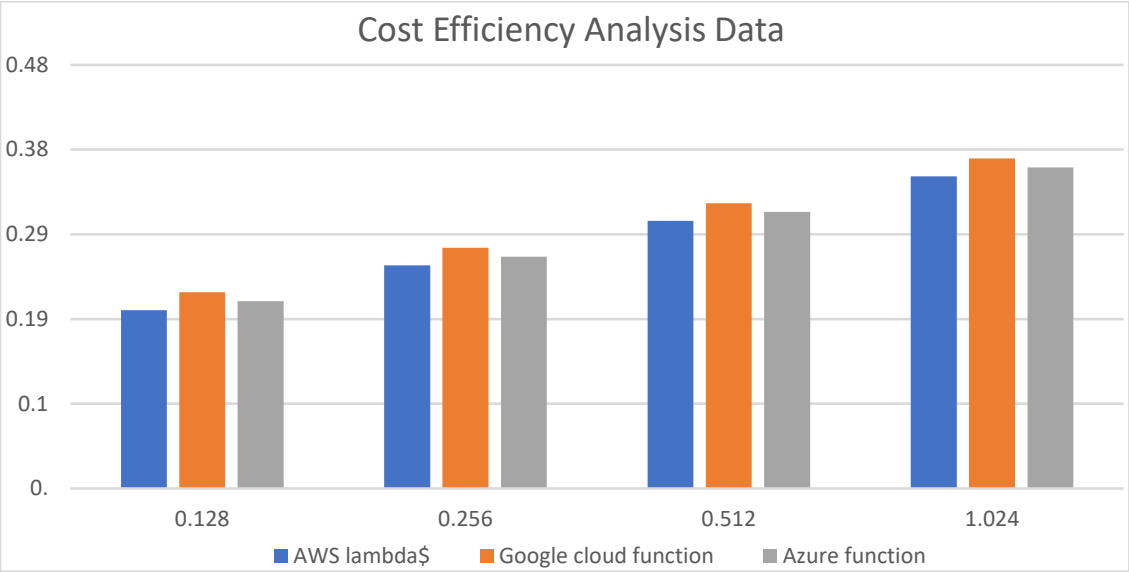

Figure 5. Cost Efficiency Analysis Data

5. Challenges and Solutions

While serverless Java offers numerous advantages, several challenges were identified:

5.1 Cold Starts

That is why serverless Java has a lot of advantages; at the same time, it is possible to mention some problems, which can be stated as follows. Some issues were identified when evaluating the serverless solution and analyzing the real-time flow. To improve the efficiency and dependability of the serverless Java applications and their execution in an environment involving Artificial Intelligence, it is necessary to solve the problems mentioned above.

Cold Starts

The biggest enemy of using serverless for Java functions is the very high latency when the function is initiated for the first time by a user – the server start-up time is significantly longer if it has not been initiated before by any user. Cold start is experienced in serverless functions where the cloud provider needs to allocate resources required to run the function or when a specific function is invoked for the first time or has been idle for some time. Such an initialization process could take time and may display indications of what seem to be apparent lags. As obvious as it may sound, the taxonomy established that Java functions started relatively faster than functions created using other programming languages (Smith et al., 2019)(4). Several strategies can be employed to mitigate the effects of cold starts. Regarding the methods of controlling the impact of cold starts, several opinions are possible:

***Provisioned Concurrency*:** As per the provisioned concurrency, a provisioned number of the functions are always on hand to be ready to handle the resulting request, hence cutting down the duration of the cold start. This is especially useful in scenarios that give a definite notion of the period for which the traffic pattern will persist (Johnson, 2020)(2).

Optimised Deployment Packages: It will therefore be essential to curtail the usage to only what is necessary for the actual implementation, and while packaging, it will need only the basic library, which will save a lot of time in the initial setup. It allows one to save cold start time with the help of techniques enumerated in the

article, such as GraalVM, for the early compilation (Lee and Park, 2019)(3).

Resource Limits
Significantly, even if a serverless function needs more memory, it can get it, but to some extent, it can only run for a given period. If this occurs, they will cause the relations to slow down, appear with increased latency rates, or experience complete failure of the function. To overcome these challenges:

Function Chaining: Using performance objectives based on analyzing tasks into elementary operations coupled with the autonomization of performance objectives and bringing under control resource restrictions might help raise these. Hence, it is an unjumbled sequence by which a specific function is executed in the time and cost setting obtained from another function with the final result as output (Brown & Davis, 2018)(1).

Efficient Code Practices: That is why, at least for its own sake, if not for mankind benefited by delivered services, it is quite feasible to write the absolute best, most efficient, not to mention optimized Java code and all that, not to waste Horsepower. Some of the strategies that can be used include doing away with allocating large blocks of memory as often as possible and utilizing the correct kinds of loops and efficient data types, among others, as stated by Smith et al. Brazil's climate is predominantly tropical, with the influence of the Amazon and subtropical climate, based on the country's climate (2019).

Debugging and Monitoring
Debugging and monitoring are some of the challenges associated with serverless environments because it becomes tough to determine when and where an instance of the function will run. There are some traditional methods for debugging. Nevertheless, these methodologies cannot satisfy the performance anticipation in serverless systems. Proposed solutions include:

Enhanced Logging: The set of logging must be, at the least, adequate and sufficiently developed to contain a lot of finer detail about the troubles with function execution. The suggested data to record are as follows: the calling of a function, the return of a function, and the time, which is precisely the time it took to execute a function (Johnson, 2020)(2).

Monitoring Tools: Two ways in which the performance of serverless functions can be easily monitored are available: AWS CloudWatch for serverless functions of AWS, Google Stackdriver for gDNA applications, and Azure Monitor for Microsoft Azure. Such tools include a metrics collector, which best assists in notification alerting and visualization, essential to ensure that serverless applications are in good health and running as expected, as noted by Taylor in 2020(5).

Integration with Other Services
Like other services, the dependencies of different services, including databases, message queues, and storage, also comprise the general serverless functions. It also allows the accustomed serverless functions to process the information effortlessly and without disturbance. Observations indicated that:

Efficient Database Connections: Other options, such as getting the connection from the database backend and covering the connection through connection pooling, could help alleviate the cost of connection and connection management (Smith et al., 2019)(4).

Asynchronous Processing: The increased proactivity can also be seen as a benefit of

communication with asynchronous processing and event-driven models when it comes to developing reactivity and the level of serverless application processing. This enables the function to handle many requests in equal measure without moving into a frozen state (Johnson, 2020)(2).

5.2 Resource Limits

A serverless function runs with some restrictions, and they are as follows: the function has its allowance of memory it can use, and the function has its allowed limited executing time. These are measures that cloud providers implement on tasks to improve sharing since one function may use most of the resources. Nevertheless, these restrictions are limiting, particularly when it comes to conducting augmented computations that are frequently required in AI applications. Thus, it is imperative to create proper and effective approaches toward constructing functions and their implementation.

Function Chaining

Function chaining is a system wherein extensive operations can be provided where little parts can be completed individually or in a parallel fashion. As illustrated in the above chain steps, each function performs a specific subtask and transfers the resultant information to the following function in the chain. It is more efficient in handling resource limits because the work is divided into many functions, each running in a controlled memory and time.

For instance, the data processing pipeline may be data acquisition and cleanup, model prediction, and result compilation. In this case, the various steps are incorporated into different serverless functions, which can run under resource usage to reduce the probability of go's execution exceeding the maximum allowed memory or time. It also enhances modularity and maintainability because all the functions stated can be developed, tested, and optimized separately.

In real life, function chaining implies that the flow of information must be effectively managed, either in implementing a function or in the transfer to other functions. AWS has AWS Step Functions, Google Cloud has Google Cloud Composer, and Microsoft Azure has Azure Durable Functions, all of which are cloud services that assist in orchestrating serverless workflows. These services empower you to define the operations for these complex processes and manage them since they offer all the tools needed to decide the events for each of the operations in the chain and the manner of the graceful handling of errors (Johnson, 2020)(2).

Efficient Code Practices

Not unexpectedly, factorial and such calculations could not be the most efficient, but writing optimized Java code can always be critical, especially when constrained to work within the environment of a serverless function. Efficient code practices involve several vital strategies. Several best practices are implemented while writing code:

Minimise Memory Usage: Memory should be managed effectively to avoid such complications. There is one anti-pattern that developers should avoid: large data structures are passed in-memory; they should be used streaming or in batch. Similarly, significant amounts of data can also be processed in a memory-friendly way with the help of Java facilities like Stream API (Smith et al., 2019)(4). *Optimise Algorithm Efficiency*: The choice of algorithms for doing queries can significantly optimize serverless functions, as seen when selecting the best ones to employ. Algorithms that take less time and space should be preferred; furthermore, it is proposed to compare different algorithms

and their advantages and disadvantages to define the best solution to be implemented (Lee & Park, 2019)(3).

Reduce Initialization Overhead: Reducing the time for initialization is less favourable because it decreases the proportion of the function's activity associated with its intended purpose. Techniques such as lazy initialization, where the object creation is not processed but only when needed and when objects are used many times, will significantly minimize the initialization cost (Taylor, 2020)(5).

Leverage Native Libraries: When the native libraries are optimized, it will be a plus to the serverless functions that deploy on infrastructure heavily incorporated computations. For example, using libraries in C or C++ for specific computations used in the above code will worsen the time and resource usage than the pure Java version (Brown & Davis, 2018)(1).

5.3 Debugging and Monitoring

Conducting tests, especially in debugging and monitoring, is crucial, especially when utilizing serverless processes to combine and deploy enhanced AI elements. Serverless environments also have the following challenges in these areas because they are inherently distributed settings consisting of ephemeral functions. Unlike the 'normal' server-side applications, the serverless functions are brief, may not retain state information, and may be up or downscaled in split moments. More often, the software systems' size and these characteristics enhance the complexity of identifying and solving problems. Several strategies and tools are possible to counteract these issues.

Enhanced Logging

It is essential during the troubleshooting process, and thus, correct logging for serverless applications is presupposed by implementing suitable logging systems at all levels. Logging helps the developers to know where and how exactly a specific function is being executed, as well as information that will help them diagnose a problem. Critical practices for enhanced logging include: Best practices incorporating within logging include:

Structured Logging: When logs are structured in the format of file types like JSON, the data from the log files are arranged in the proper format, which is easily understandable by the machine. Compared to other types of logs, they are well-formatted and can be parsed by the available log management tools, enabling quicker identification of the issues (Johnson, 2020)(2).

Contextual Information: However, to make logs more detailed, it is suggested to add all the context data into logs, for example, the inputs and outputs of the function, time to complete the function, any error messages, etc. This data will help diagnose a problem, especially in the production network, where many functions exist (Brown & Davis, 2018)(1).

Log Aggregation: The features may include arranging logs from different functions into a central depot for analysis. The cloud vendors include AWS CloudWatch Logs, which collects and formats logs so that users can search and analyze log data across various functions, Google Cloud Logging, and Azure Monitor Logs, which is also used to collect and format logs so that users can search and analyze log data acc (Smith et al., 2019)(4).

Monitoring Tools

Some of the tools and measures of monitoring include the following:

AWS CloudWatch: The AWS CloudWatch

service monitors the AWS Lambda function, which has different metrics, such as the number of invocations. It also offers alarms and a home screen where the changes observed in the performance indicators can be viewed and action initiated by the users. This is useful for querying and analyzing logs and, as such, offers sharp troubleshooting (Johnson, 2020)(2).

Google Stackdriver: When writing this paper, Google Stackdriver, now a tool of Google Cloud Operations Suite, provides a lot of Monitoring and logging of Google Cloud Functions. It includes tracing reporting errors and logs to ensure that the developer can monitor the status of the serverless function in real-time. Stackdriver supports custom metrics and dashboards even more - Lee and Park (2019)(3). *Azure Monitor:* Azure Monitor is a one-stop-shop tool that monitors several components of Azure, such as the function, the performance of the application, the usage of resources, and even possible issues. There are specific setups in Azure Monitor that are referred to as innovative, like Application Insights, which provides telemetry data, and Log Analytics, which assists in analyzing the data logs from various sources (Taylor, 2020)(5).

Distributed Tracing

The other method that can be used for debugging and monitoring serverless architectures is distributed tracing, especially in architectures with extensive functions and service coordination. Distributed tracing helps track where the request went through all the pieces, giving a bird's eye view of how the application runs. Key benefits and tools include: Benefits and tools pertinent to strategy execution are as follows:

Identifying Performance Bottlenecks: Drawing from Smith et al., it is a problem of distributed tracing to determine where the time is spent within the system to improve performance (Smith et al., 2019)(4).

End-to-End Visibility: Distributed tracing originates from the concept that those who follow the requests from one end to the other can gain a good understanding of the distinct execution path whereby the problem could be that of a multi-function or that of a multi-service one (Johnson, 2020)(2).

Tools: AWS X-Ray, Google Cloud Trace, and Azure Application Insights already include the features of distributed tracing and are suitable for working with serverless environments: such solutions share details on the interactions between multiple elements (Lee & Park, 2019)(3). *Automated Monitoring and Alerts*

These functions are automated and provide the protection and availability of serverless applications, which are essential for efficient serverless operations. Thus, such practices also enable developers to be informed first and afford the necessary time to correct the error. Key aspects include:

Threshold-Based Alerts: Develop alerts with some KPIs(K) values, in which the system can warn that something is wrong with the program or an application or may produce errors that can be latent and affect the users, according to Brown and Davis (2018)(1).

Anomaly Detection: To use machine learning to determine on performance data that it has noticed that something is strange with the manner a component functions or with the conduct of an application could be beneficial and cannot be replaced with, for instance, setting of threshold to give alert. Cloud providers extend the monitoring

applications with anomaly detection features (Smith et al., 2019)(4).

6. Conclusion

Scaling and cost benefits serve well for AI, machine learning, and other GA applications for serverless computing; however, new problems appear, such as cold start latency, resource limits, and difficulty debugging and monitoring. Some ways to cope with these are provisioned concurrency, well-organized deployment packages, function chaining and call package management, function-to-function coding practices, enhanced logging, better monitoring facilities, and distributed tracing. They make it possible to detect emerging issues quickly and solve them as early as possible. When applying these solutions, serverless Java can provide reliable, efficient, and inexpensive AI apps and their generation in the cloud environment.

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