Serverless on Machine Learning: A Systematic Mapping Study

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ABSTRACT Machine Learning Operations (MLOps) is an approach to managing the entire lifecycle of a machine learning model. It has evolved over the last years and has started attracting many people in research and businesses in the industry. It supports the development of machine learning (ML) pipelines typical in the phases of data collection, data pre-processing, building datasets, model training, hyper-parameters refinement, testing, and deployment to production. This complex pipeline workflow is a tedious process of iterative experimentation. Moreover, cloud computing services provide advanced features for managing ML stages and deploying them efficiently to production. Specifically, serverless computing has been applied in different stages of the machine learning pipeline. However, to the best of our knowledge, it is missing to know the serverless suitability and benefits it can provide to the ML pipeline. In this paper, we provide a systematic mapping study of machine learning systems applied on serverless architecture that include 53 relevant studies. During this study, we focused on (1) exploring the evolution trend and the main venues; (2) determining the researchers’ focus and interest in using serverless on machine learning; (3) discussing solutions that serverless computing provides to machine learning. Our results show that serverless usage is growing, and several venues are interested in the topic. In addition, we found that the most widely used serverless provider is AWS Lambda, where the primary application was used in the deployment of the ML model. Additionally, several challenges were explored, such as reducing cost, resource scalability, and reducing latency. We also discuss the potential challenges of adopting ML on serverless, such as respecting service level agreement, the cold start problem, security, and privacy. Finally, our contribution provides foundations for future research and applications that involve machine learning in serverless computing.

INDEX TERMS Serverless, FaaS, function as a service, machine learning, systematic mapping, systematic literature review, SM, SLR.

I. INTRODUCTION
Cloud computing is beneficial to businesses of all sizes in the marketing sector. It offers the abstraction of online services hosted on the cloud rather than complex local infrastructure. These services include everything from simple cloud storage to cloud infrastructure platforms. Cloud computing offers different benefits i.e., high speed, efficiency and cost reduction, data security, scalability, back-up and data restore, control and level access, and unlimited storage capacity [1]. These services are offered in different proportions according to the provided service, such as Infrastructure as a Service (IaaS), Platform as a Service (PaaS), Software as a Service (SaaS), Function as a Service (FaaS) or Serverless. Moreover, these platforms have grown significantly over the last decade and are widely adopted for the delivery of computing services. In particular, serverless computing provides a simplified architecture in which code execution is fully managed by the cloud provider, in such case, developers can focus only on code writing, increasing their productivity. Recently, serverless has been used as an infrastructure to build total ML pipelines or partially with faster deployment and elastic scalability.
On the one hand, serverless popularity is increasing, and it is receiving attention from developers, especially after Amazon launched AWS Lambda in November 2014.1 Recently, Wen et al. [2] found that questions about Serverless on StackOverflow have grown 380% from 2015 to 2020. The size of the serverless market is estimated to grow from 3.33 USD Billion in 2018 to USD 31.53 Billion in 2026 [3]. On the other hand, ML has been widely used in cloud computing, mainly when it is divided into a small pipeline stage (ML as a Service). The need becomes to use Serverless since the high cost of cloud resource management.

Thus, Serverless computing [4] is an interesting option regarding the resolution of small tasks, mainly when companies cannot estimate the traffic of their ML applications, scalability, and cost accurately [5]. Furthermore, several studies are exploiting serverless computing to accomplish tasks of the ML pipeline, such as training [6], hyperparameter tuning [7], and model deployment [8].

This paper aims to map the current state-of-the-art to understand how Serverless was used in the machine learning pipeline and the challenges and opportunities for different stakeholders.

For achieving this goal, we perform a systematic mapping to answer three research questions by analyzing relevant studies. First, our study identified, classified, and evaluated the current state-of-the-art in machine learning on Serverless architecture. Next, we selected 50 primary studies from the Scopus database; then, we rigorously classified the studies to precisely categorize research results on ML and Serverless challenges.

The audience of this study is composed of both (i) researchers interested in contributing to this research area and (ii) practitioners interested in understanding existing research on machine learning applying Serverless architecture.

The main contributions of this study is to respond these research questions:

- WHAT ARE THE PUBLICATION TRENDS OF RESEARCH STUDIES ABOUT SERVERLESS ON MACHINE LEARNING?
- WHAT IS THE FOCUS OF RESEARCH OF APPLIED MACHINE LEARNING ON SERVERLESS COMPUTING?
- WHAT ARE THE POTENTIAL CHALLENGES OF ADOPTING MACHINE LEARNING ON SERVERLESS COMPUTING?

The rest of the paper is organized as follows. In Section II we set the stage by giving the basic concepts around machine learning lifecycle and the serverless architecture. The design of the study is presented in Section III, whereas its results are elaborated in Sections IV. We have made a discussion in Section IV-C where we broadened our perspective and the potential implications for both researchers and practitioners. Threats to validity and related work are described in Sections V and VI. With Section VII, we close the paper and discuss future work.

II. BACKGROUND
This section provides background information on defining Serverless and ML pipeline, as we found during our systematic mapping.

A. MACHINE LEARNING PIPELINE
Microsoft team members introduced a typical ML pipeline [10], where they show a series of steps chained together to form the machine learning workflow essential stages. These stages include data and model-oriented artifacts from data collection and cleaning until model evaluation deployment. These stages construct an ML pipeline lifecycle. Recently, with the commercial use of AI, the MLOps field has been introduced, aiming to automate the ML pipeline [11]. A standard ML pipeline broadly consists of the following five stages shown in Figure 1:

- **Data retrieval**: is the process of identifying and extracting data from a database, based on a query provided by the user or application.
- **Data preparation**: is the process of gathering, combining, structuring and organizing data.
- **Model training**: The process of training an ML model involves providing the data features to an ML method or algorithm to reduce errors and generalize the representations learned from the data.
- **Model evaluation**: is evaluating the built model against certain criteria to assess its performance. Model performance is usually a function defined to provide a numerical value to help us decide the effectiveness of any model.
- **Hyperparameters tuning**: is choosing a set of optimal hyperparameters for a learning algorithm. A hyperparameter is a parameter whose value controls the learning process.
- **Model Deployment and monitoring**: is the method by which you integrate a machine learning model into an existing production environment to make practical business decisions based on data.
- **Model Monitoring**: is the close tracking of the performance of ML models in production.

B. CLOUD PROVISIONING SERVICES
Cloud computing is a widely adopted paradigm for the delivery of computing services. Leading cloud platforms such as AWS,2 Google Cloud,3 and Microsoft Azure4 offer a variety of provisioning services that can be used for model serving. In addition, they provide several architectures with different access management. These are the list of the most common cloud computing architecture.

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1 https://docs.aws.amazon.com/lambda/latest/dg/lambda-releases.html
2 https://aws.amazon.com/
3 https://cloud.google.com/
4 https://azure.microsoft.com/en-us/
In this research, we follow the guidelines for systematic mapping studies [14]. We present the procedure to review the literature on machine learning usage on serverless architecture. In the following, we present the design of our study, including the search keywords, search technique, data sources, and inclusion and exclusion criteria are explained.

A. RESEARCH QUESTIONS

We set the following list of research questions as a guideline during the systematic mapping review:

RQ1 - WHAT ARE THE PUBLICATION TRENDS OF RESEARCH STUDIES ABOUT SERVERLESS ON MACHINE LEARNING?

By answering this research question, we aim to characterize the intensity of scientific interest in using machine learning on top of serverless architecture, the relevant venues where academics publish their results on the topic and their types of contribution over the years.

RQ2 - WHAT IS THE FOCUS OF RESEARCH OF APPLIED MACHINE LEARNING ON SERVERLESS COMPUTING?

By answering this research question, we aim to provide a solid foundation to classify existing research on machine learning in a serverless architecture.

RQ3 - WHAT ARE THE POTENTIAL CHALLENGES OF ADOPTING MACHINE LEARNING ON SERVERLESS COMPUTING?

By answering this research question, our objective is to profile the state-of-the-art on challenges and opportunities to use machine learning on serverless architecture.

B. DOMAIN EXPLORATION

In the following, we describe the interesting domain covered by this research during the systematic mapping study.

Cloud infrastructure: The types of cloud computing services vary, they provide access to IT infrastructure, hardware, and software resources. Cloud computing is all about delivering computing services like databases, software, analytics,
servers, storage, networking, and intelligence. There are many benefits of cloud computing, including cost savings, scalability, and access to data centers around the world [15]. Cloud computing services fall into four main categories: Infrastructure as a Service (IaaS), Platform as a Service (PaaS), Software as a Service (SaaS), and Functions as a Service (FaaS) which is a relatively new Cloud service model.

**Computing on machine learning pipeline**: cloud services are a good option for anyone looking to train and deploy memory-intensive, complex Machine Learning/Deep Learning models. Cloud services are a cost-effective solution for both individual users and companies. The cloud allows employees to access files on any device [16].

**Serverless on Machine Learning**: Serverless architecture gives many opportunities and advantages to make the machine learning model more efficient and smoother [17]. As shown in Figure 3, we focus on this systematic literature mapping on collecting research papers on applying serverless on machine learning.

**C. SEARCH AND SELECTION PROCESS**

As shown in Figure 2, we present our search and selection process. We designed a two-stage process, a systematic search similar to a previous study [18], to identify the current literature on serverless usage of machine learning. On Stage 1, we performed an automated search since it is the typical search strategy to identify relevant studies for a Systematic Mapping [19].

Defining the review goal, keywords were carefully selected to obtain relevant articles. In stage 1, several keywords were formulated and later narrowed down based on the research objectives. We designed our search query based on “machine learning” and “serverless.” We executed the following search query on Scopus:

```
('serverless' OR 'lambda architecture' OR 'function as a service') AND ('machine learning' OR 'deep learning')
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Since we are looking for a particular subject, we applied the default automatic search, including the title, abstract, and keywords. We executed the query in June 2022, where we found 198 studies. The papers were either included among the relevant articles or excluded as irrelevant for the review by studying their titles, abstracts, conclusions and complete content.

To extract only relevant articles for review, certain inclusion (IC) and exclusion (EC) criteria were set, specifically:

- **IC1**: The study must be an article, conference paper, or workshop;
- **IC2**: The study must be in the Computer Science area;
- **IC3**: The study must be a primary study;

9https://www.scopus.com/
TABLE 1. List of included peer-reviewed studies.

| #  | Reference | Title                                                                 | Year  |
|----|-----------|-----------------------------------------------------------------------|-------|
| P01| [20]      | A Case for Serverless Machine Learning                                | 2018  |
| P02| [21]      | Exploring Serverless Computing for Neural Network Training           | 2018  |
| P03| [12]      | Implementation of unsupervised k-means clustering algorithm within amazon web services lambda | 2018  |
| P04| [22]      | Pay-Per-Request Deployment of Neural Network Models Using Serverless Architectures | 2018  |
| P05| [23]      | Serving deep learning models in a serverless platform                | 2018  |
| P06| [24]      | BARISTA: Efficient and scalable serverless serving system for deep learning prediction services | 2019  |
| P07| [25]      | Behavior analysis using serverless machine learning                  | 2019  |
| P08| [26]      | Cirrus: A Serverless Framework for End-To-end ML Workflows           | 2019  |
| P09| [27]      | Distributed Machine Learning with a Serverless Architecture          | 2019  |
| P10| [28]      | Function-as-a-Service Application Service Composition: Implications for a Natural Language Processing Application | 2019  |
| P11| [29]      | Mark: Exploiting cloud services for cost-effective, slo-aware machine learning inference serving | 2019  |
| P12| [30]      | On the FaaS track: Building stateful distributed applications with serverless architectures | 2019  |
| P13| [31]      | Seneca: Fast and low cost hyperparameter search for machine learning models | 2019  |
| P14| [32]      | Serving machine learning workloads in resource constrained environments: A serverless deployment example | 2019  |
| P15| [33]      | Stratum: A serverless framework for the lifecycle management of machine learning-based data analytics tasks | 2019  |
| P16| [34]      | Towards a Serverless Platform for Edge AI                            | 2019  |
| P17| [35]      | TriMIS: Transparent and isolated model sharing for low latency deep learning inference in function-as-a-service | 2019  |
| P18| [36]      | A cloud-based framework for machine learning workloads and applications | 2020  |
| P19| [37]      | Automatic Tuning of Hyperparameters for Neural Networks in Serverless Cloud | 2020  |
| P20| [38]      | Batch: Machine learning inference serving on serverless platforms with adaptive batching | 2020  |
| P21| [39]      | Benchmarking Deep Neural Network Inference Performance on Serverless Environments With MLPerf | 2020  |
| P22| [40]      | Enabling Cost-Effective, SLO-Aware Machine Learning Inference Serving on Public Cloud | 2020  |
| P23| [41]      | FAASM: Lightweight isolation for efficient stateful serverless computing | 2020  |
| P24| [42]      | Implications of Public Cloud Resource Heterogeneity for Inference Serving | 2020  |
| P25| [43]      | Migrating Large Deep Learning Models to Serverless Architecture      | 2020  |
| P26| [44]      | Prognostics by classifying degradation stage on lambda architecture   | 2020  |
| P27| [7]       | Refactoring of Neural Network Models for Hyperparameter Optimization in Serverless Cloud | 2020  |
| P28| [45]      | STOIC: Serverless Telescopable Hybrid Cloud for Machine Learning Applications on Edge Device | 2020  |
| P29| [46]      | Towards Federated Learning using FaaS Fabric                         | 2020  |
| P30| [6]       | A Hybrid Framework for Effective Prediction of Online Streaming Data | 2021  |
| P31| [47]      | A serverless gateway for event-driven machine learning inference in multiple clouds | 2021  |
| P32| [48]      | AMPS-Inf: Automatic Model Partitioning for Serverless Inference with Cost Efficiency | 2021  |
| P33| [49]      | Automatic Hyperparameter Optimization for Arbitrary Neural Networks in Serverless AWS Cloud | 2021  |
| P34| [50]      | Cross-Platform Performance Evaluation of Stateful Serverless Workflows | 2021  |
| P35| [51]      | Distributed double machine learning with a serverless architecture   | 2021  |
| P36| [52]      | Dorylas: Affordable, scalable, and accurate GNN training with distributed CPU servers and serverless threads | 2021  |
| P37| [53]      | Edge-adaptible serverless acceleration for machine learning Internet of Things applications | 2021  |
| P38| [54]      | Experience Paper: Towards enhancing cost efficiency in serverless machine learning training | 2021  |
| P39| [55]      | FedLess: Secure and Scalable Federated Learning Using Serverless Computing | 2021  |
| P40| [56]      | Gillis: Serving large neural networks in serverless functions with automatic model partitioning | 2021  |
| P41| [8]       | High performance serverless architecture for deep learning workflows  | 2021  |
| P42| [57]      | Leveraging the serverless paradigm for realizing machine learning pipelines across the edge-cloud continuum | 2021  |
| P43| [58]      | Performance and cost comparison of cloud services for deep learning workload | 2021  |
| P44| [59]      | SLA-Aware Workload Scheduling Using Hybrid Cloud Services             | 2021  |
| P45| [60]      | Toward Sustainable Serverless Computing                               | 2021  |
| P46| [61]      | Towards Demystifying Serverless Machine Learning Training            | 2021  |
| P47| [62]      | Towards situational awareness with multimodal streaming data fusion: Serverless computing approach | 2021  |
| P48| [63]      | You Do Not Need a bigger boat: Recommendations at Reasonable Scale in a (Mostly) serverless and open stack | 2021  |
| P49| [64]      | AXDNN: Achieving Predictable Distributed DNN Training With Serverless Architectures | 2021  |
| P50| [65]      | Serverless Computing Approach for Deploying Machine Learning Applications in Edge Layer | 2022  |
| P51| [66]      | Stateful Serverless Computing with Crucial                            | 2022  |
| P52| [67]      | INFiess: A native serverless system for low-latency, high throughput inference | 2022  |
| P53| [68]      | MLLess: Achieving Cost Efficiency in Serverless Machine Learning Training | 2022  |

- **IC4**: The study should address machine learning practices using serverless;
- **EC1**: The study is not written in English;
- **EC2**: The study is duplicate;
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IV. RESULTS

The final set of publications presented in Table 1 was carefully read to answer the raised research questions. In the following, we are addressing carefully (1) the evolution trend of the set of papers and the different venues that were published; (2) the focus of the set of researchers on applying machine learning on Serverless architecture; (3) discussion of the challenges and opportunities to use Serverless on machine learning.

A. WHAT ARE THE PUBLICATION TRENDS OF RESEARCH STUDIES ABOUT SERVERLESS ON MACHINE LEARNING?

This research question aims at (1) the characterization of the intensity of scientific interest and (2) the active publication venue on the usage of machine learning on serverless architecture.

1) PUBLICATION FREQUENCY

The selected papers of this study were analyzed to determine the trends in publication and the thematic evolution. Figure 4 shows the number of publications per year where researchers start exploring machine learning usage on serverless architecture. The results show that the average number of publications per year is approximately 12 from 2018 to 2021, with five papers in 2018 until 20 published papers in 2021.

Serverless computing has trended a significant engagement over the past years [2]. This boost has been caused by industry, academia, and developers for several reasons [69]. With the appearance of MLOps that include continuous and repetitive tasks (i.e., code integration, training, deployment [70]), Serverless has started attracting ML developers.

2) PUBLICATION VENUE

Researchers have been contributing on the usage of serverless on ML pipelines. Table 2 shows the various publication venues we find in the selected research papers.

The percentages of publications in conference papers, journal papers, workshop papers, and symposium papers are approximately 60% (31/53), 16% (10/53), 14% (7/53), and 10% (5/53), respectively. The topic Serverless for ML practices has started attracting more researchers, we found ten journal papers that were published which reveal the subject relevance where more studies can present additional contributions.

Following the interpretation of publications, the most productive and primary journals, symposiums, conferences, and workshop venues related to serverless computing can be clarified. The list of journals we found is shown with their full names in Table 3. All eight journal venues were mentioned only once each.

The list of conferences is shown in Table 4. The “Cloud”, “WOSC”, “ICPE”, “IC2E”, “USENIX”, “CCGRID”, and “EC3: The study is published as part of textbooks, abstracts, editorials, and keynote speeches. After applying the IC1, IC2, EC1, EC2, we obtained 147 studies. Then we analysed the title and abstract of each study and, after filtering by IC3, IC4 and EC3, we kept 51 studies. We read all 51 papers, filtering by IC3, IC4 and EC3 on the full text; we obtained the seed data set with 44 studies. In Stage 2, we used our seed data set to perform two rounds of snowballing, backward and forward, detailed in 2. The snowballing research comes out with 8 additional studies. Thus, we identify in the final dataset 52 studies for this systematic mapping (Table 1). Our work is shredded on a public repository for study reproducibility.10

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10https://github.com/AmineBarrak/Serverless-on-ML.
TABLE 4. List of conferences.

| Name                                                      | #Venue |
|-----------------------------------------------------------|--------|
| International Conference on Cloud Computing (CLOUD)      | 3      |
| International Workshop on Serverless Computing (WoSoC)    | 3      |
| International Conference on Performance Engineering (ICPE) | 3      |
| International Conference on Cloud Engineering (IC2B)      | 2      |
| International Middleware Conference (Middleware)           | 2      |
| USENIX Annual Technical Conference (ATC)                  | 2      |
| International Conference on Big Data (Big Data)           | 2      |
| International Symposium on Cluster, Cloud and Internet Computing (CCGRID) | 2 |
| Service-Oriented Computing and Applications (SOCA)        | 1      |
| International Conference on Prognostics and Health Management (ICPHM) | 1 |
| International Conference on Information and Communication Systems (ICICS) | 1 |
| Innovation in Clouds, Internet and Networks and Workshops (ICIN) | 1 |
| International Conference on Parallel Processing (ICPP)    | 1      |
| USENIX Operational Machine Learning (OpML)                | 1      |
| USENIX Hot Topics in Edge Computing (HotEdge)             | 1      |
| International Symposium on Software Reliability Engineering Workshops (ISSRE) | 1 |
| Pervasive Computing and Communications (PerCom)            | 1      |
| International Conference for High Performance Computing, Networking, Storage and Analysis (SC) | 1 |
| North American Chapter of the Association for Computational Linguistics (NAACL) | 1 |
| International Conference on Distributed Computing Systems (ICDCS) | 1 |
| High Performance Serverless Computing (HiPS)               | 1      |
| International Conference on Computing for Sustainable Global Development (INDIACOM) | 1 |
| International Conference on Management of Data (SIGMOD)   | 1      |
| Symposium on Cloud Computing (SoCC)                       | 1      |
| International Conference on Software Engineering Workshops (ICSEW) | 1 |
| Big Data in Emergent Distributed Environments (BDIEDE)     | 1      |
| Conference on Recommender Systems (RecSys)                | 1      |
| Neural Information Processing Systems (NeurIPS)            | 1      |
| International Symposium on Workload Characterization (IISWC) | 1 |
| International Conference on Information Networking (ICIN)  | 1      |
| Operating Systems Design and Implementation (ODID)         | 1      |
| Architectural Support for Programming Languages and Operating Systems (ASPLOS) | 1 |

“Middleware”, “ATC” and “Big Data” are considered the most active conferences held 19/42 (45%).

B. WHAT IS THE FOCUS OF RESEARCH OF APPLIED MACHINE LEARNING ON SERVERLESS COMPUTING?

In this research question, our objective is to provide a solid classification of the existing research.

1) RESEARCH STRATEGIES OF SERVERLESS USAGE ON ML PIPELINE

Machine Learning pipelines are composed of four main stages, as shown in Figure 1 (1) data processing, (2) model training, (3) Hyperparameter tuning, and (4) model deployment. We examine the papers to determine the main goal and the main solution each study proposes. As shown in Table 5, the most recurrent usage targeted by the primary studies are in deploying ML models on Serverless (33/53), followed by model training (16/53), hyperparameter tuning (9/53) and data preprocessing (9/53). There are (6/44) studies

| ML pipeline                      | #Studies | Studies |
|----------------------------------|----------|---------|
| Data preprocessing              | 9        | P01, P07, P08, P10, P25, P26, P34, P46, P48 |
| Training/Learning               | 16       | P01, P02, P03, P08, P09, P23, P29, P30, P36, P38, P39, P46, P49, P50, P51, P53 |
| Hyperparameter Tuning           | 9        | P01, P02, P08, P13, P19, P27, P33, P35, P46 |
| Model Deployment (inference)    | 33       | P04, P05, P06, P10, P11, P12, P14, P17, P18, P20, P21, P22, P23, P24, P25, P26, P27, P31, P32, P33, P34, P35, P36, P37, P39, P40, P41, P41, P42, P43, P44, P45, P47, P49, P51, P52 |
| End-to-end ML pipeline          | 6        | P01, P08, P15, P16, P34, P42 |

TABLE 6. Serverless platforms usage.

| Serverless provider | #Studies | Studies |
|---------------------|----------|---------|
| AWS Lambda          | 39       | P01, P02, P03, P04, P05, P08, P09, P10, P11, P12, P13, P14, P19, P20, P21, P22, P24, P25, P26, P27, P31, P32, P33, P34, P35, P36, P37, P39, P40, P41, P43, P44, P45, P46, P47, P49, P51, P52 |
| IBM Cloud Functions  | 4        | P07, P18, P39, P43 |
| Google Cloud Functions | 3     | P29, P39, P40 |
| Azure Functions      | 13       | P34, P39, P49 |
| OpenFaaS             | 3        | P29, P39, P52 |
| Knative              | 12       | P25, P50 |
| KNIX                 | 1        | P40 |
| Kubeless             | 1        | P28 |

that tried to employ Serverless in the end-to-end ML pipeline. These results confirm that the use of serverless benefits in the different stages of ML is advantageous.

2) THE DIFFERENT SERVERLESS PROVIDERS

Table 6 presents the serverless platforms used in the considered research papers included in this study. It can be noticed that “AWS Lambda” has significant usage in 39 studies. We also found that “Apache OpenWhisk”, “IBM Cloud Function” and “Google Cloud Function” are used with 4, 4, and three published papers, respectively. Each platform has its own set of features and differs from others. We later compare the different providers in RQ3 IV-C.

3) THE MAIN RESOLVED/DISCussed CHALLENGES AND ISSUES

The main solved / discussed challenges are cost / pricing (37/53) and resource scalability (30/53), as reported in Table 7. The high number of studies that discussed (1) cost/price and (2) scalability might indicate that Serverless provides a fair price architecture that provides a pay-per-use model that auto-scales in need. Researchers seem to be interested in using Serverless for model deployment and make sure to keep a rational inference latency (22/53),
in contracts (6/53), (2/53) and (2/53) focused on the storage, network, and training latencies, respectively. There were proposed solutions to reduce latency and improve performance by varying the batch size; this solution was present in (16/53). The cold start was discussed in (10/53) studies trying to mitigate it since Serverless containers have start-up latencies in the hundreds of milliseconds to several seconds, leading to the cold-start problem [71]. A significant number of studies (10/53) discussed the Service Level Objective (SLO). We mention that the SLO is an agreement set by a Serverless provider where there is the pre-defined service minimum response time [40]. Interestingly, few papers considered security and privacy with (4/53) and (4/53), respectively. However, only (2/53) paper mentioned the portability and reproducibility of the run-time environment.

4) MACHINE LEARNING FRAMEWORKS USED IN THE STUDIES

The machine learning frameworks helped the researchers to test their proposed solution easily, without understanding the underlying algorithms. Therefore, the choice of framework depends on the complexity of the targeted task. As reported in Table 8, the predominant ML frameworks are: Tensorflow (22/53), Keras (10/53) and MXNet (9/53). Indeed, other frameworks have been used in recent studies such as Pytorch (8/53) since it can be used for distributed training in parallel machines [61], Numpy (5/53) and OpenCV (3/53).

5) TYPE OF MACHINE LEARNING ALGORITHM USED TO TRAIN MODELS

The type of machine learning used to train the models depends on the research goals. Table 9 shows what type of algorithms were used in the studies.

| ML frameworks | #Studies | Studies |
|---------------|----------|---------|
| Tensorflow    | 22       | P02, P08, P09, P11, P17, P19, P20, P21, P22, P23, P24, P25, P27, P28, P29, P32, P37, P39, P41, P49, P50, P52 |
| Keras         | 10       | P11, P19, P22, P27, P28, P32, P33, P37, P40 |
| MXNet         | 9        | P05, P09, P17, P16, P17, P20, P22, P24, P40 |
| Pytorch       | 8        | P04, P14, P36, P38, P43, P44, P46, P53 |
| Scikit-learn  | 6        | P10, P28, P34, P35, P37, P42 |
| Numpy         | 5        | P10, P23, P35, P42, P43 |
| PyWren        | 4        | P01, P08, P12, P38 |
| Spark ML      | 13       | P08, P12, P26 |
| OpenCV        | 13       | P21, P25, P41 |
| ONNX          | 10       | P05, P14 |
| Tensoract     | 2        | P23, P41 |
| Pandas        | 2        | P35, P42 |
| Rosen         | 2        | P07, P08 |
| Pillow [73]   | 11       | P32 |
| Caffe         | 11       | P17 |
| MNIST         | 11       | P50 |

| Types of ML models | #Studies | Studies |
|--------------------|----------|---------|
| Neural Network (DNN, CNN, RNN, GNN) | 22       | P02, P04, P13, P14, P17, P18, P19, P21, P27, P28, P29, P52, P33, P36, P37, P40, P42, P43, P44, P45, P49, P50 |
| Supervised ML (LR, RF, SVM) | 14       | P01, P06, P07, P08, P12, P26, P30, P31, P34, P42, P46, P51, P53 |
| ResNet            | 12       | P05, P06, P11, P17, P20, P22, P24, P32, P40, P49, P46, P52 |
| Inception         | 8        | P06, P17, P20, P22, P24, P32, P40 |
| LSTM              | 7        | P17, P18, P36, P39, P42, P51, P52 |
| Stochastic Gradient Descent (SGD) | 8        | P01, P09, P23, P38, P46, P53 |
| MobileNet         | 5        | P20, P32, P49, P46, P52 |
| squeezeNet        | 3        | P03, P17, P24 |
| NLP               | 3        | P04, P10, P21 |
| K-means           | 3        | P03, P12, P46, P51 |
| VGG               | 13       | P06, P33, P52 |
| Reinforcement Learning (RL) | 12       | P09, P40 |
| Federated Learning | 12       | P29, P39 |
| NASNet            | 12       | P11, P22 |
| OpenNMT           | 12       | P11, P22 |
| Optical Character Recognition (OCR) | 12 | P25, P41 |
| Yolo              | 12       | P31, P47 |
| Gym openAI        | 11       | P09 |
| Bert              | 11       | P52 |
machine learning was used. The results show that neural network models dominate the studies with (22/53). Neural network models are more challenging to be used, especially in distributed environment i.e., distributed ML training [54]. Surprisingly, we found the use of supervised ML, such as logistic regression, random forest, and SVM, in (14/53) studies. These models are not resources costly in the training phase. Their usage is mostly for comparison purposes of the proposed architecture [30]. There are several other machine learning algorithms. We mention ResNet (12/53) and Inception with different versions (8/53). These models are based on a conventional neural network used for intensive computing i.e., image recognition [73].

C. WHAT ARE THE POTENTIAL CHALLENGES OF ADOPTING MACHINE LEARNING ON SERVERLESS COMPUTING?

In this research question, our objective is to profile state of the art on challenges of machine learning usage on serverless architecture.

1) SERVERLESS PROVIDERS

It is interesting to see Serverless providers evolving their services over the years. Carreira et al. [20] discussed about the Serverless capacity as they were not able to run TensorFlow [76] or Spark [77] functions on AWS lambda due to size limits (3GB RAM). Today the limit RAM size has increased to 10 GB for each serverless function [78]. We present in Table 10 the Serverless performance functionalities offered by the different providers we found in the primary studies. This table was filled in January 2022. We did not include Kubeless in the comparison table, since it is not an active project. In the previous RQ, we found that 77% of the studies (34/44) were using AWS Lambda. We can explain that result because this tool provides a high Random Access Memory allocation to reach 10Gb. Moreover, since the serverless function works only on demand, it has a timeout where the instance is shutdown after a timeout set by the provider. We can see that Amazon has the longest function timeout.

We noticed that the deployment package size is small and differs from one provider to another. It is the total size allowed for the function source code i.e., model. Providers offer the possibility of hosting the deployed model in extra storage if the model exceeds the limit for the serverless package size. For example, there is an option to use an external database or S3 bucket to store large payloads and pass the data identifier to the function calls. However, this option will cause additional latency to the system.

For better services, the serverless providers may ensure better user performance, especially the timeout function, to keep the instance warm and avoid the cold start latency.

2) SERVICE LEVEL AGREEMENT/OBJECTIVE

A Service Level Agreement/Objective is an agreement set by the serverless provider. Cloud providers claim different SLAs due to their unique technics. In such case, the performance may vary for the same code from one cloud service provider to another [40]. We found that all the studies discussing the SLO agreement use the serverless for ML model deployment [24], [29], [38], [40], [42], [48], [56], [67]. They ensured that the inference model in their proposed solution was respected. For example, Amazon SLO regarding inference latency is that at least 98% of inference queries must be served in 200 ms. However, failing to acquiesce with the SLOs results will lead to compromised quality of service or even financial loss, e.g., end users will not be charged for queries not responded in time [79]. Regarding the machine learning models inference, the execution of small models (e.g., MNIST, Textcnn-69) can respond within 50ms under each memory configuration, but for the other large models, such as Bert-v1, ResNet-50 and VGGNet, a small memory configuration leads to quite a long execution time (exceeding hundreds of milliseconds). If configured with the maximum allowable memory size, the execution time for a single request exceeds 200ms, which makes it challenging to meet the latency SLO in the production environment [67]. Therefore, providers should share such agreements and statistics of service violations to help customers choose the best one, leading to a competitive environment for better services.

3) ENSURE RESOURCE SCALABILITY AND PREDICTIVE SCALING

In general, serverless architecture provides autoscaling features to handle workload spikes smoothly. Forecasting resource usage is no longer necessary to ensure that we always have the right amount of resources to host our applications. Compared with cluster computing, a serverless base model enables a rapid adjustment on-demand of the number of workers overtime [61]. Moreover, in multithread computation, a single-machine solution quickly degrades when the number of threads exceeds the number of available cores, while in a serverless base solution, the scale-up is faster regarding the execution time [66].

However, serverless functions do not support customized scaling. Barista uses predictive scaling to achieve low-latency

### Table 10. Comparison between the most known providers for Function as a Service (Serverless).

| Serverless Provider | Function timeout (second) | Maximum Memory Allocation | Deployment package size |
|---------------------|---------------------------|---------------------------|------------------------|
| AWS Lambda [75]     | 900                       | 10,240 MB                 | 50MB zip 250 MB unzip  |
| Apache OpenWhisk    | 600                       | 2048 MB                   | 48 MB                  |
| Google Cloud Functions | 540                      | 8560 MB                   | 100MB zip 500 MB unzip |
| IBM Cloud Functions | 600                       | 2048 MB                   | 48 MB                  |
| OpenPaaS            | 300                       | 42 MB                     | 1MB                    |
| Azure Functions     | 600                       | 1500 MB                   | n/a                    |
| KNIX [76]           | 30                        | 2000 MB                   | 100 MB                 |
| Knative             | 600                       | 200 MB                    | 256 MB unzip           |
inference serving in the serverless cloud [24]. Moreover, a hybrid architecture between Serverless and VM is proposed, and even machine learning models to predict scaling to reduce over-provisioning to the best execution environment [29], [40].

The machine learning inference services are commonly latency critical, and the auto-scaling ability of serverless computing could deal with bursty workloads well [8]. Yang et al. [67] presented a solution called INFLess that reduces the allocation of resources for each serverless instance to reach optimal performance in inference services.

The resource scalability is a critical property of any ML training system since only the active workers at any given time will be billed. ML training is typically an iterative process in which a higher number of workers is desirable during the first training steps to diminish loss. When loss reduction stagnates and reaches convergence, the number of workers scales down once the learning curve starts to flatten out [54], [68].

4) SERVERLESS VS. IaaS FOR ML SERVING
Several works in primary studies (37/53) developed the idea of reducing costs by using serverless in their ML solution (deployment, testing, etc.) instead of an infrastructure environment.

Serverless providers are proposing pay-as-you-go services, only paying for those resource usage - compared to other cloud resources such as IaaS compute service AWS EC2, where customers would be paying for the instance even when there is no traffic. Concretely, it is not all the time that Serverless is better than IaaS. When a company’s traffic is known to deploy their model online, they must choose the service that performs their business model. If the traffic is unknown, it is better to use serverless since the payment is only for executions [80]. A hybrid architecture can be considered as an additional solution [29].

5) COLD START
Cold start in serverless is somehow expensive and causes significant performance degradation for serverless functions [81]. However, it is still better than other cloud resources i.e., VM. There were several solutions for the cold start, for example, periodically warming the instance [56] or predicting the window timing where a request is expected, or scheduling the tasks [45]. To reuse against the cold start, in [28] presented a switchboard architecture composed of 6 serverless with the principle to warm the first function and trigger the rest of the functions. Another proposed to keep the instance warm for several minutes [82]. In [29], authors showed that keeping the instance warm has a low cost. They explained how $1 could spin up 7K inception-v3 Lambda instances, which can serve more than 20K requests per second. To avoid the cold start latency, Yang et al. [67] proposed a Long-Short Term Histogram (LSTH) to track application idle times and draw two histograms. The two histograms represent the request patterns in the last short (e.g., 1 hour) and long durations (e.g., one day). By tracking the application, they can select the pre-warming window to send inference requests to continuously keep the function instance alive. Their method helped to reduce resource waste while avoiding cold starts.

6) SECURITY AND PRIVACY
Privacy and security are always major concerns in serverless computing, especially for managing and analyzing sensitive data, such as healthcare data.

We observed that it is essential to set roles for every cloud function with specific security policies to provide only necessary access and prevent non-permitted operations. For example, Kaplanovich and Yesha [49] applied special protection to the hyperparameter metadata spreadsheet, where metadata is loaded directly during the startup and stored safely and securely in the protected Cloud location.

The Federated Learning-based architecture was proposed in the primary dataset [46], [55], [65]. This computing model supports edge computing, where the processing edges can learn from a shared machine learning model while keeping the model training on remote clients, followed by global aggregation of the updated model parameters. This keeps the training data local, which provides privacy and security benefits. Grafberger et al. [55] considers that the challenges of FL systems, such as scalability, complex infrastructure management, and wasted computing, can be solved with the Function-as-a-Service (FaaS) paradigm. However, it is necessary to be aware of the threats caused by malicious participants. For example, Tolpegin et al. [83] showed that a malicious subset of participants could decrease the accuracy of the model by injecting poisoned data when sending updates to the global model.

Several additional security measures can be applied, where only authorized and authenticated entities can invoke client functions. A practice of security between clients was applied in [55], where the FL server allows clients authenticated to read only from a shared global model and write back results without access to other clients. Another security measure was applied in [55], where HTTP function requests exchanges can be encrypted using Transport Layer Security (TLS).

Rausch et al. [34] chose to transmit the base model to an edge device to refine the base model locally using a serverless function with the private data to ensure data privacy. The edge computing paradigm allows training distributed machine learning models between local edge data to secure data privacy and save resources in the cloud [65]. Bac et al. [65] applied a federated learning approach on serverless edge computing, where they saved bandwidth and ensured the data privacy of the edge nodes.

Moreover, Anthony S. Deese [12] handled the used access by applying AWS Cognito and Identity Access Management services. These services allow a user to access and monitor only the lambda function instances he created, which maintains the privacy of user training data and machine results.
7) Batching
Another essential factor that heavily impacts both the cost and the performance of ML serving inference is batching. For example, the batch size cannot be arbitrarily increased, as it leads to longer queuing latency and batch inference latency [84]. Tuning batch or resource configuration adaptively can improve the model performance. Clipper [84] introduces caching, batching, and adaptive model selection techniques to reduce the latency. INFaaS [85] automatically adapts the model variant batch size and hardware according to the required model performance.

For smaller batch sizes, the processing time increases linearly, but for larger batch sizes, it increases exponentially in an on-premise environment [8]. Deese [12] used the batch mode (maximum size) read and write requests within AWS and found a significant speed increase from batch write operations, but a relatively small benefit from batch reads. Carreira et al. [26] finds that data fetching latency becomes low when applied mini-batches buffers. Wang et al. [27] considered that machine learning serverless functions should have a different size of data batch since many training samples need to be processed by different workers in parallel. Zhang et al. [29] showed that inference serving could benefit significantly from batching using costly hardware accelerators (e.g., GPU and TPU). The appropriate batch size with GPU instances can achieve a lower cost and shorter inference latency. However, serving inference queries using GPUs is not economically justified when there is not enough load. MLLess [68] kept the same mini-batch size in their distributed workers architecture to avoid changing the number of workers incurring costly data repartitioning transfers to adjust the mini-batch size.

Depending on the usage purpose of serverless computing in the machine learning pipeline phase, batching can play an important role in reducing processing time, deployment latency, and data fetching.

8) Serverless Portability
When using platform services from public cloud providers, there is a risk of dependence on the services and products they offer. This case is named the ‘vendor lock-in’ since switching technologies and vendors can be costly due to technical incompatibilities. Naranjo et al. [47] proposed to use open-source frameworks instead of public cloud providers. Most open-source serverless platforms rely on Kubernetes for orchestration and management of function pods, which makes the portability task more affordable [86]. Unfortunately, portability did not take enough chances in the set of the studied papers. We found only two journal papers [36], [47] that took into account the level of portability of the run-time environment.

Portability is an important aspect; only when portability is ensured is a helpful simulation to test if the function shows better performance on another platform [69]. The Serverless Framework [87] offers plug-ins to simplify the deployment and execution of serverless functions across multiple clouds and FaaS environments. Junfeng Li et al. [86] compared the performance of four open-source serverless platforms using CloudLab testbed. Their work was provided to help developers to differentiate and select the appropriate serverless platform for different demands and scenarios.

9) Edge Computing
Edge computing is a distributed computing paradigm that brings computation and data storage closer to the data sources, especially popular with IoT device architecture. Edge computing has several benefits, such as reducing latency and bandwidth associated with public cloud [53], ensuring data privacy [34], and reducing computational resources relative to public and private clouds [45].

The serverless edge computing platform that provides the appropriate support to define AI workflow functions has been extended to work at the edge of the network to reduce response latency and bandwidth associated with the public cloud [34], [53], [65].

The ML module can be placed on the edge devices, or it can be placed on the Cloud or Fog layer for live or in-depth analysis of the data [33]. Zhang et al. [45] proposed a hybrid cloud system consisting of edge and cloud resources and integrating GPU acceleration. The usage of edge computing depends on the user requirements and the analysis of available capacity.

10) Cost Reduction
One of the primary purposes of using serverless with machine learning is cost reduction. High service costs are the major issue that papers try to reduce in different ways. Serverless usage is adopted to reduce unnecessary costs and improve manageability, like the allocation of virtual machines without full resource usage. For example, Wang et al. [27] demonstrated that a substantial amount of cost savings can be achieved by replacing dedicated IaaS cloud clusters with a serverless architecture. They proposed a solution called SIREN to reduce the training cost compared MXNet architecture. The AMPs-Inf achieves up to 98% cost savings without degrading response time performance [48]. Chahal et al. [59] presented an architecture based on load balancing the ML inference workload to reduce costs.

Cost reduction is a primary concern for developers and researchers. The cost is related to the design architecture, computing, inference deployment, and read/write queries. Depending on the machine learning project, a serverless-based architecture could be an effective option to reduce the cost.

11) Inference Latency
Inference latency was well studied in the primary set of papers. Yu et al. [56] showed that the inference latency increases as the model grows. They proposed a serving model and generated a parallelization scheme deployed on serverless platforms to achieve optimal inference latency.
Zhang et al. [39] required a benchmark analysis to find an efficient inference workload. They found that the amount of memory allocated for each serverless function instance plays an important role in inference latency time reduction. The latency can be influenced by the serverless cold start, or continued serverless warming [43]. Moreover, the hardware usage, such as GPU instances with the appropriate batch size, can have shorter inference latency compared to the CPU instances [29]. Gujarati et al. [88] proposed an autoscaling framework that aims to minimize resource waste for ML inference by using a predictive provision model. BATCH [38] designed a buffer layer on top of the serverless platform and bundles requests with batching for cost-saving serverless inference. Moreover, inference latency can be dominated by data fetching when there are queries involving cross-machine requests [22].

12) MLOps AND SERVERLESS
The MLOps is modeled to make the intersection between machine learning, data engineering, and DevOps practices that associate software developers (the Devs) with IT operations teams (the Ops) to collaborate [89].

The machine learning pipeline contains several repetitive steps (data collection, data integration, data preparation and cleaning, model retraining, predictions) that need special operations to be automated in MLOps environments. The serverless architecture can be used to (1) automate the infrastructure; (2) build event-driven applications; (3) build APIs i.e., API with Amazon gateway.

**Serverless with data preprocessing:** The serverless can be scheduled to pull data from the backend; trigger a serverless function when objects are written in data buckets i.e., AWS S3; build APIs to transform and clean data.

**Serverless with model retraining:** Schedule or trigger new training when conditions are met.

**Serverless with model inference:** Schedule a serverless function for batch predictions; use step functions for ensemble predictions.

The serverless architecture can be feasible and optimal for projects adapting the MLOps approach. We plan as future work to explore how serverless can fit and optimise the MLOps-based projects.

V. RELATED WORK
This section presents related work that realised a literature review on serverless computing and cloud computing applied to machine learning.

A. LITERATURE REVIEWS ON SERVERLESS
serverless computing is getting more popular. Wen et al. [2] mined and analyzed serverless-based questions from Stack Overflow to show an increasing popularity trend of the subject and presented a list of challenges that present an overhead for developers during the usage of serverless computing, such as programming language support, database connection, and Resource Configuration to Security.

Several studies have searched on serverless challenges. For example, Khatri et al. [90] presented a review of the potential bottleneck and measured the performance of serverless computing. Their work was more related to serverless limitations such as peak and spike scenarios, scalability, cold start, and portability. They showed especially the difficulties of testing and performance measurement of serverless applications and how machine learning can monitor and predict performance. Moreover, Hassan et al. [69] applied a survey including 275 research papers that examined the challenges that serverless computing faces nowadays and how future research could enable its implementation and usage. Furthermore, Wu et al. [91] presents several practical recommendations for data scientists on using serverless for scalable and cost-effective model serving.

The main challenge in serverless computing is reproducibility. Scheuner and Leitner [92] conducted a multivocal literature review on the evaluation of function as a service performance, covering 112 studies. They evaluated these studies from the reproducibility perspective and found that most studies do not follow reproducibility principles in cloud experimentation. More challenges were discussed by Sadaqat et al. [93]. They conducted a multivocal literature review to define the core components of serverless computing, its benefits, and its challenges. They found that serverless computing is a solution that allows users to create functions that intercept and operate on data flows in a scalable manner without the need to manage a server, discussing that vendor lock-in, skilled workers, testing complexity, and monitoring are the most recurrent challenges. They also presented the expected evolution of serverless computing, such as the adoption of serverless by companies and the expected market growth.

Tiabi et al. [94] identified 32 patterns composing and managing serverless functions by applying for a multivocal literature review on 24 selected papers. They classified the patterns as orchestration, aggregation, event management, availability, communication, and authorization. They show that depending on the serverless provider. The pattern may not be the same, i.e., AWS lambda adapted their queue service (SQS) to enable FIFO messages. However, FIFO messages still need to be manually managed in Azure. They present their work as a pattern catalog that provides a valuable basis for practitioners and researchers on serverless computing.

The different challenges identified in the literature related to the serverless were discussed in our set of papers on machine learning perspectives.

B. LITERATURE REVIEWS ON MACHINE LEARNING & CLOUD COMPUTING
Machine learning has been used in several architectures of cloud computing. John et al. [95] conducted a systematic literature review of 13 primary studies related to AI deployment in the context of edge/cloud/hybrid architectures. They presented a list of practices and challenges of practitioners related to the design, integration, deployment, operation,
and model evolution. They conclude their work by proposing an end-to-end model deployment framework. Moreover, Kuhlenkamp et al. [96] conducted a systematic literature review on machine learning operationalization. They investigate the techniques, tools, and infrastructures to operationalize ML models. They reviewed 24 studies that discussed the presence of several tools for model operationalization i.e., Polyaxon,11 and MLflow.12 They found that cloud computing is widely used in model deployment due to resource hardware heterogeneity and the possible variety of network connection quality. Furthermore, Jauro et al. [97] realized a survey on the usage of deep learning algorithms to solve complex problems in emerging cloud computing architectures. Their study included 34 studies focusing on edge, fog, serverless, volunteer, and software-defined computing. During their study, they identified the strengths and limitations of the different deep learning algorithms regarding their suitability to the problem of solving i.e., image processing, time series, and regression. Distributed machine learning is widely used, especially with IoT devices. Filho et al. [98] realized a systematic literature review on 106 research papers about the distributed machine/deep learning intelligent algorithms in edge devices i.e., IoT. They investigated the challenges of running ML/DL on edge devices in a distributed way, such as limited resources, communication efficiency, and ensuring data privacy and security. They found several techniques to mitigate the challenges related to edge computing i.e., caching, training, inference, and offloading. Setti Cassel et al. [99] analyzed 60 research papers on serverless IoT devices during a systematic literature review. They find that serverless computing is a promising technology for IoT applications that can bring functions closer to the devices to reduce latency and avoid unnecessary energy and resource consumption.

In this work, we focus mainly on studies realised on machine learning usage on top of serverless computing architecture.

VI. THREATS TO VALIDITY

We applied Peterson guidelines to make our systematic mapping study [14]. However, threats to validity are unavoidable. This section presents the main threats to the validity of our study and how we mitigated them.

External validity. External validity relates to the generalizability of our results. The most severe external threat is that finding all the relevant studies on machine learning applied to serverless architecture from the designed query is absurd. As a solution, we applied a search strategy to the initial set of papers consisting of both automatic search and recursively backward-forward snowballing. Additionally, we applied a well-established peer-reviewed analysis to ensure that we have high-quality publications. We carefully defined the inclusion/exclusion rules that respect the requirements of our study with the agreement of all authors.

Internal validity. Internal validity relates to the experiment errors and biases. We mitigate the internal validity threats caused by author bias when selecting and interpreting data by applying well-assessed descriptive statistics of the collected data. Several re-verification steps between authors were performed to ensure a good classification dataset.

Construct validity. Construct validity is related to the degree to which an evaluation measures what it claims. We mitigated this potential bias by carefully defining the research query on the Scopus database. This database was preferred since it offers a more extensive list of modern sources [100]. In the keywording process, we included different taxonomies that can be mentioned to refer to the serverless, i.e., lambda architecture, function as a service. Also, we are fairly confident about constructing the search string since the automatic search has been followed by snowballing. Also, we rigorously selected the potentially relevant studies according to well-documented inclusion and exclusion criteria. The first author performed this selection stage, and randomly a sample set was verified by the second author and agreement was ensured.

Conclusion validity. Conclusion validity is related to random variations and inappropriate use of statistics. To mitigate it, we rigorously defined and iteratively refined our classification framework, such as suggested by [101], so that we could reduce potential biases during the data extraction process. In addition, we ensured that we aligned with our research question and our main research objectives. We mitigated potential threats to conclusion validity by applying the verification agreement between authors in case of disambiguating cases. We provide a public repository for the reproducibility of the study to determine whether other researchers could obtain similar results from this study.13

VII. CONCLUSION

This study aims to provide a broader survey investigating the relationships among research contributions on Machine Learning usage on Serverless architecture. Specifically, we performed a systematic mapping on 50 primary studies and produced an overview of the state of the art on machine learning applications on serverless architecture. We found that (1) serverless usage on machine learning applications is a growing field starting from 5 on 2018 until 20 published papers on 2021, and more publication venues are interested to the subject; (2) serverless was adopted on the different ML pipeline, especially on ML model deployment with 33/53 papers. The most used serverless provider is usually AWS lambda, and the used ML model was the neural network. The main challenge of using serverless on ML was reducing cost and pricing (37/53), ensuring enough scalable resources (30/53), and reducing inference latency (22/53). There are several potential challenges of adopting ML on serverless,

11https://polyaxon.com/
12https://mlflow.org/
13https://github.com/AmineBarrak/Serverless-on-ML
such as respecting the service level agreement, serverless provider, cold start problem, security and privacy, serverless portability, resource scalability, batch size, edge computing, cost reduction, and inference latency.

Depending on the targeted architecture and the solution, a trade-off between inference latency, serverless cold start, cost, scalability, batch size, and portability must be considered. For example, an open source provider would be a good solution if portability is essential. The results of this study will benefit both researchers willing to contribute further to the area and practitioners willing to understand existing research.

In future work, we plan to explore the effectiveness of serverless benefits with MLOps practices, especially in a distributed computing environment. Moreover, hybrid cloud architecture for machine learning pipeline phases can be a subject to study its validity depending on the user objectives and their data flow type.

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