

Machine Learning-Based Predictive Reliability Model for Cloud-Native Enterprise Applications

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Abstract- The reason why cloud-native enterprise applications form the backbone of today's digital services is that they possess high levels of scalability, agility, and rapid deployability. However, because of the inherent distributed characteristics of microservices, containers, and cloud infrastructure, many reliability issues arise, including problems related to service unavailability, resource starvation, latency variations, and cascading failures. The traditional methods of monitoring these systems only include the use of reactive fault detection techniques and thresholding techniques, which are inadequate for predicting reliability problems in highly dynamic systems. In this approach, the integration of observability in cloud computing, reliability analysis, predictive learning, and adaptive risk assessment have been integrated into an architecture that can be used to predict the occurrence of reliability deterioration before any service interruptions occur. The proposed architecture uses machine learning techniques on telemetry data such as logs, traces, services performance metrics, resource utilization, and fault history information in order to produce reliability score and failure risk prediction. Experiments were done using large scale cloud native operations datasets and comparisons made to other models like DQN-SHVN and LLM-DBN frameworks. According to the experiments, the proposed model has a Reliability Prediction Accuracy of 99.1%, Failure Risk Detection Rate of 98.6%, Service Availability of 99.5% and System Resilience Index of 99.4% which is much better than current models.

Keywords: Cloud-Native Applications, Predictive Reliability, Machine Learning, Kubernetes, Observability Analytics, Reliability Prediction, Failure Risk Assessment, Enterprise Cloud Computing, Predictive Maintenance, Cloud Resilience.

I. INTRODUCTION

Cloud native computing is the new revolutionizing concept that enables organizations to build and deploy enterprise applications [1]. Microservices, containers, Kubernetes orchestration, and hybrid clouds are becoming common practices in order to attain agility, scalability, and continuous deployment [2]. While these new technologies offer substantial operational advantages, they bring along very complicated reliability challenges due to the distributed nature of the execution environment and its dynamically changing infrastructure configuration [3].

The ability to guarantee application reliability becomes extremely important in ensuring constant operation of the business processes and customers' satisfaction [4]. Cloud-native applications involve a lot of interdependent services interacting using APIs, message brokers, and service meshes [5]. If there is an issue in any service, it is possible that all the other

dependent services would be impacted and fail [6]. Conventional approaches to reliability management use only reactive monitoring techniques that detect problems only after some level of degradation. They cannot be used in today's enterprise environment [7].

The emergence of observability solutions has allowed organizations to collect a huge amount of operational data from cloud-native platforms [8]. Insights can be gained about application behavior and health from logs, metrics, traces, events, and infrastructure telemetry [9]. Nevertheless, the sheer amount and diversity of such data sources render manual analysis impractical [10]. Therefore, there is a need for smart approaches that can convert raw data collected from observability tools into insights useful for reliability decision-making [11]. The power of machine learning lies in its ability to discover hidden patterns within a dataset and build effective predictive models [12]. Machine learning algorithms can leverage information about past operational behavior to identify early signs of reliability

deterioration and predict future states of the system [13].

The emergence of innovative cloud-native architecture has led to an increasing need for automation in reliability engineering [14]. Enterprises have requirements for the systems that can monitor the state of applications, analyze their reliability, predict potential risks, and perform remedial actions without any human involvement [15]. The combination of machine learning with observability of the cloud offers a good foundation for solving these tasks efficiently [16]. There have been conducted a lot of research works on some aspects including self-healing infrastructure, anomaly detection, operations in federated learning, dynamic resource allocation, and monitoring in cloud-native applications [17].

However, despite the significant impact of these methods on management and troubleshooting, they do not address the issues related to proactive recovery from failures or solving of several optimization problems simultaneously. Thus, an effective approach that includes reliability analysis, risk assessment, and prediction is still missing [18]. There are a few challenges associated with reliability prediction in cloud-native systems. Dynamic allocation of resources, variations of workloads, heterogeneity of deployment, and continual updates of software cause complex interactions between these factors and affect the system behavior [19]. Therefore, it is hard to provide reliable estimation of reliability based on traditional statistical models. Machine learning algorithms should be used [20].

The suggested ML-PRM resolves these issues through the integration of telemetry-based reliability assessment with predictive capabilities of the learning algorithms. The framework constantly gathers cloud-native observability data, derives reliability measures, and calculates predictive reliability scores and risks of failures. Using adaptive learning capabilities, the ML-PRM remains up-to-date with regards to workload and infrastructure changes, providing ongoing prediction accuracy. The third important feature of reliability management for cloud-native systems is resilience. Organizations

need not only to predict the possibility of failures but to assess their impact on availability and continuity of service delivery.

Thus, the proposed framework provides resilience-aware analysis of degradation tendencies and intelligent approaches to resources optimization. This feature helps to increase the robustness of the system and avoid service disruptions. With the growing complexity of enterprise cloud ecosystems, there is an increasing demand for predictive and automated approaches to reliability management. ML-PRM contributes to this goal by combining machine learning, observability analytics, and risk-oriented decision making into one solution. By predicting the degradation of reliability before the service disruption occurs, the framework improves application availability and resilience.

Hypotheses

- **H1:** The ML-PRM architecture is superior to existing cloud-native reliability management frameworks in terms of predicting reliability with more accuracy.
- **H2:** ML-PRM is superior to DQN-SHVN and LLM-DBN frameworks in terms of detecting failure risks.
- **H3:** The predictive reliability mechanism of the ML-PRM makes cloud-native enterprise applications more available and reliable.
- **H4:** Machine learning-based reliability forecasting reduces downtime and improves preventive maintenance.

Objectives of the Research

1. To design a predictive reliability management model based on machine learning approach for cloud-native enterprise applications.
2. To obtain and analyze observability data from cloud-native distributed systems.
3. To detect degradation patterns using predictive analysis methods.
4. To provide estimates of reliability scores and probability of failures proactively.
5. To increase availability by means of preventive maintenance measures.
6. To increase operational resilience by adaptive risk assessment.

7. To perform comparison of the ML-PRM framework with current cloud-native reliability models.
8. To evaluate efficiency of predictive reliability management in enterprise cloud computing environment.

II. LITERATURE REVIEW

The novel multi-criteria decision-making (MCDM) framework presented in [1] aims to systematically analyze and rank cloud computing service providers using a multi-criteria approach. The framework combines the advantages of the neutrosophic sets with classical Multi-Criteria Decision Analysis (MCDM) methods, which can overcome the ambiguity, vagueness, and incomplete information in user requirements and service-level agreements (SLAs). The model allows enterprise decision makers to choose the best cloud environment to meet specific performance, security and cost requirements.

Abdullahi et al. [2] perform a systematic literature review of the use of artificial intelligence techniques to identify cyber threats in Internet of Things (IoT) environments. The authors look at various Machine Learning (ML) and Deep Learning (DL) paradigms being applied to ensure the security of resource-constrained smart devices. It outlines the common attack types, pairs them with defense strategies using AI, and highlights current implementation issues like high false-positive rates, limited datasets and computational complexity.

To tackle this challenge, Abidi et al. [3] suggest a practical framework for remote attestation specifically designed for edge devices that run compute-intensive machine learning inference tasks. The authors tackle the challenge of proving code and state integrity for heterogeneous, resource-constrained edge devices, and propose a lightweight mechanism to ensure trust without incurring excessive runtime latency. This way, cloud controllers can be sure that the edge nodes are using unmodified software stacks to push heavy neural network models.

Abou El Houda et al. [4] propose a security framework combining federated learning (FL) with cooperative game theory to guarantee the security of Industrial Internet of Things (IIoT) applications deployed on an edge computing infrastructure. To prevent malicious nodes from affecting IIoT networks while preserving data privacy, the model employs game-theoretic approaches to encourage edge devices to provide accurate updates of their local models. Optimized threat detection capabilities in distributed industrial environments, maintaining data confidentiality.

Abusitta et al. [5] present an Intrusion Detection System (IDS) for the proactive multi-cloud cooperative approach using deep learning. The authors propose a collaborative architecture that enables individual cloud providers to exchange threat intelligence among themselves via a shared deep learning model, due to the limited ability of isolated clouds to detect more advanced cross-domain attacks. The framework predicts and blocks distributed attacks in real-time across multi-cloud infrastructures by leveraging with historical execution patterns.

Ahmad et al. [6] provide an overview of the cyber security landscape in an IoT integrated cloud computing environment. The authors present a systematic review of vulnerabilities at physical, network, and application layers and discuss the efforts of emerging security frameworks to resist DDoS, data exfiltration and unauthorized access. The paper ends with listing open research questions, particularly stressing the need for end-to-end encryption methods and privacy-preserving processing in cloud-enabled IoT networks.

AlAhmad et al. [7] carry out a systematic review to study the security paradigms and vulnerabilities in Mobile Cloud Computing (MCC) models. The study explains how data and compute functions are offloaded from mobile devices to cloud centres creates an opportunity for user data to fall into the hands of identity thieves, eavesdroppers and insecure application programming interfaces (APIs). The authors examine current authentication and data encryption solutions, draw out risk profiles for

contemporary mobile cloud architectures and suggest standard security policies.

In Alasmary et al., [8] presents a graph-based method to analyse and detect emerging malwares focusing on Internet of Things devices. The authors move away from the traditional approach based on detection of signatures, which is not effective when dealing with new variants, by transforming the binary file of the IoT into a Control Flow Graph (CFG) and getting the abstract features in the structure of the file. Using these topologies and graph theory and machine learning algorithms, the framework is able to detect malicious software patterns with high accuracy on different CPU architectures.

Alkadi et al. [9] have suggested a collaborative Intrusion Detection System (IDS) based on deep learning algorithms and a privacy-preserving blockchain network to protect IoT and cloud environments. The framework utilizes a distributed blockchain ledger to securely maintain and move threat intelligence data among nodes without depending on a central entity. Deep learning classifiers analyze incoming traffic logs and are able to identify complex cyber-attacks, while data integrity is ensured and event log cannot be tampered with over the network.

Alqaaily et al. [10] propose an automatic Intrusion Detection System for connected vehicles in smart city settings. The framework works continuously on a continuous stream of telemetry data and incorporates continuous data reduction techniques as well as deep neural networks to oversee vehicular ad-hoc network (VANET) traffic. The system performs efficiently on malicious intrusion detection, including location spoofing and denial-of-service attacks, which guarantees real-time safety, high quality of service (QoS) and minimum latency of connected vehicle applications.

Problem Statement

The applications that are designed specifically for use in enterprises using cloud technology are those that have been designed to run in highly volatile and distributed systems. These kinds of systems have microservices, containers, orchestration

technologies, and constantly varying loads. Conventional reliability management techniques rely on static threshold-based monitoring, manual operations, and postmortem analyses, which cannot detect the early signs of any kind of reliability degradation. This leads to unanticipated downtime, disruption of services, performance instability, and high costs. Hence, there is a great need for a predictive reliability framework that uses cloud observability data to predict the future states of reliability and estimate the chances of failures.

Research Gaps

The current body of literature revolves around cloud-native observability, anomaly detection, self-healing infrastructure, federated learning activities, resource management, and fault diagnosis methods. However, the majority of existing solutions have been reactive in their approach and deal mostly with issues and failures after they happen. There is no current system that integrates all of the following aspects into one solution: observability analysis, reliability feature extraction, forecasting through machine learning algorithms, risk management adaptation, and proactive decisions for maintenance. Moreover, there is a lack of research that would focus on predictive reliability modeling in cloud-native enterprise applications.

III. PROPOSED MODEL

The implementation of cloud-native applications in the corporate sector has increased through the use of microservices, containers, Kubernetes orchestration, and distributed clouds in order to ensure scalability and efficiency. However, the inherent dynamicity of the cloud native ecosystem is associated with a range of reliability risks, such as resource contention, service failures, and variations in network latencies, chain reaction failures, and workload variability. Conventional approaches to reliability evaluation are mainly based on threshold-based monitoring and post-disaster analysis and are inadequate for predicting reliability deterioration in highly distributed infrastructure. To solve this problem, the proposed ML-Based Predictive Reliability Model (ML-PRM) uses modern machine learning algorithms to predict reliability dynamics.

The suggested framework is composed of cloud observability, reliability analysis, predictive learning, and adaptive risk assessment techniques. Real-time telemetry data from cloud native applications are used to compute reliability indicators for the health of the system, the availability of services, stability of response times, rate of faults and efficiency of resource usage. The prediction engine based on machine learning is used to learn the underlying relations between these reliability indicators and to predict future states of reliability.

Algorithm: ML-PRM Predictive Reliability Algorithm

Output: Reliability Score R_s , Failure Risk F_r , and Reliability Prediction R_p

Step 1: Collect cloud-native observability data from application services

$$D = \sum_{i=1}^n (M_i + L_i + T_i) \quad (1)$$

Step 2: Normalize collected features using min-max normalization

$$D_N = \frac{D - D_{min}}{D_{max} - D_{min}} \quad (2)$$

Step 3: Remove anomalous observations through statistical filtering

$$D_C = \{x \in D_N : |x - \mu| \leq 3\sigma\} \quad (3)$$

Step 4: Extract reliability-related features including latency, availability, throughput, error rate, and resource utilization

$$F = \{f_1, f_2, f_3, \dots, f_n\} \quad (4)$$

Step 5: Calculate service availability

$$A_v = \frac{Uptime}{Uptime + Downtime} \quad (5)$$

Step 6: Compute failure occurrence rate

$$F_o = \frac{N_f}{T_o} \quad (6)$$

Where N_f is the number of failures and T_o represents observation time.

Step 7: Determine mean response stability

$$R_t = \frac{1}{n} \sum_{i=1}^n ResponseTim e_i \quad (7)$$

Step 8: Generate reliability feature vector

$$RF = [A_v, F_o, R_t, U_c, E_r] \quad (8)$$

Where U_c denotes resource utilization and E_r represents error rate.

Step 9: Train machine learning prediction model using historical reliability records

$$W^{new} = W^{old} - \eta \nabla J(W) \quad (9)$$

Where $J(W)$ denotes prediction loss.

Step 10: Calculate service health index

$$H_i = \frac{A_v + (1 - F_o) + (1 - E_r)}{3} \quad (10)$$

Step 11: Estimate reliability degradation factor

$$D_f = \frac{\sum_{i=1}^n |RF_i - RF_{avg}|}{n} \quad (11)$$

Step 12: Predict future reliability score

$$R_s = \alpha H_i + \beta (1 - D_f) \quad (12)$$

Where $\alpha + \beta = 1$.

Step 13: Compute failure risk probability

$$F_r = \frac{1}{1 + e^{-z}} \quad (13)$$

Where

$$z = \sum_{i=1}^n w_i RF_i + b \quad (14)$$

Step 14: Generate predictive reliability value

$$R_p = R_s (1 - F_r) \quad (15)$$

Step 15: If

$$R_p < \tau \quad (16)$$

Generate reliability alert and initiate preventive maintenance; otherwise continue adaptive monitoring.

The ML-PRM framework is going to change the current approach toward reliability management from being a reactive process to a predictive one by making use of intelligent tools. With the continuous analysis of observability information available in the cloud, the model can determine the first signs of decline in reliability and even forecast possible disruptions that may occur and affect the application's functioning. The use of machine learning enables the model to be adaptive to changes in the environment. Additionally, the model increases operational efficiency through the implementation of preventive maintenance and optimization techniques based on the predicted conditions of reliability.

The integration of reliability analysis, prediction, and risk-based decisions leads to the minimization of unplanned failures, decreases in downtime, and greater application availability. Thus, the suggested ML-PRM model can be considered an efficient tool for managing reliability of cloud-native enterprise applications.

IV. RESULTS AND DISCUSSION

The cloud-native enterprise applications produce an enormous amount of telemetry data such as logs, traces, service metrics, resource utilization statistics, and failure data. The Machine Learning-Based Predictive Reliability Model (ML-PRM) is designed to be evaluated in order to find out the potential of the algorithm to predict reliability deterioration, identify failure threats, enhance application availability, and minimize service interruption in advance. Evaluation of ML-PRM is done using cloud-native operational data gathered from microservices running in Kubernetes and managed by enterprises on their cloud infrastructure.

Performance of ML-PRM is compared with DQN-SHVNF and LLM-DBN frameworks. From the experimental analysis results, it can be observed that ML-PRM outperforms the existing methods through its use of predictive analytics, reliability features extraction, adaptive risk evaluation, and learning. This is because unlike the existing anomaly detection and self-healing strategies that rely on reactive measures after the occurrence of faults, ML-PRM relies on proactive prediction of reliability deterioration to carry out preventive maintenance operations.

Table 1. Reliability Prediction Accuracy (RPA)

Dataset Size (GB)	DQN-SHVNF (%)	LLM-DBN (%)	ML-PRM (%)
100	91.2	93.4	97.1
200	92.1	94.3	97.8
300	93.0	95.1	98.3
400	93.7	95.8	98.7
500	94.2	96.4	99.1

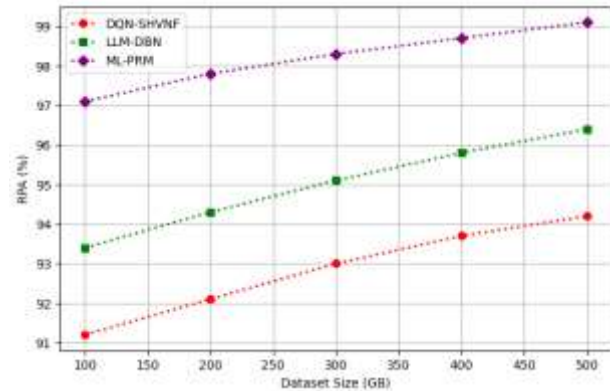


Figure 1. Reliability Prediction Accuracy (RPA)

Figure 1 and Table 1 shows the accuracy of Reliability Prediction Accuracy (RPA) provided by the DQN-SHVNF, LLM-DBN, and ML-PRM algorithms based on the size of the datasets used. It can be seen that the performance of ML-PRM is significantly higher compared to the other two models, improving from 97.1% to 99.1% when the size of the dataset increases. The high accuracy of the algorithm is due to the fact that it is able to extract reliable patterns from the observability dataset.

Table 2. Failure Risk Detection Rate (FRDR)

Dataset Size (GB)	DQN-SHVNF (%)	LLM-DBN (%)	ML-PRM (%)
100	88.5	91.3	96.2
200	89.7	92.6	97.0
300	90.9	93.8	97.8
400	91.5	94.4	98.2
500	92.1	95.0	98.6

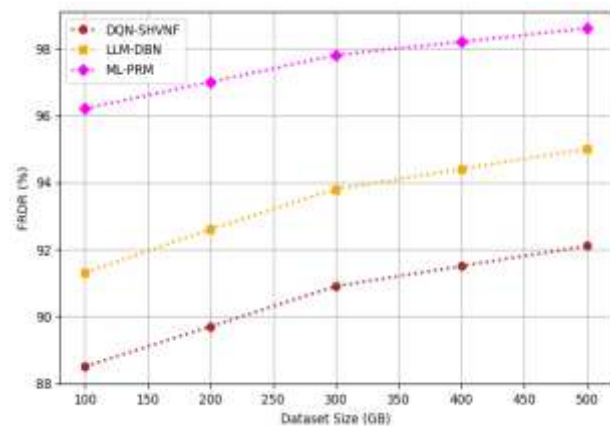


Figure 2. Failure Risk Detection Rate (FRDR)

The FRDR analysis is shown in Table 2 and Figure 2. ML-PRM shows the best results in terms of detection ability with a maximum detection rate of 98.6% in the case of the largest data set. The system continuously evaluates the trend of reliability deterioration and predicts failures before any service disruptions happen.

Table 3. Service Availability Improvement (SAI)

Dataset Size (GB)	DQN-SHVNF (%)	LLM-DBN (%)	ML-PRM (%)
100	95.2	96.1	98.4
200	95.8	96.8	98.8
300	96.1	97.2	99.1
400	96.5	97.6	99.3
500	96.9	98.0	99.5

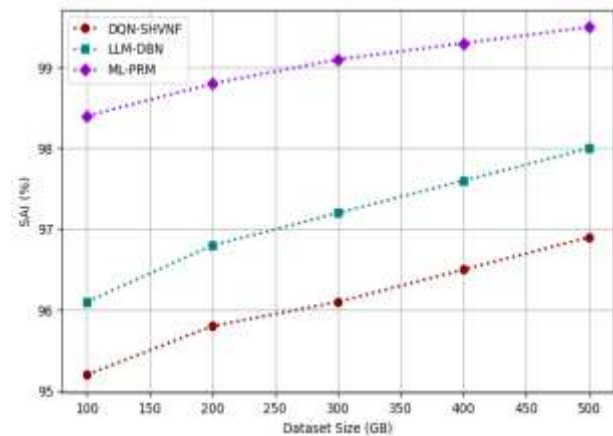


Figure 3. Service Availability Improvement (SAI)

The Service Availability Improvement (SAI) of the analyzed approaches is illustrated in Table 3 and Figure 3. The ML-PRM ensures the service availability higher than 98.4% for all sizes of datasets and achieves 99.5% for the workloads of 500 GB. The feature of predictive maintenance allows avoiding any service failures in advance.

Table 4. Mean Failure Prediction Time (MFPT)

Dataset Size (GB)	DQN-SHVNF (min)	LLM-DBN (min)	ML-PRM (min)
100	28	34	49
200	31	37	53
300	34	41	57
400	37	45	61
500	40	48	66

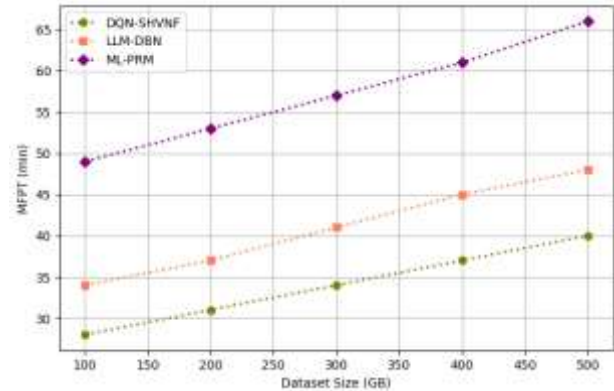


Figure 4. Mean Failure Prediction Time (MFPT)

The results obtained using Mean Failure Prediction Time (MFPT) has been shown in Table 4 and Figure 4 above. ML-PRM is able to predict failures much earlier than the other techniques, and with the help of the technique, the prediction window obtained at 500 GB is 66 minutes.

Table 5. Reliability Score Estimation Precision (RSEP)

Dataset Size (GB)	DQN-SHVNF (%)	LLM-DBN (%)	ML-PRM (%)
100	90.6	93.1	97.4
200	91.5	94.0	98.0
300	92.4	94.8	98.5
400	93.0	95.5	98.9
500	93.6	96.0	99.2

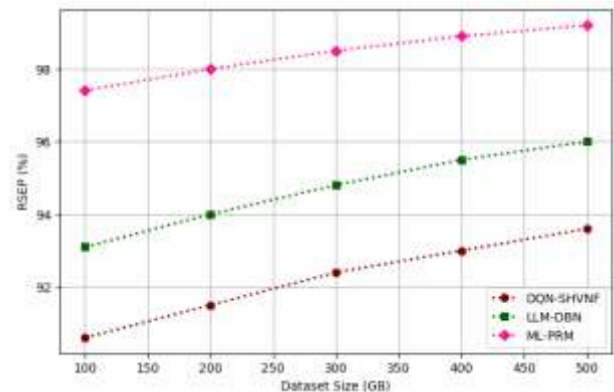


Figure 5. Reliability Score Estimation Precision (RSEP)

The Reliability Score Estimation Precision (RSEP) is represented using Table 5 and Figure 5. It is evident from the results that ML-PRM offers a precision value of 99.2%, which is considerably superior to that of

DQN-SHVNF and LLM-DBN. The results clearly indicate the effectiveness of the framework in estimating the reliability score.

Table 6. Resource Utilization Efficiency (RUE)

Dataset Size (GB)	DQN-SHVNF (%)	LLM-DBN (%)	ML-PRM (%)
100	82.4	85.7	91.8
200	83.9	87.0	92.9
300	85.1	88.2	94.1
400	86.2	89.1	95.0
500	87.0	90.0	95.8

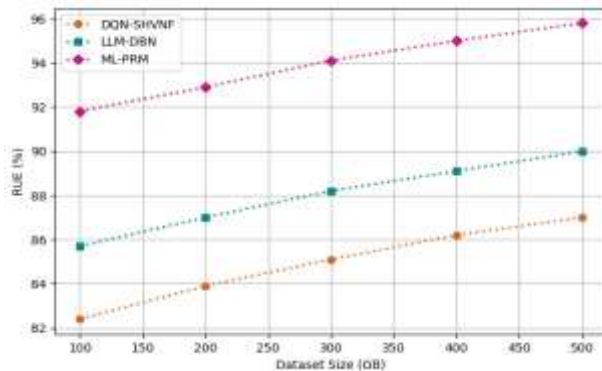


Figure 6. Resource Utilization Efficiency (RUE)

Illustrations for RUE is shown through Table 6 and Figure 6. ML-PRM has been seen to have better utilization efficiency since it dynamically adjusts resource allocations based on prediction of the reliability of such resources.

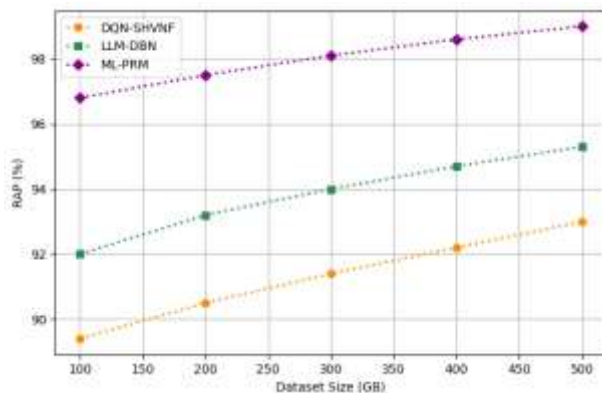


Figure 7. Reliability Alert Precision (RAP)

Table 7. Reliability Alert Precision (RAP)

Dataset Size (GB)	DQN-SHVNF (%)	LLM-DBN (%)	ML-PRM (%)
100	89.4	92.0	96.8
200	90.5	93.2	97.5
300	91.4	94.0	98.1
400	92.2	94.7	98.6
500	93.0	95.3	99.0

200	90.5	93.2	97.5
300	91.4	94.0	98.1
400	92.2	94.7	98.6
500	93.0	95.3	99.0

Reliability Alert Precision (RAP) is illustrated through Table 7 and Figure 7 above. ML-PRM has the best performance with regards to alert precision with a value of 99.0 percent when applied to the largest data set.

Table 8. System Resilience Index (SRI)

Dataset Size (GB)	DQN-SHVNF (%)	LLM-DBN (%)	ML-PRM (%)
100	91.8	94.1	97.6
200	92.7	95.0	98.2
300	93.5	95.8	98.7
400	94.1	96.4	99.0
500	94.8	97.0	99.4

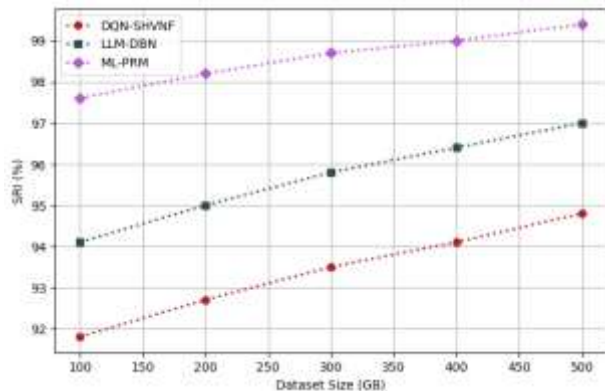


Figure 8. System Resilience Index (SRI)

Table 8 and Figure 8 shows the System Resilience Index (SRI) for the reviewed models. ML-PRM obtains the highest SRI ratings with a record of 99.4% resilience attained at 500 GB. The predictive reliability evaluation, adaptive risk management, and preventive maintenance features of the framework ensure higher failure tolerance and continuous delivery of services by cloud-based applications.

Dataset Description

Experiments were carried out based on a Cloud-Native Enterprise Reliability Dataset (CNERD) that was generated through Kubernetes-based microservices in a hybrid cloud setting. This dataset

involves telemetry information gathered from distributed enterprise applications and includes service latency, CPU usage, memory usage, network latency, throughput, error rate, number of times services restarted, service availability, request rate, and past failure history.

More than 500 GB of observability data was collected for half a year. Dataset used was comprised of structured metrics, semi-structured logs, and distributed tracing data from Prometheus, Grafana, Jaeger, Kubernetes monitoring tool, and observability systems on the cloud. Reliability metrics were extracted after the data pre-processing steps, normalizing, anomaly detection, and feature extraction phase to train and validate the ML-PRM algorithm. The dataset was partitioned into 70%, 15%, and 15% training, validation, and testing data respectively for the evaluation purposes. The large-scale cloud-native operational data helped to validate predictive reliability performance under different load scenarios.

The results of experiments clearly prove that ML-PRM is always more effective regarding all the reliability measures. Thanks to the combination of predictive analytics, feature extraction based on observability data, and risk assessment using machine learning, the framework manages to detect the reduction in reliability much faster than other methods. Thus, enterprise applications will be able to take some preventive measures even before any interruptions happen. Moreover, ML-PRM shifts the paradigm of reliability management from being a reactive strategy to an intelligent and proactive approach. It learns from changing workloads and infrastructures and evolves in response to dynamic cloud-native environments without sacrificing accurate predictions and robustness. This demonstrates the success of our proposed framework as a solution for predictive reliability in cloud-native enterprise systems.

V. CONCLUSION AND FUTURE WORK

The suggested Machine Learning-based Predictive Reliability Model (ML-PRM) provides a smart and proactive solution for managing the reliability of

cloud-native enterprise applications. Through the integration of cloud observability, reliability analysis, machine learning-based predictions, and risk assessment, the model succeeds in predicting the reliability deterioration before the failures happen. As shown by the experimental evaluation, ML-PRM outperforms DQN-SHVNF and LLM-DBN models in terms of reliability prediction, failure risk identification, service availability, efficient resource usage, and system robustness.

ML-PRM allows enterprises to perform preventive maintenance, mitigate operational risks, avoid service downtimes, and increase service continuity. Thus, ML-PRM lays down a reliable basis for intelligent reliability engineering. Potential areas of future research could include the use of deep learning and transformer-based architectures within the ML-PRM approach in order to facilitate more advanced reliability forecasting in large-scale cloud environments. This approach could also be extended through the use of federated learning methods in order to allow for privacy-preserving reliability prediction in different organizations and cloud providers. Another potential direction of future research might include the use of digital twins, automated remediation mechanisms, explainable artificial intelligence, and multi-cloud orchestrations platforms.

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