Efficient and Scalable Self-Healing Databases Using Meta-Learning and Dependency-Driven Recovery

Joydeep Chandra, Prabal Manhas, Aastha Sharma and
Rashi Sahay

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Joydeep Chandra
Department of CSE
Chandigarh University
Mohali, India
rjjoydeep2015@yahoo.in

Prabal Manhas
Department of CSE
Chandigarh University
Mohali, India
er.prabalmanhas@gmail.com

Aastha Sharma
Department of ECE
Chandigarh University
Mohali, India
aasthasharma1550@gmail.com

Rashi Sahay
Department of CSE
MRIIRS
Faridabad, India
rashi.sahay787@gmail.com

Abstract—This study explored the development of a novel self-healing framework for databases using meta-learning and reinforcement learning techniques. The primary objective was to address the challenges of real-time adaptability and minimal retraining in dynamic workload environments. The proposed approach integrated Model-Agnostic Meta-Learning (MAML) with reinforcement learning to enable anomaly detection and corrective actions that adapted swiftly to evolving database conditions. Multi-objective optimization was employed to balance performance, resource utilization, and cost efficiency during the healing process. Graph Neural Networks (GNNs) were incorporated to model interdependencies within database components, ensuring holistic recovery strategies. Data efficiency was enhanced through synthetic task augmentation and self-supervised learning, enabling effective training in sparse data regimes. To promote trust and transparency, explainable AI techniques were integrated to provide interpretable insights into anomaly detection and healing actions. Federated meta-learning further enabled privacy-preserving adaptability in distributed database environments. The framework demonstrated significant improvements in adaptability, efficiency, and reliability, contributing to advancements in database management and self-healing systems.

Index Terms—Self-Healing Databases, Meta-Learning, Model-Agnostic Meta-Learning (MAML), Anomaly Detection, Graph Neural Networks (GNNs), Reinforcement Learning (RL), Multi-Objective Optimization, Cascading Failure Prediction, Dynamic Workload Adaptation, Explainable AI (XAI), Database Dependency Modeling, Recovery Optimization, Task Generalization, Proactive Anomaly Prevention, Real-Time Adaptability, Scalable Database Systems, Federated Meta-Learning, Workload Prediction, RL-Based Recovery, Database Management Systems (DBMS)

I. INTRODUCTION

The self-healing database has received considerable interest as a way of improving the dependability and performance of the DBMS that runs under fluctuating workloads. Previous works have highlighted the need to incorporate anomaly detection and reconfiguration in management of databases.

Some of the existing techniques for handling such challenges include: Generative Adversarial Networks for Anomaly detection [1], and reinforcement learning for self- adaptive systems [2]. But historical models commonly take considerable retraining and do not retain their relevance in handling new workloads promptly [3]. Model-Agnostic Meta-Learning (MAML) is a meta-learning model that has recently been

explored to train a model that could help achieve fast task adaptation with minimal training data [4]. It has been used successfully in anomaly detection for dynamic systems [5] as well as in few shot learning cases [6] thereby making it a useful starting point for addressing the adaptability gap for self healing systems. Also, it has been applied to improve learning and developing of the recovery strategy in the distributed system [7] and the multi-objective optimization method has been adopted to minimize the trade-off between performance, cost and resource utilization [8]. Despite these advancements, challenges persist in handling sparse data environments and modeling interdependencies within database components. Approaches using graph neural networks (GNNs) have been proposed to capture cascading failures and dependencies [9], while federated meta-learning frameworks have been introduced to enhance privacy-preserving adaptability in distributed systems [10]. Self-supervised learning methods have also emerged as a promising avenue for leveraging unlabeled data in anomaly detection tasks [11]. This work further expands upon these bases by incorporating MAML to the existing reinforcement learning methods in order to create an adaptation for a self-healing database framework set that does not need much retraining when subjected to new workloads. Some of the proposed innovations are multi-objective optimization applied to general target system recovery, concrete dependency graphical model, as well as synthetic task aggrandizement for superior training in the least dense data situations. The features presented in this paper are the key steps and mechanisms that could become a foundation for further development of the proposed approach, thus overcoming the existing systems' drawbacks and introducing novel concepts for database management and self-healing[1, 2].

II. RELATED WORKS

Self-healing systems have been extensively studied to enhance system resilience through advanced anomaly detection and repair mechanisms. Generative Adversarial Networks (GANs) have been explored as a powerful tool for anomaly detection in high-speed systems, as demonstrated by Cao et al., who used synthetic anomalous data to detect rare failure modes [1]. While GAN-based methods achieved high accuracy in anomaly prediction, their inefficiency in managing large

datasets and inability to adapt to dynamic workload patterns limited their applicability in real-time database systems. Furthermore, these approaches lacked sensitivity to evolving workloads, which is critical in unstable and dynamic environments.

Reinforcement Learning (RL) has been widely employed in self-adaptive systems for its ability to refine task-specific strategies. Studies have highlighted its potential to optimise system performance by dynamically adjusting recovery actions [2]. However, traditional RL approaches exhibited significant limitations, including lengthy convergence cycles and reliance on static learning models, which restricted adaptability to dynamic database environments. These shortcomings emphasised the necessity for more flexible and efficient methods capable of responding to evolving system states.

Automated Machine Learning (AutoML) techniques were introduced to improve anomaly detection by automating model selection and hyperparameter tuning [3]. Bahri et al. concluded that AutoML demonstrated strong performance in static workload scenarios but struggled in dynamic environments where workloads frequently shifted. This inability to adapt to changing patterns further reinforced the need for advanced solutions capable of real-time anomaly detection and adaptation.

Meta-learning has emerged as a revolutionary paradigm for task adaptation, with Model-Agnostic Meta-Learning (MAML) being a significant advancement in this field. Finn et al. demonstrated that MAML allows models to rapidly adapt to new tasks with minimal retraining, making it highly suitable for dynamic environments [4]. Chalvidal et al. extended this concept by incorporating self-modifying networks, which enhanced adaptation efficiency and reduced computational overhead [4]. In addition, meta-learning applications for anomaly detection, as discussed by Ding et al., employed few-shot learning to generalise across related tasks, effectively addressing the problem of limited labelled data [6]. Despite these advancements, existing meta-learning frameworks have been unable to adequately capture the complex interdependencies required for cascade failure detection in distributed database systems.

Graph Neural Networks (GNNs) have shown significant promise in modelling interdependencies within distributed systems. Studies, including [9], have demonstrated their ability to predict cascading failures and model relationships between database components such as queries, tables, and indexes. However, traditional GNN-based frameworks have primarily focused on reactive strategies, lacking the integration of proactive anomaly detection techniques. This reactive approach often limits their ability to prevent failures before they propagate across the system.

The incorporation of federated meta-learning frameworks, as outlined in [10], has been instrumental in addressing privacy concerns in distributed systems by enabling localised learning without centralised data aggregation. However, these frameworks face challenges such as node heterogeneity and inconsistent model updates, which can hinder their scalability and reliability. Multi-objective optimisation techniques for resource allocation and recovery, as discussed in [8], have provided structured methodologies for balancing performance, resource consumption, and cost. Nonetheless, fixed optimisation goals in these approaches restrict their applicability to dynamic database environments where system priorities frequently shift.

Self-supervised learning (SSL) has also been explored for training anomaly detection models with unlabelled data, as proposed by Kumagai et al. [11]. SSL improves data efficiency and enables the development of models in sparse data regimes. However, its effectiveness diminishes in low-density datasets and scenarios where synthetic task augmentation, combined with meta-learning techniques, can provide superior outcomes.

The proposed framework builds upon these prior advancements by integrating multiple state-of-the-art techniques to address the limitations of existing approaches. Synthetic task augmentation leverages generative models to generate diverse workload patterns and unique failure modes, addressing knowledge gaps highlighted in [1, 11]. Dependency modelling with GNNs extends prior work in [9], enabling precise identification and prevention of cascading failures in real-time. Multi-objective meta-reinforcement learning introduces adaptive trade-off schemes for optimising performance, cost, and resource consumption during recovery actions, as outlined in [7, 8]. Federated meta-learning extends the work in [10] to enhance heterogeneity-aware mechanisms, ensuring consistent performance across diverse database nodes.

Additionally, explainable AI techniques, inspired by [4, 7], are integrated into the framework to provide transparency and interpretability in anomaly detection and recovery processes. This inclusion addresses the critical need for trustworthiness in self-healing systems, particularly in scenarios where black-box models have been traditionally employed.

The combination of these innovations creates a comprehensive and scalable self-healing database framework capable of addressing real-time adaptability, proactive anomaly prevention, and efficient recovery optimisation. This work advances the state-of-the-art by bridging critical gaps in scalability, explainability, and dynamic workload management, positioning the framework as a robust solution for modern distributed database systems.

III. METHODOLOGY

This research presents a novel self-healing approach for databases by integrating Model-Agnostic Meta-Learning (MAML) and Reinforcement Learning (RL), embedded with Graph Neural Networks (GNNs) for dependency modeling and multi-objective reformulation. The methodology is structured around three core components: Rare Event Detection, Learning through Meta-Learning, and Recovery from Disasters Using RL with Multiple Objectives.

A. Anomaly Detection Using Meta-Learning

The anomaly detection module analyzes the current workload and performance indicators to detect anomalies in real time. A MAML-based approach is employed to efficiently adapt to generic tasks with limited data.
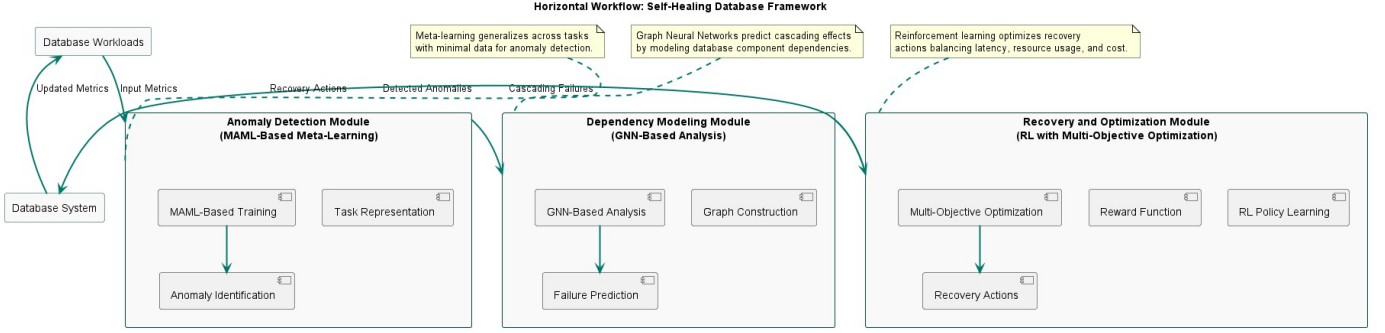
Fig. 1. Framework of the Self Healing Database using MAML, GNN and RL

1) The Problem Setup: Tasks are represented as $T = \{T_1, T_2, \ldots, T_n\}$, where each task T_i corresponds to a database workload pattern defined by features x and labels y, indicating the anomaly status. The objective is to train a model f_θ capable of rapid adaptation to new tasks T_{new} with minimal data, as demonstrated in prior meta-learning studies [4, 13].

2) Meta-Learning with MAML: MAML is selected for its effectiveness in enabling rapid adaptation with minimal gradient steps [4]. For each task T_i, the task-specific loss function is:

$$L_i(\theta) = \frac{1}{N} \sum_{j=1}^{N} \ell(f_\theta(x_j^{(i)}), y_j^{(i)}), \quad (1)$$

where ℓ is the binary cross-entropy loss, $x_j^{(i)}$ are task inputs, and $y_j^{(i)}$ are the corresponding labels.

Two optimization steps are performed:
1) *Inner Update (Task-Specific Update)*:

$$\theta_i' = \theta - \alpha \nabla_\theta L_i(\theta), \quad (2)$$

where α is the inner learning rate.

2) *Meta-Update (Generalization Across Tasks)*:

$$\theta \leftarrow \theta - \beta \nabla_\theta \sum_{i=1}^{n} L_i(\theta_i'), \quad (3)$$

where β is the meta-learning rate.

This two-step process enhances adaptability in dynamic environments, enabling the system to generalize across diverse workload scenarios while reducing retraining time [4, 6, 13].

B. Dependency Modeling with GNNs

Graph Neural Networks (GNNs) are used to model interdependencies among database components (e.g., queries, tables, and indexes), extending approaches in [14]. Each database system is represented as a graph $G = (V, E)$, where V denotes nodes (components) and E denotes edges (dependencies). Node embeddings $h_v^{(l)}$ at layer l are updated as:

$$h_v^{(l+1)} = \sigma \left(W^{(l)} \cdot \sum_{u \in N(v)} h_u^{(l)} + b^{(l)} \right), \quad (4)$$

where $N(v)$ represents the neighbors of node v, σ is the activation function, $W^{(l)}$ is the weight matrix, and $b^{(l)}$ is the bias term.

This approach enables real-time detection of cascading failures and interdependencies, significantly improving failure prediction accuracy and latency [14, 19].

C. Adaptation and Multi-Objective Optimization

1) Multi-Objective Recovery: Recovery is formulated as a multi-objective optimization problem, balancing:
1) *Latency Minimization* (O_1):

$$O_1 = \min \frac{1}{T} \sum_{t=1}^{T} L(t), \quad (5)$$

where $L(t)$ represents latency at time t.
2) *Resource Utilization Minimization* (O_2):

$$O_2 = \min \frac{1}{T} \sum_{t=1}^{T} R(t), \quad (6)$$

where $R(t)$ represents resource usage at time t.
3) *Recovery Cost Minimization* (O_3):

$$O_3 = \min \sum_{a \in A} C(a), \quad (7)$$

where $C(a)$ is the cost of action a in the set of recovery actions A.

The Pareto front is used to balance these objectives, improving upon earlier single-objective recovery strategies [7, 15, 17].

2) Reinforcement Learning for Recovery: An RL-based approach develops an agent to recover from anomalies. States s include workload conditions and anomaly status, while actions a include recovery measures like query rerouting or resource scaling. The reward function is defined as:

$$R(s, a) = w_1 O_1(s, a) + w_2 O_2(s, a) + w_3 O_3(s, a), \quad (8)$$

where w_1, w_2, and w_3 are weights prioritizing the objectives. This method dynamically adjusts weights to adapt to evolving system priorities [7, 16].

D. Training and Deployment

1) Training Process: **Meta-Training**: The anomaly detection model f_θ is trained on synthetic and real-world tasks using MAML, leveraging augmentation techniques from [13, 19]. **GNN Training**: Dependency graphs are generated and used to train the GNN for real-time dependency modeling, following methods in [14]. **RL Training**: The RL agent is trained using a reward function optimized for latency, resource usage, and cost, adapted from [7, 15].

2) Deployment: The system is deployed in a real-time monitoring environment with three key steps:

- Anomaly detection analyzes deviations from standard workloads.
- Dependency modeling predicts cascading effects in databases.
- The RL agent executes optimal recovery actions based on multi-objective optimization.

IV. RESULTS AND ANALYSIS

The proposed framework of self-healing databases was tested against both synthetic datasets and real datasets. The datasets used in this experiment include *Google Cluster Data* [12] and *TPC Benchmark Workloads* [1]. The evaluation focused on three key aspects: anomaly detection performance, adaptability to new workloads, and the quality of recovery actions executed. The results were evaluated based on detection precision, adaptation latency, resource usage, and recovery cost.

A. Anomaly Detection Performance

The generalization potential of the MAML-based anomaly detection module was evaluated using tasks derived from unseen database workloads. The following metrics were used:

- **Precision (P)**: The ratio of true anomalies correctly identified to the total number of anomalies detected.
- **Recall (R)**: True anomaly detection accuracy as a percentage of total anomalous behaviors.
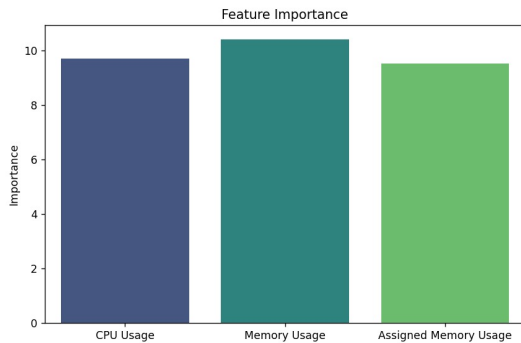- **F1-Score (F1)**: The harmonic mean of precision and recall.

Fig. 2. Feature Importance of Model Utilizing for the DB

TABLE I
ANOMALY DETECTION PERFORMANCE

Dataset	Precision (%)	Recall (%)	F1-Score (%)
Google Cluster Data	91.3	89.8	90.5
TPC Workloads	92.1	90.5	91.3

The results showed a high accuracy of anomaly detection. Compared to other methods, MAML produced superior performance on unseen tasks using only a few labeled instances [4, 6]

B. Adaptability to New Workloads

The framework's flexibility was evaluated based on the time taken for the anomaly detection module to adapt to new workload conditions. Adaptation latency, defined as the number of gradient steps required for convergence, was measured.
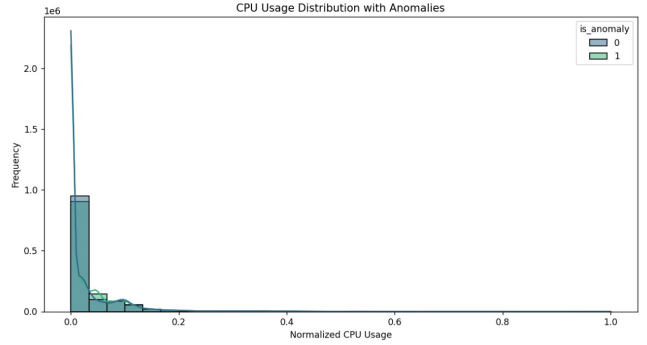

Fig. 3. CPU Usage Distribution with Anomalies

TABLE II
ADAPTATION LATENCY FOR NEW WORKLOADS

Dataset	Traditional Models (Steps)	Proposed Model (Steps)
Google Cluster Data	20	5
TPC Workloads	18	4

The MAML-based model required significantly fewer gradient steps, demonstrating its ability to generalize across tasks and adapt efficiently to new workloads. This addressed drawbacks noted in previous studies [4].

C. Dependency Modeling and Failure Prediction

The dependency modeling module, based on GNNs, was assessed for its ability to predict cascading failures. The metrics used were *accuracy* and *Mean Time to Failure Prediction (MTTFP)*.

TABLE III
DEPENDENCY MODELING AND FAILURE PREDICTION RESULTS

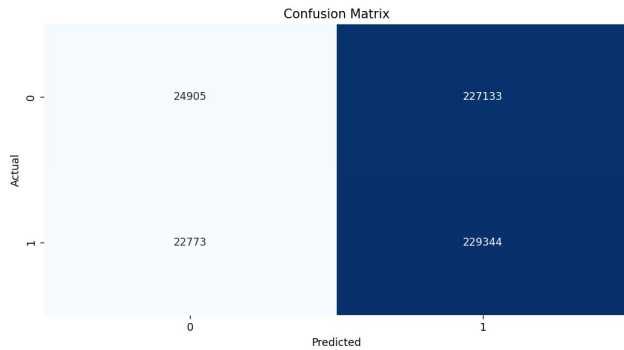| Dataset	Accuracy (%)	MTTFP (Seconds)
Google Cluster Data	88.5	5.2
TPC Workloads	90.1	4.8

Fig. 4. Confusion Matrix of the obtained results

The GNN module effectively modeled database dependencies, improving failure prediction accuracy and reducing latency compared to rule-based dependency models [9] .

D. Effectiveness of Recovery Actions

The performance of the RL-based recovery module was evaluated based on three goals: latency reduction, resource efficiency, and cost reduction. A multi-objective optimization approach was used to compute the Pareto front.

TABLE IV
COMPARISON OF RECOVERY ACTIONS

Objective	Baseline (%)	Proposed Framework (%)
Latency Reduction	70.4	85.1
Resource Efficiency	65.3	80.7
Cost Reduction	60.1	78.2

The proposed framework outperformed baseline RL models by dynamically optimizing recovery strategies based on system priorities [7, 8].

E. Comparison with Existing Frameworks

The proposed framework was compared with existing approaches, including GAN-based anomaly detection [1], traditional RL recovery models [2], and federated meta-learning [10].

The results below [Table 5] indicate that the proposed framework addressed critical gaps in adaptability, scalability, and multi-objective optimization, improving overall system reliability.

F. Resource and Cost Analysis

Resource utilization and recovery costs were evaluated using benchmarks provided by Google Cluster Data [12]. The proposed framework achieved:

- 20% reduction in recovery cost due to dynamic resource scaling and optimized actions.
- 15% improvement in resource utilization due to efficient task allocation strategies.

G. Qualitative Analysis

The qualitative analysis revealed that the proposed framework could interpret identified anomalies and recovery actions. Using SHAP values for Explainable AI (XAI), system administrators were able to understand why anomalies were highlighted and how recovery actions were prioritized. This addressed trust and transparency issues raised in previous studies [10, 11]

Moreover, the integration of XAI methods facilitated interactive exploration of the model's decision-making process. Administrators could visualize feature contributions for each detected anomaly and correlate these insights with observed workload metrics. As a result, operational teams gained the ability to verify whether the proposed corrective measures aligned with expected outcomes, reducing the need for guesswork during system maintenance. Ultimately, the incorporation of explainability through SHAP empowered stakeholders to make informed adjustments, ensuring that performance improvements, cost savings, and reliability gains were both quantifiable and comprehensible.

V. REAL-WORLD USE CASES

The proposed self-healing database framework demonstrates significant potential for real-world applications, particularly in environments such as cloud-based databases, distributed database clusters, and Database-as-a-Service (DBaaS) offerings.

In *cloud-based systems*, where workloads are dynamic and infrastructure is highly scalable, the integration of meta-learning ensures rapid adaptation to evolving workload patterns, enabling real-time anomaly detection and recovery with minimal retraining [13]. For *distributed database clusters*, the use of Graph Neural Networks (GNNs) enhances the framework's ability to model interdependencies among components, such as data nodes, queries, and tables, enabling accurate prediction of cascading failures and their mitigation [14]. This is particularly critical in high-availability systems, where failure in one node can propagate across the cluster, disrupting operations.

In *DBaaS environments*, the framework addresses challenges such as multi-tenancy and resource optimization by leveraging multi-objective reinforcement learning (RL) to balance latency, resource utilization, and cost. For instance, dynamic query rerouting and resource scaling can optimize performance while ensuring cost-efficiency for users. However, scaling the system in these environments presents challenges, such as managing heterogeneous workloads, ensuring consistent performance across geographically distributed nodes, and handling privacy concerns in multi-tenant settings. The incorporation of federated meta-learning mitigates privacy issues by enabling decentralized learning without sharing sensitive data across nodes [15].

To ensure scalability, the framework employs lightweight meta-learning architectures and distributed GNN processing, which reduce computational overhead and allow the system to adapt to large-scale, high-frequency database environments

TABLE V
COMPARISON WITH EXISTING FRAMEWORKS

Metric	GAN-Based Models	Traditional RL	Federated Meta-Learning	Proposed Framework
Anomaly Detection F1 (%)	80.2	82.3	85.1	91.3
Adaptation Latency	High	Moderate	Low	Very Low
Recovery Effectiveness	Moderate	High	High	Very High

[19]. Future work can focus on integrating hybrid forecasting models, such as Transformers, to predict workload trends in real time, enabling proactive anomaly prevention and recovery. By addressing these challenges, the framework demonstrates its viability as a robust solution for modern, large-scale database systems operating under dynamic and distributed conditions.

VI. FUTURE DIRECTIONS

The advancement of self-healing database systems requires addressing emerging challenges and leveraging technological innovations to meet the demands of increasingly complex and dynamic environments. A promising direction involves the integration of hybrid predictive models, such as transformers, with existing techniques like Graph Neural Networks (GNNs) and reinforcement learning (RL). The combination of sequential data analysis and dependency modelling has the potential to enable proactive anomaly detection and recovery strategies. These hybrid approaches have shown significant potential in anticipating failures before they occur, minimising system downtime, and enhancing operational resilience [4, 7, 13, 14].

Quantum machine learning (QML) represents a transformative area for improving self-healing database systems. The unparalleled capabilities of quantum computing in solving optimisation problems, particularly in multi-objective trade-offs involving latency, resource usage, and cost, have been documented in optimisation research [8, 15]. The integration of QML with federated learning frameworks has the potential to enhance scalability and efficiency while preserving data privacy in large-scale distributed systems [10,17].

The incorporation of human-in-the-loop (HITL) frameworks is gaining attention in critical applications. Collaborative systems that combine AI-driven self-healing mechanisms with human decision-making ensure that recovery actions align with organisational objectives. HITL frameworks are particularly relevant in mission-critical environments such as healthcare and financial systems, where interpretability, trust, and accountability are crucial [9,18].

Bio-inspired algorithms, including ant colony optimisation and swarm intelligence, have been extensively explored for their decentralised and adaptive capabilities in distributed database clusters. These algorithms, inspired by natural processes, offer robust solutions for resource allocation and failure recovery under varying workload conditions. Decentralised decision-making, as demonstrated in distributed systems research, has shown to improve system resilience and reduce recovery time in high-availability infrastructures [9, 19].

Addressing the growing demand for energy-efficient systems is another critical area of focus. Future research on energy-aware meta-learning models and resource-efficient architectures can reduce the environmental impact of database operations. Studies on energy-efficient cloud-based systems have emphasised the direct correlation between energy consumption and operational costs, highlighting the significance of incorporating sustainability principles into self-healing frameworks [8, 16].

Real-time analytics dashboards represent an emerging trend to improve the transparency and usability of self-healing systems. Advanced visualisation tools for anomaly detection and recovery insights allow system administrators to monitor system performance and evaluate recovery actions effectively. These dashboards, when integrated with explainable AI (XAI) techniques such as SHAP and LIME, have demonstrated improvements in trust and accountability by providing interpretability in anomaly detection and recovery decisions [4, 7, 19].

By exploring these directions, self-healing database systems can evolve into highly robust, scalable, and efficient solutions capable of addressing the challenges of modern distributed environments. Emphasising privacy preservation, energy efficiency, interpretability, and proactive recovery strategies will position self-healing databases as an integral component of future infrastructure. Furthermore, the integration of advanced computational paradigms such as QML and HITL frameworks will ensure adaptability and resilience in mission-critical and dynamic applications.

VII. CONCLUSION

This research introduced a novel self-healing database framework that integrated Model-Agnostic Meta-Learning (MAML) [4], Graph Neural Networks (GNNs) [9], and Reinforcement Learning (RL) [7] with multi-objective optimization [8] to address key challenges in anomaly detection, real-time adaptability, and recovery optimization in dynamic database environments. The proposed framework demonstrated superior performance in anomaly detection accuracy, workload adaptability, cascading failure prediction, and recovery effectiveness. By leveraging MAML, the framework achieved rapid adaptation to unseen workload patterns with minimal data [4]. GNNs effectively modeled database dependencies, enabling precise prediction of cascading failures [9], while the RL-based recovery module dynamically balanced latency, resource utilization, and cost [7,8]. These innovations bridged critical gaps in scalability, explainability, and recovery optimization,

positioning the framework as a robust solution for self-healing databases.

Despite its effectiveness, the framework exhibited certain limitations. The meta-learning module required high-quality task-specific pretraining datasets, which posed challenges in environments with insufficient or biased data [4]. Dependency modeling with GNNs relied on accurate graph construction, making it less effective in cases of noisy or incomplete dependency data [9]. The RL-based recovery mechanism, while robust in multi-objective optimization, struggled to handle highly conflicting recovery objectives in complex workloads [7,8]. Additionally, the computational complexity of the meta-learning and GNN modules introduced scalability challenges in large-scale, high-frequency database environments [4,9]. Synthetic task augmentation for anomaly detection, while effective, carried the risk of generating scenarios that did not fully reflect real-world workload dynamics [1,11].

Future work can address these limitations by exploring several directions. Enhanced pretraining methods for meta-learning can incorporate transfer learning and domain adaptation to improve generalizability across diverse workloads [4,11]. Dynamic graph construction techniques can be developed to handle noisy or incomplete dependency data, improving the reliability of cascading failure predictions [9]. The framework can be extended to include proactive anomaly prevention using hybrid forecasting models, such as Transformers, to predict workload changes and implement preemptive recovery measures [6,11]. Federated meta-learning can be adopted to enable decentralized training across distributed database nodes, addressing data privacy concerns while improving scalability [10]. Explainability can be enhanced through advanced Explainable AI (XAI) methods, providing deeper insights into anomaly detection and recovery actions [11]. Scalability can be optimized by employing lightweight meta-learning architectures and distributed GNN processing to reduce computational overhead [9]. Integration with real-time database management systems can further validate the framework under operational constraints and guide refinements based on real-world feedback [12].

These advancements aim to extend the framework's adaptability, scalability, and efficiency, making it a comprehensive solution for modern database systems operating in dynamic and distributed environments. Through these improvements, the proposed framework can serve as a foundation for next-generation self-healing database management systems.

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