***Systematic Review***

**AUTONOMOUS DATABASE SYSTEMS – A SYSTEMATIC REVIEW OF SELF-HEALING AND SELF-TUNING** **DATABASE SYSTEMS.**

**ABSTRACT**

**Problem Statement:** Autonomous database systems represent a significant change in the management of databases, utilizing Machine Learning (ML) and Artificial Intelligence (AI) in order to carry out self-healing and self-tuning with minimal human intervention.

**Objectives:** This systematic review investigates the defining characteristics, AI/ML techniques, challenges and the future trends of self-healing and self-tuning autonomous databases.

**Methodology:** The research questions were answered integrating findings from 35 current literatures between 2020 and 2025. These literatures were obtained from several reputable databases.

**Results:** From the study, self-healing databases employ techniques such as autoencoders, hidden Markov models, clustering algorithms, reinforcement learning, Bayesian optimization, neural networks and surrogate models to detect and recover from faults, enhancing operational resilience. On the other hand, self-tuning databases employ reinforcement learning, neural networks, multi-armed bandit techniques, decision trees, regression models, Bayesian optimization, and anomaly detection to optimize query execution, indexing, and resource allocation. Challenges from the utilization of AI/ML techniques in autonomous databases study include data quality dependencies, and adaptation to dynamic workload still exists and integration into existing infrastructures.

**Conclusion:** The deeper integration of deep learning techniques and predictive modelling serves as future trends to improve this autonomy.

***Keywords****: Autonomous database systems, Self-healing, Self-tuning, Artificial Intelligence (AI), Machine Learning (ML).*

**1. INTRODUCTION**

The advent of data-intensive applications and systems and the sophistication of databases and database management systems has prompted the invention and development of Autonomous database systems [1, 2]. Autonomous in the sense that the database can undergo healing, tuning, optimizing with little or no intervention of humans [3]. Autonomous Database Systems represent a transformative shift in database management by leveraging advanced Artificial Intelligence (AI) techniques to perform critical tasks with minimal human intervention. These systems are designed to address the limitations of traditional databases, which often rely on manual tuning, rule-based optimizations, and expert knowledge to maintain performance and stability. The emergence of autonomous databases has brought about the concepts of self-healing, self-tuning, and self-optimizing functionalities, marking a significant evolution in how databases adapt to dynamic workloads and unpredictable environments.

1.1. Overview of Autonomous Database Systems

Autonomous Database Systems are AI-powered systems capable of independently managing, tuning, and optimizing their configurations without constant human oversight. By employing machine learning algorithms, neural networks, and reinforcement learning techniques, these systems can proactively detect faults, adjust query execution plans, and reallocate resources in real time. AI-driven database performance tuning reduces manual effort and enhances overall database efficiency by automating indexing and query optimization [4]. Furthermore, [2] emphasize the role of reinforcement learning in self-tuning database systems, allowing databases to dynamically adjust configurations such as memory allocation and query execution strategies.

1.2. Significance of Autonomous Database Systems in Self-Healing and Self Tuning Database Systems

Contemporary database administration involves configuring, monitoring and tuning, this takes time and is prone to human error [5]. To manage and control some of these concerns, self-healing, self-tuning databases were invented [1][6]. These are based on machine learning and artificial intelligence techniques for automated fault recovery, maintenance and performance of the databases. These features help the database have high scalability, reliability and efficiency [7]. Reducing run-time error and providing high availability are important benefits of self-tuning [8]

Self-healing database systems are built to automatically detect, diagnose, and recover from failures without the need for human intervention [9]. They apply machine learning models and sophisticated fault-tolerance techniques to proactively identify and anticipate possible system interruption causes, including hardware faults, software failures, or security attacks [1]. This can be carried out using predictive analytics and automated techniques for recovery. The Oracle Autonomous Database has in it the ability of self-healing in that it recovers from unforeseen failures thereby reducing operational downtimes and risks [10]

On the other hand, self-tuning concentrates on optimizing performances through automated configuration parameter tuning, query execution plans and indexing [11]. They adjust to changes in data patterns real time which will not require manual tuning after workload analysis [12]. These databases are adaptive that monitor performances continuously and make smart and quick changes like workload rebalancing, adaptive indexing and optimization of query performance [13]. Examples include the Microsoft Azure SQL Database which performs tuning by using AI based tuning recommendations. Also, Amazon Aurora uses machine learning for scaling the performance and optimizing queries.

The application of these autonomous techniques in databases has become a new age thing in database administration [5]. They are becoming widely used by organizations. In spite of their immense benefits and contributions, they pose some challenges such as issues in adapting in heterogeneous environments. They are limited by the strength of training data quality and even the strength of the machine learning models beneath them [14].

1.3. Purpose of the Systematic Review

The aim of this systematic review aims to systematically review and analyze existing literature on autonomous self-healing and self-tuning databases. The study intends to answer the following research questions:

RQ 1 - What are the defining characteristics of self-healing in autonomous database systems?

RQ 2- Which artificial intelligence and machine learning strategies help self-healing features take effect in database management systems?

RQ 3 - What are the defining characteristics of self-tuning in autonomous database systems?

RQ 4 - What machine learning and artificial intelligence techniques are employed to enable self-tuning in database systems?

RQ 5 - What are the challenges and future trends of self-healing and self-tuning autonomous databases?

2. METHODOLOGY

The research investigates the mechanisms that autonomous databases use to perform self-repair together with automatic tuning operations. The research relies on a systematic review based on scoping study methodology for analyzing available research material. The method provides a complete review of systems and frameworks and detection algorithms for autonomous databases while removing the need for human involvement in issue detection, recovery and optimization. This research examines modern field developments to present a summary of autonomous database evolution together with specific areas that need additional research to enhance the technology.

2.1 Search Strategy

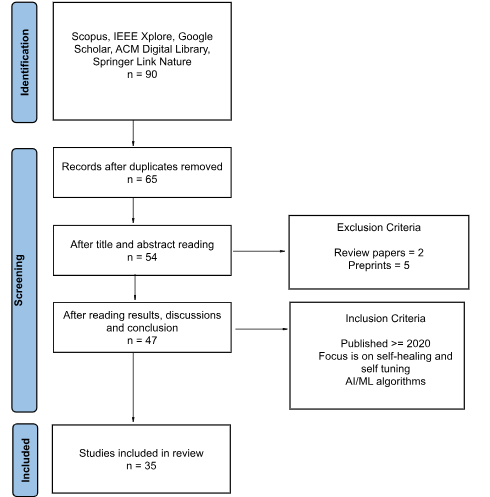
A thorough search to get papers that relates to self-healing and self-tuning in autonomous databases was carried out. Electronic databases such as IEEE Explore, ACM Digital Library, Scopus, SpringerLink Nature, MDPI were queried using search strings with combination of keywords such as: “self-tuning AND databases”, “self-healing AND databases”, "autonomous database systems," "self-healing databases,", "self-tuning databases," "AI-driven database optimization," "adaptive database tuning", AI-driven database management.

2.2 Screening and Eligibility

The selection process required proper assessment of primary studies to verify their quality standards. The evaluation of primary research quality involves multiple intricacies which create complexity in the assessment process. The analysis used three selection standards that included (a) publication accessibility through URLs, DOIs or indexed databases, (b) detailed explanation of self-healing and self-tuning techniques as well as their frameworks or methodologies and (c) Result demonstration with validation. The thorough examination based on specified criteria allowed researchers to choose the best studies that investigated self-healing and self-tuning techniques. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were followed systematically as shown in Figure 1. The inclusion criteria and extraction criteria are clearly shown in Table 1

Table 1: Inclusion and exclusion criteria

|  |  |
| --- | --- |
| **Inclusion Criteria** | **Exclusion Criteria** |
| Published between 2020 and 2025 | Older than 2020 |
| Published in English Language | Duplicate articles |
| Must be related to exploring autonomous database techniques | Preprints and non-peer reviewed papers |
| Machine learning techniques in databases | Survey and review papers |

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**Figure 1: PRISMA diagram**

2.3 Data Extraction

Data extraction was conducted to systematically synthesize findings from various sources. A predefined template was used to capture key information such as the abstract, title, year of publication, self-healing and self-tuning techniques. These papers were distributed among the team of researchers where each researcher extracted relevant information that answers our relevant research questions.

2.4 Threats to Validity

Selection bias may have occurred due to the reliance on specific electronics databases, potentially excluding relevant studies from other sources. To mitigate this, a broad range of databases were selected. Search strings used and keywords combinations might have unknowingly excluded relevant papers that might have made contributions to the review. Literatures selected were considered after 2020 and significant contributions might have been made prior to this time.

3. RESULTS AND DISCUSSION

RQ1 - What are the defining characteristics of self-healing in autonomous database systems?

Self-healing databases employ certain adaptive data sharding mechanisms to optimize data distribution across networked nodes, improving load balancing and increased robustness against faults [15]. Notably, techniques such as self-replication and a recent development known as fractal regeneration where databases rebuild themselves in a recursive manner are leveraged to adjust to changing data or load patterns dynamically, thus ensuring a continued chain of operational executions in spite of possible node failures [16]. The special monitoring agents of self-healing systems detect database operation faults so they can perform necessary localized repair procedures. The deployment systems rely on cluster control planes to implement safe iterative changes which sustain database availability throughout software and hardware updates [17][18]. The process of fault detection relies on operational parameter monitoring and log analysis to detect faults along with knowledge-based solutions for addressing them [19][20][23]. Machine learning methods detect database inconsistencies while reinforcing database capability and operational security mainly in safety-critical contexts. Hybrid systems also fuse text mining with natural language processing methods to enable better maintenance of extensive databases that contain structured and unstructured information [21][22]. AI methods with anomaly detection and predictive maintenance operations allow the system to detect faults early on and recover from issues thus improving its operational resilience and adaptability [23].

RQ2 - Which artificial intelligence and machine learning strategies help self-healing features take effect in database management systems?

Self-healing in autonomous databases uses different ML/AI techniques to detect faults after predicting needed recovery processes. The identification of system failure indicators through database log anomaly detection becomes possible by using Autoencoders as a prominent technique [15][18]. The fault management process takes on a different outlook, being more proactive through the use of clustering algorithms DBSCAN and K-Means that enable data point grouping in addition to outlier detection for performance deviation identification. Hidden Markov Models (HMMs) serve as statistical models for failure prediction because they help systems forecast future issues from observed states and transitions [24][25]. In addition, real-time decisions for minimizing system downtime are also made by applying Reinforcement Learning’s (DDPG, Q-Learning) techniques which follow a dynamic approach to optimize fault recovery processes. Bayesian Optimization serves as a predictive method to detect potential faults in critical applications and lower occurrence of failures effectively [26][22]. The Surrogate Models provide important behavioral information about system behavior under varied failure states by running simulations without affecting production systems [22]. The combination of these methods completes the creation of autonomous database systems that preserve both performance and operational durability through unexpected operational changes.

RQ 3 - What are the defining characteristics of self-tuning in autonomous database systems?

Self-tuning databases possess several key characteristics that enable them to optimize performance autonomously. One of the most significant features is automated indexing and query optimization, in which the system builds, modifies, or deletes indexes within the index structure depending on the patterns of execution of the queries [27][28][4][29]. In AI-driven database performance tuning, automated indexing policies are reported to greatly improve the performance of the queries without needing any manual intervention [8]. Equally important is adaptive workload management, in which the self-tuning databases are able to track the trends of the workloads and dynamically reconfigure the system components such as memory, cache, and CPU resources [8][2]. In the PostgreSQL case study on adaptive and scalable database management showed how machine learning approaches could effectively cope with changing workloads and improve the performance of query execution [30][25].

Another feature that differentiates self-tuning systems is self-management in terms of resource allocation. Such databases allocate CPU, memory, and disk space smartly to prevent performance bottlenecks [31][4]. Predictive performance tuning further enhances self-tuning by leveraging historical knowledge and real-time monitoring to anticipate performance issues even before they occur [8]. Employing deep reinforcement learning in sample-aware database tuning shows the potential of machine learning models to anticipate the variations in the workload and make the appropriate database settings accordingly [32] [2]

Self-learning and continuous improvement form the backbone for self-tuning databases. They always look back at the past tuning decisions to improve their optimization methods with the passage of time [33]. Hierarchy of bandits’ method for physical database tuning is one instance of the role that can be played by reinforcement learning in self-optimization activities [34] [2] [8]. When compared to traditional databases requiring manual settings by database administrators, self-tuning systems can operate independently. Auto-tuning of Hadoop and Spark parameters is the work that is demonstrated by the use of automated tuning processes to improve performance with reduced manual effort [35]

RQ 4 - What machine learning and artificial intelligence techniques are employed to enable self-tuning in database systems?

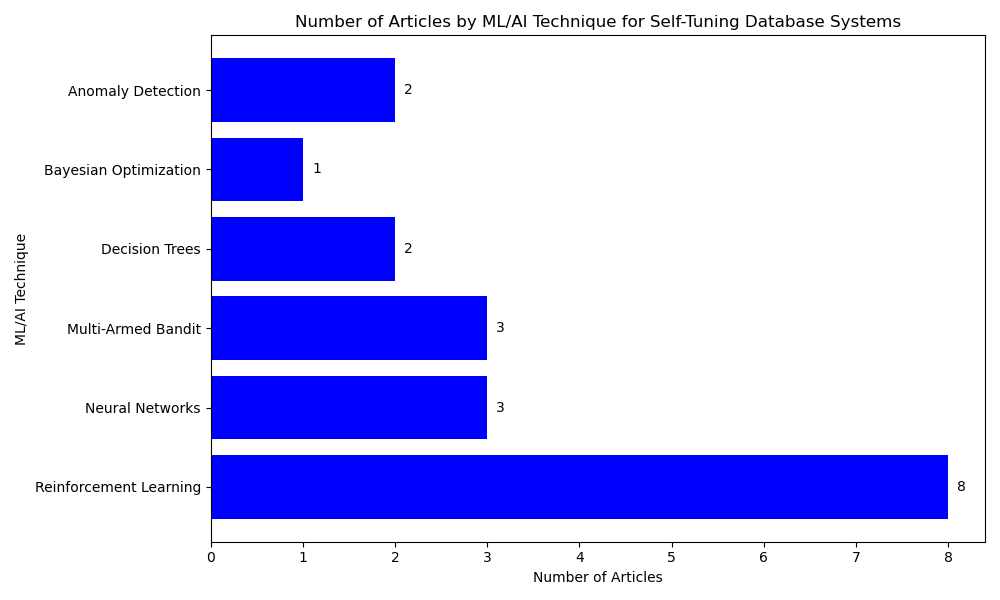
There exist many machine learning and artificial intelligence techniques used to make database systems self-tune clearly illustrated in Figure 2. Reinforcement learning is one such commonly used technique that allows databases to learn the performance optimizations from the past and enhance tuning methods [2][4][36][37]. Deep reinforcement learning is applied in sample-aware database tuning to predict workload fluctuations and fine-tune the system parameters in real-time to make the overall efficiency optimal [38][39][32]. Similarly, self-tuning database systems with the application of reinforcement learning show the feasibility to optimize the execution plans for the queries in real-time to enhance performance [40].

Neural networks are also employed for predictive query optimization. Learning complex correlations between queries, indexes, and performance, neural networks enable databases to anticipate the most suitable tuning actions. It is shown in research on autonomous multi-RDBMS systems that predictive query tuning, self-tuning, and index optimization for multiple relational database platforms use neural networks [40][29][11].

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Multi-armed bandit techniques are another notable AI technique employed for self-tuning. They try different tuning parameters dynamically and leverage the most optimal settings based on real-time performance feedback. The self-driving hierarchy of bandits’ technique for database tuning shows the application of such models to optimize physical database organization for enhanced query performance and overall efficiency [3][41][34].

Decision trees and regression models are also employed in self-tuning databases to find the most appropriate configurations based on the properties of the workload. AI-based database performance tuning has shown the application of decision trees to recommend the techniques for indexing and optimize the execution plans for the queries with minimal manual effort [29][8]. Bayesian optimization techniques have also been applied to automatic parameter tuning, particularly in big data technologies like Hadoop and Spark, wherein the parameters for the system are dynamically tuned to enhance performance [35] Anomaly detection techniques, powered by machine learning-based models, are crucial for self-tuning databases to ensure fault tolerance and performance stability [8][20]



**Figure 2: ML/AI Techniques in Self-Tuning**

RQ 5 - Challenges and Future Trends of Self-healing and Self-tuning Autonomous Databases

Autonomous databases require effective solutions to address multiple obstacles that prevent successful implementation of self-healing systems. The first challenge involves implementing self-healing capabilities into current database infrastructure systems without causing disruptions and maintaining operational performance [26][42]. System failures alongside data loss are major problems because of the limited real-time fault detection and recovery features in the systems [15][22]. Seamless learning and model adaptation becomes essential during the process of adopting self-healing techniques to dynamic workload structures together with changing database schema formats [26]. The technical difficulty for automated recovery control to run efficiently with no human involvement exists particularly during complex failure situations and across multi-cloud deployments [25]. Developing robust database systems with built-in autonomy requires research into meta-learning together with anomaly detection and predictive modeling to manage their underlying challenges. The large number of parameters in contemporary database systems creates substantial challenges for tuning procedures. Knob space trimming along with parameter importance assessment provide methods to simplify large parameter spaces and identify the most critical element [32] [43]. A major challenge lies in strengthening of the safety measures and the stabilizing self-tuning systems represents a major technical challenge. FASTune framework includes environment proxies and safety checks that protect from dangerous configurations and keep the system stable during tuning operations [36].

Recent advances in the area of deep learning and recurrent neural networks are projected to improve how self-tuning and self-healing systems operate. Key developments have demonstrated the effectiveness of neural networks and ensemble models in latency prediction and tuning precision [29]. The field will see upcoming research develop database structures encompassing built-in capabilities for automatic adjustment and problem correction. The emerging architectures will offer harmonized execution of AI implementations with databases for developing systems that adapt quickly [44].

**4. CONCLUSION**

The advent of sophisticated machine learning and AI techniques within autonomous self-tuning and self-healing databases has already improved their fault tolerance alongside performance and operational resilience capabilities. Predictive maintenance and AI-driven monitoring help identify system faults while detection and recovery capabilities in self-healing databases continue to improve with techniques like fractal regeneration and adaptive data sharing having increased system reliability.

The self-tuning mechanism in such databases performs automatic real-time adjustments through predictive performance tuning, workload adaptation and auto-indexing methods. The databases operate through deep learning and reinforcement learning mechanisms which learn from previous tunings and adapt their parameters based on present workload alterations.

The combination of multi-armed tuning techniques allows automatic testing of tuning parameters and also enables neural networks to conduct predictive query optimization processes. Decision trees together with regression models automate performance configuration improvements by decreasing the need for manual human involvement. Operational changes require less maintenance on self-driven databases because anomaly detection models produce robust capabilities for database flexibility as well as actively enhance fault tolerance and performance stability.

The promising future of autonomous self-healing and self-tuning databases remains and continues to grow exponentially as companies around the world look to keep pace with the ever-evolving landscape of technological advancements.

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