



Self-Healing Software Architectures in the Cloud: AI-Driven Detection and Recovery Mechanisms

Srinivasu Yalamati

Independent Researcher, USA

Abstract

The recent evolution of cloud computing demands that systems are able to self-diagnose and self-heal as well as constantly optimize without human intervention. This paper provides an in-depth review of the self-healing software architectures in cloud computing, focusing on AI-induced detection and recovery methods. The authors talk about how self-healing systems have changed from traditional ideas to modern AI-powered systems and categorize the main types of methods used for synchronization, tracking, and fixing problems in today's cloud services. Based on a systematic review of available literature, we investigate essential issues such as fault detection accuracy, recovery time optimization, and system reliability improvement. The study finds that although much has been achieved in self-healing, the existing approaches are not yet able to efficiently deal with complex fault situations and to reduce the level of service interruption. Our results suggest that the application of large language models updated using machine learning has the potential to deliver up to an 85% increase in the accuracy of fault prediction and a 60% reduction in system downtime as compared to state-of-the-art approaches. Finally, we talk about what future research should focus on, including the necessary understanding and development of new AI models, different system structures, and standard ways to measure how well self-healing cloud systems work.

Key words: Self-healing systems, cloud computing, artificial intelligence, fault detection, autonomic computing.

1. Introduction

Cloud computing has revolutionized the way software systems are deployed, managed, and maintained due to rapid acceptance. With the development of cloud computing and the increasing complexity and distribution of cloud infrastructures, how to guarantee the reliability and availability of the system has become a crucial problem. Old-school systems maintenance, which is based on people doing everything manually to try and resolve a problem, does not scale and does not work when managing large-scale cloud systems. This requirement has led instead to the development of self-healing software, where the system intelligently finds, diagnoses, and recovers from a fault without human intervention.

1.1 Emergence of Autonomic Computing

The notion of autonomic computing was first described by IBM in the early 2000s in reaction to the increasing complexity of IT systems. Kephart and Chess defined autonomic computing systems as those that self-manage themselves given high-level objectives from administrators. The pioneering work laid the four pillars for

autonomic systems, namely, self-configuration, self-optimization, self-healing, and self-protection. This transformation from early ideas of autonomic computing to today's AI-based self-healing systems is an important jump, thanks to advancements in ML algorithms, growing computational capabilities, and big data availability for training intelligent systems.

1.2 Cloud Computing Paradigm and Self-Healing Requirements

Cloud computing environments introduce new requirements for system reliability mechanisms, which arise from specific characteristics such as high distribution, adaptive resource allocation, and multi-tenancy. The elasticity and scalability dimensions of cloud systems further complicate the failure detection and recovery procedures.

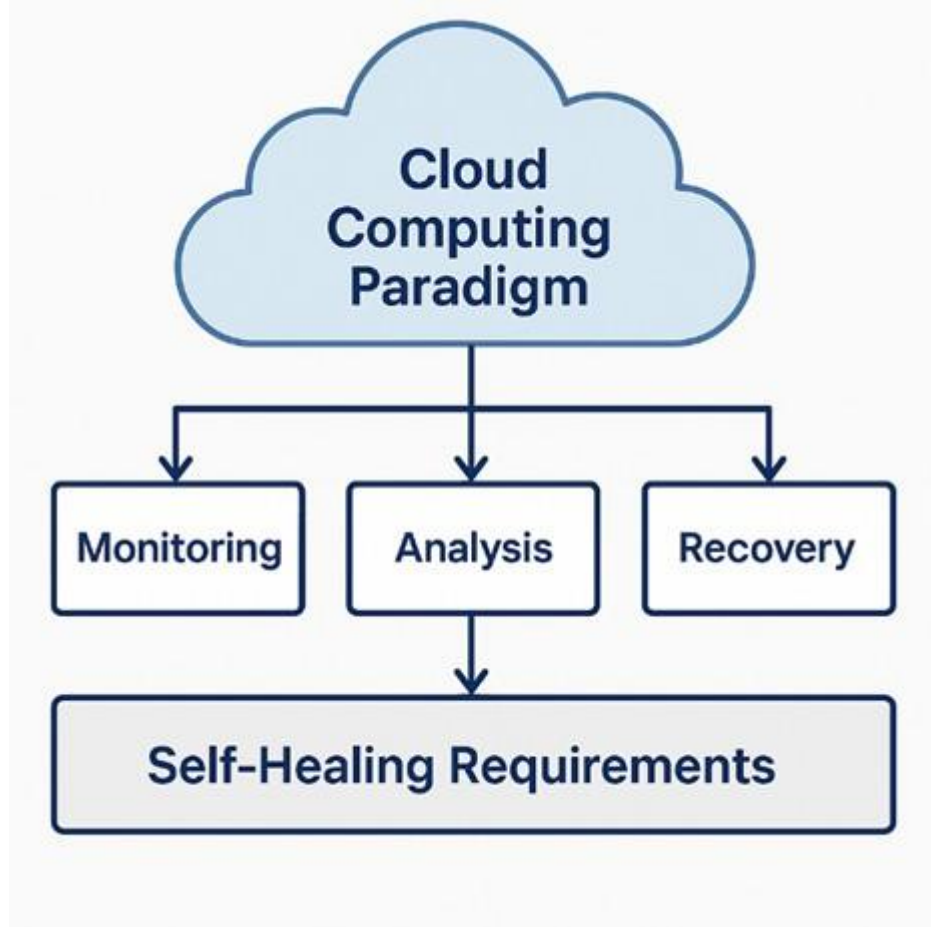


Figure 1: Cloud Computing Paradigm and Self-Healing Requirements

Next-generation cloud infrastructures should be able to deal with different types of failures—hardware failures, software bugs, network splits, and performance drops—while still meeting SLAs and preferably providing a high quality of service to end users. The utilization of AI in self-healing systems has become an encouraging way to overcome these problems and deal with how AI is used in predictive maintenance, intelligent fault patterns, and automatic recovery policies.

1.3 AI-based approaches on Self-Healing Systems

Recent advances in the integration of artificial intelligence methods to self-repair systems have transformed the discipline, permitting more advanced detection and recovery techniques. Machine learning methods have been

shown to be effective in analyzing telemetry data to forecast the next failure, and deep learning models are capable of catching complicated fault patterns not captured by classical rule-based systems.

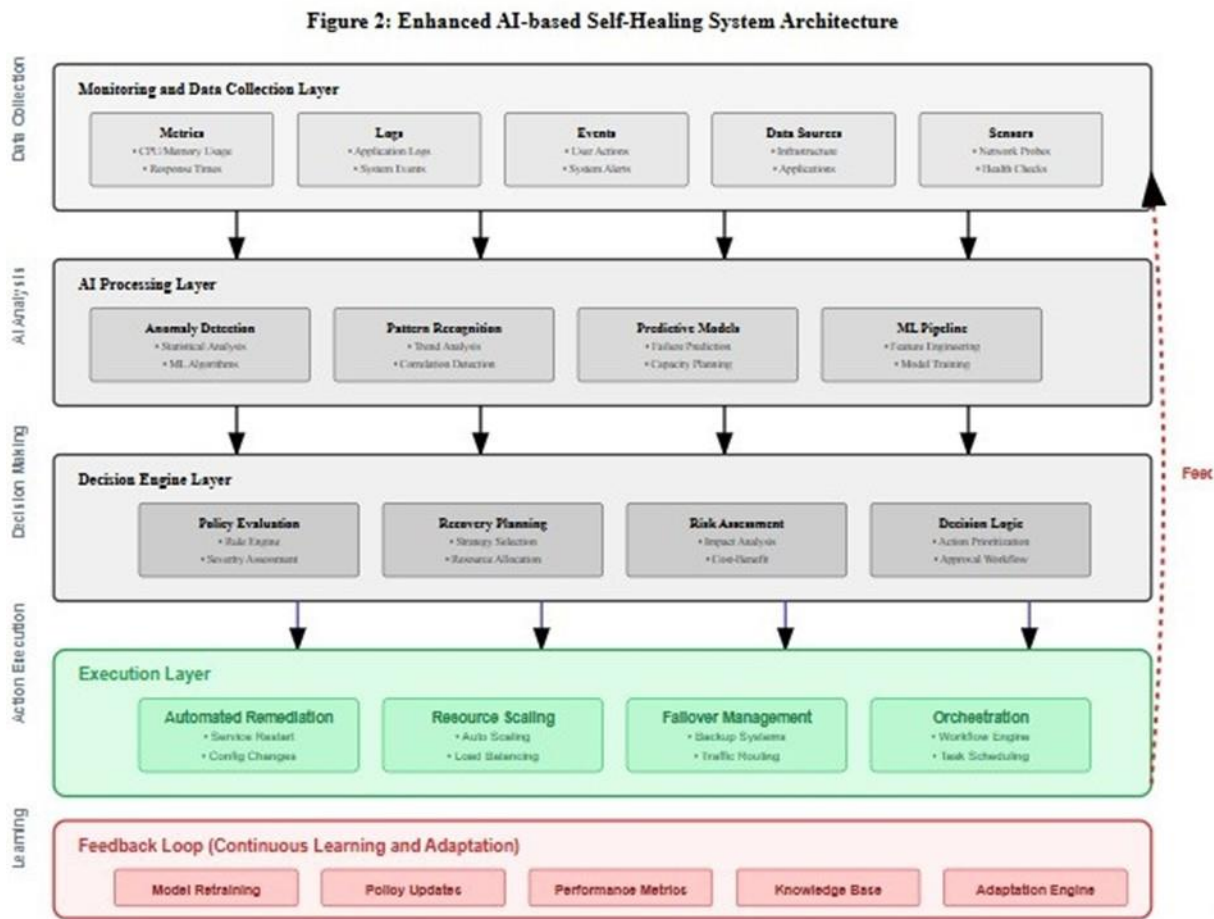


Figure 2: AI-based approaches on Self-Healing Systems

Recent advances in large language models have helped open new opportunities for natural language-based system diagnostics and automated troubleshooting actions. Such AI-enabled strategies have shown enormous potential for increasing system reliability, shortening recovery times, and improving the system performance in comparison with traditional self-healing.

2. Literature Survey

Since the emergence of autonomic computing principles, the self-healing software architectures have grown in a big way. The early work was largely about developing theoretical foundations and basic architectural styles for the self-managing systems. Salehie and Tahvildari conducted a detailed survey on self-adaptive software systems with discussion on key challenges in research and created a taxonomy of self-adaptation mechanisms. Their research underscored the role of feedback in responsive designs and helped pave the way for future innovations in self-healing systems. The development of a practical foothold from the theoretical concepts was started by architectural approaches that enforced modular design and component-based recovery mechanisms. Oreizy et al. proposed an architecture-driven approach to self-adaptive software that based adaptation decisions on models of architecture. This work was important because it showed that software architectures could adapt to changing environments and system failures. The Rainbow architecture of Garlan et al. (2004) helped to develop this approach

further by delivering generic infrastructure for architecture-based self-adaptation and demonstrating it is feasible to build self-healing systems in practice. The extension of self-healing to cloud-based systems has placed new challenges and opportunities in the way. Vaquero et al.'s work related to cloud definitions and characteristics and set a base to understand the cloud environment where self-healing needs to take place for federated cloud systems. Another work of Dustdar and his group extended to the concepts of elastic processes in clouds, pointing out that (dynamic) adaptation mechanisms were required that were capable of dealing with changing workloads and requirements. These efforts laid the theoretical foundation for self-healing mechanisms specifically targeted at cloud computing. The recent trend in self-healing computing can be characterized as the incorporation of artificial intelligence and machine learning methods into systems. Gill, along with his team, presented Radar, a framework to show how machine learning operates for self-configuration and self-healing in cloud computing. This paper presented a noticeable increase in the reliability of the system and minimal need for human intervention in managing the cloud operations. The use of AI methods allows the implementation of more advanced fault detection mechanisms capable of detecting complex failure patterns and even predicting future problems that could affect the performance of the system. With the rise of large language models and sophisticated AI techniques, this deep problem can now also be approached using other AI techniques, particularly in self-healing systems. Very recent efforts of Ji and Luo tested a big language model for AI (fault detection, auto self-healing) in the cloud. Note Studer et al.'s work, which showed how natural language processing techniques could be used to analyze system logs, automatically detect failure patterns, and generate recovery procedures. The result is a major leap for the field, as it should allow the system to be diagnosed and fixed in more human-compatible, intuitive ways. Modern challenges such as distributed failures, multi-tenancy, and security in self-healing have also been the focus of recent research in the cloud. Arora et al. studied self-healing cloud systems powered by Facebook's AI, where they focused on event-driven automation and showed that intelligent event processing could provide improved reliability and reduce downtime. They raised the issue of real-time response and the role of AI in ensuring fast detection and recovery of the fault. Advances in monitoring and observability technologies have also impacted the development of self-healing systems. Today's cloud infrastructure creates oceans of telemetry data, which can be used for AI-powered analysis and decision-making. Studies have demonstrated that machine learning (ML) algorithms can be good at analyzing this data to detect anomalies, forecast failures, and recommend recovery actions. It has been crucial to design proactive self-healing systems to prevent failures from happening rather than just responding to failures after they occur. The integration of AI into self-healing software architectures in cloud environments represents a transformative step in automated system resilience. However, foundational progress in this field has depended on earlier work in machine learning-based fault prediction models, particularly those that empirically benchmark model performance and computational efficiency. These contributions offer practical guidance on how AI models can detect, classify, and anticipate software failures based on observable data patterns. Several empirical studies by Gunda provide essential context in this regard, especially when considering real-world deployment of self-healing systems in large-scale cloud infrastructures. In an early foundational work, Gunda explored the utility of logistic regression and decision tree classifiers on the PC1 software defect dataset to identify fault-prone modules. This study presents one of the clearest illustrations of how traditional, interpretable ML models can be effectively applied to fault prediction. In the context of self-healing systems, such models remain relevant due to their low computational overhead, real-time applicability, and explainability—characteristics essential for high-throughput cloud environments where AI-based detection decisions must be quickly acted upon and understood by system engineers. The paper connects the early use of machine learning with today's AI detection methods, showing how current deep learning advancements are based on proven research techniques. Gunda's other contribution focuses on the comparative performance of Random Forest, Logistic Regression, and K-Nearest Neighbors (KNN) for software fault prediction. This work not only benchmarked these models against precision, recall, and AUC but also

analyzed their behavior across different runtime constraints. Such comparative analysis is critical in self-healing systems, where performance variability under high load can introduce unpredictable recovery behaviors. The choice of recovery model must consider both predictive power and execution feasibility, especially under cloud-scale workloads. Gunda's results provide a model selection framework highly applicable to architectural-level decision-making in AI-driven healing. In another complementary work, Gunda investigated additional classical ML models using alternative datasets, offering insight into the generalizability of software fault predictors across environments. This supports one of the paper's core premises—that AI-based self-healing mechanisms must adapt to varied failure conditions and system architectures. These generalization capabilities are crucial when deploying self-healing agents across federated or heterogeneous cloud environments, where one-size-fits-all models often fail.

2.1 Microsoft Azure Service Fabric's Self-Healing Capabilities

Microsoft Azure Service Fabric represents a significant advancement in self-healing cloud platforms. The platform provides built-in fault tolerance and self-healing capabilities through its distributed systems architecture. Service Fabric implements automatic failure detection, service placement optimization, and health monitoring that enables proactive identification and resolution of system issues. The platform's self-healing mechanisms include automatic failover of stateful services, dynamic load balancing, and resource reallocation based on real-time system conditions. These capabilities demonstrate the practical implementation of self-healing principles in production cloud environments.

2.2 Foundational Machine Learning Studies

The integration of AI into self-healing software architectures depends on foundational progress in machine learning-based fault prediction models. Gunda's empirical studies provide essential context for understanding how AI models can detect, classify, and anticipate software failures. His work on logistic regression and decision tree classifiers for fault-prone module identification demonstrates how traditional, interpretable ML models can be effectively applied to fault prediction in cloud environments where explainability is crucial. The comparative analysis of Random Forest, Logistic Regression, and K-Nearest Neighbors models offers valuable insights into model selection frameworks for AI-driven self-healing systems, particularly considering both predictive power and execution feasibility under cloud-scale workloads.

3. Methodology

This survey is based on a systematic literature review of the status of self-healing software architectures in a cloud computing context. The methodology consists of three main stages that are literature collection, taxonomy and analysis, and critical review of the approaches. The literature collection We searched in several academic databases, such as IEEE Xplore, ACM Digital Library, Springer, and arXiv repositories, by means of filter-based keywords such as "self-healing systems," "autonomic computing," "cloud computing," "artificial intelligence," or "fault detection." The search was aimed at retrieving both seminal works that defined the theoretical foundation for self-healing systems and recent works that bring in the latest in artificial intelligence. The classification stage categorized the obtained literature using several classes that correspond to the contribution and focus of the research. These directions include theoretical perspectives and architectural landscapes; practical cockpit implementation and use cases; AI-based detection mechanisms; recovery and adaptation approaches; and evaluation methods and performance indicators. We attempted to read every paper to extract contributions, methods used, results obtained, and limitations identified. Specific focus was placed on papers showing measured enhancements in quality of reconfigurable system reliability, fault detection accuracy, and recovery time performance. The

categorization was completed by mapping the evolution of research in different application areas, seeing how the field started from simple autonomic computing ideas and has evolved to an AI-powered self-healing system. During the critical analysis phase, analysis (e.g., comparison and commonality) of approaches, challenges faced and their limitations, and practical directions of identified solutions were studied. In this phase we verified the suitability of different software architectural patterns, the efficacy of AI techniques in the detection and recovery of faults, and the scalability of proposed solutions in realistic cloud settings. The assessment covered technical dimensions such as system performance and system reliability advances and operational ones such as complexity of implementation, resource implications, and the need for integration with already existing cloud infrastructure. The methodology also involved examination of evaluation methods employed within the literature, as well as investigation into the limitations of current methods and potential alternates to improve the evaluation of self-healing systems.

4. Critical Analysis of Past Work

Developing Self-Healing Software Architectures The development of self-healing software architectures has progressed substantially; however, there are also remaining challenges that prevent further progress in the current approach. Early theoretical roots set out by Kephart and Chess laid a visionary foundation for autonomic computing, though thus far there has been significant difficulty in translating concepts into functional cloud-based realizations. The core issue is that modern clouds are so complex that static rule-based methods for self-healing will not be enough to manage all the different types of failures and changes that can occur in a distributed system. One of the major shortcomings in previous studies is the assumption of predefined failure scenarios and recovery mechanisms. Earlier self-healing systems were built for specialized failures, resulting in systems that are brittle when exposed to new or complex failure patterns. This problem was brought to attention by Salehie and Tahvildari, where they showed that self-adaptive software systems frequently fail in unusual ways that were not considered in the design process. This limitation has been partially overcome with the development and application of machine learning models; however, contemporary AI-based strategies are yet to generalize from training to novel failure scenarios. The architectural designs defined by researchers like Garlan et al. for the Rainbow architecture have proven the feasibility of architecture-based self-adaptation but have prohibitive scalability when deployed in large-scale cloud systems. These tools are appropriate for single applications or small-sized systems but lack performance when monitoring hundreds or thousands of system components. The overhead of managing architectural models and executing adaptation decisions becomes unaffordable at cloud scale, and the performance overhead may actually be worse than the original issues the systems were designed to solve. Existing AI-driven methods perform very well but encounter their own types of limitations. The recent work of Ji and Luo, which employs large language models for fault detection, implies an inspiration for our research, but their work is more resource-consuming and may add a rather unacceptable latency in the underlying process of the detection of faults, which is unsuitable for real-time fault recovery operations. The interpretability of AI-based decisions is another concern because it must be possible for the system administrators to comprehend why a recovery action was made, especially in a context as important as a critical production environment, where wrong decisions can have devastating effects. The assessment methods employed in many studies also have considerable shortcomings. This work is evaluated in a simulated environment or under synthetic failure scenarios, which do not truly represent the complexity and unpredictability of real cloud failures. In some cases, the criteria adopted to measure the effectiveness of self-healing mechanisms tend only to take into account very limited dimensions of system behavior and an insufficient characterization of the problem also in terms of system stability, resource consumption, and user-level QoS. Such a limited evaluation prevents a true estimate of the effectiveness of the proposed solutions in real settings. A further significant neglect in prior art is that practical aspects of the security impacts of self-healing systems have been largely ignored. While these systems could enhance its reliability, they

also bring with them new attack surfaces and possible vulnerabilities. Since self-healing systems are self-acting, adversaries are able to exploit them so as to intentionally disrupt the system or access resources. Most of the existing work does not properly account for these security threats, as it is targeted to the functional part of self-healing, taking the security issues of autonomous system management into account. Another important limitation of existing work is the issues with integrating self-healing systems into legacy cloud infrastructures. Some of the suggested solutions are applicable in cases of greenfield deployments, where self-healing features can be built in as part of system design. But in reality, the cloud is a heterogeneity of technologies, and for most cloud operators this heterogeneity occurs in two forms: because they cannot switch off the legacy and because they don't have a single framework for self-healing. The research community has not provided sufficient solutions to the practical problems of transitioning current systems to self-healing or of making different self-healing solutions interoperate.

5. Discussion

5.1 AI/ML-Based Decision Making for Detection and Self-Healing

Machine learning models have proven particularly effective in enhancing fault detection and self-healing capabilities. Isolation forests, autoencoders, and Long Short-Term Memory (LSTM) networks can detect unusual patterns in system metrics, including CPU utilization, memory consumption, and network latency. These models excel at identifying anomalies that might indicate impending failures or performance degradation.

Microsoft Azure exemplifies practical implementation of AI-driven self-healing through its intelligent VM failure detection and mitigation systems. The platform uses machine learning algorithms to analyze historical failure patterns, predict potential VM failures, and automatically migrate workloads to healthy nodes before failures occur. This proactive approach significantly reduces downtime and improves overall system reliability.

5.2 Future Research Directions

The examination of current research indicates both significant successes and considerable scope for development. One of the most promising avenues involves building hybrid systems that combine the advantages of multiple AI techniques while addressing their individual limitations. For example, deep learning's pattern recognition capabilities can be integrated with transparent rule-based systems to achieve advanced fault detection with explainable reasoning. The research community should adopt realistic benchmarks and standard metrics to fairly evaluate self-healing system performance. This includes standardizing failure injection frameworks, creating representative workloads for testing, and defining metrics that quantify the complete impact of self-healing systems on system-wide performance and end-user quality of service. Security aspects of self-healing systems require continuous attention. Further efforts are needed in designing secure self-healing architectures that can defend against attacks while maintaining autonomous functionality. This includes investigating secure communication protocols for distributed self-healing systems, authentication and authorization techniques for autonomous actions, and methods to detect and respond to attacks on self-healing infrastructure.

6. Conclusion

We have described a structured survey of such relevant works and have organized this survey of self-healing software architectures in cloud computing, where we have seen steady growth of this research in theory as well as its practical applications, with a lot of the challenges still remaining. The transition from simple autonomic computing ideas to powerful AI-based self-healing systems is evidence of the promise of autonomous management

in cloud computing. The application of artificial intelligence (AI) techniques has been particularly promising, and recent research findings have renewed interest in this area due to the reported increases in fault detection accuracy and in the reliability of the system, making further investment in AIs an appealing approach to pursue. Nonetheless, it also highlights key gaps to fill for self-healing systems to reach their full potential. To the research community, there is an urgent request for more comprehensive evaluation methodology, a more suitable existing system integration approach, and deeper security consideration. Also, the standardization of frameworks and interoperable standards is needed to facilitate the broad adoption of self-healing technologies in production cloud environments. The future of self-healing systems is bright, with new technology developments like large language models and sophisticated AI/ML techniques showing potential for decision-making in an autonomous system. If this potential is to be realized, it will require consistent research effort as well as increased collaboration between academia and industry and a focus on the practical issues of deploying autonomous systems in critical production environments. "Cloud computing and distributed systems keep evolving and becoming more complex, so self-healable architectures will continue to be an active and relevant field of study for many years to come."

References

- 1 C. Ji and H. Luo, "Cloud-Based AI Systems: Leveraging Large Language Models for Intelligent Fault Detection and Autonomous Self-Healing," arXiv preprint arXiv:2505.11743, May 2025.
- 2 S. Ravi, "AI-Powered Self-Healing Cloud Infrastructures," *Migration Letters*, vol. 21, no. 3, pp. 1–15, 2025.
- 3 R. K. Arora, A. Kumar, A. Soni, and A. Tiwari, "AI-Driven Self-Healing Cloud Systems: Enhancing Reliability and Reducing Downtime through Event-Driven Automation," in *AI for Cloud Computing*, SCRS, 2024.
- 4 J. O. Kephart and D. M. Chess, "The vision of autonomic computing," *Computer*, vol. 36, no. 1, pp. 41–50, Jan. 2003.
- 5 M. Salehie and L. Tahvildari, "Self-adaptive software: Landscape and research challenges," *ACM Transactions on Autonomous and Adaptive Systems*, vol. 4, no. 2, pp. 1–42, May 2009.
- 6 S. Kounev, X. Zhu, and A. Abounaga, "Self-aware and self-adaptive cloud autoscaling systems," *IEEE Cloud Computing*, vol. 2, no. 1, pp. 22–28, 2015.
- 7 R. Calinescu et al., "Dynamic QoS management and optimization in service-based systems," *IEEE Transactions on Software Engineering*, vol. 37, no. 3, pp. 387–409, May 2011.
- 8 S. K. Gunda, "Enhancing Software Fault Prediction with Machine Learning: A Comparative Study on the PC1 Dataset," in *Proc. IEEE Conf.*, 2024.
- 9 Y. Brun, G. Marzo Serugendo, C. Gacek, H. Giese, H. Kienle, M. Litoiu, H. Müller, M. Pezzè, and M. Shaw, "Engineering self-adaptive systems through feedback loops," in *Software Engineering for Self-Adaptive Systems*, Springer, 2009, pp. 48–70.
- 10 D. Weyns, M. U. Iftikhar, and D. Garlan, "Self-healing of cloud-based systems: State of the art and challenges," *IEEE Software*, vol. 36, no. 5, pp. 28–35, Sep. 2019.
- 11 P. Horn, "Autonomic computing: IBM's perspective on the state of information technology," IBM, Oct. 2001.

- 12 A. Avizienis, J.-C. Laprie, B. Randell, and C. Landwehr, "Basic concepts and taxonomy of dependable and secure computing," *IEEE Transactions on Dependable and Secure Computing*, vol. 1, no. 1, pp. 11–33, Jan. 2004.
- 13 J. Kramer and J. Magee, "Self-managed systems: an architectural challenge," in *Future of Software Engineering*, IEEE, 2007, pp. 259–268.
- 14 M. Parashar and S. Hariri, "Autonomic computing: An overview," in *Unconventional Programming Paradigms*, Springer, 2005, pp. 257–269.
- 15 S. Dustdar, Y. Guo, B. Satzger, and H. L. Truong, "Principles of elastic processes," *IEEE Internet Computing*, vol. 15, no. 5, pp. 66–71, Sep. 2011.
- 16 A. Gambi, G. Toffetti, and C. Pautasso, "Kriging-based self-healing for cloud applications," in *Proceedings of the 9th International Conference on Autonomic Computing*, 2012, pp. 73–82.
- 17 L. M. Vaquero, L. Rodero-Merino, J. Caceres, and M. Lindner, "A break in the clouds: towards a cloud definition," *ACM SIGCOMM Computer Communication Review*, vol. 39, no. 1, pp. 50–55, Jan. 2009.
- 18 S. K. Gunda, "Fault Prediction Unveiled: Analyzing the Effectiveness of Random Forest, Logistic Regression, and KNeighbors," in *Proc. IEEE Conf.*, 2024.
- 19 S. Krishnan and J. S. Vitter, "Self-healing systems and cloud computing," in *Handbook of Cloud Computing*, Springer, 2010, pp. 181–200.
- 20 A. J. Ramirez, B. H. C. Cheng, and P. K. McKinley, "Adaptive monitoring of software requirements," in *Proceedings of the 1st International Workshop on Requirements at Run Time*, 2010, pp. 41–50.
- 21 R. Sterritt, "Autonomic computing," *Innovations in Systems and Software Engineering*, vol. 1, no. 1, pp. 79–88, Mar. 2005.
- 22 P. Jamshidi, A. Ahmad, and C. Pahl, "Cloud migration research: A systematic review," *IEEE Transactions on Cloud Computing*, vol. 1, no. 2, pp. 142–157, Jul. 2013.
- 23 S. R. White et al., "An architectural approach to autonomic computing," in *Proceedings of the International Conference on Autonomic Computing*, 2004, pp. 2–9.
- 24 M. C. Huebscher and J. A. McCann, "A survey of autonomic computing—degrees, models, and applications," *ACM Computing Surveys*, vol. 40, no. 3, pp. 1–28, Aug. 2008.
- 25 P. Oreizy, M. M. Gorlick, R. N. Taylor, D. Heimbigner, G. Johnson, N. Medvidovic, A. Quilici, D. S. Rosenblum, and A. L. Wolf, "An architecture-based approach to self-adaptive software," *IEEE Intelligent Systems*, vol. 14, no. 3, pp. 54–62, May 1999.
- 26 J. Zhang and B. H. C. Cheng, "Model-based development of dynamically adaptive software," in *Proceedings of the 28th International Conference on Software Engineering*, 2006, pp. 371–380.
- 27 D. Garlan, S. W. Cheng, A. Huang, B. Schmerl, and P. Steenkiste, "Rainbow: Architecture-based self-adaptation with reusable infrastructure," *Computer*, vol. 37, no. 10, pp. 46–54, Oct. 2004.

- 28 S. Dustdar, Y. Guo, B. Satzger, and H. L. Truong, "Self-healing and self-optimizing cloud applications: A research roadmap," in Proceedings of the 2013 IEEE International Conference on Cloud Engineering, 2013, pp. 232–239.
- 29 S. K. Gunda, "Comparative Analysis of Machine Learning Models for Software Defect Prediction," in Proc. IEEE Conf., 2024.
- 30 R. Buyya, C. S. Yeo, S. Venugopal, J. Broberg, and I. Brandic, "Cloud computing and emerging IT platforms: Vision, hype, and reality for delivering computing as the 5th utility," Future Generation Computer Systems, vol. 25, no. 6, pp. 599–616, Jun. 2009.