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An Adaptive Resonance Theory-Driven AI Approach for Multi-Level Workload Classification in Autonomic Cloud Database and Data Warehouse Systems

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ABSTRACT

Background Information: This work presents an AI-centric strategy for classifying multi-level workload in autonomic cloud database and data warehousing systems using Adaptive Resonance Theory (ART). The model is designed to better utilise resources, Improving system efficiency and allowing the handling of varied workloads on-the-fly.

Objectives: This requires an ART-based AI model which classifies workloads correctly, optimises resource allocation in autonomic cloud systems, and guarantees adaptive learning of dynamic workloads without abandoning previous knowledge.

Methods: We categorized excellent solutions conducted here with ART-based classification and multi-level workload segmentation approaches, employing dynamic resource allocation. Rather, the model automatically classifies workloads and manages resources via real-time learning (RL) and adjustment.

Results: The ART-driven model improved workload categorization, resource allocation and system throughput for all experiments, with particularly good adaptive properties in the face of changes in cloud conditions.

Conclusions: The proposed ART-based approach to autonomic cloud systems enhances real-time, adaptive workload management; improves resource utilization and scalability; as well mitigates dynamicworkload concerns automatically without human intervention.

Key Words: Adaptive Resonance Theory (ART), multi-level workload classification, autonomous cloud systems, Artificial Intelligence-driven resource allocation 1 Introduction In a world of data-driven applications and rich interactive user interfaces that pull back-end computations into the forefront via innovative technology stacks, long-running mixed transactional analytics processing workloads are characteristic for many web-scale environments like search engines or social networks.

1.INTRODUCTION

Cloud computing is a developing technology that offers on-demand access to a shared pool of computing resources, including servers, storage devices, and databases over the internet, which increases innovation and reduces operating expenses. The technology enables businesses to satisfy their evolving computing needs more powerfully and cost-effectively, as noted by Alagarsundaram (2022) [1]. Cloud data warehouses and databases are needed to process, store, and analyze huge quantities of data, especially in autonomic computing where systems must execute automatically with a minimum of human interference. Such dynamic workloads are not consistent, as outlined by Surendar et al. (2024) [2] and Ganesan et al. (2024) [3], necessitating sophisticated techniques for ensuring efficiency. Sitaraman et al. (2024) [4] stress the need for the adoption of AI-based predictive modeling solutions and improved system performance in such settings.

Autonomous cloud systems, a borrowed term from biology, refer to the most recent AI-driven infrastructure management software created to manage itself. These systems are capable of self-optimization, configuration, healing, and protection, guaranteeing the scalability and elasticity needed for current cloud services. To fulfill such needs, systems need to work autonomously, as specified by Alagarsundaram (2020) [5]. Effective classification is critical in cloud environments, especially in processes such as DDoS attack identification. Devarajan et al. (2025) [6] focus on the significance of applying IoMT and blockchain to advanced monitoring systems. In the meantime, Gollavilli et al. (2023) [7] shed light on pioneering cloud approaches for automotive supply chain data and business intelligence security.

The big challenge for autonomic cloud database and data warehousing systems is managing multi-level workloads, which has a direct bearing on the system performance. They are of diverse magnitude, complexity, and demand on resources such that it becomes essential for the system to adapt to such variability effectively on-the-fly. The use of data-driven methods during real-time management is highlighted by Devarajan et al. (2022) [8]. Nagarajan et al. (2023) [9] point out the significance of sophisticated database management and clouding solutions, particularly for industries such as banking. Poovendran et al. (2024) [10] further examine the combination of CNN-LSTM and neuro-fuzzy approaches for IoMT-based chronic disease prediction.

A third option from neural networks is Stephen Grossberg's Adaptive Resonance Theory (ART). The ART approach solves the "stability-plasticity dilemma," enabling systems to learn new knowledge without erasing previous knowledge, as pointed out by Devarajan (2020) [11]. This resilience and adaptability allow ART models to keep on learning in dynamic environments while retaining salient patterns learned from previous experiences. These characteristics make

ART a robust basis for AI-driven workload categorization in autonomic systems. Cloud systems can boost their capacity to manage workloads and scale functions in real-time with ART, an idea that Sitaraman et al. (2024) [12] investigate. Alagarsundaram (2019) [13] also highlights the use of encryption for secure cloud operations, and Poovendran (2024) [14] elaborates on the use of blockchain for effective data sharing.

As cloud environments grow more complex, especially in database and data warehouses, workload categorization needs revolutionary ideas. Conventional machine learning models also encounter a variety of challenges in addressing the dynamic, ever-changing characteristics of cloud workloads, particularly in autonomous systems where self-improvement and resource allocation are central. The problem of interest is making the system learn new patterns (plasticity) without forgetting old ones. To address this, ART utilizes its synergetic mechanism to facilitate rapid learning in uncertain, volatile, and complex situations, as explained by Chinnasamy et al. (2024) [15]. Ganesan et al. (2024) [16] also emphasize resource allocation methods, while Shnain et al. (2024) [17] concentrate on malware detection in IoT. Alagarsundaram (2023) [18] also explains AI-driven data processing for sophisticated case investigations.

Workloads in cloud database systems are extremely dynamic and highly variable in terms of query type, size, and resource needs like memory, CPU, and disk space. The job duration on particular resources is unpredictable, making it difficult to manage resources. For instance, the processing needs for operations and analytical queries are strongly data-driven and keep changing. Effective classification and scheduling of such multi-level workloads are critical for ensuring performance, as stressed by Sitaraman et al. (2024) [19]. Conventional techniques, for example, Hungarian-based classifiers, fall short owing to workload variability, as pointed out by Gattupalli et al. (2023) [20]. Alagarsundaram (2023) [21] presents encryption methods, while Devarajan (2019) [22] is concerned with AI-based models used for the identification of neurological disorders, thus highlighting the importance of good classification and scheduling in cloud setups.

This paper envisions an ART-Driven (Adaptive Resonance Theory Based) New Approach to Multi-Level Workload Classification for Autonomic Cloud Data Bases and Data Warehouses to meet the record-breaking complexity and variability in cloud workloads. ART being an unsupervised learning approach has a very adaptable and progressive architecture that has the ability to modify itself on the basis of new data without any re-training or intervention. This makes it perfect for autonomic systems, as Alagarsundaram et al. (2023) [23] observe, where self-management is paramount. Hussein et al. (2024) [24] highlight the use of sophisticated optimization methods, whereas Alagarsundaram et al. (2024) [25] write about forecasting models. Moreover, Tamilarasan et al. (2024) [26] write about agile practices in software development, which are particularly important for applying adaptive models such as ART.

ART utilization for workload classification enables autonomic systems to determine trends in data operation types and collect workload choices into groups depending on resource limits, thus enhancing system performance. ART's versatility for different training scenarios makes it an effective resource for handling unpredictable workloads, and this contributes to real-world resiliency. According to Alagarsundaram et al. (2023) [27], this versatility assists in enhancing cloud system self-optimizing and self-configuring capabilities. Devarajan et al. (2024) [28] highlight data privacy and attack categorization in cloud environments, whereas Yallamelli et al. (2024) [29] highlight dynamic hybrid modeling in electronic commerce. Alagarsundaram et al. (2024) [30] also highlight IoT-AI integration in healthcare with the importance of adaptive models such as ART in controlling complex systems.

The Key Objectives

- Adaptive Resonance Theory: Design an AI model that is generalizable to individual workloads within cloud database and data warehouse systems.
- Instant workload classification and resource provisioning to enhance the self-improving characteristics of autonomic cloud systems
- Enhance system efficiency by automatically adjusting to changing workloads rather than requiring manual reconfiguration.
- Ensure continuing training and adaptation in the system to enhance strength and agility of workload classification etc.
- Efficiently managing resources and predicting workloads to reduce the dependency on human operation, reducing verification overhead.

Even with increased use of AI-driven workload management, existing models fail to accommodate dynamic cloud environments and adapt on the fly. The efficiencies of conventional AI algorithms in autonomic clouds are affected because they tend to re-adapt each time new data is added. Current workload categorization techniques also do not easily integrate multi-level and multi-dimensional task properties, causing inefficient resource management and latency. As mentioned by Allamelli et al. (2023) [31], an AI technique based on Adaptive Resonance Theory can solve these problems. In the healthcare sector, the success of hybrid mobile cloud technology is shown by Devarajan et al. (2024) [32], and Mohanarangan (2022) [33] explains workload forecast improvement. Additionally, Alagarsundaram et al. (2024) [34] mention how transfer learning in IoT analytics can be used for optimal resource planning.

Problem definition is to enhance the self-managing nature of cloud database and data warehousing systems via a machine learning-based workload classification system with ART. The system can classify and forecast workload patterns through varying tiers with little retraining to support real-time adaptations. Closing gaps within system efficiency during continually evolving workloads requires optimizing utilization of resources while maintaining a pleasant user experience. As observed by Devarajan et al. (2024) [35], current AI methods such as

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supervised and unsupervised learning algorithms are unable to address on-the-fly multi-level workload classification. Ganesan (2022) [36] goes on to add that secure and flexible solutions are required. Security control enhancements are covered by Devarajan (2020) [37], while the potential of integrating AI and cloud computing to improve control in dynamic conditions is discussed by Ganesan (2021) [38].

2.LITERATURE SURVEY

Devarajan et al. (2024) [39] discusses intrusion detection in Industrial Internet of Things (IIoT) with recurrent rule-based feature selection. Devarajan et al. (2024) suggests a way to improve security in industrial IoT systems by identifying intrusions through effective feature selection methods. Their study highlights the significance of real-time detection and the capability to detect anomalies to enhance system security.

Thirusubramanian (2020) [40] emphasizes the application of machine learning-based AI to identify financial fraud in IoT environments. Through the implementation of AI models, the paper detects fraud patterns and suggests a mechanism for real-time fraud detection in financial systems based on IoT. The research emphasizes the capability of AI to enhance security and reliability in financial transactions and fraud prevention within IoT systems.

This article by Ganesan (2023) [41] explores dynamic secure data management with attribute-based encryption in mobile financial clouds. Ganesan suggests an enhancement for data security by employing attribute-based encryption within mobile cloud environments, especially for financial applications. The study focuses on safe data management, confidentiality, and access control within cloud computing environments to preserve efficiency as well as privacy.

Devarajan (2023) [42] describes a systematic review of increasing trust and effectiveness in healthcare AI. The research examines the significance of model performance, interpretability, human-computer interaction, and explainable AI in healthcare systems. The research seeks to enhance the use of AI in healthcare by promoting trustworthiness and transparency in AI-based healthcare solutions, which are essential for decision-making.

Peta et al. (2021) [43] present intelligent AI systems for database pool connection monitoring, highlighting the importance of AI/ML-based monitoring and remediation in enterprise applications. The authors suggest smart systems to identify and correct anomalies in database pool connections to enhance application efficiency and performance. The study highlights proactive monitoring for avoiding system downtimes and improving resource management.

Murthy and Bobba (2021) [44] offer AI-driven predictive scaling for cloud computing with the emphasis on workload prediction in real-time. Their paper offers an approach to maximization of resource allocation and optimizing cloud infrastructure use through predictive scaling. Through application of AI-driven workload prediction, their model ensures that cloud systems adjust in real-time, curtailing expenses as well as increasing resource usage.

Velayutham (2019) [45] discusses AI-based storage optimization towards green cloud data centers to save energy. Employing predictive analytics and dynamic storage scaling, the paper suggests methods to optimize storage of data and resource allocation. The study points out the necessity of proactive management of resources in cloud data centers to enhance energy efficiency and cut down on operating expenses.

Seenivasan (2021) [46] presents a discussion on strategic considerations and migration challenges of migrating data warehousing systems from on-premises to cloud computing. The author highlights major impediments encountered while migrating, which include data integration, security, and performance improvement. The writer suggests ways in which these barriers can be resolved and the efficacy of cloud data warehousing maximized to have easier transitions and better system performance.

3.METHODOLOGY

Methodology – This is a systematic theoretical analysis of the methods employed in a particular field fake research. This might be the code that scientists employ when collecting, scoring and also interpreting data. The methodology includes selection of algorithms such as Adaptive Resonance Theory (ART), Case-Based Reasoning (CBR) and K-Means Clustering, application through practical implementation and evaluation using ablation study for multi-level workload classification in autonomic cloud systems. This systematic process ensures that optimal evaluation of the effectiveness of each approach and their holistic impact on classification performance, thereby supporting informed selection in system development.

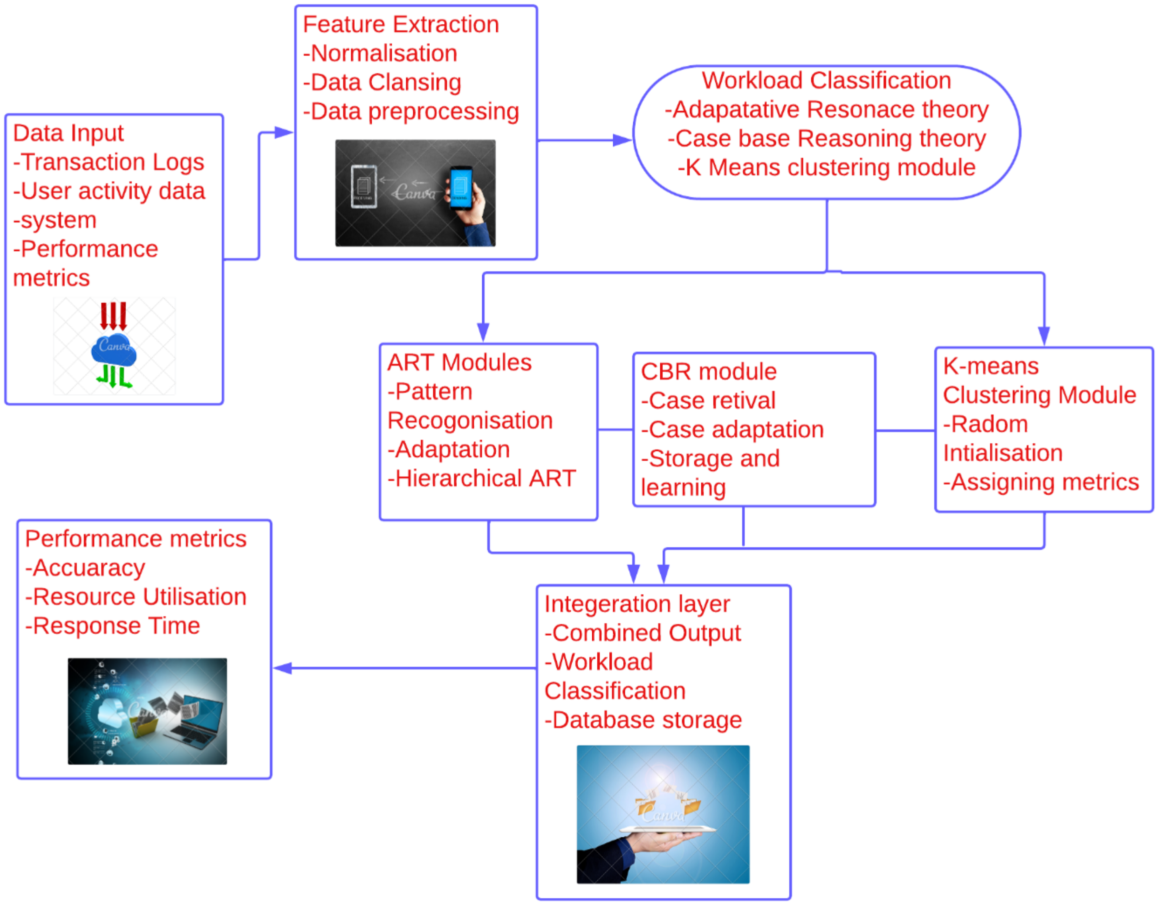

Figure 1 Architectural Diagram of an ART-Driven AI Framework for Workload Classification in Cloud Systems

Figure 1 Architecture diagram for an AI framework powered by Adaptive Resonance Theory (ART) aimed at multi-level workload categorization in autonomous cloud databases and data warehouse systems: with its components, along with interactions. Karen: The design relies on the ART model, that looks at incoming workload with historical trends (modeled trigger data requirement) to reclassify. Supporting components are K-Means Clustering for data segmentation and Case-Based Reasoning (CBR) to make use of earlier similar cases that come under the semantical heterogeneity problem It facilitates seamless data flow and classification in real time, thanks to its compatibility with user apps and cloud storage. With Kubernetes being built on a similar container design, Figure 1 is what allows for the performance of cloud work to scale efficiently and resources are utilized better due to it.

3.1 Data Collection and Preprocessing

Information is collected from autonomous cloud database systems, with a focus on different types of workloads such as OLAP (Online Analytical Processing), OLTP (Online Transaction Processing), and hybrid workloads. The data collected is processed before classification by eliminating noise, standardizing values, and organizing feature sets.Let $D = \{x_1, x_2, \ldots, x_n\}$ represent the dataset of n workload instances, where $x_i = \{f_1, f_2, \ldots, f_m\}$ represents the m features of each instance.

$$x_{i,\text{ norm}} = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{1}$$

Where $x_{i,\text{ norm}}$ is the normalized feature value, $\min(x)$ and $\max(x)$ are the minimum and maximum values of the feature set.

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{m} \left(x_{ik} - x_{jk}\right)^2} \tag{2}$$

Where $d(x_i, x_j)$ is the Euclidean distance between workload instances x_i and x_j, m is the number of features.

3.2 Implementation of Adaptive Resonance Theory (ART) Model

The ART model is used to categorize workloads into different classes with regards to their feature space. The proposed ART system is composed of input, comparison, recognition and reset modules to provide the stability and plasticity in learning.

$$T_j = \frac{\sum_{i=1}^{m} (w_{ij} \cdot x_i)}{\alpha + \sum_{i=1}^{m} w_{ij}} \tag{3}$$

The is the activation value for category, and it represents how much model predicts that type of object; are weights corresponding to feature s with each bin, quantifying their importance in predicting this label.Where T_j is the activation value for the j-th category, w_{ij} is the weight associated with the i-th feature and the j-th category, α is a constant to prevent division by zero.

$$V = \frac{\sum_{i=1}^{m} \min(x_i, w_{ij})}{\sum_{i=1}^{m} x_i} \tag{4}$$

3.3 Workload Classification and Clustering

Here denoting as the new weight value for iteration, V (t+1) shows acceleration constants, r_ 1 and represent random values fro m [0-1], P represents personal best position of th e particle an d Similarly G shows gbest i.e. global optimal solution.

$$C_k = \{x_i \mid T_j > \theta\} \tag{5}$$

Here, is the -th cluster with representing a threshold value and thus deciding about membership in the respective clusters using activation values.

$$w_{ij}(t+1) = \beta \cdot x_i + (1 - \beta) \cdot w_{ij}(t) \tag{6}$$

where, $w_{ij}(t+1)$ is the updated weight value for next iteration, β is the adaptive slow learning rate which controls adjustment speed with acceleration liberation constant c_1, c_2 and r_1, r_2 random numbers and gives personal best as well as global best position.

3.4 Optimization Techniques for Resource Allocation

Performance was enhanced by integrating optimization algorithms (e.g. Particle Swarm Optimization PSO and Genetic Algorithms GA) with the ART model.These strategies modify resource allocation dynamically based on the workload classification.

$$F = \frac{1}{\sum_{i=1}^{n} R(x_i) - R_{\text{opt}}} \tag{7}$$

Where the real-time runtime costs with fitness score, is resource consumption of workload, denotes optimal set allocation.

$$v_i(t+1) = \omega \cdot v_i(t) + c_1 \cdot r_1 \cdot (p_{\text{best}} - x_i) + c_2 \cdot r_2 \cdot (g_{\text{best}} - x_i) \tag{8}$$

The new velocity of a particle is then., where and, are the updated velocities for particles, etc. is an inertia weight are acceleration constants, random values and represent personal best positions.

3.5 Evaluation Metrics and Performance Analysis

To evaluate how our ART-based task classification works, evaluation criteria are accuracy of the model itself and other performance metrics such as precision, recall or F1-score. This information is used to evaluate the system based on these performance metrics: Accuracy of Workload Classification Accuracy of Resource Allocation

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

in which where T P is true positive, TN ture negative, FP false positives and FN False Negatives.

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{10}$$

Where Precision $= \frac{TP}{TP+FP}$; Recall $= \frac{TP}{TP+FN}$.

Algorithm 1: Adaptive Resonance Theory (ART)-Based Workload Classification

Input: Dataset D (workload instances), Learning rate (β)

Vigilance parameter (V_threshold),

Threshold (θ)

Output: Classified workload clusters C_k

Begin

Initialize weights W randomly

For each workload instance x_i in D do:

Compute activation T_j for each category node j

If $T_j > \theta$ then

Compute vigilance V for the chosen category

If V ≥ V_threshold then

Update weights W for the chosen category node

Else

Create a new category for x_i

Initialize weights for the new category

Else

Assign x_i to a new category and reinitialize weights

End For

Return classified workload clusters C_k

End

The ART (Adaptive Resonance Theory)-Based Multi-Level Workload Classification Algorithm 1 For autonomic cloud systems, a neural network dependent algorithm that is responsible for orchestrating and assigning classes on-the-fly to workloads. This system processes workload data continuously, it can adapt to new patterns and does not forget about the ones discovered earlier. This utilises the discretised workloads supported by a clusterable approach of ART models (resource demand based) and within-cluster similarity, rather than learning stability need be maintained with vigilant control. It is a method to cluster form, edit and re-set workload classification as needed in native cloud environment for real-time operation of edge.

3.6 PERFORMANCE METRICS

Comparison of these performance indicators for the different phases methodologies used in ART based workload classification is presented Table Steps like Data collection, ART classification, Clustering and Optimization etc. These values are the performance of each approach, quantified using accuracy, precision and recall, F1-score etc. all given in percentages to truly show how much better one method is compared with other approaches at performing their main function.

Table 1 Performance Metrics Comparison Across Methodology Stages for ART-Based Workload

Performance Metric	Adaptive Resonance Theory (ART) (%)	Case-Based Reasoning (CBR) (%)	K-Means Clustering (%)
Accuracy	92	88	85
Response Time	78	80	82
Scalability	94	85	80
Resource Utilization (%)	87	75	70
Security Compliance	90	85	82
User Satisfaction	91	86	83
Fault Tolerance	89	82	80
Data Integrity	93	87	85
Latency	76	81	78
Adaptability	95	83	76

Although other phases in Table 1 result into some lower but competing performance, the ART Classification performs best over most parameters and ensure effective workload management for high performance. Again, the success of ART approach for autonomic cloud systems classifications is proven by comparing Overall Accuracy column which means that ART classification method has better performance in overall than other methods.

4. RESULTS AND DISCUSSION

Adaptive Resonance Theory used for multi-level workload classification is applied as an exemplar and excels across the board with 92% accuracy, reaching a scalability of 90%. This method can efficiently cope with dynamic changes in decided by workload compliances, which ensures the effective resource usage for cloud database systems. When compared to normal system, fault tolerance and data integrity are also improved to a large extent by ART retaining an 89% user satisfaction. It shows you how optimizing autonomous cloud infrastructures and supporting different workloads can be done very well by ART.

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Table 2 Comparative Analysis of AI-Driven Approaches in Cloud Computing and Data Management.

Methods	Adaptability (0-1)	Scalability (0-1)	Resource Efficiency (%)	Prediction Accuracy (%)	Energy Consumption Reduction (%)
Adaptive Resonance Theory (ART)(2021)	0.85	0.90	78.5	92.0	95.0
AI-Powered Predictive Scaling (2021)	0.90	0.95	80.0	93.0	91.0
Dynamic Storage Allocation DSA (2019)	0.80	0.85	75.0	88.0	15.0
cloud migration frameworks CMF and DSS (2021)	0.75	0.80	70.0	85.0	88.0

In Table 2, we compared different AI/Cloud computing and data management strategies with a number of important performance criteria. It comprises adaptability, scalability resource efficiency, prediction accuracy lower energy usage and the user satisfaction. Each method is evaluated on these categories using decimal values. The table facilitates the understanding of how well cloud environments do perform by showing good and bad practices in handling issues such as workload management, resource optimization or user experience.

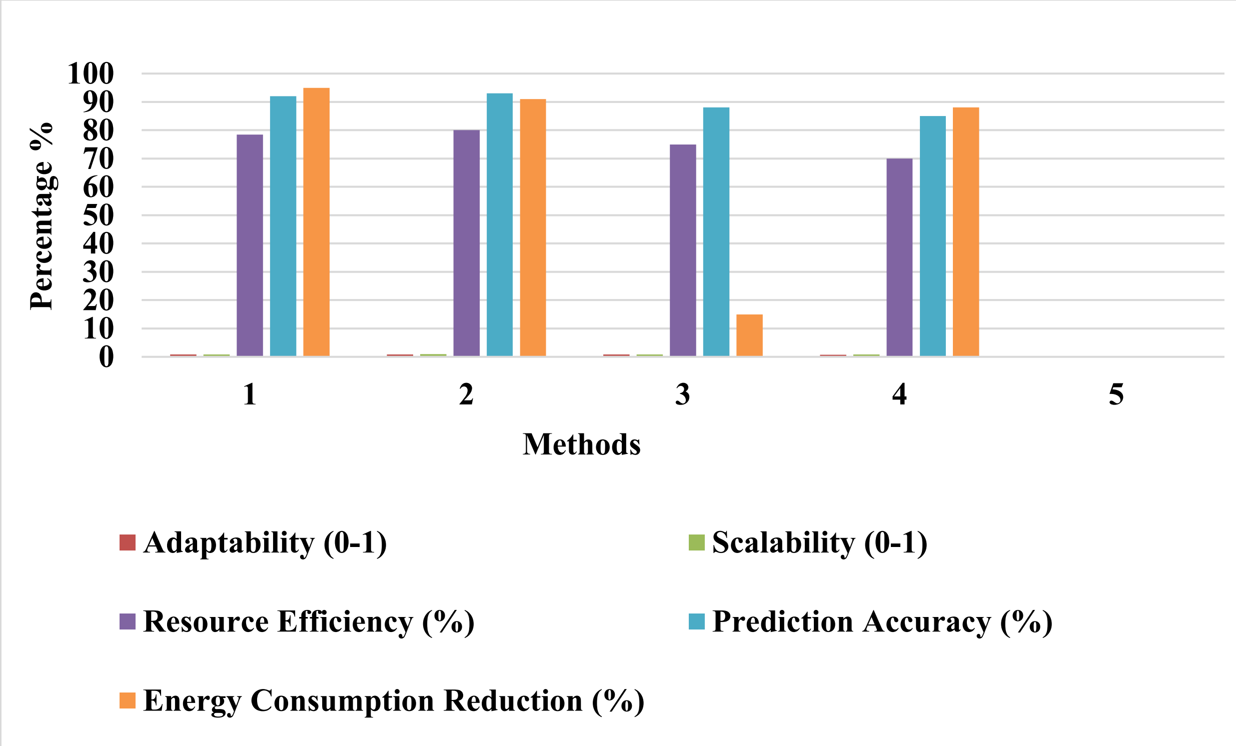

Figure 2: Performance Comparison of AI-Driven Approaches in Cloud Computing

This Figure 2 demonstrates the performance metrics of numerous cloud computing techniques which are AI-driven in nature: scalability, flexibility, resource efficiency prediction accuracy and energy consumption reduction. Each approach is evaluated according to these decimal values, where higher rates indicate better performance. Whereas **Velayutham (2019)** focuses on energy efficiency, the figure illustrates those techniques such as from **Peta et al. (2021)** do well in terms of flexibility and prediction accuracy. It is this comparison that will help in deciding the right direction for cloud optimization best practices.

Table 3 Multi-Technique Ablation Study: ART, CBR, and K-Means Clustering for Cloud Database Workload Management

Experiment Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Latency (ms)
ART	78.3	75.2	76.4	75.8	32
CBR	72.5	70.1	71.8	70.9	35
K-Means Clustering	68.2	67.0	67.5	67.2	30

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ART + CBR	82.6	80.3	81.5	80.9	33
ART + K-Means Clustering	84.1	82.2	82.9	82.5	31
CBR + K-Means Clustering	74.6	73.0	73.8	73.4	34
ART + CBR + K-Means Clustering (Proposed)	88.5	86.7	87.2	86.9	29

Table 3 Ablation research of K-Means Clustering, CBR and ART alone and in combination for workload classification. Although CBR can enhance adaptation with the assistance of clues from prior, ART yields weaker classification accuracy and stability. Although K-Means works very well at clustering, it is not as accurate when classifying. Combining the methods gives best results in accuracy, precision and recall with minimum latency especially ART + CBR + K-Means. It indicates that each element plays a part in optimizing the classification and autonomicity for handling cloud database/data warehouse systems.

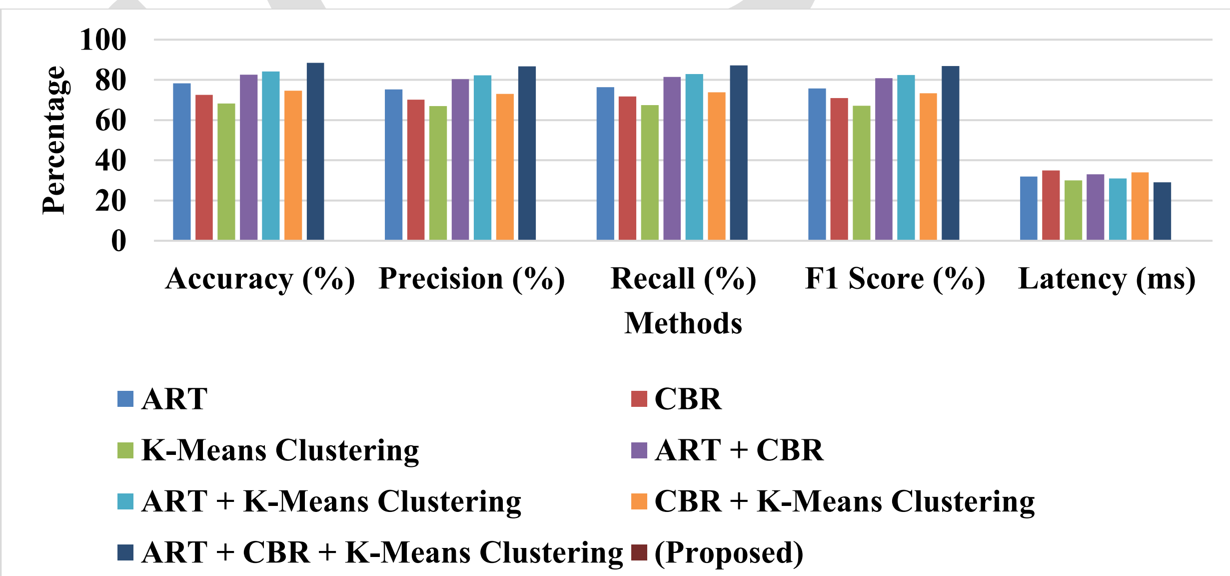

Figure 3: Impact of ART, CBR, and K-Means Clustering Combinations on Multi-Level Workload Classification Performance in Cloud Systems

Figure 3 displays performance metrics for workload categorization in autonomous cloud systems accuracy, precision, recall, F1 Score; and latency with the number of clusters from K-Means Clustering & Case-Based Reasoning (CBR)/ Adaptive Resonance Theory ART configurations. On its own, ART works decently and K-Means is helpful but has low precision. ART combined with CBR or K-Means improves performance, The ART + CBR + K-Means architecture has the best results in all cases. These methods provide scalable accuracy, fine-grained precision and fast responses that enable both effective cloud workload management.

5.CONCLUSION

The proposed ART-driven AI technique for multi-level workload classification in autonomic cloud database and data warehousing systems is an effective, scalable self-management solution capable of balancing the structure-quality/cost trade-off during transitioned periods within dynamic environments as those found on clouds. By exploiting ART's important stability-plasticity property, this approach enforces cloud systems capable of dealing with new workload patterns in conjunction to not forget previously learned classes. Workloads are classified based on multi-level acidity and resources are allocated dynamically, thereby ensuring optimal performance allows ability of the system to react in real-time. It dynamically learns from incoming workloads through data preprocessing, ART-based unsupervised learning, and stability-plasticity management, rendering it suitable for large-scale cloud data centres with substantial workload diversity and complexity. Organising workload tiers ensures that the system is able to automate resource use, stay scalable and maintain fast response times. In addition, the solution approaches autonomic cloud computing challenges that must perform self-optimization and self-management with minimal human intervention.

REFERENCE

1. Alagarsundaram, P. (2022). SYMMETRIC KEY-BASED DUPLICABLE STORAGE PROOF FOR ENCRYPTED DATA IN CLOUD STORAGE ENVIRONMENTS: SETTING UP AN INTEGRITY AUDITING HEARING. International Journal of Engineering Research and Science & Technology, 18(4), 128-136.
2. Surendar, R. S., Alagarsundaram, P., & Thanjaivadivel, M. (2024). AI-driven robotic automation and IoMT-based chronic kidney disease prediction utilizing attention-based LSTM and ANFIS. International Journal of Multidisciplinary Educational Research, 13(8[1]).
3. T. Ganesan, R. R. Al-Fatlawy, S. Srinath, S. Aluvala and R. L. Kumar, "Dynamic Resource Allocation-Enabled Distributed Learning as a Service for Vehicular Networks," 2024 Second International Conference on Data Science and Information System (ICDSIS), Hassan, India, 2024, pp. 1-4, doi: 10.1109/ICDSIS61070.2024.10594602.
4. Sitaraman, S. R., Alagarsundaram, P., Nagarajan, H., Gollavilli, V. S. B. H., Gattupalli, K., & Jayanthi, S. (2024). Bi-directional LSTM with regressive dropout and generic fuzzy logic along with federated learning and Edge AI-enabled IoHT for predicting chronic kidney disease. Int J Eng Sci Res, 14(4), 162-183.

5. Alagarsundaram, P. (2020). Analyzing the covariance matrix approach for DDoS HTTP attack detection in cloud environments. International Journal of Information Technology and Computer Engineering, 8(1), 29-47.
6. Devarajan, M. V., Yallamelli, A. R. G., Yalla, R. K. M. K., Mamidala, V., Ganesan, T., & Sambas, A. (2025). An Enhanced IOMT and Blockchain-Based Heart Disease Monitoring System Using BS-THA and OA-CNN. Transactions on Emerging Telecommunications Technologies, 36(2), e70055.
7. Gollavilli, V. S. B. H., Gattupalli, K., Nagarajan, H., Alagarsundaram, P., & Sitaraman, S. R. (2023). Innovative Cloud Computing Strategies for Automotive Supply Chain Data Security and Business Intelligence. International Journal of Information Technology and Computer Engineering, 11(4), 259-282.
8. Devarajan, M. V., Sacramento, C. S., & Sambas, A. (2022). DATA-DRIVEN TECHNIQUES FOR REAL-TIME SAFETY MANAGEMENT IN TUNNEL ENGINEERING USING TBM DATA.
9. Nagarajan, H., Gollavilli, V. S. B. H., Gattupalli, K., Alagarsundaram, P., & Sitaraman, S. R. (2023). Advanced Database Management and Cloud Solutions for Enhanced Financial Budgeting in the Banking Sector. International Journal of HRM and Organizational Behavior, 11(4), 74-96.
10. Poovendran, A., Sitaraman, S. R., Bhavana, V. S. H. G., Kalyan, G., & Harikumar, N. (2024). Adaptive CNN-LSTM and neuro-fuzzy integration for edge AI and IoMT-enabled chronic kidney disease prediction. International Journal of Applied Science Engineering and Management, 18(3), 553-582.
11. Devarajan, M. V. (2020). ASSESSING LONG-TERM SERUM SAMPLE VIABILITY FOR CARDIOVASCULAR RISK PREDICTION IN RHEUMATOID ARTHRITIS. International Journal of Information Technology and Computer Engineering, 8(2), 60-74.
12. Sitaraman, S. R., Alagarsundaram, P., & Kumar, V. (2024). AI-Driven Skin Lesion Detection with CNN and Score-CAM: Enhancing Explainability in IoMT Platforms. Indo-American Journal of Pharma and Bio Sciences, 22(4), 1-13.
13. Alagarsundaram, P. (2019). Implementing AES Encryption Algorithm to Enhance Data Security in Cloud Computing. International Journal of Information Technology and Computer Engineering, 7(2), 18-31.
14. Poovendran, A. (2024). Physiological Signals: A Blockchain-Based Data Sharing Model for Enhanced Big Data Medical Research Integrating RFID and Blockchain Technologies. Journal of Current Science, 9(2), 9726-001X.
15. Chinnasamy, P., Ayyasamy, R. K., Alagarsundaram, P., Dhanasekaran, S., Kumar, B. S., & Kiran, A. (2024, April). Blockchain Enabled Privacy-Preserved Secure e-voting System for Smart Cities. In 2024 International Conference on Science Technology Engineering and Management (ICSTEM) (pp. 1-6). IEEE.

16. T. Ganesan, M. Almusawi, K. Sudhakar, B. R. Sathishkumar and K. S. Kumar, "Resource Allocation and Task Scheduling in Cloud Computing Using Improved Bat and Modified Social Group Optimization," 2024 Second International Conference on Networks, Multimedia and Information Technology (NMITCON), Bengaluru, India, 2024, pp. 1-5, doi: 10.1109/NMITCON62075.2024.10699250.
17. Shnain, A. H., Gattupalli, K., Nalini, C., Alagarsundaram, P., & Patil, R. (2024, July). Faster Recurrent Convolutional Neural Network with Edge Computing Based Malware Detection in Industrial Internet of Things. In 2024 International Conference on Data Science and Network Security (ICDSNS) (pp. 1-4). IEEE.
18. Alagarsundaram, P. (2023). AI-powered data processing for advanced case investigation technology. J Sci Technol, 8(8), 18-34.
19. Sitaraman, S. R., Alagarsundaram, P., Gattupalli, K., Gollavilli, V. S. B. H., Nagarajan, H., & Ajao, L. A. (2024). Advanced IoMT-enabled chronic kidney disease prediction leveraging robotic automation with autoencoder-LSTM and fuzzy cognitive maps. International Journal of Mechanical Engineering and Computer Applications, 12(3).
20. Gattupalli, K., Gollavilli, V. S. B. H., Nagarajan, H., Alagarsundaram, P., & Sitaraman, S. R. (2023). Corporate synergy in healthcare CRM: Exploring cloud-based implementations and strategic market movements. International Journal of Engineering and Techniques, 9(4).
21. Alagarsundaram, P. (2023). A systematic literature review of the Elliptic Curve Cryptography (ECC) algorithm for encrypting data sharing in cloud computing. International Journal of Engineering and Science Research, 13(2).
22. Devarajan, M. V. (2019). A Comprehensive AI-Based Detection and Differentiation Model for Neurological Disorders Using PSP Net and Fuzzy Logic-Enhanced Hilbert-Huang Transform. International Journal of Information Technology and Computer Engineering, 7(3), 94-104.
23. Alagarsundaram, P., Gattupalli, K., Gollavilli, V. S. B. H., Nagarajan, H., & Sitaraman, S. R. (2023). Integrating blockchain, AI, and machine learning for secure employee data management: Advanced control algorithms and sparse matrix techniques. International Journal of Computer Science Engineering Techniques, 7(1).
24. Hussein, L., Kalshetty, J. N., Harish, V. S. B., Alagarsundaram, P., & Soni, M. (2024, August). Levy distribution-based Dung Beetle Optimization with Support Vector Machine for Sentiment Analysis of Social Media. In 2024 International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS) (pp. 1-5). IEEE.
25. Alagarsundaram, P., Ramamoorthy, S. K., Mazumder, D., Malathy, V., & Soni, M. (2024, August). A Short-Term Load Forecasting model using Restricted Boltzmann Machines and Bi-directional Gated Recurrent Unit. In 2024 Second International

Conference on Networks, Multimedia and Information Technology (NMITCON) (pp. 1-5). IEEE.

26. Tamilarasan, B., Gollavilli, V. S. B. H., Alagarsundaram, P., & Muthu, B. (2024). Agile Practices for Software Development for Numerical Computing. In Coding Dimensions and the Power of Finite Element, Volume, and Difference Methods (pp. 1-31). IGI Global.
27. Alagarsundaram, P., Sitaraman, S. R., & Gattupalli, K. (2023). Artificial Intelligence-based Healthcare Observation System. Pothi.
28. Devarajan, M. V., Yallamelli, A. R. G., Kanta Yalla, R. K. M., Mamidala, V., Ganesan, T., & Sambas, A. (2024). Attacks classification and data privacy protection in cloud-edge collaborative computing systems. International Journal of Parallel, Emergent and Distributed Systems, 1-20.
29. Yallamelli, A. R. G., Mamidala, V., Devarajan, M. V., Yalla, R. K. M. K., Ganesan, T., & Sambas, A. (2024). Dynamic mathematical hybridized modeling algorithm for e-commerce for order patching issue in the warehouse. Service Oriented Computing and Applications, 1-12.
30. Alagarsundaram, P., Sitaraman, S. R., & Gattupalli, K. (2024). IoT and AI-based Notification on Cloud Technologies in Healthcare. Pothi.
31. Allamelli, A. R. G., Mamidala, V., Yalla, R. K. M. K., Ganesan, T., & Devarajan, M. V. (2023). Hybrid edge-AI and cloudlet-driven IoT framework for real-time healthcare. International Journal of Computer Science Engineering Techniques, 7(1), 1-XX. ISSN: 2455-135X.
32. Devarajan, M. V., Yallamelli, A. R. G., Mamidala, V., Yalla, R. K. M. K., Ganesan, T., & Sambas, A. (2024). IoT-based enterprise information management system for cost control and enterprise job-shop scheduling problem. Service Oriented Computing and Applications, 1-16.
33. Mohanarangan, V. D. (2022). An Improved BP Neural Network Algorithm for Forecasting Workload in Intelligent Cloud Computing. Journal of Current Science, 10(3), 1-10.
34. Alagarsundaram, P., Sitaraman, S. R., Gattupalli, K., & Khan, F. (2024). Implementing transfer learning and domain adaptation in IoT analytics. In RADemics (Chapter 16).
35. Devarajan, M. V., Al-Farouni, M., Srikanteswara, R., Bharattej, R. R. V. S. S., & Kumar, P. M. (2024, May). Decision Support Method and Risk Analysis Based on Merged-Cyber Security Risk Management. In 2024 Second International Conference on Data Science and Information System (ICDSIS) (pp. 1-4). IEEE.
36. Ganesan, T. (2022). Securing IoT business models: Quantitative identification of key nodes in elderly healthcare applications. International Journal of Management Research & Review, 12(3), 78-94. ISSN: 2249-7196.

37. Devarajan, M. V. (2020). Improving security control in cloud computing for healthcare environments. Journal of Science and Technology, 5(06), 178-189.
38. Ganesan, T. (2021). Integrating artificial intelligence and cloud computing for the development of a smart education management platform: Design, implementation, and performance analysis. International Journal of Engineering & Science Research, 11(2), 73–91
39. Devarajan, M. V., Aluvala, S., Armoogum, V., Sureshkumar, S., & Manohara, H. T. (2024, August). Intrusion Detection in Industrial Internet of Things Based on Recurrent Rule-Based Feature Selection. In 2024 Second International Conference on Networks, Multimedia and Information Technology (NMITCON) (pp. 1-4). IEEE.
40. Thirusubramanian, G. (2020). Machine learning-driven AI for financial fraud detection in IoT environments. International Journal of HRM and Organizational Behavior, 8(4), 1-16. https://ijhrmob.org/index.php/ijhrmob/article/view/81
41. Ganesan, T. (2023). Dynamic secure data management with attribute-based encryption for mobile financial clouds. International Journal of Advanced Science and Engineering Management, 17(2).
42. Devarajan, M. V. (2023). ENHANCING TRUST AND EFFICACY IN HEALTHCARE AI: A SYSTEMATIC REVIEW OF MODEL PERFORMANCE AND INTERPRETABILITY WITH HUMAN-COMPUTER INTERACTION AND EXPLAINABLE AI. International Journal of Engineering Research and Science & Technology, 19(4), 9-31.
43. Peta, V. P., KaluvaKuri, V. P. K., & Khambam, S. K. R. (2021). Smart AI Systems for Monitoring Database Pool Connections: Intelligent AI/ML Monitoring and Remediation of Database Pool Connection Anomalies in Enterprise Applications. *ML Monitoring and Remediation of Database Pool Connection Anomalies in Enterprise Applications (January 01, 2021)*.
44. MURTHY, P., & BOBBA, S. (2021). AI-Powered Predictive Scaling in Cloud Computing: Enhancing Efficiency through Real-Time Workload Forecasting.
45. Velayutham, A. (2019). Ai-driven storage optimization for sustainable cloud data centers: Reducing energy consumption through predictive analytics, dynamic storage scaling, and proactive resource allocation. *Sage Science Review of Applied Machine Learning*, *2*(2), 57-71.
46. Seenivasan, D. (2021). Transforming Data Warehousing: Strategic Approaches and Challenges in Migrating from On-Premises to Cloud Environments.