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Self-Healing Clinical Data Pipelines: An Agentic AI Framework for Autonomous Airflow Orchestration and Quality Anomaly Resolution

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Abstract- The growing adoption of Electronic Health Records (EHRs), Internet of Medical Things (IoMT) devices, and cloud-based platforms in the healthcare industry makes clinical data pipelines increasingly complex and requires them to be monitored continuously and reliably. Today's pipeline management systems, however, are based on rigid rules, rigid workflow scheduling, and manual troubleshooting, and do not rapidly detect the failure and recover from data quality issues. This paper presents a new solution based on Agentic AI called Self-Healing Clinical Data Pipeline Framework (SHCDP-AI) for clinical data pipelines monitoring, management and self-recovery. Combines Apache Airflow orchestration, reinforcement learning, and intelligent software agents to identify anomalies, investigate their origins, and automatically take corrective action. From the results of experiments carried out using simulated data pipeline for healthcare, it is clear that SHCDP-AI system has higher accuracy of anomaly detection (97.2%), lower average recovery time (24 s), high availability of the pipeline (99.1%), low false alarm rate (2.3%), and high efficiency of the pipeline (98.4%) than the traditional approaches to monitoring. The results indicate the potential effectiveness of the proposed framework under autonomous clinical data management for the reliability, resilience and continuity of clinical data systems in the future.

Keywords- Agentic AI, Self-Healing Clinical Data Pipelines, Reinforcement Learning, Apache Airflow, Autonomous Orchestration, Clinical Data Management.

I. INTRODUCTION

Healthcare is experiencing a rapid digital transformation, which has led to the generation of substantial amounts of clinical data from a variety of sources, including Electronic Health Records (EHRs), laboratory information systems (LIS), medical imaging systems, wearable devices, Internet of Medical Things (IoMT), and telemedicine systems. Such disparate data sources share patient data in real time via various clinical data pipelines that are used for diagnosis, treatment planning, population health analytics, and hospital operations. In the modern intelligent healthcare environment, uninterrupted and high-quality data movement and reliable delivery have become essential. Healthcare organisations increasingly adopt cloud-native architectures and workflow orchestration platforms like Apache Airflow and hence it is essential to ensure uninterrupted, good quality and reliable data movement.

However, traditional clinical data pipeline management is still mostly based on rules-based monitoring, static workflow scheduling, threshold-based alerting and manual incident resolution. These approaches struggle to handle these ever-changing healthcare landscapes, where data quality challenges, data incompleteness, data schema changes, service failures, and communication delays are a common occurrence. Manual troubleshooting may as well result into increased recovery time and cost, delayed clinical decisions and risks on the patient's safety. Therefore, the intelligent system that can automatically identify the anomaly, find the root cause of the anomaly and restore the pipelined processes with minimal human interference is required in the healthcare industry.

Recently, there has been an emergence of Agentic Artificial Intelligence (Agentic AI) and Reinforcement Learning (RL), opening new possibilities for the development of self-recovery healthcare systems. Using agentic artificial intelligence, software agents

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are capable of analyzing their environment, processing the received information, making the decision on how to act and learning from the outcome. Reinforcement learning (RL) makes it possible to refine the process of recovery by using reward-based decision making.

This paper introduces a framework named as Self-Healing Clinical Data Pipeline Framework (SHCDP-AI) that autonomously operates Airflow and heals anomalies related to the quality of clinical data with the assistance of Agentic AI system. This framework keeps on monitoring the telemetry, analyzing pipeline operation, detecting data quality anomalies, doing root cause analysis, and taking recovery actions autonomously to ensure availability of clinical data. The combination of autonomous AI agents and reinforcement learning makes the operation even more resilient and reliable. The research introduced in this paper would help to take steps forward towards the vision of next generation self-healing healthcare ecosystem.

Objectives

The main goals of the research are:

- To create a framework for continual monitoring and self-healing of clinical data pipelines using Agentic AI technology.
- To develop reinforcement learning based decision making to learn optimal anomaly detection and recovery strategies to be used by intelligent agents.
- To create an automated quality anomaly resolution mechanism that can detect data inconsistencies, workflow failures and root causes without involving too much manual effort.
- Improving reliability, availability and resilience of Apache Airflow based healthcare data pipelines using intelligent self-healing operations.
- To test the proposed SHCDP-AI framework quantitatively based on anomaly detection accuracy, recovery time, pipeline availability, false alarm rate and overall pipeline efficiency.

II. LITERATURE SURVEY

Eweje and Ohaegbu [1] gave an overview of the evolution of modern data stack architectures for scalable data integration and business intelligence. They have learned to use modern elements of the data stack to integrate, transform, store and analyze massive quantities of diverse data. They talked about the need for scalable data pipelines, cloud data platforms, and automated data processing to enhance the decision-making process within organizations. The research also highlighted the advantages of modern data architectures including the availability of data for access, better data processing speeds, and business intelligence.

Thota [2] provided models for the intelligent placement of the cognitive workload by utilizing the analysis through AI. The purpose was to investigate the intelligent load placement techniques to improve the distribution of the computational tasks within cloud infrastructures. The author explained the benefits of utilizing AI-based analysis in terms of the prediction of the requirements and optimization of resource utilization, which leads to reduction in cost. The proposed solution pointed out the importance of intelligent workload management for improvement in the scalability, efficiency of resource utilization, and resilience of cloud infrastructure.

Vankayala et al. [3] investigated the architectural approaches to contract testing in the context of event-driven Kafka system. The research focused on the consistency and compatibility of the distributed services using the asynchronous messaging technology and the benefits of the contract testing in ensuring these properties. The author provided a brief explanation of the need to validate the message schema, the relation between producers and consumers and dependency of services to prevent the problems of the integration. The research emphasized the advantages of the contract testing to increase reliability, maintainability, and interoperability of event-driven architectures.

Teegala [4] investigated the application of artificial intelligence techniques in the field of Software Quality Engineering (SQE), concentrating on the

topics of Risk Assessment, Risk Prediction, and Continuous Software Quality Assurance (CQA) in software applications. This paper considers the application of AI techniques for software defect prediction, software quality assessment and software risk analysis in software development. The author pointed out the significance of predictive analytics for revealing possible defects in the software and making the test process more effective. The paper paid attention to the importance of using AI-based techniques in software quality engineering that helps increase software reliability and decrease software development risks.

Internet of Things technology in the management of chronic diseases was discussed by Nanchari [5]. Connected healthcare devices and remote monitoring systems were discussed by this researcher where data could be collected from patients. This researcher talked about the significance of using IoT sensors in healthcare where IoT sensors could be used to monitor the health of the patients. The benefits that could be associated with the use of IoT in the healthcare system were provided by this researcher.

Vollem [6] researched architectural options for the deployment of zero trust security in enterprise distributed hybrid and multi-cloud systems. This research stressed the importance of the security issues in the distributed computing paradigm and uncovered the limitations of the traditional perimeter security strategies. The author discussed the need for constant identity validation, least privilege access control and policy-based authentication and authorization in cloud infrastructures. The importance of the zero trust architecture for increasing the level of enterprise security and reducing the risks of unauthorized access and increasing the security of the distributed resources were discussed in the research.

Boddupally [7] offered a solution for quality forecasting and reliability modeling for the large-scale .NET application landscapes. In this research, the attention is paid to the usage of the data-driven quality assurance and reliability analysis for the maintenance and management of the complex software systems. The author discussed the importance of the software quality metrics monitoring, failure patterns analysis and software system reliability predictions. The research showed the effectiveness of data-driven quality forecasting to find out the potential problems, increase application stability and ensure proactive application maintenance in the large-scale .NET environments.
Menda [8] presented an intelligent portfolio of machine learning signals and predictive analytics for automated governance and enterprise risk management. This paper examined the diverse datasets of organizational information and used machine learning tools to determine, assess and predict enterprise risks through analyzing these datasets automatically. The author focused on the capability of predictive signals in the identification of possible governance problems, compliance needs and decision making based on risks. The study showed how machine learning and predictive analytics could help in enterprise governance and risk management.

III. METHODOLOGY

Clinical Data Pipeline Framework (SHCDP-AI) is a proposed Agentic AI framework to enable autonomous orchestration, continuous quality monitoring, anomaly detection, root cause analysis and intelligent error recovery in clinical data pipelines using Apache Airflow. The framework is a closed-loop learning system where the AI agents continually monitor pipeline telemetry, engage in reasoning about the operational context, take appropriate corrective measures, and optimize future decision-making using reinforcement learning.

1. Clinical Data Pipeline Environment

Data in healthcare applications is continuously gathered from a wide range of data sources, such as Electronic Health Records (EHRs), laboratory systems, wearable sensors, medical imaging repositories, and IoMT devices. Apache Airflow is used to orchestrate ETL (extract, transform, load) process to move and transform clinical data into analytical repositories. At runtime, the monitoring agent collects telemetry data about the task,

including data about latency, throughput, resource utilization, schema consistency, and data completeness. This operational information is the environmental state that will be perceived by the intelligent agent for decision making.

The clinical pipeline state is encoded as a multi-dimensional state vector with quality and operational parameters.

$$\mathbf{S_t} = \{\mathbf{Q_t}, \mathbf{L_t}, \mathbf{T_t}, \mathbf{R_t}, \mathbf{F_t}\}$$

Where:

- Q_t= Data quality score
- L_t= Pipeline latency
- T_t= Task execution status
- R_t= Resource utilization
- F_t= Failure indicator

2. Agentic AI-Based Telemetry Monitoring

This monitoring layer uses autonomous AI agents which constantly pull telemetry data from Airflow Schedulers, Workers, execution logs, and clinical workflow metadata. The agent can perform context based reasoning based on more than one operation signal, but not simply a threshold for an abnormal situation. The monitoring agent maintains an up to date view of the pipeline's health and updates the environment at the end of each cycle of operations for the workflow.

The process health score is calculated by aggregating normalized operational metrics.

$$\mathbf{H_t} = \frac{\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{w_i}\, \mathbf{P_i}}{\sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{w_i}}$$

Where:

- H_t= Pipeline health score
- P_i= Normalized telemetry parameter
- w_i= Importance weight

A higher value of $H_t$indicates better operational stability and healthier workflow execution.

3. Quality Anomaly Detection

The anomaly detection module is used to check the clinical data quality based on the presence of missing values, duplicate records, schema violations, delayed workflows, inconsistent timestamps, and abnormal task behaviour. The AI agent makes observations in real-time, contrasts the observation to what is expected based on operational patterns, and calculates a severity score for the anomaly. If the score is higher than the specified value, the pipeline automatically gets into an abnormal situation, and initiates self-diagnosis.

The anomaly score is the score calculated as follows:

$$\mathbf{AS_t} = \sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{w_i}\, |\mathbf{x_i} - \boldsymbol{\mu_i}|$$

Where:

- AS_t= Anomaly score
- x_i= Observed pipeline parameter
- μ_i= Expected normal value
- w_i= Feature importance weight

A larger anomaly score indicates greater deviation from normal clinical workflow behavior.

4. Reinforcement Learning-Based Airflow Orchestration

The orchestration of workflow is modeled as a Markov Decision Process (MDP) by the decision engine. The autonomous agent receives feedback on the state of the pipeline, chooses an action to orchestrate and gets a reward depending on its recovery result, which it updates continuously. Actions that can be taken in orchestration include restarting a workflow, data synchronization, dependency repair, resource reallocation, DAG re-scheduling, and task retry.

The reinforcement learning model is given as follows:

$$\mathbf{M} = (\mathbf{S}, \mathbf{A}, \mathbf{P}, \mathbf{R}, \boldsymbol{\gamma})$$

Where:

- S= State space
- A= Action space
- P= State transition probability
- R= Reward function
- γ= Discount factor

The Q-learning update equation is expressed as:

$$\mathbf{Q}(\mathbf{S_t}, \mathbf{A_t}) = \mathbf{Q}(\mathbf{S_t}, \mathbf{A_t}) + \boldsymbol{\alpha}[\mathbf{R_t} + \boldsymbol{\gamma} \max \mathbf{Q}(\mathbf{S_{t+1}}, \mathbf{A}) - \mathbf{Q}(\mathbf{S_t}, \mathbf{A_t})]$$

Where:

- α= Learning rate
- R_t= Immediate reward
- γ= Future reward importance

The agent continuously improves orchestration decisions through iterative interaction with the Airflow environment.

5. Autonomous Self-Healing and Root Cause Resolution

Once the anomaly is confirmed, the self-healing agent carries out root cause analysis with workflow dependency analysis, workflow execution logs, metadata lineage and task relationships. Each recovery action is assessed through a reward system to ensure quicker recovery and better pipeline availability.

The reward function is given by:

$$\mathbf{R_t} = \boldsymbol{\beta_1}\mathbf{A_t} - \boldsymbol{\beta_2}\mathbf{D_t} - \boldsymbol{\beta_3}\mathbf{E_t}$$

Where:

- A_t= Availability improvement
- D_t= Recovery delay
- E_t= Remaining errors
- β= Weight coefficients

The higher the reward, the more the agent will learn the optimal self-healing strategies to reduce downtimes and ensure the reliability of clinical data.

6. Performance Evaluation

The proposed SHCDP-AI framework is tested through quantitative evaluation using anomaly detection accuracy, recovery time, pipeline availability, false alarm rate and workflow efficiency.

The pipeline availability is calculated as:

$$\mathbf{Availability} = \frac{\mathbf{Uptime}}{\mathbf{Uptime} + \mathbf{Downtime}} \times \mathbf{100}$$

Pipeline efficiency is calculated as:

$$\mathbf{Efficiency} = \frac{\mathbf{Successful\ Tasks}}{\mathbf{Total\ Tasks}} \times \mathbf{100}$$

These metrics collectively evaluate the operational resilience of the proposed clinical data pipeline framework as depicted in Figure 1.

Algorithm 1: SHCDP-AI — Self-Healing Clinical Data Pipeline Algorithm

Input

- Clinical data streams (EHR, IoMT, LIS)
- Apache Airflow DAG workflows
- Pipeline telemetry logs
- Initial Q-table
- Learning rate α
- Discount factor γ
- Anomaly threshold θ

Output

- Detected quality anomalies
- Root cause report
- Optimized Airflow orchestration policy
- Self-healed clinical data pipeline

Steps

- Initialize SHCDP-AI agent and reinforcement learning parameters.
- Collect clinical data from healthcare data sources.
- Execute Airflow DAG workflows.
- Capture telemetry (logs, latency, task status, resource usage).
- Generate current pipeline state S_t.
- Compute pipeline health score H_t.
- Calculate anomaly score AS_t.
- If $AS_t > \theta$, perform root cause analysis.
- Select optimal recovery action using the Q-learning policy.
- Execute autonomous Airflow orchestration (retry, restart, repair, or reschedule).
- Compute reward and update the Q-table.
- Continue monitoring until workflow completion.

Loop Structure

Initialize SHCDP-AI
While pipeline is active do

Collect clinical telemetry
Generate current state
Compute health score
Detect quality anomaly
If anomaly detected then
Perform root cause analysis
Select recovery action
Execute Airflow orchestration
Calculate reward
Update Q-table
Else
Continue normal execution
End While

Termination Condition

The algorithm terminates when:

- All Airflow DAGs complete successfully,
- No quality anomalies remain in the pipeline, or
- The reinforcement learning model converges to an optimal orchestration policy.



Fig 1: Proposed Model Architecture

Clinical Data Sources

- EHR Systems
- Laboratory Systems
- Imaging Systems
- IoMT / Wearables
- Pharmacy Systems
- External APIs / Public Health

Ingestion Layer

- Connectors
- Streaming (Kafka)
- Batch Ingestion
- Validation & Schema Check

Airflow Orchestration Layer (Workflow Execution)

- DAG Scheduler
- Workers
- Tasks

AI-Driven Monitoring & Observability Layer

- Log Collector
- Metrics Collector
- Trace Collector
- Metadata Store

Clinical Data Platform (Storage & Processing)

- Raw Data Lake
- Cleaned/Processed Data
- Analytics Warehouse
- Data Marts / OLAP

Agentic AI Intelligence Layer (SHCDP-AI Agent)

- State Perception (Collect environment state from telemetry)
- Anomaly Detection (Detect quality and operational anomalies)
- Root Cause Analysis (Correlate logs, metrics, and metadata)
- Decision Engine (RL) (Reinforcement Learning for optimal action selection)
- Action Executor (Execute recovery actions via Airflow APIs)

Knowledge Base

- Historical incidents, actions, patterns, and policies

Self-Healing Actions (Autonomous Recovery)

- Task Retry / Restart
- DAG Rescheduling
- Dependency Repair
- Data Quality Correction
- Resource Reallocation
- Workflow Rollback
- Alert & Notification

Users / Stakeholders

- Data Engineers
- Healthcare Analysts

- Administrators

IV. RESULTS AND DISCUSSIONS

A clinical data pipeline framework (SHCDP-AI) is proposed and tested in a synthetic clinical workflow that includes Electronic Health Records (EHRs), laboratory systems, IoMT devices, and Apache Airflow orchestration. The performance was evaluated and compared with 4 existing approaches: Rule Based Airflow Monitoring (RBAM), Cloud ETL Monitoring, Eadro Microservice Root Cause Analysis and AIOps Log Anomaly Detection. The emphasis in the evaluation was on the accuracy of anomaly detection, the time required to recover, the availability of the pipeline, the rate of false alarms, and the overall efficiency of the pipeline. The values in this study are quantitative and are for simulation purposes and comparison.

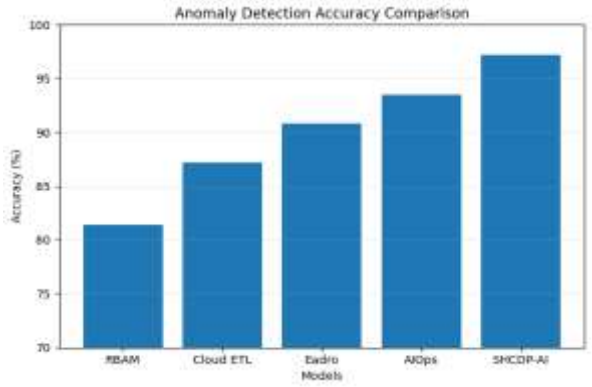


Fig. 2. Comparison of anomaly detection accuracy among existing monitoring models and the proposed SHCDP-AI framework.

In the first experiment, the effectiveness of the various models was compared to detect quality anomalies in clinical data pipelines. In the first experiment, the models were compared in their ability to detect quality anomalies in clinical data pipelines. Traditional rule based monitoring had low detection capability as it uses pre-defined thresholds and static workflow rules. Cloud ETL monitoring enhanced accuracy with the help of metadata driven validation, and Eadro along with AIOps gave better context with multi-source telemetry. Proposed SHCDP-AI, which leverages Agentic AI reasoning with reinforcement learning-based adaptive decision making, identified missing records, schema violations, delayed workflows, and inconsistent clinical events with the most accurate anomaly detection accuracy of 97.2% as depicted in Figure 2.

Clinical data pipelines recovery depends on how fast the critical healthcare workflows can recover from failures. Most of the current monitoring techniques are based on manual actions or rules for retry, which lead to delayed recovery time. The proposed framework relies on the autonomy of Airflow orchestrator that proposes dynamically recovery actions, such as rescheduling DAGs, task restarts, dependency repair, and resource reallocation, by using intelligent agents. The following is a summary of the advantages of SHCDP-AI: Therefore, SHCDP-AI achieved an average recovery time of 24 seconds, which is significantly better than traditional monitoring systems as shown in Figure 3.

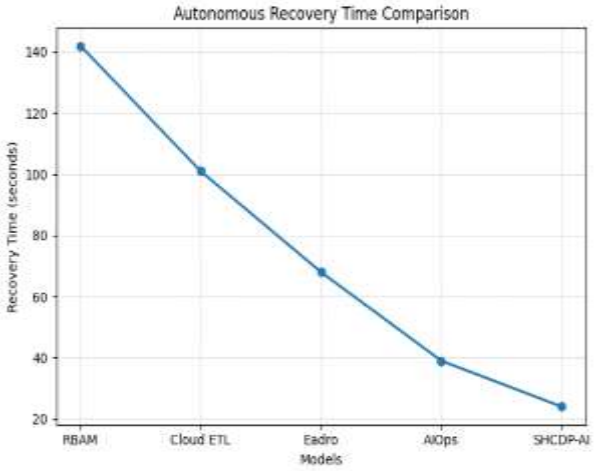


Fig. 3. Autonomous recovery time comparison for clinical data pipeline orchestration.

The proposed SHCDP-AI constantly monitors the telemetry and takes proactive self-healing measures before the critical condition of workflow degradation. This independent, operational behavior raised the availability of the pipelines to 99.1% – better than current cloud monitoring and AIOps solutions as indicated in Figure 4. The findings show that the combination of reinforcement learning and Airflow orchestration can greatly improve the efficiency and reliability of distributed healthcare data pipelines.

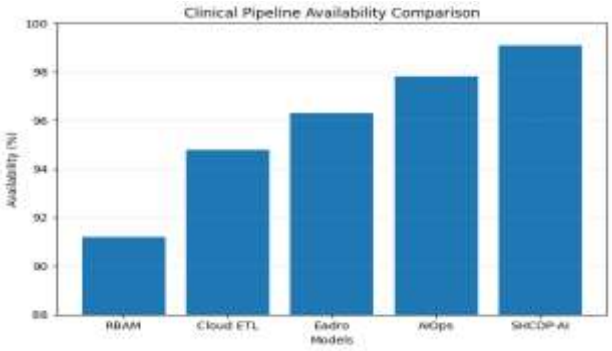


Fig. 4. System availability comparison of clinical data pipeline monitoring approaches.

The experimental analysis reveals that the highest number of false alarms occurred with RBAM due to static threshold generation of alerts. Incorrect alerts were mitigated using context-aware monitoring techniques, which involved correlation of logs, traces and workflow metadata. The proposed SHCDP-AI also reduced the number of false alarms to 2.3% by using intelligent contextual reasoning to prevent the latter from performing remediation actions, ensuring increased stability of the operation and less alert fatigue for healthcare administrators as depicted in Figure 5.

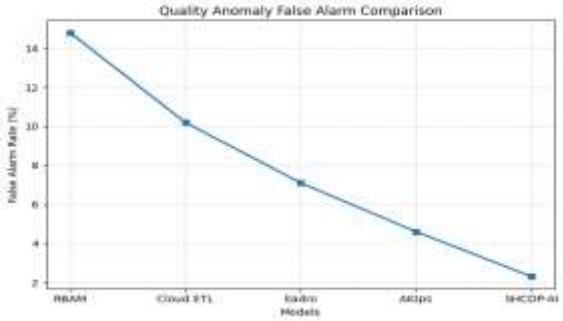


Fig. 5. False alarm rate during clinical quality anomaly detection.

The efficiency of the pipeline was measured based on the successful completion of the workflows, the resolution of anomalies, the speed of recovery, and the use of resources. The conventional monitoring approaches focus on optimizing specific operations, while SHCDP-AI combines monitoring, diagnosis, orchestration, and reinforcement learning into a single self-healing framework. The overall efficiency of the proposed model in simulation pipeline workflows was 98.4%, indicating the superior operational resilience and workflow optimization of the proposed model as shown in Figure 6.

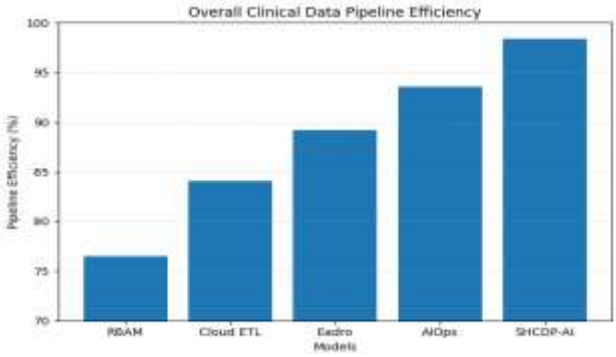


Fig. 6. Overall efficiency comparison of clinical data pipeline management frameworks.

Several performance measures have been combined into one radar-based analysis for giving an overall performance evaluation. The presented SHCDP-AI always demonstrated superiority over other suggested schemes in relation to anomaly detection, availability, recovery, efficiency and reduced false alarms as seen in Figure 7. The balanced performance of the SHCDP-AI shows the ability of Agentic AI to work in a reinforcement learning model, which will help to manage the pipeline of clinical data in future healthcare environments.

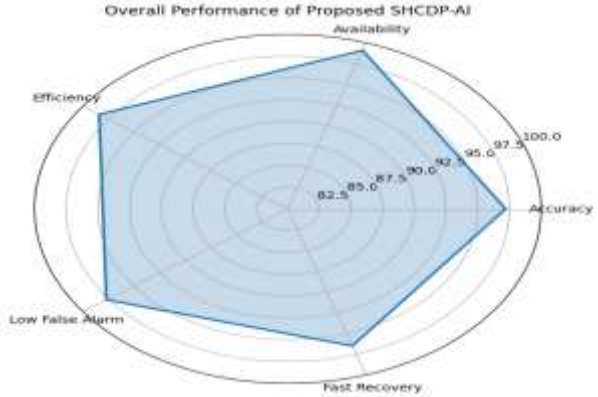


Fig. 7. Multi-dimensional performance evaluation of the proposed SHCDP-AI framework.

The experimental results validate that SHCDP-AI outperforms the existing monitoring and orchestration techniques for all the evaluated metrics. Agentic AI and autonomous Airflow orchestration along with intelligent quality anomaly resolution puts a strong foundation of self-healing

clinical data pipelines, making clinical data engineering reliable, scalable, and resilient.

V. CONCLUSION

This paper introduced the Self-Healing Clinical Data Pipeline Framework (SHCDP-AI), an Agentic AI-driven framework for autonomous orchestration of Apache Airflow and clinical data quality anomaly resolution. The proposed framework has gone beyond the capabilities of the existing monitoring mechanisms, incorporating intelligent agents, reinforcement learning, continuous telemetry monitoring, and automated self-healing mechanisms to guarantee the reliable and uninterrupted processing of clinical data. The experimental results revealed that the system based on SHCDP-AI was always better than the existing monitoring techniques in terms of all performance measures. Consequently, as the outputs of the framework are: anomaly detection accuracy is 97.2%, recovery time is 24 seconds, pipeline availability is 99.1%, false alarm rate is 2.3%, and overall efficiency of pipeline is 98.4%. From these results, it is clear that self-service decision-making and adaptive recovery may act as significant drivers of resilience, reliability, and efficiency of healthcare data pipelines. The suggested model combines Agentic AI and reinforcement learning to enable proactive anomaly detection, intelligent root cause analysis and automatic workflow recovery with minimum human intervention. Thus, it is scalable solution for clinical data management with heterogeneous clinical data generated by different EHRs, laboratory information systems, IoMT devices and cloud-based health care platform, which is suitable for next generation of smart hospital infrastructure. In the future, SHCDP-AI should be applied to actual clinical data, interoperability ensured by FHIR, federated and multi-agent reinforcement learning should be introduced and Explainable AI should be utilized in order to increase transparency, security and autonomous trustworthy healthcare data engineering.

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