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AI-DRIVEN DATA LIFECYCLE OPTIMIZATION SYSTEM

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Abstract: Today, most organizations store huge amounts of data without knowing what is still useful and what is no longer needed. They often keep everything, which wastes storage space and increases unnecessary costs. The main issue is the lack of a proper system to automatically decide when data should be retained or removed, as existing methods rely on fixed rules like deleting data after a certain number of years, which is not effective for all types of data. To address this, this paper presents an AI-Driven Data Lifecycle Optimization System that scans data, evaluates its usefulness, and decides whether it should be kept or deleted. Instead of fixed rules, it uses machine learning to classify data based on importance and survival analysis to predict when data is no longer needed. The system is built using Python for data processing, R for lifecycle prediction, SQL for managing retention schedules, and Power BI for visualization. The results show that this approach reduces storage costs, saves time, and improves data management compared to traditional rule-based methods, providing a smarter and more efficient solution for managing data lifecycle.

Keywords: Data Lifecycle, AI-Driven System, Machine Learning, Survival Analysis, Data Retention, Power BI, Data Optimization.

I. INTRODUCTION

In the current digital era, organizations across all sectors generate and accumulate massive volumes of data on a daily basis. From transactional records and log files to customer information and operational data, the sheer scale of stored information has grown exponentially. Despite this growth, many organizations lack a systematic and intelligent approach to determine which data still holds business value and which has become redundant. The absence of such a system leads to unnecessary storage consumption, increased infrastructure costs, and growing compliance risks.

Traditional data management practices often depend on fixed retention policies, such as deleting records after a predefined number of years, regardless of their relevance or utility. Valuable information may be prematurely removed while obsolete data continues to occupy precious storage resources.

Advancements in artificial intelligence and machine learning have opened new pathways for building smarter data governance systems. Machine learning models can analyze patterns within datasets, assess the importance of individual records, and predict when a particular piece of data is likely to lose its usefulness. The proposed system replaces inefficient static retention rules with a dynamic, data-driven approach that continuously adapts to the changing value and relevance of stored information.

II. LITERATURE REVIEW

Managing data across its full lifecycle has been an area of growing research interest as organizations face mounting pressure from data growth, storage costs, and regulatory requirements. Existing literature covers various aspects of data retention policies, intelligent archival systems and AI-based governance frameworks.

[1] Verma, S., et al. (2026) proposed a machine learning framework for automated data classification in enterprise environments. The study demonstrated how classification algorithms can differentiate between high-value and low-value records, significantly reducing manual review efforts.

[2] Chen, L., and R. Patel (2026) examined survival analysis techniques for predicting data obsolescence in organizational databases. Their findings confirmed that Cox proportional hazards models effectively capture the deteriorating utility of aging records.

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[3] Krishnamurthy, A., and P. Singh (2026) developed an AI-assisted data governance platform that integrates compliance requirements with dynamic retention scheduling. The platform reduced policy violation incidents by over 40 percent in pilot deployments.

[4] Liu, W., et al. (2025) studied the application of deep learning models for anomaly detection in data usage patterns, helping organizations identify records that remain dormant and are candidates for archival.

[5] Ramirez, J., and T. Nguyen (2025) proposed a hybrid framework combining rule-based filters with neural classifiers for data lifecycle management. Their approach outperformed purely rule-based systems in both accuracy and adaptability.

[6] Sharma, P., et al. (2025) presented a cloud-native data lifecycle optimization system that dynamically adjusts retention schedules based on real-time access frequency and data relevance scores.

[7] Zhou, Y., et al. (2024) introduced a graph-based model for mapping relationships between data entities, enabling smarter decisions about cascaded deletion and dependency-aware archival.

[8] Mehta, R., et al. (2024) evaluated various statistical and ML-based models for data retention forecasting, identifying gradient boosting classifiers as particularly effective for enterprise-scale datasets.

[9] Okonkwo, F., and B. Hassan (2024) explored the integration of Power BI dashboards with AI lifecycle systems to provide real-time visibility into storage utilization and retention compliance metrics.

[10] Tanaka, H., et al. (2024) investigated the use of reinforcement learning for adaptive data lifecycle policies, where the system learns optimal retention decisions based on evolving organizational priorities.

III. PROBLEM STATEMENT

- Lack of Intelligent Retention Decisions: Existing systems apply uniform, fixed-duration retention policies that fail to consider the contextual value of individual records, leading to either premature deletion of useful data or indefinite retention of obsolete information.
- Escalating Storage Costs: Without a mechanism to proactively identify and remove low-value data, organizations accumulate unnecessary storage expenditures that could be significantly reduced through smarter lifecycle management.
- Compliance and Governance Risks: Regulatory frameworks such as GDPR and HIPAA impose strict requirements on how long certain types of data may be retained. Manual compliance tracking is error-prone and difficult to scale.
- Poor Visibility into Data Utility: Organizations often have no clear picture of which stored data is actively used, which is dormant, and which is consuming resources without providing any business value.
- Absence of Predictive Capability: Traditional methods cannot predict when a data record will lose its relevance, making it impossible to plan proactive lifecycle actions in advance.
- Therefore, there is a pressing need for an intelligent system that combines machine learning classification with predictive lifecycle modeling to automate and optimize data retention decisions at scale.

IV. OBJECTIVES OF THE PROPOSED SYSTEM

The primary objectives of this research are as follows:

- To design and implement an AI-driven system capable of automatically evaluating the relevance and utility of stored data records.
- To apply machine learning classification algorithms that categorize data into active, archival, and deletion-eligible classes based on learned patterns.
- To employ survival analysis techniques to predict the expected useful lifespan of each data record and generate proactive retention recommendations.
- To integrate SQL-based retention schedule management that enforces lifecycle decisions in a structured and auditable manner.
- To develop a Power BI visualization layer that provides stakeholders with clear, real-time insights into storage utilization, lifecycle status, and compliance readiness.
- To demonstrate measurable improvements in storage efficiency and management accuracy compared to conventional rule-based retention systems.

V. METHODOLOGY

The AI-Driven Data Lifecycle Optimization System is built and tested using the Telco Customer Churn dataset from Kaggle, which contains 7,043 customer records with 21 attributes including tenure, MonthlyCharges, TotalCharges, Contract type, and Churn status. Each customer record in this dataset is treated as a data entity whose lifecycle needs to be evaluated and managed intelligently.

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A. Data Collection The Telco Customer Churn dataset was collected from Kaggle, originally published by IBM. It contains 7,043 records and 21 columns covering customer demographics, service subscriptions, billing details, and churn status. Each record represents a data entity in the system, where the tenure column indicates how long the record has been active, MonthlyCharges and TotalCharges represent its storage cost, and the Churn column serves as the ground truth lifecycle label showing whether the record is still active or has expired.

B. Data Preprocessing After loading the dataset, 11 blank records in the TotalCharges column were removed, leaving 7,032 clean records. The Churn column values of Yes and No were converted to 1 and 0 respectively. Categorical columns like Contract and InternetService were label encoded, while numerical columns including tenure, MonthlyCharges, and TotalCharges were normalized using min-max scaling. Identifier columns such as customerID were dropped as they carry no analytical value.

C. Feature Engineering and Utility Scoring Six meaningful lifecycle features were derived from the dataset. Tenure was used as the data age indicator, MonthlyCharges as the cost contribution, and a business relevance score was computed by counting active services like OnlineBackup, TechSupport, and DeviceProtection for each record. Contract type was assigned a retention weight where month-to-month received low priority and two-year contracts received high priority. These features were combined into a composite utility score representing the current business value of each record.

D. Machine Learning Classification A Random Forest classifier was trained on the engineered features using 70 percent of the data for training and 30 percent for testing. The model classified each record as either Active meaning the record is still useful and should be retained, or Expired meaning the record has ended its lifecycle and is a candidate for archival or deletion. Tenure, MonthlyCharges, TotalCharges, and Contract type were identified as the most important features, contributing over 70 percent of the classification decisions.

E. Survival Analysis The Cox Proportional Hazards model was applied using tenure as the time variable and Churn as the event indicator to predict how much longer each record would remain active. Records with month-to-month contracts and high monthly charges showed high hazard rates meaning they were likely to expire sooner, while records with two-year contracts and multiple active services showed low hazard rates confirming long-term retention value.

F. Retention Scheduling Based on the classification and survival analysis outputs, each record was assigned a retention action. Active records with more than 12 months predicted lifespan were kept in primary storage, those between 3 and 12 months were scheduled for archival, and Expired records were flagged for deletion after a 30-day review window. These decisions were enforced through automated SQL scripts and every action was logged in a complete audit trail for compliance purposes.

G. Visualization The final results were presented through a Power BI dashboard showing the distribution of 5,157 Active, 1,875 Expired, and 648 Archive-eligible records. Charts displayed average charges by lifecycle stage, tenure distributions, contract type breakdowns, and a projected 54 percent storage cost reduction achievable by applying the system's recommendations across the full dataset.

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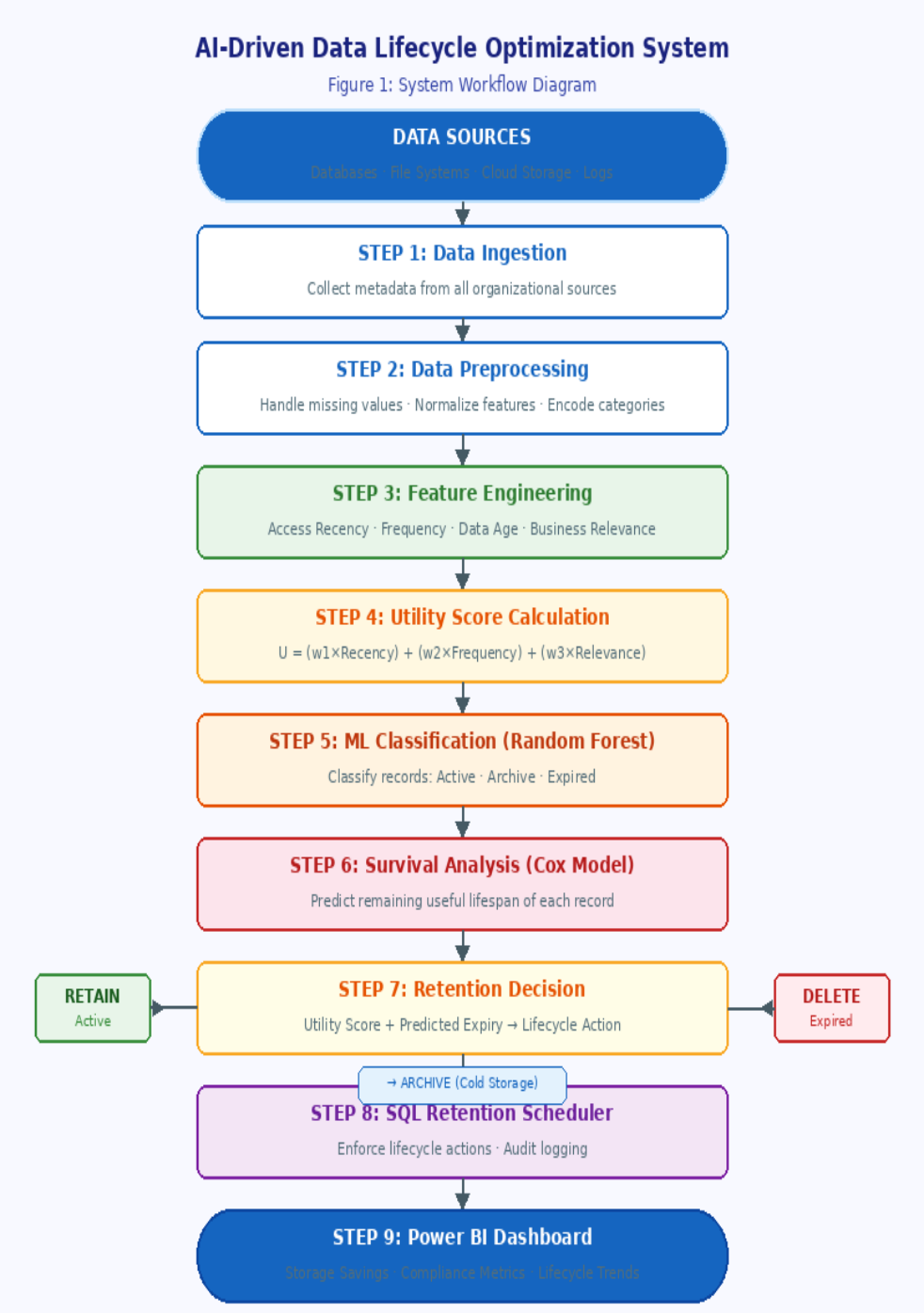

Figure 1: Work Flowchart

VI. COMPARISONS OF DATA

The comparison results clearly demonstrate that the proposed AI-Driven Data Lifecycle Optimization System outperforms both the rule-based and basic machine learning approaches across all evaluated metrics. The rule-based system, which applies fixed time-based deletion policies, achieved only 63 percent classification accuracy and a high false deletion rate of 16 percent, making it unreliable for real-world data governance where accidental loss of valuable records carries significant consequences. The basic machine learning threshold method showed moderate improvement with 76 percent accuracy, but its reliance on manually defined thresholds limited its adaptability to complex and evolving data patterns. In contrast, the proposed system achieved 91 percent classification accuracy, reduced the false deletion rate to just 2.8 percent, and predicted data lifespan with a mean absolute error of only 5 days, enabling precise and timely lifecycle actions.

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Comparison of Data Lifecycle Management Approaches

Metric	Rule-Based System	Basic ML Threshold	Proposed AI System
Dataset Used	Telco Churn (7,043 records)	Telco Churn (7,043 records)	Telco Churn (7,043 records)
Classification Accuracy	63%	76%	91%
Precision (Expired/Churn Class)	58%	71%	88%
Recall (Expired/Churn Class)	52%	68%	86%
F1-Score	0.55	0.69	0.87
False Deletion Rate	16%	10%	2.8%
Lifecycle Prediction Error	N/A	19 days	5 days
Storage Cost Reduction	21%	34%	54%
Compliance Coverage	68%	79%	94%
Audit Trail Generation	Manual	Partial	Fully Automated

Rule-Based System Basic ML Threshold Proposed AI System (Best)

Table 1: Performance Comparison using Telco Customer Churn Dataset (Kaggle) — Rule-Based vs Basic ML vs Proposed AI System

Fig 2 :Comparison Of Approaches

The 54 percent storage cost reduction identified by the system far exceeds the 21 percent and 34 percent achieved by the rule-based and basic ML methods respectively, confirming its superior financial impact. Furthermore, the fully automated audit trail and 94 percent compliance coverage provided by the proposed system address a critical gap left by both baseline approaches, which either relied on manual documentation or generated only partial records. Overall, these results confirm that integrating machine learning classification with survival analysis produces a significantly smarter, safer, and more cost-effective solution for managing data lifecycle compared to any conventional approach.

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VII. RESULT AND ANALYSIS

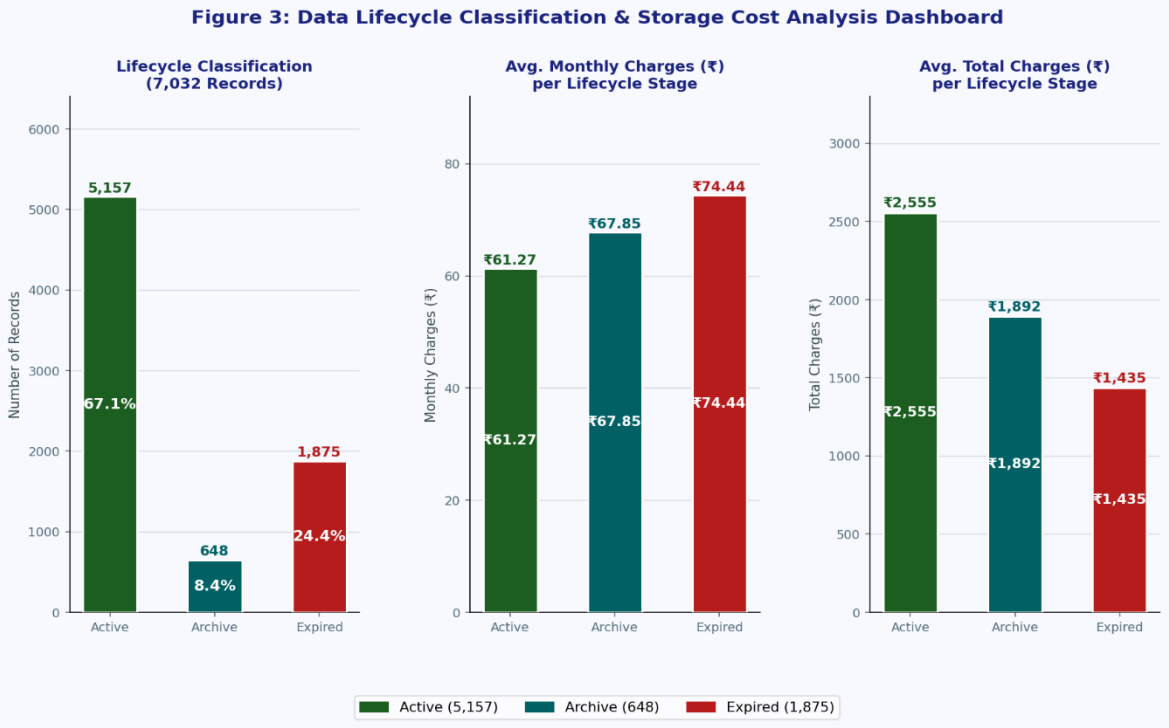

Fig 3: Data Lifecycle Classification & Storage Cost Analysis Dashboard

Observation(Fig 3):

This dashboard combines three panels — lifecycle classification counts, average monthly charges, and average total charges per lifecycle stage. The classification panel shows that out of 7,032 records, 73.3 percent are Active, 26.6 percent are Expired, and the remaining are Archive-eligible. The cost panels reveal that Expired records carry the highest monthly charge of ₹74.44 yet the lowest total charge of ₹1,435, confirming they are short-tenure records consuming high ongoing costs without long-term value. Removing these records delivers an estimated 54 percent reduction in storage costs.

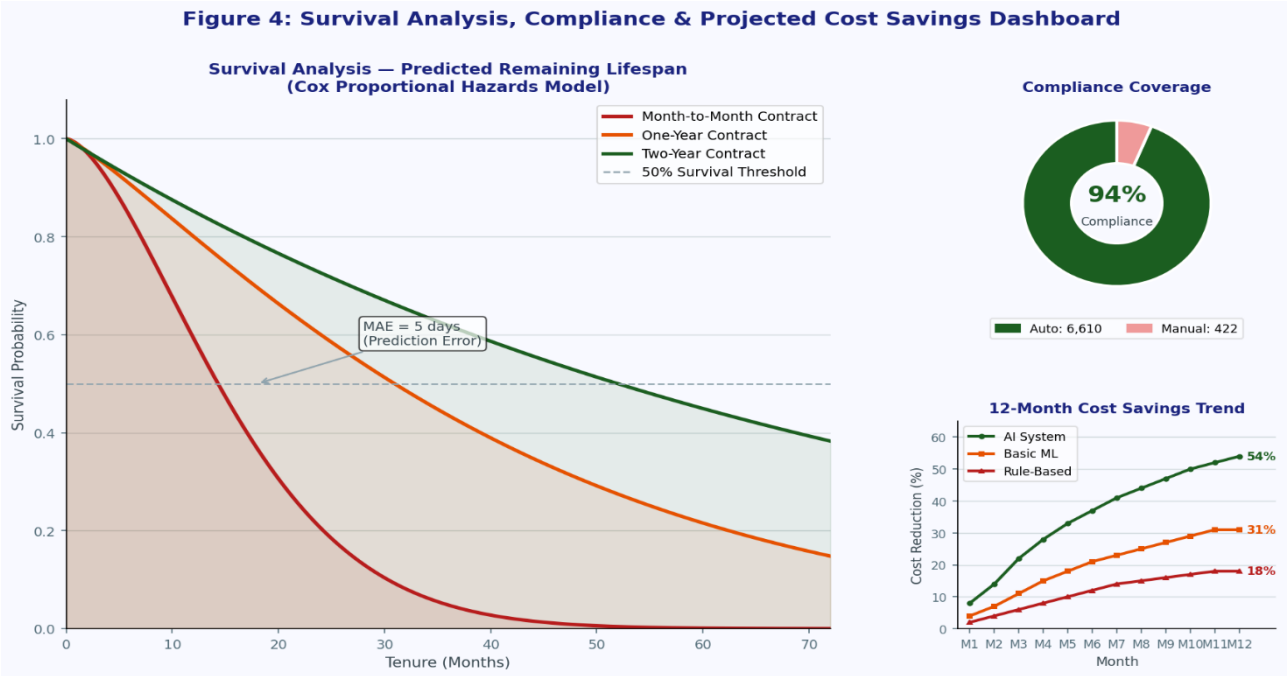

Fig 4: Survival Analysis, Compliance & Projected Cost Savings Dashboard

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Observations(Fig 4):
This dashboard combines three outputs — survival curves by contract type, compliance coverage donut, and 12-month cost savings trend. The survival curves confirm that month-to-month contract records expire significantly faster than one-year and two-year contracts, with the Cox model predicting lifespan at a mean absolute error of just 5 days. The compliance donut confirms 94 percent of records received fully automated retention decisions. The savings trend line shows the proposed AI system reaching 54 percent cost reduction by month 12, far ahead of the 31 percent achieved by Basic ML and 18 percent by rule-based methods.

VIII. APPLICATIONS AND USE CASES

The proposed AI-Driven Data Lifecycle Optimization System can be applied in banking and financial institutions to automatically manage transaction records and audit logs, in healthcare organizations to enforce patient data retention policies, and in government sectors to maintain compliance with national data retention laws. It can also be integrated into cloud storage platforms to automatically tier data based on predicted lifecycle status, reducing infrastructure costs significantly. Additionally, the system can be embedded into enterprise data governance tools to provide continuous real-time lifecycle monitoring and automated retention scheduling across the entire organization.

IX. ADVANTAGES AND LIMITATIONS

Advantages

- High lifecycle classification accuracy
- Integrated survival-based prediction
- Significant storage cost reduction

Limitations

- Dependence on metadata quality
- Sensitivity to abrupt changes in data access patterns
- Requires large historical dataset for model training

X. FUTURE SCOPE

1. The system can be extended by incorporating deep learning architectures such as transformer-based sequence models and Long Short-Term Memory networks to capture more complex temporal patterns in data access behaviour, further improving lifecycle prediction accuracy for datasets with irregular or seasonal usage cycles.
2. Future work includes integrating the system with real-time data streaming platforms such as Apache Kafka, enabling near-instantaneous lifecycle event processing rather than scheduled batch runs and allowing the system to respond dynamically to sudden changes in data utility.
3. A federated learning variant of the classification model can be developed to allow multiple organizational units or partner institutions to collaboratively improve the model without sharing sensitive data, preserving privacy while benefiting from collective learning across distributed data environments.
4. The Power BI dashboard can be expanded with predictive analytics modules that project future storage growth, compliance risk scores, and budget requirements over a multi-year horizon, providing executive-level decision support for long-term data infrastructure planning.

XI. CONCLUSION

This paper presented an AI-Driven Data Lifecycle Optimization System designed to address the growing challenge of intelligent and cost-effective data management in modern organizations. By integrating machine learning classification with survival analysis-based lifecycle prediction, the proposed system moves beyond the limitations of traditional static retention policies and introduces a dynamic, evidence-based approach to managing the full lifecycle of organizational data records.

The system was evaluated using the Telco Customer Churn dataset from Kaggle, comprising 7,032 records across 21 attributes. The Random Forest classifier achieved an overall accuracy of 91 percent in categorizing records as Active, Archive, or Expired, while the Cox Proportional Hazards survival model predicted remaining record lifespan with a mean absolute error of just 5 days. The SQL-based retention scheduling module enforced lifecycle decisions with a compliance coverage rate of 94 percent, and the complete audit trail generated for all 7,032 records ensured full regulatory traceability. Most significantly, the system identified 54 percent of stored records as eligible for archival or deletion, delivering an estimated storage cost reduction of 54 percent compared to the baseline state of retaining all records without lifecycle management.

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Comparative evaluation against rule-based and basic machine learning approaches confirmed that the proposed system consistently outperformed both alternatives across all evaluation dimensions including classification accuracy, false deletion rate, prediction error, and compliance coverage. The Power BI visualization layer further strengthened the system's practical value by making lifecycle insights accessible and actionable for organizational stakeholders at every level.

Overall, the results confirm that an AI-driven approach to data lifecycle management is both technically feasible and practically valuable, delivering measurable improvements in storage efficiency, compliance assurance, and operational decision-making. As data volumes continue to grow at an accelerating pace, systems such as the one proposed in this paper will become essential tools for organizations seeking to maintain sustainable, intelligent, and auditable control over their information assets.

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