# Intelligent Process Automation for Data Lifecycle Management (Data Retention and Data Destruction) Through Process Mining

L Chingwaru[1]; S Chaputsira[2]; M Mutandavari[3]

[1,2,3]School of Information Science and Technology, Harare, Zimbabwe

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**Abstract: In an era of rapidly growing data, effective data lifecycle management has become crucial for organizations. This paper addresses the challenge of identifying and classifying data columns as either demographic or transactional across various systems, where column names may differ significantly (e.g., "Sex" in one system and "Gender" in another). The purpose of this research is to develop a model that can accurately classify these data columns, enabling automated data retention and destruction processes. The proposed model leverages intelligent process automation and process mining to identify and categorize data, allowing transactional data to be archived automatically after a specified timeframe. By implementing this model, organizations can improve their data management efficiency, ensuring compliance with data retention policies while optimizing storage use.**

***Keywords:*** *Data Lifecycle Management, Column Classification, Intelligent Process Automation, Process Mining, Data Retention.*

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## I. INTRODUCTION

Data Lifecycle Management (DLM) encompasses all processes involved in the creation, storage, utilization, and eventual disposal of data within an organization. As organizations continue to generate and collect vast amounts of data from various sources, managing this data throughout its lifecycle has become increasingly complex. Effective DLM is not only crucial for operational efficiency but also for ensuring that data is stored securely, accessible when needed, and disposed of in compliance with regulatory requirements. As data continues to grow in volume and variety, so do the challenges associated with managing it effectively.

One of the most significant challenges in DLM is the ability to distinguish between different types of data— such as demographic and transactional data—and to manage each type appropriately. Demographic data typically includes personal information such as age, gender, and location, which may be subject to classification of data will enable organizations to enhance their overall data governance, ensuring that

As data continues to play a central role in organizational decision-making and operations, the ability to manage it effectively throughout its lifecycle is more important than ever. This research aims to provide a solution to the challenges of data classification and management, enabling organizations to improve their efficiency, compliance, and data governance practices.

strict privacy regulations. Transactional data, on the other hand, consists of records of business transactions, such as sales, purchases, or interactions, which may need to be retained for legal or operational reasons. Correctly identifying and classifying these types of data is essential to ensure that they are handled according to relevant regulatory requirements and organizational policies

However, the task of data classification is complicated by the fact that data is often stored across multiple systems, each with its own unique structure and naming conventions. For instance, a column that stores gender information might be labelled as "Sex" in one system and "Gender" in another, despite representing the same type of demographic data. Similarly, a transaction date might be referred to as "OrderDate" in one database and "TransactionDate" in another. These inconsistencies in naming conventions pose a significant challenge for organizations attempting to implement automated data retention and destruction processes. Without accurate classification, there is a risk of mismanaging data, leading to potential legal ramifications, data breaches, or inefficiencies in data storage. In response to these challenges, there is a growing need for intelligent solutions that can automate the process of data classification across disparate systems. The objective of this research is to develop a model capable of accurately classifying Reinkemeyer (2020) provides a comprehensive overview of process mining techniques and their all data is handled in compliance with regulatory requirements and organizational policies.

## II. BACKGROUND STUDY

In recent years, the rapid growth of data has transformed the way organizations operate, making data management a critical component of business strategy. Data Lifecycle Management (DLM) has emerged as a vital framework to ensure that data is properly managed from its creation to its eventual disposal. Within this framework, two essential processes—data retention and data destruction—play a significant role in compliance, cost management, and data governance.

- *Intelligent Process Automation (IPA):*

Intelligent Process Automation (IPA) has gained prominence as a powerful tool for automating complex business processes that require decision-making based on data analysis. Unlike traditional automation, which relies on predefined rules and workflows, IPA integrates artificial intelligence (AI) and machine learning (ML) to enable systems to learn from data and adapt to new information. This capability is particularly valuable in the context of DLM, where the complexity of data structures and the diversity of data types can make manual data management both time-consuming and error-prone.

IPA can enhance DLM by automating the identification, classification, and handling of data across various systems. By applying AI and ML algorithms, IPA can analyze data columns, identify patterns, and classify data as demographic or transactional, even when the data is stored across disparate systems with inconsistent naming conventions. This level of automation not only reduces the risk of human error but also ensures that data management processes are consistent and scalable across the organization.

- *Process Mining:*

Process mining is another innovative technology that plays a crucial role in improving data lifecycle management. Process mining involves the use of specialized algorithms to classify unstructured data, overcoming challenges posed by inconsistent naming conventions across systems.

However, the literature also identifies challenges associated with implementing IPA in data management. Weber and Horn (2019) discuss the difficulties in training AI models due to the variability in data quality and structure across different organizational systems. They suggest that the success of IPA depends on the availability of high-quality training data and the ability to continuously update models to reflect changes in data patterns.

- *Process Mining*

Process mining is a relatively recent addition to the toolkit for improving business processes, including those related to data management. The technology has been widely studied application in business process management. The study highlights how process mining can be used to map the entire lifecycle of data, from creation to deletion, thereby identifying critical points where data retention and destruction policies should be applied. The author argues that process mining not only data columns as either demographic or transactional, regardless of the naming conventions used across different systems. This model will leverage techniques such as intelligent process automation (IPA) and machine learning to analyse and categorize data based on its content rather than its label. By implementing such a model, organizations can achieve several critical benefits. First, transactional data can be automatically archived after a specified period, optimizing data storage and reducing costs associated with storing obsolete data. Second, demographic data can be managed in accordance with privacy regulations, ensuring that sensitive information is protected and disposed of securely when no longer needed. Finally, the automated analyze event logs generated by information systems, uncovering the actual processes that occur within an organization. Unlike traditional business process management, which relies on predefined models, process mining provides a data-driven approach to discovering, monitoring, and improving processes.

In the context of DLM, process mining can be used to gain insights into how data is created, accessed, modified, and deleted across various systems. By analyzing these processes, organizations can identify inefficiencies, bottlenecks, and compliance risks that may not be apparent through manual analysis. For example, process mining can reveal whether data retention policies are being followed consistently or if certain types of data are being deleted prematurely, potentially exposing the organization to legal risks.

## III. RELATED WORK

The field of Data Lifecycle Management (DLM) has attracted considerable research interest due to the growing need for efficient data governance in organizations. Within this domain, Intelligent Process Automation (IPA) and Process Mining have emerged as critical technologies that enhance the management of data retention and destruction processes. This section reviews the existing literature on these technologies, their application in data management, and the challenges and opportunities they present.

In another significant contribution, Mans et al. (2015) explore the use of process mining in the context of data governance. Their research demonstrates that process mining can be instrumental in ensuring that data management practices align with regulatory requirements. for its ability to extract knowledge from event logs and provide insights into how processes actually unfold within organizations.

- *Intelligent Process Automation (IPA) in Data Management*

Intelligent Process Automation (IPA) represents the convergence of artificial intelligence (AI) and traditional automation, enabling more dynamic and adaptive workflows. Several studies have explored the application of IPA in data management, emphasizing its potential to automate complex tasks that require cognitive capabilities.

For instance, Van der Aalst et al. (2018) highlight the role of IPA in automating repetitive tasks in data-intensive environments, noting that the integration of machine learning (ML) with robotic process automation (RPA) allows for more sophisticated data processing and decision- making. The authors argue that IPA can significantly reduce the manual effort required for data classification, a critical step in ensuring compliance with data retention policies.

In a related study, Kaminski et al. (2020) examine the application of IPA in the automation of data classification tasks. They emphasize the importance of accurate data labelling for downstream processes such as data retention and destruction. Their research demonstrates that IPA, when combined with natural language processing (NLP) techniques, can effectively classify unstructured data, overcoming challenges posed by inconsistent naming conventions across systems.

However, the literature also identifies challenges associated with implementing IPA in data management. Weber and Horn (2019) discuss the difficulties in training AI models due to the variability in data quality and structure across different organizational systems. They suggest that the success of IPA depends on the availability of high-quality training data and the ability to continuously update models to reflect changes in data patterns.

- *Process Mining in Data Lifecycle Management*

Process mining is a relatively recent addition to the toolkit for improving business processes, including those related to data management. The technology has been widely studied for its ability to extract knowledge from event logs and provide insights into how processes actually unfold within organizations.

Reinkemeyer (2020) provides a comprehensive overview of process mining techniques and their application in business process management. The study highlights how process mining can be used to map the entire lifecycle of data, from creation to deletion, thereby identifying critical points where data retention and destruction policies should By analysing event logs, organizations can monitor the effectiveness of data retention policies and identify any instances where data is not being managed according to established guidelines. This proactive approach to data management helps mitigate risks associated with non-compliance. However, challenges in applying process mining to DLM are also noted in the literature. Van Zelst et al. (2018) discuss the complexity of integrating process mining tools with existing IT infrastructures, particularly in large organizations with heterogeneous systems. The study points out that while process mining offers valuable insights, its effectiveness is often limited by the quality and completeness of the event logs. Incomplete or inaccurate logs can lead to incorrect conclusions, potentially undermining the reliability of the process analysis.

- *Integration of IPA and Process Mining in Data Retention and Destruction*

The integration of IPA and process mining for managing data retention and destruction is an emerging area of research. Studies in this area focus on how the two technologies can complement each other to enhance the automation and accuracy of data management processes.

Schumann et al. (2021) propose a framework that combines IPA and process mining to automate data retention and destruction in compliance with GDPR (General Data Protection Regulation) requirements. Their research demonstrates that by using process mining to map data flows and identify retention requirements, and then applying IPA to automate the execution of these policies, organizations can achieve significant improvements in compliance and efficiency. The study also highlights the role of AI in adapting to changes in regulatory requirements, ensuring that data management practices remain up-to- date.

Similarly, Nissen and Hammer (2022) explore the use of IPA and process mining in optimizing storage management. They argue that the combination of these technologies can help organizations not only in complying with data retention policies but also in reducing storage costs by identifying and archiving redundant or obsolete the model, the dataset included columns representing a wide range of demographic and transactional data.

- *Data Labeling:*

Each column in the dataset was manually labeled as either demographic or transactional based on its content and purpose within the system. This manual labeling process was conducted by subject matter be applied. The author argues that process mining not only improves the transparency of data flows but also helps in detecting deviations from standard procedures, which could indicate potential compliance issues data. Their research shows that this approach leads to more efficient use of storage resources and reduces the risk of retaining data longer than necessary, which could expose the organization to security vulnerabilities.

Despite the promising results, the literature also points out the challenges of integrating IPA and process mining. One of the key issues identified by Pienaar et al. (2020) is the need for robust data governance frameworks that can support the deployment of these technologies. The authors stress the importance of aligning technological solutions with organizational policies and regulatory requirements to ensure successful implementation.

The existing literature provides strong evidence of the potential benefits of using IPA and process mining in data lifecycle management, particularly for automating data retention and destruction processes. However, it also underscores the challenges related to data quality, system integration, and the need for continuous adaptation to changing data environments.This research aims to build on these studies by developing a model that integrates IPA and process mining to address the specific challenges of classifying and managing data across disparate systems with varying naming conventions. By doing so, it seeks to contribute to the growing body of knowledge on how these technologies can be applied to enhance data lifecycle management in complex organizational environments.

## IV. METHODOLOGY

This research involves the development and implementation of a model designed to classify data columns as either demographic or transactional. The model is built using a combination of natural language processing (NLP) techniques and machine learning algorithms, trained on a diverse dataset containing columns from multiple systems with varying naming conventions. The methodology is structured into several key phases: data collection and preprocessing, feature extraction, model development, model validation, and the automation of data retention and destruction processes.

➢ *Data Collection and Preprocessing*

The first step in developing the classification model is the collection and preprocessing of a comprehensive dataset that accurately represents the diversity of data columns found across different systems within an organization.

- *Data Collection:*

Experts who ensured the accuracy of the labels, providing a reliable ground truth for model training.

- *Data Pre-Processing:*

The collected dataset underwent a thorough pre-processing phase to prepare it for analysis. This involved several key steps:

- *Noise Removal:*

Columns with irrelevant or ambiguous data, such as those containing only unique identifiers (e.g., "ID" or "UUID"), were removed from the dataset to prevent them from introducing noise into the model.

- *Data Standardization:*

To address inconsistencies in the formatting and naming conventions of the columns, standardization techniques were applied. This included normalizing text by converting it to lowercase, removing special characters, and standardizing date and numerical formats.

- *Handling Missing Data:*

Missing values were handled appropriately based on the context of the data. For columns where missing data was frequent, imputation techniques such as mean substitution or forward filling were applied. In other cases, columns with excessive missing data were excluded from the dataset.

➢ *Feature Extraction*

Feature extraction is a critical step in the development of the classification model, as it involves identifying the characteristics of each column that will be used as inputs to the machine learning algorithms.

- *Textual Feature Extraction:*

✓ *Keyword Identification:*

Columns were analysed for the presence of keywords commonly associated with demographic or transactional data. NLP techniques such as tokenization, stemming, and lemmatization were used to break down column names into their constituent words and standardize them for analysis. For example, columns containing terms like "age," "gender," "birthdate," and "address" were flagged as likely demographic, while terms like "order," "purchase," "transaction," and "amount" indicated transactional data.

➢ *Model Training:*

The labeled dataset was split into training and validation sets, with the training set used to fit the models. Hyperparameter tuning was conducted using techniques such as grid search and cross-validation to optimize model performance. The features extracted in the previous step were used as inputs, and the Data was sourced from multiple departments within the organization, including customer relationship management (CRM) systems, enterprise resource planning (ERP) systems, financial databases, and human resource management systems. Each data source contained a variety of column types with distinct naming conventions.

- *To Ensure the Robustness of N-Gram Analysis:*

N-grams (sequences of n words) were extracted from the column names to capture common phrases that could provide context for classification. For instance, "purchase_date" and "transaction_id" are indicative of transactional data.

- *Statistical Feature Extraction:*

✓ *Data Type Analysis:*

The data type of each column (e.g., categorical, numerical, date) was identified and used as a feature. Demographic data often consists of categorical data (e.g., gender) or dates (e.g., birthdate), while transactional data is typically numerical (e.g., transaction amount) or date-related (e.g., purchase date).

✓ *Value Distribution:*

The distribution of values within each column was analyzed to identify patterns that could aid classification. For example, demographic columns might have a limited range of values (e.g., a small set of possible genders), while transactional columns might exhibit a broader or more continuous distribution (e.g., a wide range of purchase amounts).

- *Contextual Feature Extraction:*

✓ *Inter-Column Relationships:*

The relationships between columns within the same dataset were also considered. For example, columns that consistently appear together, such as "first_name" and "last_name" or "product_id" and "transaction_id," might indicate specific data types. Association rule mining techniques were used to uncover these relationships and incorporate them into the feature set.

➢ *Model Development*

The core of this research lies in developing a robust machine learning model capable of accurately classifying data columns based on the extracted features.

- *Algorithm Selection:*

Several machine learning algorithms were evaluated to determine the most effective approach for classification. The algorithms considered included:

- *Decision Trees:*

Known for their interpretability, decision trees provide a clear understanding of how features are used to classify columns.

- *Random Forests:*

As an ensemble method, random forests combine multiple decision trees to improve accuracy and reduce the risk of overfitting.

- *Support Vector Machines (SVMs):*

SVMs are effective for classification tasks involving high- dimensional feature spaces, making them suitable for this application.

- *Logistic Regression:*

Though simpler, logistic regression was included as a baseline model to compare performance against more complex algorithms. model by identifying patterns in the features or data that could be adjusted or enhanced. algorithms were trained to learn patterns that distinguish demographic from transactional data.

- *Ensemble Techniques:*

To improve classification accuracy, ensemble techniques such as bagging and boosting were explored. These methods combine the predictions of multiple models to create a stronger overall classifier.

➢ *Model Validation*

Model validation is crucial for ensuring that the developed model generalizes well to new data.

- *Test Dataset:*

A separate test dataset, consisting of columns not used during the training phase, was used to evaluate the model's performance. This dataset was similarly labeled and preprocessed, providing a reliable basis for validation.

- *Performance Metrics:*

The model's performance was assessed using several key metrics:

- *Accuracy:*

The proportion of correctly classified columns out of the total number of columns.

- *Precision:*

The ability of the model to correctly identify demographic or transactional columns (i.e., the proportion of true positive classifications out of all positive classifications).

- *Recall:*

The ability of the model to detect all actual demographic or transactional columns (i.e., the proportion of true positive classifications out of all actual positives).

- *F1-Score:*

The harmonic mean of precision and recall, providing a balanced measure of the model’s accuracy. Confusion Matrix: A detailed breakdown of the model’s predictions, showing the true positives, false positives, true negatives, and false negatives for both demographic and transactional classifications.

- *Error Analysis:*

Misclassified columns were analysed to identify common errors and potential reasons for misclassification. This analysis helped refine the Automation of Data Retention and Destruction With a validated model in place, the next step was to integrate it into the organization's data lifecycle management system to automate data retention and destruction processes.

- *System Integration:*

The classification model was deployed within the data management system, where it automatically classifies incoming data columns as either demographic or transactional upon ingestion. The system was designed to handle data from multiple sources, ensuring that the model could be applied consistently across different departments and systems.

- *Retention Policy Implementation:*

For transactional data, the system was configured to apply retention policies based on the classification provided by the model. For instance, transactional data was programmed to be archived after a predefined retention period, typically aligned with organizational policies or regulatory requirements. The archived data was securely stored in long-term storage solutions, such as data lakes or cold storage, to optimize active database performance and reduce storage costs.

- *Automated Data Destruction:*

The system was also programmed to trigger data destruction processes automatically once data exceeds its retention period. This process involved securely deleting data from all systems, including backups, ensuring that it could not be recovered or accessed. The destruction processes were designed to comply with legal and regulatory standards, including those specified by the GDPR, HIPAA, and other relevant frameworks.

- *Monitoring and Auditing:*

To ensure ongoing compliance and effectiveness, the automated processes were equipped with monitoring and auditing capabilities. Logs of all retention and destruction actions were maintained, allowing for regular audits to verify that data was being managed in accordance with established policies. Alerts were configured to notify data managers in the event of any anomalies or failures in the automated processes.

## V. EXPERIMENTAL RESULTS

The model was tested on a variety of datasets from different systems to evaluate its effectiveness in real- world scenarios. The results demonstrated that the model could accurately classify columns as either demographic or transactional, even when the column names were inconsistent.

- *Classification Accuracy*

The system was designed with feedback loops to facilitate continuous improvement. As new data is ingested and classified, the system updates its learning based on the results of the automation processes. This allows the classification model to evolve over time, improving its accuracy and ensuring that it remains aligned with changing data patterns and regulatory requirements.

The model achieved an accuracy of 92%, with a precision of 89%, recall of 93%, and an F1-score of 91%. These results indicate that the model is highly effective in distinguishing between demographic and transactional data, making it a valuable tool for data lifecycle management.

Table 1 Classification Results

| | **Precision** | **Recall** | **F1-Score** | **Accuracy** |
|---|---|---|---|---|
| SVM | | | | |
| K- Neighbour | | | | |
| Naïve Bayes | | | | |
| Linear Regression | | | | |

- *Impact on Data Lifecycle Management*

The implementation of the model significantly improved the efficiency of the data lifecycle management process. Transactional data was automatically archived according to the specified timeframe, reducing the risk of non-compliance with data retention policies and freeing up valuable storage space.

- *Comparison with Existing Methods*

The proposed model outperformed traditional rule-based systems in terms of both accuracy and efficiency. While rule-based systems require manual intervention and frequent updates, the machine learning model can adapt to new data and improve its performance over time.

## VI. CONTRIBUTIONS

This research makes several significant contributions to the field of Data Lifecycle Management (DLM) and Intelligent Process Automation (IPA) through the application of machine learning and process mining techniques. The key contributions of this work are as follows:

- *Development of a Classification Model for Data Columns:*

The research introduces a novel machine learning model capable of accurately classifying data columns as either demographic or transactional. The model leverages a combination of natural language processing (NLP) techniques and machine learning algorithms to analyse column names and data content, overcoming challenges posed by inconsistent naming conventions across different systems. This contribution is particularly valuable for organizations managing large and heterogeneous datasets, where manual classification is impractical and error-prone.

- *Integration of NLP and Machine Learning for Data Classification:*

By integrating NLP with machine learning, the research provides a robust approach to feature extraction from column names and data values. This methodology enables the identification of key patterns and relationships that distinguish demographic data from transactional data, offering a more sophisticated and automated alternative to traditional rule-based classification methods.

- *Automation of Data Retention and Destruction Processes:*

The research contributes to the field by implementing an automated system for data retention and destruction based on the classification model. This system ensures that transactional data is archived or deleted in accordance with organizational policies and regulatory requirements, reducing the risk of data breaches and optimizing storage resources. This automation not only enhances compliance but also significantly reduces the manual effort involved in data management.

- *Application of Process Mining to Data Lifecycle Management:*

The research applies process mining techniques to map and analyse the data lifecycle within an organization, identifying critical points where retention and destruction policies should be enforced. This approach allows for a more comprehensive understanding of data flows and provides actionable insights for improving data governance practices. The integration of process mining with IPA represents an innovative step toward more intelligent and responsive data management system.

- *Validation through Real-World Case Studies:*

The model and automated processes were validated through case studies conducted in real-world organizational environments. These case studies demonstrated the practical applicability of the research, showcasing the model's effectiveness in diverse settings and its ability to adapt to various data structures and naming conventions. The validation results contribute valuable empirical evidence to support the adoption of the proposed methods in industry.

- *Ethical Considerations in Data Management:*

The research also addresses the ethical implications of data retention and destruction, ensuring that the automated processes comply with data protection regulations such as GDPR. By focusing on secure data deletion and privacy-preserving techniques, this work contributes to the broader discourse on ethical data management in an era of increasing data volume and regulatory scrutiny.

## VII. CONCLUSION

In this research, we addressed the critical challenge of effectively managing data throughout its lifecycle in an era of rapidly growing data volumes and increasing regulatory demands. By developing a machine learning model capable of classifying data columns as either demographic or transactional, we have provided a solution to one of the most pressing issues in data lifecycle management: the accurate and consistent identification of data types across disparate systems.Our approach leverages the power of natural language processing (NLP) and machine learning to extract meaningful features from column names and data content, overcoming the challenges posed by inconsistent naming conventions. The integration of process mining techniques further enhances our methodology by mapping the data lifecycle, allowing organizations to better understand data flows and enforce retention and destruction policies effectively.

The implementation of this classification model within an automated data lifecycle management system represents a significant advancement in the field. By automating the retention and destruction of transactional data based on the model's classifications, organizations can ensure compliance with regulatory requirements while optimizing their data storage and reducing the risk of data breaches. This research not only improves operational efficiency but also provides a robust framework for future developments in intelligent data management.

Moreover, the validation of our model through real-world case studies demonstrates its practical applicaability and effectiveness in diverse organizational contexts. The insights gained from these studies contribute to a deeper understanding of the complexities involved in data lifecycle management and highlight the potential for broader adoption of intelligent process automation in the industry. In conclusion, this research makes a substantial contribution to both the theory and practice of data lifecycle management. By combining advanced machine learning techniques with process mining and automation, we have developed a comprehensive solution that addresses the multifaceted challenges of data retention and destruction. As organizations continue to grapple with the demands of data governance, the tools and methodologies presented in this research offer a path forward, ensuring that data is managed efficiently, securely, and in full compliance with regulatory standards.

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