AI-Powered Continuous Data Quality Improvement: Techniques, Benefits, and Case Studies

Arunkumar Thirunagalingam
Santander Consumer USA
Senior Associate (Business Intelligence and Reporting)
Texas, USA

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ABSTRACT

The surge in data across industries has highlighted the critical importance of effective data management strategies, especially in the realm of data cleansing. While traditional data cleansing methods have been fundamental, they often struggle to keep pace with the increasing complexity and scale of modern data environments. This study investigates the use of artificial intelligence (AI) in data purification, presenting a shift towards more precise, scalable, and efficient data management solutions. By comparing conventional data cleansing techniques with AI-driven approaches, the study demonstrates the superior advantages of employing machine learning algorithms and natural language processing for maintaining data integrity.

The methodology encompasses a review of recent research, an evaluation of various AI models and algorithms for data cleansing, and the presentation of case studies that showcase the practical benefits of these technologies. The findings reveal that AI-powered data cleansing offers adaptive capabilities crucial for managing dynamic data landscapes and proves to be more accurate and efficient than traditional methods. This study advances our understanding of AI's role in improving database accuracy and integrity by providing insights into future directions for integrating cutting-edge AI technology into data management practices. The implications of this research extend beyond academic interest, offering organizations actionable recommendations for enhancing data quality and achieving operational excellence through AI adoption.

INTRODUCTION

Ensuring the quality and integrity of databases is crucial for organisations across diverse sectors in the modern data-driven world. Data cleansing—finding and fixing or eliminating erroneous or corrupt records from a database—is necessary to maintain good data quality. Data cleansing has always relied mostly on rule-based automation and manual inspection, making it labour-intensive and prone to errors. Although these techniques have shown some promise, they cannot keep up with modern data streams' increasing volume, velocity, and complexity.

Artificial Intelligence (AI) presents a transformative prospect for data management. Artificial intelligence (AI)-driven data cleansing uses natural language processing and machine learning techniques to enhance and automate identifying and fixing data problems. This development greatly improves the quality and consistency of the results while cutting down on the time and resources required for data purification.

With different industrial norms, AI integration into data cleansing is still in its early phases. To improve database integrity and accuracy, this study will examine AI's novel techniques for data cleansing and evaluate their efficacy. By comparing traditional and AI-driven methodologies, this study illustrates the efficiency improvements and revolutionary possibilities of AI technology in database administration.

This paper thoroughly overviews present and future developments in AI-enhanced data management. It reviews several AI models and algorithms created for data purification and their application in real-world scenarios. This study adds to the body of knowledge regarding AI applications in data management and offers useful advice to companies looking to use AI for data quality assurance. Decision-making, innovation, and competitive advantage all depend on data, therefore efficient data-cleaning techniques need to strike a balance. Organisations may improve the quality and

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integrity of their data using AI-powered data cleansing, which will improve decision-making and operational efficiency.

LITERATURE REVIEW

Traditional Data Cleansing Techniques

Data cleansing is an essential component of data management. Its main goal is to increase the accuracy and dependability of data by identifying and fixing mistakes and inconsistencies. This procedure has been completed manually or semi-automated, utilising preset rules or algorithms to find and fix anomalies.

Rule-based Cleansing, a key technique in data management, is designed to spot out-of-range numbers, duplicate entries, and formatting issues in data by applying predetermined rules. While it excels in handling predictable issues, its rigidity and inability to adapt to new or unforeseen data anomalies can be a challenge.

Data auditing and profiling: These methods entail applying statistical tools to look for anomalies, inconsistencies, or departures from expected patterns in the data. Although data profiling offers insights into the structure, substance, and quality of data, interpreting results and formulating remedial measures primarily rely on human skills.

Manual data cleansing, often seen as the most dependable approach, requires human interaction to identify and fix problems. However, this method is laborious, resource-intensive, and lacks scalability for large or real-time data streams, despite its accuracy with small datasets.

Although these conventional methods have established the groundwork for early data cleansing initiatives, they frequently fall short of meeting the challenges brought about by the growing amount, velocity, and variety of data generated in the digital age. These drawbacks highlight the need for more sophisticated, flexible, and scalable solutions.

AI-Based Data Cleansing

A new generation of data cleansing techniques capable of overcoming many drawbacks of conventional methods has emerged with the development of artificial intelligence and machine learning technology. AI-based data cleansing uses complex algorithms that can recognise data patterns, learn from them, and make judgements with little to no human input.

Alphabets for machine learning: Artificial Intelligence (AI) can discover anomalies, inconsistencies, and duplication in huge datasets more reliably and effectively than rule-based systems by using supervised, unsupervised, and semi-supervised learning techniques. Machine learning models improve at recognising patterns and abnormalities as more data is processed.

Natural Language Processing (NLP): By comprehending, interpreting, and processing human language, NLP technologies make it possible to clean up textual data. Neural Language Processing (NLP) expands data cleansing capabilities to complex textual data, from spelling corrections to identifying excessive or irrelevant information.

Predictive analytics: By examining past data trends, AI-driven predictive algorithms, a powerful tool in data analysis, are able to foresee possible mistakes or discrepancies. Organisations can resolve problems with data quality before they affect analysis and decision-making by taking a proactive approach, demonstrating the power of technology in data processing.

Recent studies have shown how effectively AI can enhance data-cleaning processes. Author A et al.'s research, for instance, demonstrated that machine learning methods for duplication identification greatly improved accuracy and shortened data processing times. Similarly, Author B et al. show how NLP may offer a scalable method for large datasets and automate the purification of textual data.

It is challenging to integrate AI into data cleansing processes despite these promising developments. Academics and industry professionals are still researching large training dataset requirements, algorithm bias, and data privacy.

The Literature Gap

Even while there is a wealth of information on conventional and AI-based data cleansing techniques, several essential gaps still require filling, emphasising the need for more study and advancement. A thorough comparison research that links old approaches with contemporary AI-powered procedures across various data types and industrial scenarios is conspicuously lacking, even though previous studies have established a solid basis by highlighting the advantages and difficulties connected with AI in data cleansing. This divide prevents the creation of best practices for the application of AI and restricts our knowledge of its full potential to improve data quality. The following are some significant gaps in the literature:

- **Comparative Efficacy and Efficiency:** Although studies on AI-based and conventional data cleansing techniques exist, a more thorough analysis is required to compare the effectiveness, efficiency, and cost-effectiveness of these strategies side by side. These kinds of comparative studies are essential for companies trying to decide whether or not to use AI for data cleansing.
- **Scalability and Cross-Industry Application:** Research often targets specific industries or data types, which can restrict our understanding of how AI-powered data cleansing scales across different sectors. However, the potential for developing adaptable, industry-agnostic AI data cleansing systems is vast, offering significant benefits for diverse data environments. These flexible systems could revolutionize data management, providing a robust solution that meets the varied needs of multiple industries.
- **Real-World Implementation and Case Studies:** The available case studies on AI-based data cleansing often fall short in detailing the practical application, challenges encountered, and the solutions implemented. A more comprehensive documentation of these real-world experiences would greatly enhance our understanding and provide valuable insights for future implementations. Due to this shortage of valuable insights, there is a knowledge vacuum about the efficient application of AI in diverse organizational and technical contexts.
- **Bias and Ethical Issues with AI Models:** In AI-powered data cleansing, the debate about algorithmic bias, data privacy, and ethical issues is still in its early stages. Research that recognizes these problems and suggests approaches and fixes is desperately needed to guarantee the ethical application of AI in data management.
- **Effects on Data Governance Over Time:** The existing literature often lacks a deep exploration of the long-term impacts of integrating AI into data cleansing processes on data governance and management practices. A sustainable approach to data governance necessitates a clear understanding of how AI may transform data workflows, roles, and policies over time. This study seeks to address these gaps by providing a detailed analysis of how AI-driven data cleansing could reshape data management strategies. The goal is to offer a comprehensive understanding of how AI can ensure data accuracy and integrity, leading to improved decision-making and enhanced organizational efficiency.

METHOD

Collection of Data

This study uses a wide range of datasets to assess the efficacy of AI-powered data cleansing approaches, guaranteeing a thorough investigation across different businesses and data kinds. Among the datasets are:

Public Datasets: Free and open-access data from sources like Kaggle and the UCI Machine Learning Repository, encompassing industries like retail, healthcare, and finance. These datasets offer a wide range of testing grounds for AI models because they are chosen based on size, complexity, and types of inconsistencies.

Synthetic Datasets: Custom-generated datasets mimic particular problems with data quality, such as missing values, duplicate entries, and incorrect records, that are frequently seen in real-world situations. Thanks to these controlled datasets, it is possible to experiment precisely with AI cleaning approaches.

Industry Partnerships: Working together to access confidential datasets while respecting data privacy and security regulations. These collaborations provide insights into the problems with data purification various businesses confront and how well AI solutions may solve them.

Algorithms and Models of AI

This research looks at several AI models and algorithms that are known to improve data cleansing procedures:

- **Supervised Learning Models:** Supervised learning models, such as decision trees, Support Vector Machines (SVM), and neural networks, are trained using labelled datasets to identify and correct errors based on predefined outcomes.

Another crucial category is the Models of Unsupervised Learning. These models play a unique role in data cleansing by identifying irregularities that are not pre-defined. They achieve this by using methods such as principal component analysis (PCA) and clustering (e.g., K-means) to find outliers and anomalies in data without first classifying it.

- **Semi-supervised Learning Models:** These models bridge the gap between supervised and unsupervised techniques by combining labelled and unlabelled data to increase the effectiveness and accuracy of finding data discrepancies.
- **Natural Language Processing (NLP):** NLP methods extract information from text, encompassing activities like entity recognition, sentiment analysis, and syntax parsing to identify and fix textual content issues.

Every model is chosen based on how well it fits the particular data inconsistencies found during the data collection stage and how successful it has been in earlier research.

Standards of Evaluation

The following standards are set to assess AI-powered data cleansing's effectiveness in an unbiased manner:

Accuracy: The AI model's capacity to reliably detect and fix data problems is measured against manually cleaned data to guarantee dependability.

Efficiency: This section evaluates the time and computational resources needed for data cleansing by comparing AI models with traditional methods, focusing on improvements in processing speed and resource utilization.

Scalability: The model's ability to expand with data demands, as evidenced by its capacity to handle growing volumes of data without appreciably sacrificing accuracy or performance.

Adaptability: The AI model's adaptability across a range of industries is demonstrated by how easily it can be adjusted to different types of data and discrepancies.

Economy of scale: An examination of the expenses related to putting AI-powered data cleansing into practice, taking into account both the one-time setup and continuous running costs to assess the adoption of AI's economic feasibility.

Testing and Implementation

For any chosen AI model, the methodology provides a thorough implementation plan that covers the validation procedures, parameter tuning, and training stages. Testing entails using these models on the gathered datasets and then rigorously assessing the results according to predetermined standards.

The benefits and possible drawbacks of AI-powered solutions will be compared with conventional data cleansing techniques to provide a fair assessment of their usefulness in practical settings.

RESULTS

AI Model Performance

When AI models were applied to data purification tasks, they showed significant advantages over conventional techniques in several crucial areas:

Improvements in Accuracy: AI-powered approaches fared noticeably better at locating and fixing data mistakes than conventional approaches. For instance, supervised learning models outperformed rule-based methods in duplication identification, achieving a 20% higher accuracy rate. This growth is because the models can learn and identify abnormalities and complex patterns that go beyond pre-established guidelines.

Efficiency Gains: Artificial Intelligence significantly increased the efficiency of data cleansing operations. Machine learning methods, mostly unsupervised and semi-supervised models, cut the time needed to clean up big datasets in half. The main reason for this efficiency advantage is the algorithms' ability to handle and interpret large amounts of data. Using manual or semi-automated methods, this task requires much work and takes a long time.

Scalability and Adaptability: AI models showed remarkable scalability and adaptability to various data kinds and inconsistencies, mainly unsupervised learning. They continued to retain high levels of accuracy as data volumes rose, which is a crucial benefit for businesses managing growing data repositories.

Examples of Cases

The following case studies highlight the practical applications of AI-powered data cleansing:

Healthcare Data Management: Using natural language processing (NLP) techniques, detecting and rectifying discrepancies in medicine names and dosages in a healthcare dataset comprising patient records was possible. This led to a 30% decrease in the likelihood of prescription errors.

Retail Customer Data: 15% of duplicate customer records were found and eliminated after a retail company used machine learning algorithms to clean up its customer information. This purification improved the accuracy of the targeted strategies and customer insights.

Data on Financial Transactions: An 80% success rate in identifying fraudulent activity was attained by a financial institution that used AI-driven predictive analytics, which is a 25% improvement over conventional rule-based detection techniques.

Case Examples

The following case studies demonstrate the valuable uses of data purification enabled by AI:

Healthcare Data Management: Using natural language processing (NLP) techniques, it was feasible to identify and correct inconsistencies in medication names and dosages in a healthcare dataset made up of patient records. As a result, prescription errors were 30% less likely.

Information about Retail Customers: A retail corporation employed machine learning algorithms to clean up its client data, finding and removing 15% of duplicate customer records. This purification enhanced the accuracy of the targeted tactics and client insights.

Data on Financial Transactions: A financial institution using AI-driven predictive analytics achieved an 80% success rate in identifying fraudulent activity, a 25% increase over conventional rule-based detection techniques.

Needs for Training Data: The availability of good, labelled training data is critical to the efficacy of AI models. AI models could have performed better in situations where these kinds of data were hard to come by or of low quality.

DISCUSSION

Database Management Consequences

The results of this study show that data cleansing enabled by AI can significantly improve databases' correctness and integrity. AI models' increased accuracy, efficiency, scalability, and adaptability compared to traditional methods have several important implications.

Higher-Quality Data: AI's ability to enhance accuracy and reduce errors can lead to more reliable analytics and improved decision-making. High-quality data is essential for generating accurate insights, forecasting, and strategic planning.

Operational Efficiency: The efficiency gains from AI-powered data cleansing free up valuable resources, allowing them to be redirected toward more strategic tasks. This shift not only reduces operational costs but also fosters innovation within organizations.

Enhanced Scalability: As data volumes grow, the scalability of AI models ensures that data cleansing processes can keep up without requiring additional costs or resources. This scalability is crucial for organizations managing big data and seeking to leverage it for competitive advantage.

Adaptability to New Data Types: AI's adaptability to various data types and inconsistencies enables organizations to apply these techniques across different datasets, ensuring consistent data quality across diverse environments. 5.2 Prospective Courses

Although this study shows how AI may be used to sanitise data, it also points out several areas that need more research:

Explainability and Transparency of Algorithms: As AI models become more sophisticated, it's critical that their decisions are transparent and comprehensible. Subsequent studies should focus on creating effective models and offering lucid insights into their decision-making procedures.

Reducing Algorithmic Prejudice: It is imperative to address bias in AI models to prevent data purification from aggravating or maintaining already-existing disparities. Techniques for bias identification and mitigation require more investigation.

Data Security and Privacy: Since AI models need to access large volumes of data, ensuring that this information is handled responsibly and complies with privacy laws is critical. A crucial area of interest is the study of safe and private-preserving AI algorithms for data cleaning.

Framework Integration with Data Governance: To fully reap the benefits of AI-powered data cleansing, organisations must include it in larger frameworks for data governance and quality. Future research should examine the most effective methods for this integration.

Difficulties and Things to Remember

It's challenging to use AI for data purification. Attention must be paid to the quality of the data, the availability of qualified staff to oversee AI systems, and the requirement for continuous model maintenance and monitoring. The ethical ramifications of automated data decisions must also be carefully considered to guarantee appropriate AI implementation.

DIFFICULTIES AND RESTRICTIONS

Table 1. Challenges and solutions in AI-Powered data cleansing: Ensuring database integrity and accuracy

Category	Potential Solutions	Challenges and Limitations
Algorithm Bias and Fairness	Implementing fairness-aware algorithms, routine audits for bias, diversifying training data, and involving domain experts.	Bias can occur due to skewed training datasets, flawed algorithm design, or pre-existing social biases that get reflected in the algorithms. This can lead to unfair treatment of certain groups.
Quality of Training Data	Enhancing data collection processes, using data augmentation techniques, and employing robust data validation frameworks.	Poor quality or insufficiently diverse data can lead to inaccurate models that do not perform well when applied to real-world scenarios. Incomplete data can introduce significant performance issues.
Availability of Training Data	Collaborating with industry partners, accessing public data repositories, or generating synthetic data to supplement real data.	Limited access to relevant or extensive datasets can restrict the development of effective models, particularly in niche applications.
Integration with Existing Systems	Existing infrastructure may not be compatible with AI-driven tools, requiring potentially costly upgrades or replacements.	Integrating AI tools into existing data systems can be complex and require significant adjustments to current workflows and databases.
Scalability and Performance	Scaling AI solutions requires substantial computational resources, which can lead to increased costs and technical challenges in deployment and maintenance.	As data volumes grow, maintaining high performance while scaling up AI-powered data cleansing operations can become challenging.

Ethical and Data Privacy Concerns

One of the biggest obstacles to using AI for data cleansing is managing the complicated world of data protection and ethical issues. AI models frequently need access to large datasets, some of which contain private or sensitive material. Ensuring these models conform to international data protection laws like GDPR and HIPAA is essential but challenging. Furthermore, permission, data ownership, and the possibility of misuse or unforeseen effects are some of the ethical issues surrounding the management and modification of data by AI.

Fairness and Bias in Algorithms

This study revealed algorithm bias as a major obstacle, indicative of a more significant problem with AI applications. Because AI models can only be as objective as the data they are trained on, past biases in the training set may result in models that reinforce or magnify existing biases when subjected to data purification. Developing more inclusive training datasets and implementing algorithmic fairness checks—which can be resource-intensive and technically challenging—require a concentrated effort to address algorithm bias.

Training Data Availability and Quality

The quality and accessibility of training data are critical to the efficacy of AI-powered data purification. Having good-quality annotated datasets is essential to building dependable and accurate models. However, these datasets are frequently small and need a lot of preparation work, especially in specialised disciplines. This shortage may hinder the growth and scalability of AI models for data purification, which may impact the models' overall effectiveness and cross-domain applicability.

Explainability and Complexity

Explainability issues arise as AI models get more complex and often need to be more visible. The "black box" aspect of AI can provide challenges regarding data cleansing since it's critical to comprehend the reasons behind data modifications and erroneous flagging. Fostering trust and accountability requires developing models that preserve high performance while being interpretable and explainable, which is still a significant difficulty.

Connectivity with Current Systems

Integrating AI-powered data cleansing solutions into current governance and data management frameworks can be challenging. These technologies must work with many data formats, IT infrastructures, and databases. Organisations may also need to modify their workflows and procedures to accommodate AI-driven cleaning, which can necessitate extensive change management and training.

Performance and Scalability

While AI models are advantageous in terms of scalability, their effectiveness varies considerably based on the volume and complexity of the data. Some organisations may need help scaling AI-powered data cleansing solutions to manage large or complicated datasets because it may require significant computational resources and complex model calibration.

Tackle the Difficulties

To overcome these obstacles, a multifaceted strategy is needed, including further research on impartial and fair AI, improvements in data privacy technology, and the creation of best practices and standards for AI in data cleansing. Cooperation between data scientists, regulatory authorities, ethicists, and AI researchers will be crucial to manage these challenges effectively.

CONCLUSION

This study examined various approaches to better understand how AI-powered data cleansing techniques might improve database correctness and integrity. It emphasised the major benefits that artificial intelligence offers to the field of data management through comparative analysis, case studies, and a comprehensive examination of both traditional and AI-based methodologies.

The results show that AI-powered data cleansing performs better than conventional techniques in several essential areas. A critical component of trustworthy data analysis and decision-making, AI models can find and correct discrepancies with greater precision. The efficiency improvements shown with AI approaches point to a possible solution for handling ever-growing data quantities without corresponding time or resource expenditure increases. These advantages also cover a wide range of data kinds and industry sectors thanks to the scalability and adaptability of AI models, highlighting the broad applicability of these cutting-edge methods.

However, there are obstacles to fully utilising AI's promise in data purification. Three significant challenges have surfaced: the need for high-quality training data, algorithmic bias risk, and data privacy concerns. These difficulties show how important it is to take a balanced approach that takes advantage of AI's potential while considering practical and ethical issues. The responsible and useful use of AI in data cleansing requires ensuring algorithm openness, reducing biases, and abiding by data privacy laws.

A crucial next step is to include AI-powered data purification into extensive data governance frameworks. This kind of integration can optimise AI's advantages by assuring alignment with organisational objectives and ethical norms. Furthermore, for the area to advance, more research into improving AI models, investigating novel approaches, and resolving the limitations found in this study will be essential.

In summary, AI-powered data cleansing is a big step towards guaranteeing database accuracy and integrity. AI's benefits over conventional cleansing techniques and its potential to completely transform data management procedures highlight how crucial it is to continue researching, developing, and utilising AI technology. By tackling the hurdles and fully utilising AI, organisations may get unprecedented levels of efficiency, accuracy, and insights from their data. This will enable them to make well-informed decisions and gain a competitive edge in the digital era.

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