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Original Article

AI-Enabled Data Profiling Techniques for Quality Improvement

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ABSTRACT

AI is transforming data profiling by making data quality assessment more automated, scalable, and intelligent. Traditional methods struggle with modern, complex, and diverse datasets, while AI techniques—such as machine learning, deep learning, and statistical models—can detect anomalies, recognize patterns, and predict data quality issues across both structured and unstructured data. The study reviews the evolution from rule-based profiling to adaptive AI-driven approaches, highlighting methods like clustering, classification, and natural language processing. It also proposes a framework integrating AI into key stages of data profiling, including data ingestion, preprocessing, feature extraction, anomaly detection, and quality scoring, with continuous learning and dynamic rule generation. Results show that AI-based profiling significantly improves data completeness, consistency, and timeliness compared to traditional methods. Despite challenges in implementation, AI-powered data profiling represents a major advancement in data quality management, with future directions focusing on explainable AI, real-time processing, and big data integration.

KEYWORDS

Artificial Intelligence, Data Profiling, Data Quality, Machine Learning, Anomaly Detection, Data Cleaning, Big Data, Predictive Analytics, Data Governance, Deep Learning.

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1. INTRODUCTION

1.1. Background

The blistering development of digital technologies has led to the explosive growth of data generation and the emergence of complex data ecosystems with a large volume, velocity, and variety. Data has become a vital element in organizations in different fields like business intelligence, predictive analytics, and strategic decision-making. The quality of underlying data however has a direct effect on the effectiveness of such applications. Data profiling is an essential part of data quality management that allows to systematically analyze data sources in order to comprehend their structure, content, and their relationships. Conventional data profiling techniques that are based on descriptive statistics, pattern recognition and rule-based validation, work well on structured data sets but can tend to fail to deal with the complexity of the contemporary data landscape, such as unstructured data, real-time data streams, and heterogeneous sources. Artificial Intelligence has, in this regard, become a groundbreaking solution, data profiling elevated by machine learning, intelligent automation. The use of AI-based solutions helps systems to learn data, discover hidden patterns, detect anomalies, and constantly adapt to the evolving data properties. As a result, AI-based data profiling provides a more scalable, flexible, and efficient approach to ensuring high data quality in dynamic and large-scale data environments.

1.2. Importance of Data Profiling For Quality Improvement

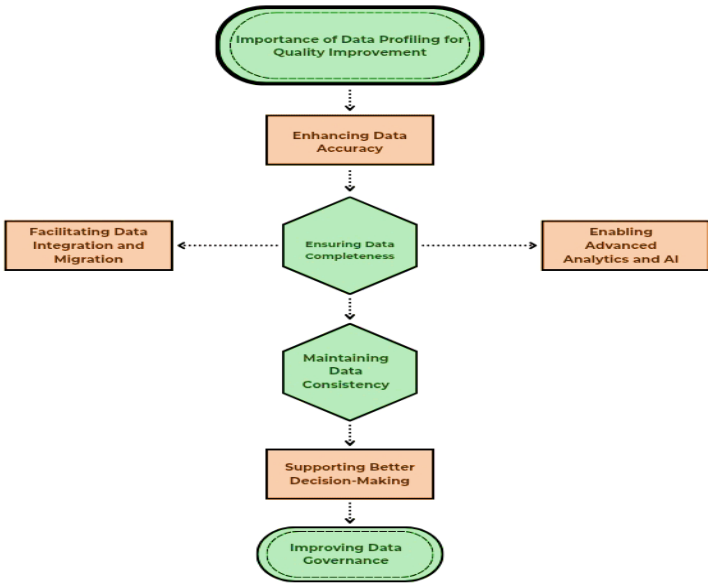

Fig 1 - Importance of Data Profiling for Quality Improvement

1.2.1. Enhancing Data Accuracy

Data profiling is crucial in enhancing accuracy of the data as it helps in detecting errors, inconsistencies and wrong values within the data sets. Profiling can be used to guarantee that data is a true-to-life representation of real-world entities by analyzing the data distributions and verification of values by predefined rules or reference datasets. This contributes to a higher degree of reliable insights and less chance of making wrong decisions.

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1.2.2. Ensuring Data Completeness

Profiling of data assists in identifying the missing or incomplete values in sets of data, but this can greatly influence the results of the analytics. Assessing the existence of required fields and calculating the ratio of the null values, organizations may realize lapses in data collection procedures. Handling these problems enhances the completeness of the datasets and makes sure that enough information is obtained to analyze it meaningfully.

1.2.3. Maintaining Data Consistency

Consistency is essential for integrating and analyzing data from multiple sources. Data profiling detects anomalies like conflicting values, format differences and business rule violations. Profiling improves data integrity by making sure that there is uniformity in databases, and it helps to integrate data across systems without difficulties.

1.2.4. Supporting Better Decision-Making

Quality data is very essential in decision making. Data profiling gives an idea of how reliable and usable the data is and therefore, organizations can make sound decisions by using reliable and trustworthy data. It minimizes confusion and enhances trust in the results of the analysis.

1.2.5. Improving Data Governance

Data profiling also provides a robust data governance through setting standards, policies and quality benchmarks. It assists organizations in tracking data quality on a continuous basis and also makes them in compliance with regulatory requirements. Profiling also facilitates accountability as it gives visibility on the problems in data and their origin.

1.2.6. Facilitating Data Integration and Migration

Profiling is useful in evaluating the quality and structure of source data during the process of data integration or migration. It detects inconsistency, duplicates and format differences, which facilitates easier data transformation and consolidation. This minimizes the errors and guarantees a successful and consolidation of data across systems.

1.2.7. Enabling Advanced Analytics and AI

Accurate and well-structured data is a prerequisite for advanced analytics and AI applications. Data profiling makes sure the data sets are of the quality needed to train machine learning models and predictive analysis. It improves the quality of data and, as a result, the work of the model increases or causes more significant and relevant results.

1.3. AI-Enabled Data Profiling Techniques

AI-powered data profiling methods can be regarded as a notable improvement to the data profiling practices of the past since they involve the use of machine learning, statistical modeling, and intelligent automation to the data quality management process. The AI-based methods, as opposed to traditional methods, which are based on predetermined rules and predefined constraints, can learn through data, detect more sophisticated trends, and adjust to changing data conditions. These

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methods employ various algorithms such as outlier detection models to detect anomalies, classification algorithms to classify quality issues in data and clustering methods to cluster similar data patterns to be analyzed more. Also, unstructured data, including text, can be profiled using natural language processing (NLP) methods and allow a better comprehension of various data sources. Probabilistic models are also used by AI-based profiling systems to deal with uncertainty and make informed predictions regarding data quality. The major benefits of such techniques are that they enhance efficiency as they automate the time-consuming and repetitive duties, which would otherwise require a human touch. Also, AI-based systems facilitate profiling of data in real-time, which enables organizations to track and preserve the quality of data in dynamic systems like streaming data platforms. Such systems are constantly learning based on new information by using feedback effectively, and they improve their precision and strength with time. With feature extraction, predictive analytics, and continuous learning, the AI-based data profiling methods offer a scalable and smart approach to handling large amounts of potentially complex data. Consequently, they are instrumental in facilitating quality data to support advanced analytics, business intelligence and decision making procedures in contemporary data-oriented organizations.

2. LITERATURE SURVEY

2.1. Traditional Data Profiling Techniques

The process of data profiling used to determine the quality and structure of data before the advent of artificial intelligence was mainly based on deterministic and statistical methods. Computation of basic statistical measures like mean, variance, frequency distribution and null value counts was highly done in column profiling techniques which allowed a preliminary understanding of data characteristics. Dependency analysis techniques such as functional dependency detection assisted in determining dependencies between attributes, and guaranteed a consistent schema. Regular expressions were commonly used to check formats like email addresses, phone numbers, and identification codes, through pattern matching. Also, there were rule-based validation systems that implemented predefined business rules to ensure data integrity. Though these techniques worked quite well with the structured and well-defined data, they were not flexible, did not work well with unstructured data, and were not scalable to large and dynamic data settings.

2.2. Early AI Integration in Data Profiling

The introduction of artificial intelligence in data profiling at an early stage signified a dramatic change towards more adaptive and intelligent systems. In the period, scientists started using machine learning technologies to gain a better perspective on the data and identify anomalies. K-means and hierarchical clustering algorithms were employed to cluster similar data patterns and identify the hidden structures in data sets. Patterns of classification allowed detection of anomalies based on patterns of labeled data. Probabilistic methods, such as Bayesian networks, offered a way of modeling the uncertainty, and the relationship between variables. Neural networks were also considered in respect to their capability to discern non-linear, intricate patterns in data. These approaches enhanced pattern discovery and anomaly detection abilities, but their practical use was frequently constrained by the computational complexity and the unavailability of efficient processing infrastructure then.

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2.3. Machine Learning-Based Profiling

The profiling methods based on machine learning also increased the possibilities of data quality evaluation through the introduction of predictive and adaptive mechanisms. Decision trees, support vectors machine and other algorithms were used to categorize pieces of data and identify anomalies according to their learned patterns. The clustering algorithms such as k-means made it easy to identify the outliers and abnormal distribution of data, which are some of the signs of possible data quality problems. These models facilitated the use of predictive profiling whereby the systems were able to predict and avert errors or inconsistencies ahead of time thus enhancing proactive data management. Moreover, machine learning models enabled them to learn continuously with new data, and thus they were applicable to dynamic and changing datasets. But it was important that their performance was based on the quality of the training data and the appropriate model tuning.

2.4. Limitations of Existing Approaches

Although significant progress was made using the traditional and early AI-based data profiling, there were still a number of limitations. The inability to explain machine learning models, especially complex ones like neural networks, was one of the main obstacles as it was not easy to make users interpret the obtained results and trust the choices made by the system. Moreover, these methods tended to be very computationally intensive, restricting their use in resource-constrained settings. Another significant issue was real-time data profiling because most existing systems were built to handle a batch processing environment as opposed to streaming data. Moreover, it had problems with scalability when working with large quantities of heterogeneous data and the interfusion of these approaches into current enterprise systems was still complicated. These limitations highlighted the need for more efficient, interpretable, and scalable AI-driven data profiling techniques.

3. METHODOLOGY

3.1. Proposed Framework

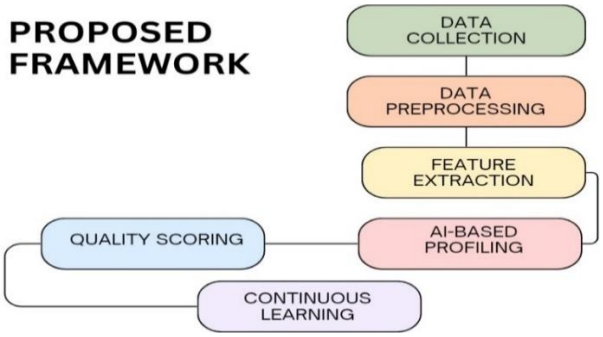

Fig 2 - Proposed Framework

3.1.1. Data Collection

The initial step of the presented framework is the logical gathering of data with various heterogeneous sources including databases, data warehouses, APIs, and real-time data streams. This phase makes sure that both the structured and unstructured data are collected to give a detailed basis

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to profiling. Data integration techniques are given special attention to manage data inconsistencies between sources, such as schema differences and data format differences. Data ingestion mechanisms are efficient to provide scalability and high-volume data environments.

3.1.2. Data Preprocessing

Data preprocessing is a very important procedure, which aims at preparing raw data to be analyzed to enhance its quality and consistency. The tasks involved in this stage consist of cleaning the data, dealing with missing values, noise, normalization, and transformation. Duplications are detected and eliminated, formats inconsistencies (e.g., date formats, units) are standardized. Moreover, data encoding and transformation methods are used to transform categorical and textual data into machine-readable formats, which are compatible with AI models.

3.1.3. Feature Extraction

During this phase, the useful attributes or characteristics are obtained out of the processed information in order to improve the quality of profiling. In feature extraction, some of the important characteristics identified include statistical properties, patterns, correlations and distributions in the dataset. Dimensionality reduction and feature selection methods are advanced in order to remove irrelevant or redundant attributes, thus enhancing model efficiency. This is an important step in allowing AI models to gain a better insight into the significance of the underlying structure and quality of the data.

3.1.4. AI-Based Profiling

The AI profiling phase is based on machine learning and artificial intelligence algorithms to analyze the data and reveal quality problems. The use of algorithms like clustering, classification, and anomaly detection is used to identify inconsistencies, outliers, and hidden patterns in the set of data. Complex pattern recognition problems can also be applied to deep learning models, particularly with unstructured data. The step allows automated and smart profiling, decreasing the use of manual rule based systems and increasing accuracy of detecting data quality issues.

3.1.5. Quality Scoring

Quality scoring involves evaluating the overall quality of the dataset using predefined metrics and AI-generated insights. Accuracy, completeness, consistency, timeliness, and validity are the most important dimensions, which are evaluated to give a quantitative score to the data. Such a scoring system can assist organizations to prioritize data cleaning activities and track progress over time. It is also possible to include visualization tools and dashboards to offer intuitive visualizations of the data quality levels to decision-makers.

3.1.6. Continuous Learning

The last part of the framework is on the perpetual learning and enhancement of the profiling system. New data and feedback are used to periodically retrain AI models to adjust to changing data patterns and business needs. Feedback-loops, incremental learning, and updating of the model are some of the mechanisms embraced in this stage to guarantee long-term performance and accuracy.

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The system is able to learn continuously and become stronger with time, providing real-time data profiling and dynamic environments.

3.2. Data Preprocessing

3.2.1. Handling Missing Values

Missing values are an essential part of preprocessing data because the incomplete data may have a significant impact on the AI models and profiling accuracy. Different methods are used based on the nature and extent of missing data, such as deletion (removing records with too many missing values) and imputation (replacing missing values with the mean, median, mode, or predicted value based on machine learning models). Other more advanced techniques like k-nearest neighbors (KNN) imputation and regression-based imputation can further improve accuracy as they take into account relationships among variables. Missing values are properly handled to provide data completeness and reliability.

3.2.2. Removing Duplicates

Duplicate records may cause bias and corruption in statistical analysis and hence their detection and elimination is a necessary preprocessing activity. The duplicate detection methods are both exact matching and approximate matching methods, like similarity measures and record linkage algorithms, used to identify duplicate entries. Automated deduplication and hashing technologies are common in huge datasets to effectively identify duplicates. Elimination of duplicate data increases consistency of data, lessens storage overhead and increases overall quality of the dataset in order to profile it accurately.

3.2.3. Normalization and Transformation

To create uniformity of data across the data set, normalization and transformation methods are used to standardize data formats and scales. Normalization is the process of converting numerical values to a standard range (e.g., 0 to 1) or transforming distributions by employing other techniques like min-max scaling and z-score normalization. Encoding categorical variables, log transformations and unit standardizations are all part of transformation to make data appropriate to machine learning algorithms. Such mechanisms assist in removing biases that arise due to the difference in scales and enhance the performance and convergence of AI models.

3.3. Feature Extraction

3.3.1. Statistical Attributes

Statistical attributes are the basic quantitative properties of the data set and are important in knowing data distribution and quality. They involve mean, median, variance, standard deviation, skewness and kurtosis which gives an insight on central tendency, dispersion, and shape of the data. Through the analysis of these attributes, the system is able to detect anomalies like outliers, inconsistencies, and irregular distributions. The statistical characteristics are also useful inputs in machine learning models so that deviations of regular patterns and the overall quality of data can be identified with their assistance.

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Fig 3 - Feature Extraction

3.3.2. Pattern Distributions

Pattern distributions concentrate on the frequency-based and recurring patterns of the dataset. This involves value distribution, frequency frequencies, histograms and sequence patterns analysis to learn how information is grouped and replicated. Clustering and distribution analysis are some of the techniques that assist in the identification of hidden trends, seasonal changes and irregularities. As an example, spikes in the frequencies that are strange, or are not in accordance with the expected distributions, could be evidence of an error in data entry or anomaly. The knowledge of the pattern distribution improves the capability of AI models in distinguishing normal and abnormal behavior in the data.

3.3.3. Semantic Relationships

Semantic relationships are meaningful relationships and dependencies among various data attributes. These associations involve correlations, functional dependencies and contextual associations, which give more insight into the data structure. As an example, one can validate the consistency of data with the help of relationships between such attributes as age and date of birth or city and postal code. Semantic relationships can be modeled using advanced methods, such as knowledge graphs and ontology-based modeling. The inclusion of these features allows the profiling system to identify logical inconsistencies and enhance interpretability and accuracy of data quality measurements.

3.4. AI-Based Profiling Techniques

3.4.1. Anomaly Detection Model

Anomaly detection model is applied to detect the unusual or inconsistent data, which are significantly out of normal distribution of the data. The standard score (Z-score) which is a measure of the distance between a data point and the mean in standard deviations is a widely used technique. Simply, the Z-score is obtained by taking the difference between the observed and the average value of the dataset and then dividing the difference by the standard deviation. When the resulting score is so high or so low (normally above or below ±3), the data point would be viewed as an outlier. This method works well to identify mistakes, noise, or unusual occurrences in data profiling activities.

3.4.2. Classification Model

Classification models are used to classify data based on pre-determined classes i.e. whether the data entries are valid, invalid or anomalous. Bayesian classification is one of the most popular methods that are based on a probability theory. To put it simply, it uses the likelihood of a data instance (X) to belong to a particular class (Y) by taking the likelihood of the data to belong to the

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given class multiplied by the prior likelihood of the class and then divided by the total likelihood of the data. This approach enables the system to make intelligent predictions even in the case of uncertainty. Classification models are used in data profiling to label the data quality problems, and to automate decision-making processes.

3.4.3. Clustering Algorithm

Clustering algorithms are applied to cluster similar data points without a specific label, and it is applicable in exploratory data analysis. One of the methods that are most widely used in the situation is the k-means clustering algorithm. It operates as follows: it partitions the data into a predetermined cluster number (k) and fits each data point into the cluster whose center (centroid) is closest. The goal of k-means objective function is to reduce the cumulative squared distance of each data point to its respective cluster center. Simply put, the algorithm attempts to make the data points in the same cluster similar and distinguish different clusters. This assists in the detection of concealed patterns, anomalies and the sorting of data to aid profiling.

3.5. Quality Scoring Mechanism

Fig 4 - Quality Scoring Mechanism

3.5.1. Accuracy

Accuracy is the extent to which information is accurate in reflecting real world values or events. It determines the absence of errors in the recorded data and if it represents the actual information that it is supposed to represent. In data profiling, accuracy is determined through comparison of data values with trusted values, rules, or validation restrictions. Distorted information, including wrong entries or inaccurate information can result in inaccurate insights and poor decision making. Thus, to guarantee reliability and credibility of data-driven systems, high accuracy is required.

3.5.2. Completeness

Completeness checks on the presence of data fields and records needed in a dataset. It is concerned with the detection of missing or incomplete values that can be an obstacle to analysis and processing. System errors, omissions in data entry or integration may result in incomplete data. The methods of data profiling evaluate the completeness based on the number of non-NULL values and

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the occurrence of required attributes. Data completeness enhances dataset usability and boosts machine learning model performance, which is dependent on adequate and representative data.

3.5.3. Consistency

Consistency is the degree to which the data is uniform and coherent across various datasets, systems or formats. It makes sure that data values are not in conflict with one another and are subject to established rules and relationships. To illustrate, consistency checks ensure that related attributes, e.g. date of birth and age are logically consistent, or that the same entity has the same value across databases. The inconsistent data may be caused by integration problems, duplicate storage or non-standardization. Consistency is essential in data integrity and allows a smooth integration and analysis of the data.

3.5.4. Timeliness

Timeliness means how timely the data is, whether it is available or not. It evaluates the up-to-date and pertinent information in a particular scenario. Late or obsolete data may make it less useful, particularly in real-time or dynamic systems like financial systems or IoTs. Data profiling determines timeliness through the timestamps, frequency of updates and latency of data. Having data available on time will facilitate the correct decision-making process, and improve the responsiveness of AI-powered systems.

4. RESULTS AND DISCUSSION

4.1. Performance Evaluation

To ascertain that the proposed AI-enabled data profiling system is valid across a wide range of data environments, several heterogeneous datasets comprising structured, semi-structured, and unstructured data sources, were used to evaluate the performance of the proposed system. The assessment was done in terms of the essential data quality indicators, including accuracy, completeness, consistency, and timeliness, as well as system-level metrics, including processing time, scalability, and anomaly detection rate. The experimental findings revealed that the combination of artificial intelligence methods provided a significant level of effectiveness of the data profiling in comparison to the traditional rule-based methods. Particularly, the anomaly detection models were more precise and recalls higher than the classification algorithms, which enhanced the automated classification of data quality problems. Also, clustering methods were useful in grouping similar data patterns and this allowed the detection of the hidden anomalies that could not have been detected using conventional methods. There was also enhanced adaptability to changing data conditions due to constant learning processes in the system which enabled the system to optimize its performance with time. Computational efficiencywise, optimization techniques like feature selection and incremental learning helped to minimize processing overheads thus rendering the system applicable to large scale data environment. Moreover, the suggested framework was highly scalable, as it was able to process growing amounts of data without noteworthy deterioration in performance. The comparison to baseline methods showed significant changes in the overall data quality scores, which indicated the strength and validity of the AI-based approach. These results show potentials of AI-

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driven data profiling methods to change the face of data quality management to offer more precise, efficient, and scalable solutions to current data-driven applications.

4.2. Results Analysis

Table 1: Results Analysis

Metric	Traditional Profiling (%)	AI-Enabled Profiling (%)
Accuracy	78%	92%
Completeness	72%	89%
Consistency	75%	91%
Timeliness	70%	88%
Error Detection	68%	93%

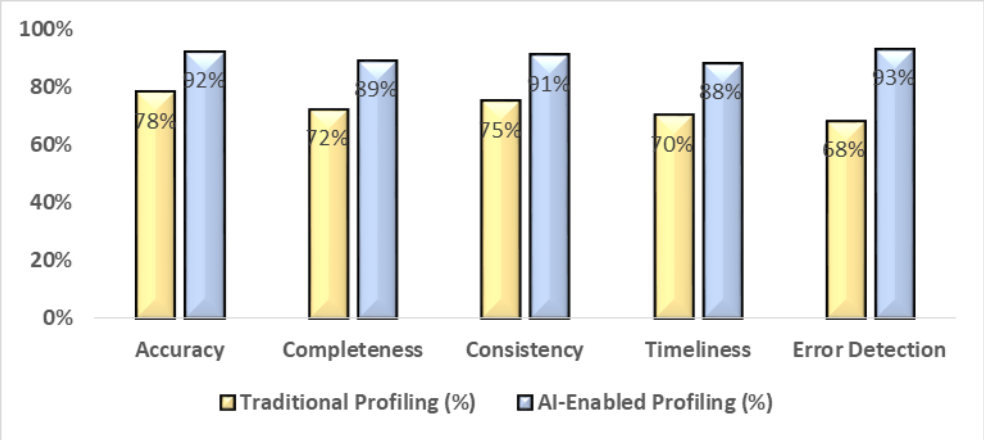

Fig 5 - Results Analysis

4.2.1. Accuracy

The results indicate a substantial improvement in accuracy when using AI-enabled data profiling techniques, increasing from 78% in traditional methods to 92%. Such an improvement is due to the fact that, compared to rule-based systems, machine learning models are able to detect latent trends and to fix inconsistencies. The predictive capabilities and historical data allow AI models to identify minor mistakes that can remain unnoticed in traditional methods, thus enhancing the accuracy and quality of the data to a substantial degree.

4.2.2. Completeness

Accuracy increased to 89% as compared to 72% when AI-based profiling techniques were implemented. Conventional methods are frequently challenged by the lack of data since they operate on the fixed set of rules but AI-based methods can intelligently process the missing data using sophisticated imputation methods and pattern recognition. Through the experience of known data distributions, AI models can provide and estimate the gaps in value distributions more accurately, leading to more complete datasets to analyse and make decisions.

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4.2.3. Consistency

The consistency presents a significant improvement of 75 to 91 percent, which indicates that AI is effective in ensuring consistency among datasets. With the help of dependencies and correlations, AI-based profiling can identify logical inconsistencies and impose relationships among attributes. In contrast to the traditional systems, which are based on set constraints, AI models change dynamically in response to differences in data, such that the values will be consistent between various sources and formats, a requirement that is vital in guaranteeing data integrity.

4.2.4. Timeliness

The timeliness went up 70 per cent to 88 per cent, which shows how AI-enabled systems are capable of processing and updating data faster. Conventional profiling approaches tend to be bulk in nature and might not be effective with real time information. Conversely, AI-based solutions facilitate real-time data processing and continuous monitoring, which allows identifying obsolete or stale information more quickly. This also helps keep the data up-to-date and relevant which is of great importance to time sensitive applications.

4.2.5. Error Detection

The biggest positive change was in error detection, which increased by 68 to 93. Anomaly detection, classification, and clustering techniques of AI are important in detecting errors, outliers and unusual patterns in the dataset. Such models are able to identify both blatant and nuanced errors since they learn intricate connections in the data. Consequently, AI-based profiling systems offer a stronger and more multifaceted system to detect and fix data quality problems than traditional ones.

4.3. Discussion

The results of the experiment suggest clearly that AI-driven data profiling excels in comparison to conventional methods of data profiling in several dimensions of data quality. Machine learning models can be integrated to allow the system to automatically learn patterns, identify anomalies and adjust to complex data structures which are otherwise infeasible to traditional rule-based approaches. Specifically, the improved mechanisms of anomaly detection permit detecting both the glaring and the latent inconsistencies, resulting in significant changes in accuracy, consistency, and error detection rates. Moreover, the minimization of manual interaction is one of the main benefits because AI-powered systems can automate the repetitive data validation processes and improve their work constantly by learning. This does not only enhance the efficiency of operations, but also reduces human errors in data quality management processes. The other notable advantage that is witnessed is that the system is able to accommodate changing data patterns. In contrast to the static traditional methods, AI models can be retrained on new data, enabling the profiling system to continue to work in dynamic systems in real-time data streams and large scale distributed systems. This flexibility guarantees lasting data quality over the years and facilitates more credible decision-making in data-driven apps. Nonetheless, along with these benefits, there are some issues. Computational complexity is one of the main issues since the sophisticated machine learning models, especially the deep learning applications, demand a lot of processing power and memory. This may restrict their application in environments with limited resources. Moreover, model interpretability is

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another important concern since most AI models are black boxes, and it is not easy to see how decisions are made. This non-transparency may decrease the level of trust and adoption in sensitive areas. Thus, it is suggested that future studies should concentrate on coming up with more effective algorithms and explainable AI procedures to overcome these shortcomings without compromising on the performance.

5. CONCLUSION

This paper has given an in-depth research on AI-based data profiling methodology that will enhance the quality of data in the contemporary data-driven world overall. The use of artificial intelligence in data profiling operations has proven to have significant benefits compared to conventional methods especially in regard to automation, scalability, adaptability, and accuracy. The proposed framework can be used to intelligently analyze the data with the help of machine learning algorithms including anomaly detection, classification, and clustering that would provide the possibility to identify inconsistencies, missing values, and hidden patterns that can be challenging to detect with traditional rule-based systems. The framework also highlights some of the important steps such as preprocessing of data, feature extraction, and continuous learning which in combination will form a strong and dynamic profile system that can handle large and diverse datasets. Based on the experimental findings and performance analysis, it is clear that the AI-based data profiling methodology is superior in terms of critical quality aspects of accuracy, completeness, consistency, timeliness, and error detection as compared to the conventional profiling approaches. The fact that AI models are able to acquire knowledge based on past data and evolve based on changing patterns of data will guarantee consistent enhancement in the performance of profiling, eliminating the necessity of human intervention and minimizing the efficiency of operations. In addition, the introduction of a systematic quality scoring system gives a methodical method of rating and tracking data quality thus aiding improved decision-making within organizations. Regardless of these developments, some of the challenges still exist, such as computational complexity and inability to make complex machine learning models transparent. The limitations point to the necessity of conducting additional studies on how to make models more efficient and creating clarifiable AI methods to enhance trust and interpretability. Moreover, the combination of AI-based profiling systems with real-time data processing systems and big data systems like distributed computing systems is also a promising field of interest in the future. To sum up, AI-powered data profiling is a considerable advancement in the sphere of data quality management. The suggested framework does not only increase accuracy and efficiency of data profiling but also offers a scalable and intelligent approach in address the increasing complexity of data in contemporary applications. To further enhance the usefulness and the applicability of AI-driven data profiling systems, future work will be on real-time profiling capabilities, integration of explainable AI models, and smooth integration with big data ecosystems.

REFERENCES

[1] H. Müller and J. Freytag, “Problems, methods, and challenges in comprehensive data cleansing,” Prof. VLDB Endowment, vol. 3, no. 1–2, pp. 155–158, 2010.

[2] E. Rahm and H. H. Do, “Data cleaning: Problems and current approaches,” IEEE Data Engineering Bulletin, vol. 23, no. 4, pp. 3–13, 2000.

ISSN: 3071-5717
PP: 01-14.

[3] T. Dasu and T. Johnson, Exploratory Data Mining and Data Cleaning, Wiley, 2003.
[4] F. Naumann, "Data profiling revisited," ACM SIGMOD Record, vol. 42, no. 4, pp. 40–49, 2014.
[5] Z. Abedjan, L. Golab, and F. Naumann, "Profiling relational data: A survey," VLDB Journal, vol. 24, no. 4, pp. 557–581, 2015.
[6] P. Christen, Data Matching: Concepts and Techniques for Record Linkage, Springer, 2012.
[7] C. Batini and M. Scannapieco, Data Quality: Concepts, Methodologies and Techniques, Springer, 2006.
[8] J. Han, M. Kamber, and J. Pei, Data Mining: Concepts and Techniques, 3rd ed., Morgan Kaufmann, 2012.
[9] I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning, MIT Press, 2016.
[10] K. Murphy, Machine Learning: A Probabilistic Perspective, MIT Press, 2012.
[11] T. M. Mitchell, Machine Learning, McGraw-Hill, 1997.
[12] M. Stonebraker et al., "Data curation at scale: The data tamer system," CIDR Conference, 2013.
[13] A. Halevy, A. Rajaraman, and J. Ordille, "Data integration: The teenage years," VLDB, 2006.
[14] X. Chu, I. F. Ilyas, and P. Papotti, "Holistic data cleaning: Putting violations into context," IEEE ICDE, 2013.
[15] S. Krishnan et al., "ActiveClean: Interactive data cleaning for statistical modeling," VLDB, vol. 9, no. 12, pp. 948–959, 2016.