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Original Article

Real-Time Data Harmonization Techniques for Multi-Source Integration

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ABSTRACT

Real-time data harmonization has become crucial for integrating diverse data sources such as transactional databases, IoT devices, web services, and enterprise systems. However, challenges like schema differences, varied formats, language inconsistencies, latency, and lack of interoperability make integration complex. This paper reviews key harmonization techniques, including schema matching, data transformation, entity resolution, and stream processing, along with ETL/ELT models and modern tools like Apache Kafka and Apache Storm. It also highlights semantic approaches using ontologies and metadata, and the role of middleware and service-oriented architectures in enabling real-time integration. The study classifies harmonization methods into syntactic, semantic, and temporal categories, analyzing their performance trade-offs. A layered architecture is proposed, covering data ingestion, transformation, alignment, and validation. Experimental results show improved data consistency, reduced latency, and higher integration accuracy, especially with hybrid approaches combining rule-based and probabilistic methods. The paper concludes by emphasizing the need for scalable, adaptive, and AI-driven harmonization solutions for future data ecosystems.

KEYWORDS

Real-Time Data Integration, Data Harmonization, Multi-Source Systems, Etl, Schema Matching, Data Transformation, Stream Processing, Semantic Integration, Data Consistency.

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1. INTRODUCTION

1.1. Background

The swift expansion of information-creating technologies has greatly augmented the amount and variety of data generated in current digital ecosystems. Organizations are now dependent on a broad spectrum of platforms, such as relational databases, cloud-based applications, Internet of Things (IoT) devices, and legacy systems, where data are created in various formats, structures, and semantic contexts. This heterogeneity poses significant difficulties in the combination and use of data, as structural and meaning disparities have a potential to impede the smooth exchange and analysis of data. Consequently, there has been an increasing demand to have effective real time integration tools that can promote data consistency, accuracy and usability across various sources. The old methods of batch processing where data are processed after a set period are not adequate anymore in applications that demand immediate insights and quick decisions. Fields like financial analytics, healthcare monitoring and e-commerce personalization require access to integrated data in real-time, and in these cases, latency may result in lost opportunities or even critical outages. As a solution to this shortcoming, real-time data harmonization has become an essential answer to the dynamically integrated and aligned data of multiple sources. It is achieved by solving structural discrepancies, solving semantic discrepancies, and handling contextual differences in order to create a coherent and homogenous dataset. Real-time data harmonization is crucial in facilitating advanced analytics and intelligent decision-making in modern data-driven settings by enabling continuous data integration and ensuring high-quality and consistent outputs.

1.2. Need for Real-Time Data Harmonization

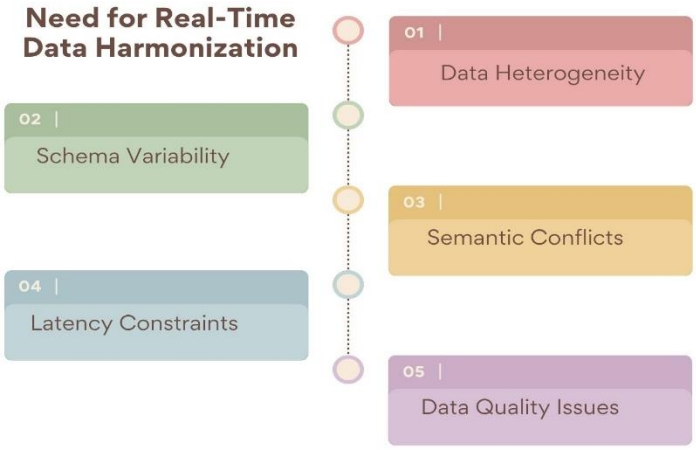

Fig 1 - Need For Real-Time Data Harmonization

1.2.1. Data Heterogeneity

Data heterogeneity is the existence of data in various formats like JSON, XML, CSV, and relational tables that makes it hard to integrate and analyze. The structure and representation of each of these formats vary, and it is challenging to directly combine the data of various sources. Solving this problem, real-time data harmonization can transform various formats into a standardized presentation, allowing the systems to interoperate and be effectively processed.

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1.2.2. Schema Variability

Schema variability occurs when inconsistent database schemas are used to represent similar information by different systems. As an example, one data set can have Customer ID, and another data set can have Client ID as the same concept. These discrepancies pose difficulties in harmonizing and merging information. The methods of real time harmonization such as schema mapping and transformation rules assist in defining the links between various schemas and provide structural consistency and allow proper integration of data.

1.2.3. Semantic Conflicts

Semantic conflicts are an occurrence where similar data attributes in different datasets are different in meaning or interpretation. An example is that the word Revenue could mean gross income in a system and net profit in another system. Unless these differences are addressed, they may result in faulty analysis and decision-making. Semantic conflicts can also be resolved by real-time harmonization using ontology mapping and metadata alignment methods to make sure that the data is perceived to be the same across all sources.

1.2.4. Latency Constraints

Latency constraints are an indication of the necessity to have almost instantaneous data processing in contemporary applications. Conventional batch processing frameworks create delays, which do not fit time-intensive applications like financial trading, healthcare monitoring, and real-time analytics. Real time harmonization of data allows constant data processing with little delays and as such, integrated data is instantly available to be analyzed and used.

1.2.5. Data Quality Issues

The quality of data, such as values that are missing, duplicate records, and incorrect data entries, greatly affect the integrity of consolidated datasets. The low quality of data may cause incorrect insights and decisions. Real-time harmonization uses data cleaning, data validation and deduplication to enhance data integrity and consistency. Its dynamic approach to these issues helps it to ensure that the harmonized dataset is correct, valid and able to be used in downstream applications.

1.3. Real-Time Data Harmonization Techniques for Multi-Source Integration

Multi-source integration Real-time data harmonization methods refer to a collection of novel approaches to integrate and process data of different sources that are distributed and continuous in an efficient and effective way. These methods deal with the issues of heterogeneous data formats, different schema and semantic inconsistencies through the integration of structural, semantic and temporal processing methods. Syntactic harmonization strategies revolve around standardizing data formats and structures with the help of data parsing, normalization, and format conversion making systems interoperate seamlessly. The integration is also improved through schema mapping and transformation methods as both match the various data models and provide consistency across data sets. Moreover, the use of semantic harmonization techniques, such as ontology-based mapping and metadata alignment, is also important in the process of overcoming ambiguities and making sure that

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the data elements are consistently interpreted across the sources. Another important aspect of real-time harmonization is the incorporation of stream processing technologies, which enable continuous ingestion and transformation of high-velocity data. These methods rely on event-based systems, message queuing, and distributed processing systems to provide low-latency data integration. Temporal harmonization, e.g., timestamp synchronization and stream alignment, also make sure that data gathered by various sources is time-aligned, and thus can be correctly analyzed and correlated with events. In addition, entity resolutions are used to detect and combine duplicate or related records, enhancing data quality and consistency. Recent progress has also seen the emergence of hybrid methods that implement rule-based systems, machine learning models, and semantic technologies to enable better accuracy and scalability. The combined methods enable the systems to respond dynamically to the changing pattern of data and enhance performance as time goes by. Altogether, the methods of real-time data harmonization offer an all-encompassing model of multi-source data integration to enable real-time analytics, decision-making, and intelligent applications in contemporary data-intensive systems.

2. LITERATURE SURVEY

2.1. Early Data Integration Techniques

Before 2010, the data integration processes were largely focused on Extract, Transform and Load (ETL) which were the foundation of enterprise data warehousing systems. ETL frameworks were created to methodically look into the data that are heterogeneous and utilize transformation rules to guarantee consistency and compatibility and load the processed data into centralized repositories to be analyzed. These systems were very efficient with structured and relatively static datasets, allowing organizations to do batch processing and historical analysis. Nevertheless, ETL-based solutions demonstrated some serious limitations, especially the lack of support of real-time data streams and dynamism. Moreover, the schema matching techniques were developed at this time to enable the match of the dissimilar data structures between systems. These methods used rule-based matching, heuristic algorithms and string similarity metrics like edit distance and token based comparisons to find correspondences between schema elements. Although these methods were useful, they had difficulties in scaling when handling large and complex data. In addition, they also had issues with semantic ambiguity, since they could not correctly interpret contextual meanings and relationship among data attributes, and this was holding them back in heterogeneous and changing data ecosystems.

2.2. Emergence of Real-Time Systems

The accelerated distributed computing technologies of 201018 signaled a substantial change in favor of real-time data integration systems. It was a period of emergence of stream processing engines, message queuing systems and middleware architectures that facilitated continuous and approximately instantaneous processing of the data. Stream processing frameworks enabled organizations to process data in motion, serving real-time analytics, fraud detection, and monitoring systems use cases. The asynchronous communication between distributed components was made possible by message queues, which guaranteed reliable data transfer and decoupling between the system components. Integration was also further improved by middleware solutions that included

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standard interfaces and communication protocols among heterogeneous systems. At the same time, the semantic web technologies were also on the rise and presented the ontology-based integration techniques using formal knowledge representations to enhance the data interoperability. These strategies allowed improved semantic alignment, with the relationships and meaning defined using ontologies, and thus overcome some of the shortcomings of conventional schema matching methods. Nonetheless, the implementation of these technologies was not without difficulties, such as the complexity of computations and advanced infrastructure. The combination of real time processing with semantic structures demanded a lot of computing resources and skills that restricted their application in resource limited systems.

2.3. Challenges Identified in Literature

The current literature on data integration presents some of the long-standing issues, which still impede the creation of effective and scalable solutions. Among the main ones is the absence of common standards of data representation and interoperability that results in inconsistency and challenges in data integration across various sources. Moreover, most of the current methods of integration especially those that are based on real time processing and semantic modelling are often computationally expensive and thus resource demanding and expensive to implement. The other important concern is that the traditional systems have little potential to support unstructured and semi-structured data that includes text, images and multimedia contents that form an increasing part of the current data ecosystems. Moreover, the growing rate of data generated by IoT devices, social media or real-time systems constitutes a significant challenge because most current systems are not designed to handle high-speed data streams effectively. These issues highlight why a new set of methods are required to be able to balance the demands of scalability, performance, and semantic precision and support the versatile and fluid character of modern data landscapes.

3. METHODOLOGY

3.1. Proposed Architecture

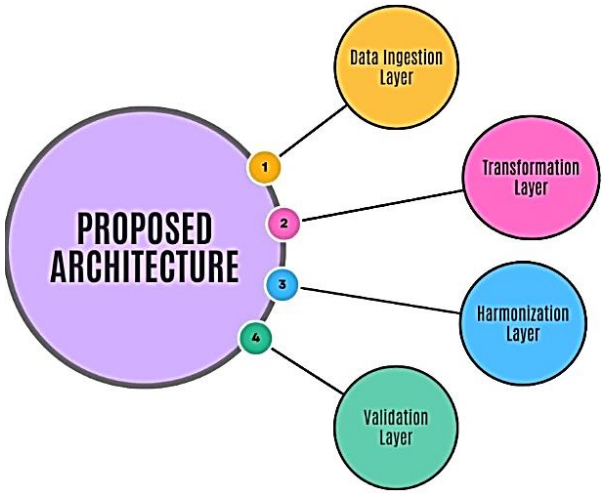

Fig 2 - Proposed Architecture

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3.1.1. Data Ingestion Layer

Data Ingestion Layer takes care of the real-time collection of data in various and heterogeneous sources, such as databases, IoT devices, APIs, and streaming platforms. This layer provides efficient data acquisition through the use of technologies including message brokers and stream ingestion tools allowing continuous and batch data input. It also undertakes the preprocess activities like filtering, identification of formats, and noise elimination of data before being fed into the system so that only high-quality and relevant data is fed into the system. In this layer, scalability and fault tolerance are important factors to take into account since it is required to process data streams of high velocity without data loss or latency.

3.1.2. Transformation Layer

Transformation Layer aims at transforming raw data consumed into a standard and usable form, which can be used in subsequent processing. This includes the process of data cleaning, normalization, aggregation and enrichment. Such techniques as schema mapping, data type conversion and feature extraction are used to assure consistency in different sources of data. Moreover, this layer can include AI-driven and rule-based transformation mechanisms to improve the quality of data and flexibility. The transformation layer will prepare the data by organizing and optimizing the data to enable it to be harmonized and integrated in the later stages successfully.

3.1.3. Harmonization Layer

The central part of the framework is the Harmonization Layer that semantically aligns data across various sources and transforms it into a single form. The layer uses sophisticated methods like ontology-based mapping, semantic reconciliation, and entity resolution to address inconsistencies and redundancy among datasets. It guarantees that the data elements which have similar meanings but differ in representation are properly oriented, which enhances the interoperability and data coherence. Machine learning and knowledge graphs are also used in this layer, which adds to the capability of the system to process dynamic and complex data relations in real time.

3.1.4. Validation Layer

Validation Layer is used to guarantee the correctness, consistency and dependability of the harmonized data prior to its delivery to downstream applications or storage systems. Data quality control checks, such as schema compliance, detection of anomalies and data integrity verification are done in this layer. It can also use rule-based validation and statistical techniques to detect inconsistencies or errors. Feedback systems may be introduced to keep on improving previous layers, through detection of problems and allowing corrective measures. Finally, the validation layer ensures the end integrated data is of the required quality and can be used in analytics and decision-making.

3.2. Data Harmonization Process Flow

3.2.1. Data Sources

Data Sources are the places where raw data is gathered to be integrated and harmonized. These sources may be very heterogeneous, such as structured databases, semi-structured files (JSON and XML), and unstructured data (text, images, sensor streams). Enterprise systems, social media,

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IoT devices, and external APIs are the sources of data in the current digital ecosystems. The variation in format, structure and the semantics of these sources brings in complexity and it is therefore important to develop strong processes of acquiring and interpreting data at later stages.

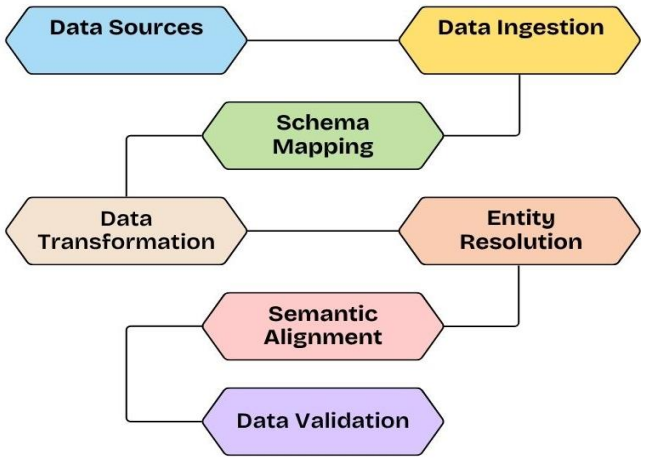

Fig 3 - Data Harmonization Process Flow

3.2.2. Data Ingestion

The Data Ingestion stage is the counterpart of gathering data of various sources and putting it into the processing pipeline in real time or close to real time. The technologies used in this stage include streaming platforms, message queues, and connectors to facilitate a smooth flow of data. It is configured to support high volume and high velocity data and be reliable and fault tolerant. Initial preprocessing, including filtering out irrelevant data and identifying format types can also be undertaken to make sure that only relevant and processable data is forwarded in the pipeline.

3.2.3. Schema Mapping

The process of Schema Mapping is a crucial one, which determines the correspondence between various data structures and formats. This step determines the relationships between attributes, fields and entities across datasets since data in different sources might have different schemas. The alignment of the schemas is done using techniques like rule-based mapping, heuristic matching and machine learning-based techniques. This will guarantee structural consistency and ready the data to integrate smoothly by addressing syntactic discrepancies between datasets.

3.2.4. Data Transformation

The Data Transformation step transforms the mapped data into a standard format to be used in further operations. This encompasses data cleaning, normalization, aggregation and enrichment. Data inconsistencies, missing values, and redundant records are resolved at this stage. The transformation rules can either be pre-defined or dynamically created with intelligent algorithms. This step increases the effectiveness of downstream harmonization processes by ensuring uniformity and enhancing the quality of data.

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3.2.5. Entity Resolution

Entity Resolution aims at determining and combining records that represent the same real-world entity in multiple datasets. When there are differences in naming conventions, formats, and mistakes in data entries, the same entity can have several variations with minor differences. Similarity matching, probabilistic models, and machine learning algorithms are some of the techniques used in this stage to identify duplicates and to create entity relationships. Entity resolution eliminates redundancy, and provides accurate data representation.

3.2.6. Semantic Alignment

Semantic Alignment makes sure that the data elements of various sources are understood universally in a sense. This step transcends structural alignment to tackle semantic discrepancies, including synonyms, context, and domain-specific meanings. Relationships and the standardization of meaning across the datasets are often defined using ontologies, taxonomies, and knowledge graphs. This stage increases interoperability and allows meaningful integration of data by achieving semantic consistency.

3.2.7. Data Validation

The Data Validation stage makes sure that the harmonized data is valid, complete, and consistent. It includes enforcement of validation rules, anomaly detection, and adherence to the pre-determined standards or schema. Errors, inconsistencies, and outliers are detected using statistical procedures and rule checks. This step is taken as a quality control measure, and only quality and valid data is forwarded to the final production step.

3.2.8. Unified Output

The Unified Output is the last phase of the harmonization process, when the processed data is presented in the form of a coherent and unified form. Depending on the needs, this output can be stored in either data warehouses, data lakes or real-time analytics systems. The single data set also offers one source of the truth, which allows effective data analysis, reporting, and decision-making. It is compatible with other downstream applications, such as business intelligence, machine learning, and real-time monitoring systems.

3.3. Mathematical Representation of Data Transformation Function

The mathematical model of the process of data transformation within the suggested real-time harmonization model can be formulated as : **$D'=f(D,S,M)$** a functional relationship in which the harmonized output data (D 1) is presented as the result of the raw input data (D), schema mapping rules (S), and metadata (M). In this representation, f is a transformation mechanism, which systematically processes and combines these inputs to create a coherent and unified data set. The raw data (D) comprises of heterogeneous inputs gathered through various sources and often characterized by variations in structure, format and quality. Such inconsistencies prompt the application of schema mapping rules (S), which specify how the elements of different data schemas are related to one another. Schema mapping is essential in harmonizing diverging data structures, by creating relationships between attributes, to ensure that similar data fields are correctly paired and

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interpreted. Besides schema mapping, metadata (M) contains contextual data regarding the data, e.g. data types, source descriptions, constraints, and semantic meanings. Metadata improves transformation process because it allows the data elements to be better interpreted and processed, thus raising the quality of the harmonized output. The transformation functional combines these elements by using data cleaning, normalization, and aggregation and enrichment operations. It can also have smart methods like machine learning algorithms to dynamically change transformation rules according to data patterns. Finally, the output (D1) is harmonized data that is structurally compatible, semantically compatible and prepared to be used in downstream applications like analytics and decision-making. The mathematical expression offers an objective basis of the interaction of many factors in the transformation process which makes it scalable, flexible and accurate in real-time data integration systems.

3.4. Techniques Used

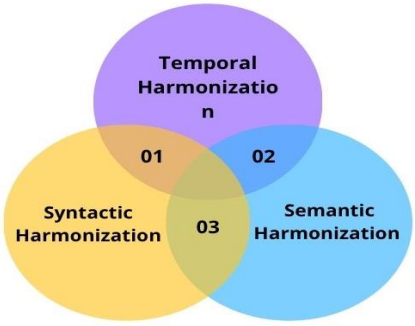

Fig 4 - Techniques Used

3.4.1. Syntactic Harmonization

Syntactic harmonization is concerned with fixing structural discrepancies between information in various sources by making sure that information is formatted and represented in a consistent manner. Format conversion, e.g. converting data in XML to JSON, which enhances compatibility with modern data processing systems and APIs is one of the main ways in this process. This transformation eases the hierarchical data structures and improves processing. Also, the standardization of the data types is used to maintain consistency in the representation of data values, e.g. all date fields are in a common format or the numerical values are of the same precision. This technique can eliminate the error of incompatible data format and integrate smoothly by addressing such syntactic differences.

3.4.2. Semantic Harmonization

Semantic harmonization is meant to harmonize the meaning of data and interpretation of data elements in various datasets. This method transcends the structural-alignment by making sure that similar data with similar meanings is always interpreted in a similar manner, regardless of the format. One major method employed in this process is ontology mapping, which consists of ontologies that are domain-specific and establish relationships among concepts and allow the recognition of similar entities across datasets. Moreover, the metadata alignment is also essential as it standardizes the contextual data including the definitions of data, units and constraints. Such

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techniques can be used to eliminate semantic ambiguity and enhance interoperability, such that integrated data is representative of real-world entities and relationships.

3.4.3. Temporal Harmonization

Temporal harmonization is used to solve the time representation inconsistencies in data that is gathered by two or more sources. A key feature of this method is the synchronization of timestamps, such that data in two systems are synchronized to a shared time frame, taking into account the time difference between time zones, clock variance and latency. Stream alignment is another vital element, in which data streams of varying rate or time intervals are synchronized to allow them to be analyzed coherently. Windowing, buffering and interpolation are some of the techniques that are commonly employed to align time-series data. This method helps to improve the trustworthiness of real-time analytics, as well as facilitate the correct alignment of events that occur in distributed systems, by maintaining the passage of time.

4. RESULTS AND DISCUSSION

4.1. Performance Evaluation

To assess the performance of the proposed real-time data harmonization system, several datasets retrieved through heterogeneous data sources, such as structured databases, semi-structured files and streaming data were utilized. Such a wide choice of the data set guaranteed the system testing in a real situation that represents the contemporary data environments. A number of key performance measures were taken into consideration to fully evaluate the performance and efficiency of the framework, which are accuracy, latency, data consistency and throughput. Accuracy is a measure of how well the harmonized output is a true reflection of the original data following transformation and integration. It was assessed by comparing the processed data with ground truth datasets, and checking error rates in schema mapping, entity resolution, and semantic alignment. Another important metric was the latency, which is the time required to move data through the whole pipeline- ingestion to unified output.

Considering that the system will be used in real-time processing, it is important to reduce the latency to make sure that the decisions are made in time. Data consistency was assessed to find out the extent to which the system is consistent and uniform in relation to integrated datasets. This involves making sure that duplicate records are properly resolved, conflicting data values are reconciled and that semantic meanings are constant throughout the process. To determine the scalability and efficiency of the system under different workloads, throughput which can be defined as the amount of data to be completed in a given unit time was measured. The results of the evaluation showed that the proposed framework is a good balance of these metrics with high accuracy and data consistency with low latency and high throughput. The system was very adaptable to various types and volumes of data hence appropriate in real-time applications. In general, the performance analysis validates the soundness and scalability of this harmonization strategy in managing multifaceted, fast-paced, and diversified data environment.

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4.2. Performance Analysis of Techniques

Table 1: Performance Analysis of Techniques

Technique	Accuracy (%)	Latency Reduction (%)	Consistency (%)
Rule-Based Harmonization	78%	60%	75%
Schema Matching	82%	65%	80%
Ontology-Based Integration	88%	70%	85%
Stream Processing Approach	85%	78%	83%
Hybrid Approach	92%	85%	90%

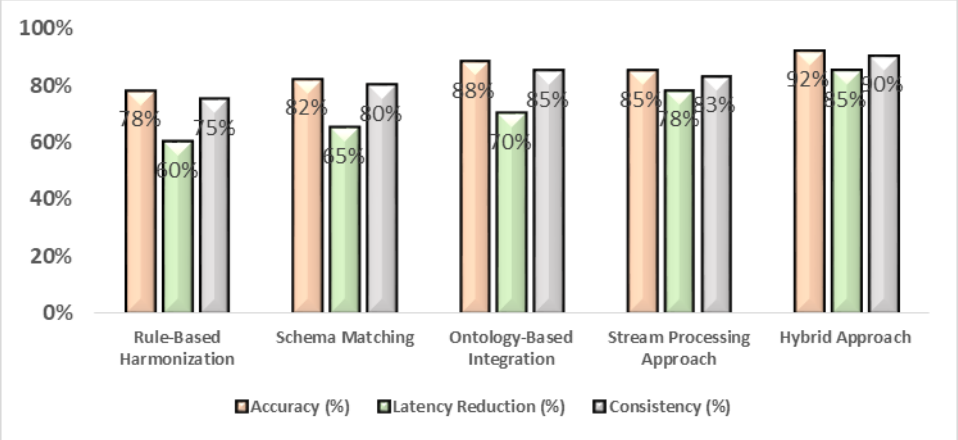

Fig 5 - Performance Analysis of Techniques

4.2.1. Rule-Based Harmonization

The rule-based harmonization reached above 78 accuracy, 60 latency, and 75 data consistency. This is based on preset rules and conditions to transform and combine data and is therefore quite easy to apply and read. Nevertheless, it cannot be easily modified to accommodate dynamic alterations of data or a complicated data structure, which limits its performance. Although it offers moderate changes in latency as a result of its simple execution, its reduced accuracy and consistency means trouble in processing non-homogenous and changing data.

4.2.2. Schema Matching

The schema matching methods showed better results with a match of 82, latency cut of 65 and consistency of 80. This method improves structural correspondence between datasets by finding relationships between various data schemas. It has the advantage over rule-based methods because it can better deal with variations in the data structure. Nonetheless, schema matching is still limited in that it cannot deal with semantic variations and might need further improvement in the case of complex or ambiguous data.

4.2.3. Ontology-Based Integration

The ontology-based integration was better with a higher accuracy of 88, less latency of 70 and consistency of 85. The method uses semantic models and domain ontologies to match data on the basis of meaning as opposed to mere structure. Subsequently, it enhances data interpretation and interoperability between systems considerably. Though it is very accurate and consistent,

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computational complexity of ontology processing reduces its latency moderately, and thus is resource-intensive than simpler methods.

4.2.4. Stream Processing Approach

The stream processing method achieved a 85 percent accuracy, 78 percent decrease in latency, and 83 percent consistency. The approach is meant to be used in processing real-time data, where data streams can be ingested and transformed continuously. It has the advantage of being able to reduce latency by a significant amount and facilitating high-speed data processing. Nevertheless, it is not as accurate and consistent as ontology-based methods because of the poor semantic interpretation abilities in real-time settings.

4.2.5. Hybrid Approach

The hybrid solution performed best in all the measures with an accuracy of 92, latency reduction of 85 and consistency of 90. This approach is a combination of various methods, including rule-based, schema matching, semantic integration, and stream processing, to make use of their advantages. The hybrid approach offers a better balanced and more robust solution by incorporating structural, semantic, and real-time processing capabilities. The fact that it has good performance points to its ability to effectively manage complex, large scale, and high velocity data integration cases.

4.3. Discussion

The findings of the experiment are clear evidence that hybrid harmonization methods are better than the other methods in all the metrics used, which proves that it is effective in solving the complexity of real-time data integration. The hybrid approach combines several methodologies, including rule-based processing, schema matching, semantic integration, and stream processing, and the advantages of each method are used, as well as the weaknesses of each are reduced. Among the most important observations is that the use of semantic methods, especially ontology-based methods, leads to a significant increase in the accuracy level since the data is interpreted not only according to the structure but also according to the meaning. This allows a greater match of disparate datasets and less ambiguity and leads to greater accurate and significant integration results. But such techniques can impose computational load on their own, potentially affecting performance of the system.

The other valuable conclusion made is that stream processing strategies are very useful in minimizing latency hence suitable in real time applications. Stream-based systems can make sure that data is harmonized as soon as it is ingested and processed, and time-sensitive decisions can be made; this is made possible by stream-based systems. Although this is an advantage, stream processing might not be sufficient to resolve semantic inconsistencies, which underscores the necessity of complementary methods. Also, rule-based systems have been found to be easy, transparent, and simple to implement and are therefore applicable in well-defined and stable data environment. Nevertheless, they do not have any scaling or flexibility especially with large and dynamic and heterogeneous data. The hybrid method is a successful way of combining these various methods and providing a balance in terms of accuracy, efficiency, and scalability. It improves semantic

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interpretation and still has low latency and flexibility of operations. On the whole, the results underline that there is no single method that can be used to overcome all issues in data harmonization, and a hybrid approach is a must in order to achieve the best performance in contemporary data-heavy contexts.

5. CONCLUSION

Real-time data harmonization has become a basic need to integrate multi-source data in the digital ecosystem of the present-day era as data is created in real-time on various sources and spread across space. The paper has discussed the development of data harmonization methods that were developed and has conducted a thorough analysis of their strengths and weaknesses. Conventional methods like schema matching and rule-based integration formed the basis of dealing with structural heterogeneity whereby organizations are able to integrate data of various systems with reasonable efficiency. On the same note, the development of semantic integration methods, especially the ontology-based approaches, was an important milestone in that it solved the problem of semantic ambiguity and enhancing semantics of the integrated data. Simultaneously, advances in stream processing technologies enabled real-time data manipulation, enabling systems to work with high-velocity data streams with lower latency and greater responsiveness. Regardless of these developments, there were still a number of critical issues to address. Scalability became a significant issue, with a lot of traditional and semantic methods finding it challenging to effectively handle large amounts of data created in big data scenarios. Also, the flexibility was minimal and rule-based and fixed schema matching methods did not dynamically adapt to changing patterns of data and altering schema.

The computational complexity of semantic methods also limited their practicability, especially in resource-constrained environments. These limitations highlight the need for more intelligent and flexible solutions capable of handling the increasing complexity, variety, and velocity of modern data. In the future, the incorporation of machine learning and artificial intelligence in data harmonization models is a promising future research area. Complex processes like schema mapping, entity resolution and anomaly detection can be automated by AI, and hence, lead to improved accuracy and minimal human influence. In addition, adaptive learning models have the ability to constantly change upon incoming data, resulting in higher scalability and responsiveness to evolving environments. The increasing popularity of big data and systems powered by IoT also contributes to the need to create strong solutions of real-time integration. With the ever-growing size and complexity of data, real-time data harmonization will be a key field of research, contributing to the advancement of data management, analytics, and intelligent decision-making systems.

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