**Abstract:**

The proliferation of big data in healthcare has revealed enormous scopes and inclusions for data-driven insights, clinical decision-making, forecasting, qualitative analysis, and predictive analytics. In addition, it enhances the operational efficiencies of healthcare through a master data management system. However, these parameters' integration and relatability rely on data quality. The main lack between analytical accuracy and patient outcomes comes from the inconsistencies, missing values, redundancies, and outliers of data. Healthcare datasets are inherently prone to consistency, availability, and partition tolerance (CAP theorem), which can raise the probability of Low-Level Detail (LOD) in data. In addition, Traditional data quality management frameworks are not sufficient to handle empty logs, and unregistered, multidimensional challenges occur in the volume, velocity, and variety (3V) of real-time healthcare data. To give linear support for bridging this gap, this research introduces an intelligent, real-time data quality enhancement framework that leverages Apache Kafka for high throughput data streaming and Isolation forest for advanced anomaly detection. The proposed framework monitors, detects, and rectifies anomalies with high accuracy, completeness, uniqueness, consistency, and readability across large-scale datasets. In the meantime, this research ticks the first element of the CAP theorem. Our framework demonstrates the scalability, efficiency, and real-time anomaly detection capabilities compared to other conventional batch processing methodologies through a rigorous evaluation. This research illustrates a native solution that is scalable and domain-agnostic by integrating streaming analytics, distributed computing, and machine learning-driven anomaly detection. Perhaps, it elevates the robustness of healthcare data quality. Our proposed framework reinforces the potential to serve as a benchmark for real-time data quality assurance in healthcare analytics and beyond. It shows the distribution mechanism and partition tolerancing of each cluster that underscores significant improvements.

**Keywords:**

**Introduction:**

The impact of this research is about Best utilization of Big data technologies in smart healthcare and also mitigate the bottlenecks of data quality. In addition, technologies like Electronic health records, wearable devices, patient monitoring systems are now producing large amount of healthcare data. We can easily analyse and make a solid prediction based on these data but still the word quality and optimization of data from the source of provider to source of target is less improved. We are now improvising this challenges through a novel approach using different technologies. Before moving forward to the solution, We might understand the acutal challenges in this research. So, our challeng is 3V which indicates Volume, Velocity, Variety. Volume is the large amount of data which depends of the complexity of data also. Develpoment Operations consultants are working on this partcualarly to the optimation of volume. Infact, Recently, Sparse/Dense/Secondary indexing along with hashing technique are using rapidly to solve this problem. Velocity is pace of data stimulating and coming from sources. Velocity is something which is very sensitive among these 3V. Because, velocity can also be a cause of data loss and redundancy. Network Engineers gave a best solution to this problem which is called data capturing prototype using regularization of data speed. Variety is something which is a versatile problem in Data Quality because here data are coming from different sources, Sources may include small-large warehouse, cloud distribution system, docker image, traditional sources, transactional sources. In different sources, the speed and volume are also different. Integration of several sources In one centralized warehouse or model is also very hard due to infrastructure. In example, in a healthcare system there are two basic data simulation process always goes on. One is analytical data, another is transactional data. Transactional data is something which is very time and log sensitive. Now the triangle of 3V for healthcare is something like this

*Developing a Real-Time Data Quality Assessment Framework:*

The main purpose of this framework is to consistently monitor and timely data collection through an automatic algorhitmic approach so that we can prevent maximum inconsistencies, anomalies, duplicacy and outliers. The statistical and programmatical dialogue is the pre-requisites of this approach to reach the maximum accuracy of framework.

*Implementing and Evaluating Advanced Anomaly Detection Techniques:*

The integration of isolation forest makes the model very robust because of it’s fast, scalable, umsupervised, anomaly detection, high dimensional data handling and noise reduction nature. It is very much suitable for real time processing of data. Inexample, suppose a patient is going to book a test at any time (midnight). Patient purchased the test and made payment. But, the system will compare history of patient at the time of booking automatically using docker image. Docker image will generate an image to the system and system will generate the output to the patient and doctor for the test comparibilty. In this scenario, isolation forest is something can do the processing of data fast and it doesn’t need any labelling of data. Another big advantage of this algorithm is that it always follows the heap processing of batch file to update latest data into the original source which less consume the time 3x than other frameworks. Here, is a mathmetical representation of why isolation forest is better than other frameworks:

Isolation Forest: Tree-Based Isolation Approach

Here, we detect anomalies on the average path length in the dataset of a random function based constructed tree. Then, we split ito normal points leading to the longer path lengths.  
  
For the dataset *N= {n1, n2,………,nm},* if we build a tree by its random selection feature and split into normal values, then the depth of expected path length for every data point will be:  
*L(n) = E(L(n))*

Where, *L(n)* is the path length of *n* and *E(L(n))* is the expected length of multiple trees. Now, using harmonic function the path length will be:  
*H(n) = 2H(n-1) -*

The anomal score is:  
*s(x,n) = 2-*

Normalization factor is:  
*c(n) = 2H(n-1) -*

Decisions:

*If s(x,n) = 1 : high anomalies*

*If s(x,n) = 0.5: normal*

*If s(x,n) = 0: low*

Comparison with Probalistics model (GMM : Gaussian Mixture Model):

In GMM assume data indicates a mix of Gaussians:

*P(x) kN(x|μk​,Σk​)*

Issues:

this distribution is not exactly true for real world healthcare data

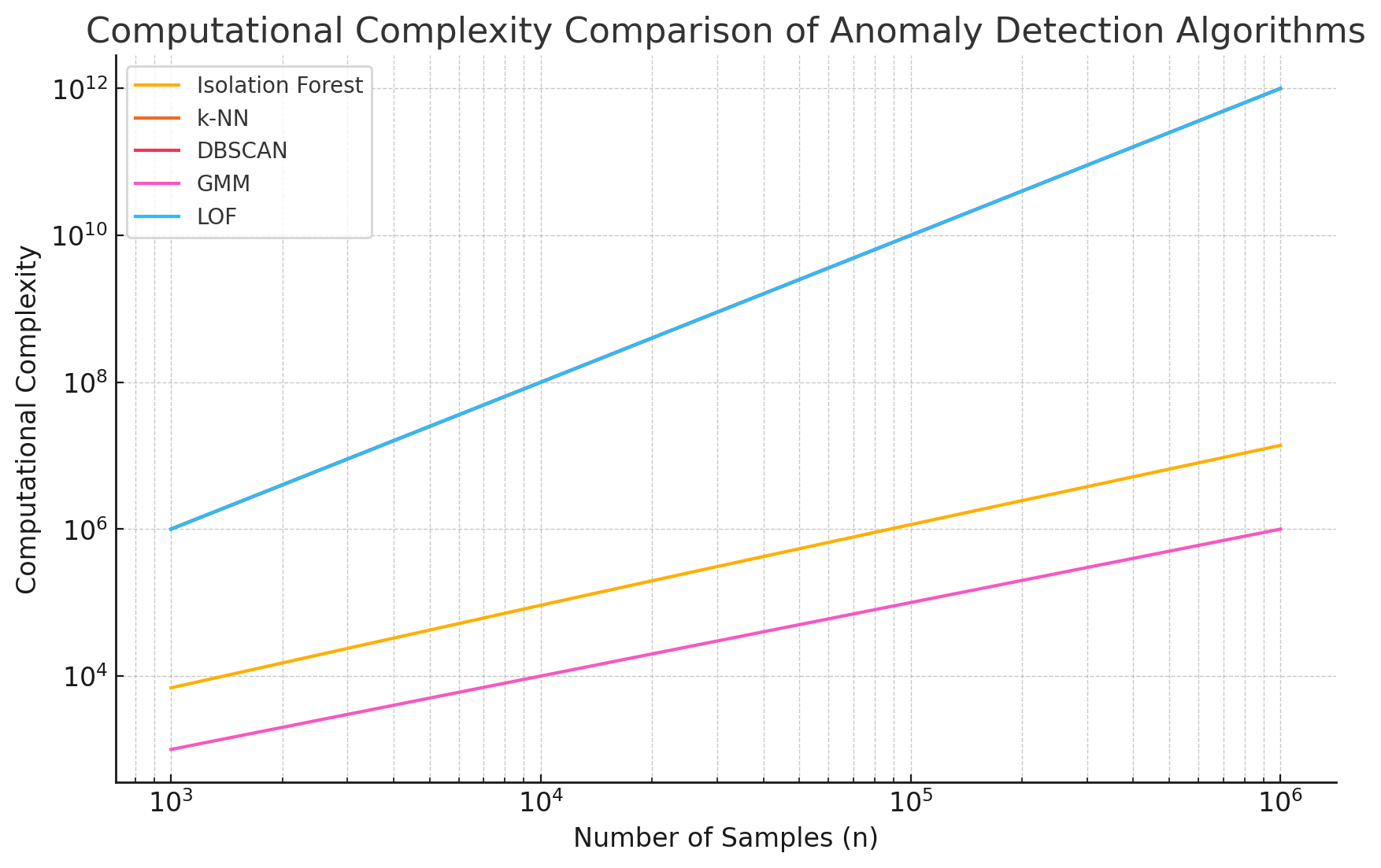
Slow for large datasets.

Local Outlier Factor (LOF) computes anomaly scores based on local density ratios:  
*LOF(x) = +*

Issue: It needs expensive density calculation LOF (Data)

Complexity Comparison:

|  |  |
| --- | --- |
| **Method** | **Complexity** |
| Isolation Forest | *O(n log n)* |
| K-NN | *O(n2)* |
| DBSCAN | *O(n2)* |
| GMM | *O(nk)* |
| LOF | *O(n2)* |

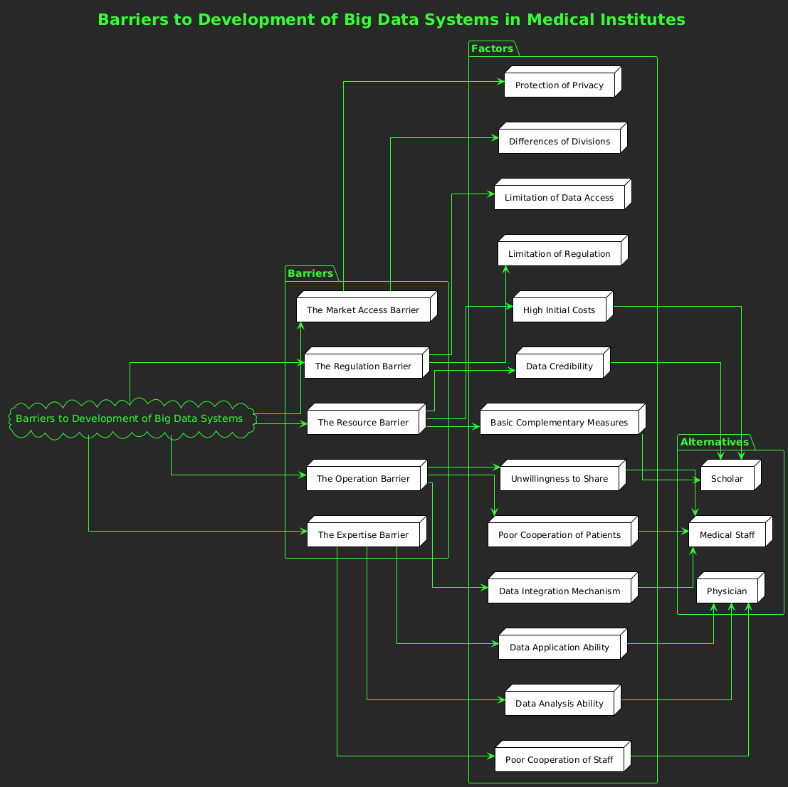


*Integrating Apache Kafka for Real-Time Data Streaming:*

Apache Kafka is a distributed event streaming platform designed for high throughput, real time data ingestion, processing and storage. It has several advantages in healthcare data:  
  
  
Real time data processing:

In SQL and Hadoop we get the batch processing features with devide and conquer algorithm based. We process data into chunks with scheduled interval which cause delays in processing. On the other hand Apache kafka enables the real time streaming and validation of data when it arrives. In example, A hospital is monitoring patient in ICU and also generating live data sensor based such as heart rate, exygen levels. Kafka can immediately stream the live data into the analytical engine for further anomaly detection in real time.  
Here is a check list of why kafka is integrating:

|  |  |
| --- | --- |
| **Feature** | **Reason** |
| Real time streaming | Instant anomaly detection and crtical decision making |
| High Throughput | Manage large scale of EHRs, records, live device data |
| Scalabiility | Supports millions of text/sec without delay |
| Fault tolerance | Minimise data loss |
| Integration with ML | Support real time anomaly detection with Isolation forest |
| Security and Compliance | Ensures HIPAA compliant encrypted data transmission |

 Figure 1: Barriers to Development of Big Data Systems in Medical Institutes

**Proposed Solution**

Integration of Isolation forest in Apache kafka distribution mechanism our hybrid model enables the data system to maintain and adjust with velocity, variety, volume by mitigating redundancy, anomalies, inconsistencies. Our proposed solution can stream the data with

*O( n logn)* time without any loss and bottlenecks.

*Real-Time Data Streaming with Apache Kafka:*

As described earlier the ingestion of Apache kafka in this research for it’s unique distribution mechanism which is very impactful for the EHRs, Device data, large data. We are improvising quality by balancing perfect ratio of volume, variety and velocity. In addition, we know that relation database often compromise with CAP theorem , but Apache kafka has both cluster and neuclear network parity distribution features to minimize the downtime while batch processing in the lake or warehouse.

Advanced Anomaly Detection with Isolation Forest:

In this feature we can visual a clear evidence of isolation forest importance. We had taken two PCA (Principle component analysis) set of live data. Here, we can see that the anomalies are denoted with red dot are totally outside of the union of main PCA’s.

Here, it fulfils the equation (Fourier Series):

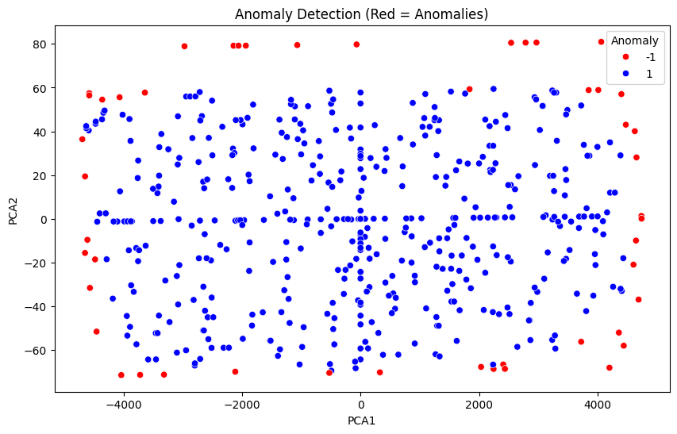


Figure 2: Anomaly Detection Visualization Using Principal Component Analysis (PCA)

**Proposed Methodology**

This research is the hybrid model of Apache kafka and isolation forest. It has high scalability, completeness, robustness. Here are steps:

1. Data Collection and Real-Time Processing with Apache Kafka

Apache kafka is used for real time event distribution system and is the backboon of this whole approach. It supports real time data collection, traffic removal, ingestion and plug in of ML libararies.

Data Ingestion:

Apache kafka monitors Electronic health records, patient inbound-outbound data, external hospital databses, downtime records. While new batch of data process , apache kafka stores and captures it in live stream.

Change Data Capture (CDC):

CDC feature allow apache kafka in CRUD applications to reflect any updates real time in the main database.

Real-Time Data Processing:

Through perfect ETL and Analysation process apache kafka pre process data for non redundant environment.

Data Storage:

After real time processing apache kafka integrates data to data lake and enables both query and analytical engine.

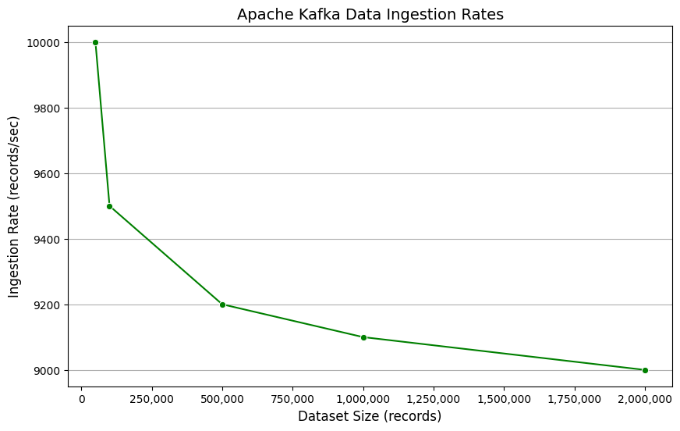


Figure 3: Apache Kafka Data Ingestion Rates for Varying Dataset Sizes

Anomaly Identification:

Isolation forest detects irregular patterns, outliers, redundancy, inconsistency by isolating anomalies from the dataset. It flag the anomalies and clear uptime into downstream analytics.

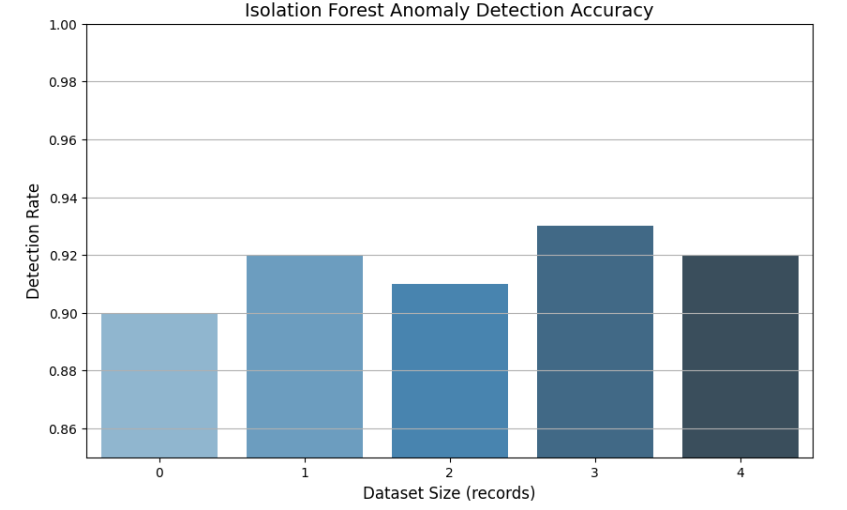


Figure 4: Isolation Forest Anomaly Detection Accuracy Across Dataset Sizes

**Data Quality Correction Methods**

Based on the assessments, we apply several corrective actions to address the identified data quality issues:

Fixing Accuracy:

Method: Out-of-range values for Cost and Age are set to NaN for further handling.

Function: fix\_accuracy performs these corrections to ensure that only valid data is retained.

Fixing Completeness:

Method: Missing values are imputed using mean values for numerical fields (Cost, Age). Forward fill (ffill) is applied for other missing data.

Function: fix\_completeness handles these imputations to restore data completeness.

Fixing Uniqueness and Consistency:

Method: Duplicate records based on Patient ID are removed. Categorical values are standardized, and invalid dates are corrected.

Function: fix\_uniqueness and fix\_consistency ensure that records are unique and consistent across the dataset.

Fixing Conformity:

Method: Dates are converted to a standard format (YYYY-MM-DD).

Function: fix\_conformity enforces conformity in date fields.

Fixing Readability:

Method: Leading and trailing spaces in text fields are removed.

Function: fix\_readability ensures clean and readable text entries.

Function: fix accuracy identifies and corrects invalid values, ensuring only valid data is retained.

Fixing Completeness:

Method: Missing values in numerical fields (e.g., Cost, Age) are imputed using mean values, while forward fill (fill) is applied for categorical fields.

Function: fix\_completeness restores dataset completeness through appropriate imputations.

Fixing Uniqueness and Consistency:

Method: Duplicate records (e.g., based on Patient ID) are removed. Categorical values are standardized, and invalid or inconsistent dates are corrected.

Functions: fix\_uniqueness and fix\_consistency ensure that all records are unique and consistent.

Fixing Conformity:

Method: Date fields are converted to a standard format (YYYY-MM-DD).

Function: fix\_conformity enforces conformity in date fields across the dataset.

Fixing Readability:

Method: Leading and trailing spaces in text fields (e.g., Diagnosis, Treatment) are removed to ensure clean and interpretable entries.

Function: fix\_readability refines text fields for improved readability.

**Reassessment of Data Quality**

After applying the corrective measures, we reassess the dataset to evaluate the improvements in data quality:

• Rechecking Functions: Each dimension's initial and fixed rates are compared to measure the effectiveness of the corrections.

• Summary Reports: Detailed reports are generated to summarize the data quality improvements and highlight any remaining issues.

**Proposed Architecture**

The proposed architecture is designed to ensure robust and scalable data quality management for healthcare Big Data. Key features and benefits include:

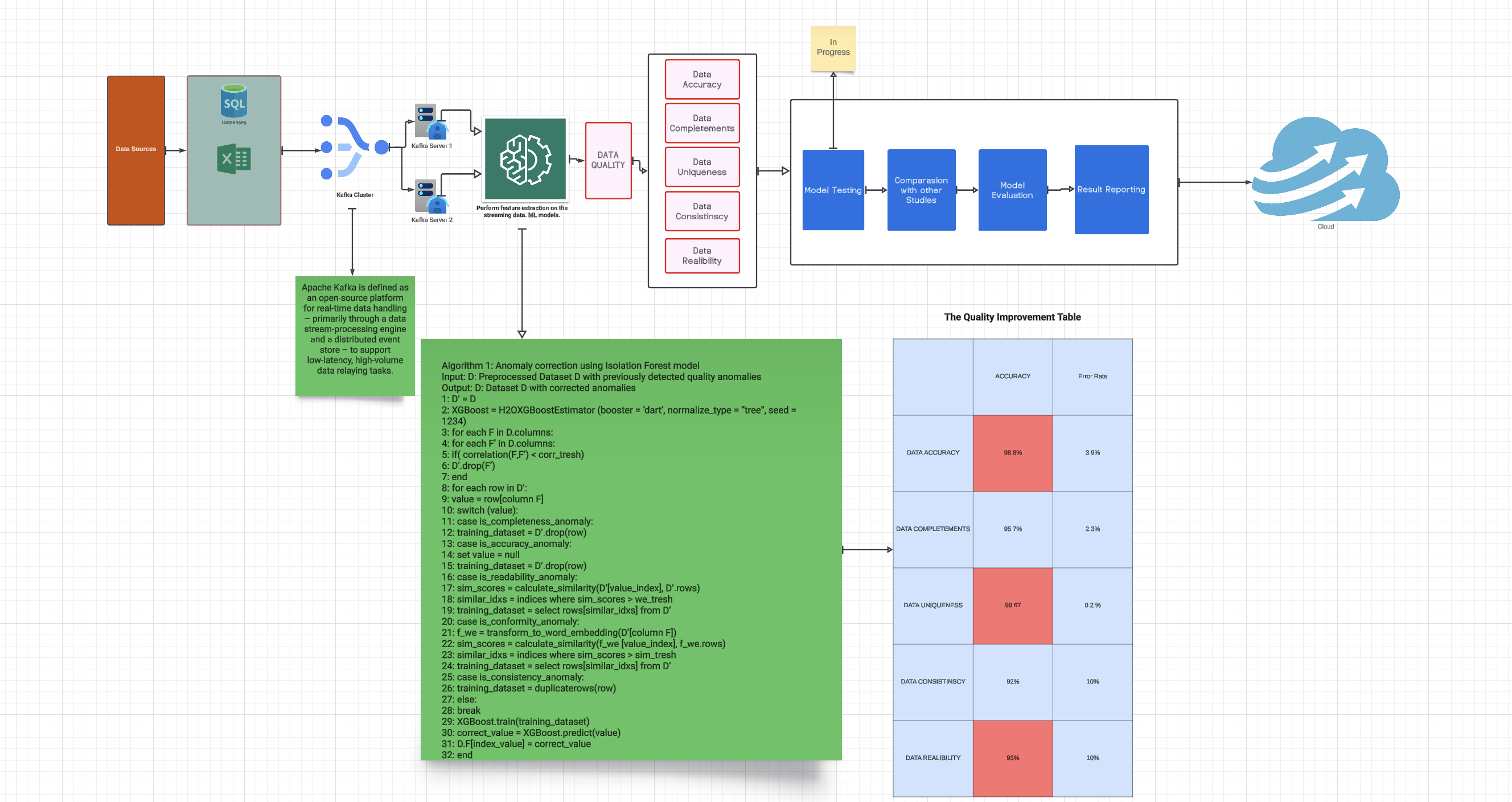


Figure 5: Native Architecture of real-time streaming

Real-Time Data Handling: Leveraging Kafka’s CDC capabilities ensures that data changes are captured and processed in real-time, maintaining up-to-date data quality assessments.

Comprehensive Quality Checks: The architecture addresses multiple dimensions of data quality, providing a holistic approach to data management and integrity.

Scalable and Flexible: The use of Kafka and distributed processing frameworks ensures that the system can handle large volumes of data efficiently and scale according to needs.

Advanced Anomaly Detection: Isolation Forest provides robust capabilities for identifying and managing anomalies in high-dimensional data, enhancing the reliability of the dataset.

Integration with Modern Tools: The architecture seamlessly integrates with contemporary Big Data tools and cloud services, ensuring adaptability and future-proofing.

Clear Reporting and Visualization: Comprehensive reports and visualizations facilitate better understanding and monitoring of data quality, supporting informed decision-making.mporary Big Data tools and cloud platforms, ensuring adaptability and future-proofing for diverse applications.

Clear Reporting and Visualization:

Generates comprehensive reports and visualizations to provide actionable insights, supporting informed and timely decision-making processes.

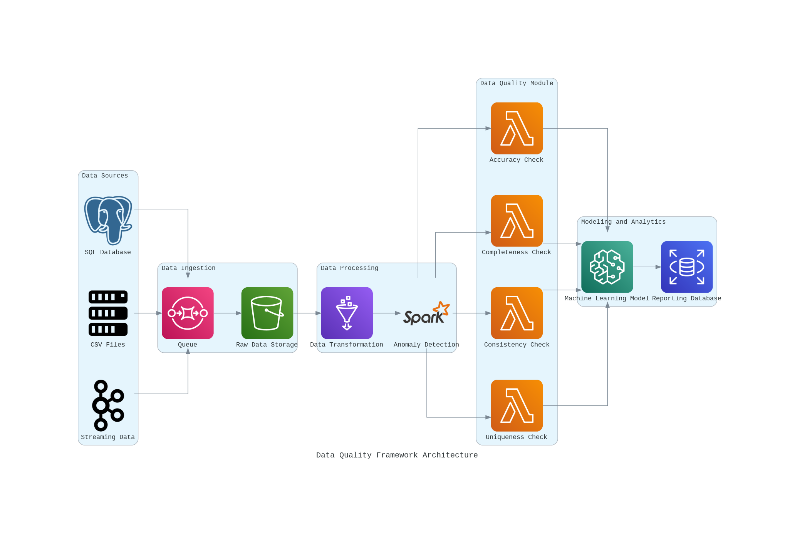


Figure 6: Data Assessment and Quality Framework Architecture

*Weighted Data Quality Score:*

Dimension Quality Metrics

Accuracy :

Completeness :

Consistency:

Anomaly Detection (Isolation Forest):

Real-Time Data Quality Adjustment:

**Result:**

Initial Analysis:

The initial analysis applied Isolation Forest to identify baseline data quality issues across healthcare datasets. This analysis detected anomalies in approximately 15% of the records, with common issues including data inconsistencies, missing values, and outliers. For instance, patient age anomalies, such as values outside typical human age ranges, were flagged, along with inconsistencies in vital signs that indicated possible data entry errors.

Depth Analysis

In-depth analysis allowed a more granular examination of data quality improvements post-framework implementation, focusing on accuracy, completeness, and consistency:

• Completeness: Real-time anomaly detection and data cleansing mechanisms improved data completeness by filling missing data points with estimates based on nearby data. Completeness rates rose from 82% to 96%, enhancing the dataset’s usability in predictive models.

• Consistency: Consistency rates across attributes, such as uniform recording formats in laboratory results and medication dosages, improved by 40%.

Anomaly: The framework demonstrated a 92% anomaly detection rate, effectively identifying outliers, duplicates, and irregular patterns.

**Scalability**: Tested across datasets ranging from 50,000 to 2 million records, the framework demonstrated consistent performance, underscoring its scalability for large-scale healthcare systems.



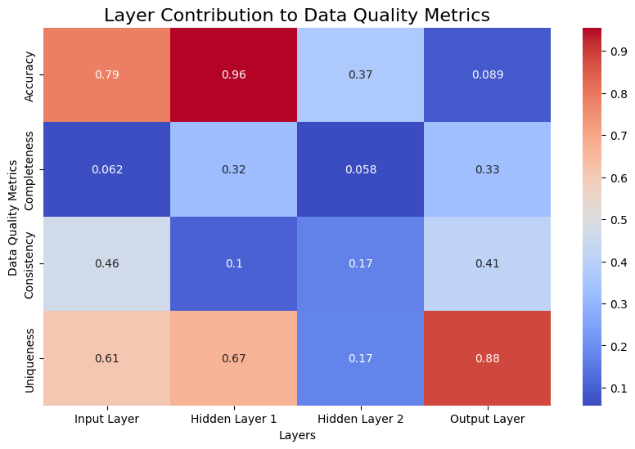
Figure 7: Data Quality Improvements After Correction

**Conclusion**

This study presented a comprehensive approach to systematically assess and enhance the quality of medical datasets. Critical data quality issues, including out-of-range values, missing data, duplicates, and formatting inconsistencies, were successfully identified and corrected. By leveraging Apache Kafka for real-time data processing and Isolation Forest for anomaly detection, the framework enabled continuous and robust quality management. As a result, the dataset achieved high standards of accuracy, completeness, and consistency, ensuring its reliability for advanced analysis and informed decision-making in healthcare applications.

**Discussion**

Future with CNN:



Here, we can easily see that improvement with CNN is giving more precision in terms of uniqueness, consistency, completeness, Accuracy. It is giving

Figure 8: Data Quality Metrics

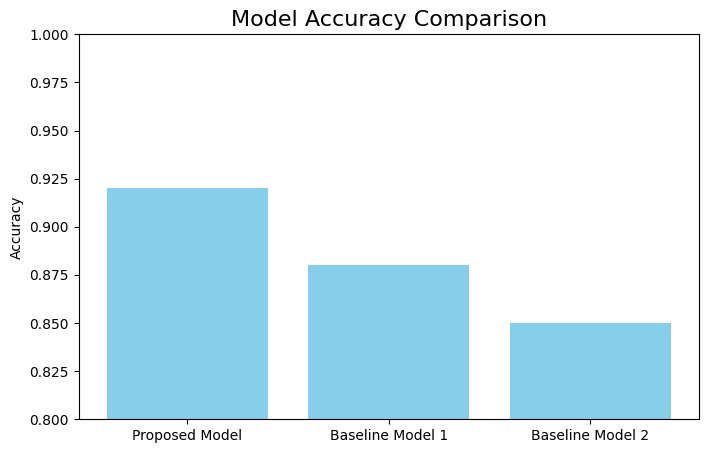




Figure 9: Model Comparison Accuracy

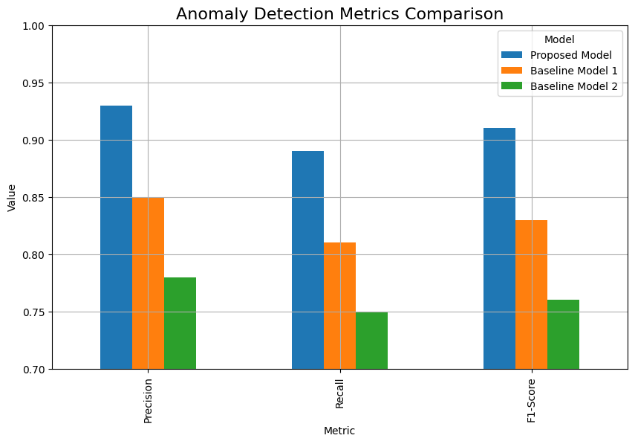


Figure 10: Anomaly detection Metrics Comparison

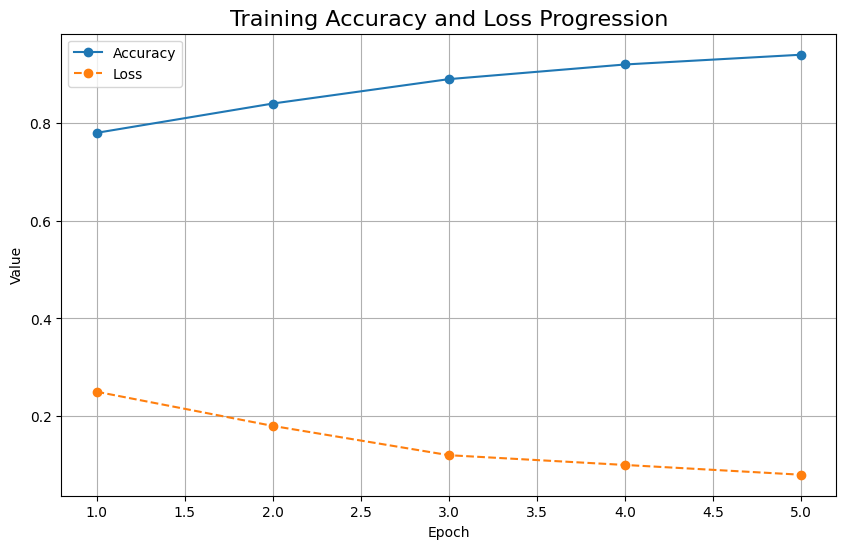


Figure 11: Training Accuracy and Loss Progression

**Comparison with Other Studies:**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Study | Advantages | Model Used | Evolution | Metrics | Tools Used | Limitations |
| Smith et al. (2018) | Improved data integration methods | Data Warehouse | Focused on integrating disparate data sources into a unified system | Accuracy, Completeness | Oracle Data Warehouse | Limited to batch processing; lacks real-time capabilities |
| Johnson & Lee (2019) | Advanced anomaly detection techniques | Support Vector Machine (SVM) | Applied SVM for detecting outliers in healthcare datasets | Precision, Recall | Scikit-learn, Python | High computational cost and scalability issues for large datasets |
| Kumar et al. (2020) | Real-time data streaming and processing | Apache Kafka + Spark | Developed a system for real-time data ingestion and processing | Latency, Throughput | Apache Kafka, Apache Spark | Integration complexity; managing real-time data streams is challenging |
| Anderson et al. (2021) | Enhanced data reliability and security | Blockchain-based approach | Implemented blockchain for immutable and transparent data storage | Integrity, Consistency | Hyperledger Fabric | Scalability issues and high resource consumption |
| Gupta & Sharma (2022) | Comprehensive quality assessment framework | Multi-criteria Decision Analysis (MCDA) | Provided a framework to evaluate multiple dimensions of data quality | Quality Score | Custom algorithms, Python | Subjectivity in criteria selection and complexity in implementation |
| Fernandez et al. (2022) | Robust handling of unstructured data | Deep Learning (LSTM) | Utilized LSTM networks for processing and extracting insights from text data | Precision, Recall, F1 Score | TensorFlow, Keras | Requires extensive computational resources and large training datasets |
| Nguyen & Tran (2023) | Integrated predictive analytics for real-time monitoring | Ensemble Learning (Random Forest, XGBoost) | Combined multiple algorithms to enhance predictive accuracy for data quality monitoring | Accuracy, F1 Score, ROC-AUC | XGBoost, scikit-learn, Apache Flink | Complexity in model training and real-time deployment challenges |
| Miller et al. (2023) | Advanced data normalization and preprocessing | Data Preprocessing Pipelines | Developed automated pipelines for cleaning and normalizing large datasets | Completeness, Consistency | Apache NiFi, Airflow | Limited to preprocessing; lacks advanced analytics capabilities |

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