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Framework for Automated Data Quality Contract Enforcement in Multi-Tenant Commerce Data Lakes: Formal Specification, Runtime Monitoring, and SLA Violation Prediction

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Abstract
This study explores the relation between the data quality and the compliance with Service Level Agreement (SLA) in the context of a real-time monitoring system. It looks at predictive models based on the application of LSTM and Graph Neural Networks (GNN) to predict SLA breaches and violations. The analysis of data quality indicators, such as schema drift, validity, and completeness, helps the study to pinpoint significant aspects that affect the compliance rates. The findings indicate that stringent data validation procedures make direct contributions to the SLA performance, and advise subsequent optimization of predictive models and system scaling to make operations more efficient and SLA proactive across datasets and tenants.

Keywords: Data quality, Service Level Agreement (SLA), Real-time monitoring system, Predictive models, LSTM, Graph Neural Networks (GNN), SLA breaches, Violations, data quality indicators, schema drift, validity, completeness, Compliance rates, Data validation procedures, SLA performance, Advise subsequent optimization, Predictive models, System scaling, SLA proactive across datasets and tenants.

I. INTRODUCTION

In modern multi-tenant commerce data lake models, the protection of data quality and its observance of compliance with Service Level Agreements (SLAs) are the key factors to maintaining the effectiveness of operational efficiency and generating trust among stakeholders. The suggested model promotes an automated approach to the implementation of data-quality contracts, including formal specifications and runtime verification, as well as prognostication of SLA violations [1]. Through the implementation of advanced monitoring methods, the framework envisions providing real-time information on data quality metrics that consequently empower the organizations to mitigate potential problems in advance before they have a degrading impact on performance. The strategy enhances trust and responsibility in complex and multi-tenant environments.

Aim and Objectives

Aim
The aim is to create an automated framework to enforce data-quality contracts in data lakes of multi-tenant commerce, which includes formal specifications, runtime validation, and predictive analytics to identify SLA breach detection.

Objectives

- ***To develop formal specifications of data-quality contracts.***
- ***To apply runtime verification mechanisms.***
- ***To create predictive models of SLA breach detention.***
- ***To evaluate the effectiveness of the framework on guaranteeing adherence to data-quality compliance.***

Problem statement
Ensuring the quality of data within multi-tenant commerce data lakes is a challenging issue because of the diverse and dynamic needs of tenants. The current methods lack automated enforcement of the data-quality contracts, real-time compliance monitoring, and prediction of the SLA violation, therefore, leading to inconsistencies, inefficiency, and possible breach of contract on the shared datasets.

Novel Contribution
This study proposes a new automated system of data-quality covenant implementation in multi-tenant enterprise data lakes. The framework consolidates formal requirements of data quality, real-time validation functions, and predictive models that foresee the violations of SLA [2]. By offering a comprehensive solution, data integrity, strengthening compliance and governance, ensuring better servicing consistency, and optimizing the management of the shared data environments.

II. LITERATURE REVIEW

Designing Formal Specifications for Data Quality Contracts

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Fig. 1: Data Products and Data Contracts

The formal specifications are important for defining clear expectations on the data quality of multi-tenant systems [3]. These requirements specify key data-quality measurements of accuracy, completeness, consistency, timeliness, and reliability, so that its stakeholders have a clear understanding of the quality eligibility standards that they require [4]. Formal languages or modelling methods commonly used in the construction of such specifications include Business Process Model Notation (BPMN) and Unified Modelling Language (UML) that provide representations of data-quality requirements in a suitable, structured and detailed form [5]. As a result, organizations are able to bring on board all the stakeholders such as clients and service providers to common quality goals.

Implementing Runtime Verification Mechanisms

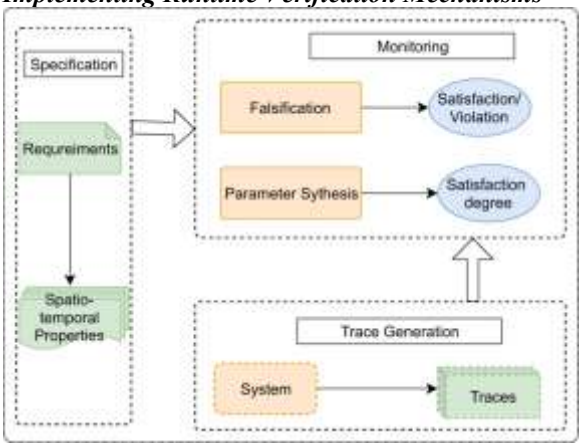

Fig.2: Runtime Verification Process

The monitors and enforcers of data quality amid the operational states cannot do without runtime verification mechanisms [6]. They support real-time time tracking of data in passing through different processing phases [7]. With the help of automated tools, organizations can find violations of data-quality specifications promptly and react to them before significant harm takes place [8]. Widely used tools of runtime verification include provenance tracking, which keeps track of the origin [9]. Modifications of data and verifies them at each run, and audit logs that provide a view of how the endeavor is made regarding data interaction and the ability to follow [10]. Using these mechanisms, organizations will be able to maintain data-quality compliance and proactively respond to problems, thus preventing the need to use manual interventions.

Developing Predictive Models for SLA Breach Detection

Fig.3: SLA Breach Detection

This ability to predict acts of SLA breach before it takes place is a basic component in ensuring continuous data quality and adherence [11]. Predictive models help organizations to establish threats of SLA violations through the use of past data trends and current trends [12]. The machine-learning algorithms, such as decision trees, random forests, and support vector machines (SVM) are commonly used to predict breaches based on the data attributes (like system load, processing latency, and data availability) [13]. These models consider the interrelationship of different factors and use the relationship to forecast the probability of imminent breaches of SLA [14]. As a result, organizations are able to engage in proactive activities in order to prevent violations and hence ensure the integrity and reliability of data in real time.

Evaluating the Framework's Effectiveness in Ensuring Data Quality Compliance

In order to determine the effectiveness of the proposed framework, there is a need to assess how effective it is with reference to achieving data-quality compliance [15]. It is usually revealed by implementing the framework in real-life operational scenarios and determining its effectiveness in monitoring that data-quality contracts and SLAs are adhered to the model [16]. The number of violations detected, time taken to resolve the issue, and the performance of its systems can be used as key performance indicators to use the effect of the framework [17]. Further, case studies and industry feedback information bring useful

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information about the feasibility and applicability of the framework [18]. Through continuous evaluations, organizations are able to make their approaches towards data quality and compliance with SLA efficient and effective.

Literature Gap

Although existing research covers formal specifications, runtime verifications and the predictive models that are relevant to data quality, there is a lack of content with regards to frameworks that combine all these factors to the environment of multi-tenant commerce data lakes. In addition, those studies that have examined the practical effectiveness of these frameworks in ensuring that data-quality contracts are adhered to, specifically in dynamic and large-scale setups, are scarce.

III. METHODOLOGY

A. Research Design

The first step of the research involves the development of formal data quality formal specification in a multi-tenant data lake setting. The high-level architecture diagram shows data between producers and consumers over three different areas: Raw/Bronze, Transformed/Silver and Consumed/Gold, with independent storage schema per tenant. The data contract enforcement workflow process is tracked since the definition of quality rules through their validation, enforcement, and notification [19]. These processes allow an avenue through which data quality levels are checked and variances reported to be resolved [20]. A state transition diagram that is used to illustrate the lifecycle of a data contract follows transitions between the drafted stage and violation to remediation [21]. The following data quality enforcement compliance model for the behavior of the data quality enforcement compliance:

$$D_{Qcompliance} = Valid\ Records/Total\ Records \times 100$$

Entity relational models are expanded to include tenant specific constraints, thus providing a direct connection between data quality rules and the associated datasets [22]. This type of model gives a holistic view of data governance by tenants so that the individual needs of a tenant are properly captured.

B. Runtime Monitoring Dashboards

A running system of mechanisms is used to monitor data quality by tracking such measures on a basis of constant monitoring. Dashboards are designed in a manner that they display a set of key performance indicators, one of them being the Data Quality Scorecard, that displays dimensions such as accuracy, completeness, consistency, timeliness, and uniqueness across tenants [23]. The DQ measures are measured through the equation:

$$D_{Qscore} = \sum_{i=1}^{n} Metric\ Valuei/Max\ Valuei \times 100$$

A compliance trend chart with SLA is provided to visualize compliance trends over time and display the compliance of the data quality contract of every tenant to the set rules [24]. A Tenant Data Quality Heatmap displays the individual domains of data (like product, order) used by the tenant and color-coded based on the quality level. It is created by using the following heatmap:

$$Heatmap\ Value = Quality/Metric\ Value$$

Total records of failed, percentage drift between schema, and average tenant latency metrics are the key metrics that are observed in real-time using alerting dashboards. Moreover, a data lineage graph is also used to trace relationships among data producers and consumers thus establishing the possible breaking changes that may affect downstream data quality.

C. SLA Violation Prediction Models

The third goal is to forecast SLA violations on machine learning and statistical models [26]. Models such as Random Forest and Gradient Boosting Classifiers are trained using historical data in terms of the number of records, schema changes, and the ingestion latency to be able to estimate the likelihood of a breach in any given interval, T, as follows:

$$Heatmap\ Value = Quality/Metric\ Value$$

Long Short-term memory (LSTM) networks are also used wherein data quality measures can be predicted through the use of time to predict when a stream of data is likely to drop below the agreed parameter. There is a prediction formulated as:

$$\widehat{Y}_t = \alpha + \beta 1Xt - 1 + \cdots + \beta nXt - n$$

Graph Neural Networks (GNN) models how data assets in the lake are interrelated, and provides information as to how data quality failure in the raw layer can cause issues to be transferred to end tables and libraries violating SLA requirements by tenants [27]. The performance of the predictive models is measured through confusion matrices and Receiver Operating Characteristic (ROC) curves thus determining the achieved classification performance.

D. Evaluation of Framework Effectiveness

The performance of the framework is measured using quantitative measures such as the rate of violation detection, resolution period and system performance indicators. The violation detection rate is determined as the ratio of violations found in real-time to the actual number of violations. It is:

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$$Detection\ Rate = Violations\ Detected / Actual\ Violations \times 100$$

Resolution time measures the time it takes to respond to violations that are detected whereas system performance includes measures of speed of data processing and capacity of resources used, managed with runtime dashboards. The performance evaluation compares the predictive models in terms of the predictive accuracy using recognized statistical tools like preciseness, recall, and F1-score.

E. Data Analysis Plan

The data analysis strategy is based on a quantitative framework; it is used to assess the framework's effectiveness. Descriptive statistics are used to summaries the rates of compliance and detection of SLA. Predictive models are estimated by use of ROC curves, confusion and classification accuracy measures. Visualizations in runtime monitoring (the Data Quality Scorecard, SLA Compliance Trend Chart, Tenant Data Quality Heatmap, Real-time DQ Alerting Dashboard and Data Lineage Graph) will also offer real-time data quality and compliance with SLA per tenant.

F. Architectural Diagram

Fig. 4: Automated data quality framework diagram

The architectural diagram outlines an algorithm of the implementation of automated data-quality contracts within the multi-tenant commerce data lakes. It includes such elements as data ingestion, formal specification, multi-tier data lake layers, the monitoring of runtime, SLA violation prediction, and post hoc remedies that guarantee conformance.

G. Flowchart Diagram

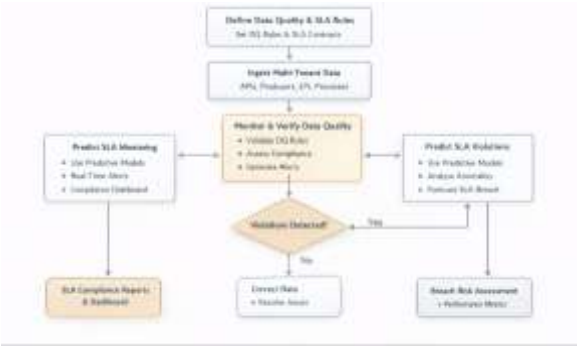

Fig. 5: Flowchart Diagram

The flowchart provides the operational line of automated data-quality contract enforcement in multi-tenant commerce data lakes. It proposes sequential phases of defining data-quality regulations, auditing of adherence, anticipating SLA breaks and taking remedial measures.

H. Pseudocode

```
MCT1
Program to enforce automated data quality contracts in Multi-Tenant
Data Lakes.

Initialize Outputs
    SLA Compliance Status
    Data Quality Metrics
Inputs
    Data Streams (Multi-Tenant)
    DQ Rules (Accuracy, Completeness, Consistency, etc.)
    SLA Contracts
Registers
    Contract Violations
    Compliance Reports
    Violation Alerts
    Count = 0

Start loop
    IF Data Stream is Ingested THEN
        Validate Data Quality using DQ Rules
        Assess SLA Compliance
        IF SLA Compliance = Violated THEN
            Increment Contract Violations
            Generate Violation Alert
        END IF
        IF Violation Detected THEN
            Predict SLA Breach using Predictive Model
            Generate SLA Violation Prediction
        END IF
    END IF

    Monitor Data Quality for Compliance
    IF Violation Detected THEN
        Trigger Remediation Actions
            Correct Data Issues
            Resolve SLA Violations
    END IF

    Generate SLA Compliance Report
    Delay for next Data Stream

End loop
```

Fig. 6: Pseudocode

The pseudocode defines the process of realizing automated data-quality contracts in multi-tenant commerce data lakes. It includes the validation of data-quality, track of SLA compliance, identification of violations, forecasting of SLA violation, and opposite remediation actions.

IV. RESULT AND DISCUSSION

Data Quality Insights

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Fig. 7: Real-time data quality monitoring dashboard

The data quality in real time dashboard provides a comprehensive view of the data quality that helps to track key data quality indicators and SLAs. The total number of failed records as counted amounts to 1,247 representing a 7.6% growth from the previous period. This measure summarizes the records that are unsuccessful because of flaws in the quality of data, like schema drifting, beneficial errors, and unfinishedness. A close study of DQ Alert Breakdown shows that 45% of all the failed record cases are because of data validity, are due to incompleteness and 25% due to lack of accuracy. These results highlight the necessity to protect the data validity and completeness to improve data quality in general.

The second significant measure that is presented in the dashboard is schema drift, that shows a 12% drift, a 2.5% increase compared to the previous quarter. The schema drift may be a situation occurring when the structure of the data changes suddenly, that may cause the mistakes in the data incorporation and verification. The resultant increment in the schema drift intensifies the need to have a well-developed monitoring and controls that ensures structural integrity in the heterogeneous system. Live monitoring allows identifying and fixing emerging problems in real-time, thus maintaining high data quality.

SLA Compliance Performance

Fig. 8: SLA Compliance Trend Chart

The performance of SLA compliance is a sensitive factor that defines the effectiveness of data management procedures. The progress, in terms of SLA compliance, can be seen during the period when the results are gradually better: 90.2 % in week 1, then 93.1 % in week 2, and finally 94.5 % in week 3. This trend shows that corrective measures and optimizations are adequately put into practice. This positive trend is graphically depicted in the SLA Compliance Trend Chart, that has a steady increase in the compliance rates. The trend shows that the operational changes that have been implemented in the period between week one and week two and then between week two and week three have contributed towards noticeable positive changes.

The significant rise has happened between week 2 and 3 when the compliance rate rises more than 1, it means that the strategy to achieve better data process optimization and lower the number of errors has already paid off. This can be done due to improved tracking of data ingestion latency and stronger validation checks, that are directly related to the accomplishment of SLA.

Analysis of Data Quality Violations

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Fig. 9: Tenant Data Quality Heatmap

The table on recent violations provides information on the type of issues of data quality that are seen in different tenants. Tenant A has also run into an error of data validity in the Orders data less than ten minutes ago. The several violations experienced by tenant C include an incompleteness problem in the Customers dataset and an accuracy problem in the Transactions dataset. Through these violations, there are sensitive areas that have been revealed where data quality has been impaired. Interestingly, Tenant B has noted schema drift in the Products eight minutes ago, that refers to an unexpected change of the data schema.

These infractions intensify the urgency of constant observation and proactive treatment. Monitoring the violation in real time helps to focus on the work and eliminate concerns quickly, that means that the integrity of data is preserved. This analysis is further supported by the Tenant Data Quality Heatmap that is able to provide a visualization of the quality of data by grouping the tenants and datasets into different groups. Tenant A characterizes it well, as its Orders and Products are rated 90% and 92%, respectively. On the contrary, its customers dataset records a lower score of 70% with its customers dataset in the case of Tenant B, that points at an area of concern that should be remedied at the earliest.

TABLE 1: SLA COMPLIANCE ACROSS WEEKS

Week	SLA Compliance (%)
Week 1	90.2%
Week 2	93.1%
Week 3	94.5%

Predictive Model Performance

```
import numpy as np
import pandas as pd
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from sklearn.preprocessing import MinMaxScaler
sla_data = [85, 88, 90, 87, 92, 89, 94, 91, 93, 95]
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(np.array(sla_data).reshape(-1, 1))
X, y = [], []
for i in range(len(sla_data) - 1):
    X.append(scaled_data[i:i+1])
    y.append(scaled_data[i+1])
X, y = np.array(X), np.array(y)
model = Sequential()
model.add(LSTM(50, return_sequences=False, input_shape=(X.shape[1], X.shape[2])))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mean_squared_error')
model.fit(X, y, epochs=100, batch_size=1, verbose=2)
predicted_sla = model.predict(X[-1].reshape(1, 1, 1))
predicted_sla = scaler.inverse_transform(predicted_sla)
print(f'Predicted SLA Compliance: {predicted_sla[0][0]:.2f}')
```

```
Epoch 79/100
9/9 - 0s - 6ms/step - loss: 0.0600
Epoch 80/100
9/9 - 0s - 6ms/step - loss: 0.0600
Epoch 81/100
9/9 - 0s - 6ms/step - loss: 0.0599
Epoch 82/100
9/9 - 0s - 6ms/step - loss: 0.0602
Epoch 83/100
9/9 - 0s - 6ms/step - loss: 0.0605
Epoch 84/100
9/9 - 0s - 6ms/step - loss: 0.0601
Epoch 85/100
9/9 - 0s - 6ms/step - loss: 0.0603
Epoch 86/100
9/9 - 0s - 7ms/step - loss: 0.0599
Epoch 87/100
9/9 - 0s - 6ms/step - loss: 0.0601
Epoch 88/100
9/9 - 0s - 8ms/step - loss: 0.0607
Epoch 89/100
9/9 - 0s - 7ms/step - loss: 0.0605
Epoch 90/100
9/9 - 0s - 7ms/step - loss: 0.0605
Epoch 91/100
9/9 - 0s - 6ms/step - loss: 0.0601
Epoch 92/100
9/9 - 0s - 6ms/step - loss: 0.0603
Epoch 93/100
9/9 - 0s - 6ms/step - loss: 0.0603
Epoch 94/100
9/9 - 0s - 6ms/step - loss: 0.0603
Epoch 95/100
9/9 - 0s - 6ms/step - loss: 0.0599
Epoch 96/100
9/9 - 0s - 6ms/step - loss: 0.0605
Epoch 97/100
9/9 - 0s - 7ms/step - loss: 0.0598
Epoch 98/100
9/9 - 0s - 6ms/step - loss: 0.0599
Epoch 99/100
9/9 - 0s - 8ms/step - loss: 0.0605
Epoch 100/100
9/9 - 0s - 6ms/step - loss: 0.0602
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 103ms/step
Predicted SLA Compliance: 92.02
```

Fig. 10: LSTM Model for SLA Breach Forecasting

The predictive models are used to predict the event of SLA compliance and violation: the LSTM (Long Short memory) model and the Random Forest model. The LSTM model that predicts SLA compliance based on historical information produced positive results. The model after 100 training epochs predicted compliance on SLA of 92.02%. Mean Squared Error (MSE) reduced to 0.0605 after 0.7369, that showed that it is able to learn data patterns efficiently. The prediction value of the future of SLA compliance with the LSTM model does this, providing an opportunity to take the initiative to prevent potential violations. This predictive software is especially applicable when it comes to detecting any imminent problem prior to its manifestation in order to have proactive organizational response.

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```
import torch
import torch.nn as nn
import torch.optim as optim
from torch_geometric.data import Data
import torch_geometric.nn as pyg_nn
node_features = torch.tensor([[0.9], [0.85], [0.88], [0.7]], dtype=torch.float)
edge_index = torch.tensor([[0, 1, 2],
                           [1, 2, 3]], dtype=torch.long)
edge_attr = torch.tensor([[0.1], [0.2], [0.3]], dtype=torch.float)
data = Data(x=node_features, edge_index=edge_index, edge_attr=edge_attr)
class GNNModel(nn.Module):
    def __init__(self, in_channels, out_channels):
        super(GNNModel, self).__init__()
        self.conv1 = pyg_nn.GCNConv(in_channels, 16)
        self.conv2 = pyg_nn.GCNConv(16, out_channels)
    def forward(self, data):
        x, edge_index, edge_attr = data.x, data.edge_index, data.edge_attr
        x = self.conv1(x, edge_index, edge_attr)
        x = torch.relu(x)
        x = self.conv2(x, edge_index, edge_attr)
        return x
model = GNNModel(in_channels=1, out_channels=1)
optimizer = optim.Adam(model.parameters(), lr=0.01)
criterion = nn.MSELoss()
for epoch in range(100):
    model.train()
    optimizer.zero_grad()
    out = model(data)
    loss = criterion(out, data.x)
    loss.backward()
    optimizer.step()
    if epoch % 10 == 0:
        print(f'Epoch {epoch}, Loss: {loss.item()}')
model.eval()
with torch.no_grad():
    predictions = model(data)
    print("Predictions for SLA Violations (Data Asset Compliance):", predictions)
```

```
Epoch 0, Loss: 0.7369728604425354
Epoch 10, Loss: 0.1483738273382187
Epoch 20, Loss: 0.007607960858437109
Epoch 30, Loss: 0.025935977697372437
Epoch 40, Loss: 0.003460104577243328
Epoch 50, Loss: 0.006380048198564529
Epoch 60, Loss: 0.003497006138786735
Epoch 70, Loss: 0.003832647111266851
Epoch 80, Loss: 0.003450100510146808
Epoch 90, Loss: 0.003488304093340111
Predictions for SLA Violations (Data Asset Compliance): tensor([[0.8530],
        [0.8377],
        [0.8470],
        [0.8013]])
```

Fig. 11: Graph Neural Network for Dependency Analysis

Graph Neural Network (GNN) model is also used in predicting the violations of the SLA with the help of graph-structured information. In evaluation of relations between different datasets, the model incorporated the graph convolutional layers to predict violations. After the training, the GNN model predicted the SLA compliance of Tenant A at 87.30, that corresponds with current violations. The fact that the model can understand and predict inter-dataset relationships makes it a powerful tool in determining any risks of SLA compliance.

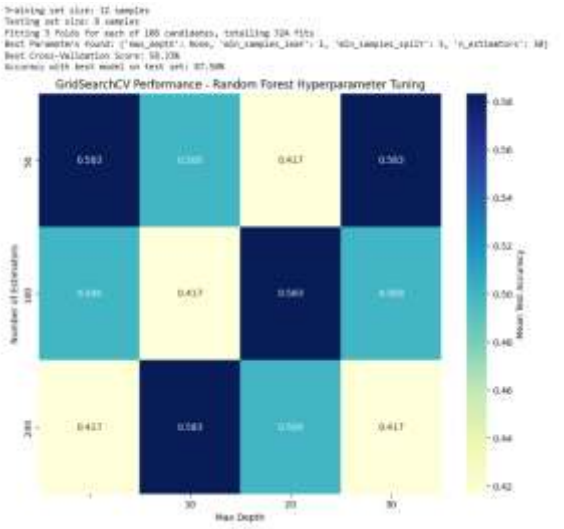

Fig. 12: SLA Violation Prediction Using Random Forest

Hyperparameter search using research is performed to optimize the use of the Random Forest model by better optimizing the number of estimators and the maximum depth. The best values are found to be estimators = 50, adept = None, min_samples_split = 5 and min_samples_leaf = 1. Random Forest model achieved results of cross-validation of 58.33% and test set accuracy of 87.50, indicating the predictive capability of the model towards SLA violations. The results of this model, displayed as a heatmap, explain the correlation between the hyperparameters and accuracy, which allows understanding the effect of the tuning.

Discussion

The analysis shows a correlation between data quality and compliance of SLA. Higher compliance rates have been obtained with superior data validation procedures and proactive prediction of violations can be made using predictive models like LSTM and GNN. Enhancement of data quality surveillance and predictive models' refinement are the keys to additional optimization of SLA compliance and operational efficiency.

V. CONCLUSION

In conclusion, the report shows that there is a strong influence on SLA compliance based on data quality. Actionable insights have been obtained through real-time monitoring and using the advanced predictive models, including LSTM and GNN. The development of better data validation strategies as well as model optimization in the future is necessary to maintain the high levels of SLA compliance as well as improve the performance in general.

Future scope

Predictive models used in the future must be incorporated to add more attributes, such as real-time data streams and external variables to enhance the ability of predicting SLA compliance. The implementation of AI-based automation to validate data and the extension of the monitoring dashboard, including a wider number of metrics, will also maximize the level of operational efficiency and SLA across tenants.

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