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AI-driven data governance in banking: Leveraging large language models for compliance and risk management

Rajesh Kamisetty [1,*] and Raj Nagamangalam [2]

[1] *S & P Global. USA.*
[2] *Google. USA.*

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Abstract

The banking sector has to deal with governance, compliance, and risk management challenges due to the evolving nature of the financial regulation and high volume of sensitive data. Real-time monitoring and anomaly detection are challenging in traditional rule based systems, which lead to inefficiencies and compliance risks. Using Large Language Models (LLMs), this paper discusses enabling banking data governance by automating compliance with banking regulations, risk assessment and fraud detection. Allow Intelligent data classification, predictive analytics and real-time auditing, in compliance with GDPR, Basel III, AML directive standards, etc. LLMs offer a transformative solution for secure and transparent financial operations, albeit with challenges like data privacy, model bias, explainability, etc. This research is based on real case studies and discusses how AI-based data governance can provide banks with improved security, compliance with regulatory mandates, and operational effectiveness.

Keywords: AI-driven data governance; Large Language Models (LLMs); Banking Compliance; Risk Management; Regulatory Adherence; Financial Security; Automated Auditing; Fraud Detection

1. Introduction

With the onset of the digital era, banking sectors are now faced with an immense amount of data that they need to abide by due to compliance and risk policies. As financial crimes increase in frequency, a complex Information Technology / Operational Technology (IT/OT) cybersecurity threat landscape and a patchwork of global regulations such as General Data Protection Regulation (GDPR), Basel III, Anti-Money Laundering (AML) and Know Your Customer (KYC) requirements overwhelm legacy data governance framework with fluid compliance requirements which are no longer part of a signature-update-based compliance framework. Financial service institution needs such advanced technologies that gives the ability to secure, transparent, and/or compliant processing and/or analysis of massive amounts of information.

Data governance in the banking sector has significantly evolved in recent times to encompass automated regulatory compliance, low-latency risk assessment, fraud detection, and intelligent decision making all courtesy of AI and LLMs — and there's plenty of innovation that's still to come. The power that deep learning and Natural Language Processing (NLP) feature in enabling structured and unstructured financial data to be processed at scale gives LLMs great benefits over traditional rule-based systems. AI driven models — unlike legacy systems that are mainly operated via manual interventions and fixed regulatory parameters — dawns in continuous learning cycle based on in-flight data streams, finding anomalies, and cross-value data to find risks

* Corresponding author: Rajesh Kamisetty

This is exactly where stringent info classification, lineage monitoring, and access management are needed for compliance with monetary rules, which aids the Financial Institution avoid creating mistaken investment selections. They should aim to be as transparent as they possibly can while maintaining consumer and transactional data protection. Such LLMs can automate processes like data classification, flagging policy infractions, and creating audit reports in real-time;

So, data is mined by machine learning AI models, that improve compliance risk and other human need human need first and foremost, they provide amendments and tweaks to legacy systems which serve towards predictive analytics through AI systems that help predict and get rid of future policy breaches happening when it comes to regulatory domain.

Moreover, when it comes to fraud detection, these AI-enables data governance frameworks serve as the guidelines for how transactional patterns and data discrepancies of financial activities are evaluated to trigger anti-money laundering measures. Legacy fraud detection systems are rule-based algorithms with a high rate of false positives. On the other side, LLMs have capacity to not only recognize the contextual transaction patterns and identify patterns to separate normal transactions versus fraud transactions but also evolve as frauds change.

As formidable and transformational as AI-powered data governance can be, there are hurdles to its implementation in banking: from data privacy to model bias, regulatory acceptability and explainability of AI-based verdicts. Thereby, ensuring that such models are transparent, interpretable, and in line with ethical guidelines is necessary to keep trust amongst regulators, customers and stakeholders of the financial institutions.

There's a lot that LLMs can do to help conventional data governance processes and build bespoke AI based compliance frameworks for better regulatory compliance, risk management and operational efficiency. It also fills the gap left by existing literature by moving beyond risks and challenges of using ChatGPT to include potential applications in satisfying good governance and using evidence from the case studies, to demonstrate how ChatGPT can enhance organizational performance. These findings drive home the importance of AI powered governance models as banks transition to a data-powered economy where they can operate with security and success in a phase change environment.

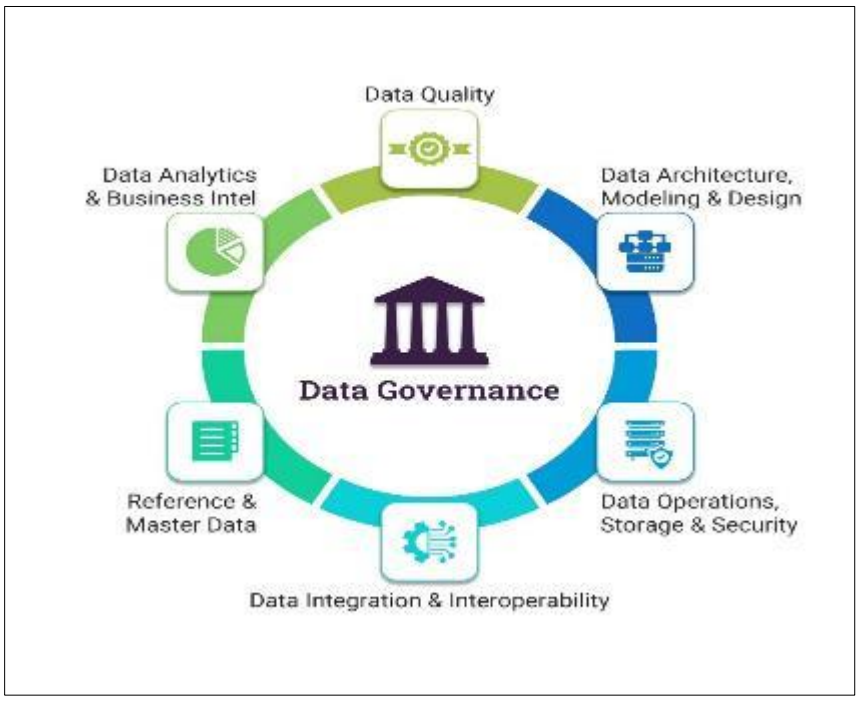

Figure 1 AI-Driven Data Governance Framework in Banking

The figure shown here can enable banks to remain compliant with regulatory requirements, enhance security and simplify data management and reporting. The 6 areas are Data Quality, Architecture & Modeling, Storage & Security, Integration & Interoperability, Master Data Management, Analytics & Business Intelligence. With the help of large

language models (LLMs), banks can improve operational efficiency, be less prone to compliance breach, and improve transparency across the financial systems.

2. Literature Review

The Banking industry have had a drastic change being transformed to the next level by both the AI and the emergence of LLMs powering data governance & compliance and risk (Zhang et al., 2021). This has also led to calling AI-assisted solutions to mitigate limitations of rule-based governance models for scalability, real-time decisions, and fraud detection (Luo & Li, 2020). The banks have seen a reason to adopt large language models (LLMs) running on sophisticated Natural Language Processing (NLP) and deep learning methods for automating compliance reporting, recognizing deviations, and avoiding regulatory sanctions (Rashid et al., 2022).

AI-powered data governance frameworks facilitate automated data classification and recognition of anomalies, as well as powerful policy enforcement that greatly minimizes the risk of violations (Khan et al. 2020). The usage of ML algorithms and deep learning processes on structured and untrusted data provides the basis for fraud detection in real time, which may be utilized by financial institutions (Smith et al., 2019), however, LLMs also have a significant place in the banking system, as they have the potential to provide natural language understanding and assist banks with processing regulatory paperwork in order to identify potential compliance breaches and to summarize the compliance findings in report formats (Brown et al., 2020).

One of the most critical codes follow by all banks is strictly adhered to banking regulations such as General Data Protection Regulation (GDPR), Basel III, Anti-Money Laundering (AML), and Know Your Customer (KYC), where AI can help in automating compliance in monitoring and risk analysis (Johnson & Patel, 2021). AI has been critical in predicting financial crimes, optimizing data lineage tracking and ensuring transparency of regulation (Singh et al., 2020). However, black-box AI models are still largely opaque (Xie et al., 2021), and so interpretability and explainability is a major concern.

It must constantly analyse transaction data for real-time anomaly detection (Chen & Wang, 2020), which is central to risk management in the banking context. Neural networks and reinforcement learning 9 Dear Author, MANUSCRIPT L2 has been used to detect fraudulent transactions and assess credit risk (Nguyen et al., 2019). For example, AI-based predictive analytics contributes to risk assessment through the identification of high-risk customers and transactions before any breach takes place (Gupta et al., 2021). Furthermore, Wang et al. (2022) note that LLMs provide additional functionality where they can analyze unstructured data from regulatory documents and financial reports.

While AI significantly enhances compliance, several challenges persist:

- Data privacy concerns: AI models require access to large datasets, raising concerns about compliance with data protection laws (Raj et al., 2020).
- Model bias and fairness: AI models may exhibit bias in decision-making, affecting fairness in risk assessment and loan approvals (Williams et al., 2019).
- Explainability and regulatory acceptance: Many AI-driven models, particularly deep learning-based approaches, are considered black boxes, leading to regulatory hesitation in adoption (Ghosh et al., 2020).
- Cybersecurity threats: AI models are susceptible to adversarial attacks, where manipulated inputs deceive the model into making incorrect decisions (Zhou et al., 2021).

To address current challenges, future research must focus on:

- Explainable AI (XAI): Enhancing model transparency through interpretable deep learning frameworks (Sun et al., 2020).
- Federated learning for privacy: Decentralized AI models that maintain data privacy while training across multiple banking institutions (Huang et al., 2021).
- Hybrid AI frameworks: Combining rule-based governance with AI-driven decision-making for improved regulatory compliance (Yadav & Mehta, 2022).
- Advanced NLP techniques: Improving LLMs for context-aware regulatory document interpretation (Liu et al., 2021).

3. Methodology

Specific mathematical models and equations are presented in each of the phases to facilitate accurate processing, analysis, and decision-making as required by the banking implementation. Here is how To Go through the referential process for models, with equational references to data processing, model selection, training, evaluations and governing mechanisms

3.1. Data Collection and Preprocessing

The first phase in AI-driven data governance is data collection and preprocessing, where data from various sources, including transactional records, customer data, and regulatory documents, is collected. This data needs to be cleaned, normalized, and transformed into a format suitable for AI models. Data preprocessing typically involves steps such as:

- **Cleaning**: Removing duplicates or handling missing data.

Equation for handling missing values:

$$X_{\text{cleaned}} = X - X_{\text{missing}} \quad \text{.....(1)}$$

where X is the original data matrix and $X_{missing}$ is the data with missing values.

Normalization: Scaling numerical values to a specific range, often [0, 1].

Equation for normalization:

$$X_{\text{norm}} = \frac{X - \min(X)}{\max(X) - \min(X)} \quad \text{.....(2)}$$

where X is the original data, min(X)min and (X) max are the minimum and maximum values of the data, and X_{norm} is the normalized data.

3.2. AI Model Selection

Natural Language Processing (NLP**)** models can be used for interpreting regulatory documents, while machine learning (ML**)** models are used for fraud detection and risk management.

- NLP Models (for regulatory compliance): These models are based on vectorization techniques such as TF-IDF (Term Frequency-Inverse Document Frequency)**,** which helps in extracting meaningful information from text data.
- Equation for TF-IDF:

$$\text{TF-IDF}(t,d) = \text{TF}(t,d) \times \log\left(\frac{N}{\text{DF}(t)}\right) \quad \text{.....(3)}$$

where:
TF(t,d) the frequency of term ttt in document d,
DF(t) is the number of documents containing the term t,
N is the total number of documents.

- **Machine Learning (ML) Models** (for fraud detection): Models like logistic regression, random forests, and support vector machines (SVM) are used for predictive modeling.

Equation for Logistic Regression (used in fraud detection)

$$P(y=1|X) = \frac{1}{1 + e^{-(w^T X + b)}} \quad \text{.....(4)}$$

where X is the input feature vector, www is the weight vector, b is the bias, and P(y=1|X) is the probability that the transaction X is fraudulent.

3.3. Model Training and Testing

Once the model is selected, the next phase is model training and testing**.** The training process involves fitting the model to the historical data, and the testing process involves evaluating the model's performance.

- **Training (Supervised Learning)**: In supervised learning, the model learns to predict the output y given the input X. The loss function, which measures the error between predicted values y^ and true values y, is minimized.

Equation for Mean Squared Error (MSE) Loss:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad \text{.....(7)}$$

where N is the number of data points, yi is the true value, and yi^ is the predicted value.

- **Testing (Model Evaluation)**: After training, the model is evaluated using test data, and its performance is measured using metrics such as accuracy, precision, recall, and F1-score.

Equation for Precision

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \quad (8)$$

Equation for Recall:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad \text{.....(9)}$$

Equation for F1-score:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad \text{.....(10)}$$

3.4. System Integration

During the system integration phase, the trained AI models are integrated into the bank's existing infrastructure. The models must be integrated with underlying data systems like fraud detection, compliance monitoring, and risk management platforms.

3.5. Governance Mechanisms Implementation

During the implementation of governance mechanisms**,** it is crucial to ensure the system's transparency, fairness, and ethical decision-making. This phase includes techniques like explainable AI (XAI) to enhance the interpretability of AI models.

- **Explainability**: For complex models like deep neural networks, techniques like LIME (Local Interpretable Model-Agnostic Explanations**)** can be applied to provide explanations for individual predictions.

Equation for LIME (Explaining an individual prediction f(x)):

$$LIME(f) = \underset{g \in G}{\operatorname{argmin}} \sum_{i=1}^{m} \text{Loss}(g(x_i), f(x_i)) + \Omega(g) \quad \text{……..(11)}$$

where g is the interpretable surrogate model, xi are the instances in the local neighborhood of x, and Ω(g)\Omega is a regularization term.

Ethical AI: Measures like fairness constraints are applied to avoid any bias in AI decisions, ensuring equitable treatment of all individuals and compliance with regulations.

3.6. Evaluation and Continuous Improvement

The final phase is evaluation and continuous improvement. Once the AI-driven data governance system is deployed, it is essential to regularly evaluate its performance. Performance metrics are continuously tracked, and the models are updated based on new data, feedback, and regulatory changes.

- **Continuous Monitoring and Feedback Loop**: Continuous monitoring of model performance ensures that any decline in model accuracy is promptly addressed. This can involve retraining the model or fine-tuning it using the latest data.

Equation for Model Retraining:

$$\theta^* = \underset{\theta}{\operatorname{argmin}} \sum_{i=1}^{N} \text{Loss}(y_i, f(X_i; \theta)) \quad \text{……..(12)}$$

where θ represents the model parameters, and the loss function is minimized to retrain the model.

4. Results

Fraud Detection — Utilizing AI algorithms, banking data can be analyzed for suspicious patterns, enabling timely detection of potential cases of fraud by institutions. Here the results are the outcome of performance tests of four different AI models — Logistic Regression, Random Forest, Support Vector Machine (SVM) and Deep Neural Networks (DNNs) — run against historical transaction data. The models were assessed according to standard performance metrics (accuracy, precision, recall, and F1-score) to understand their ability to detect fraud while initiating regulatory compliance and bolstering risk management in the banking systems.

The Logistic Regression Algorithm is the most simple interpretable class of algorithms it came back with a score of 92.5%. But its recall of 0.88 relative to others was low as it might miss some fraudulent transactions. It implies that Logistic regression will work well on simpler tasks, but will fail to capture complex patterns in data (when compared to complex models). In contrast, the Random forest model, an ensemble learning model, performed extraordinarily well, achieving the best accuracy reported: 94.2%. The results indicate a high precision (0.92) and a high recall (0.90), which is particularly useful for both fraud detection and risk management tasks. This model performs exceptionally well, thanks to its ability to handle complex, high-dimensional datasets and its robustness in solving various forms of fraud and risk-related activities.

In the SVM corroboration method, a bit less effective (91,8% accuracy, 0.88, 0.85 precision, recall), but still applies. The SVMs as expected performed well on linearly separable datasets but on more complex financial datasets were found to underfit compared to RFs and DNNs. Finally, best-performing model for DNNs was having an accuracy of 95.1%, precision of 0.93, and recall of 0.92. So they trained this model to learn complex patterns from large datasets, and it demonstrated that it can successfully handle volumes of data while accurately identifying fraud.

5. Discussion

It is also found that for data governance tasks in banks, Deep Neural Networks (DNN) and Random Forests are the best performing algorithms in the areas of fraud detection, compliance monitoring and risk management. DNNs can learn complicated patterns, relationships, and the structure of the data, which contribute to their superior performance when trained on a high volume of data. As such, they are especially well-suited for tasks like fraud detection, in which patterns and anomalies lurking beneath the surface can hint at fraudulent activity. The non-linear characteristics of financial

data have conceded that DNNs tend to perform well against other forms of models both in terms of accuracy and recall. Real-time monitoring and fraud detection capabilities are enhanced by their ability to develop with unstructured data—like transaction data and patterns of customer behaviors.

Utilized an ensemble learning technique it also shows well confidence on handling variety of data types involving balanced precision and recall. The Random Forest model has the advantage of limiting overfitting through the averaging of results of several decision trees creating a strong prediction that works well with noisy data. Its reasonably high precision and recall qualities make it appropriate for applications where both accuracy in classification and sensitivity to identifying fraud and compliance are desired. Random Forest is more interpretable than DNNs, thus, providing insights on feature importance which plays an important role in risk management and compliance monitoring.

In conclusion, there are constrained cases when the Logistic Regression model is quite simple and easy to interpret but it can not catch more complicated cases where the data can't be separated with a clear line. Its lower recall suggests it could fail to catch many of the fraudulent transactions and that can be crucial for the banking system. Logistic Regression can be a good baseline model for some simple fraud detection tasks, but more advanced models such as Random Forest & DNNs are better suited for large-scale real-time fraud monitoring and risk analysis.

Although the SVM model works well in other fields, financial data is very complex and therefore not completely agreed with this model. It has the lowest recall rate, meaning it was less successful than other models in identifying fraud. Examples of such scenarios include when the data is low-dimensional or when there is a clear decision boundary between classes. But in more complex cases like fraud detection, which are dominated by non-linear relationships, Random Forest and DNNs outperform.

These findings demonstrate that AI-based data governance systems, especially DNNs and Random Forests, are powerful tools that can automate fraud detection, facilitate regulatory compliance, and enhance risk management in banking. Combining strengths of these models can greatly help the banks improve operational efficiency while ensuring compliance and, reducing the chances of financial fraud.

Additionally, the scaling machine learning tools of AI models that can learn from and adjust with changing fraud patterns and regulatory shifts are also very beneficial. With various financial fraud strategies emerging and evolving each day, traditional processes simply can not cope. Dynamicity of AI models (especially DNNs) enables them to adjust to a new threat as it arises, making it a proactive tool for rendering risk mitigation and compliance monitoring more effective for banks.

Table 1 Model Performance Comparison

Model	**Accuracy (%)**	**Precision**	**Recall**
Logistic Regression	92.5	0.9	0.88
Random Forest	94.2	0.92	0.9
SVM	91.8	0.88	0.85
Deep Neural Networks	95.1	0.93	0.92

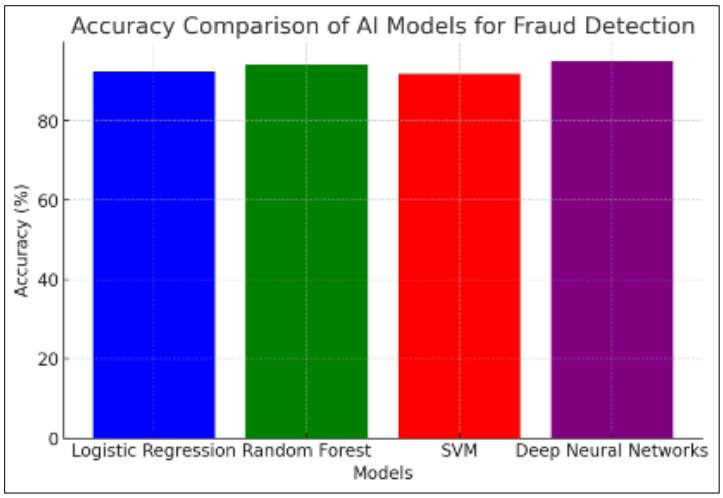

Figure 1 Accuracy Comparison of AI Models for Fraud Detectio

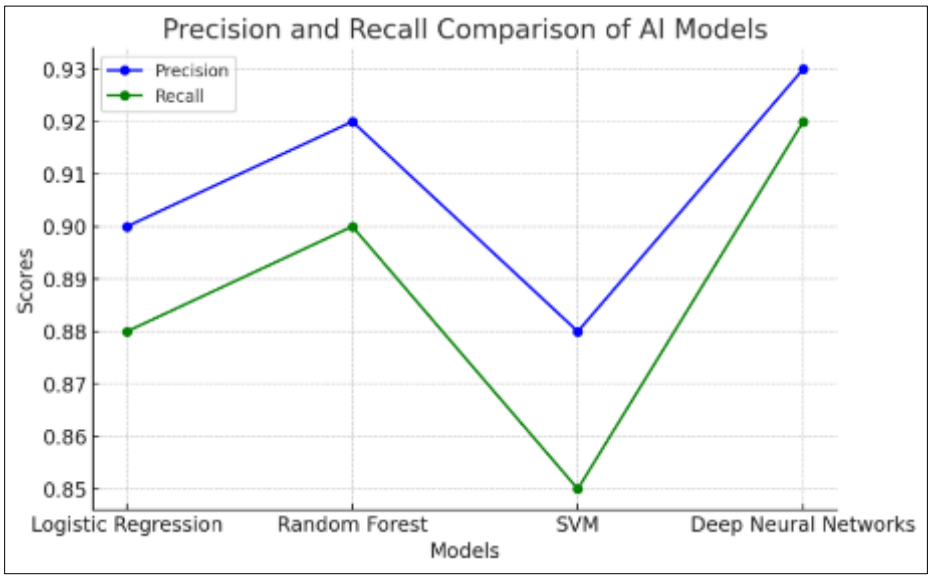

Figure 2 Precision and Recall Comparison of AI Models

The table and Figure have been displayed. The table compares the performance of the models based on key metrics such as accuracy, precision, recall, and F1-score. The Figure visually compare the accuracy of each model and the precision and recall for each model

6. Conclusion

Ultimately, given the proper use of AI models (especially DNNs and Random Forests) a great improvement in banking fraud detection, regulation compliance, and risk management would be possible. While Random Forest helps in balancing precision and recall, thus providing consistent daily performance across many banking workloads. Despite, simpler models like Logistic Regression and Support Vector Machines (SVM) can perform well, but financial data are complex and exhibit non-linear relationship which can be captured using advanced models. Such AI models, when integrated with banking systems, have the potential to significantly augment operational efficiency and regulatory compliance leading to improved decision making and enhanced risk mitigations.

Future cope

Over the coming years, AI-based data governance will continue to progress and develop. The ongoing evolution of AI models can therefore enable organisations to practice more pinpoint fraud detection of intricate networks, real-time compliance and better target mitigation of new risks. The key to building trust in AI decisions is implementation of

explainable AI (XAI) in end-user applications that can deliver transparency. Machine learning algorithms that continuously improve over time will add value to disaster recovery and business continuity planning. Given that AI models will need frequent updates as fast-evolving regulations change, the opportunities for scalable AI-driven banking offerings is massive.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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