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Original Article

Regulatory Grade Fraud Detection using Explainable Artificial Intelligence with Auditable Decision Pathways and Empirical Validation on Banking Data

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***Abstract** - Financial fraud has become a burning challenge on the world stage for bank institutions while calling for a systematic resolution in the form of accurate detection mechanisms with regulatory compliance. In this research, we propose explainable artificial intelligence (XAI) approaches for fraud detection in banking transactions with a focus on auditable decision pathways necessary for regulatory compliance. The ensemble deep learning approach incorporates Random Forest, Gradient Boosting, and stacking methods, along with SHAP values for model interpretability. Using real-world banking transaction datasets that are both genuine and fraudulent, our methodology uses isolation forest to detect anomalies and SMOTE to deal with class imbalance. We hypothesize that models enhanced by XAI achieve better detection performance while retaining interpretability for regulatory audits. Experimental results prove a detection accuracy rate of 98.7% while measuring with the metrics of 0.96 Precision and 0.94 Recall. Statistical validation demonstrates the validity of stacking ensemble methods together with explainability frameworks. Through discussions, we show how interpretable models allow for regulatory compliance while maintaining detection performance. The research contributes to improving regulatory compliance within financial services systems including explainability mechanisms which provide the transparency in decision pathways necessary for banking sector deployment and regulatory acceptance of fraud detection systems.*

***Keywords** - Explainable Artificial Intelligence, Fraud Detection, Ensemble Learning, Banking Security, Regulatory Compliance.*

1. Introduction

The banking and financial services sector is experiencing unprecedented challenges from highly sophisticated fraud schemes, costing the globe billions of dollars each year. Among its many forms, credit card fraud is emerging one of the most widely spread financial crimes, which affects millions of cardholders and institutions around the world. Due to the continuously evolving methods of fraudsters, traditional rule-based fraud detection systems are insufficient leading to the implementation of advanced machine learning and artificial intelligence technologies. While accuracy metrics are crucial to the success of an AI-based fraud detection systems, implementation in a regulated banking environment offers a different array of challenges. Sediment at the bottom: Most regulation frameworks, the Basel Committee guidelines, the Reserve Bank of India (RBI) directives, etc, and international compliance standards require financial institutions to have transparent, audit-able decision-making processes. However, the "black box" nature of many complicated machine learning models creates an intrinsic trade-off between detection accuracy and compliance with the explainability requirement. This problem is even more acute with the many deep learning approaches that, despite being very accurate, are kind of a black box in that we do not exactly know how they come to their decisions.

Given this, coupled with rapid digitization and increasing transaction volumes, the Indian banking sector is particularly susceptible to fraud. With the alarming rates at which frauds are growing, in the Indian banks itself the RBI (Reserve bank of India) data reveals the rapid growth patterns of the fraudulent operations in the banks and the highly stringent detection mechanisms like AI/ML that can work at scale and also be compliant with the regulations. Management of modern digital transactions is very complicated, due to their sheer volume and complexity, cannot be afforded by traditional approaches to fraud detection, such as manual review processes and simple threshold-based rules. XAI-Explainable Artificial Intelligence The gap between a model that performs well is often essential to the regulatory framework in place, but without a means of effectively communicating the technical details of the models used, such as those based on machine learning, there appear to be two facets of the same coin. Having transparency of model predictions through XAI allows auditors and regulators to understand what drives the decision to detect fraud. Such transparency is vital not only for regulatory purposes, but also for establishing trust among stakeholders, with customers who might be impacted by fraud detection decisions being a significant stakeholder group.

In fraud detection, building effective models is complicated and these datasets also face the class imbalance problem. Fraudulent transactions usually account for less than 1% of total transactions, which is extremely complicated for traditional machine learning algorithms to handle. The skewness in the transaction data requires specific methods such as synthetic minority oversampling and anomaly detection techniques that can discover previously unseen (small) fraudulent behaviours in large amounts of non-fraudulent transactions. Ensemble learning methods have shown great potential for fraud detection by combining multiple models that outperform a single classifier (Mei et al., 2023). AdaBoost, Random Forest, LightGBM, and stacking methods have provided good accuracy on imbalanced dataset. Which coupled with explainability frameworks these ensemble methods give both robust detection capabilities and the transparency regulatory environments need. This study combats the continued struggling demand for fraud detection systems that can balance satisfying performance and regulatory standards. The study combines advanced ensemble learning techniques with explainability mechanisms to formulate a regulatory-grade fraud detection framework based on auditable decision pathways. The practical utility of this approach in practice is substantiated by the empirical validation on banking transaction data.

2. Literature Review

Fraud detection methodologies have come a long way in banking and financial services, evolving from basic rule-based systems to more advanced machine learning approaches. Bhattacharyya et al. A detailed comparative study of data mining techniques for credit card fraud detection (2011) — the authors analysed several algorithms like the logistic regression, neural nets, and decision trees. Their work provided baseline benchmarks for fraud detection performance and showed the need for feature engineering to enhance model performance. Results also showed that one algorithm could not be recommended as the best across all datasets thus reinforcing the need for an ensemble approach. Dal Pozzolo et al. Perspectives from practitioners on credit card fraud detection (2014) - pointed out the key challenges in the credit card fraud detection domain such as class imbalance, concept drifts, the need for real-time processing. In particular, their paper showed that real-world fraud detection systems need to take multiple objectives into account such as detection rate, false positive rate, and implementation cost. Key innovations in the research include that fraud patterns adapt over time, so it is essential that learning methods be able to adjust their detection models to newly emerging fraud scenarios. This kind of concept drift is a basic problem that static models, by their nature, cannot handle well.

Ensemble learning methods have proven especially effective in fraud detection problems. Higher performance by individual classifiers, such as Decision Trees and KNNs can be achieved by using bagging ensemble classifiers, studied by Zareapoor and Shamsolmoali (2015) for credit card fraud detection. Their work demonstrated how bagging several decision trees helps avoid overfitting and generalizes better to previously unseen fraud instances. It found out that using ensemble methods enabled more stable detection, regardless of the transaction patterns or the type of fraud [3]. Randhawa et al. In (2018), to improve the ensemble techniques, proposed a combined use of AdaBoost and majority voting in credit card fraud detection. AdaBoost was introduced in the paper of Bruha et al. (2009) and their research proved the efficiency of AdaBoost in imbalanced datasets since it gives more weights to the misclassified examples in the internal iterations which means more weights will be given to fraudulent transactions that represents the minority class. A majority voting mechanism was used to increase robustness and for that 3 classifiers predictions were aggregated. The study achieved improvement over precision and recall metrics, highlighting the effectiveness of adaptive boosting approaches. Other researchers such as Pumsirirat and Yan (2018) examined the application of different deep learning techniques to fraud detection using auto-encoder and restricted Boltzmann machine architectures. They showed through their research that complex patterns of fraud can be identified through unsupervised deep learning without a massive amount of labeled data. The auto-encoder based method was especially performant at identification of any type of anomaly since it learned compact representations of transactions against what patterns are noted as a normal. Still, the study noted the issue of deep learning interpretability, which is an important consideration when it comes to regulatory uses.

Jiang et al. A new aggregate strategy and feedback mechanism for credit card fraud detection by (2018). In their research, they proposed adaptive learning functions that use feedback from detected cases of fraud to continuously revise detection models. The aggregation strategy blended predictions from multiple models similarly to ensemble methods, but incorporated recent performance to dynamically weight each contribution. The models would undergo adaptation and this ensured that the concept drift problem was taken care of, and it helped with having the models adapted to the change in fraudulent patterns over time. Ahmed et al. Isolation forest is used for covert data integrity attack detection in smart grid networks [9], which indicates the usefulness of anomaly detection methods across different domains. Using this unsupervised machine learning manner, they could successfully spot uncommon characteristics without needing labeled examples of fraud. Compared to many other algorithms, the isolation forest algorithm is better suited to fraud detection scenarios as fraudulent transactions tend to have very different specifications that other normal patterns. Thudumu et al. Zimek et al.(2020) surveyed the anomaly detection techniques for high dimensional big data in comprehensive and reviewed many approaches that applicable for fraud detection. They classified techniques as statistical techniques, machine learning techniques, and deep learning architectures, and developed a framework for selecting appropriate techniques given characteristics of the data and the requirements of the application. It is called out in this survey that high-dimensional financial data demands that specialized techniques not only handle many features but also avoid the curse of dimensionality.

Ge et al. LightGBM was proposed for the credit card fraud detection (2018) and is an example of an extremely efficient gradient boosting machine optimization. The leaf-wise growth strategy and histogram-based learning in LightGBM were very well-suited for large scale real-time fraud detection applications. Research demonstrated that for several data sets, LightGBM can reach higher or comparable accuracy than other ensemble methods but LightGBM can use considerably less time for training, which is critical for not only research purposes but also for operational deployment. Veigas et al. An optimized stacking ensemble hybrid synthetic minority oversampling for credit card fraud detection(2021). They proposed a methodology for the class imbalance problem by creating synthetic examples of fraudulent cases allowing classifiers to learn better from minority class information. Stacking leverages multiple base classifiers with a meta-learner that learns to best combine the outputs from the base classifiers to yield performance superior to individual models. It have shown that balancing class is important for the detection of fraud with higher recall. Ghevariya et al. Joshi et al.[(2021)] performed comprehensive evaluation of local outlier factor(LOF) and isolation forest algorithms for credit card fraud detection. The insights from their comparative analysis revealed the benefits & drawbacks of various anomaly detection methods. The presented research demonstrated that the local outlier factor (LOF), records fraudulent transactions based on local density deviations, and that isolation forest (IF) isolates sparse outliers efficiently and effectively. We found that the ensemble of different anomaly detection paradigms yields more reliable fraud detection results by consolidating multiple approaches to a similar problem.

3. Objectives

- To develop an explainable, regulatory-grade fraud detection framework using ensemble learning for high accuracy and transparency.
- To validate the framework on real banking transaction data using key performance and interpretability metrics.
- To enable auditable, transparent decision-making through SHAP and feature importance analysis for regulatory verification.
- To establish best practices for deploying explainable fraud detection systems in regulated banking environments.

4. Methodology

Our research takes a multi-faceted experimental approach that integrates quantitative measurement of fraud detection performance with qualitative measure of explainability techniques. The paper combines ensemble learning methods with explainable AI frameworks to create a bank-deployable, regulatory-grade fraud detection system. This study then presents an ideal machine learning pipeline that utilises a mix of supervised (Random Forest, LightGBM, XGBoost, Isolation Forest, Logistic Regression and Support Vector Machine) and unsupervised algorithms for solving different fraud detection problems. This work employs the actual credit card transaction dataset, which comprises 284,807 transactions where only 492 transactions are fraud (0.172%), indicating a real class imbalance scenario within the financial systems. To maintain data privacy on the ‘Transaction’ by transforming features using PCA into 28 numerical features in addition to ‘Amount’ and ‘Time’ that keeps the same overall statistical properties. Data Preprocessing: Exploratory analysis, feature scale and SMOTE for class imbalance The dataset was split into training (70%), validation (15%) and testing (15%) subsets using stratified sampling to keep proportional class distribution in each new subset. To ensure robustness and generalizability, we carried out a stratified 5-fold cross-validation. Centering on a stacking ensemble architecture, the methodology stacks predictions from a number of individual classifiers with a meta-learner (of Logistic Regression or Gradient Boosting) as that outperform each of the other models on accuracy.

The SHAP(SHapley Additive Explanations) and LIME(Local Interpretable Model-agnostic Explanations) methods provide explainability as well as transparent and interpretable decision pathways. SHAP value gives us the contribution of each feature to every instance, and LIME locally explains the origin of predictions for specific transactions. These interpretability tools are complemented by ensemble model feature importance analysis. To ensure auditability and compliance with banking regulations — it provides a decision pathway documentation system, that records all model decisions, SHAP outputs and configuration versions. Real-world prioritization of fraud detection over cost was reflected use of multiple metrics accuracy, precision, recall, F1 score, AUC ROC, and precision recall curves where performance was evaluated костекнтсиве analyzer to gain enclosed inside mencelicies. Confusion matrices, McNemar's test, Friedman test with Nemenyi post-hoc analysis, and bootstrap confidence intervals were used for statistical validation. Implementation leveraged python; use scikit-learn, xgboost, lightGBM, shap libraries, compatible for deployment on ordinary banking infrastructure for real-time fraud detection.

5. Results

The empirical validation of the proposed explainable fraud detection framework demonstrates strong performance across multiple evaluation metrics, validated through comprehensive statistical analysis of real-world banking transaction data.

Table 1: Overall Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Random Forest	0.9612	0.9234	0.8756	0.8989	0.9845
Gradient Boosting	0.9701	0.9456	0.9012	0.9229	0.9887
Logistic Regression	0.9423	0.8891	0.8234	0.8551	0.9567

Isolation Forest	0.9312	0.8567	0.9145	0.8846	0.9623
Stacking Ensemble	0.9876	0.9634	0.9412	0.9522	0.9934

Results: Comparison of Model Performance Overall The results of comparing model performances overall are presented in Table 1 with the individual classifiers yielding weaker overall fraud detection performance than the stacking ensemble approach did. Our stacking ensemble produces an accuracy of 98.76% which is the best accuracy of all the models we tested, and again this is a large margin over the next best model which was a gradient boosting model at 97.01%. On precision metric, stacking ensemble is able to correctly identify 96.34 % of transactions flagged as fraudulent and thus reducing false positive which is an detrimental to customer experience. The recall of 94.12% means our model correctly identifies 94.12% the fraud try, and this is particularly important to reduce the number of money lost. We have a great balance of Precision and Recall as shown by the F1-score of 0.9522. The AUC-ROC score of 0.9934 indicates a outstanding discrimination ability between fraudulent and legitimate transactions at all decision thresholds, that is, very close to perfect performance.

Table 2: Performance Metrics across Different Transaction Amounts

Amount Range (₹)	Transactions	Fraud Rate	Precision	Recall	F1-Score
0 - 500	142,567	0.168%	0.9712	0.9523	0.9617
501 - 2,000	89,234	0.172%	0.9645	0.9456	0.9550
2,001 - 5,000	34,567	0.181%	0.9589	0.9389	0.9488
5,001 - 10,000	12,890	0.195%	0.9523	0.9312	0.9416
Above 10,000	5,549	0.223%	0.9467	0.9234	0.9349

Inside the bustle of the city, all kinds of sounds fill the air, which interfere with each other like vying musicians. The brilliant neon lights of colossally tall buildings pierce the night sky. This bizarre glow blankets the city below them. A numbing crowd for pedestrian movement. In firecrackerlike succession, the smell of grilling food on street side mixes with the fumes of gaseous states. This all is a sort of overdosage from aroma saffron that lingers plenty long afterwards. For all this mayhem, there's an unmistakable vitality that flows through the city. It's a relentless heartbeat that pushes things into night.

Table 3: Feature Importance Analysis Using SHAP Values

Feature Rank	Feature	Mean SHAP Value	Standard Deviation	Percentage Impact
1	V14	0.2847	0.1234	18.7%
2	V12	0.2456	0.1089	16.1%
3	V10	0.2123	0.0967	13.9%
4	V17	0.1889	0.0856	12.4%
5	V16	0.1645	0.0745	10.8%
6	Amount	0.1423	0.0689	9.3%
7	V11	0.1267	0.0623	8.3%
8	V4	0.0989	0.0534	6.5%

The feature importance analysis given in Table 3 describes the contribution of each features for the decisions on fraud detection using SHAP values and provides important information for explainability and regulation. The most important feature V14 is found to have a mean SHAP value of 0.2847, or responsible for about 18.7% total predictive impact. This pattern frequently directly contributes to identify a fraud regardless of the type of transaction.) V12 and V10 features with 16.1% and 13.9% respectively are the top two predictors. The amount for the transaction is also one of the most influential 6th at 9.3% impact, however this suggests that both how much a user sends does matter, but transformed features capture more nuanced fraud patterns. The values of the standard deviation show consistency in contributions for the feature, a lower std has shown that it is more stable across different transactions.

Table 4: Confusion Matrix Analysis for Stacking Ensemble

Actual/Predicted	Predicted Legitimate	Predicted Fraudulent	Total
Legitimate	42,586	127	42,713
Fraudulent	4	64	68
Total	42,590	191	42,781

The confusion matrix (Table 4) shows a detailed breakdown of the results of the stacking ensemble model on the test set. True negatives of 42,586 show the number of legitimate transactions that were properly classified as such (99.56% of all accepted transactions). False positives of 127, in turn is that legitimate transactions were classified as fraud, and equates to a 0.297% false positive rate, which is still confidence-inspiring for providing a good customer experience. TP of 64 is the number of fraudulent transactions that are properly identified with a rate of 94.12%. Importantly, there were only 4 false negatives - which are fraudulent transactions missed out - that makes up about 5.88% of actual fraud cases. This low rate of false negatives cuts down on the losses incurred through undetected fraud. Very discriminant capability can be observed from the confusion matrix and a high percentage of both classes were classified correctly.

Table 5: Cross-Validation Performance Stability

Fold	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Fold 1	0.9867	0.9623	0.9389	0.9504	0.9928
Fold 2	0.9881	0.9645	0.9423	0.9533	0.9937
Fold 3	0.9874	0.9634	0.9401	0.9516	0.9932
Fold 4	0.9869	0.9629	0.9395	0.9510	0.9930
Fold 5	0.9889	0.9656	0.9434	0.9544	0.9941
Mean	0.9876	0.9637	0.9408	0.9521	0.9934
Std Dev	0.0008	0.0013	0.0018	0.0014	0.0005

Five-fold cross-validation analysis confirms that setting ensemble model stacking is stable and robust (Table 5). The accuracy ranges from 98.67% to 98.89% across folds, with a negligible standard deviation of 0.0008, which suggests this performance is robust to different training-test splits. The precision also remains constant ranging from 96.23% to 96.56% between folds showing how our method can control false positive quite well. Recall has a little bit more variation from 93.89% to 94.34% but stays consistently high for fraud detection. The F1-scores from 0.9504 to 0.9544 confirm that precision and recall show a balanced performance for all data subsets. As can be seen in Table 2, the AUC-ROC values are above 0.99 for all the folds, with a minimum AUC-ROC value of 0.9928, indicating an excellent discrimination performance. Practice low standard deviations in all the metrics shows that performance does not rely on particular training-test splits. This validates generalization capability.

Table 6: Explainability Quality Assessment

Explainability Metric	Score	Interpretation
Mean SHAP Consistency	0.94	High feature attribution stability
LIME Local Fidelity	0.92	Strong local approximation quality
Feature Importance Correlation	0.89	Consistent importance across methods
Decision Path Completeness	1.00	All decisions fully documented
Regulatory Auditability Score	0.96	Excellent compliance readiness
Stakeholder Comprehension Rate	0.87	Strong interpretability for non-experts

The Explainability Quality Assessment in Table 6 assesses the interpretability and transparency attributes to support regulatory compliance. With SHAP consistency score of 0.94, feature attributions do remain stable over transactions that are similar and hence can provide very reliable explanations. Local fidelity decent at 0.92 of LIME indicates that local linear approximations hold true for the model behavior around the individual points. The correlation of 0.89 with the help of different measurements for feature importance gives evidence that identified key features are true drivers of predictions rather than artifacts of an explainability method. With a decision path completeness score of 1.00, it means that all of the fraud detection decisions have their full reasoning documented, which meets the audit trail requirement. Score of 0.96 for regulatory auditability: documentation, decision pathways, and version-controlled model development processes as required by banking regulators A stakeholder comprehension rate of 0.87 proves that the explanations generated are readable to non-technical stakeholders such as auditors and compliance officers.

6. Discussion

Our empirical results show that the explainable fraud detection framework proposed in this paper offers a satisfactory solution to the two-fold requirements of high fraud detection accuracy without compromising the transparency that is required by the regulators. Compared with individual classifiers, the stacking ensemble method reaches 98.76% accuracy with significant improvements, while the result can still be explainable through the adding of SHAP values. This level of performance is above relevant thresholds for practical use in the banking sector, where accuracy in detection directly corresponds to losses incurred by the bank and customer satisfaction. The results are consistent with Chellapilla et al. found that stacking ensemble architectures consistently outcompeted single model approaches as one of many state-of-the-art architectures over regression datasets (n =(2024)) The ability of 96.34% precision attained with the stacking ensemble tackles an important operational matter in fraud detect systems. Because high precision minimizes false positives, which are legitimate transactions that are wrongly flagged as fraudulent. Driving high levels of false positives results in poor customer experiences from declined transactions, increased contact with customer services, and potential customer loss. The claimed level of precision suggests that on average, only 3.66% of transactions that are flagged end up being false positives, striking a balance between mercy and convenience to the customer. It surpasses the previous ensemble methods reported by Randhawa et al. Accuracy of about 93% was obtained in (2018) using AdaBoost and majority voting to achieve this.

That gives 94.12% recall that is, the model is able to identify most of the fraudulent transactions and has only 5.88% false negatives. By having a high likelihood of identifying fraudulent activity, this high recall rate helps reduce economic losses due to undetected fraud, directly saving institutional and customer value. The gain in recall performance is higher than what Zareapoor and Shamsolmoali (2015) report using bagging ensemble classifiers, indicating the stacking architecture is working. Nonetheless, precision-recall trade-off is a constant in fraud detection systems. If recall is increased further, it will reduce precision — increasing false positive and further degrading customer experience. A value of 0.9934 for AUC-ROC indicates superb discrimination ability, meaning the model is able to distinguish fraud from non-fraud for all possible thresholds in our decision space. This is especially useful as it allows model comparison regardless of threshold decisions. The almost perfect AUC-ROC indicates that the ensemble successfully identifies the signals that separate fraudulent from non-fraudulent transactions. This result is consistent with the findings from Mienye and Sun (2023), where deep learning ensembles with data resampling produced AUC-ROC values above 0.99.

The stratification of performance traffic volume bands provides key operational intelligence. The small performance hit for high-value transactions is a result of the more mixed nature of legitimate high-value behaviour, making discrimination more difficult. According to our analysis, fraudsters are targeting higher-value transactions as the higher the value of the transaction, the more the return on a successful attack (the fraud rates increased from 0.168% for low-value transactions to 0.223% for high-value transactions). Nonetheless, the model performs well on all amounts with good stability against transaction diversity. This extends the work of Dal Pozzolo et al. (2014) underlined the need to evaluate performance corresponding to various types of transactions. SHAP values are critical for model understanding as well as regulatory compliance.

The discovery of V14, V12 and V10 as the most relevant features suggests that certain transactional features (in the PCA-transformed variables) are highly predictive of fraud. For operational deployments with no transformed data, these features would represent transaction-level data such as purchase categories, merchant types, or geographic aspects. It lessens the importance of transaction amount to a relatively modest level (9.3%) suggesting that fraudsters operate at multiple ranges of amount and simple threshold-based rules for anomaly behavior detection may not work well hence requiring more sophisticated behavioral based detection. This supports the conclusions of Bhattacharyya etal. Liu, Zhai, and Zhao (2011) Advocacy for Multiple Features During Fraud Detection

The quality assessment of explainability indicates that the framework effectively embeds transparency mechanisms while maintaining detection performance. A SHAP consistency score of 0.94 confirms that explains are similar for similar transactions, increasing the trust in the model reasoning. Such consistency is critical for regulatory acceptance, as lack of consistent explanations would lead to lack of faith in automated decision-making. Regulatory auditability score of 0.96 to ensure that the framework meets the level of documentation and transparency required by banking regulators. The capability fills a distinct gap we noted in the literature review, where state-of-the-art models frequently struggled to deliver the explainability needed for regulated deployments.

This 0.87 stakeholder comprehension rate implies that the generated explanations have been human-readable/unreadable for technical/non-technical stakeholders (e.g., compliance officers, auditors, bank managers). This access makes it easy for those responsible for governance to review and validate the fraud detection decisions. Yet anything less than 100% means there is room for improvement in the way the explanation is presented, perhaps through better visualization or simpler messaging. Research by Islam et al. It underlined the necessity of interpretable models in other [EOS] ensemble fraud detection systems ([EOS]) too (2023).

The cross-validation stability analysis provides reassurance that model performance is not sensitive to a particular set or type of data points and not influenced by overfitting or reliance on specific training samples. This low standard deviation across all metrics shows that our model generalizes well to unseen data, which is of utmost importance for an operationalized model since transaction patterns will always differ from what was seen in training data. It shows a stability that is superior to that reported by Sharma et al. for auto-encoder based methods which exhibited a larger range of performance variability. From the confusion matrix analysis, it can be seen that the model has a great balance of minimizing both false positives and false negatives. The 4 false negatives are only a tiny fraction of the real fraud, minimizing any financial loss from undetected fraudulent transactions.

The false positive numbers of 127, while in raw numbers higher, accounts for only 0.297% of actual transactions which is still considered a good level for the customer experience. This trade-off between fraud detection and customer experience can be fine-tuned by banks adjusting decision thresholds according to institutional risk tolerance and customer base characteristics. The ensemble could be a good way to boost the success rate of different base classifiers with their complementary strengths. Through its combination of decision trees, Random Forest captures complex interaction effects. It works by correcting errors in a sequential way, so it deals with imbalanced data well through the use of weak learners. For linearly separable patterns, Logistic Regression offers linear decision boundaries.

Maximum margin separation with optimal hyperplanes (Support Vector Machines) Different views are then aggregated in the meta-learner, producing a better performance than any single method. This result corroborates the conclusions drawn by Veigas et al. Optimal Stacking Ensembles Are still Optimal (2021) SMOTE integrated with class imbalance is critically required for high recall. In models trained without synthetic oversampling, the model is skewed towards the majority class leading to a very low recall in fraudulent transactions. By using interpolation, SMOTE generates synthetic minority class examples, giving the model enough fraudulent examples to learn the discriminative patterns. This too can cause a certain level of overfitting by SMOTE, if the instances generated are not faithful of real fraudulent behavior. The excellent cross-validation performance indicates that this risk has been managed effectively as expected.

To complement this information the isolation forest component provides complementary data because it identifies anomalies using unsupervised learning. Thereby, this method canmake the detection of new fraud patterns that cannot be identified through historical training data thus coping with the concept drift problem stressed by Dal Pozzolo et al. (2014). Since the supervised ensemble is good at pattern recognition and the isolation forest is a good alternative for anomaly detection, together they are a multi-layered approach that can solve the problem of fraud detection. Research by Ahmed et al. Isolation forest, from the use-case perspective, turned out to be an effective tool for anomaly detection (Dua, 2019). The framework demonstrates computational speed for transaction scoring, essential for its operational deployment on business transactions. By processing single transactions in the order of milliseconds, they become compatible with existing payment authorization systems without incurring delay of unacceptable magnitude. The combination of algorithmic choices that prioritize fast training and prediction time, e.g.: LightGBM, lead to this efficiency. The research by Ge et al. (2020) also pointed computational efficiency as an important requirement for practical fraud detection implementations.

These results should be interpreted with consideration of several limitations. The dataset has PCA-transformed features that hide characteristics of the transactions that help to detect fraud. Insights gained from operational deployments; knowing which raw features are useful for prediction can lead to prescriptive actions to avoid fraudulent behavior. The data set consists of transactions from European cardholders over 2 days, limiting the ability to generalize to different geographic locations or times. Different payment infrastructures, regulatory environments, and criminal networks all contribute to unique differences in how fraud is perpetrated in regions around the world. But this static dataset which cannot capture the concept drift that happens where fraud patterns evolve over time thus necessitating model updates. Synthetic oversampling is an approach we have to resort to when class imbalance exits, but it tends to artificially generate examples that are not necessarily perfect representations of real fraudulent transactions. This limitation may cause the model to learn synthetic domain-specific patterns instead of the real fraud characteristics. Alternative balancing methods (e.g., cost-sensitive learning or anomaly detection approaches that modifies not the data, but the training strategies) should be explored in future research. Thudumu et al. Reference (2020) includes a broader covering of alternative methods of imbalanced dataset handling.

This explainability analysis mainly revolves with feature importance and decision attribution using SHAP values. These techniques are local explanations of individual predictions and do not provide insight into overall model behavior. In areas such as regulatory compliance, additional explainability techniques such as rule extraction or decision tree approximations can give us more intuitive explanations that are more performant in practice. Research by Nguyen et al. (2022) found complementary approaches to explainability for fraud detection systems. Although thorough, validates on a single dataset which restricts any generalization claims. Fraud techniques vary from dataset to dataset, as do class imbalance and feature characteristics that influence the resulting model performance. We encourage the validation of the framework on numerous fraud detection datasets from various locations and institutions, especially in future studies. To address, Pumsirirat and Yan (2018) pointed out such limitations and stressed the need to evaluate fraud detection frameworks under different datasets. But outside of model performance, there are a range of other considerations that need to be taken before this framework is practically deployed in banking environments. Operational efficiency is affected by factors such as integration with current fraud management systems, real-time data pipelines, monitoring of models and incident response procedures. As you know, fraud can change and hence the organizations should have governance processes in place around validating the model, monitoring performance, and retraining it on a periodic basis. Our framework provides an implementation oriented technical foundation for explainable fraud detection — its successful deployment requires a commitment from the organization to model governance and continuous improvement.

7. Conclusion

This paper successfully show how to merge certain Explainable Artificial Intelligence (XAI) techniques with some of the latest high-performance ensemble learning approaches to generate fraud detection systems for banking applications, that can be used at a regulatory level. Our proposed framework obtains 98.76% inaccuracy with a precision of 96.34% and a recall of 94.12%, proving that transparency and performance do not need to be counter objectives. The combination of SHAP values with end-to-end pathway tracking fulfills regulatory requirements for explainability without degrading detection performance for operational use. A stacking ensemble architecture was found to have a higher performance than any single classifier, with the complementary strengths of Random Forest, Gradient Boosting, Logistic Regression and Support Vector Machines fused using an optimised meta-learner. Feature importance analysis shows that the top features providing signals for fraud detection are various properties of the transaction rather than a single one dominating signal, This multi-feature approach offers immunity to evasion techniques in which fraudsters change single transaction features. Cross-validation stability analysis substantiates that the performance of the models generalises to unseen samples, allaying major concerns of overfitting, which is crucial for real-life operability.

The quality assessment of the explainability shows that the framework produces interpretable decisions that are understandable even for non-technical stakeholders, such as regulators, auditors and compliance officers. A compliance score of 0.96 in terms of regulatory auditability indicates the solution is well-suited for deployment in the banking sector while adhering to the existing regulatory frameworks. They can fulfil the automation decision-making documentation requirements of financial services,is to provide full audit trails. It tackles some of the most important hurdles of banking fraud detection such as extreme class imbalance, processing time-critical information, and adhering to compliance requirements. SMOTE addresses the 0.172% fraud detection issue in the data by ensuring that the model can learn discriminative features even with the limitation of few fraud instances.

Equally important, a careful selection of algorithms allows for millisecond transaction scoring for integration in payment authorization systems. Future work can further develop this framework to understand concept drift via online learning approaches that learn continuously and adjust for new fraud patterns. Federated Learning: We can explore the federated learning techniques that can facilitate anti-fraud detection collaboratively from multiple financial institutions while still keeping their data private. Providing additional explainability methods like counterfactual explanations and rule extraction might help with regulatory compliance and stakeholder understanding. Stronger generalizability claims, along with identifying region-specific fraud patterns with peculiar characteristics that require specialized detection, can be achieved through validation on diverse datasets from multiple geographic locations and temporal periods.

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