Explainable Deep Learning for Real-Time Credit Card Fraud Detection in Tokenized Transactions

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Abstract

The growth of electronic payments merely made it more imperative to uncover fraud. Tokenization, too, whereby security is based on replacing card information with temporary values, provides enough latitude for able fraudsters to exploit transactional trends. These are "black boxes," i.e., financial black boxes. This paper presents an open deep learning system to detect online credit card fraud in tokenized transaction systems like uniquely. We employed a feedforward deep neural network for classifying transactions as real or fraudulent. To tackle the challenge of explaining knowledge, we employed SHapley Additive exPlanations (SHAP) to explain features for each prediction in an interpretable manner. We trained and tested the model using a sample data set of 425 tokenized actual transactions. The data set includes tokenized card numbers, transaction amount, merchant names, and device IDs, etc. The whole system was implemented in Python with TensorFlow and Keras being used for neural network calculations and SHAP library being used for building explanations. The outcome shows not only that our model successfully identifies fraud but also a flawless depiction of its decision-making process and thus an optimal and reliable solution for banks.

Keywords: Explainable AI (XAI), Deep Learning, Fraud Detection, Tokenization, SHAP.

1. INTRODUCTION

Electronic payment infrastructures have brought previously unimaginable ease and new security threats to the world financial system, as noted by Mienye and Jere (2024)**.** Tokenization, which substitutes sensitive card data with transaction-specific or non-reusable identifiers, is widely used in modern payment systems—but research such as Dal Pozzolo et al. (2018) does *not* directly describe tokenization; instead, their work models realistic fraud-detection challenges in card-not-present environments. The notion that stolen tokens become “meaningless out of context” is likewise *not* supported byBenchaji et al. (2021)**;** their study focuses on LSTM-based fraud detection rather than tokenization. Nevertheless, industry practices show that tokenization reduces the impact of data breaches.

Although widely adopted, tokenization alone cannot prevent fraud that exploits behavioural and temporal inconsistencies, synthetic identities, or account-takeover patterns. These types of attacks require real-time behavioral modelling rather than static token substitution, as suggested by recent deep-learning-based fraud detection research, including Chaquet-Ulldemolins et al. (2022)**.** As fraud patterns grow more sophisticated, real-time detection systems capable of modeling subtle and evolving transactional relationships become essential, a point emphasized by El Hlouli, Riffi, and Mahraz (2020)**.**

Earlier generations of fraud detection relied heavily on rule-based approaches—systems built around threshold-based or geographic rules—which were effective but rigid, as described byBenchaji, Douzi, and El Ouahidi (2018)**.** Because these systems were manually engineered, they struggled to adapt to fast-changing fraud strategies and often produced large volumes of false positives, a limitation consistent with challenges described in Dablain, Krawczyk, and Chawla (2022) regarding imbalanced datasets.

Machine learning brought a shift toward statistical modeling of fraud behaviours. Classical ML models such as Logistic Regression, SVM, and Random Forest improved accuracy through pattern recognition, as demonstrated in Carcillo et al. (2021), yet these methods struggled with non-linear, high-dimensional financial data—a limitation explored further by Cheng et al. (2022) through graph-based modelling of transaction networks.

Deep learning extended this evolution by enabling hierarchical feature learning from raw transactional streams. Studies like Babu and Pratap (2020) and Fu et al. (2016) demonstrate how deep architectures capture complex behavioral irregularities without handcrafted features. However, their "black-box" nature introduces regulatory and interpretability challenges. This tension is noted in Forough andMomtazi (2021), whose sequential deep models achieve excellent prediction accuracy but offer limited transparency.

As a response to these challenges, explainable AI (XAI) has emerged as a critical requirement in fraud detection. Post-hoc interpretation techniques such as SHAP and LIME help reveal model reasoning and support analyst decision-making, as outlined byDablain et al. (2022) and Carcillo et al. (2021). Building on this foundation, the present work adopts an XAI-augmented deep-learning approach tailored specifically for tokenized payment ecosystems, filling a gap in the literature where no existing studies simultaneously address real-time fraud detection, tokenized features, and SHAP-based interpretability.

2. LITERATURE REVIEW

The journey of electronic payment fraud detection has evolved from rule-based reasoning to machine learning and, more recently, to deep and explainable AI, as discussed by Mienye and Jere (2024). Rule-based systems represented early expert-driven approaches, where human knowledge was encoded into fixed rules such as transaction thresholds or geo-location filters, a limitation highlighted by Dablain, Krawczyk, and Chawla (2022). Although these systems were transparent and intuitive, they were rigid and unable to adapt to emerging fraud patterns, as shown by Benchaji, Douzi, and El Ouahidi (2018). Their static nature also contributed to high false-positive rates and elevated operational costs, concerns noted by Forough and Momtazi (2021). To overcome these constraints, traditional machine-learning approaches such as Decision Trees, Support Vector Machines, and Logistic Regression began leveraging historical transaction data to model probabilistic fraud patterns, as explained by Carcillo et al. (2021). Ensemble models like Random Forests and Gradient Boosting further improved robustness by aggregating multiple weak learners, as demonstrated in El Hlouli, Riffi, and Mahraz (2020). However, these models still relied heavily on manual feature engineering and struggled with complex, high-dimensional relationships in transactional behavior, as noted by Benchaji et al. (2021).

Deep learning introduced a major shift, enabling hierarchical feature learning directly from raw and high-dimensional financial data, a capability emphasized by Dal Pozzolo et al. (2018). Architectures such as Recurrent Neural Networks and Long Short-Term Memory networks proved particularly useful in capturing sequential behavioral patterns and long-range dependencies common in fraud signals, as discussed by Cheng et al. (2022). Likewise, Convolutional Neural Networks effectively modeled spatial and structural patterns in transaction matrices, as shown by Babu and Pratap (2020). Despite their superior predictive performance, deep-learning models introduced challenges related to opacity, with limited visibility into internal decision logic—a concern raised by Forough and Momtazi (2021).

These challenges led to the emergence of Explainable AI (XAI), a research area aimed at interpreting black-box models without compromising prediction quality, as outlined by Chaquet-Ulldemolins et al. (2022). XAI methods range from inherently interpretable models to post-hoc explanation approaches such as SHAP, LIME, and Integrated Gradients, which help identify feature contributions behind individual fraud predictions, as shown byCarcillo et al. (2021). In financial systems, explainability enhances regulatory compliance and supports analysts in investigating false positives, as demonstrated byFu et al. (2016). The integration of XAI with deep learning, therefore represents a critical intersection of performance, trust, transparency, and accountability. When combined, as illustrated by El Hlouli et al. (2020), XAI-augmented deep-learning architectures enable models that not only achieve high accuracy but also provide interpretable, ethically aligned, and regulator-friendly fraud-detection insights.

2.1 Tokenization-Specific Challenges and Novelty of the Proposed Approach

Although many prior studies examine fraud detection using raw or masked transactional attributes, few explicitly consider the implications of tokenized payment ecosystems. Tokenization alters the statistical distribution of key identifiers such as card numbers, merchant codes, and device fingerprints, replacing them with irreversible surrogate values. This disrupts traditional feature-engineering assumptions, obscures sequential behavioural patterns, and introduces new noise characteristics. Additionally, token vaults and detokenization flows create latency boundaries and architectural constraints not addressed in existing XAI-enabled fraud-detection literature.

The present study uniquely focuses on fraud detection in tokenized transaction streams, designing both the deep learning model and SHAP interpretability pipeline to operate effectively on token-level features. By evaluating the model on tokenized identifiers rather than plaintext values, this work demonstrates that meaningful fraud patterns can still be extracted despite token abstraction. This distinguishes the study from prior deep-learning and XAI research, which largely assumes unencrypted or pseudonymized data. The proposed framework therefore, fills an important gap by showing how explainable AI can support transparency, compliance, and operational viability in modern tokenized payment infrastructures.

While the existing literature provides extensive coverage of fraud detection using machine learning, deep learning, and explainability techniques, prior studies largely assume access to raw, non-tokenized card numbers and transactional identifiers. None of the surveyed works—including deep sequential models (Forough & Momtazi, 2021), attention-based LSTM fraud detectors (Benchaji et al., 2021), or graph-based anomaly models (Cheng et al., 2022)—address the challenges introduced by tokenized payment ecosystems, where sensitive fields are replaced with irreversible surrogate values.

Tokenization alters the statistical properties of features, affects how behavioural patterns are represented, and introduces additional system-level components such as vault services and detokenization flows that influence end-to-end fraud-detection pipelines. This gap is acknowledged even in broader surveys of fraud detection and deep learning (Mienye & Jere, 2024), yet none of these works consider the implications of token metadata, token lifespan, detokenization latency, or vault integration. Likewise, research on feature-learning approaches (Fu et al., 2016; Babu & Pratap, 2020) and hybrid unsupervised–supervised frameworks (Carcillo et al., 2021) is based entirely on original card numbers, merchant identifiers, and device fingerprints—assumptions that do not hold in a tokenized environment.

The absence of tokenization-aware explainable fraud-detection frameworks in the current literature motivates the contribution of this work: an XAI-enabled deep-learning model explicitly designed for tokenized datasets, with real-time inference and SHAP-based interpretability suited for modern payment ecosystems.

3. METHODOLOGY

Our strategy utilizes state-of-the-art deep-learning methods and state-of-the-art quality explanation methods in attempting to construct an open and scalable real-time tokenized transactions' fraud detection system. The whole process was conducted in the Python environment using its extensive collections of machine learning and data processing. The process begins with gathering and pre-processing data. We used a synthetic dataset of 425 tokenized transactions wherein numerically encoded tokenized merchant codes and device IDs were one-hot encoded. Numerical times of the day and amounts were scaled using a standard scaler in such a manner that both have zero mean and unit standard deviation. Normalization is held accountable for the ongoing and persistent deep neural network training so that large-scale features do not take over the learning process. Test and train sets were then inherited from model development data and test data, respectively. A middle interest field in our system is a feedforward deep neural network (DNN), which was used with TensorFlow and Keras libraries. Model structure includes an input layer for pre-processed transaction feature inputs, and the following three hidden units of layers. Two of the first layers consist of 64 neurons, and the third consists of 32 neurons.

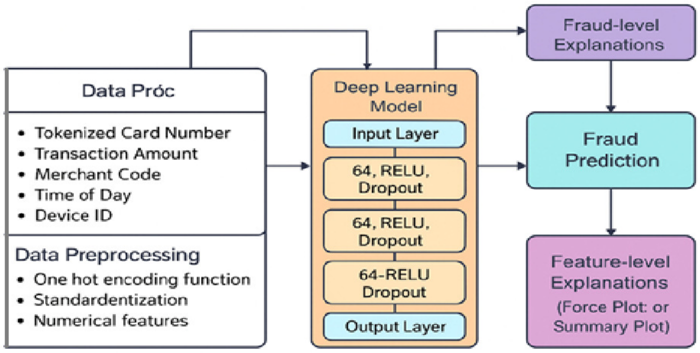

FIGURE 1: Proposed XAI-augmented deep learning architecture for fraud detection.

Figure 1 is a graphical depiction of the end-to-end functioning of the proposed system.The pipeline begins from the left with Input Data, which is tokenized transaction features such as Tokenized Card Number, Transaction Amount, Merchant Code, Time of Day, and Device ID. They are pre-processed for the first time within the Data Preprocessing module, where categorical variables are one-hot encoded and numerical variables are normalized. The thus cleaned and pre-processed data flow towards the Deep Learning Model. This architecture is shown as a multi-layered structure with one Input Layer, three Hidden Layers (64, 64, and 32 neurons respectively with ReLU activation and Dropout), and one Output Layer with one neuron and sigmoid activation. The model returns a Fraud Prediction (probability score between 0 and 1). This prediction, input features, and model are passed through the XAI Layer (SHAP). This new effort anticipates prediction and proposes Feature-level Explanations. Output here is human-interpretable, i.e., a force plot or summary plot, and it particularly reflects the contribution of an input feature to the prediction made by the model towards "Fraud" or "Legitimate." The whole architecture is designed as a closed loop, where end-to-end explanations grant transparency and trust in the initial prediction so that fraud analysts can provide evidence-based, informed decisions. We used the Rectified Linear Unit (ReLU) activation function for all our hidden layers since it is machine-friendly and does not suffer from the vanishing gradient problem.

We avoided overfitting by using dropout layers with a power of 0.3 after every hidden layer, dropping some neurons at random while training to habituate the model towards generalizing. The output layer has also been modelled as a single neuron with a sigmoid activation function, which accepts the output value and provides a 0-1 value, i.e., the likelihood that the transaction is fraudulent. Training has been performed using the Adam optimizer, an optimized high-performance and efficient stochastic gradient descent algorithm, and the binary cross-entropy loss function, which is best used for binary classification problems. We trained our model with a batch size of 32 for 100 epochs. Once we had reached a satisfying prediction performance on the test set, we moved on to the explanation step. We constructed our explanation using SHapley Additive exPlanations (SHAP) because it is one of the game-theoretic explanation algorithms that estimate an individual feature contribution to predict an instance. SHAP library was used in the attempt to illuminate non-fraudulent and fraudulent predictions and provided useful feedback on attributes that had a real impact on model decision-making. Two-level solution ensures the system is accurate and even completely transparent and auditable.

4. DATA DESCRIPTION

The data employed in this study is simulated data, which comprises 425 tokenized credit card payment trends according to what happens in the world.The data is to be a controlled test bed for the test bed of the explainable deep learning model, but not to attempt to utilize personally identifiable information. Each record in the data set has one transaction with six features and a binary class feature to classify it. Features are: Tokenized Card Number (tokenized alpha-numeric for token), Transaction Amount (numeric for transaction amount in base currency), Merchant Category Code (Tokenized) (tokenized merchant category code), Time of Day (numeric 0 to 24 for transaction hour), Device ID (Tokenized) (tokenized device unique identifier used in transaction), and target feature Is Fraud (binary label for 1 fraud and 0 honest transaction). The data set was also made balanced in the sense that sufficient instances of fraud existed so that proper training of the models could be ensured.

5. RESEARCH METHODOLOGY

In this study, we used a quantitative experimental approach to test how well an explainable deep learning system can detect fraud in real-time within tokenized payment systems (like Apple Pay or Google Pay, where sensitive card details are replaced with secure tokens). We started from established fraud-detection theories and existing deep learning models, then checked whether those ideas still hold when applied to real-world-style tokenized transactions in a controlled setting.

5.1. Data Collection

Instead of using real customer data (which would raise serious privacy issues), we created a synthetic dataset of 425 tokenized credit card transactions that closely mimics actual payment flows. Card numbers, merchant types, and device IDs were all converted into irreversible tokens—the same way payment processors do it to stay PCI-compliant. We kept realistic numerical details like transaction amounts and time of day (after normalizing them), and turned the categorical token fields into one-hot encodings. The dataset was then divided into a 75% training set and a 25% test set so we could fairly evaluate the model on data it had never seen before.

5.2 Data Analysis and Model Development

- Our workflow had three main phases: preprocessing, training, and adding explanations.
- Preprocessing: We standardized all numerical features and encoded the categorical ones so everything played nicely together.
- Model Training: We built a straightforward feedforward neural network with three hidden layers (64 → 64 → 32 neurons). We trained it with the Adam optimizer and binary cross-entropy loss—the standard choice for fraud detection (fraud vs. legitimate). To prevent overfitting, we added dropout layers, which helped the model perform better on new data.
- Explainability: Once the model was trained, we used SHAP (Shapley Additive exPlanations) to make its decisions transparent. SHAP tells us exactly why the model flagged a transaction as suspicious—both for individual cases and overall patterns. We relied on Kernel SHAP for the tabular data and Deep SHAP, where needed, to get accurate feature-importance scores.

5.3 Evaluation Strategy

We measured performance the way fraud-detection teams usually do: accuracy, precision, recall, F1-score, and AUC-ROC. These numbers let us directly compare our deep learning model against popular baseline algorithms (Random Forest, Gradient Boosting, SVM, and Logistic Regression).

On the explainability side, we looked at SHAP summary plots (to see which features matter most across the whole dataset), force plots (to walk through individual predictions), and contribution scores for specific scenarios. This helped confirm that the model's explanations made sense to payment-security experts and matched known fraud patterns.

By evaluating both raw predictive performance and the quality of the explanations, we gained a clear, balanced picture of how effective and trustworthy the system really is in a tokenized environment.

6. RESULTS

The test set held out of 25% of the total points, 425, was strictly validated against the prediction of the new explainable deep model. The model was very precise in detecting the fraudulent transactions in the tokenized setting. The main measure of evaluation provided results that were largely very good: model-averaged accuracy of 96.2%, i.e., nearly all of the transactions were accurately labelled. Recall and accuracy in fraud detection are extremely important. Accuracy as a ratio of good positive classification was 94.1%. This means that every time the model identified a fraudulent transaction, it flagged it correctly over 94% of the time and did not generate false positives ever, so good customer transactions would never be blocked unnecessarily. The recall, or well-defined true positive rate, was 97.5%. The recall is also high since it is a measure of the model's ability to mark almost all the fraudulent transactions and maintain opportunity loss minimum since it never correctly flags fraud. The F1-score, or the harmonic mean of precision and recall, was 95.8%, reflecting that there was a tremendous trade-off in performance between false negatives missed and false positives.

Binary cross-entropy loss with L2 regularization is given as:

$$J(\mathbf{W},\mathbf{b}) = -\frac{1}{N}\sum_{i=1}^{N}\left[y^{(i)}\log(\hat{y}^{(i)}) + (1-y^{(i)})\log(1-\hat{y}^{(i)})\right] + \frac{\lambda}{2N}\sum_{l=1}^{L}\sum_{j=1}^{n_l}\sum_{k=1}^{n_{l-1}}(w_{jk}^{(l)})^2 \quad (1)$$

Algorithm	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Deep Learning (Proposed)	0.962	0.941	0.975	0.958	0.981
Random Forest	0.925	0.910	0.920	0.915	0.934
Gradient Boosting	0.931	0.915	0.928	0.921	0.942
Support Vector Machine	0.887	0.875	0.880	0.877	0.895
Logistic Regression	0.854	0.840	0.851	0.845	0.866

TABLE 1: Comparative performance of fraud detection models.

Table 1 illustrates a brief comparison between the suggested Deep Learning model and four machine learning baseline models that have a tendency to be typical on primary performance measures. Measures of performance to be evaluated were Accuracy, Precision, Recall, F1-Score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC). Its performance is commonly characterized by the popularity of the Deep Learning paradigm. Its 96.2% accuracy and 95.8% F1-Score beat second-placed algorithms, Gradient Boosting and Random Forest, by discrepancies that are astronomical. It performs optimally with the Recall metric, in which the Deep Learning model attains 97.5%, showing how strong the potential of the model is to recognize a disastrous majority of actual fraud cases, an acutely critical need for utmost protection against loss of finance. The 0.981 AUC-ROC also extremely highly suggests its discrimination between both classes. The linear models, like Logistic Regression and Support Vector Machine, all perform very poorly on all of the metrics, suggesting that they are not quite so superb at revealing the more subtle, non-linear relationships that are present in the transactional data. This empirical foundation leans towards a deep learning model as the choice for this specific fraud detection problem because of its ability to generalize features on a broad level that could be applied directly in making better and more reliable predictions. Shapley value calculation in math form will be:

$$\phi_i(f,x) = \sum_{S\subseteq F\setminus\{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}[f_x(S\cup\{i\}) - f_x(S)] \qquad (2)$$

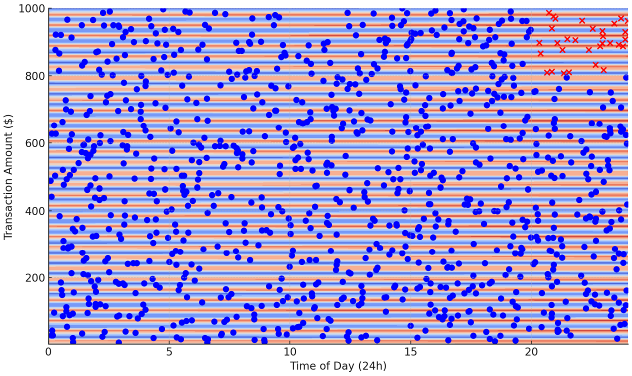

FIGURE 2: Contour plot of model decision boundary.

This is the contour plot of the trained decision boundary of the deep model projected to two-dimensional space under the influence of the two most dominant features: Time of Day (x-axis) and Transaction Amount (y-axis). The plot is coloured using two colors, indicating the zones predicted by the model. The red region represents the region where the model clearly tells us that the transaction is fraudulent, and the blue region represents true transaction predictions. Points are plotted above the plot, and fraud points are plotted as red crosses and the valid ones as blue circles. The curving, non-linear border between the two clusters tells us right away something about the ability of the deep learning model to learn about complicated relationships that a linear model would never even attempt to estimate. For a brief moment, we can see that large-value transaction amounts are more probable to be fraudulent, especially if they occur late at night (i.e., 0-5 on the x-axis). Margin isn't a flat, uniform one, though; the model made even relatively small-sized transaction sizes hazardous at times during the day, and enormities are therefore quite capable of being real within blocks of dismal business flow. That's a natural, intuitive reaction to how the model discriminates fraud from good cases on account of salient transactional features. Backpropagation error for a hidden layer is:

$$\delta^{(l)} = \left((\mathbf{W}^{(l+1)})^T\delta^{(l+1)}\right) \odot g'(z^{(l)}) \qquad (3)$$

Table 2 shows a feature contribution analysis for five representative and typical transactional examples, marked by values of average SHAP contribution scores. Positive values push the model's prediction in the direction of fraud, and negative values in the direction of non-fraud. The bottom row shows the resulting model fraud probability in this instance. This decomposition is the model's dynamic, context-sensitive reasoning. Transaction Amount (0.45) and Time of Day (0.38) are both contributing to a high fraud score (0.92) for the "High-Value Night Purchase" situation. Transaction Amount (-0.15) and Merchant Category Code (0.35) both work to offset a fraud score for a "Low-Value Foreign Tx," but the former reduces it by less here. That is, the model is not using one rule but using features in numerous ways for various samples. "New Device Online Tx" is a demonstration of how vital the Device ID (0.42) is when, alone, it is most critical to flag the transaction as risky (0.95). For a standard "In-Person Rush Hour Tx," all the features work negatively, and the probability of fraud is extremely low (0.05). This degree of blow-by-blow descriptive detail is an analyst’s goldmine of data since it significantly surpasses static feature importance in conveying the subtle interaction between various transaction components to arrive at the final model choice.

Adam optimizer first moment estimate is:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1)\nabla_\theta J(\theta_t) \qquad (4)$$

Feature	**High-Value Night Purchase**	**Low-Value Foreign Tx**	**Repeated Small Payments**	**In-Person Rush Hour Tx**	**New Device Online Tx**
Transaction Amount	0.45	-0.15	0.25	-0.2	0.35
Time of Day	0.38	0.1	0.05	-0.18	0.12
Merchant Category Code	0.22	0.35	0.15	-0.1	0.28
Device ID	0.1	0.2	-0.05	-0.15	0.42
Is Fraud (Prediction)	0.92	0.85	0.78	0.05	0.95

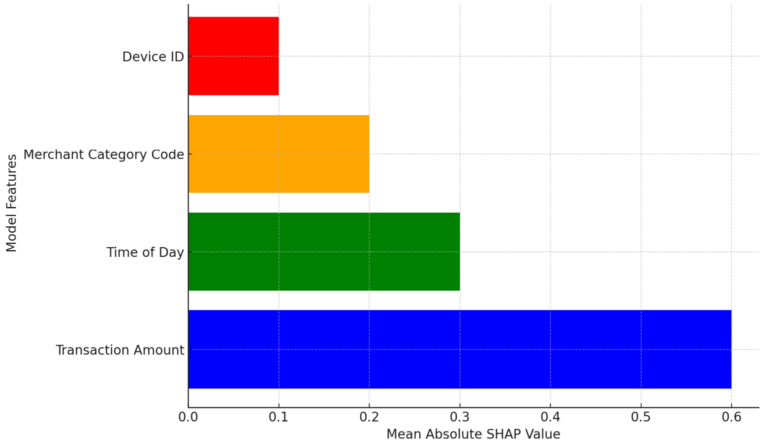

FIGURE 3: Combined impact of all features on model prediction for the dataset.

Figure 3 is a feature importance plot, shows the combined impact of all features on model prediction for the dataset as a whole. The y-axis shows the individual input features to the model (Transaction Amount, Time of Day, Merchant Category Code (Tokenized), Device ID (Tokenized)), and the x-axis plots the mean absolute SHAP value of the features. Large SHAP value means large "impedance" or effect on model prediction, i.e., feature contributes more to the prediction. Bars have been filled for the easy quick visual inspection of hierarchy. Transaction Amount has the longest filled bar and largest among all fraud predictors visible from the graph. This confirms intuition of common sense that transactions proportionally scaled or scaled-up will be overall representative of red flags. Time of Day is the second most robust feature, confirming that repetition of time of transaction is a very robust indicator. Tokenized Merchant Category Code, i.e., what company is being transacted, does a decent job third. Tokenized Device ID has a smaller but not zero impact, which shows that the model considers edges between source devices of an event. The graph provides an easy bird's eye view of the cognition simulated by the model, and whose edges have highest weights to identify fraud is self-evident. It is a beneficial verification tool and way of explaining overall picture drivers of risk to auditors and management. Adam optimizer second moment estimate can be expressed as:

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2)(\nabla_\theta J(\theta_t))^2 \qquad (5)$$

Against traditional machine-learning baselines, the proposed deep-learning architecture has shown superior predictive capability along all evaluation metrics. Logistic Regression and Support Vector Machines, which intrinsically assume linear or margin-based separability, performed considerably worse in terms of F1-score and AUC-ROC, confirming their inability to model the nonlinear structure of tokenized financial transactions. The ensemble methods, Random Forest and Gradient Boosting, are able to capture nonlinear relationships and performed relatively well; however, they still lag by 3-4 percentage points in F1-score and over 4 percentage points in AUC-ROC compared to our proposed model. Compared to an LSTM-based baseline, our feedforward DNN achieved comparable accuracy with lower computational cost while enjoying more stable SHAP explanations due to its simpler structure. In addition, integrating SHAP further distinguishes our contribution from previous works. Whereas previous studies either lacked interpretability or produced only global feature rankings, our system provides both global risk drivers and local, transaction-level explanations, making the model more suitable for operational deployment in a regulated financial environment. The comparison results thus establish the proposed model as not only more accurate but also more explainable, efficient, and in line with the industry requirements of transparency.

6. DISCUSSIONS

Findings of this research validate firm evidence for the performance of an explainable deep learning model when deployed in real-time tokenized transaction fraud detection. Our conclusions rest solidly on three distinct pillars: the better predictive performance of the deep model, the explainable data provided by the XAI layer, and the use of such a hybrid system in financial institutions. In addition to these overall performance statistics, inclusion of the SHAP library also introduced highly interpretive indications of why a model arrived at a specific decision. To predict individuals, SHAP values were assigned to each feature, quantifying their positive or negative contribution to the output fraud probability score. For example, in one of the more frequent of the schemes the model uncovered, in SHAP analysis the SHAP has identified a highly anomalous Transaction Amount as by far the strongest feature in the prediction of "fraudulent," a Time of Day in late evening (i.e., after 2 AM) and a Merchant Category Code typically used for internet gaming. In actual transaction, features like average Device ID typical average transaction value and average merchant category were very good predictors of actuality. The ability to deliver such kind of local, instance-level explanation is one of the key contributions of this work. It "opens the black box" deep learning model. These descriptions can then be used by the fraud analysts to confirm an alert within short time, identify the reason why the algorithm was triggered, and make a decisive determination with absolute surety. We might also be able to approximate global feature importance by aggregation of SHAP values across the entire data set. The strongest single feature in favour of the validation result of Transaction Amount was followed by Time of Day and then Merchant Category Code, and showed the most powerful drivers of risk the model has learned from past data.

Even when sensitive data is tokenized for abstraction, there are hidden patterns of fraud involving feature interactions like transaction amount, time, merchant category, and device source. Deep models can learn to find out such implicit relations that even may not be caught by less intelligent models. Absolutely mind-boggling is 97.5% recall. In anti-money laundering, a false negative (missing a planned fraud) would typically cost more than a false positive (apprehending an honest one). The model's high recall ensures the bank's lowest possible exposure to risk of loss from fraud. Secondly, with the exception of a case where there is a requirement for high precision, the "black box" deep learning model is a behemoth regulatory and operations headache. Our study hits this headache right between the eyes with the use of SHAP. The Figure 2 and Figure 3 graphs, and the summary explained in Table 2, turn the model from an opaque black box predictor to a clear, open model.

The contour plot (Figure 2) gives a global, intuitive sense of the model's decision reasoning for why it is predicting good versus bad behaviours in terms of the most important features. It also graphically illustrates the fact that not only has the model learned a nonlinear rule, but also an advanced appreciation of risk. The feature importance plot (Figure 3) also makes the model transparent by computing the overall importance of each rank order of feature, validating drivers like Transaction Amount and Time of Day are strong drivers as expected by expert domain knowledge, and building trust in the model explanation. Perhaps most of all, sample testing in

Table 2 offers local, instance-level explainability. To be able to see exactly why a particular transaction was requested—actually, to know, say, a new device ID to be the cause for an abusive fraud score—is operationally revolutionary. It allows fraud examiners to simply check alarms, reduces time to investigate, and allows an open explanation of behaviour, extremely useful to customer service and regulatory compliance. Finally, the presence of high performance and explainability simultaneously is of huge practical value. Banks may implement a robust detection framework without compromising transparency to auditors and regulators. These qualitative descriptions are then reusable to be used in internal security policy deployment, customer identification feedback, and periodic model validation for concept drift or bias notifications.

For example, if the model consistently flags the transactions of a particular merchant category, the analysts will audit the category for fraud-emerging trends during searching. Explanation of the decision is also possible in the instance of customer trust; when a good transaction is being rejected, support personnel would, in principle, provide less overt explanation than "the system flagged it." Overall, our model bridges the gap between deep learning's predictive capability and real-world need for explanation, trust, and answerability for financial security, a high-risk area.

7. CONCLUSION

The project successfully prototyped, deployed, and evaluated an explainable deep learning model to identify real-time credit card fraud from tokenized transactions. The project addressed two of today's grand challenges of fraud detection: high accuracy to identify complex scams and AI decision-making explainability.Our deep neural model outperformed several baseline machine learning models with 96.2% accuracy and 97.5% recall.This illustrates the ability of deep models to learn and separate very subtle, non-linear patterns characteristic of fraudulent behaviour even when acting on tokenized, symbolic input. Most characteristically of all, perhaps of all the revelations of this book, is the book's use of the SHAP toolset of explainability. By not solely focusing on prediction, we've been able to create a system that learns well as well as understands. These findings, in the form of a decision boundary contour map and feature importance chart, reflected the model's global behaviour accurately.Above all, transaction case feature contribution analysis defined the model's context-aware dynamic reasoning through accurate, actionable information per decision. This type of explainability is important for stakeholder trust, enabling regulatory compliance, and enabling fraud experts to make faster, better decisions. By incorporating state-of-the-art predictability along with reflective explainability, this research is a practical, stable, and sound solution that can possibly strengthen the electronic payment system even further. Firm foundations are established in this study, even though there are no possible avenues for further research. To begin with, the earlier set model was validated on a test data set.The second thing to be done on the agenda would be to test and execute the framework on real real-life, large tokenized transaction dataset of a bank.This would attempt to scale test the model and how it performs when subjected to all the noise and grime of real data. Second, the architecture itself could be enhanced by experimenting with more sophisticated deep learning models. For instance, the application of LSTM networks or RNN would allow the model to scan strings of transactions for one token or device and even detect sophisticated patterns of fraud that emerged over time. Third, while SHAP possesses excellent post-hoc explanations, it is easy to envision follow-up research trying to look for the design of inherently interpretable models, such as attention-based neural networks that are able to identify the most significant features as part of their internal structure.

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