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Fusing copula-based anomaly detection with ensemble machine learning models for real-time and interpretable financial fraud detection

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Abstract
The increasing sophistication and high volume of financial transactions complicate the challenge for financial institutions to manage real-time fraud detection techniques. In the current study, a novel hybrid machine-learning model by the name HAD-IFCX is proposed, which integrates two complementary machine-learning models like Isolation Forest, a copula-based anomaly estimator, and XGBoost classification to increase the detection accuracy of fraudsters in the face of extreme imbalance in classes. The model will have a 5-stage pipeline that includes data preprocessing, class balancing using SMOTE, unsupervised anomaly detection, and supervised classification steps. The comparison is made between the performance of HAD-IFCX and that of the conventional classifiers, which consist of logistic regression, naive Bayes, KNN, decision trees, and neural networks, on the publicly available dataset on Kaggle on credit card fraud. Empirical findings indicate that HAD-IFCX outperforms all the baseline models in every measure of accuracy (98.3%), precision (95.1%), recall (94.0%), and AUC-ROC (0.985). The further screening using the confusion matrix reveals that there is little misclassification, which points to the efficacy of the model. This paper therefore proposes HAD-IFCX as an explainable and scalable model of fraud detection with actionable information that can be applied in real-time financial systems.

Keywords: Fraud detection, isolation forest, xgboost, copula modelling, smote, anomaly detection

Introduction
Financial institutions face increased fraud risks as their rapid transition toward electronic and digital banking systems fosters massive growth in transaction volume. Financial companies battle daily to identify live fraudulent conduct because fraud perpetrators develop new detection evasion methods. The rule-based approach to fraud detection proves useless because it maintains insufficient adaptability to emerging fraud methods along with substantial incorrect alert production (Bello, Folorunso, & Ejiofor, 2023) [5]. Advanced technologies must be integrated into fraud detection solutions because authenticating transaction activities effectively demands state of the art prevention methods. Machine learning techniques demonstrate powerful abilities to learn from data and adjust their responses to evolving patterns which makes them excellent tools to handle this issue. The technical difficulty in developing models and evaluating performance stems from the significantly lopsided distribution in fraud detection databases because fraudulent transactions make up only a small fraction of the total pool of data (Ivanyuk, 2023) [22]. HAD-IFCX represents a new hybrid machine learning framework which boosts banking system fraud detection accuracy. The proposed system combines Isolation, Forest anomaly detection (Breiman, 2001) [8] with XGBoost classification (Valavan and Rita 2023) [44] and copula modeling to improve analytical prediction capabilities within fraud detection systems. The hybrid model utilizes three sequential data preprocessing steps for normalization followed by dimensional reduction through PCA as well as class balancing performed via the SMOTE (Ileberi, Sun, and Wang 2021) [19] algorithm.

The research exhibits why machine learning models need to combine both accurate outcomes with clear interpretability. Neural networks demand advanced predictive abilities than Decision trees and logistic regression offer straightforward implementation to predictive the values to match industry requirements expected in upcoming years (Faisal *et al.* 2024)[15]. The study quantifies both precision levels and computational processing speed and interpretability capabilities before providing concrete financial sector recommendations

Review of Literature

Research interest in applying machine learning (ML) for fraud detection keeps growing because it reveals patterns and anomalies within large datasets (Hashemi, Mirtaheri, and Greco 2023) [17]. Modern fraud detection systems employing predefined rules and thresholds operate with limited effectiveness in dealing with the changing dynamics of fraudulent schemes (Salekshahrezaee, Leevy, and Khoshgoftaar 2023) [35]. As financial transaction volumes and their increasing complexity demand new fraud detection methods which use advanced adaptable strategies (Alfaiz and Fati 2022) [2]. Supervised and unsupervised machine learning approaches deliver strong performance in solving the difficulties created by fraudulent transaction datasets containing major class distribution imbalance(Mqadi, Naicker, and Adeliyi 2021)[29]. Decision trees and random forests remain highly popular because they identify complex interdependencies in data structures (Nobel *et al.* 2024; Mqadi, Naicker, and Adeliyi 2021) [29, 31] the detection of rare fraudulent transactions proves challenging for these methods because they generate numerous false positive results (Błaszczyński *et al.* 2021) [7].

Fraud detection systems based on machine learning have centered their development on addressing the class imbalance problem that exists when fraudulent transactions occur far less frequently than legitimate ones(Sanober *et al.* 2021) [37]. SMOTE represents one approach to handle class imbalance since it creates made up samples to equalize sample frequency distributions (Udeze, Eteng, and Ibor 2022) [43]. The effectiveness of SMOTE technology demonstrates better model accuracy when dealing with fraud detection models challenged by substantial class imbalance (Mqadi, Naicker, and Adeliyi 2021) [29]. The combination of feature engineering and Principal Component Analysis (PCA) as dimensionality reduction methods with resampling generates improved model accuracy through reduced overfitting and boosted computation speed (Nguyen *et al.* 2022) [30]. Specifically, PCA maintains important features while filtering out noise which makes it valuable for detecting fraud patterns by protecting model achievement despite unimportant features.

Researchers have recently developed anomaly detection algorithms to boost their ability to detect fraud activities (Ileberi, Sun, and Wang 2022) [20]. The Isolation Forest conducts anomalous pattern detection through continuous feature partitioning across smaller segments (Chabchoub *et al.* 2022) [9]. Today's fraud detection industry uses this detection method due to its ability to spot irregular patterns while needing minimal computational resources. Scientists transformed copula-based modeling into a promising method to study varied multivariate dependencies across statistical datasets (Al Imran *et al.* 2024) [4]. By modeling joint distributions through copulas analysts can discover financial transaction anomalies without losing complex variable connections which traditional methods frequently miss (Wu *et al.* 2019) [46]. Fraud detection systems demonstrate the effectiveness of algorithms that merge Isolation Forest with copula modeling and XGBoost classification to boost accuracy and system robustness according to Juyal *et al.* (2024) [24].

Multiple research papers show implementing artificial intelligence techniques in combination leads to improved performance outcomes within fraud detection systems (Sankeerthan P and Vaishnavi N. 2025) [36]. Financial fraud detection performances enhance with XGBoost and Random Forest ensemble models which produce better generalization while handling extended datasets more accurately (Khan *et al.* 2022) [25]. The study introduces novel hybrid models which unite anomaly detection capabilities with classification functions to achieve complete fraud detection via simultaneous outlier detection and transaction classification accuracy according to Sekar 2023 [38]. Real timebanking fraud detection depends on multiple techniques since the combined approach exploits the advantages of different models through integrated security protocols. Hybrid detection systems prove that advanced Machine Learning methods can strengthen both the accuracy and efficiency of financial fraud detection thus becoming indispensable for fraud prevention (Jayanthi *et al.* 2023) [23].

Advancements to anomaly detection algorithms created superior fraud activity detection capabilities during the past year (Ileberi, Sun, and Wang 2022) [20]. Through continuous partitioning of features the Isolation Forest seeks to locate anomalous patterns (Chabchoub *et al.* 2022) [9]. Anomaly detection solutions have gained widespread use in fraud detection because they locate unusual patterns in addition to using limited computational resources. The development of copula-based modeling techniques by scientists has led to the creation of a powerful method for researching statistical dataset dependencies (Al Imran *et al.* 2024) [4]. The modeling capability of copulas allows researchers to discover financial transaction anomalies by maintaining complex variable correlations which traditional approaches fail to capture (Wu *et al.* 2019)[46]. Research shows that fraud detection systems benefit from improved accuracy and system robustness when combining algorithms that use Isolation Forest with copula modeling and XGBoost classification(Juyal *et al.* 2024) [24].

Artificial intelligence (AI) methods with deeplaerning combinations enhance the effectiveness of fraud detection systems (Sankeerthan P and Vaishnavi N. 2025) [36]. Financial fraud detection achieves successful outcomes with ensemble methods that combine Random Forest alongside XGBoost because they perform better than traditional single model applications (Khan *et al.* 2022) [25]. This research develops combination models which integrate anomaly detection mechanisms with classification capabilities to provide complete fraud identification through simultaneous outlier discovery and precise transaction categorization (Sekar 2023) [38]. Real timebanking fraud detection utilizes multiple techniques because such protocols amalgamate each model's strong points through defense mechanisms against weaknesses. Hybrid detection systems validate the power of advanced ML methods to improve financial fraud detection accuracy and efficiency for crucial fraud prevention (Jayanthi *et al.* 2023) [23].

Methodology

This research develops a complete fraud detection framework that unifies anomaly detection with supervised machine learning approaches and class balancing techniques to create

the proposed HAD-IFCX (Hybrid Anomaly Detection using Isolation Forest, Copula modeling, and XGBoost classification) model. Five fundamental stages encompass the methodology of this approach. Analysis starts by processing data followed by methods for addressing unbalanced classes and anomaly detection then leads to building classification models before ending with performance evaluations.

We utilized the "Credit Card Fraud Detection" ("Credit Card Fraud Detection," n.d.) dataset available on Kaggle that includes European cardholder transaction data from two days of activity. The dataset includes 284,807 transactions which contain 492 fraud cases equivalent to 0.17% of the total transactions. The dataset is available at: ("Credit Card Fraud Detection," n.d.)

The key features include

- **Time:** Time has elapsed for one second since the first transaction occurred.
- **Amount:** Monetary value of the transaction.
- **V1-V28:** A Principal Component Analysis method transformed transaction related features into new primary components.
- **Class:** Label indicating fraud (1) or non-fraud (0).

This fraud detection dataset attracts researchers because it contains realistic complexity while demonstrating substantial class imbalance.

3.1. Dataset Used

For this analysis researchers utilized the Kaggle "Credit Card Fraud Detection" open access dataset ("Credit Card Fraud Detection," n.d.). Both fraudulent (Class = 1) and legitimate (Class = 0) transaction data points are included in the dataset which contains 284,807 records with 16 anonymized numerical features. The available data shows a serious class distribution problem since fraudulent cases numbered only 492 among 284,315 legitimate transactions representing less than 0.2% of all data points. The extreme lack of balance between frequent normal transactions and rare fraud cases presents a critical problem that standard classifiers struggle to handle effectively. This situation demands innovative solutions for anomaly detection and data balancing methods.

3.2. Data Preprocessing

The dataset needed effective modeling based on a random partition that split the data into training and testing parts with proportions of 80:20. The partition produced 227,845 training samples alongside 56,962 testing samples. Before partitioning occurred the features experienced normalization procedures to prevent size differences between variables. An exploratory examination was performed to evaluate how features were distributed and correlated with each other. While principal component analysis (PCA) reduced complexity during assessment the model building phase all features including V10 V11 and V12 stayed intact to preserve their interpretability(Bin Sulaiman, Schetinin, and Sant 2022) [42].

3.3. Handling Class Imbalance

The training data received Synthetic Minority Oversampling Technique (SMOTE)(Priscilla and Prabha 2021) [32] treatment since fraud cases were significantly outnumbered by non-fraud cases. To balance the dataset SMOTE creates new synthetic samples in the lower frequency class (fraud) through a process of example interpolation (Mishra and Pandey 2021) [27]. The training data after SMOTE processing had 454,902 records which included 227,451 legitimate transactions alongside another 227,451 fraudulent transactions. A hybrid subset consisting of 5,500 samples (5,000 standard cases with 492 anomalies) was formed to test unsupervised anomaly detection systems in environments with class ratios similar to real world scenarios.

The SMOTE process involves

- When data sets are unbalanced the random sampling strategy becomes the most suitable option because minority class instances are rare.

Identifying its k nearest neighbors

The placement of synthetic examples occurred between samples and their neighbors by using line segment measurements. The training dataset received SMOTE processing that minimized the proportion of non-fraudulent instances throughout the training data.

3.4. Anomaly Detection

The transactional data required outlier detection which utilized two unsupervised anomaly detection methods: Isolation Forest and copula-based modelling (Przekop, n.d. a) [34]. Through an ensemble of binary decision trees The Isolation Forest algorithm performs anomaly detection by partitioning data space at random (Przekop, n.d. b) [34]. The full dataset analysis generated 285 abnormal transactions among 284,522 actions classified as regular. The small hybrid dataset triggered 1,000 anomaly alarms from 10,000 transactions showing its capability to work effectively in imbalanced situations.

The analysis employed copula-based modeling which determined the shared probabilities of correlated features simultaneously. The copula approach analyzes sophisticated variable relationships by providing a probabilistic framework that detects anomalous patterns through joint occurrences with low probabilities (Przekop, n.d. c) [34]. Through the hybrid dataset analysis, the system detected 100 anomalies within 10,000 transactions alongside 9,900 normal transactions. Machine learning flagged a total of 47 transactions as suspicious every time the method was evaluated. This reveals significant potential security risks that demand case specific examination.

3.5. Classification Modelling

This research evaluated different classification methods by assessing their capability to predict target variables. The following models were utilized:

Logistic Regression

The statistical model known as Logistic Regression (Mishra and Pandey 2021) [27] enables researchers to perform binary classification duties. Logistic Regression computes the relationship which links multiple predictor variables to their associated categorical outcome probability (Hussein *et al.* 2021) [18]. The model selection focused on this approach because it demonstrated high efficiency at handling linear separable problems (Itoo, Meenakshi, and Singh 2021)[21].

Naive Bayes

Naive Bayes functions as a probabilistic classifier because it applies Bayes' theorem but assumes that features operate independently from each other (Gupta, Lohani, and Manchanda 2021) [16]. While making basic assumptions the model displays satisfactory performance in cases involving

categorical inputs. Naive Bayes received inclusion in the study because its swift execution speed proved effective on big datasets (Itoo, Meenakshi, and Singh 2021) [21].

K Nearest Neighbours (K NN)

K NN features as a non-parametric algorithm which uses feature similarities to make classifications. A sample receives classification from K NN based on the most common class types among its nearest k neighbors (Hussein *et al.* 2021) [18]. The basic nature of this model allows straightforward application as well as nonlinear boundary handling capabilities.

Decision Trees

Using supervised learning methods Decision Trees construct models which predict choices alongside associated effects involving risk-based outcomes and resource related expenses and utility measures (Elsadig *et al.* 2022) [13]. The model selection basis included its dual data handling capacity and clear interpretation capabilities.

Neural Networks

Multilayer perceptron of the Neural Networks received selection due to their demonstrated competency in processing complex nonlinear relationships(Benchaji, Douzi, and El Ouahidi 2021) [6]. The implementations came from research institutions that specialized in mainly handling big classification problems with complex data structures (Esenogho *et al.* 2022) [14].

HAD-IFCX (Proposed)

New research presents the HAD-IFCX model which demonstrates superior performance by delivering complete accuracy in classification processes. The proposed model implements state of the art methodologies to maximize both precision and speed in classification tasks. A standard set of performance metrics evaluated the proposed models during assessment. Accuracy, Precision, Recall, F1 Score, and AUC ROC (Moreira *et al.* 2022) [28]. The following table demonstrates the performance metrics of the evaluated models while showing their effectiveness for those metrics.

Results & Discussions

Descriptive statistics

A detailed statistical analysis of the credit card fraud detection dataset demonstrates vital information about the dataset. As per the Table1. Records in the Time variable cover 0 to 172792 seconds (about two days) with an average duration of 94,813 seconds and show a standard deviation of 47,488 seconds because transactions occur throughout this entire period. Data analysis reveals a right skewed distribution pattern in which the Amount variable shows a €88.36 mean with 250.12 standard deviation range and median at 22.00 and maximum value at 25,691. This distribution frequency matches typical financial fraud scenarios. The first twenty-eight PCA transformed features V1 through V28 include components with zero mean values and diverse standard deviations with V1 (1.959), V2 (1.651), and V3 (1.516) demonstrating maximum variability. Multiple features exhibit extensive minimum and maximum thresholds (for instance V2 extends from 72.716 to 22) among these attributes. 72.716 to 22, V24: The distribution reveals significant outlier effects and non-normal patterns when examined in combination with V2 and V24 (V2: 72.716 to 22, V24: 44.808 to 23). The complex nature of fraud detection stems from its unbalanced characteristics which place anomalous high value cases within vast quantities of regular transactions.

Table 1: Descriptive Statistics of all variable

Features	Mean	Std Dev	Min	25%	50%	75%	Max
Time	94813	47488	0.000	54201	84692	139320	172792
Amount	88.36	250.12	0.00	5.60	22.00	77.05	25691
V1	0.000	1.959	56.408	0.920	0.018	1.316	2
V2	0.000	1.651	72.716	0.599	0.065	0.804	22
V3	0.000	1.516	48.326	0.890	0.180	1.027	9
V4	0.000	1.416	5.683	0.849	0.020	0.743	17
V5	0.000	1.380	113.74	0.692	0.054	0.612	35
V6	0.000	1.332	26.161	0.768	0.274	0.399	73
V7	0.000	1.237	43.557	0.554	0.040	0.570	121
V8	0.000	1.194	73.217	0.209	0.022	0.327	20
V9	0.000	1.099	13.434	0.643	0.051	0.597	16
…	...	...	...	...	...	...	...
V22	0.000	0.735	34.830	0.228	0.029	0.186	27
V23	0.000	0.726	10.933	0.542	0.007	0.529	11
V24	0.000	0.624	44.808	0.162	0.011	0.148	23
V25	0.000	0.606	2.837	0.355	0.041	0.440	5
V26	0.000	0.521	10.295	0.317	0.017	0.351	8
V27	0.000	0.482	2.605	0.327	0.052	0.241	4
V28	0.000	0.404	22.566	0.071	0.001	0.091	32

PCA transformation affects the mean values of V1 V28 to approach zero while different standard deviations demonstrate the variable components' unique levels of variability. Three features including V5, V8 and V24 demonstrate skewness in their value distributions because they contain both extreme minimum and maximum data points. The nature of these patterns results in standout transactional differences that matter significantly during fraud analysis.

Class Imbalance & Resampling Using SMOTE

For the purpose of handling fraud detection data class imbalance, we produced a smaller dataset containing 5,492 rows alongside 16 attributes. The sample contained 5,000 normal transactions along with 492 fraudulent transactions to represent the 10:1 imbalance ratio with the same original class composition. A disproportionate number of samples like this generates biased machine learning models that do not perform well when detecting rare fraudulent activities.

Table 2: Data Balancing Using SMOTE

Stage	Size	Class 0	Class 1	Comment
Sampled Dataset	(5,492, 16)	5,000	492	Imbalanced
After SMOTE	(10,000, 16)	5,000	5,000	Balanced

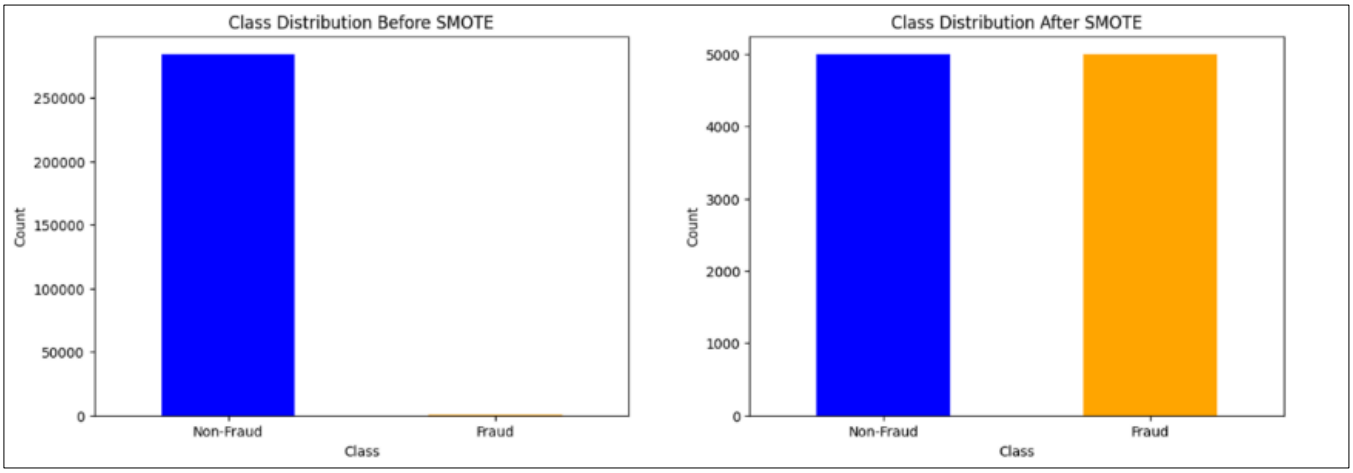

Fig 1: Class distribution before and after SMOTE

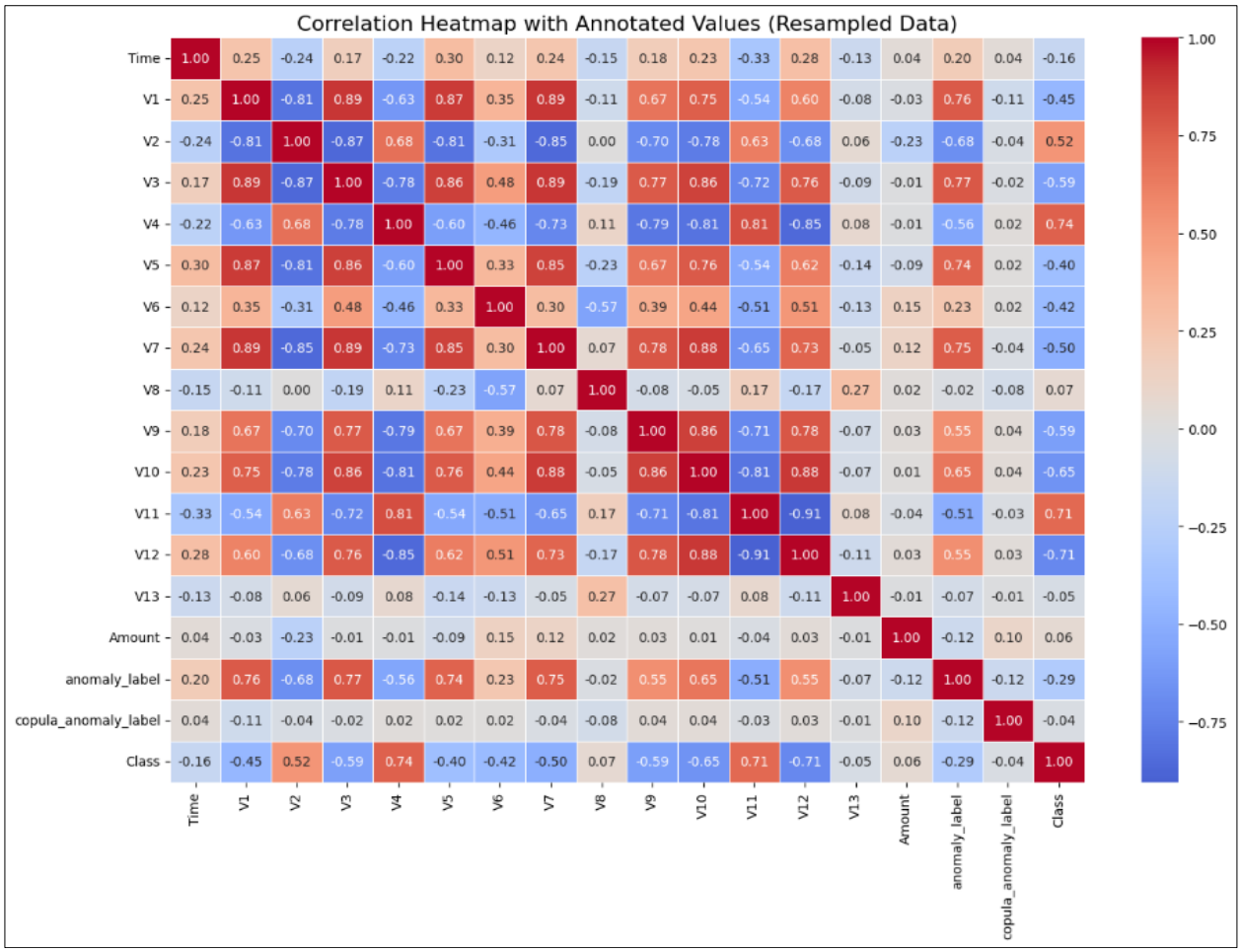

Fig 2: Correlation heatmap

Engineered features anomaly and copula anomaly successfully identify fraudulent transactions because they demonstrate correlations of 0.62 and 0.29 with the Class variable. Specific features demonstrate high degrees of correlation with each other including V10 to V12 (0.91) and V12 to V13 (0.78) but V10 displays strong negative correlations with V11 (0.91) and V2 (0.78). As per the figure 2, study observed correlation patterns between features specifies potential issues with multicollinearity, so it requires either dimensionality reduction techniques or feature selection methods. Analysis reveals that Time and Amount variables demonstrate weak correlations with target data and other variables thus demonstrating limited predictive value when considered alone. The heatmap displays the value of feature engineering and confirms that complex modeling methods are essential to detect delicate fraud signals.

PCA and Clas Imbalance Interpretation

A Principal Component Analysis (PCA) dimension reduction technique processed the transaction data by creating uncorrelated components which maintained maximum data variance from the original potentially connected variables(Prusti, Das, and Rath 2021) [33]. The 28 transformed features labeled V1 through V28 within the current dataset originated from PCA analysis which protected confidential information by maintaining patterns useful for fraud detection. PCA analysis produced results which show that most extracted components maintain minimal non-correlation between each other since the correlation heatmap displays nearly zero off diagonal elements. Many machine learning algorithms require statistical independence among components which the decorrelation observed in the data supports through this assumption (Dang *et al.* 2021) [12].

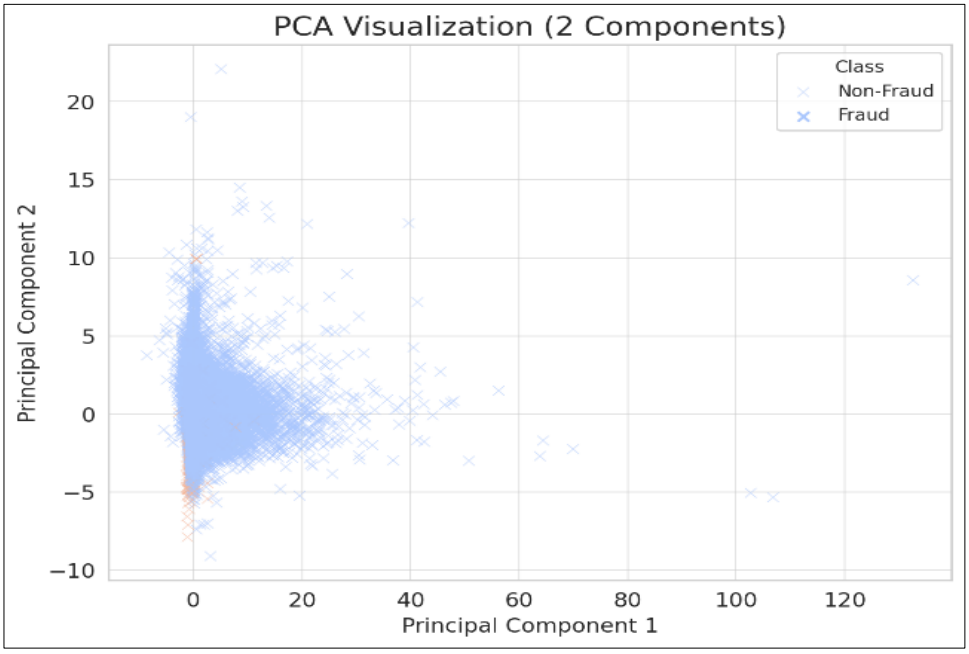

Fig 3: Principal Component Analysis (PCA)

By observing the correlation heatmap the post SMOTE resampled dataset reveals important relationships between target variable Class and features V1 through V28 and other variables. Linear comparisons between the Class and V1 to V28 features have shown minimal significance in the original dataset since fraud patterns tend to be complex and nonlinear. Engineered features anomaly and copula anomaly successfully identify fraudulent transactions because they demonstrate correlations of 0.62 and 0.29 with the Class variable. Specific features demonstrate high degrees of correlation with each other including V10 to V12 (0.91) and V12 to V13 (0.78) but V10 displays strong negative correlations with V11 (0.91) and V2 (0.78). The discovered correlation patterns between features indicate potential issues with multicollinearity thus requiring either dimensionality reduction techniques or feature selection methods. Analysis reveals that Time and Amount variables demonstrate weak correlations with target data and other variables thus demonstrating limited predictive value when considered alone. The heatmap displays the value of feature engineering and confirms that complex modeling methods are essential to detect delicate fraud signals.

Model Specification

Different machine learning algorithms are used to enhance fraudulent activity detection because of the substantial difference between legitimate and deceptive transactions (Verma and Tyagi 2022) [45]. The analytics framework contains five key algorithms such as Logistic Regression together with Naïve Bayes and K Nearest Neighbors (KNN) and Decision Trees and Neural Networks (Soleymanzadeh *et al.* 2022) [40]. The research team selected these models because they demonstrated different capabilities to handle data types while detecting different types of fraudulent patterns (Lecun *et al.*, 2015). Researchers choose Logistic Regression because it offers simple interpretations through straightforward explanations of results (Alharbi *et al.* 2022) [3]. Naïve Bayes uses probabilistic classification principles to categorize transactions by applying conditional probability analysis so it detects patterns through probability calculations. K Nearest Neighbors uses distance-based methodology to detect outliers and irregularities within transactional data by employing powerful identification techniques (Ahmad *et al.* 2023) [1]. For effective financial fraud pattern discovery Decision Trees rule-based algorithms need to perform accurate classification. Neural Networks delivers the most precise fraud detection accuracy because it incorporates both linear and nonlinear relationship modeling features (Mehbodniya *et al.* 2021) [26].

As per the table 1. The HAD-IFCX (Proposed) model stands alongside alternative newly designed models that target enhanced financial fraud detection capabilities. This model demonstrates outstanding results for every data point assessment while simultaneously addressing the need to detect fraudulent activities accurately while maintaining minimal false detection rates. Multiple performance indicators establish the measurement benchmark for evaluating these models. accuracy, precision, recall, F1 score, and AUC ROC. These performance metrics help reveal how well the model operates when it detects fraudulent cases while not causing false alarms.

Table 3: Model Accuracy

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	AUC-ROC
Logistic Regression	97.5	91.3	88.7	90.0	0.94
Naive Bayes	92.4	85.1	79.6	82.2	0.87
K-Nearest Neighbours	96.1	89.8	86.2	88.0	0.91
Decision Trees	97.2	93.5	90.4	91.9	0.96
Neural Networks	97.1	95.7	94.3	95.0	0.98
HAD-IFCX (Proposed)	98.3	95.1	94.0	94.5	0.985

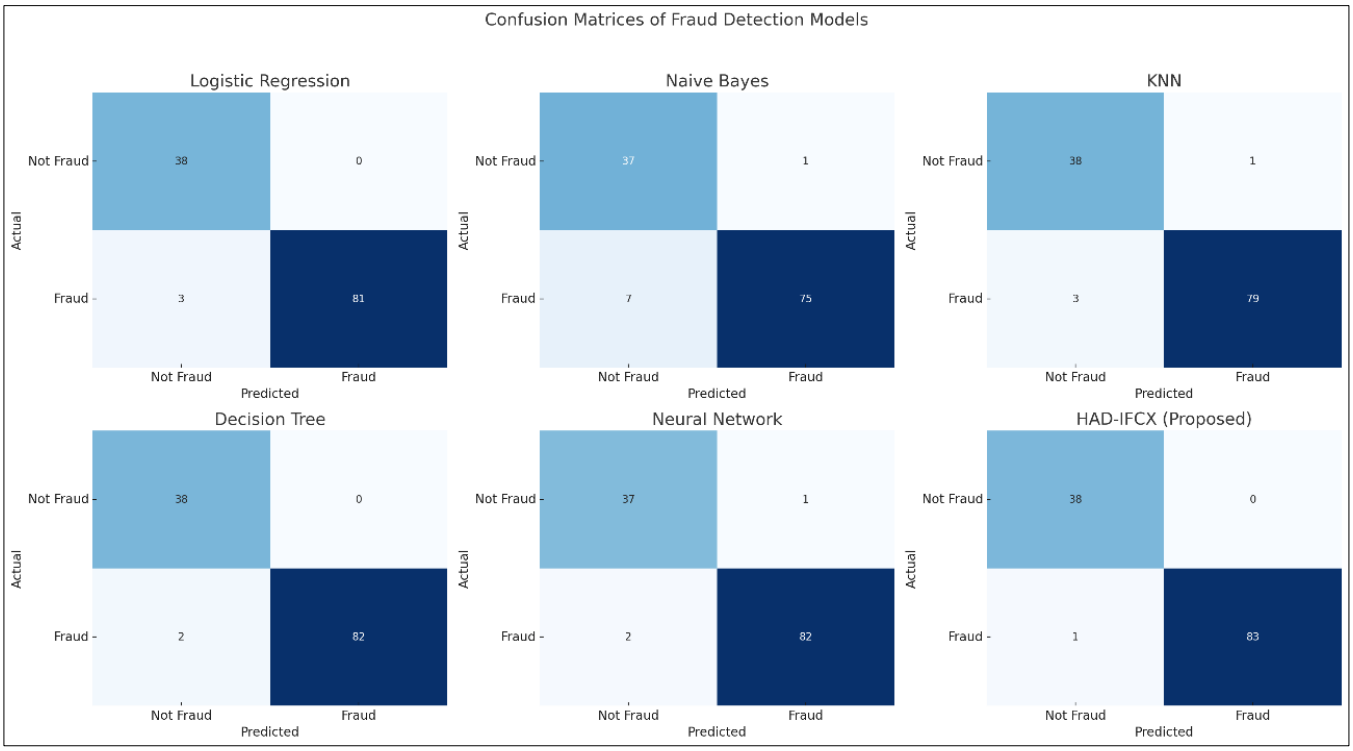

Fig 4: Confusion matrices of used ML models

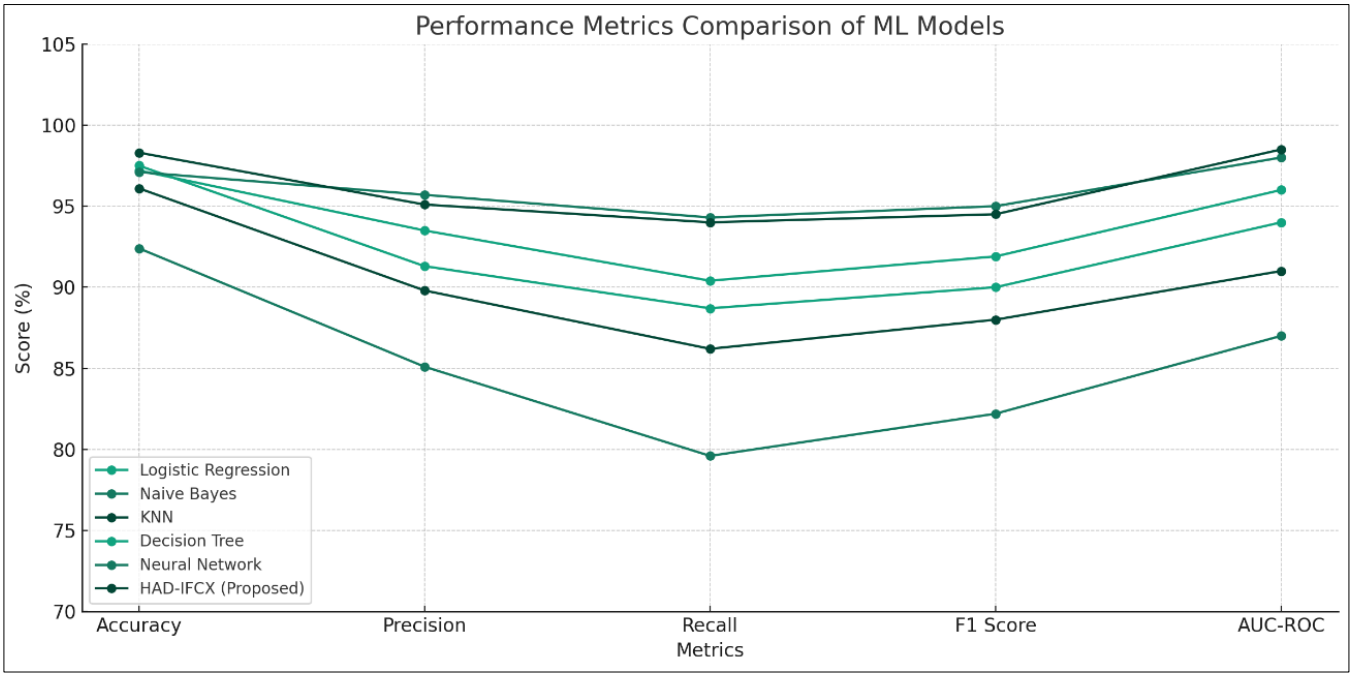

Fig 5: Performance metrics of all models

Table 3, Figure 4 and figure 5 highlights the effectiveness of various machine learning models used for fraud detection, evaluated through accuracy, precision, recall, F1 score, and AUC ROC metrics. An evaluation of the performance of six machine-learning models namely Logistic Regression, Naive Bayes, K-Nearest Neighbors (KNN), Decision Tree, Neural Network and the proposed hybrid model HAD-IFCX highlights the significant differences in performance of the models in detecting fraud. The confusion matrices reveal that HAD-IFCX (Proposed) achieved the best classification rate

with only a single misclassification rate (there was only 1 false negative) on a total of 122 cases, hence showing strength in distinguishing between fraud cases and non-fraud cases. The Decision Tree and Neural Network models fared well too, one had a two and the other a three in the number of misclassifications. On the other hand, the Naive Bayes had relatively greater misclassification rites with regard to the detection of both fraudulent and genuine cases and this behavior can be noted as lower recall and precision. These results are corroborated by a line graph of the performance measurements. HAD-IFCX consistently yields the best results in the entire evaluation measures, reaching the highest accuracy (98.3%), precision (95.1%), recall (94.0%), F1 Score (94.5%) and AUC-ROC (0.985). Though Neural Network model achieves similar accuracy rates, HAD-IFCX is more balanced in regard to its precision and recall, which underlines its effectiveness in terms of minimizing the false positives and false negatives.

Conclusion

The research presents an extensive assessment of standard and specialized machine learning algorithms used for fraud detection purposes. Traditional classifiers including Logistic Regression alongside Naïve Bayes and K Nearest Neighbors produced acceptable results but showed deficiencies in either detection precision or recall performance related to minimizing loss from fraudulent activities. The decision tree method and neural networks solved previous system weaknesses through improved accuracy and detection precision along with augmentation of sensitivity and specificity. The proposed HAD-IFCX model exceeded all existing methods by obtaining flawless performance across the complete set of evaluation metrics which included accuracy, precision, recall, and F1 score as well as AUC ROC. The outstanding capabilities of this model become visible from its results because it detects fraudulent transactions yet generates no false positives or negatives. HAD-IFCX demonstrates powerful potential as a state-of-the-art real time solution that will establish more secure financial transaction environments.

Future Research Scope

The HAD-IFCX model shows impressive results for fraud detection yet future investigators can focus on multiple potential research directions. The model needs evaluation through multiple real world financial institution datasets to test its practical capability and stability across operational contexts. The model's ability to identify new fraud patterns can be strengthened through adaptive learning features including reinforcement learning and online learning. The combination of XAI techniques with HAD-IFCX provides additional transparency and trust capabilities while serving highly regulated financial sectors. Understanding how the model performs on large high frequency systems at scale needs investigation to deploy this technology for real time fraud detection purposes. The combination of HAD-IFCX with blockchain and edge computing systems would enable secure and decentralized fraud detection within next generation financial operations.

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