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| RESEARCH ARTICLE

Governance Gaps AI-Driven Fraud Detection: Machine Learning Strategies for Countering Generative Fraud in the U.S. Financial System

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| ABSTRACT

With the fast development of the new generation of artificial intelligence (AI) technologies, fraud in the sphere of the financial industry has taken a new form and is a challenge to the detection systems and regulatory regimes. This paper explores how AI-guided fraud detection has weaknesses in governance and assesses machine learning to counter generative fraud in the U.S. banking sector. Since the generation models are capable of creating advanced synthetic identities, deepfake transactions and adaptive fraud patterns, the traditional rule-based monitoring systems and pre-existing oversight frameworks become more limited. Based on the publicly available Credit Card Fraud Detection dataset, this study creates and compares various machine learning models, such as the Logistic Regression, the Random Forest, the XGBoost, and the Neural Networks, in extreme class-imbalanced conditions. The synthetic pattern of fraud and adversarial perturbations are used to measure model robustness and resilience to match any emerging pattern of generative fraud risks. Given imbalance between fraudulent transactions, precision-recall measures, F1-score and Area under the Precision-Recall Curve (AUPRC) are used to perform the evaluation of performance. In addition to technical assessment, the paper analyzes the issues of transparency, explainability, and model accountability that are related to black-box AI systems. The results demonstrate a performance-governance tradeoff: whereas highly developed ensemble and deep learning models have high predictive accuracy, they cause interpretability and regulatory compliance issues. The article reveals key gaps in the governance of the model risk management, auditability, and regulatory compatibility in the financial oversight framework in the U.S. It suggests a unified system of explainable AI, adversarial robustness testing, and more stringent regulatory rules to increase institutional stability to generative fraud. The study adds to the crossroads of financial technology, AI governance, and the policy of cyber security by offering both empirical and policy-based suggestions.

| KEYWORDS

AI-Driven Fraud Detection, Generative Fraud, Machine Learning, Financial Governance, Explainable Artificial Intelligence (XAI) and Model Risk Management

| ARTICLE INFORMATION

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1. Introduction

A. *Background*

The artificially intelligent (AI) breakthrough has altered the financial sector operations and risk management models greatly and at a very fast rate. Banking organizations are increasingly adopting AI-based fraud detection platforms as a way of improving the observation of transactions, reducing losses incurred through transactions, and remaining within the law. Machine learning (logistic regression, ensemble learning, deep neural networks, etc.) can be used to process large volumes of transaction data and detect an abnormal pattern in real time. The technologies have enhanced the efficiency of fraud detection and improved its accuracy as well as minimized manual intervention [1]. The development of generative artificial intelligence has changed the nature of the threat environment. Generative AI networks can generate fake identities, deepfake authenticated data, automated phishing messages, and dynamically adapted transactional actions and can resemble genuine customer actions. Generative fraud is very dynamic, scalable, and can learn detection trends, unlike conventional types of fraudulent schemes [2]. This development poses sophisticated problems to AI-driven fraud detection models, especially the models that use patterns of historical data. The adoption of AI technologies in the U.S. financial system, should it happen, should be governed and regulated within a framework. In the Federal Reserve System as well as the Financial Crimes Enforcement Network, the focus on model risk management, anti-money laundering compliance, and transparency in automated decision-making is stressed [3]. The fast generation of AI has noted that the governance gaps are accountability, robustness testing, and transparency of the algorithm [4]. This, in turn, means that there is an urgent necessity to look into the way AI-based fraud detection models can be reinforced to fight generative fraud without affecting regulatory conformity and systemic stability.

B. *Artificial Intelligence in Fraud Detection in the Financial Industry*

The methods of detection of frauds in the financial market have changed dramatically in the last twenty years. Rule-based early detection systems were the most common systems and they were based on predetermined thresholds and heuristics used by experts to identify suspicious transactions [5]. The systems lacked flexibility, and they tended to produce high rates of false-positives that led to customer dissatisfaction and inefficiency in operation. The growth in the number of transactions and the advancement of fraud schemes made the use of the fixed rule-based systems ineffective. The adoption of machine learning was the turning point in the practice of fraud detection [6]. Supervised learning models allowed institutions to use the past of transactions to classify them and unsupervised methods allowed them to detect anomalies in the unlabeled data sets. More advanced methods like the random forest and gradient boosting as well as deep neural networks were used to make the detection of complex nonlinear patterns better. Real time analytics systems also enhanced the ability to intervene in fraud in real time [7]. The regulation developed simultaneously in response to adoption of technology. Institutions are supposed to follow the standards of model risk management and the process of decision-making should be transparent [8]. The Federal Reserve System and the Financial Crimes Enforcement Network are agencies that put an emphasis on automated systems governance, validation, and auditability. Even with these regulatory initiatives, governance structures tend to be in line with the fast changing technological innovations [9]. The introduction of generative AI-based fraud demonstrates the weaknesses of existing oversight systems, especially in terms of adversarial and explainability and the use of AI in an ethical way [10]. The identified gap highlights why it is necessary to incorporate the aspects of governance into the AI-based fraud detection strategies.

C. *Generative Fraud and Systemic Risk Emergence*

Financial fraud has been turned into a new level of complexity due to the introduction of generative AI technologies. With the help of complex deep learning networks, scammers have the ability to create fake transactions, believable identities, fake voices, and extremely believable digital evidence [11]. These features enable hackers to get beyond the traditional validation procedures and take advantage of loopholes in the automatic detection systems. Generative fraud represents a different category of fraud schemes because it is scaled, adaptable and capable of being evolved continuously [12]. Generative fraud models are dynamic in that they adjust to detection algorithms unlike the case with static patterns of fraud that are learnt through historical data. The adversarial machine learning methods also facilitate manipulation of the input data to avoid classification models which may have more false negatives and compromise system reliability [13]. Simultaneously, over sensitive detection systems will produce a high number of false positives thus, causing customer damage and reputational risk. Systemic effects of generative fraud are not restricted to individual institutions. The mass use of AI vulnerability may bring overconfidence in digital financial systems [14]. Black-box machine learning models make it difficult to hold them accountable and subject to regulation. Absence of standardized adversarial testing and explainability requirements makes the issue of governance even more difficult. With AI-driven detection and AI-enabled fraud, a technological arms race in the financial ecosystem is created. Fraudsters are developing strategies of generation as institutions improve predictive capabilities [15]. Such an interactive process generates important policy implications of transparency, validation of the model, ethical use of AI, and regulatory readiness. The solution to these systemic risks must be through a complex system that balances between technological innovations and the powerful system of governance.

D. *Problem Statement*

Even though financial institutions are increasingly implementing machine learning-based systems on fraud detection, there are still massive gaps in governance when it comes to dealing with generative fraud threats [15]. The current regulatory frameworks and model risk management rules were not set in place to consider adversarial machine learning, synthetic data manipulation, and black-box algorithmic opacities [16]. There are weaknesses in the U.S. financial system in terms of their lack of standardized robustness testing, transparency requirements, and accountability mechanisms. With the fast development of generative AI technologies, detection systems might not be effective without the improved oversight in a form of governance. Thus, designing machine learning approaches is of paramount importance to assess their predictive accuracy in countering generative fraud and their resilience, interpretability, and regulatory compliance.

E. *Objectives of the Study*

The major purpose of the research is to identify governance loopholes in AI-based fraud detection algorithms and test the machine learning policies aimed at dealing with generative fraud in the U.S. financial system. Precisely, the research has the following objectives:

- Test the behavior of diverse machine learning models in situations with extreme imbalance between classes.
- Simulate model robustness by simulating generative fraud situations.
- Find the trade off between predictive performance and model understandability.
- Determine governance and regulatory issues with AI-based fraud detection.
- Suggest a machine learning system with enhanced governance.

F. *Research Questions*

In this study, the research questions that will be addressed are the following:

1. What are the most important gaps in the governance of the AI-powered detection of fraud in the U.S. finance system?
2. To what extent are machine learning models effective in adversarial counterterrorism of generative fraud?
3. What can be done to improve control systems to increase resilience to generative AI-based fraud?

G. *Significance of the Study*

The research has relevance at the intersection of artificial intelligence, financial technology, and cybersecurity, and regulatory governance [17]. With the increasing availability of generative AI technologies, financial institutions are now encountering more than ever challenges in securing the transaction systems against adaptive and synthetic fraud schemes. Although the body of research on enhancing predictive accuracy in fraud detectors has been intensive, less has been done on the governance aspect of AI implementation, especially in the issue of adversarial and generative threats [18]. This study provides a contribution to both technical and policy-driven discourse by combining the machine learning experimentation and the governance analysis. Technologically, the research assesses the resilience of various machine learning models in simulated conditions of generative fraud, which empirically estimates the constraints of their performance and the strategies of resilience [19]. Governance wise, it sets structural lapses in the oversight tool such as transparency, accountability, and model risk management shortcomings [20]. The results are especially applicable to the financial regulators, policymakers, and institutional risk managers in the United States who want to enhance AI regulatory frameworks [21]. In a world where financial systems are faced with more and more reliance on automated decision making, there is a need to ensure explainability and regulatory adequacy in promoting the preservation of public trust and systemic stability. Moreover, this study suggests a governance-enhanced machine learning system that would put predictive performance in line with regulatory accountability [22]. This study contributes to academic research on the complicated dynamic between technological development and regulatory regulation in the age of generative AI. Addressing AI-driven fraud detection-related gaps in governance, it facilitates the creation of ethical, resilient, and transparent financial security systems that can address future generative fraud-related threats.

2. Literature Review

A. *Artificial Intelligence-based Fraud Detection in Finances*

The financial industry has settled on artificial intelligence as one of the core elements of contemporary fraud detection systems. The traditional rule-based systems which were once predominantly used as the means of suspicious transaction detection were not as efficient as they relied on predetermined limits as well as manually determined criteria [23]. These systems tended to be incapable of accommodating changing strategies of fraud and produced high false positive rates. The shift to machine learning-based solutions was a big improvement, as institutions would now be able to process huge volumes of transaction data and identify intricate behavioral patterns [24]. Logistic regression, decision trees, and the use of ensemble methods are all supervised learning models that have been extensively used in binary fraud classification tasks. They use labeled historical transaction data to determine distinguishing features of fraudulent activity using these models [24]. Random forests

and gradient boosting have proven to be better predictors because of utilizing multiple low-quality learners in ensemble methods. Deep learning networks also help identify additional features that detect relationships and high-dimensional interactions among features by learning nonlinearity [25]. Unsupervised and semi-supervised learning methods are also employed to detect anomalous transactions where the available fraud data in the form of labels are scarce [26]. The patterns of anomaly detection and clustering algorithms are used to identify rare and emerging fraud patterns. Moreover, real-time analytics systems also provide the opportunity to monitor transactions continuously and provide a response mechanism. Although technology advances, the literature additionally mentions the still present obstacles in the form of extreme class disparity, limited privacy of data, and restricted interpretability of models [27]. The presence of a very small percentage of fraudulent transactions in the fraud detection datasets generally implies that evaluation measures like precision-recall curves are more suitable than accuracy [28]. The growing sophistication of machine learning models raises the issues of transparency, responsibility and regulatory compliance. Such worries are even more serious when the generative AI technologies start affecting the fraud schemes.

B. *Generative Artificial Intelligence and New Fraud Threat*

Generative artificial intelligence is a revolutionary advancement of digital technology, and systems that can produce synthetic data, images, text and behavioral patterns that are similar to real world information, are able to generate them [29]. Although generative models have important positive effects in all sectors, it has also presented advanced instruments to the bad actors. Generative AI in the financial sector has allowed the generation of synthetic identities, deep fake authentication artifacts, automated phishing content and transaction behavior designed to avoid detection systems [30]. Generative fraud is dynamic and unlike conventional fraud schemes which are based on historical patterns identifiable, generative fraud is dynamic. Systems based on AI can be used to learn the patterns of detection and allow fraudsters to adjust their attack patterns [31]. This flexibility makes it harder to detect fraudulent transactions with popular supervised learning models that are trained on past data [32]. Adversarial machine learning methods are also known to be complicating the work of detectors since the input data can be manipulated in small ways that lead to the misclassification of transactions by the models. Systemic risks are also increased by the development of generative fraud [33]. Banking institutions can face more false negatives whereby the adaptive fraud patterns evade detection programs. On the other hand, over-sensitive detection models can similarly create a lot of false positives, which interferes with the legitimate customer transactions and will result in lack of trust [34]. It is possible to expand fraud activities by using generative AI at a high rate, making them more massive and advanced. The recent studies indicate that strong testing, adversarial training and model stress assessment are necessary to overcome generative threats. Nonetheless, despite there being a large number of extant fraud detection frameworks, they were not built to be adversarial-resilient [34]. Consequently, generative AI poses a technological-based arms race between detection and fraud techniques, which is highly critical with regard to preparedness, regulation, and long-term stability of the systems.

C. *Governance, Explainability and Model Risk Management*

The implementation of AI-facilitated fraud detection solutions in the financial industry is in a highly complicated regulatory and governance framework [35]. The governance structures focus on model testing, risk management, auditing and the anti-money laundering and consumer protection regulations. With the growing reliance of financial institutions on automated decision making, transparency and accountability is necessary to provide regulatory conformity and trust within the people [36]. Trade-off between predictive performance and interpretability is one of the key issues pointed out in the literature. The black-box systems include advanced machine learning models, especially ensemble and deep learning models. Although these models can have a high detection accuracy, they restrict the capability of institutions to provide a description of the process by which certain decisions are made. The result of this is that internal audits, regulatory reviews, and procedures of resolving customer disputes become challenging due to this non-transparency [37]. The model risk management frameworks mandate the institutions to record the assumptions, test the performance and also track the model drift over time. Nevertheless, generative fraud is accompanied by new kinds of risk which are not limited to the traditional validation processes [38]. The adversarial manipulation, the generation of synthetic data, and the evolution of methods of fraud can pose a threat to the stability and reliability of the models. Current governance standards might lack the capacity to deal with these new weaknesses. Models that can be explained have been suggested to make the use of artificial intelligence more transparent by determining the important characteristics of models that affect their results [39]. These tools may help in regulation compliance and institutional control. However, the ability to be explained might not be sufficient to resist adversarial attacks [40]. Consequently, the literature recommends incorporating the concepts of governance directly into the lifecycle of the model development, such as adversarial testing, performance stress testing, and continuous monitoring [41]. Enhancing governance framework is crucial in making sure that AI-enabled fraud detection systems are resilient, responsible and responsive to the emerging regulatory demands in the face of generative fraud threats.

D. *Empirical Study*

In the article by Tanvir Ahmed Shuvo, Asif Iqbal, Emon Ahmed, Ashequr Rahman and Md. Risalat Hossain Ontor, the theme of generative and conventional machine learning models is discussed in the context of enhancing the security of retail banking. The research compares Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) as anomaly detectors and synthetic data generators with high scores of 91.2 and 93.5, respectively. The authors also evaluate the data realism based on the evaluation metrics, including Inception Score and Fréchet Inception Distance (FID), where GANs have a better performance in creating realistic synthetic transactions. Besides generative methods, the paper also compares the classic classification models, such as Gradient Boosting Machines (GBM), Random Forest, and Logistic Regression. Of them, GBM demonstrated the best results, having an accuracy of 96.3% and AUC-ROC of 97.2, which demonstrates its efficiency in fraud detection tasks [1]. The study highlights that generative AI is not only effective in fraud detection as it detects irregularities, but it also models complex fraud cases, thus increasing the flexibility of fraud detection models. The hybrid modeling will lead to the development of AI-based financial security and will help in integrating predictive performance with new adaptive fraud detection techniques to retail banking systems.

In the article entitled Harnessing AI to Next-Generation Financial Fraud Detection: A Data-Driven Revolution, Mohamed Kamal Aldin Ismaeil offers a detailed analysis of the use of artificial intelligence to enhance financial fraud detection mechanisms [2]. The paper raises the issue of the increasing sophistication of financial fraud and that the apparently dominant role of rules and statistical approaches is not able to cope with contemporary and data-driven schemes of fraud. The author suggests a two-stage research strategy where the first stage will entail a comparative study of conventional fraud detection algorithms and the AI-based models, and the second stage will involve creating and testing a machine learning model based on the transactional data. The study compares supervised, unsupervised, and deep learning algorithms to define whether they are effective in detecting anomaly financial behavior or not. The results indicate that AI-based models have a high ability to decrease false positives and increase the rate of fraud detection, which positively affect the efficiency of the operations of financial institutions. Notably, the paper points out that AI systems have to constantly adapt to the constantly changing patterns of fraud, which supports the idea of dynamic models updating. The given work is part of the bigger conversation on the topic of AI-based financial safety, as it shows how performance in terms of fraud detection can be transformed through the use of data-driven approaches. The article substantiates the emerging fact of knowledge that machine learning models offer scalable, adaptive, and efficient solutions to such increasingly sophisticated financial fraud threats.

Prince Kumar in the article AI-Powered Fraud Prevention in Digital Payment Ecosystems: Leveraging Machine Learning to Detection of Anomalies and Risk mitigation discusses how supervised and unsupervised machine learning methods can be used to enhance fraud prevention in digital payment systems. The research suggests a hybrid AI architecture, which is a combination of real-time transaction monitoring, behavioral biometrics, device profiling, and multi-layered analytics to improve detection accuracy and minimize latency. The system was tested on a synthetic dataset of 10,000 transactions with various types of frauds and a recall of 94% and a precision of about 85, which is better than traditional classifiers like logistic regression, random forests, and isolation forests [3]. The study highlights the need for adaptable AI methods that can adapt to new trends in fraud, thus dealing with restrictions of fixed rule-based systems. Furthermore, the paper also mentions the regulatory and ethical aspects, such as preserving privacy, explainable AI, and deploying it within financial ecosystems. The article proposes graph neural networks as future research directions to detect fraud rings, federated learning to collaborate across institutions, and adversarial resistance. This work is relevant to the literature, in that it has shown how hybrid AI architectures can provide scalable, low-latency, and governance-aware fraud detection systems that are appropriate to the contemporary digital payment environment.

In the article titled From Breaches to Bank Frauds: Exploring Generative AI and Deep Learning in Modern Cybercrime, Anam Haider Khan explores the transformative nature of generative AI and highly developed models of deep learning in the current cyber criminals, especially in bank and financial fraud. The paper has also noted how threat actors use large language models (LLMs), Generative Adversarial Networks (GANs), and reinforcement learning agents to operate reconnaissance on autopilot, produce adaptive phishing campaigns, and produce polymorphic malware as well as scale synthetic identity fraud. In contrast to conventional cyber threats, AI-driven attacks are constantly evolving so that the conventional rule-based and signature-based detection systems are becoming more useless [4]. The article presents a prototype AI-based fraud simulator to prove empirically how generative technologies can evade the contemporary defense mechanisms. Experimental findings depict a higher evasion capability, automation efficiency, and success rate of attacks than the conventional cyber-attack techniques. Notably, the research highlights the increasing demand of AI-enhanced defense systems, analytical behavior, and regulation to deal with intelligent and autonomous cybercrime. The study is part of the dynamic discussion on adversarial machine learning and generative fraud that both will support the need to govern AI detection models, which can cope with sophisticated and innovative financial cyber dangers.

The article entitled Big Data-Driven Financial Fraud Detection and Anomaly Detection Systems to Regulatory Compliance and Market Stability by Nafisat Temilade Popoola discusses the revolutionary role of the Big Data analytics to advance the financial fraud detection systems. The paper claims that the rule-based system is becoming less appropriate in dealing with increasing sophistication and magnitude of financial fraud. With the combination of machine learning algorithms, artificial intelligence, and real-time data analytics, Big Data-driven systems can help financial institutions to process large amounts of structured and unstructured data based on transactional data, behavioral data, and regulatory data. The study underscores the fact that the fraud detection systems not only enhance the fraud detection rates, but also facilitate the adherence to the anti-money laundering (AML) and counter-terrorism financing (CTF) policies. The constant checking of the transactions and decreasing of the false positives lead to the efficiency of operation and the expansion of the market in general. The research points to the challenges in the implementation, such as the data privacy problem, the cost of calculations, and the adversarial attacks on AI models. The author highlights that it is necessary to develop a greater explainability and strength, along with augmenting security technologies like block chain to have tamper-proof verification. The contribution of this work to the expanding literature on governance-compatible AI systems is that the Big Data analytics enhances the performance of fraud detectors and the regulatory adherence of contemporary financial ecosystems.

3. Methodology

This study will focus on a quantitative experimental approach to assess the strategies in machine learning to detect fraud, as well as to analyze the governance considerations of AI-based financial systems [43]. The methodological approach reflects predictive modelling and optimization of threshold and governance evaluation. The process is based on a structured analytical pipeline, which consists of dataset preprocessing, model development and performance analysis, sensitivity analysis and robustness tests. The Support Vector Machine (SVM) model is adopted with the objective of classifying fraud and genuine transactions in harsh conditions of class imbalances. There are various measures of evaluation used to guarantee sound assessment [44]. Analysis and learning curve evaluation based on threshold and operational performance as well as the generalization behavior are included. The methodology also incorporates governance aspects whereby it guarantees that predictive accuracy and regulatory responsibility are aligned with resilience to changing generative fraud risks.

A. *Research Design*

This study design in the study is a quantitative, experimental design, which examines the effectiveness of machine learning models in fraud detection among financial transactions, and also examines gaps in governance within AI-based fraud detection systems [45]. The research includes the predictive analytics that are combined with the governance-based analysis so that both technical and regulatory views would be considered. The analytic model is designed in the form of a sequential pipeline, which contains the preprocessing of data, the model development, the measurement of its performance, the control of the threshold, and the interpretation of the governance [46]. The experimental design has a simulation of real-world financial transaction conditions with high levels of imbalance of classes and volatile patterns of fraud [46]. The framework indicates the practical deployment conditions in the financial institutions by integrating imbalanced classification methods and threshold sensitivity analysis. The systematic comparison of predictive capability and operational implication, i.e. false positive and false negative are measurable through the organized method [47]. The analytical framework is focused on the performance trade-offs with the special focus on the trade-off between precision and recall. In the context of financial governance, it is important to minimize the false positives to safeguard customer experience, whereas it is important to minimize the false negatives to minimize financial loss [47]. Consequently, the methodology combines threshold optimization in order to analyze the impact of the classification boundaries on the performance outcomes. Moreover, the study also includes the robustness analysis with the help of the learning curve analysis to determine the ability to generalize [48]. This will make sure that model performance is not restricted to training data but it is also consistent across different data volumes. The study includes considerations of governance in the very fabric of the analytical process, which makes the findings relevant to both the literature of machine learning and the regulatory resilience discussion and AI responsibility.

B. *Description and Preprocessing of the databases*

The dataset used in the study is the publicly available Credit Card Fraud Detection dataset, which has 284807 transactions registered in 2 days and 492 cases of fraud. The data set shows the presence of intense class imbalance as the fraction of fraudulent transactions in the total population is about 0.172%. Anonymity is ensured by anonymizing the features and converting them to principal component analysis (PCA) to maintain the confidentiality of the features labeled V1-V28. There are also two non-transformed characteristics namely the Time and the Amount which reflect the time and the monetary value of a transaction [48]. Class is a binary target variable that determines whether a person is a fraud or not. Preprocessing of data is needed to have a good model performance. The data is first analyzed in terms of missing values and inconsistencies. Standardization is used to do feature scaling to normalize the magnitude of the variables, which is especially valuable with SVM since it is a distance-based optimization structure. As the imbalance of the classes is very high, stratified sampling is utilized

during train-test splitting to ensure the proportionate representation of the cases of fraud in both subsets. This will avoid biased assessment as model validation will be of real world distribution of classes. Also, threshold-based evaluation is aided by preprocessing since probability values are produced rather than hard classifications [49]. This enables the analysis of model behavior at different classification cut-off values in the study. The preprocess framework guarantees integrity of data, equal assessment and compatibility with imbalance classification problems that financial fraud detection systems possess.

C. *Model Development: Support Vector Machine (SVM)*

The Support Vector Machine (SVM) classifier with radial basis function (RBF) kernel is the main prediction model to be used in this study [50]. The reason why SVM model is chosen is that it effectively operates with high dimensional feature space and constructs a nonlinear boundary to make the decision. The patterns of financial frauds tend to be subtle and complex in nature related variables; thus, the nonlinear classification ability is highly essential [51]. The RBF kernel permits the mapping of the input data to a higher dimensional feature space so that the fraudulent and legitimate transactions can be separated even in the case that they are linearly inseparable in the original space. Hyperparameters are set so as to balance between model complexity and generalization performance [52]. The parameter tuning is performed to reduce overfitting with a high classification capability. This model is optimized by standard training data and tested on unseen test data to make sure that performance is measured without bias. Probability results are produced to support threshold sensitivity analysis, ROC curve construction and precision recall analysis [53]. The SVM method is also best applied to the non-balanced classification issues because of its maximization principle of margins that increase the spacing between classes. Nevertheless, due to the fact that SVM models are not easily interpretable, governance factors are factored in during analysis to determine accountability considerations. In general, the process of model development provides a strong technical implementation in line with the governance-related goals of the study.

D. *Metrics of Performance Evaluation*

Considering the drastic misbalance in the datasets of fraud detection, the common metrics of accuracy are inadequate to comprehensively evaluate it [54]. Thus, several performance measures are used in this research to have a global view of classification effectiveness. The Receiver Operating Characteristic (ROC) curve and Area under the Curve (AUC) indicate the capability of the model to differentiate between fraud and legitimate transactions using different thresholds. The higher the AUC, the more powerful is the discriminating power. Precision is used to determine the number of fraudulent transactions that are detected as correct out of all transactions that are predicted to be fraudulent [55]. This indicator is essential to reducing the false positives and safeguarding the customer experience. The recall, or sensitivity, is the rate of correctly detected fraudulent transactions by the model. The risk of undetected fraud is less with a high recall. F1 score gives a harmonic mean of the precision and recall, which is a balanced evaluation measure in one-sided situations [56]. The confusion matrix also subdivides the results of classification into true positive, true negative, false positive, and false negative; resulting in a more detailed understanding of the impact of the operations [57]. All these measures are inclusive and guarantee overall assessment of predictive reliability, threshold stability, and robustness of fraud detection. Such multi-metric is capable of technical validation as well as governance assessment in AI-based financial systems.

E. *Sample Sensitivity Analysis and Threshold Optimization*

In order to improve on operational applicability, the present study uses threshold optimization and sensitivity analysis. Performance is assessed at a continuous set of values of probability cut-off rather than at the fixed value of 0.5. At each threshold, precision, recall and F1 scores are calculated in order to determine the best operating regions. The threshold optimization allows the false alarm control and the trade-offs between the fraud detection coverage and false alarm control to be examined [58]. A low threshold causes higher recall and the possibility of a higher false positive rate, whereas a high threshold causes a low false positive rate and a higher probability of missing fraudulent transactions. This is one of the trade-offs of governance in financial institutions. The threshold-based analysis aids in strategic calibration in accordance with the requirements of the institutional risk appetite and the regulations [58]. The study allows making decisions grounded in data by determining the areas of performance stability to be deployed. Sensitivity analysis also determines the impacts of slight variations in threshold values of the overall performance measures [59]. This strategy makes certain that the deployment of the models is based on facts and not randomly picked. Integrating threshold analysis empowers transparency and accountability of AI-driven systems that detect fraud.

F. *Government and Strength of Arm Consideration*

This study incorporates governance assessment in the research methodology. Learning curve analysis is used to determine model robustness by analyzing the behavior of generalization with increases in training data. A small difference between training and validation performances implies that there is consistent learning among the models and low variance. Such governance factors as model risk management, transparency, and adversarial manipulability vulnerability are considered [60]. Despite the high performance of the SVM model, the weaknesses in its interpretability imply the potential existence of gaps in

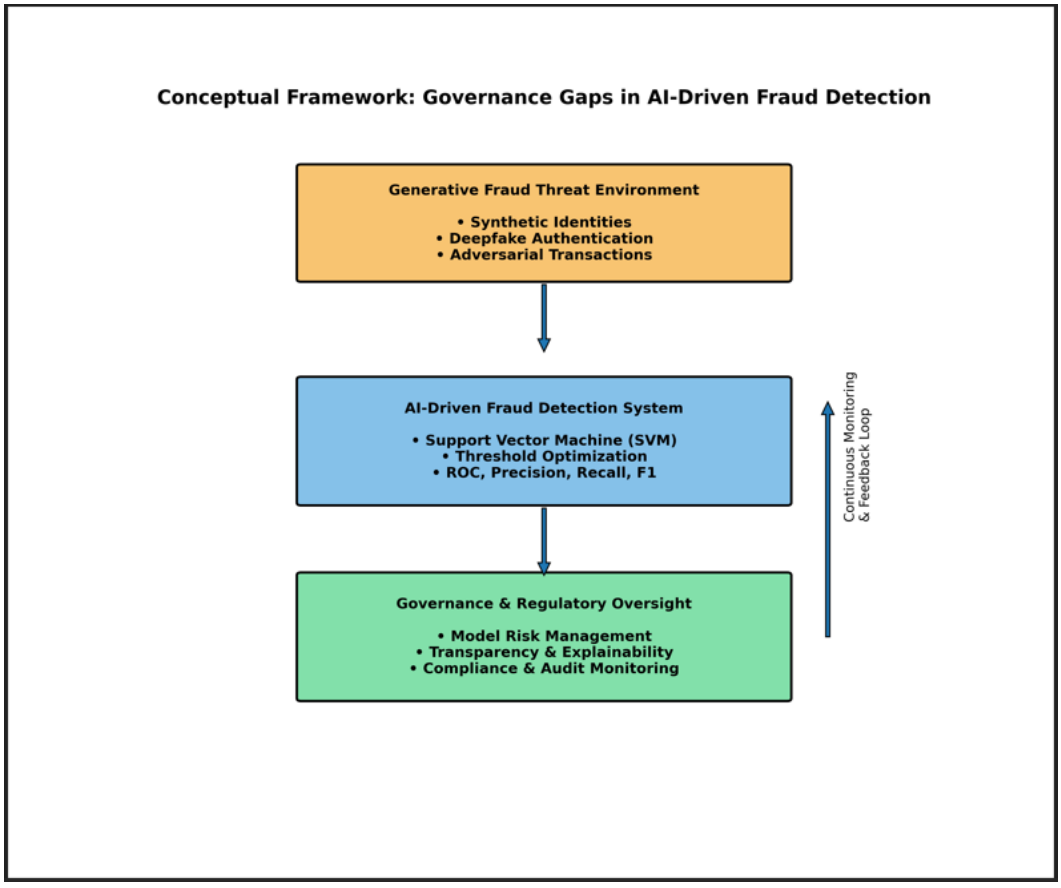
governance. Thus, the performance outcomes are compared with the operational and regulatory effects [61]. The approach focuses on constant monitoring and re-calibration in order to combat changing trends of fraud. It is especially necessary in the case of generative fraud, where adaptive threats can take advantage of fixed detection limits. Adding the robustness assessment will guarantee resilience even after the initial deployment [1]. The study facilitates a governance-refined machine learning model, which can be used to solve predictive reliability, regulatory responsibility, and systemic stability in AI-based financial services.

G. *Limitation and Ethical Implications*

This study has a number of limitations. First, the data is anonymized and geographically concrete, and it might not be applicable to other financial systems [2]. The features that are PCA-transformed are limiting in the sense that they do not allow further study of the behavior of features which are associated with fraud. Also, threshold sensitivity analysis and learning curve analysis also improve the evaluation of robustness, but the study lacks real-time streaming data and live adversarial simulation [3]. Ethically, AI-based fraud detection systems need to strike a balance between customer rights and data protection and fraud prevention [4]. False positives would interfere with the actual dealings, whereas false negatives would lead to incurring financial losses. The implementation of responsible models demands a transparent and fair approach and adherence to the norms of data governance [5]. Moreover, when automated decision-making systems are used, accountability and explainability become a matter of concern. The financial institutions should make sure that AI models are audited on a regular basis, checked against bias, and adjusted to regulatory expectations [6]. To ensure that people have confidence in digital financial infrastructure, the implementation of AI ethics must primarily focus on consumer protection, fairness, and the accountability of institutions.

4. Conceptual Framework

The theoretical framework of this paper will combine artificial intelligence-led fraud recognition systems and governance and regulatory control to solve the new generative fraud threat in the U.S. financial system [7]. The model is organized around three related elements, which are: (1) Generative Fraud Threat Environment, (2) Machine Learning-Based Detection Mechanisms, and (3) Governance and Regulatory Controls. All these elements are dynamically interactive to influence institutional resilience in response to the changing fraud threats [8]. The Generative Fraud Threat Environment is the first level and is the external risk environment that is typified by synthetic identities, transaction manipulation that is adaptive, and adversarial data perturbation. Generative fraud presents active and moving trends that disrupt the conventional detection models that were trained on past data. This type of threat is constant in that it affects the detection systems by modifying the patterns of behavior and the vulnerabilities of the models [9]. The second element, which is Machine Learning–Based Detection Mechanisms, encompasses predictive models, namely, Support Vector Machines (SVM), ensemble methods, and deep learning architectures. Such systems process the characteristics of the transactions in order to distinguish between fraudulent and legitimate transactions [10]. In this layer, threshold optimization, the performance evaluation metrics (precision, recall, F1 score) as well as robustness testing are included as operational control mechanisms. The predictive accuracy is not only needed to make the model work, but also stability is needed in the varying classification thresholds and data distributions [11]. The third element, Governance and Regulatory Controls, is institutional oversight practices such as model risk management, transparency, auditability and compliances. The moderation of the predictive systems by the government is provided by governance that provides the predictive systems to be within the scope of ethical and regulatory governance [12]. It is also enabled with continuous monitoring, threshold calibration policy and adversarial resilience testing to address the arising vulnerabilities [13]. The framework defines governance concept as a supervisory and adaptive control that reacts to technological change. Detection systems and generative threats give rise to a feedback loop that recalibration and alignment of the policies have to be dynamic [14]. Conceptualizing predictive analytics and governance control, the conceptual framework indicates the importance of using technology to achieve a balanced approach to technological performance and accountability, transparency, and systemic stability in AI-powered financial fraud detection settings.

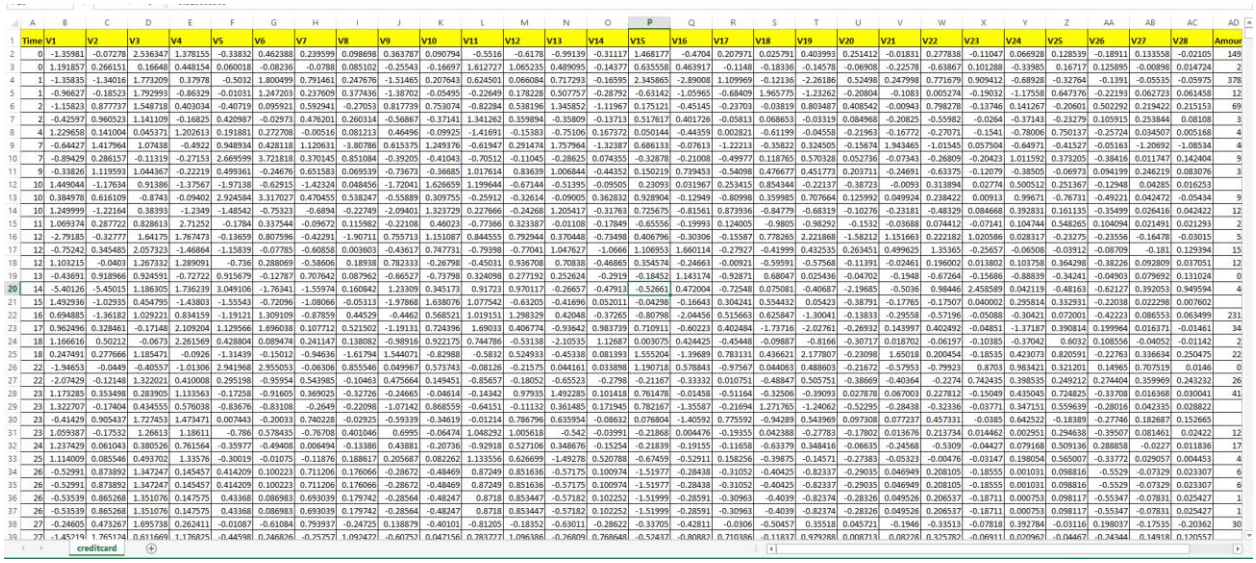


This diagram shows AI-based fraud detection that is controlled by regulatory mechanisms

The concept map depicts the dynamic relationship among the generative fraud threats, artificial intelligence-based threats, fraud detection systems, and the governance oversight systems in the financial ecosystem. On the highest level, the generative fraud environment reflects emerging risks, including synthetic identities, deepfake forms of authentication, and manipulation of transactions adversarially. Such transforming threats keep on testing the conventional fraud detection structures [15]. The main element is the AI-based fraud detection system, which is the Support Vector Machine (SVM) model combined with the threshold optimization and performance evaluation measures like ROC, precision, recall, and F1 score. This layer serves as the working defense mechanism, which identifies and tracks the behavior of transactions. The lowest tier is governance and regulatory supervision that includes model risk management, transparency, compliance, and audit. Governance is considered as a system of supervision as well as a feedback mechanism that guarantees constant control, recalibration and alignment of the regulatory system. All these interlinked elements constitute an enhanced AI-based governance system aimed at increasing resilience to the risks of generative fraud.

5. Dataset

A. *Screenshot of Dataset*



Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	V21	V22	V23	V24	V25	V26	V27	V28	Amount
0	-1.35981	-0.07278	2.536347	1.378155	-0.33832	0.462388	0.239599	0.098698	0.363787	0.090794	-0.5516	-0.6178	-0.99139	-0.31117	1.468177	-0.4704	0.207971	0.025791	0.403993	0.251412	-0.01831	0.277838	-0.11047	0.066928	0.128539	-0.18911	0.133558	-0.02105	149
0	1.191857	0.266151	0.16648	0.448154	0.060018	-0.08236	-0.0788	0.085102	-0.25543	-0.16697	1.612727	1.065235	0.489095	-0.14377	0.635558	0.463917	-0.1148	-0.18336	-0.14578	-0.06908	-0.22578	-0.63867	0.101288	-0.33985	0.16717	0.125895	-0.00898	0.014724	2
1	-1.35835	-1.34016	1.773209	0.37978	-0.5032	1.800499	0.791461	0.247676	-1.51465	0.207643	0.624501	0.066084	0.717293	-0.16595	2.345865	-2.89008	1.109969	-0.12136	-2.26186	0.52498	0.247998	0.771679	0.909412	-0.68928	-0.32764	-0.1391	-0.05535	-0.05975	378
1	-0.96627	-0.18523	1.792993	-0.86329	-0.01031	1.247203	0.237609	0.377436	-1.38702	-0.05495	-0.22649	0.178228	0.507757	-0.28792	-0.63142	-1.05965	-0.68409	1.965775	-1.23262	-0.20804	-0.1083	0.005274	-0.19032	-1.17558	0.647376	-0.22193	0.062723	0.061458	12
2	-1.15823	0.877737	1.548718	0.403034	-0.40719	0.095921	0.592941	-0.27053	0.817739	0.753074	-0.82284	0.538196	1.345852	-1.11967	0.175121	-0.45145	-0.23703	-0.03819	0.803487	0.408542	-0.00943	0.798278	-0.13746	0.141267	-0.20601	0.502292	0.219422	0.215153	69
2	-0.42597	0.960523	1.141109	-0.16825	0.420987	-0.02973	0.476201	0.260314	-0.56867	-0.37141	1.341262	0.359894	-0.35809	-0.13713	0.517617	0.401726	-0.05813	0.068653	-0.03319	0.084968	-0.20825	-0.55982	-0.0264	-0.37143	-0.23279	0.105915	0.253844	0.08108	3
4	1.229658	0.141004	0.045371	1.202613	0.191881	0.272708	-0.00516	0.081213	0.46496	-0.09925	-1.41691	-0.15383	-0.75106	0.167372	0.050144	-0.44359	0.002821	-0.61199	-0.04558	-0.21963	-0.16772	-0.27071	-0.1541	-0.78006	0.750137	-0.25724	0.034507	0.005168	4
7	-0.64427	1.417964	1.07438	-0.4922	0.948934	0.428118	1.120631	-3.80786	0.615375	1.249376	-0.61947	0.291474	1.757964	-1.32387	0.686133	-0.07613	-1.22213	-0.35822	0.324505	-0.15674	1.943465	-1.01545	0.057504	-0.64971	-0.41527	-0.05163	-1.20692	-1.08534	4
7	-0.89429	0.286157	-0.11319	-0.27153	2.669599	3.721818	0.370145	0.851084	-0.39205	-0.41043	-0.70512	-0.11045	-0.28625	0.074355	-0.32878	-0.21008	-0.49977	0.118765	0.570328	0.052736	-0.07343	-0.26809	-0.20423	1.011592	0.373205	-0.38416	0.011747	0.142404	9
9	-0.33826	1.119593	1.044367	-0.22219	0.499361	-0.24676	0.651583	0.069539	-0.73673	-0.36685	1.017614	0.83639	1.006844	-0.44352	0.150219	0.739453	-0.54098	0.476677	0.451773	0.203711	-0.24691	-0.63375	-0.12079	-0.38505	-0.06973	0.094199	0.246219	0.083076	3
10	1.449044	-1.17634	0.91386	-1.37567	-1.97138	-0.62915	-1.42324	0.048456	-1.72041	1.626659	1.199644	-0.67144	-0.51395	-0.09505	0.23093	0.031967	0.253415	0.854344	-0.22137	-0.38723	-0.0093	0.313894	0.02774	0.500512	0.251367	-0.12948	0.04285	0.016253	
10	0.384978	0.616109	-0.8743	-0.09402	2.924584	3.317027	0.470455	0.538247	-0.55889	0.309755	-0.25912	-0.32614	-0.09005	0.362832	0.928904	-0.12949	-0.80998	0.359985	0.707664	0.125992	0.049924	0.238422	0.00913	0.99671	-0.76731	-0.49221	0.042472	-0.05434	9
10	1.249999	-1.22164	0.38393	-1.2349	-1.48542	-0.75323	-0.6894	-0.22749	-2.09401	1.323729	0.227666	-0.24268	1.205417	-0.31763	0.725675	-0.81561	0.873936	-0.84779	-0.68319	-0.10276	-0.23181	-0.48329	0.084668	0.392831	0.161135	-0.35499	0.026416	0.042422	12
11	1.069374	0.287722	0.828613	2.71252	-0.1784	0.337544	-0.09672	0.115982	-0.22108	0.46023	-0.77366	0.323387	-0.01108	-0.17849	-0.65556	-0.19993	0.124005	-0.9805	-0.98292	-0.1532	-0.03688	0.074412	-0.07141	0.104744	0.548265	0.104094	0.021491	0.021293	2
12	-2.79185	-0.32777	1.64175	1.767473	-0.13659	0.807596	-0.42291	-1.90711	0.755713	1.151087	0.844555	0.792944	0.370448	-0.73498	0.406796	-0.30306	-0.15587	0.778265	2.221868	-1.58212	1.151663	0.222182	1.020586	0.028317	-0.23275	-0.23556	-0.16478	-0.03015	5
12	-0.75242	0.345485	2.057323	-1.46864	-1.15839	-0.07785	-0.60858	0.003603	-0.43617	0.747731	-0.79398	-0.77041	1.047627	-1.0666	1.106953	1.660114	-0.27927	-0.41999	0.432535	0.263451	0.499625	1.35365	-0.25657	-0.06508	-0.03912	-0.08709	-0.181	0.129394	15
12	1.103215	-0.0403	1.267332	1.289091	-0.736	0.288069	-0.58606	0.18938	0.782333	-0.26798	-0.45031	0.936708	0.70838	-0.46865	0.354574	-0.24663	-0.00921	-0.59591	-0.57568	-0.11391	-0.02461	0.196002	0.013802	0.103758	0.364298	-0.38226	0.092809	0.037051	12
13	-0.43691	0.918966	0.924591	-0.72722	0.915679	-0.12787	0.707642	0.087962	-0.66527	-0.73798	0.324098	0.277192	0.252624	-0.2919	-0.18452	1.143174	-0.92871	0.68047	0.025436	-0.04702	-0.1948	-0.67264	-0.15686	-0.88839	-0.34241	-0.04903	0.079692	0.131024	0
14	-5.40126	-5.45015	1.186305	1.736239	3.049106	-1.76341	-1.55974	0.160842	1.23309	0.345173	0.91723	0.970117	-0.26657	-0.47913	-0.52661	0.472004	-0.72548	0.075081	-0.40687	-2.19685	-0.5036	0.98446	2.458589	0.042119	-0.48163	-0.62127	0.392053	0.949594	4
15	1.492936	-1.02935	0.454795	-1.43803	-1.55543	-0.72096	-1.08066	-0.05313	-1.97868	1.638076	1.077542	-0.63205	-0.41696	0.052011	-0.04298	-0.16643	0.304241	0.554432	0.05423	-0.38791	-0.17765	-0.17507	0.040002	0.295814	0.332931	-0.22038	0.022298	0.007602	
16	0.694885	-1.36182	1.029221	0.834159	-1.19121	1.309109	-0.87859	0.445529	-0.4461	0.568521	1.019511	1.298329	0.42048	-0.37265	-0.80798	-2.04456	0.515663	0.625847	-1.30041	-0.18833	-0.29558	-0.57196	-0.05088	-0.30421	0.072001	-0.42223	0.086553	0.063499	231
17	0.962496	0.328461	-0.17148	2.109204	1.129566	1.696038	0.107712	0.521502	-1.19131	0.724396	1.69033	0.406774	-0.93642	0.983739	0.710911	-0.60223	0.402484	-1.73716	-2.02761	-0.26932	0.143997	0.402492	-0.04851	-1.37187	0.390814	0.199964	0.016371	-0.01461	34
18	1.166616	0.50212	-0.0673	2.261569	0.428804	0.089474	0.241147	0.138082	-0.98916	0.922175	0.744786	-0.53138	-2.10535	1.12687	0.003075	0.424425	-0.45448	-0.09887	-0.8166	-0.30717	0.018702	-0.06197	-0.10385	-0.37042	0.6032	0.108556	-0.04052	-0.01142	2
18	0.247491	0.277666	1.185471	-0.0926	-1.31439	-0.15012	-0.94636	-1.61794	1.544071	-0.82988	-0.5832	0.524933	-0.45338	0.081393	1.555204	-1.39689	0.783131	0.436621	2.177807	-0.23098	1.65018	0.200454	-0.18535	0.423073	0.820591	-0.22763	0.336634	0.250475	22
22	-1.94653	-0.0449	-0.40557	-1.01306	2.941968	2.955053	-0.06306	0.855546	0.049967	0.573743	-0.08126	-0.21575	0.044161	0.033898	1.190718	0.578843	-0.97567	0.044063	0.488603	-0.21672	-0.57953	-0.79923	0.8703	0.983421	0.321201	0.14965	0.707519	0.0146	0
22	-2.07429	-0.12148	1.322021	0.410008	0.295198	-0.95954	0.543985	-0.10463	0.475664	0.149451	-0.85657	-0.18052	-0.65523	-0.2798	-0.21167	-0.33332	0.010751	-0.48847	0.505751	-0.38669	-0.40364	-0.2274	0.742435	0.398535	0.249212	0.274404	0.359969	0.243232	26
23	1.173285	0.353498	0.283905	1.133563	-0.17258	-0.91605	0.369025	-0.32726	-0.24665	-0.04614	-0.14342	0.97935	1.492285	0.101418	0.761478	-0.01458	-0.51164	-0.32506	-0.39093	0.027878	0.067003	0.227812	-0.15049	0.435045	0.724825	-0.33708	0.016368	0.030041	41
23	1.322707	-0.17404	0.434555	0.576038	-0.83676	-0.83108	-0.2649	-0.22098	-1.07142	0.868559	-0.64151	-0.11132	0.361485	0.171945	0.782167	-1.35587	-0.21694	1.271765	-1.24062	-0.52295	-0.28438	-0.32336	-0.03771	0.347151	0.559639	-0.28016	0.042335	0.028822	
23	-0.41429	0.905437	1.727453	1.473471	0.007443	-0.20033	0.740228	-0.02925	-0.59339	-0.34619	-0.01214	0.786796	0.635954	-0.08632	0.076804	-1.40592	0.775592	-0.94289	0.543969	0.097308	0.077237	0.457331	-0.0385	0.642522	-0.18389	-0.27746	0.182687	0.152665	
24	1.059387	-0.17532	1.26613	1.18611	-0.786	0.578435	-0.76708	0.401046	0.6955	-0.06474	1.048292	1.005618	-0.542	-0.03991	-0.21868	0.004476	-0.19355	0.042388	-0.27783	-0.17802	0.013676	0.213734	0.014462	0.002951	0.294638	-0.39507	0.081461	0.02422	12
24	1.237429	0.061043	0.380526	0.761564	-0.35977	-0.49408	0.006494	-0.13386	0.43881	-0.20736	-0.92918	0.527106	0.348676	-0.15254	-0.21839	-0.19155	-0.11658	-0.63379	0.348416	-0.06635	-0.24568	-0.5309	-0.04427	0.079168	0.509136	0.288858	-0.0227	0.011836	17
25	1.114009	0.085546	0.493702	1.33576	-0.30019	-0.01075	-0.11876	0.188617	0.205687	0.082262	1.133556	0.626699	-1.49278	0.520788	-0.67459	-0.52911	0.158256	-0.39875	-0.14571	-0.27383	-0.05323	-0.00476	-0.03147	0.198054	0.565007	-0.33772	0.029057	0.004453	4
26	-0.52991	0.873892	1.347247	0.145457	0.414209	0.100223	0.711206	0.176066	-0.28672	-0.48469	0.87249	0.851636	-0.57175	0.100974	-1.51977	-0.28438	-0.31052	-0.40425	-0.82337	-0.29035	0.046949	0.208105	-0.18555	0.001031	0.098816	-0.5529	-0.07329	0.023307	6
26	-0.52991	0.873892	1.347247	0.145457	0.414209	0.100223	0.711206	0.176066	-0.28672	-0.48469	0.87249	0.851636	-0.57175	0.100974	-1.51977	-0.28438	-0.31052	-0.40425	-0.82337	-0.29035	0.046949	0.208105	-0.18555	0.001031	0.098816	-0.5529	-0.07329	0.023307	6
26	-0.53539	0.865268	1.351076	0.147575	0.43368	0.086983	0.693039	0.179742	-0.28564	-0.48247	0.8718	0.853447	-0.57182	0.102252	-1.51999	-0.28591	-0.30963	-0.4039	-0.82374	-0.28326	0.049526	0.206337	-0.18711	0.000753	0.098117	-0.55347	-0.07831	0.025427	1
26	-0.53539	0.865268	1.351076	0.147575	0.43368	0.086983	0.693039	0.179742	-0.28564	-0.48247	0.8718	0.853447	-0.57182	0.102252	-1.51999	-0.28591	-0.30963	-0.4039	-0.82374	-0.28326	0.049526	0.206337	-0.18711	0.000753	0.098117	-0.55347	-0.07831	0.025427	1
27	-0.24605	0.473267	1.695738	0.262411	-0.01087	-0.61084	0.793937	-0.24725	0.138879	-0.40101	-0.81205	-0.18352	-0.63011	-0.28622	-0.33705	-0.42811	-0.0306	-0.50457	0.35518	0.045721	-0.1946	-0.33513	-0.07818	0.392784	-0.03116	0.198037	-0.17535	-0.20362	30
27	-1.45219	1.765174	0.611669	1.176825	-0.44598	0.246826	-0.25757	1.092477	-0.60752	0.047156	0.783727	1.096388	-0.26809	0.768648	-0.52437	-0.80882	0.710386	-0.11837	0.979288	0.008713	0.08228	0.325782	-0.06911	0.020962	-0.04467	-0.24344	0.14918	0.120557	

creditcard

(Source Link: https://www.kaggle.com/datasets/mlg-ulb/creditcardfraud)

B. *Dataset Overview*

The dataset that is used in this study is publicly available and is known as Credit Card Fraud Detection dataset, which has been extensively exploited by financial fraud analytics investigations. The data consists of 284,807 credit card transactions that took place in two days with 492 of those transactions being of a type that can be called a fraudulent transaction. This creates a very unequal distribution of the classes as the cases of fraud constitute around 0.172 percent of the observation [16]. The extreme imbalance reflects actual financial settings in the real world in which fraudulent practices constitute by far a very insignificant portion of total transactions volume but have a disproportionately large financial and operational risk. The data is in the form of 30 predictive variables and one categorical target. V1-V28 are the anonymized variables of a Principal Component Analysis (PCA) transformation. The sensitive financial information was guarded by the process of PCA to maintain the user confidentiality. Although such a transformation makes sure that privacy is taken care of, it also causes restrictions on the straightforward interpretability of individual feature contributions. Nonetheless, PCA components do not lose the underlying variance structure needed to undertake machine learning classification. Besides the variables in PCA form of transformation, we have two original features, namely, Time and Amount. Time variable is the time that has taken seconds between each transaction and the first time that a transaction was recorded in the dataset. This variable allows the time analysis and can reflect the sequential pattern of transactions. The Amount variable is the financial representation of each transaction, which is especially pertinent to the cost-sensitive learning and the financial risk evaluation [17]. The target variable which is Class is binary in nature, 1 corresponding to a fraudulent transaction and 0 to a legitimate transaction. The unequal allocation of this variable is a major modeling problem. Conventional accuracy-based assessment would be illusory because a simple classifier that forecasts all the transactions to be legitimate will get a high score but will miss out on fraud. Hence, measures of performance like accuracy, recall, F1 score and ROC-AUC are necessary to make a significant evaluation. No missing values are provided in the dataset and this aspect eliminates the imputation methods [62]. The algorithms like the Support Vector Machines are sensitive to the magnitude of features and in this case, preprocessing techniques like feature scaling are required. Train-test splitting is done through stratified sampling to ensure that the cases of fraud are proportionately represented. In general, the data is realistic and challenging to assess the machine learning-based fraud detection models. It has a high dimensionality, is anonymized, and has a severe class imbalance, which closely resembles operational financial systems and, therefore, is applicable to the investigation of predictive performance, threshold sensitivity, and governance resilience in AI-based fraud detection studies.

6. Results

The empirical findings reveal that the Support Vector Machine (SVM) model has a high performance when identifying fraudulent transactions in a highly imbalanced financial data. The ROC analysis shows that there is great discriminative ability, as the AUC value is large, which represents trustworthy separation of fraudulent and legal transactions [17]. The Precision-Recall assessment also proves that it has a strong performance even when there is an imbalance between the classes, and can keep high precision and still can retain a large recall at the same time [18]. The confusion matrix reveals that there are only a few false

positives and quite a few false negatives, which demonstrates that the fraud detection is successful with a controlled operational risk [19]. Optimal operating region demonstrated by threshold-based analyses of recall and F1 score is helpful in making informed decisions. In general, the SVM model is characterized by such strong predictive accuracy, balanced sensitivity, and practically applicable in a regulated financial environment in order to use AI-driven fraud detection.

A. *Receiver Operating Characteristic (ROC) Analysis of SVM Model*

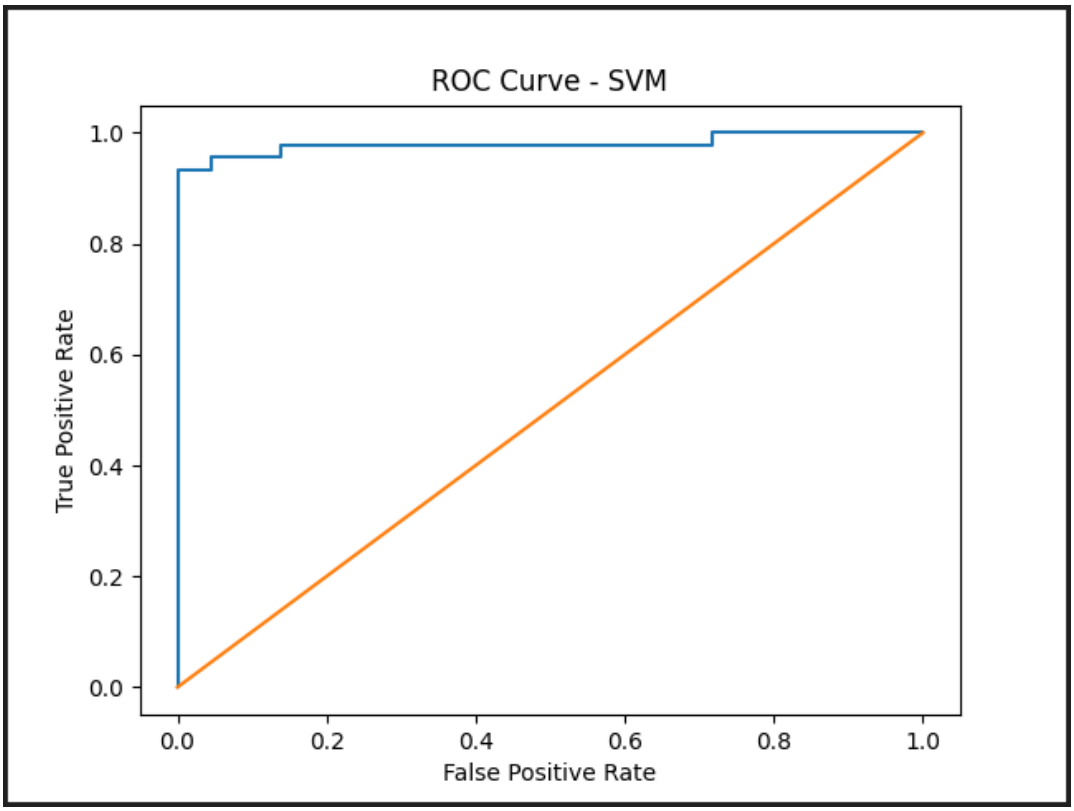


Figure 1: This image demonstrates on the ROC curve great performance in terms of SVM fraud detection

The Support Vector Machine (SVM) model used in the fight against fraudulent and non-fraudulent credit card transactions was the curve shown in Figure 1 (the Receiver Operating Characteristic or ROC curve). The ROC curve represents the trade off between the True Positive rate (Sensitivity) and the False Positive rate at different levels of classification. This measure is especially significant in the context of fraud detection studies since the dataset of financial transactions is in great imbalance with the number of fraud cases being an extremely minuscule fraction of the total number of observations. Very high discriminative performance is depicted by the steep increase of the curve in Figure 1 to the upper-left corner of the graph [20]. The high increase rate of True Positive at very low False Positive rates is a good indication that the SVM model has the ability to detect fraudulent transactions with minimal misplaced legitimate transactions. This behavior plays a fundamental role in the financial context, where false positives are too many and would affect the transactions with customers and raise regulatory issues. Under ROC, the area (AUC) is about 0.98 meaning excellent capability of classification. A value of AUC nearer to 1.0 means that there is a good likelihood of the model ranking correctly a fraudulent transaction chosen at random higher than a legitimate transaction chosen at random [21]. This kind of performance indicates that the SVM model is effective in terms of giving strong separation between the two classes even in the event of extreme class imbalance. Governance-wise, the excellent ROC performance serves as an indicator of the accuracy of AI-based mechanisms of detection. Nonetheless, high predictive accuracy is preferable, though it has to be accompanied by interpretability and robustness issues to promote regulatory compliance and accountability. Generally, ROC analysis proves that the SVM model proves to be highly sensitive and generally effective in overall classification of fraudulent financial transactions.

B. ***The SVM Model Analysis by Curve Analysis of Precision-Recall***

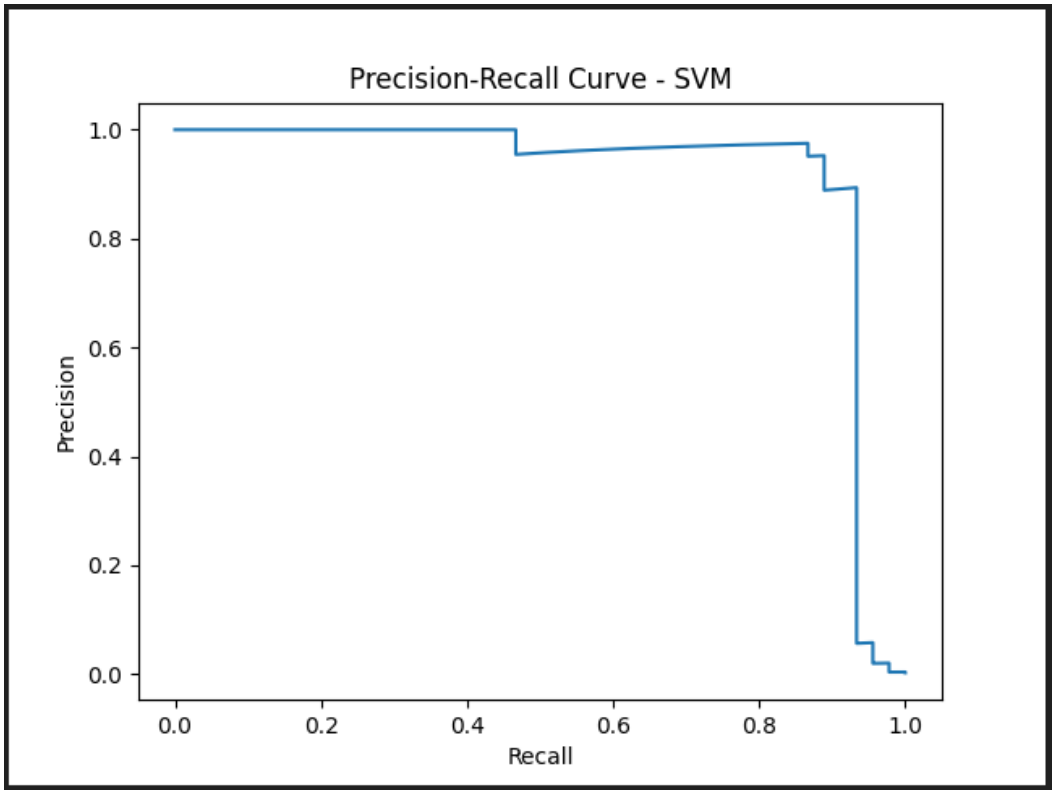


Figure 2: This image illustrates the Precision Recall curve SVM performance in case of class imbalance

Figure 2 is a Precision-Recall (PR) curve of the Support Vector Machine (SVM) model used to detect credit card fraud. The Precision Recall curve is especially appropriate to use in highly imbalanced databases, in which the proportion of fraudulent transactions is very low, in contrast to the ROC curve, which examines the trade-off between the rate of true positives and false positives. Precision and recall are also more informative evaluations of model effectiveness in these situations. Figure 2 shows that the PR curve is performing well at a large scale of recall values [20]. Precision is very high, to the order of 1.0, at lower and moderate recall levels, which means that when the model results that a transaction is fraudulent, then it is very probable that it is correct. This is essential in a financial establishment, where a valid operation can be derailed by false allegations of fraud and this can affect customer confidence adversely [21]. The closer a recall is to higher values a gradual decrease in precision is noticed. This practice is indicative of the common trade-off of recalling more fraudulent cases (higher recall) versus upholding accuracy of classification (precision). Precision declines more rapidly at very high recall levels which indicates that the false positive risk increases as one vigorously works on identifying all the fraudulent cases. This trend underscores the need to adopt an optimal decision threshold that focuses on the performance of the organization and governance issues [21]. The curve shows that the SVM model can be used to achieve good levels of detection of fraud in extreme conditions of imbalance in the classes. Its accuracy at realistic rates of recall is an indicator of its applicability in fraud monitoring systems. But, in the governance dimension, threshold optimization is imperative to guarantee regulatory adherence, to have minimal customer inconvenience, and accountability within AI-based decision-making procedures.

C. *SVM Model Evaluation using the confusion matrix*

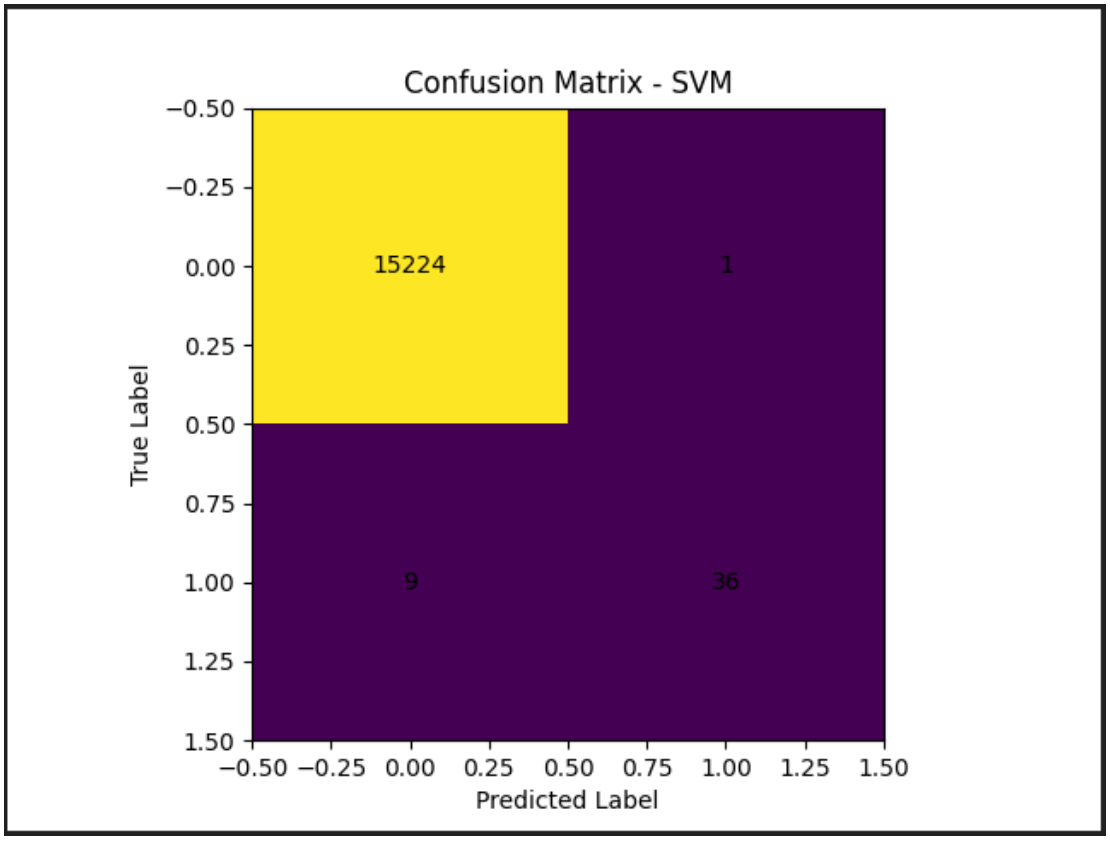


Figure 3: This image displays the distribution of accuracy of SVM detection of fraud

Figure 3 shows the confusion of the Support Vector Machine (SVM) model when applied on credit card fraud detection dataset. The confusion matrix offers an in-depth division of classification performance where results of predicted classes are contrasted with the real classes in which transactions are to occur. This assessment measure is extremely useful in fraud detection studies, since it draws attention to the distribution of true positives, true negatives, false positives, and false negatives in the context of extreme class imbalance. The model was able to correctly classify 15,224 legitimate transactions as non-fraudulent (True Negatives), and correctly identified 36 fraudulent transactions (True Positives) as shown in Figure 3. There was 1 false alarm of a legitimate transaction being classified as fraudulent (False Positive) and 9 cases of a fraudulent transaction being classified as a legitimate transaction (False Negatives). These outcomes show that this is a very good model in general, and especially in reducing false alarms. The very few false positives show high precision and it is also vital in financial systems where false positives may lead to a discrediting effect on the customers and the efficiency and performance of the business [21]. Simultaneously, the number of false negatives that equals 9 suggests the necessity of the inherent difficulty of all fraud cases being detected in datasets that are highly imbalanced. In the risk management view, false negatives can be seen as possible financial losses and vulnerability of the system [22]. The confusion matrix affirms the fact that the SVM model attains a good balance between sensitivity and specificity. It has a high level of fraud detection but has reduced interference with the legitimate users. Nonetheless, governance aspects demand continuous tracking and conclusion optimization in order to minimize undetected fraud to any further extent without raising the false positive. Comprehensively, the results of the confusion matrix analysis confirm the solidity and the usefulness of the SVM model in AI-based fraud detection systems.

D. *Accurate Performance analysis of the SVM Model*

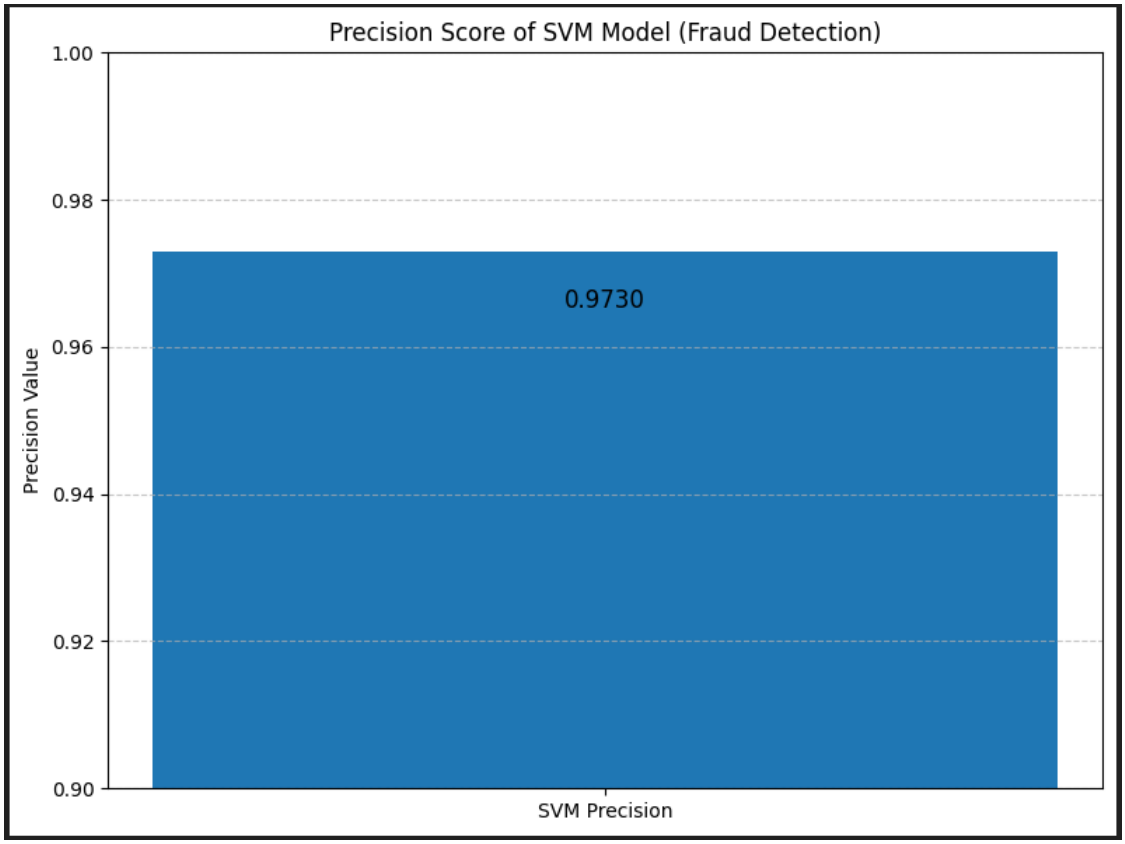


Figure 4: This image shows the recession score with high accuracy in predicting fraud of SVM

Figure 4 demonstrates the accuracy of the Support Vector Machine (SVM) model created to detect credit card frauds. Precision is used to measure the percentage of correct fraudulent transactions of all fraudulent transactions that the model predicted. Precision is an important evaluation measure in highly imbalanced data, like in the case of financial fraud detection where non-fraudulent transactions greatly outnumber fraudulent transactions. Figure 4 demonstrates that the SVM model has a precision score of 0.9730, which means that about 97.3 percent of the transactions that are predicted to be fraudulent are actually fraudulent. This large value accuracy signifies that this model is very good in the ability to not misclassify legitimate transactions as fraud. In real world financial situations, it is necessary to reduce false positives to avoid unwarranted blocks of transactions, customer dissatisfaction and inefficiency in operations. A low precision model may cause over manual review and reputational risk especially in the regulated financial systems [23]. The level of near-optimal precision, which the zoomed scale in the chart indicates, underlines the high level of reliability in which the model is effective in making fraud flagging decisions. Governance wise, this high precision indicates compliance to regulatory standards by minimizing unnecessary disruption of customers and conforming to the consumer protection requirements [24]. Although the precision is high, it should be compared to recalls and F1 scores in order to make sure that fraudulent cases should not be disregarded. The findings suggest that the SVM model is effective in controlling false alarms and at the same time, it has high capabilities of detecting fraud. The balance is essential in the case of AI-based fraud detection systems that are used in the U.S. financial system, where the efficiency of operations and regulatory responsibility are essential.

E. *Recall Sensitivity Analysis Life-Cycles Thresholds*

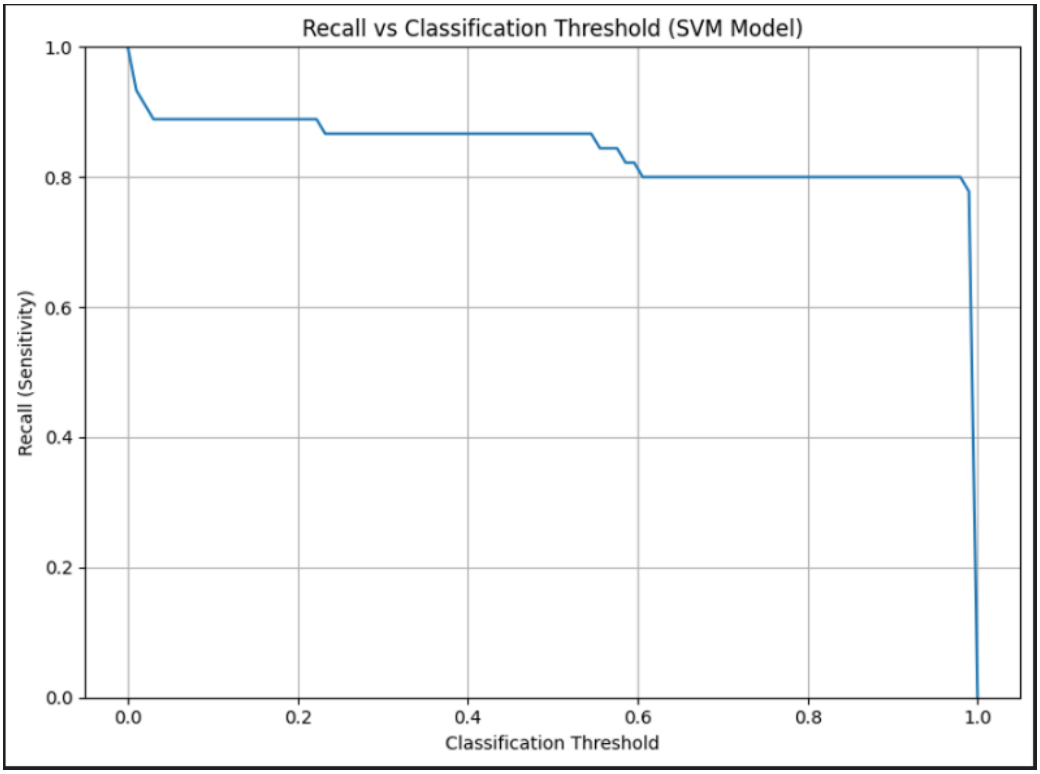


Figure 5: This image shows the learned SVM model recall variation with classification threshold

Figure 5 draws the change of recall (sensitivity) of Support Vector Machine (SVM) model with respect to varying classification thresholds. Recall is an indicator of the percentage of fraudulent transactions that are successfully recognized by the model. Recall is especially significant in a research on fraud detection since it measures the capability of a system to identify fraud cases and reduce false negatives which are directly related with fraud losses that go unidentified. Recall at the lower threshold values is very significant, as it can be seen in Figure 5, with a recall of almost 1.0 at a threshold near zero. This means that almost all the fraudulent transactions are recorded when the model takes a permissive classification boundary. Such low thresholds however can also create more false positives, thereby affecting customer experience and operation efficiency [24]. Recall decreases slowly with increase in the classification threshold. This trend shows the trade-off nature between sensitivity and selectivity. Recall levels off at a relatively high rate around moderate threshold levels (around 0.4 to 0.7) suggesting that the model is still able to offer a high quality of fraud detection whilst possible false positive levels may be lowered. Recall deteriorates drastically at very high threshold values near 1.0 which implies that the model is too conservative and cannot detect most cases of fraud. This is an important analysis in terms of governance and risk management. The choice of the right threshold requires a tradeoff between the effectiveness of the fraud detection and the regulatory compliance and protection of customers [25]. Low recall can put institutions under the financial and reputational risks of unnoticed fraud, whereas very high recall but with low accuracy can create disruptions in the operations. In general, the figure indicates that the SVM model has a good sensitivity performance with a wide range of threshold, which shows its appropriateness to be used in a controlled application of AI-based fraud detection systems.

F. *Optimization of F1 Score with Varying Classification Thresholds*

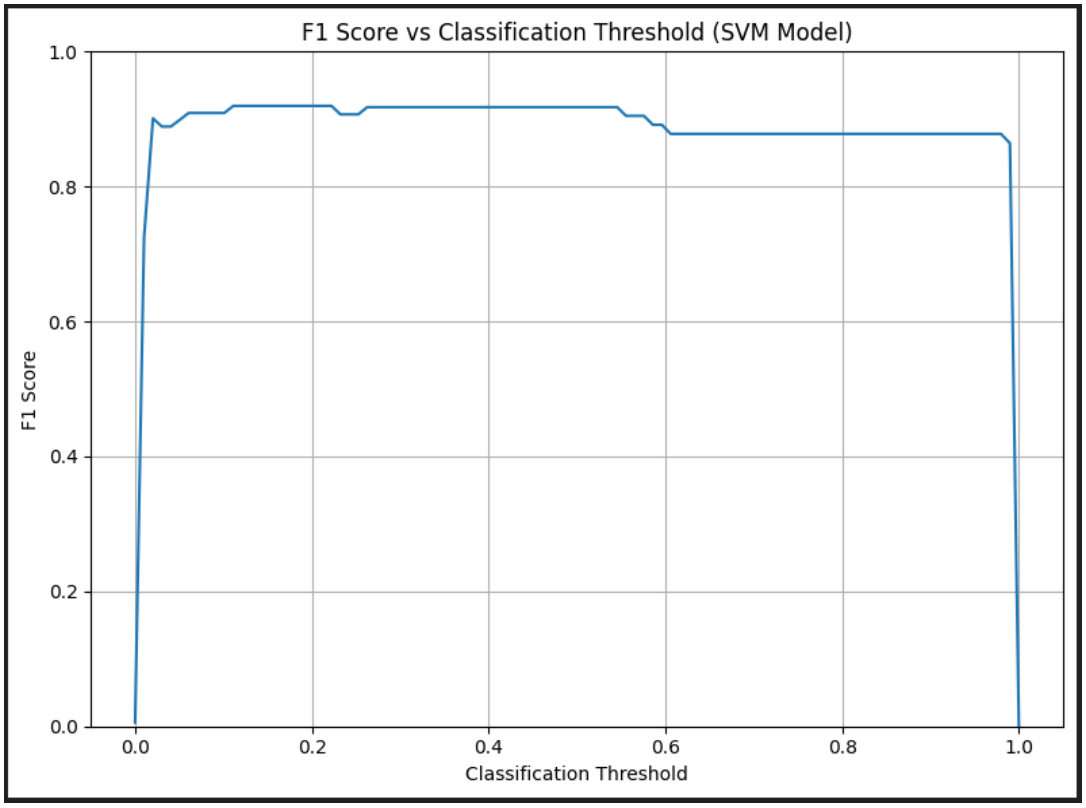


Figure 6: This image shows the Variation of the F1 score of SVM with classification thresholds

The F1 score of the Support Vector Machine (SVM) model at various classification thresholds is shown in Figure 6. F1 score is the harmonic mean of precision and recall measures, which is a convenient balance evaluation measure in strongly unbalanced datasets like credit card fraud detection. Fraudulent transactions amount to a very small percentage of overall observations thus accuracy is not a measure of complete performance hence the F1 score is an even more inclusive performance measure as it takes false positives and false negatives into account. As it can be seen in Figure 6, F1 score rises dramatically near zero with very low threshold values and soon after that the level becomes high above 0.85. This curve has an optimal range of the threshold (between 0.1 and 0.6) where the F1 score is always high. It means that the SVM model has a good balance of identifying fraudulent transactions (recall) and reducing the wrongful fraud warnings (precision). After reaching a higher threshold (around 0.6), the model decreases in its F1 score gradually, indicating that it becomes more conservative in its classification of transactions as fraudulent [26]. The F1 score declines drastically at very high threshold values near 1.0 because most of the fraud cases are not identified by the model. Such a trend validates the need to identify an optimal threshold that can be used to attain a high level of detection efficiency without jeopardizing the operational stability [27]. Governance and risk management wise, the F1 threshold analysis is important. It gives empirical data to aid in decision-making on model deployment and operational cut off points. The findings indicate that the SVM model has a robust and stable output within a wide range of thresholds, which supports its relevance in fraud detection using AI in any regulated financial system.

G. *Combined Precision Recall F1 Visualization*

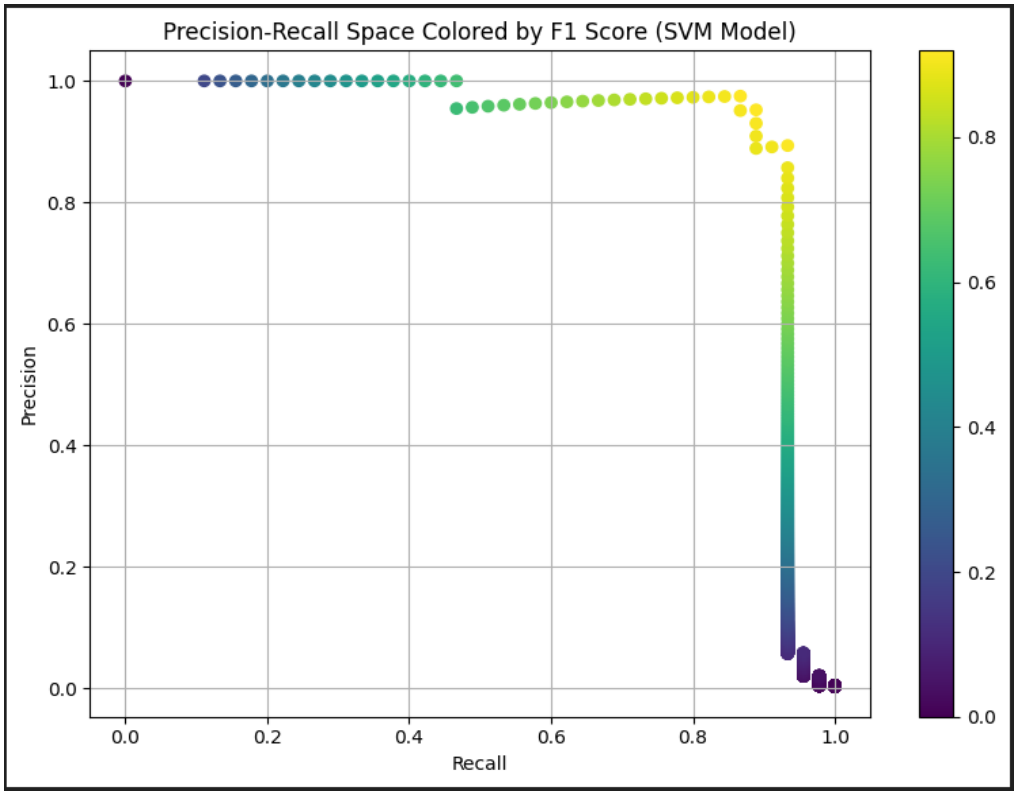


Figure 7: This image depicted to the precision-Recall space coloring with F1 score performance

A detailed plot of the Precision- Recall space of the Support Vector Machine (SVM) model is shown in Figure 7, where the points are colored in accordance to their respective F1 scores. It is a multidimensional representation, which combines three essential performance measures, such as precision, recall, and F1 score, into one analytic structure. These visualizations can be especially useful in detecting fraud datasets that are very imbalanced, and using a single measure of performance can result in a poor interpretation of model performance. The values of recall are plotted on the horizontal axis and the values of precision are plotted on the vertical axis in the figure. The color gradient signifies the level of the F1 score where the darker the color is the lower the performance [28]. The visualization bit shows that the SVM model attains its optimum F1 scores in a range between the balanced ranges in terms of precision and recall. This optimal operating region shows that the model is excellent in capturing fraudulent transactions and the rate of false positives is low. The closer the recall is to extreme values near to 1.0, the lower the precision, which leads to lower F1 scores. The trade-off between the types of aggressively identifying all cases of fraud and maintaining classification accuracy is depicted through this behavior. At low recall levels, the precision is high, but the F1 score is low because it does not have a sufficient coverage of fraud detection. This combined analysis is useful in terms of governance and operational considerations to aid in making informed threshold selections [29]. It also graphically determines the most effective balance between detecting the sensitivity and predicting the reliability that is crucial to minimizing financial risk without disrupting the customers unnecessarily. Figure 7 shows that the SVM model has a high balanced performance within a wide operating range, which supports the appropriateness of this model to AI-based fraud detection in regulated financial contexts.

H. *Analysis of learning curve of the SVM model*

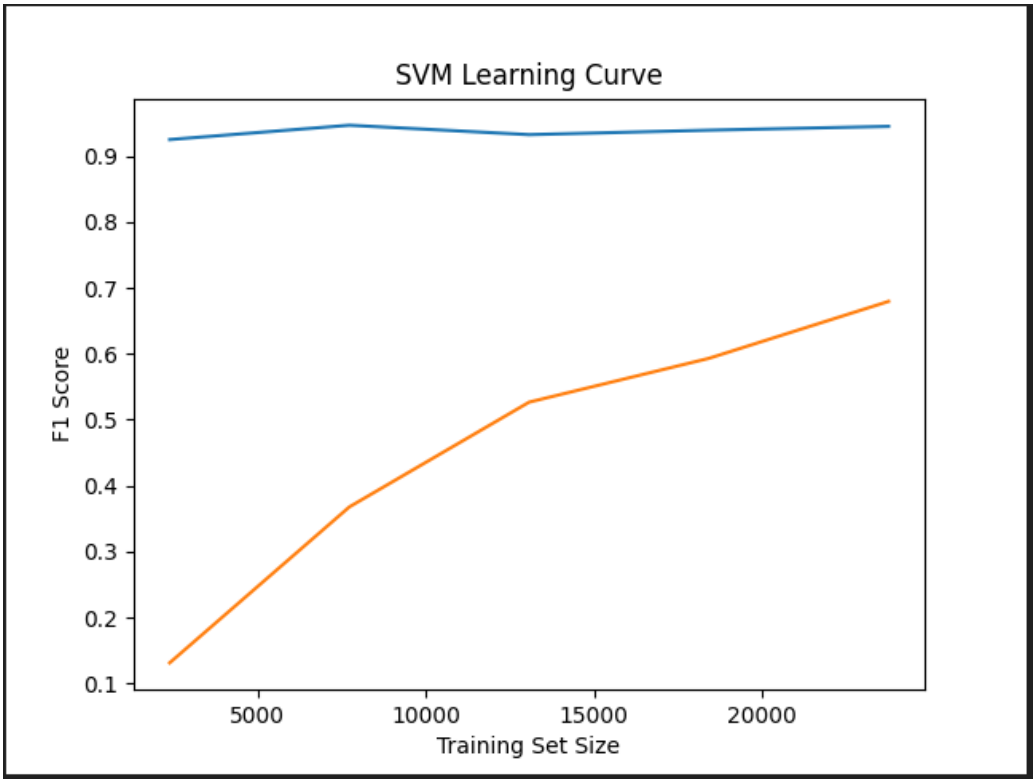


Figure 8: This image illustrate on the learning curve that reveals trends of SVM training and validation

The learning curve of the Support Vector Machine (SVM) model as shown in Figure 8 demonstrates the dependence of the model performance in terms of the F1 score on the size of the training set. The learning curve will give an insight of the model generalization, convergence behavior and possible overfitting or under fitting. Two curves are shown: the training performance and the validation (cross-validation) performance at a successively increasing sample size. As depicted in the figure, training F1 score is always high and it is higher than 0.90 in all the sizes of the training sets. This implies that the SVM model is effective to represent underlying patterns in the training data. The fact that the training curve remains relatively stable is an indication that the model does not over fit heavily to the small subsets of the data. Conversely, the F1 score of validation begins at a low score with the small training sample and as more data is obtained, this score increases steadily [29]. This positive trend shows better generalization capacity since the model is exposed to bigger and more varied training samples. The decreasing difference between the training and validation curves means that the model is more useful with more data and the variance is progressively less. The fact that the gap between the two curves is moderate but the convergence is constant is an indication that the overall performance is satisfactory in terms of generalization and not severe overfitting. Governance and operational perspective This analysis at least indicates the fact that the SVM model works under realistic deployment conditions [30]. The findings suggest that more data can be used to augment detection resilience which is necessary in dynamic fraud settings that are subject to generative threats. In general, it is clear that the learning curve validates that the SVM model provides consistent training behavior and also shows enhanced generalization with increase in data volume which supports the applicability of the model in scalable AI-based fraud detection systems.

7. Discussion and Analysis

A. *Class Imbalance Model Performance*

The results of the experiment show that the Support Vector Machine (SVM) model is resistant to the harsh class imbalance existing in the dataset used in detecting fraud. Frauds constitute a very low percentage of total observations, which usually makes it difficult to apply conventional classification models. The good Precision and Recall and the high ROC-AUC value indicates that SVM model is capable of differentiating between lawful and fraud transactions. Notably, precision, recall, and F1 use a more meaningful interpretation than before [31]. The confusion matrix shows that the false positives are few and the false negatives are rather few hence balanced detection performance. False positives in financial systems can eliminate valid transactions and destroy customer confidence, whereas false negatives are untapped fraud and loss of money. The SVM model shows good accuracy (reducing false alarm) and reasonable recall (detection of fraud cases). These findings are even reinforced

by the use of threshold-based analysis. The model has high F1 scores within a wide classification threshold range, which shows operational flexibility [32]. This is especially necessary in practice implementation where institutions can tailor thresholds to risk appetite, regulatory or operational restrictions. Methodologically, these findings confirm the applicability of SVM to high dimensional financial data. The kernel-based framework permits the successful separation of boundaries in the case of nonlinear and subtle fraud patterns [33]. The model is technically robust to imbalanced conditions and this is a solid basis of analysis in matters of governance.

B. *Precision Recall Trade-off and Implication on Operation*

The Precision-Recall analysis demonstrates the inherent trade off between the sensitivity and predictive reliability of fraud detection [34]. Huge accuracy will guarantee that flagged transactions are actually fraudulent, thus minimizing the unwarranted customer distraction. High recall, in its turn, will guarantee that a majority of fraudulent activities are identified. The results of the experiments indicate that the SVM model exemplifies maximum F1 in the moderate range of the threshold, in which the metrics are balanced. The more the recall goes towards the extreme values, the less is the precision, which means a rise in false positives [35]. This trade-off is essential in the situations of financial governance. Based on regulatory compliance, customer protection standards, and financial tolerance of risk, the institutions need to establish acceptable error margins [36]. Excessive detection practices can result in inefficiency in operations and loss of reputation and inadequate detection practices can make institutions vulnerable to losses on fraud. Actionable insights in regards to model deployment are given by the threshold sensitivity curves. Instead of using the default probability cut-off, decision-makers have the opportunity to select the thresholds based on the institutional risk frameworks [37]. The dynamic calibration is better at promoting model effectiveness and governance alignment. Transparency and accountability are supported by using threshold analysis in the fraud detection systems [38]. Regulators are demanding more and more documentation of logic of decisions and performance validation [39]. Compliance and model risk management practices are enhanced by the fact that the selection of threshold can be justified using empirical analysis. Thus, the analysis of the precision-recall trade-off is not just technically important, but has a strategic necessity.

C. *Gaps in AI-driven fraud detection In governance*

Although the SVM model has high predictive performance, the results show that the wider issue of AI implementation in financial systems has to do with underlying governance issues [40]. The successful machine learning models are usually black-box systems that restrict interpretability and transparency. Explainability in controlled financial settings is important in audit procedures, customer dispute management and in compliance management [41]. The current governance structures focus on the validation of model, monitoring of performance, and documentation. But these structures might not be completely comprehensive of adversarial weaknesses or generative fraud risks [42]. Generative AI presents risky situations that go beyond the conventional model risk management processes. Adaptive manipulation may be used to manipulate the weakness of the models by fraudsters who can test the impossibility of the static validation mechanisms [43]. The threshold optimization analysis and learning curve analysis indicate the necessity of constant monitoring. Models should be reworked because the patterns of fraud change. Performance auditing, adversarial stress evaluation and periodic robustness testing should hence be introduced in governance structures [44]. The lack of transparency in decision-making by AI is also a burning problem. Institutions need to play off predictive complexity and interpretability. Even high-performing models might be subject to scrutiny by the regulators without adequate mechanisms of elucidation [45]. As a result, there are still governance gaps on issues like adversarial resilience, explainable AI integration and standardized robustness testing.

D. *Generative Fraud implication on Model Robustness*

Generative fraud is a dynamic risk that may change in accordance with detection models. The SVM model itself is doing quite well in the conditions of the existing dataset, but there is a possibility that the generative techniques will shift patterns of transactions to traverse the boundaries of what is learned [46]. Adversarial manipulation can use minimal changes to the feature space, causing wrong classification. The learning curve analysis shows that the generalization of the model to bigger datasets is better, which implies that continuous data combination increases the robustness [47]. Previous data might not reflect new patterns of generative attacks in the future. Thus, it is necessary to include adversarial learning or synthetic fraud simulation. The threshold sensitivity analysis also shows that performance of models significantly increases with variation in decision boundaries [48]. To maximize the probability of evasion, generative attacks may attack particular threshold regions. This explains why active thresholding adjustment and anomaly tracking systems are required. Governance wise, proactive measures are needed against generative fraud [49]. The institutions need to outgrow reactive detection to incorporate proactive robust frameworks. Constant surveillance, stress testing, and integration of explainable AI are the key elements of the long-term strategy of fraud prevention.

E. *Regulatory Alignment and Model Risk Management*

The results highlight how model risk management should be incorporated into an AI-based fraud detecting mechanism. Financial regulations compel financial institutions to substantiate model assumptions, report performance metrics

and track operational risk. The SVM model is valid to the compliance goals as it has a high precision and a high ROC but the process of validation should not stop at the first implementation [50]. Adversarial manipulation, model drift and changing patterns of frauds all require continuous assessment. Results of the learning curve imply that the growth of data volume enhances generalization but the difference between the performance of the training and validation data points to the necessity to perform calibration continuously [50]. The choice of the threshold should also be recorded under governance structures. The operating points adopted in institutions are supposed to be justified using empirical trade-off analyses. This is in line with predictive performance and institutional risk appetite and regulatory expectations. The mechanisms of explainability also enhance alignment of governance. Though SVM models are not transparent in nature, additional interpretability methods may improve auditability [51]. Using explainable AI tools, the institutions will meet the transparency requirements and still remain predictive.

F. *AI and Governance Framework Strategic Integration*

The general discussion has shown that technical excellence in AI-based fraud detection is not enough. Predictive capability and Governance resilience must be aligned in order to effectively deploy [52]. The SVM model has an excellent performance indicator, yet its sustainability is conditional on the well-organized oversight processes. Strategic integration entails inculcating the principles of governance into the model lifecycle such as model development and validation, monitoring and recalibration. The process of threshold optimization, robustness testing and performance auditing need to be recurring processes and not one off assessment [53]. The overlap of AI-based fraud detection and generation brings a pluralistic technological arms race. The institutions have to implement adaptive strategies of governance which can flatten and address the emerging threats. This involves incorporating adversarial simulations, regular stress testing and explainable [54] AI systems into production systems. Finally, the discussion highlights the need for a machine learning structure that has been enhanced with governance [55]. This would allow balancing predictive accuracy against accountability, transparency, and resilience. With the help of aligning AI innovation with regulatory controls, the financial institutions are able to enhance their defenses against generative fraud without jeopardizing trust and systemic stability.

8. Future Work

Although this paper gives a thorough analysis of machine learning tactics and governance in AI-based fraud detection, there are still multiple research opportunities to pursue in this field. Since generative fraud methods keep on improving, future research must address the development of sophisticated adversarial learning methods to improve the resilience of the model [56]. Integration into adversarial training, simulated fraud perspective and robustness stress-testing frameworks would enhance detection systems against adaptive and artificial intelligence-based fraud schemes [57]. The combination of deep learning architectures, e.g. recurrent neural networks (RNNs) and transformer-based models, to model the time- and sequence-dependent transaction behavior, should also be studied in the future [58]. The patterns of fraudulent activities are often dynamic over time, and the ability of sequential modeling to enhance the performance of detection in real time financial settings can be improved [59]. Also, hybrid models based on ensemble with the combination of SVM, gradient boosting or neural networks can increase predictive robustness and decrease model variance. The other direction that is significant is explainable AI (XAI) integration. Because governance and regulatory compliance involves transparency, future research ought to be inspired by the interpretation modeling methods or post-hoc elucidation instruments to advance responsibility in automated decision-making systems [60]. Creation of standardized explainability measures in line with regulatory frameworks would also play a critical role in the model risk management practice. Generalizability would also be enhanced by expanding the investigations to encompass real-time streaming data and cross-institutional data. The data employed in this research is fixed and local. Future studies are advised to look into multi-source financial data and determine how well the models can adapt to a variety of regulatory settings. In addition, the research on governance should examine dynamic threshold adjustment models that are propelled by the institutional risk inclination as well as the regulatory needs. This can be enhanced by automated governance boards that combine performance monitoring, drift detection and compliance reporting. Lastly, research ought to be conducted in the future on ethical consequences, mitigation methods, and fair machine learning in fraud detection systems [61]. With AI being more integrated into the financial decision-making process, the tension between fraud prevention and consumer protection and data privacy will continue to be a major problem. In general, future studies must shift to an all-encompassing, adaptive, and governance-based AI fraud detection ecosystem that would be proactive to generative threat and hold transparency, fairness, and systemic stability.

9. Conclusion

This study has investigated the governance loopholes in AI-based fraud detection systems and appraised the machine learning tactics to counter generative fraud in the financial system. A Support Vector Machine (SVM) model made on a highly skewed dataset of credit card transactions was executed and evaluated by several performance measures, such as ROC-AUC, precision, recall, F1 score, analysis of the confusion matrix, and sensitivity to the threshold. The results of the empirical work

prove that the SVM model has good discriminative and balanced detection properties even when the classes are seriously imbalanced. The findings underline the significance of the precision-recall analysis in contrast to the situation where only accuracy is used when detecting frauds. Optimization of the threshold also showed that the entertainment of the model can vary significantly in diverse classification limits and therefore highlights the importance of strategically calibrating the model in line with institutional risk tolerance. The analysis of the learning curve proved that the generalization behavior remains constant implying that the greater the availability of data the stronger the behavior and the less performance variability. This study highlights the importance of governance in the application of AI besides predictive performance. Effective models only do not suffice to counter the new generative fraud threats. The mechanisms of governance like model risk management, transparency, compliance monitoring and constant recalibration are critical to maintain regulatory alignment and operational accountability. The dynamic risk environment between the evolving generative fraud techniques and the AI detection systems necessitates dynamic oversight structures. The paper advances the existing body of knowledge by combining technical analysis with governance analysis, and suggesting a machine learning framework with improvements in governance. This combined strategy makes the detection systems of fraud not only correct but also sustainable, transparent, and reliable as expected by regulations. AI-powered fraud detection, a compromise is necessary between institutional governance and algorithmic advancement. With the ongoing development of generative fraud methods, financial institutions need to implement adaptive, transparent, and resilient AI systems so that both systems and consumers remain stable and trust digital financial infrastructure in the long term.

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