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Loan Stacking Detection: Leveraging Machine learning and AI to Mitigate Risks in the Small Business Loan Industry

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ABSTRACT:

The term 'Loan Stacking' refers to the practice of securing multiple business or personal loans simultaneously from multiple lending companies. This strategy of acquiring increased capital in the short term has been on the rise among businesses seeking increased capital, specifically after the widened compliance restrictions in the banking financial institutions due to the 2008 recession. Following the 2008 fallout, stringent rules have been defined by the regulators to sanction loans to businesses and individuals by working closely with Credit bureaus to have the updated financial health available closer to real time prior to approving requested loans. This journal focuses on the issues faced by the financial institutions due to the rise of loan stacking, currently available detection techniques, and use cases to identify the impact of Loan Stacking in the current financial market. It also discusses the proposed advanced machine learning and AI technologies to early detect fraudulent practices, Risk Assessment Enhancements, and real-time integration with Credit Bureaus with Financial Lenders.

Keywords: Loan Stacking, Fraud Detection, Small Business Loan Industry, Machine Learning, Risk Scoring, Credit Monitoring, Data Sharing.

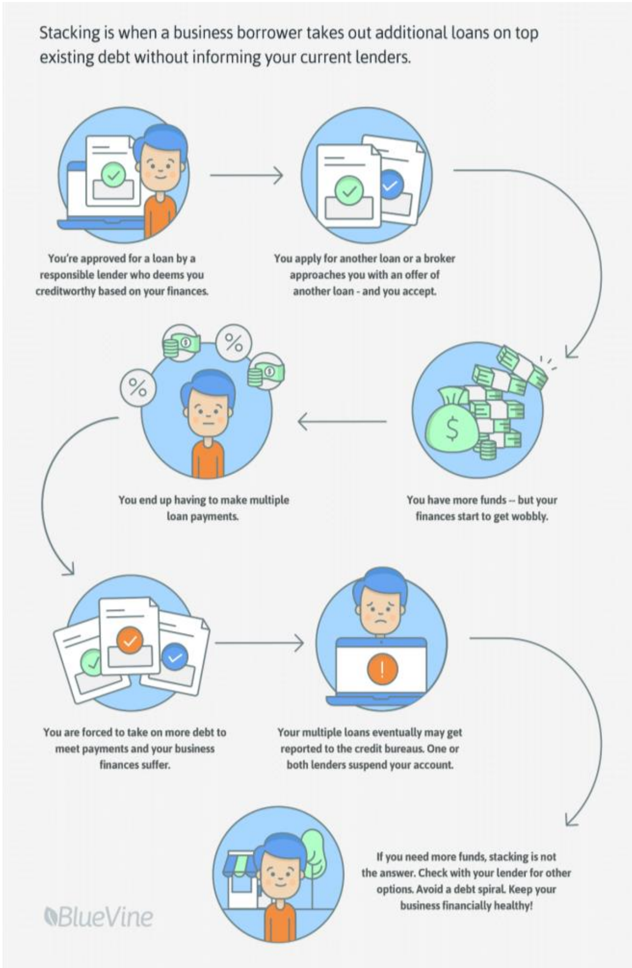
INTRODUCTION

Business Loan stacking refers to the practice of obtaining multiple loans on top of existing loans. Most of the time the stacking is in the form of short term business loans or Merchant Cash Advance provided by alternative lenders. It involves accessing additional funding from different sources, such as various alternative lenders, to supplement existing financial obligations. Rather than replacing existing loans, merchant loan stacking adds new loans into the mix, increasing the total debt burden[1] .Since the 2008 housing market burst, big banks have been wary to lend out quite as much money as they used to. This has put strain on small business owners looking for capital. To make up for the gap, some decide to stack two (or more) business loans from lenders to fund and grow their business. Though it can seem like a reasonable idea from the outside, for most this quickly spirals out of control and leads to more debt than the business can handle.[2]

This journal is aimed at providing deep insights which helps to examine the existing loan stacking concepts, its current financial impact, existing current detection methodologies. It also provides an introduction into the proposed advanced machine learning techniques using advanced data analytics and AI solutions in mitigating the financial risks posed by loan stacking. This proposal will help to understand how to attain cross functional collaboration with advanced technology , regulatory and compliance bodies, lenders and Credit bureaus to bestow an increased tightening oversight to protect lenders and dispense reasonable borrowing practices.

What is Loan Stacking?

Loan stacking occurs when a borrower has more than one loan outstanding at the same time. That means you have multiple loan payments actively due since you took out multiple loans at the same time, thus *stacking* them. [3]. Short Term Business Loans or Merchant Cash Advance stacking has become a prevalent practice among businesses seeking additional funding.



[4]Illustration of Business Loan Stacking (BlueVine)

Types of Loan Stacking

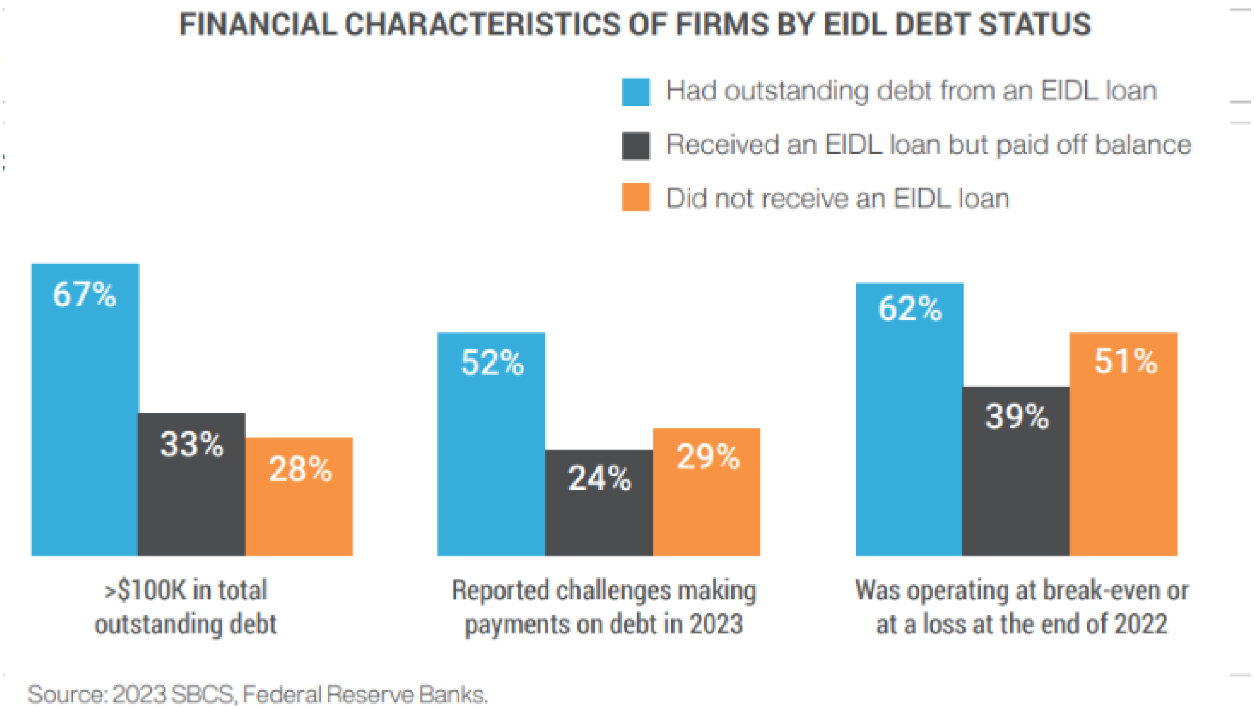
a) **Borrower Initiated -** A business owner knowingly applies and takes an additional finance capital without informing their existing or another new lender. This happens when the business owner is in a financial crunch to meet his operational costs or expenses. This is intentionally done by the borrower by desperately hiding the facts related to his existing loan commitments. As the credit bureaus data gets updated only on a monthly basis with the financial lenders, borrowers use this delay for securing additional funds.

b) **Lender Initiated -** When unethical lenders with the aim to improve their profits, encourage business borrowers to secure additional funds for their business by hiding their existing loans with another lender. These bad actors on the lender side might offer lower interests , discounts and faster approver rates to entice the borrower to end up taking the offer. They hide the fact that the borrower might end up with higher interest rates,hidden charges and longer financial terms. These lenders don't have the best interest for the borrowers.

Loan Stacking Risks

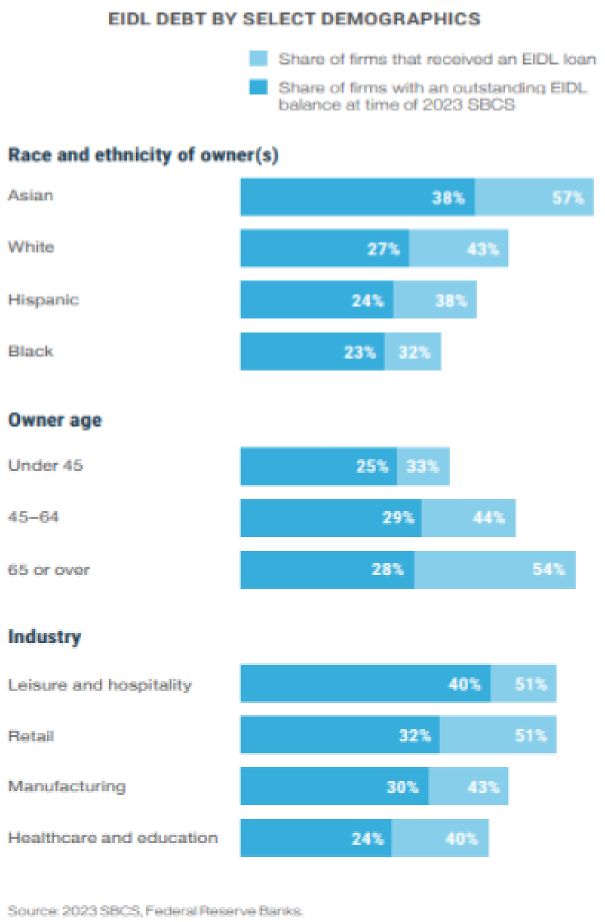
Many small businesses turned to government assistance to weather the most challenging days of the COVID-19 pandemic following its onset in March 2020. One of the largest government programs administered through the US Small Business Administration (SBA) during the pandemic was the COVID-19 Economic Injury Disaster

Loan (EIDL) program, which provided $380 billion in loans to struggling small businesses. However, many firms that stayed in business through the end of the pandemic with outstanding COVID-19 EIDL loans (hereafter referred to as "EIDL loans") have elevated amounts of outstanding debt and are in more precarious financial condition than those without outstanding EIDL loans. Data from the Federal Reserve's 2023 Small Business Credit Survey (SBCS) show that, compared to firms without outstanding EIDL debt, those with it were more likely to experience challenges making payments on debt during the year leading up to the survey and were less likely to be profitable. Additionally, compared to firms without EIDL debt, those with it were less likely to be fully approved for new financing and were more likely to attribute denials to excessive debt levels. While SBCS data suggest that the performance of firms with outstanding EIDL debt lags that of firms without it, it is unclear from SBCS data if businesses with outstanding EIDL loans would have had better outcomes had they chosen not to borrow from the EIDL program[5]



The above image indicates their various financial conditions based on total debt held, challenges with making payments on debt, and profitability. Each of these three indicators suggests that businesses with outstanding EIDL debt face considerable financial pressure. Firms with outstanding EIDL balances were more likely to have high debt burdens than those without these balances. While just 28% of firms that had never received EIDL loans had more than $100,000 in outstanding debt, 67% of those with outstanding EIDL balances had more than $100,000 in FIGURE 1. SHARE OF 2023 RESPONDENTS BY EIDL DEBT STATUS Source: 2023 SBCS, Federal Reserve Banks. Had outstanding debt from an EIDL loan 28% Received an EIDL loan but paid off balance 16% Did not receive an EIDL loan 56% Source: 2023 SBCS, Federal Reserve Banks. outstanding debt (including, but not limited to, EIDL loans). Just over half of firms with outstanding EIDL debt reported challenges with making payments on their debt in 2023 compared to just 29% of firms that had never received EIDL loans. Furthermore, firms with outstanding EIDL debt were 11 percentage points more likely than those that had never received EIDL loans to say they were either operating unprofitably or at break-even at the end of

2022. The financial burden associated with EIDL debt persists even when controlling for firm characteristics such as firm age, industry, or credit risk.



Across race and ethnicity categories in the 2023 SBCS, Asian-owned firms were most likely to have received EIDL loans and most likely to still owe on EIDL loans. As shown in image above, 38% of Asian-owned firms had outstanding EIDL balances at the time of the survey compared to just 27% of white-owned firms, 24% of Hispanic-owned firms, and 23% of Black-owned firms.

Current Loan Stacking Detection Mechanism:

a) **Bank Fraud Databases -** Lenders and financial institutions constituted data sharing of fraud databases to help them identify borrowers with intention of leveraging loop holes to pursue with loan stacking

b) **Lender Approval Manual Process** - Lenders take more time to approve high amounts due to heavily regulated manual processes. This process adds an immense amount of delay in identifying potential loan stacking businesses.

c) **Monitoring Cadence** - Lenders have regular monitoring cadences setup to identify frequent loan applications by the same business within a short span of time

d) **Credit Bureau Financial Health Checks -** Getting an updated credit bureaus details to approve or reject a loan

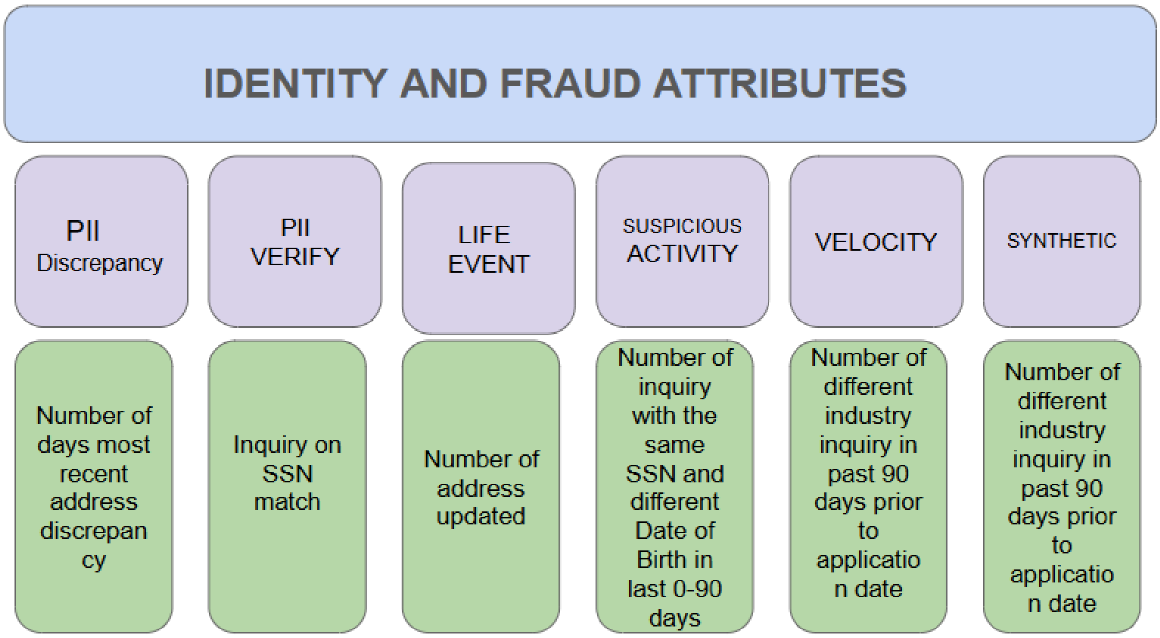
6. Proposed Advanced Loan Stacking Detection techniques

a) **Fraud Prevention Data Strategies -** Identified the following methodologies to formulate the process to identify fraud detection related to loan stacking:

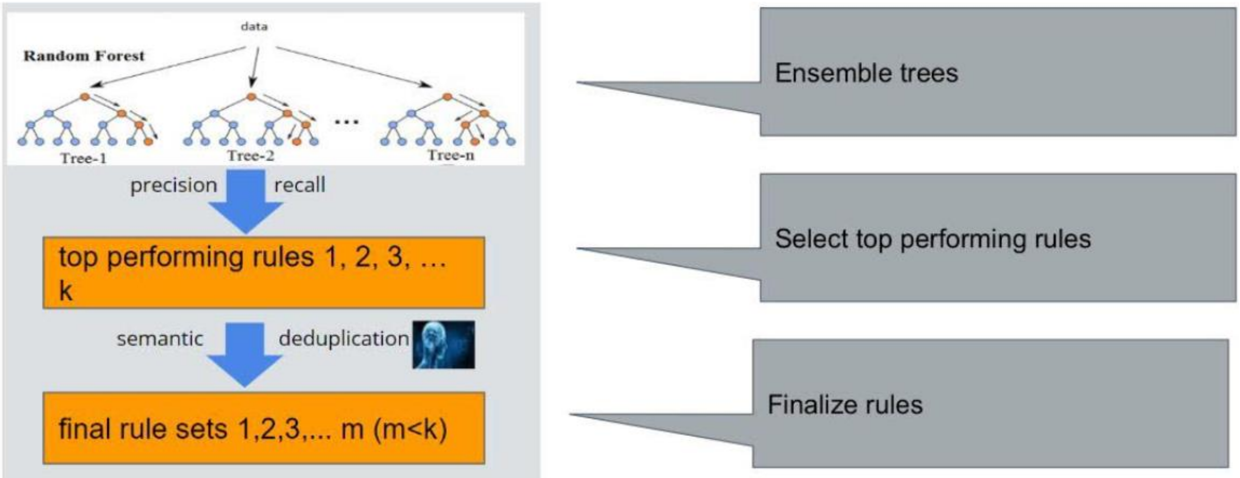
1) Fraud Analysis	Use fraud analysis to identify subtle or overt irregularities in the application by comparing identities, IP addresses, or locations used by known fraud rings to alert lenders to potentially fraudulent applications and false identities.
2) Identity and Verification Services	Employ cloud-based identity analysis and verification services to flag applications with a high probability of using false information to perpetrate fraud.
3) Alternative Credit Data Sources	Leverage alternative credit data sources, such as utility payment history, rental records, and address history, to identify discrepancies between alternative data and information provided on the loan application.
4) Real-time Data Sharing	Implement systems that allow real-time sharing of data among lenders to identify any recent loans taken out by the borrower.
5) Loan Limits and Monitoring	Establish and enforce limits on the number of loans a borrower can have simultaneously and monitor borrower behavior and patterns to identify unusual or suspicious lending activity.
6) Automated Alerts	Implement automated alerts to notify lenders of any unusual or high-risk lending activity and set up triggers for specific thresholds, such as the number of loan applications within a specific time frame.
7) Risk-based Pricing	Use risk-based pricing strategies to adjust interest rates and loan terms based on the borrower's creditworthiness and risk profile.
8) Customer Communication	Establish clear communication channels with borrowers to verify information and address any discrepancies in loan applications.

b) Data Driven Machine Learning Model

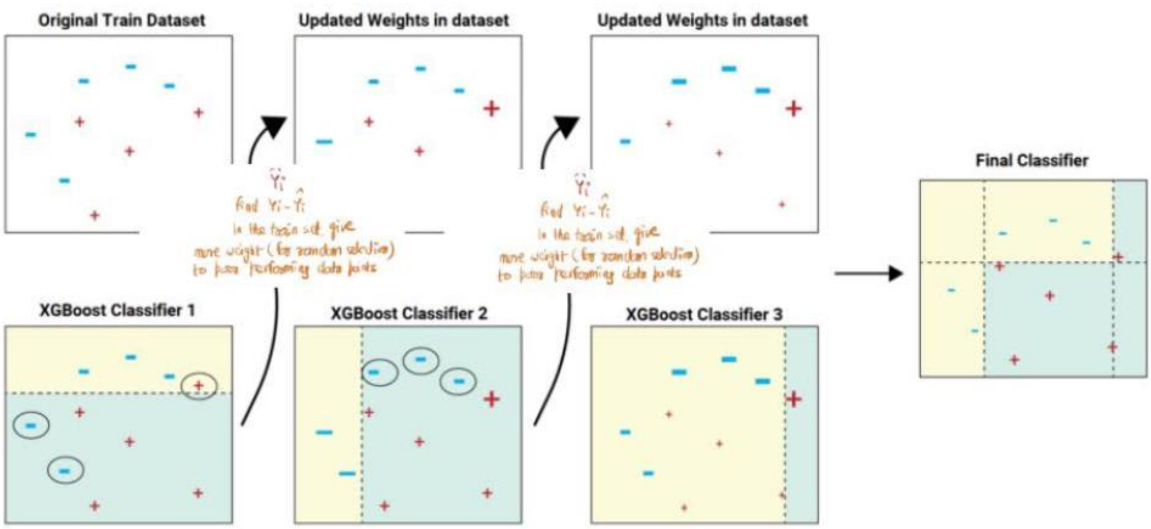
Identify the existing inventory of fraud identity parameters. This step of the model creation is mainly aimed at formulating and segregating all the fraud attributes which are needed to be applied in machine learning loan stacking detection model



Random forests or random decision forests is an ensemble learning method for classification, regression and other tasks that works by creating a multitude of decision trees during training. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the output is the average of the predictions of the trees [6]. Random forests correct for decision trees' habit of overfitting to their training set[7]. Decision trees are a popular method for various machine learning tasks. Tree learning is almost "an off-the-shelf procedure for data mining", say Hastie et al., "because it is invariant under scaling and various other transformations of feature values, is robust to inclusion of irrelevant features, and produces inspectable models. However, they are seldom accurate"



XGBoost, which stands for Extreme Gradient Boosting, is a scalable, distributed gradient-boosted[8] decision tree (GBDT) machine learning library. It provides parallel tree boosting and is the leading machine learning library for regression, classification, and ranking problems. It’s vital to an understanding of XGBoost to first grasp the machine learning concepts and algorithms that XGBoost builds upon: supervised machine learning, decision trees, ensemble learning, and gradient boosting. Supervised machine learning uses algorithms to train a model to find patterns in a dataset with labels and features and then uses the trained model to predict the labels on a new dataset’s features.XGBoost is built on the concept of gradient boosters with weak learners



7. **Data Privacy and Compliance Concerns - Limitations of Loan Stacking Detections**

The rapid advancement of artificial intelligence in recent years has brought about transformative changes across various sectors, reshaping the way we live, work, and interact with technology. Loan stacking has always been a bigger concern from the lenders and financial institutions. Particularly, the financial world has changed since Covid(2019) due to a sharp rise in loan stacking both from personnel and business loan perspective. Even Though the main goal of lenders is to detect loan stacking applications and bring it under further control to maintain the financial health of the business sector, it definitely comes with challenges and compliance oversight from the federal government. This leads us to understand the limitations and challenges lenders and financial institutions face today.

a) Data Privacy and Compliance oversight

Lenders and Financial institutions have to adhere to the legal obligation of storing, processing and using the consumer data for profiling. It not only helps us to store the information of consumers in a secure way, but also intended to protect the consumer data from data breaches due to bad actors in the market. Data privacy compliance refers to the institutions practices, policies,and technical procedures being implemented to ensure it adheres to all legal regulations and standards set by CFPB.The **Consumer Financial Protection Bureau** (**CFPB**) is an independent agency of the United States government responsible for consumer protection in the financial sector.Since its founding, the CFPB has used technology tools to monitor how financial entities used social media and algorithms to target consumers.[9]

b) Bias in Algorithm

With the evolution of Machine learning and AI, the concern of algorithmic bias in determining the financial health of a consumer or a business have been on the rise. The basic concept of an algorithm is nothing but a set of instructions defined to determine how programs read, collect, process, and analyze data to generate output[11]. As this depends upon the data being fed to the machine learning and AI algorithms, it's the responsibility of the financial institutions to train the model using a diversified data set which covers all the demographics,culture,financial,scientific,statistical,and meteorological information. This will help to prevent the model skewing the results towards one set of demographics and start rejecting genuine loan applications because of their affiliation to a specific race or place of dwelling. If this algorithmic bias is not addressed by the financial institutions then they are vulnerable to lawsuits and class action by the consumers.

c) Transparency of AI Models

Since the rise of OpenAI, financial institutions have started leveraging the features of AI to effectively identify fraud activities and prevent provisioning large sums of loans being sanctioned. This comes with an increased threat to data privacy and protecting consumer personal information being stored or manipulated in the OpenAI world. Most of the AI models are blackbox to institutions, which does not give us any transparency of how much of consumer information is anonymised and stored within the institutions data network and how much is being transferred back to AI companies. Institutions need to understand how the code is being built and how their consumer information is being processed during decision making processes.

d) AI Data Governance

With increased use of AI in the decision making process by banks and financial institutions, it shows the potential of constructing a robust AI Data governance to help scale data security, data integrity, data privacy and data compliance. This will help build and define guard rails for the use of AI and machine learning to be in compliance with regulatory and privacy rules.

e) Monitoring Oversight and Controls

In order to ensure usage of AI and machine learning are working within the guard rails set by the AI governance rules, well defined KPI (Key Performance Index)[12] have to monitored over a period of time to ensure there are no bias,ethically accepted and more importantly protecting the consumers and business interest by helping the genuine businesses in need.These KPIs needs to be revised and updated according to the new rules and regulations being defined by CFPB and also due to evolution of AI.

CONCLUSION

Banks , Financial institutions, and lenders want to increase their profit margins year over year, and at the sametime the question which comes to everyone's mind is ‘At What Cost’. Loan stacking has been an increased threat to the financial world of lending as it impacts the trust of investors,funds being used to cover debt of old loans which leads to a negative debt cycle which might drive businesses to bankruptcy. Loan stacking is being addressed with more and more modern AI technologies and advanced machine learning techniques being implemented across the financial institutions to control and detect loan stacking applications based on past historical trends of company performance and repaying capacity. Loan Stacking future efforts should concentrate and focus on:

1. Implement AI solutions which are scalable, transparent,accurate, inclusive, and not algorithmically biased.
2. Establish golden standards for data sharing, fraud identification, and fraud prevention at industry level.
3. Educate and spread awareness of Loan stacking impacts to consumers and business to understand the risks associated which might lead to bankruptcy and closure of businesses.

By embracing these proposed strategies, the business loan industry can create a more secure and trustworthy lending ecosystem, by reducing losses and at the sametime supporting genuine borrowers.

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