Blockchain Integrated Data Slicing based Model Validation for AI-ML Credit Risk Management Systems

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ABSTRACT
Credit risk assessment or management is a process of evaluating risks on customers' debt obligations and assessing whether the customer may default on debts, which are considered the finance industry's cornerstone. The main objective of this assessment is to examine good and bad debts. Assessing and managing such credit risks in banking and other businesses offering credit to customers is the most crucial problem. It has been addressed in several ways in the literature, such as i) Qualitative approaches - assessment is based managers' experience, ii) Statistical methods in which historical data is analysed for its relationship between customer characteristics and their default status, iii) Machine learning and Artificial Intelligence models which handle complex data and nonlinear relationship that exist among the data and iv) Ensembling models in which strengths of various models are combined. Among these, traditional ML models, Advanced AI-ML models, and Ensembling Models are the most adopted due to their higher levels of predictive accuracy. The AI model for credit risk assessment implements machine learning algorithms to analyze and predict credit risks in an automated way. Machine learning algorithms offer significant benefits, such as accuracy and the ability to handle complex data. However, these ML-based implementations introduce critical challenges, such as validation of model fairness, algorithmic bias, lack of transparency, etc. Also, AI-based models are black boxes, so it is very hard to analyse why the system made such a decision. Interpreting such ML algorithms will help us understand the model's weaker points towards the different data segments and enable us to handle those data segments separately to improve the efficiency of the credit risk assessment process. Hence, there is a need for a data slice-based evaluation model for performance. This paper proposes a novel framework of a slice-based validation model for an AI-ML enabled credit risk assessment model, which allows granular assessment of the AI-ML model and integrates blockchain, which provides an immutable, transparent ledger for storing slice-based validation metrics, model version, etc. The results show the increased efficiency of the proposed credit risk assessment model.

General Terms
Artificial Intelligence, Machine Learning, Blockchain.

Keywords
Slice-based Model ValidationData-Slice based Validation

1. INTRODUCTION
Credit risk is the risk that the promised cash flows from loans and securities held by Financial Institutions (banks, other businesses offering credits to the customers) may not be paid in full [1]. Basal II [2] defines credit risk as: "The potential that a bank borrower or counterparty will fail to meet its obligations following agreed terms." Credit risks happen in reality, i.e., when debtors default or their creditworthiness declines significantly, it has a wide range of impacts. It affects the lending concern and potentially disrupts the entire financial system and economy. The most immediate consequence is the loss of the loan amount and the interest payments the obligor was expected to make. This action leads to an immediate decline in the grantor's revenue and asset value [3]. Further, significant credit losses directly impact the creditor's profitability, and if these losses are substantial, they can completely erode the creditor's capital reserve and risk their financial stability. When investors face huge credit losses, they may stringent the debit criteria, which complicates the process of credit access by individuals and business organizations [4]. Lenders facing elevated or increasing credit risk may encounter higher costs when trying to raise funds from the market, whether through deposits, issuing bonds, or borrowing from other banks. This scenario is because investors and financial institutions demand greater returns to compensate for the heightened risk. Widespread business defaults lead to declining economic activity, business failures, joblessness, etc. [5]. Hence, there is a need for systematic or algorithmic ways of managing credit risks in financial institutions, which are known as credit risk management systems. In other words, the Credit Risk Management System (CRMS) involves recognizing, evaluating, tracking, and reducing the risk of financial loss if a credit recipient fails to repay a loan or fulfill agreed-upon terms. CRMS helps creditors such as banks and financial institutions lower the risk of losing money on credits. [6]

In the near past, the impact of AI has increased in various fields such as healthcare, finance, medical diagnosis, etc. AI-powered systems are gaining importance, significantly transforming conventional methods used in multiple applications. This cutting-edge technology offers efficient methods to solve real-world problems. AI technology has a higher impact on solving finance-related issues such as credit risks, fraud detection, etc., which are more crucial and sensitive. These AI-powered systems produce more efficiency than the conventional method of solving problems. However, solving using AI has its negative counterpart. For instance, analysis of the model's performance is often overlooked by its overall performance. The model shows underperformance due to certain segments of the data that need to be identified, considered, and analyzed differently to enhance the model's performance.

1.1 Problem Definition and Objectives
There is an increase in the adoption of AI in various applications, directing the implementation of credit risk management using AI, which improves accuracy and handles complex data. However, it leads to a significant challenge in evaluating the model, focused on only overall metrics, where the model underperforms with certain data segments, which leads to a lack of robustness and transparency in model evaluation. Analysing specific data segments or specific data patterns can be called data slices based performance analysis.

This analysis improves AI-Ml models by interpreting the results in fine granular level. It also identifies the areas of under performance and potential fairness. However, the process of identifying the data slices and managing it in a trustworthy manner is challenging, which could be handled by integrated blockchain in system architecture. By considering all these above-said aspects, the main objectives of the paper are i) an AI-Ml based credit risk management system (CRMS), which is capable of efficiently predicting the credit defaulter and mitigating the credit risks, ii) a Data slicing-based performance analysis process to efficiently monitor and validate the model, iii) a Blockchain-integrated approach for slice-based performance validation of CRMS.

1.2 Organization of this paper

The paper is organized in the following manner: Section 2 presents a detailed literature review of works similar to the proposed system. Section 3 shows an elaborate description of the proposed system in three implementation phases. Section 4 describes the results of the analysis of the proposed system. Section 5 concludes the paper.

2. BACKGROUND

This section shows a systematic analysis of existing systems from the literature, which are similar to the proposed system of this paper. To analyze in a better way, the literature review is categorized in three ways: i) A review of AI-ML based applications and credit risk assessment system, ii) A review of Machine learning Model Validation Methods, iii) A review of the leverage of Blockchain in AI-based Applications.

2.1 AI-Ml based Credit Risk Assessment Systems and Other Applications - A Review.

A K Sharma et al., in their paper [7] uses machine learning models like Random Forest, SVM, XGBoost, and Logistic Regression to improve credit risk assessment beyond traditional credit ratings. The results have shown machine learning methods outperform the conventional methods. Adula and Alawi in their research work [8] examine around fifteen recent works on credit risk management that use machine algorithms primarily to predict the defaulters associated with the borrowing system. Methods include artificial neural networks and other hybrid methods for managing four types of risks: credit, market, liquidity, and systematic risks. The analysis shows that ML methods are more efficient than the conventional methods. P Sharma and Logeswaran in their research work [9] propose an AI-driven credit scoring system that processes customer credit card approvals. The approval of credit cards is done based on the generation of credit scores calculated by analyzing applicants' financial history, spending patterns, etc. The proposed AI-powered method provides more accurate scores than traditional methods, which enhances the customer experience and reduces credit risk for banks. P M S Sundar et. al. addresses the most crucial issue of credit card fraud and data misuse. The proposed method in this paper uses digital twins technology, such as blockchain and AI-based multi-source data analysis, which uses both internal and external information for data analysis. The system provides enhanced security, maintains customer trust, and improves accuracy over traditional methods. V Yardrapalli in his research paper [11] proposes AI-based data coverage in which AI technologies are used to maintain data quality. The paper addresses the problem of uncertainty in the prediction model of AI-based credit scoring by implementing two profit–based uncertainty metrics: class-dependent and instant-dependent cost metrics. The results highlight the robustness and efficiency of the framework. Further, Ximing Liu et. Al. [12] proposes a novel feature selection mechanism that chooses multi-view features hierarchically and can integrate them for credit risk assessment. The experimental results show the proposed method outperforms the exciting system. Yiping Haung et al. [13] present analyses of Bigtech's credit risk assessment methods, such as big-data analytics and machine-learning models. This paper performs a comparative study of Bigtech's methods with conventional financial risk assessment methods. Xialin Wang [14] proposed a novel method of sampling the imbalanced data in credit risk assessment. Xianhua Kuang [15] proposes a privacy-preserving method for linear regression credit risk assessment models. Zhouyibu et al. [16] assess the credit risk in small and microfinance enterprises using machine learning classifiers. Based on this, XGBoost has been developed and shows the efficiency of predicting the risk much earlier.

A brief review of AI-ML-driven credit assessment systems literature shows various models such as Random Forest, Support Vector Machine, XGboost, Logistic Regression, etc. Some researchers have implemented the problem using digital twin technology, which comprises Blockchain and Artificial Intelligence. A few researchers have turned to show the results of creditworthiness using Big Data tech. Also, the literature has a trace of security and privacy analysis of credit risk assessment models.

2.2 Validation of Machine learning Models - A Review.

Yong Xu el al., [17] addresses the problem of uncertainty in the prediction model of AI-based credit scoring by implementing two profit–based uncertainty metrics: class-dependent and instant-dependent cost metrics. The results highlight the robustness and efficiency of the framework. Rafael B. Loureiro et. al., [18] proposes a correlation-based method for model fairness evaluation integrated with boot stamp sampling using the Markov chain Moute Carlo technique, one of the fairness evaluation techniques. Nga Pham et al., [19] introduce a novel framework, FAIREDU, which enhances fairness by containing features that minimize the impact of model performance in educational datasets. Anahita et al. [20] study assesses the gaps in the model fairness evaluation and algorithmic bias in ML-based risk prediction in healthcare setup. Authors also identify crucial disparities in the model when executed for various sub-groups (demographics such as gender, etc. Yifei wang et al. [21] propose a fairness detection for the ML model by examining racial disparities in predicting mortality among patients with chronic diseases. The study reveals the impact of racial and systematic bias in machine learning models. Alveiro et al. [22] propose preprocessing techniques such as resampling, hyper parameter tuning, and reweighing for ML model fairness evaluation. Results show the enhancement in model fairness without compromising overall accuracy.

A brief review shows that there are a few methods to evaluate the ML model fairness for a specific application or dataset. Most of the research results show differences in the model performance when implemented in particular chunks of data; there is algorithmic bias and no transparency concerning model evaluation.

2.3 Leveraging of Blockchain in AI-based Applications- A Review

Kajal singh et el., [23] presents a new framework using blockchain with AI for optimal energy and sustainable smart grid management. Here, blockchain enforces trust among the stakeholders to ensure data integrity across the entities involved in the transactions. Hossein Pourrahmani et al., [24] presents a novel framework integrating Blockchain, IoT, and AI technologies to defend against climate change. Rajesh Kumar [25] presents AI drive trust management with blockchain, which addresses various issues such as security and reliability in a dynamic industrial Internet of Things environment. Soumya Pokharna et al., [26] present a novel model for secured fake profile detection using blockchain and AI in recruitment platforms. Hoon Ko et al., [27] implements a blockchain-based framework to ensure data integrity in medical applications. The proposed application enhances the detection rate using the GenAI model. Here, blockchain addresses the key issue of privacy. Hadeel Alsolai et al., [28], the authors propose an integrated approach of AI and Blockchain to detect threats and maintain data privacy during model training in the healthcare system. The results show that integrating Blockchain and AI is efficient and reliable for the healthcare system. Zhaolong Liu et. al., [29], in their paper reviews AI implementation in food safety applications. To achieve transparency and traceability, a few applications integrate blockchain as well. Habib Sadri [30] depicts the AI-driven blockchain-integrated digital twin solution for smart building management. Shanqin Wang et al., [31] propose an integrated approach for an information exchange system that implements AI and directed acyclic graph-enabled blockchain. Zineb Kamal Idrissi et al., [32] present a review of the implementation of blockchain, IoT, and AI I smart logistics systems. Furthermore, Joy Dutta, Deepak Puthal et al., [33] present a novel consensus algorithm, namely proof of authentication for IoT-based applications, which also integrates AI for authentication at the block creator node. Dalila Ressi et al., [34] review an integrated framework of AI and Blockchain on various industrial applications. Hossein Omidian [35] explores the possibilities of integrating blockchain and AI in the healthcare industry. Zahoor Ali Khan et al., [36] address security issues in IoT-based systems using blockchain, ensuring authentication, data privacy, and integrity.

Leveraging blockchain in AI framework ensures data integrity, data confidentiality and data availability Authors in the literature have proposed DAG-based blockchain for various AI-based and Gen-AI applications.

2.4 Extracts from background study

The literature review shows there are ample conventional and AI-based methods to solve credit risk assessment problems, including machine learning and deep learning models. Credit risk can be effectively implemented using most of the methods illustrated. However, the actual limitation of those models is that most are black box in nature, which is less interpretable. Hence, the model's overall performance analysis results may mislead decision-making since the overall performance analysis will not asses the reliability of the model. Whatever the model produced as an output is considered for decision-making based on its overall performance. The actual working of the model for failed cases needs to be assessed. The performance analysis should be done on a segment basis or on a single-entry basis. This type of analysis or model validation is crucial for financial applications. Hence, modal validation needs to be performed segment-wise, and those data results with prediction errors are handled differently than other sets. Further, the utilization of cutting-edge technologies like blockchain, which plays a significant role in the building and security of the system, is not discussed much in the literature.

3. THE PROPOSED FRAMEWORK

3.1 AI-powered Credit Risk Management System (CRMS)

The proposed AI-powered credit risk management system has been developed using a champion-challenger (C-C) framework. In this implementation, strategy one model is chosen and utilized actively, whereas other models are designed as challenger models and are used for testing against it in parallel environments. This strategy is efficient and suitable for credit risk assessment systems since it mitigates the risks of model underperformance, is auto-comparative, and supports continuous model enhancement. Also, this C-C implementation strategy provides an innovative pipeline, which leads to constant exploration without signing off from on-set operations. AI-ML based CRMS model is implemented as a machine learning model. Generally, machine learning models learn from data and derive patterns, classify, or predict outcomes. In this proposed work, Gradient Boosting Machines (GBM), a supervised algorithm, ensembles a few models and builds them linearly so that the error encountered in the model is corrected in the new model. GBM is considered highly efficient in terms of accuracy, handling complex relationships, robustness in handling missing data values, and resilience to outliers.

Generally, when implementing credit risk prediction or management systems, the baseline model is logistic regression since it is a statistical model and shows binary results (e.g., Loan turns into default or not default). The primary advantage of this model is that it is simple and easily interpretable. It provided moderate accuracy by considering linear relationships, which may be misleading and insufficient to handle real-time data. For example, increasing income minimizes credit risk, which is a linear relationship. However, the hidden thing is that an increase in income reduces the credit risk, which may not be the same for lower and higher-income people. The income raise may be negligible for higher-income people, but credit remains stable. The baseline model logistic regression did not handle this complexity, so it ends with medium accuracy. Moreover, the most significant advantage of the logistic regression model is that it is highly interpretable, which is the most needed characteristic for financial applications like credit risk assessment. Other algorithms, like random forest (collection of decision trees), provide a slightly higher level of accuracy with moderate interpretability. This model also suffers from handling non-linear relationships among the data, which is crucial for a credit assessment system. Therefore, this proposed model uses gradient-boosting machines such as XGBoost (Extreme Gradient Boosting technique) and LightBGM (Light Gradient Boosting technique). XGBoost and LightBGM are in the simulation process with a synthetic data set created for this process, with 20+ features, each feature of 1000+ rows and a few hundred rows of defaults.

Initially, the champion-challenger model XGboost is the challenger; Logistic regression is the champion. The results show that the XGboost's prediction accuracy is 89.5%, and the ROC AUC score is 0.965. similarly, logistic regression's prediction accuracy is 75.6%, and ROC AUC is 0.826. In a later stage, the LightBGM is taken as challenger and XGBoost as champion. The prediction accuracy of the LightBGM algorithm is 85.6%, slightly lower than the XGBoost. Based on the performance analysis of GBMs, XGBoost shows high accuracy. Additionally, one more attribute is added to the data showing the prediction_error, which takes the values of 1 and

0, and 'one' indicates that the prediction is wrong by comparing it with the actual default status, and 'zero' indicates the prediction is correct.

3.2 Data slicing-based model validation

The Data-slicing model agnostics is the second phase of the implementation, in which efficient monitoring of the system and adequate model validation are done. The core part of the AI-ML CRMS is its validation phase. Instead of analyzing the model's overall performance with metrics like predicting accuracy and ROC AUC, in this phase, the data set is divided into meaningful subgroups, which are known as slices of data, and it is examined where it fails. The dataset considered for this phase is from the previous phase, which includes the prediction_error attribute. The main objective of the data slicing-based model agnostics process is to describe the high error rate data slices. The modified data set with prediction_error is trained using the CART decision tree method. The crucial step here is to identify erroneous slices automatically for the model validation. The search process is top-down until it gets k erroneous slices. For example, traversing the tree shows attributes like income, type of Loan, past credit history, job type, number of inquiries in the past period, etc. The validation model finds whether the leaf node status is erroneous for these attributes or combinations of some of these. If so, the proposed model suffers from limitations in handling these data slices. Similarly, one more algorithm lattice search is used for slice finding, in which predefined features are verified for erroneous rate and on every possible combination. Based on this Data slicing based model-agnostics, the results can be analyzed as follows. XGBoost produces an overall accuracy of 89.5%. However, slice-based analysis shows underperformance on the specific slice of data. This data suffers in defaults for entrepreneurial business individuals.

The output of model validation shows the slices of data where the AI-powered CRMS fails to predict proper defaults. Once found, the corrective measure is done in two ways: i) Flagging the application from this slice, the rest of the data is executed in the proposed XGBoost model, and the sliced data is handled manually, and ii) Analyzing why this particular slice of data shows underperformance using LIME framework. The LIME (Local Interpretable Model Agnostic Explanation) field is one of the most efficient techniques for explainable AI (XAI). Generally, it is used to explain the model's behavior (i.e.) interpretation of the model. LIME, as its first letter expands to "Local," indicates the model is utilized to describe a single entry at a time. For example, why does the model make specific entry decisions for the job type entrepreneurs? Data slicing-based model agnostic determines where the model's predictions go wrong. LIME-based validation describes why this particular decision is made for an entry. Both combined results of the sliced data are given below. The model shows default for entrepreneurs whose income history is less than 3 years and who have no credit history. This limitation is because the AI-ML CRMS works mainly with income history and credit history conditions. XGBoost implementation model underperforms for certain slices of data related to entrepreneurial business, taken separately and analyzed with other attributes such as time–to–time income ratio, etc.

3.3 Blockchain-integrated approach for slice-based performance validation of CRMS

AI-ML credit risk management system imposes two significant challenges in its implementation, and the foremost challenge is analyzing the performance thoroughly, finding exactly where the model fails (interpretability since ML model XGBoost and LightBGM models used in this proposed system are black box in nature. In our proposed model, data slicing-based model validation methods were implemented to solve interpretability problems. AI-ML CRMS imposed another challenge: high compliance risks, which resulted in high auditing costs. This challenge can be solved by integrating permissioned blockchain to store the hash value of model validation parameters, which becomes an immutable record of every model validation. Each data slice is written as an unchangeable contract and then executed its validation test. The results of these tests are permanently recorded on the blockchain and show model fairness and prediction accuracy at a particular timestamp. Data slice validation was performed off-chain, and the results were fed back into a smart contract. The following Figure 1.1 shows the System Architecture of Blockchain Integrated Slice-Based Model Validation for AI-Powered Credit Risk Management Systems.

4. RESULTS ANALYSIS OF THE PROPOSED FRAMEWORK

The proposed framework Blockchain Integrated Slice-Based Model Validation for AI-powered Credit Risk Management System is implemented in three phases: i) AI-powered Credit Risk Management System (CRMS), ii) Data slicing-based model validation, iii) Blockchain-integrated approach for slice-based performance validation of CRMS. The initial phase, AI-powered Credit Risk Management System (CRMS) results, are shown below in table 1. The first phase of AI-powered CRMS is implemented using three algorithms, namely, Logistic regression, XGBoost, and LightGBM, in a Challenger-Champion framework. The dataset used here is of dimension (23x8876).

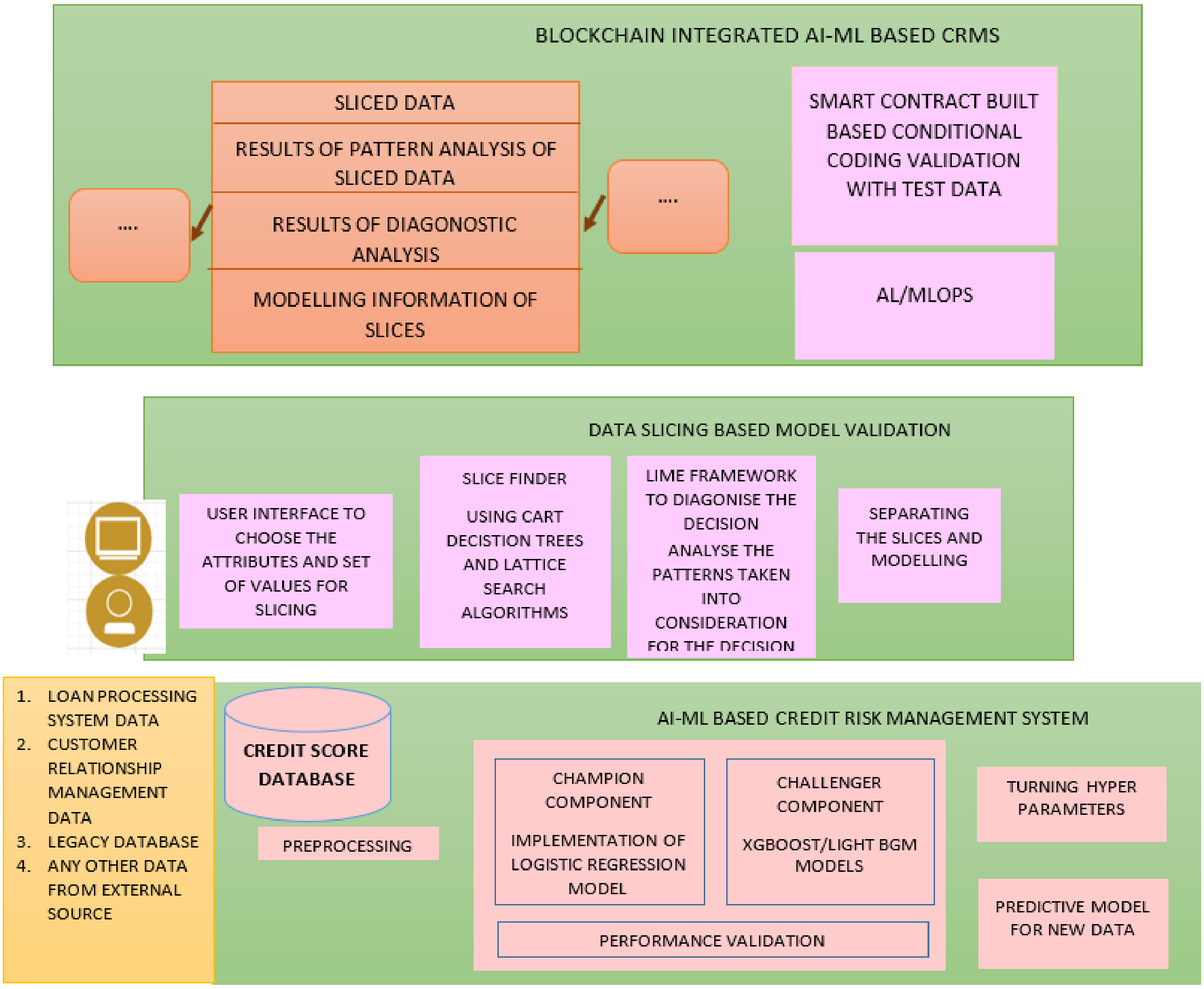

Figure 1: System Architecture Blockchain Integrated Slice-Based Model Validation for AI-ML based Credit Risk Management Systems

Table 1. The Results AI-Powered CRMS Model.

Sl.No	Machine Learning Models	Prediction accuracy
1	Logistic Regression	89.5%
2	XGBoost	75.6%
3	LightGBM	75.6%

Table 2. The Results of Data slicing-based model validation.

Col_Name	Slice_Log Loss	Counter Slice Log loss
Age	0.580980509	0.434448236
Job Type	0.610064942	0.496200435
Income	0.657102916	0.511213074
Credit_history	0.794459166	0.527645781
Income_history	0.85047808	0.521169886
Loan_Amount	0.632334371	0.518115338
Loan_Duration	0.669761189	0.527591938

The second phase, Data slicing-based model validation, is implemented using two algorithms. The results are given in Table 2. Based on the values of slice log loss [37] and counter slice log loss, the corresponding values of slice alarming rate and counter slice alarming rate were calculated. Slice log loss shows the model's prediction error for the slice, and counter slice log loss shows the error for the rest of the population. The lower the value of slice log loss, the better the model prediction accuracy. For the credit_history, Job type, and Salary history columns, the slice log loss values were slightly high, and these slices were separately handled using the LIME framework.

7. CONCLUSIONS AND FUTURE DIRECTIONS

This paper implements a Blockchain Integrated Slice-Based Model Validation for AI-Powered Credit Risk Management Systems. The proposed framework is implemented in three stages: i) AI-ML based Credit Risk Management System (CRMS), where credit risks were predicted using XGBoost and LightGBM algorithms using the Challenger-Champion framework. ii) Data slicing-based model validation was implemented to validate the AI-powered CRMS for various sets of slices, using CART decision tree and Lattice search algorithms, and iii) Blockchain-integrated slice-based model validation of CRMS was implemented to store the logs of model validation. The results of the proposed framework show the efficiency of modal validation for AI-powered CRMS. The future directions for this proposed framework are implementation of the framework for various other financial applications, like credit card fraud detection, customer churn prediction etc.

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Conflicts of interest

The authors have no conflicts of interest to declare.

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