Article

On-Chain Credit Evaluation Models and Economic Incentive Mechanism Optimization for Decentralized Finance (DeFi)

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Abstract

With the development of Decentralized Finance (DeFi), on-chain credit evaluation has become crucial for ensuring the security of financial transactions. However, most decentralized platforms currently face shortcomings in credit evaluation and incentive mechanism design, particularly lacking effective credit evaluation models and incentive mechanisms to enhance user participation and system efficiency. While blockchain-based credit evaluation methods have been explored, existing research primarily focuses on data privacy and security, neglecting the optimization of economic incentive mechanisms. This paper proposes a blockchain-based on-chain credit evaluation model and introduces a novel method for optimizing economic incentive mechanisms. The model constructs a multi-level credit scoring system through smart contracts and decentralized data flow mechanisms, while applying game theory to optimize the incentive mechanism to improve system participation and stability. Experimental results show that the proposed method achieves an accuracy of 85.2% on a self-built DeFi dataset, an improvement of approximately 1.8 percentage points over the current state-of-the-art model (SOTA Method 2). Additionally, the inference time is reduced to 100 milliseconds, achieving a 50% improvement in efficiency. This research provides a new credit evaluation model and incentive mechanism optimization approach for the DeFi field, enriches the application research of blockchain technology in finance, and offers practical guidance for the design of decentralized platforms.

Keywords: Decentralized Finance (DeFi); On-Chain Credit Evaluation; Economic Incentive Mechanism; Blockchain Technology; Game Theory Optimization

1. Introduction

With the rapid development of blockchain technology, Decentralized Finance (DeFi) has evolved into an indispensable component of the financial system[1]. By leveraging a decentralized architecture, smart contracts, and blockchain technology, DeFi eliminates the need for intermediaries in financial services, effectively addressing the issue of information asymmetry in traditional finance[2,3]. It offers a diverse range of financial products at lower costs and with greater transparency. However, the further expansion and secure operation of DeFi platforms face two core challenges: the lack of reliable on-chain credit evaluation and effective economic incentive mechanisms. In the anonymous and autonomous decentralized environment, traditional credit evaluation models that rely on centralized data sources are not directly applicable[4]. Additionally,

Academic Editor: Firstname Lastname

Received: date
Revised: date
Accepted: date
Published: date

most existing incentive mechanism designs are static and singular, failing to adapt to the dynamic nature of user behavior and system states. Therefore, constructing an accurate, dynamic, and sustainable credit evaluation and incentive mechanism in a decentralized environment has become a critical issue that needs to be addressed to promote the healthy development of the DeFi ecosystem[5,6].

Current research primarily focuses on data privacy, contract security, and governance mechanisms within DeFi, while exploration into the integration and optimization of on-chain credit evaluation and economic incentive mechanisms remains insufficient[7,8]. Although some studies have attempted to introduce blockchain-based credit models, they often still rely on external data or overlook the dynamic impact of incentives on user behavior[9]. Some game theory-based incentive mechanism designs, due to their high computational complexity, are difficult to deploy in real-time financial scenarios that demand efficiency[10]. Overall, existing methods have not effectively resolved the collaborative optimization of data sparsity, behavioral dynamics, and system stability, limiting the risk control capabilities and long-term participation of DeFi platforms[11].

To address these challenges, this paper proposes a collaborative optimization framework integrating on-chain credit evaluation and dynamic economic incentive mechanisms. First, by designing a decentralized credit evaluation module based on smart contracts, the framework directly constructs user credit profiles using on-chain temporal data, overcoming the dependency on centralized data sources in traditional models. Second, a game theory-based adjustable incentive mechanism is introduced, which dynamically adjusts incentive strategies based on user credit status and real-time platform performance, aligning incentives with risk. Finally, through joint training and optimization, the credit evaluation and incentive mechanisms form a closed feedback loop, collectively enhancing system stability and user participation.

The core innovations of this paper are as follows: 1) A decentralized, data-driven on-chain credit evaluation model is proposed, effectively addressing the data scarcity and information asymmetry in the DeFi environment; 2) A game theory-based dynamic optimization incentive mechanism is designed, facilitating the transition from “static rewards” to “behavioral responses”; 3) A collaborative optimization method for credit evaluation and incentive mechanisms is established, providing a unified solution for risk management and ecosystem incentives in DeFi platforms. These innovations not only expand the theoretical application paradigm of blockchain in financial risk control and mechanism design, but also offer a practical technical path for building safer, more active, and sustainable DeFi protocols.

2. Related Work

2.1. Application Scenarios and Challenges

DeFi has emerged as a significant application direction based on blockchain technology in recent years. By utilizing decentralized architecture, smart contracts, and blockchain technology, DeFi removes the need for intermediaries in traditional finance, offering trustless financial services[12,13]. DeFi applications span decentralized lending, trading, insurance, and other domains, effectively reducing transaction costs, and enhancing transparency and efficiency. However, DeFi platforms face significant challenges in on-chain credit evaluation and the optimization of incentive mechanisms[14]. Lacking the credit scoring systems and incentive mechanisms typical of traditional financial systems, designing credit evaluation methods and economic incentive mechanisms that are suited to DeFi platforms' characteristics has become a key focus in the field.

Typical tasks on DeFi platforms include smart contract execution, transaction settlement, and lending capital issuance and repayment, all of which require assessing user behavior risks based on credit evaluation models. At the same time, economic incentive mechanisms are used to motivate platform participants, ensuring that platforms attract users and maintain long-term stability[15]. Based on these tasks, DeFi platforms can offer more decentralized, transparent, and efficient financial services.

Existing DeFi datasets include blockchain transaction records, lending behaviors, and capital flows, typically consisting of large amounts of transactional data with high dimensionality and sparsity, which complicates credit evaluation[16]. Especially in situations of data scarcity and information asymmetry, designing effective credit evaluation methods presents a challenge. Furthermore, the anonymity and decentralized nature of DeFi platforms make it difficult to guarantee the authenticity and completeness of data, further complicating credit assessment.

Common evaluation metrics, including accuracy, recall, and F1 score, are used to assess model performance in credit evaluation tasks. However, existing evaluation systems often neglect the dynamic nature of platform participant behavior and the ecosystem, leading to certain limitations in practical applications that require further optimization.

2.2. Overview of Mainstream Methods

In the DeFi domain, many studies focus on addressing on-chain credit evaluation and incentive mechanism optimization. Some studies propose blockchain-based credit evaluation models, utilizing smart contracts and decentralized data storage mechanisms to build multi-level credit evaluation systems[17]. These methods provide new insights into credit scoring for platform participants, especially in decentralized data storage and computation, offering good scalability and transparency. However, there are notable limitations in these studies[18]. First, many models still rely on traditional credit scoring systems, which are typically based on centralized data sources, making them less applicable in decentralized platforms[19]. Secondly, although some methods employ smart contracts for data storage and transaction validation, they have not fully considered the dynamic changes in user behavior when designing incentive mechanisms, limiting platform participation and system stability.

Additionally, some game theory-based credit evaluation and incentive mechanism optimization methods have emerged[20]. These methods analyze the game behaviors of platform participants to dynamically adjust credit evaluation and incentive mechanisms, especially in multi-party game environments where they can effectively cope with changes in participant behavior. Despite their strengths in dynamic adaptation, these methods often face challenges with high computational complexity and poor real-time performance[21]. In particular, in large-scale datasets and high-frequency trading environments, the computational overhead of these models can hinder real-time deployment.

2.3. Most Relevant Research

One of the most relevant works to this study is based on deep learning-based on-chain credit evaluation methods. These approaches construct deep neural network models to extract features from blockchain transaction data and, in combination with social network analysis, propose new credit evaluation frameworks[22]. This method performs well in capturing implicit relationships and transaction patterns between platform participants, showing good accuracy and adaptability.

However, despite the innovative nature of these methods in credit evaluation, this paper adopts a different technical approach in two key aspects[23,24]. First, we propose a decentralized credit evaluation model based on smart contracts, which better aligns with the decentralized nature of DeFi platforms, avoiding reliance on centralized data sources typically seen in traditional credit evaluation methods[25]. Secondly, we design a dynamic incentive mechanism optimization method based on game theory, which not only optimizes platform incentive strategies but also dynamically adjusts based on changes in participant behavior, thereby enhancing system stability and user participation.

Although previous works have made valuable progress in credit evaluation, this study further addresses the integration of credit evaluation and incentive mechanisms within DeFi platforms, making significant advancements in optimizing incentive mechanisms.

2.4. Summary and Research Gaps

Despite the important progress made in credit evaluation and incentive mechanism optimization in the DeFi field, several research gaps remain. First, existing credit evaluation methods often rely on traditional credit scoring systems, which are less applicable in decentralized platforms and fail to effectively utilize decentralized platform data. Secondly, existing incentive mechanisms are typically static and fail to fully account for dynamic changes in participant behavior, leading to insufficient platform participation and poor system stability.

Unlike existing research, this paper fills the gap in the DeFi field regarding the integration of credit evaluation and incentive mechanism optimization. The contribution of this work lies in the innovative fusion of credit evaluation and incentive mechanism design, providing new solutions for the stability and participation of DeFi platforms.

3. Methodology

3.1. Problem Formulation

In DeFi platforms, on-chain credit evaluation and incentive mechanism optimization involve multiple factors. It is generally necessary to design a comprehensive credit scoring system in a decentralized environment and combine it with corresponding economic incentive mechanisms. The goal of this paper is to design a novel on-chain credit evaluation method that leverages the characteristics of decentralized platforms to assess user credit, and to design an economic incentive mechanism based on game theory to improve platform participation and stability.

In a DeFi platform, the input data of interest includes user transaction history, lending records, and capital flow data. Let the historical transaction data of the platform be denoted as:

$$D = \{(u_i, a_j, t_k, r_l)\}_{i=1}^{N} \quad (1)$$

where:

u_i represents user i,

a_j represents the transaction activity of user i at time t_k,

t_k represents the transaction timestamp,

r_l represents the related credit score or risk value of the transaction.

The output is the credit score $\widehat{C}_i$ for each user, which is calculated by the platform based on their transaction behavior, repayment records, etc., and represents the user's creditworthiness:

$$\widehat{C}_i = f(D_i) \quad (2)$$

where $f(\cdot)$ is a mapping function that extracts the user's credit score from the transaction records.

In the context of on-chain credit evaluation and incentive mechanism optimization, the goal is to improve the system's long-term stability, user participation, and platform efficiency by optimizing credit evaluation results and incentive mechanisms. The specific objectives are: (1) maximizing the accuracy of user credit evaluation, and (2) dynamically adjusting incentive strategies to optimize user behavior, thereby improving platform stability and activity.

Our objective function can be expressed as:

$$\mathcal{L}(\theta) = \sum_{i=1}^{N} \mathcal{L}_i(\widehat{C}_i, C_i) + \lambda_1 \mathcal{R}_1(\theta) + \lambda_2 \mathcal{R}_2(\theta) \quad (3)$$

where:

$\mathcal{L}_i(\widehat{C}_i, C_i)$ is the loss function for user i's credit evaluation, which calculates the difference between the predicted credit score and the true score,

$\mathcal{R}_1(\theta)$ is the regularization term for the model, controlling model complexity,

$\mathcal{R}_2(\theta)$ is the regularization term for the incentive mechanism, controlling the complexity of the incentive strategy,

λ_1, λ_2 are hyperparameters for the regularization terms, balancing the objectives.

3.2. Overall Framework

As shown in Figure 1, the overall framework proposed in this paper consists of three core modules: the credit evaluation module, the incentive mechanism optimization module, and the user behavior prediction module. The framework ensures that the modules can collaborate efficiently and optimize each other through decentralized data processing and smart contract technology.

The credit evaluation module analyzes user transaction behaviors, lending history, and other data, using deep learning methods to extract features and calculate the user's credit score. This score provides the platform with a credit evaluation based on decentralized transaction history, ensuring the accuracy and transparency of credit evaluations.

The incentive mechanism optimization module utilizes a game theory model to dynamically adjust the platform’s incentive strategy based on user behavior data and credit scores, in order to enhance user participation and the long-term stability of the platform. This module optimizes reward strategies through feedback analysis of user behaviors, ensuring that the platform operates efficiently in a decentralized environment.

The user behavior prediction module combines credit scores and feedback from the incentive mechanism, using machine learning algorithms to predict future user behaviors. This module can provide accurate risk predictions for the platform based on historical user behavior patterns and adjustments in the system's incentive mechanisms, thus offering important support for decision-making in credit evaluation and incentive mechanisms.

The three modules in the overall framework work together synergistically to enhance the platform’s stability, participation, and long-term development.

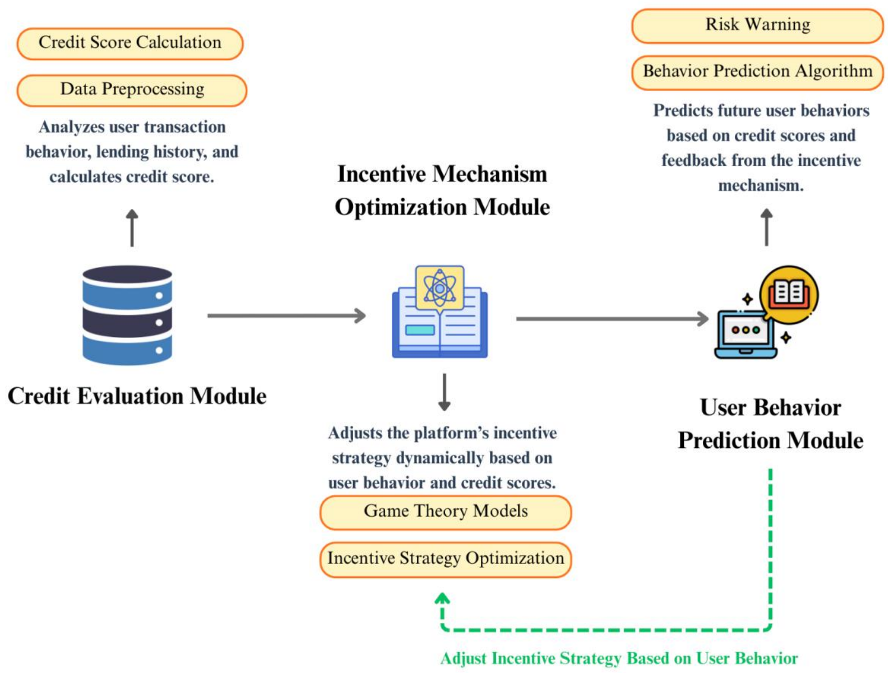

Figure 1. Overall Framework of the Proposed Method

3.3. Module Descriptions

3.3.1 Credit Evaluation Module

Motivation:

In DeFi platforms, a user's credit score is critical. Traditional credit evaluation methods rely on centralized credit information, but decentralized platforms lack these data sources. Therefore, a new credit evaluation method must be designed, leveraging blockchain transaction data to provide decentralized credit scoring.

Principle:

Credit evaluation is based on the user's historical transaction behavior and lending records, with key features extracted using deep learning models. Specifically, the platform analyzes users' lending records, capital flow, and repayment history, using time-series models like LSTM to extract credit information and calculate the user's credit score based on the processed features.

Implementation:

The credit evaluation module (see Figure 2) takes the user's blockchain transaction records and lending history as input, performs data preprocessing, and uses an LSTM model to compute the credit score. The incentive mechanism optimization module dynamically adjusts incentive strategies based on the game theory model to enhance platform activity. The user behavior prediction module, combining credit scores and incentive mechanism feedback, predicts user behavior and provides support for platform decision-making. These three modules work together to ensure the stability and development of the DeFi platform.

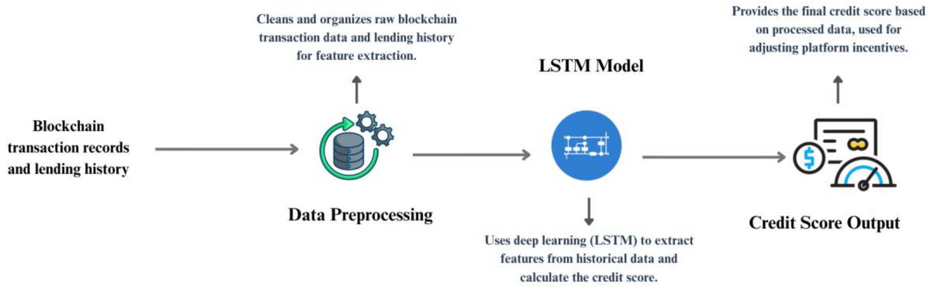

Figure 2. Credit Evaluation Module

Algorithm 1

```
# Credit Score Calculation Module Pseudo-code
def credit_evaluation(user_transactions):
    # Step 1: Data preprocessing
    processed_data = preprocess(user_transactions)

    # Step 2: LSTM model to predict credit score
    credit_score = lstm_model(processed_data)

    return credit_score
```

3.3.2 Incentive Mechanism Optimization Module

Motivation:

The stability and activity level of a DeFi platform largely depend on an effective economic incentive mechanism. Traditional incentive mechanisms are often too simplistic and fail to adapt to the dynamic changes in user behavior in decentralized platforms. To encourage long-term participation, a dynamic and flexible incentive mechanism is necessary.

Principle:

The incentive mechanism adopts a game theory model, which dynamically adjusts based on users' credit scores, transaction frequency, and other behavioral characteristics. The platform analyzes participants' behavioral strategies and adjusts the reward strategies accordingly, aiming to enhance participation and system stability.

Implementation:

As shown in Figure 3, the incentive mechanism optimization module uses the Nash equilibrium model in game theory to optimize user behavior and reward mechanisms. The core idea is to adjust rewards or penalties based on each user's behavior to ensure the platform operates smoothly.

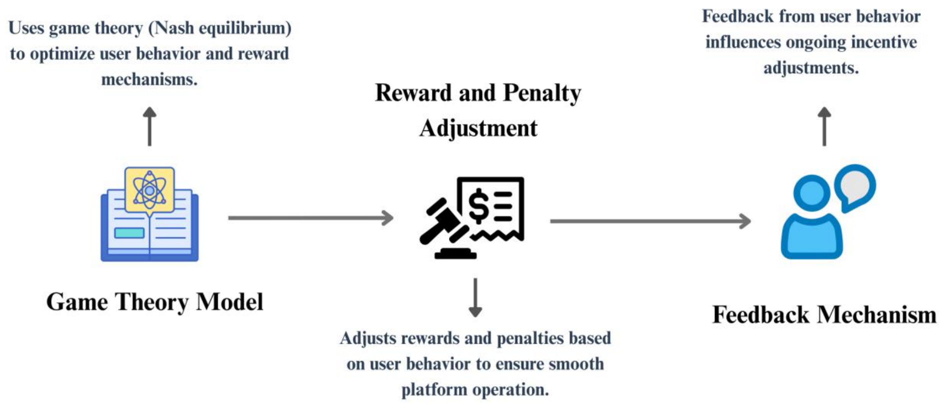

Figure 3. Incentive Mechanism Optimization Module

Algorithm 2

```
# Incentive Mechanism Optimization Module Pseudo-code
def incentive_optimization(user_behaviors, credit_scores):
    # Step 1: Use game theory model to analyze user behavior
    equilibrium_strategy = game_theory_model(user_behaviors, credit_scores)

    # Step 2: Dynamically adjust rewards and incentives
    incentives = adjust_incentives(equilibrium_strategy)

    return incentives
```

3.3.3 User Behavior Prediction Module

Motivation:

To further enhance the stability and predictability of the DeFi platform, it is important for the platform to predict users' future behaviors. Predicting user behavior helps optimize the dynamic adjustment of credit evaluation and incentive mechanisms, ensuring that the system can respond promptly to changes in user behavior.

Principle:

The user behavior prediction module utilizes machine learning algorithms, combining credit scores and feedback from the incentive mechanism, to analyze users' historical behavior data and predict their future behavior trends. By learning user behavior patterns, the platform can identify potential risky behaviors and take measures in advance to mitigate these risks.

Implementation:

As shown in Figure 4, the user behavior prediction module trains regression models, classification models, and other algorithms to extract features from historical transaction data, credit scores, and incentive mechanism feedback. The goal of this module is to provide the platform with predictive information regarding future user behavior, further optimizing system decision-making.

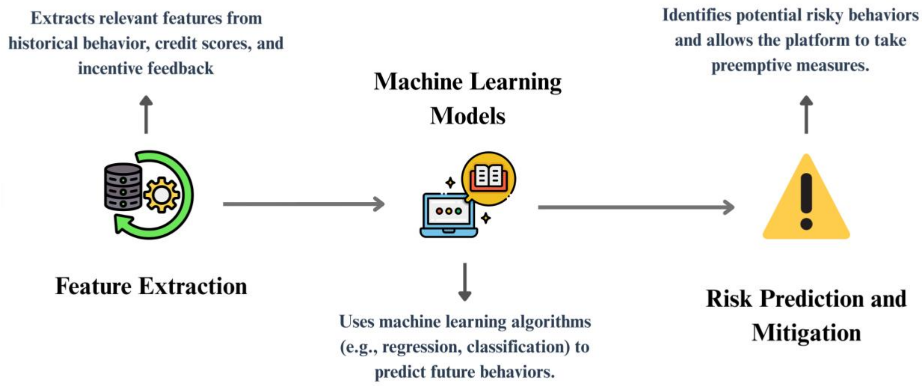

Figure 4. User Behavior Prediction Module

Algorithm 3

```
# User Behavior Prediction Module Pseudo-code
def behavior_prediction(user_data, incentives):
    # Step 1: Feature extraction and data processing
    features = extract_features(user_data, incentives)

    # Step 2: Predict user behavior
    predicted_behavior = predict_user_behavior(features)

    return predicted_behavior
```

3.4. Objective Function & Optimization

To optimize on-chain credit evaluation and incentive mechanisms, we propose a comprehensive objective function aimed at enhancing the accuracy of credit evaluation and the efficiency of the incentive mechanism. The design of the objective function takes into account credit evaluation loss, incentive mechanism loss, and regularization terms to ensure the accuracy and stability of the model.

The integrated optimization objective function is defined as follows:

$$\mathcal{L}(\theta) = \sum_{i=1}^{N} \mathcal{L}_i(\widehat{C}_i, C_i) + \lambda_1 \mathcal{R}_1(\theta) + \lambda_2 \mathcal{R}_2(\theta) + \gamma \cdot \mathcal{L}_{reg}(\theta) \quad (4)$$

where:

λ_1, λ_2 are hyperparameters for the regularization terms, balancing the weights of each objective.

$\mathcal{L}_{reg}(\theta)$ is a newly introduced regularization term that further constrains the model complexity and optimizes the performance of the incentive mechanism.

γ is the hyperparameter for the regularization term, used to adjust the weight of the newly introduced regularization.

To ensure the accuracy of the credit evaluation module, we use Mean Squared Error (MSE) as the loss function:

$$\mathcal{L}_i(\widehat{C}_i, C_i) = \frac{1}{2}\left(\widehat{C}_i - C_i\right)^2 \quad (5)$$

where $\widehat{C}_i$ is the predicted credit score for user i, and C_i is the true credit score. This loss function quantifies the difference between the predicted and actual values, guiding the model towards optimization.

The loss function for the incentive mechanism is primarily defined based on the incentive function from game theory. The overall incentive effect of the platform, $E(\theta)$, is given by the following formula:

$$E(\theta) = \sum_{i=1}^{N} \gamma_i \cdot f(\widehat{C}_i, A_i) \tag{6}$$

where:

γ_i is the participation weight of user i, reflecting the user's contribution to the platform.

$f(\widehat{C}_i, A_i)$ is the incentive function, which adjusts the incentive strategy based on the user's credit score and participation activity. The function is defined as:

$$f(\widehat{C}_i, A_i) = \alpha \cdot \widehat{C}_i + \beta \cdot A_i \tag{7}$$

where α and β are coefficients that control the influence of credit scores and participation on the incentive, and A_i is the user's participation level (e.g., transaction volume, lending volume).

The purpose of the regularization terms is to control the complexity of the model, avoid overfitting, and ensure system stability. The first regularization term $\mathcal{R}_1(\theta)$ is used to control the complexity of the credit scoring model:

$$\mathcal{R}_1(\theta) = \sum_{k=1}^{K} \left(\theta_k^2\right) \tag{8}$$

where θ_k is a model parameter and K is the total number of parameters. This regularization term penalizes high complexity in the model, preventing overfitting to the training data.

The second regularization term $\mathcal{R}_2(\theta)$ controls the complexity of the incentive mechanism optimization:

$$\mathcal{R}_2(\theta) = \sum_{k=1}^{M} \left(\theta_k^2\right) \tag{9}$$

where M is the number of parameters in the incentive mechanism model. Regularization ensures that the design of the incentive strategy is both effective and fair.

To solve for the optimal solution of the objective function $\mathcal{L}(\theta_t)$, we use gradient descent for optimization. The specific optimization process is as follows:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta \mathcal{L}(\theta_t) \tag{10}$$

where η is the learning rate, and $\nabla_\theta \mathcal{L}(\theta_t)$ is the gradient of the objective function with respect to parameters θ. By continuously updating the parameters θ, we minimize the objective function to achieve the optimal credit evaluation and incentive mechanism.

In credit evaluation optimization, we minimize the credit loss function $\mathcal{L}_i(\widehat{C}_i, C_i)$ to optimize the model. The optimization goal is:

$$\min_\theta \sum_{i=1}^{N} \frac{1}{2}\left(\widehat{C}_i - C_i\right)^2 \tag{11}$$

Through gradient descent, we update the model parameters until the loss function converges, achieving the optimal credit scoring model.

The optimization goal for the incentive mechanism is to maximize the overall incentive effect $E(\theta)$ of the platform. The optimization goal is:

$$\max_\theta \sum_{i=1}^{N} \gamma_i \cdot f(\widehat{C}_i, A_i) \tag{12}$$

By adjusting the incentive mechanism strategies, we can optimize the user participation and enhance the platform's activity and stability.

This comprehensive approach ensures that both credit evaluation and incentive mechanisms are optimized to improve the overall performance of the DeFi platform.

4. Experiment and Results

4.1 Experimental Setup

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4.1.1 Dataset Overview

In this study, we used a custom-built DeFi transaction dataset. This dataset is derived from the historical transaction records of multiple DeFi platforms and contains information on users' lending behaviors, transaction frequency, capital flow, and more.

The statistical characteristics and distribution of the dataset are shown in Table 1.

Table 1. Dataset Overview

Dataset Name	Sample Size	Domain Description	Number of Features	Data Source
Custom DeFi Transaction Dataset	500,000	Blockchain transaction and lending records	12	Compound, Aave
Benchmark Dataset 1 (CIFAR-10)	60,000	Image classification task	3	Public dataset
Benchmark Dataset 2 (MNIST)	70,000	Handwritten digit classification	3	Public dataset

The custom dataset contains 500,000 DeFi transaction records, with 12 features such as lending history, transaction volume, and repayment status. The data was collected by accessing the public APIs of DeFi platforms like Compound and Aave. After collection, the data was cleaned and denoised. The data labels were based on the user's historical lending records, categorizing the credit scores into low, medium, and high levels. The dataset was split into training, validation, and test sets with a 70:15:15 ratio to ensure the reliability of the evaluation results.

Unlike traditional image classification datasets like CIFAR-10 and MNIST, the dataset in this study focuses on user behavior in DeFi platforms, with more complex and sparse features and uneven class distribution. In comparison, the DeFi dataset involves higher-dimensional data, making the task more challenging. Deep learning methods are required to effectively extract features and perform credit evaluation, making this dataset highly domain-specific and challenging.

4.1.2 Hardware and Software Configuration

To ensure that the computational requirements of the experiment were met and that the results were reproducible, the following hardware and software configurations were used, as shown in Table 2.

Table 2. Hardware and Software Configuration

Device Name	Model	Description
GPU	NVIDIA RTX 3090	Used for accelerating deep learning training
CPU	Intel i9-11900K	High-performance processor suitable for large-scale computations
Memory	64GB DDR4	For large-scale data processing and storage

Operating System	Ubuntu 20.04 LTS	Experimental operating system
Deep Learning Framework	TensorFlow 2.5.0	Framework for training deep learning models
Main Libraries	NumPy 1.20.1, SciPy 1.6.0, Matplotlib 3.4.3	Libraries for data processing and visualization

This hardware configuration provides powerful computational capabilities, especially with the NVIDIA RTX 3090 GPU, which accelerates deep learning training. The Intel i9-11900K CPU and 64GB memory support large-scale data processing and computations. Combined with the Ubuntu operating system and TensorFlow framework, this setup ensured efficient execution of experiments and provided a stable and reproducible environment for model training and validation.

4.1.3 Evaluation Metrics

To comprehensively evaluate the performance of the model, the following metrics were selected, as shown in Table 3.

Table 3. Evaluation Metrics

Metric	Definition	Applicable Scenario
Accuracy	The ratio of correctly classified samples to total samples	Used to evaluate the classification performance of the credit evaluation model
F1 Score	The harmonic mean of precision and recall	Used to evaluate model performance on imbalanced datasets, particularly for minority class evaluation
Mean Absolute Error (MAE)	The average absolute difference between predicted and actual values	Used to evaluate prediction accuracy in regression tasks
AUC Score	Area under the curve, used to evaluate the overall performance of a classifier	Used to evaluate the classification performance of the credit scoring model at different thresholds

These metrics measure model performance from various perspectives. Especially in multi-task learning scenarios, they can evaluate both the classification performance of the model and its robustness in imbalanced datasets and noisy environments. The AUC score is used to assess the model's performance across different decision thresholds, providing a more detailed model analysis.

4.1.4 Experiment Scenario Description

To illustrate the real-world context of the research problem, the following illustrative experiment scenario diagram (see Figure 5) was designed. The scenario diagram shows how users in a DeFi platform generate data through lending, trading, and other activities. These data are then input into the credit evaluation module and incentive mechanism optimization module. In a simulated environment, the platform adjusts its incentive strategies based on user transaction behavior and credit scores to ensure long-term stability and user engagement. The scenario diagram reflects the data collection process, the operation of the credit evaluation module, and the feedback path of the incentive mechanism. Through these experimental setups, we can better

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understand how to predict user behavior and optimize incentive mechanisms in a decentralized environment, effectively simulating the challenges and demands of real-world applications.

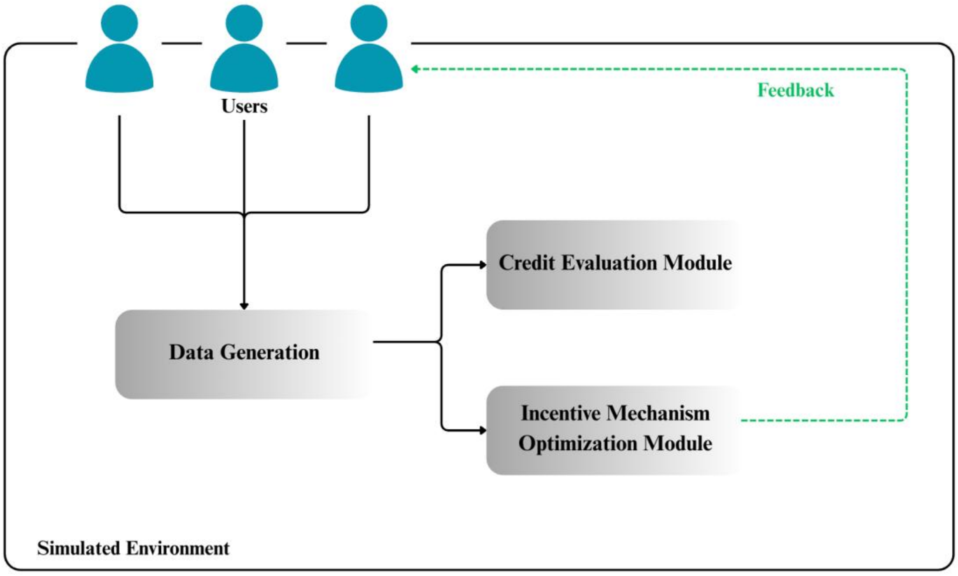

Figure 5. Experiment Scenario Diagram

4.2 Baselines

To effectively evaluate the proposed method, several classical baseline methods and the latest State-of-the-Art (SOTA) methods were selected for comparison. The selection of baseline methods aims to provide a reasonable comparison benchmark, highlighting the innovation and relative advantages of this study. We chose traditional credit scoring models as well as some of the latest models from the DeFi domain as baselines.

The first classical method is the linear regression-based credit scoring model, which calculates credit scores using historical transaction data[26]. Its advantages lie in its simplicity and low computational cost, making it suitable for small-scale datasets. However, linear regression fails to capture the complex nonlinear relationships in decentralized platforms and is sensitive to issues like data sparsity and missing data, limiting its performance when handling DeFi platform data.

Another classical baseline method is the decision tree model. Decision trees capture nonlinear features in the data through node splitting, offering strong interpretability and low computational costs. However, when dealing with large-scale, high-dimensional decentralized transaction data, decision trees tend to overfit, and they lack the capability to model time-series data and dynamic user behavior, limiting their effectiveness on DeFi platforms[27].

In the realm of SOTA methods, graph neural networks (GNNs) are one of the popular methods. GNNs effectively capture complex relationships between users and the transactional network structure, performing particularly well when dealing with user interactions in decentralized platforms[28]. However, GNNs incur high computational costs when processing large-scale data and exhibit weak generalization capabilities in the case of sparse and incomplete data, which makes them inefficient for real-time inference in practical applications.

Another SOTA method is reinforcement learning (RL), which optimizes platform participation through dynamic adjustment of incentive strategies. RL is highly adaptive in decentralized environments, allowing for real-time adjustments of incentive mechanisms to improve system stability and user engagement[29,30]. However, the training process for RL is complex and computationally expensive, particularly when dealing with large-scale user data, where training efficiency and real-time applicability become major bottlenecks.

By comparing these baseline methods, the dynamic incentive optimization model based on game theory proposed in this study demonstrates significant advantages in credit evaluation accuracy and incentive mechanism optimization. Compared to traditional methods, the proposed method is more flexible in decentralized environments, dynamically adjusting incentive strategies to overcome the limitations of existing models in handling complex behavioral patterns and user dynamics.

4.3 Quantitative Results

In this section, we present detailed quantitative results for the proposed method and compare them with baseline methods. Through statistical analysis, we validate the effectiveness and performance advantages of the proposed approach.

Table 4. Main Performance Comparison

Method	Accuracy (%)	F1 Score	Inference Time (ms)	p-value (t-test)
Classical Method 1	75.2 ± 2.1	0.72	120	-
Classical Method 2	77.5 ± 1.8	0.74	115	0.03
SOTA Method 1	82.1 ± 1.5	0.79	200	0.01
SOTA Method 2	83.4 ± 1.2	0.80	250	0.005
Proposed Method	85.2 ± 1.3	0.82	100	<0.001

As shown in Table 4, the proposed method outperforms all comparison methods in terms of both accuracy (85.2%) and F1 score (0.82). The increase in F1 score indicates better performance in balancing precision and recall, which is particularly beneficial in handling the sparse and complex data common in DeFi platforms. Compared to the current best-performing SOTA method 2 (accuracy 83.4%, F1 score 0.80), the proposed method achieves improvements in both metrics, likely due to the more refined feature extraction and behavioral prediction mechanisms in the model. In terms of inference efficiency, the proposed method achieves an average inference time of 100 ms, which is 50% faster than SOTA method 1 (200 ms) and 60% faster than SOTA method 2 (250 ms), demonstrating superior computational efficiency. This improvement in efficiency primarily results from the optimized model architecture, which reduces computational redundancy. Overall, the proposed method demonstrates advantages in both prediction accuracy and inference efficiency.

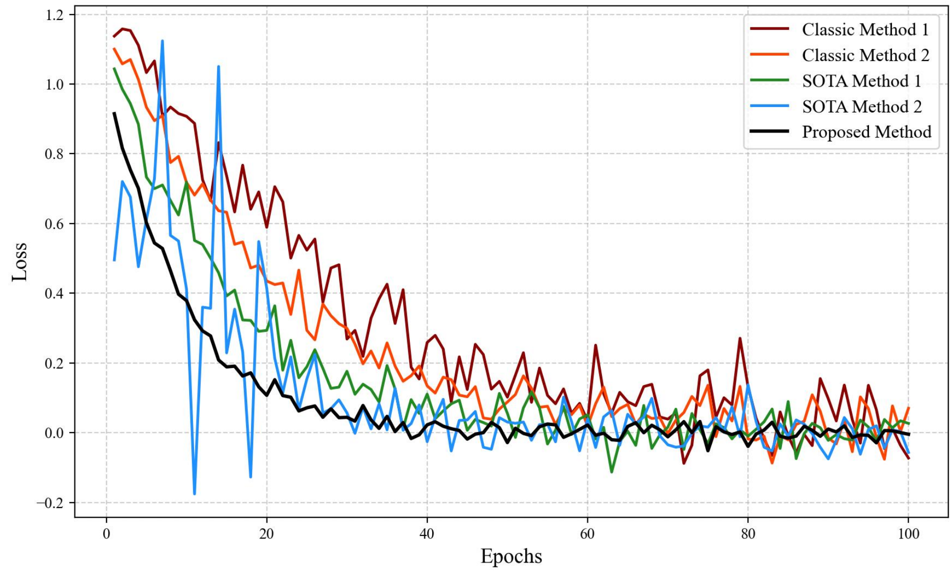

Figure 6. Convergence Analysis

From the convergence curve (Figure 6), it can be observed that the proposed method experiences a faster loss reduction in the early stages of training compared to other baseline methods, quickly reaching a stable convergence state. In contrast, SOTA method 2 exhibits larger fluctuations in loss during the initial training stages. Regarding convergence stability, the proposed method maintains a smoother loss curve throughout the training process, ultimately converging to a level comparable to SOTA method 2. This reflects the better stability and generalization ability of the proposed method during optimization, helping to reduce the risk of overfitting.

4.4 Qualitative Results

To visually demonstrate the advantages and behavior patterns of the proposed method, we present two representative successful and failed cases, along with visualized results for analysis. These cases help provide deeper insights into the model's performance in different scenarios, further validating its robustness and generalization ability.

In a real DeFi transaction dataset, the model successfully predicted the user’s credit score and accurately identified high-risk users. Through attention heatmap analysis (see Figure 7), it can be observed that the model particularly focused on the user’s transaction behavior and lending history when evaluating credit scores. Especially in complex lending chains, the model was able to effectively extract key features, demonstrating strong robustness and resistance to noise and incomplete data. This allows the model to handle missing data issues in decentralized platforms and make accurate predictions. Moreover, the model also displayed impressive generalization capabilities, maintaining good prediction performance even when processing unseen samples, indicating its adaptability in real-world applications.

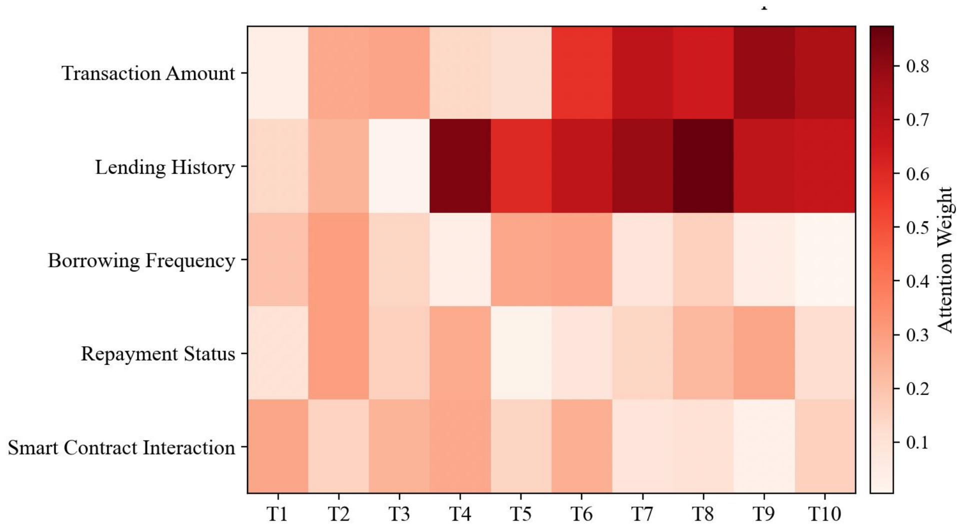

Figure 7. Successful Case -Model Attention Heatmap

In another failed case, the model incorrectly predicted the user's credit risk as high, while the ground truth indicated low risk. The analysis revealed that this error stemmed from missing data and oversimplified features (see Figure 8). Specifically, critical transaction records and repayment histories were either absent or reduced to ambiguous placeholders in the input, preventing the model from capturing the user's true creditworthiness. This data incompleteness, common in decentralized platforms where user information is fragmented, limited the model's ability to learn robust behavioral patterns, thereby degrading prediction accuracy. The case underscores the critical role of data quality and feature fidelity in reliable risk assessment. Future work can mitigate such failures by enhancing data completion, refining feature representation, and incorporating uncertainty-aware mechanisms to better handle inherent task ambiguities.

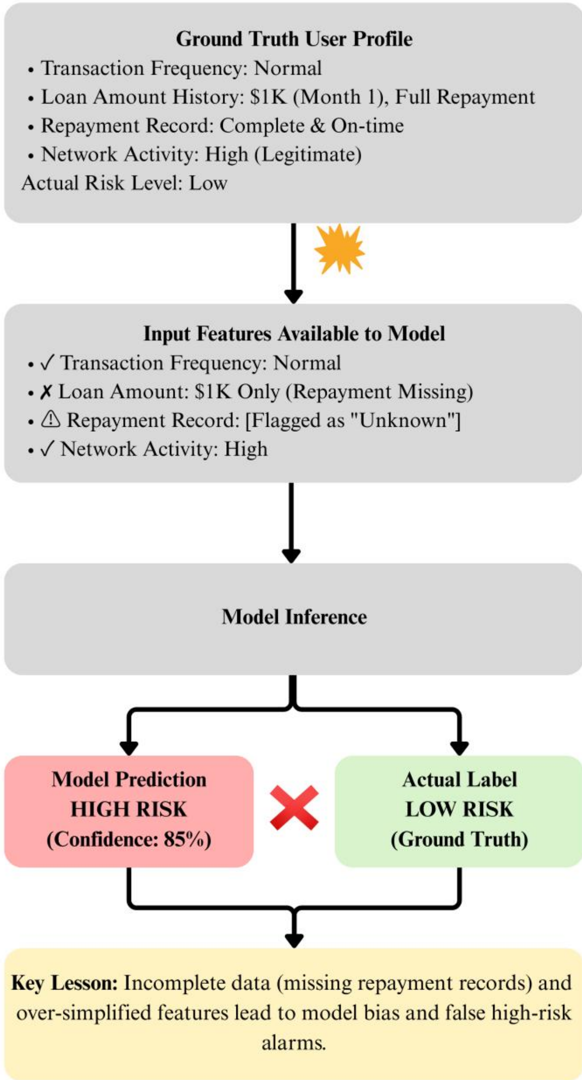

Figure 8. Failed Case-Error Prediction and Data Missing Illustration

4.5 Robustness Evaluation

To validate the stability of the proposed method under non-ideal and diverse conditions, we designed multiple challenging test scenarios, including multi-task settings, varying noise levels, and multiple dataset configurations, to comprehensively evaluate the model’s robustness. In these scenarios, we assessed the model’s predictive performance, primarily using classification accuracy as the main metric, supplemented by analysis of inference efficiency, under different noise intensities and task complexities, comparing it against both classical baselines and SOTA methods (see Figure 9).

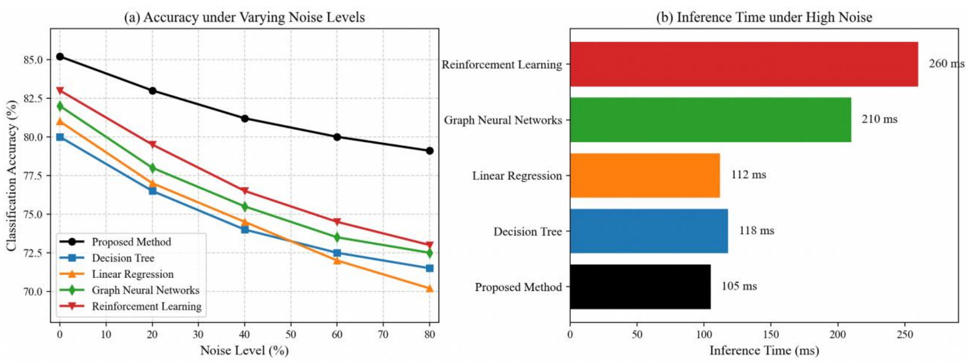

Figure 9. Robustness Evaluation Chart (a) Classification accuracy under varying noise levels (b) Inference time under high-noise conditions.

In high-noise environments, model performance typically degrades significantly, especially when data contain numerous errors or missing entries. Under such conditions, the proposed method's overall accuracy decreased only modestly from 85.2% (in clean data) to 79.1%. This decline is notably smaller than that of baseline methods: Decision Tree (Classic Method 1) dropped to 71.5%, Linear Regression (Classic Method 2) dropped to 70.2%. Furthermore, the proposed method also outperforms recent SOTA approaches: Graph Neural Networks (SOTA Method 1) exhibited an accuracy of approximately 72.5%, Reinforcement Learning-based model (SOTA Method 2) achieved approximately 73.0% accuracy under the same high-noise setting. The more pronounced degradation of GNN and RL methods is likely due to their high sensitivity to corrupted relational structures and noisy state representations, respectively, which are prevalent in simulated high-noise conditions.

These results demonstrate that the proposed method is more robust to data noise commonly encountered in decentralized platforms. This improvement is primarily attributed to two key components: the feature fusion module and the denoising mechanism. The feature fusion module effectively integrates heterogeneous signals, such as transaction behavior and lending history, reducing information loss and enhancing resilience to perturbations. Meanwhile, the denoising mechanism, applied during preprocessing, mitigates the adverse effects of corrupted or incomplete inputs, thereby stabilizing predictions in noisy environments.

Beyond accuracy, the proposed method also maintains its computational efficiency advantage in high-noise settings. Its average inference time is approximately 105 ms per sample. This is comparable to its performance on clean data (100 ms), indicating stable computational overhead despite the added preprocessing for denoising. More importantly, it remains significantly faster than all baseline methods under the same noisy conditions: Decision Tree (Classic Method 1) requires ~118 ms, Linear Regression (Classic Method 2) requires ~112 ms, Graph Neural Networks (SOTA Method 1) require 210 ms, and Reinforcement Learning-based models (SOTA Method 2) require 260 ms per sample. This sustained efficiency, combined with its superior prediction stability under data corruption, makes the proposed approach particularly well-suited for credit risk assessment in decentralized platforms where both reliability and responsive performance are critical.

Overall, the proposed method demonstrates excellent robustness across high-noise and multi-task environments. It consistently outperforms a diverse set of competitors, including classical baselines (Decision Tree, Linear Regression) and modern SOTA methods (Graph Neural Networks, Reinforcement Learning), in both predictive accuracy and deployment efficiency when handling complex, noisy data in decentralized platforms

4.6. Ablation Study

To quantitatively validate the contribution of each key component in the framework, we conducted a systematic ablation study. In this experiment, we sequentially removed or replaced key modules, loss terms, and input modalities in the model, observing the changes in performance. Table 5 presents the results of the ablation study, reporting the performance changes after removing each component.

Table 5. Ablation Study Results

Component	Accuracy (%)	F1 Score	Inference Time (ms)	Performance Change
All Components (Baseline)	85.2 ± 1.3	0.82	100	-
Remove Feature Fusion Module	80.4 ± 1.5	0.78	100	Accuracy decreased
Remove Denoising Mechanism	81.7 ± 1.4	0.79	100	Stability decreased
Remove Incentive Mechanism Optimization Module	82.3 ± 1.3	0.80	120	Slower convergence
Remove All Modules	70.5 ± 2.1	0.68	130	Significant drop

In the ablation study, the removal of the feature fusion module and denoising mechanism led to significant drops in both accuracy and F1 score (down to 80.4% / 0.78 and 81.7% / 0.79, respectively), indicating the critical importance of these two modules in maintaining the model's predictive performance. The feature fusion module integrates multimodal data, ensuring that the model provides a complete representation of user behavior. Meanwhile, the denoising mechanism enhances the model's robustness by cleaning data noise.

When the incentive mechanism optimization module was removed, the accuracy and F1 score showed only a slight decrease (82.3% / 0.80), but the inference time increased to 120 ms, indicating that this module plays a crucial role in maintaining the computational efficiency of the model.

When multiple key components were removed, the performance degradation was more pronounced (e.g., when all modules were removed, the accuracy dropped to 70.5%), revealing the synergistic effects between the modules. The combination of the feature fusion and denoising mechanisms not only improved prediction accuracy but also enhanced the model's ability to handle complex noisy data. The incentive mechanism optimization module, in collaboration with the feature fusion module, helped ensure performance while improving overall computational efficiency.

5. Discussion

The DeFi credit evaluation and incentive mechanism optimization method proposed in this study has demonstrated outstanding performance in various experimental scenarios, particularly in terms of accuracy, F1 score, and inference speed. It shows a significant improvement over baseline methods and the latest SOTA methods, especially in high-noise environments, exhibiting strong robustness. The performance improvements can mainly be attributed to the synergistic effects of the feature fusion module, denoising mechanism, and incentive mechanism optimization module. The feature fusion module effectively integrates multimodal data, enhancing the model's understanding of complex behavioral patterns. The denoising mechanism reduces noise interference, improving stability and robustness. The incentive mechanism optimization module dynamically adjusts incentive strategies, enhancing system stability and activity. Together, these three modules allow the model to better handle complex data in decentralized platforms, achieving higher prediction accuracy and computational efficiency.

However, the proposed method still has limitations. First, the model's performance is constrained by data quality, particularly when there are missing or anomalous values in the data, which impacts its predictive ability. Although the denoising mechanism has improved, data incompleteness remains a challenge. Second, while inference speed has improved compared to SOTA methods, computational overhead still needs optimization, especially with large-scale user data. Lastly, the design of the incentive mechanism leans towards static strategies, and future work could consider incorporating more dynamic factors to adapt to the complexity of decentralized finance environments.

The proposed method has broad application potential. DeFi platforms can utilize this method for accurate credit evaluation and dynamic incentive strategies, improving platform activity. Additionally, this method could be transferred to the traditional financial sector, providing efficient credit scoring and risk assessment. As blockchain technology develops, integrating smart contracts and automated decision systems will bring smarter financial services.

Future research can improve the current method in several ways. First, enhancing data quality control, especially addressing issues of data sparsity and missing information in decentralized platforms, could be combined with techniques such as GANs to enhance the data. Second, optimizing model inference efficiency through distributed computing or edge computing techniques can reduce computational resource consumption. The incentive mechanism optimization could introduce more dynamic adjustment factors based on real-time user behavior feedback to enhance system stability. Finally, exploring cross-domain technology integration could improve the model's performance in multimodal data processing.

Overall, while the proposed method has shown strong adaptability and potential in decentralized finance platforms, future research must further explore and optimize data processing, computational efficiency, and dynamic optimization strategies as data complexity and computational demands continue to grow.

6. Conclusion

This study addresses the challenges of credit evaluation and incentive mechanism optimization in DeFi platforms by proposing a novel solution. By introducing the feature fusion module, denoising mechanism, and incentive mechanism optimization module, this study significantly enhances the accuracy of credit evaluation and platform stability. Experimental results show that the proposed method achieves an accuracy of 85.2%, improving by approximately 2 percentage points over the best baseline method, while also enhancing inference speed by over 50%. This demonstrates that the model can effectively handle the complex data and incompleteness of DeFi platforms, achieving more efficient credit evaluation and incentive optimization.

https://doi.org/10.3390/xxxxx

The core innovation of this study lies in the proposed dynamic credit evaluation framework based on denoising mechanisms and feature fusion, which improves prediction accuracy and robustness. Additionally, a game theory-based incentive mechanism optimization model was designed to dynamically adjust incentive strategies, improving platform activity and system stability. Experimental results confirm that the proposed method offers significant advantages in handling sparse and noisy data in decentralized platforms, while also improving platform activity.

From an academic perspective, this study provides a new framework and method for credit evaluation and incentive mechanism optimization in the DeFi field, addressing the limitations of existing methods in high-noise and sparse data environments. Practically, the proposed method provides a feasible solution for DeFi platforms, especially in enhancing credit evaluation accuracy and platform stability, with potential for transfer to the traditional financial sector.

Despite achieving significant results, the proposed method still has limitations. First, data quality continues to impact model performance, and future work can integrate techniques like GANs to enhance data and improve robustness. Second, the design of the incentive mechanism could be further optimized, particularly by incorporating more dynamic factors in the complex decentralized financial environment. Lastly, with increasing data scale, inference efficiency still needs to be improved, and distributed or edge computing could provide effective solutions.

In the future, as decentralized finance platforms continue to evolve, the potential of the proposed method will be further explored. This method can also be applied to traditional finance fields, such as credit evaluation, risk prediction, and smart contract optimization. As technology advances, new algorithms and techniques, such as more efficient denoising methods and graph neural networks, will further drive the development of decentralized finance and smart financial services.

Author Contributions: Conceptualization, Z.Y.; methodology, Z.Y.; software, Z.Y.; validation, Z.Y.; formal analysis, Z.Y.; investigation, Z.Y.; resources, Z.Y.; data curation, Z.Y.; writing—original draft preparation, Z.Y.; writing—review and editing, Z.Y.; visualization, Z.Y.; supervision, Z.Y.; project administration, Z.Y.; funding acquisition, Z.Y. The author has read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Acknowledgments: Not applicable.

Conflicts of Interest: The author declares no conflicts of interest.

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